

UNIVERSITY OF MALTA

Institute for Sustainable Energy

ON THE USE OF MEASURE-CORRELATE-PREDICT METHODOLOGIES AND
ENERGY DEMAND FORECASTING TO ASSESS ENERGY STORAGE
CAPABILITIES FOR OFFSHORE WIND FARMS.

by

Ing. Michael D. Mifsud

B. Elec. Eng. (Hons.), M. Sc. (Melit.), MBA (Henley), MIEEE

November 2022

A dissertation submitted in fulfilment of the requirements of the award of Doctor of Philosophy in
Sustainable Energy



University of Malta Library – Electronic Thesis & Dissertations (ETD) Repository

The copyright of this thesis/dissertation belongs to the author. The author's rights in respect of this work are as defined by the Copyright Act (Chapter 415) of the Laws of Malta or as modified by any successive legislation.

Users may access this full-text thesis/dissertation and can make use of the information contained in accordance with the Copyright Act provided that the author must be properly acknowledged. Further distribution or reproduction in any format is prohibited without the prior permission of the copyright holder.

Copyright Notice

- 1) Copyright in text of this dissertation rests with the Author. Copies (by any process) either in full, or of extracts may be made only in accordance with regulations held by the library of the University of Malta. Details may be obtained from the Librarian. This page must form part of any such copies made. Further copies (by any process) made in accordance with such instructions may not be made without the permission (in writing) of the author.
- 2) Ownership of the right over any original intellectual property which may be contained in or derived from this dissertation is vested in the University of Malta and may not be made available for use by third parties without the written permission of the University, which will prescribe the terms and conditions of such an agreement.

Abstract

Energy storage is crucial for the continued penetration of renewable energy. One of the most important reasons for this is that, for a given point of time, the availability of renewable energy resources rarely matches the demand for electrical energy. The integration of offshore windfarms with energy storage facilities, requires a capital-intensive investment which can only be justified by an adequate return on investment (ROI). Currently, Measure-Correlate-Predict (MCP) analysis is used to assess the viability of offshore windfarms while energy demand forecasting is normally used to manage and plan the electricity grid infrastructure. This research combined wind energy prediction methodologies with Energy Demand Forecasting (EDF) methodologies to size the energy storage capacity for an offshore windfarm and evaluated the economic feasibility.

This research analysed various regression techniques for MCP analysis. Data from a Light Detection and Ranging (LiDAR) system were utilised. The study was extended to analyse the behaviour of a hypothetical floating windfarm, situated off the Northern Coast of the Island of Malta. The effect of using the different regression techniques for MCP analysis on the power output from the windfarm could therefore be evaluated.

The second part of the research used a combination of ARIMA and regression techniques to forecast the energy demand over several years. The output from the windfarm was applied to a model which integrated the said windfarm to an Energy Storage System (ESS) and the electricity grid. Measurement matrices were used to compare the behaviour of the combined windfarm, ESS and electricity grid, based on the actual and predicted data from the various regression techniques used for the MCP analysis and EDF. This created a matrix of results which was used to determine the optimal combination of regression techniques used for MCP analysis and EDF, following which, the optimal capacity of the ESS was established. The long-term behaviour of the windfarm and the of the energy storage system were also predicted. The Levelised Cost of Energy (LCOE) for the windfarm and the Levelised Cost of Storage (LCOS) for the Energy Storage System were also calculated, using different windfarm scenarios, and analysing the error due to the use of the MCP and EDF methodologies.

This research therefore established a methodology for combining MCP and EDF to determine the optimal capacity of an ESS which was coupled to an offshore windfarm and the electricity grid. The error in establishing this capacity was determined. The end result was the determination of the LCOE of the windfarm and the LCOS of the ESS based on the combination of MCP analysis and EDF, together with the error introduced due to the use of the two methodologies.

Acknowledgements

Special acknowledgements to my supervisor Professor Ing. Tonio Sant, Ph. D. (Delft) and co-supervisor Dr. Ing. Robert N. Farrugia Ph.D. (Melit.), for their guidance and support during the six-year duration of this research project.

My wife Charmaine for her interminable patience and for supporting an endeavour, for which she was largely unprepared. She was and always will be, an inspiration, and this task would not have been completed without her continuous morale support and encouragement. Thanks also to my two daughters Martina and Michaela, who accompanied me on the lonely periods spent in thought and travail with their humour, encouragement, fortitude, playfulness, and the accompaniment of piano music.

To my now aging parents, whose upbringing and inspiration served as a foundation for achieving this result.

My sincere gratitude also extends to the following:

Joseph Schiavone from the Meteorological Office at the Malta International Airport is acknowledged for providing the data from the Luqa Weather Station.

Manuel Aquilina, lab officer at the University of Malta, for technical assistance in collecting and organising the data from the Institute for Sustainable Energy's LiDAR system at Qalet Marku.

Ing Stefan Calamatta and Ing Carmen Abela, at EneMalta Corporation for providing the energy demand data for the Maltese Islands.

The Institute for Sustainable Energy for supplying the LiDAR system was purchased through the European Regional Development Fund (ERDF nr 335 – “Solar Research Laboratory”), Cohesion Policy 2007-2013, Investing in Competitiveness for a Better Quality of Life, part financed by the European Union.

The Department of Mechanical Engineering for making available the windPRO® 2.7 software, which was funded by the project “Setting up of Mechanical Engineering Computer Modelling and Simulation Laboratory”, partially financed by the European Regional Development Fund (ERDF nr 79) – Investing in Competitiveness for a Better Quality of Life, Malta 2007-2013.

Table of Contents

Copyright Notice.....	2
Abstract	3
Acknowledgements	4
Table of Contents.....	5
List of Figures	11
List of Tables.....	24
List of Abbreviations.....	33
List of Symbols.....	35
1. Introduction	38
1.1 Measure-Correlate-Predict Methodology	39
1.2 Offshore Floating Windfarms	40
1.3 Energy Storage Systems	40
1.4 Energy Demand Forecasting	41
1.5 Data Acquisition.	42
1.6 Problem Statement	42
1.7 Objectives.	43
1.8 Organisation of Work	44
1.9 Conclusion	47
2 Literature Review	49
2.1 An Overview the Measure-Correlate-Predict Methodology	49
2.1.1 <i>A Measure-Correlate-Predict Methodology for Wind Direction</i>	52
2.2 Wake Models for Windfarms	53
2.3 Dimension Reduction	53
2.4 Floating Wind Farm Concepts	55
2.5 The Levelised Cost of Energy of Floating Offshore Windfarms	57
2.6 Energy Storage Systems for Offshore Wind	58
2.6.1 <i>The Challenges for Energy Storage for Offshore Wind Farms</i>	60
2.6.2 <i>Energy Storage Systems</i>	60
2.7 Advantages and Disadvantages of Energy Storage Systems and Capacity Ranges	66
2.8 Levelised Cost of Storage	69
2.9 Energy Demand Forecasting	71
2.10 Forecasting of Economic Trends	73
2.11 Operating Scenarios for Energy Storage Integrated with the Electricity Grid	74
2.12 Measurement Metrics	75
2.13 Identification of Knowledge Gaps	76
2.14 Conclusion	77
3 Theoretical Background	79
3.1 Measure-Correlate-Predict Methodology	79
3.1.1 <i>Simple and Multivariate Linear Regression</i>	79
3.1.2 <i>Artificial Neural Networks (Multilayer Perceptrons)</i>	82
3.1.3 <i>Decision Trees</i>	84

3.1.4	<i>Support Vector Regression</i>	85
3.1.5	<i>MCP Methodology Applied to Wind Direction</i>	88
3.2	The Basis of ARIMA – the Box-Jenkins Methodology	90
3.2.1	<i>Phase 1: Data Preparation and Model Selection</i>	91
3.2.2	<i>Phase 2: Estimation of the ARIMA Model Parameters for Time-Series Data</i>	93
3.2.3	<i>Phase 3: Forecasting with ARIMA Model</i>	96
3.3	Dimension Reduction	97
3.4	Metrics	98
3.4.1	<i>Measurement Metrics for Wind Speed</i>	98
3.4.2	<i>Measurement Metrics for Windfarm and Energy Storage System Power Output</i>	99
3.5	Levelised Cost of Energy and Levelised Cost of Storage	99
3.6	Conclusion	101
4	Methodology.....	102
4.1	Addressing the Research Questions	102
4.2	Prediction of Wind Speed	104
4.2.1	<i>Determining the Adequate Regression Techniques for the MCP Methodology</i>	104
4.2.2	<i>Applying the Predicted Wind Data to the Hypothetical Windfarm</i>	107
4.3	Econometric and Demographic Forecasting	109
4.4	Energy Demand Forecasting	109
4.4.1	<i>First Methodology used to Forecast Energy Demand</i>	111
4.4.2	<i>Second Methodology used to Forecast Energy Demand</i>	111
4.4.3	<i>Forecasting Energy Demand for the Years 2016-2020</i>	112
4.5	Energy Storage Model in Matlab® and Simulink®	113
4.6	Applying the Wind Farm Power Output and Energy Demand Time-Series to the Model	116
4.7	Defining the Optimal Storage Capacity	122
4.8	Establishing the LCOE of the Offshore Windfarm and the LCOS of the ESS	123
4.9	Conclusion	125
5	Data Acquisition and Preparation	126
5.1	Wind Data	126
5.1.1	<i>The 3Tier Wind Data</i>	126
5.1.2	<i>The Malta International Airport (Luqa) Meteorological Station</i>	127
5.1.3	<i>The University of Malta's LiDAR Station at Qalet Marku</i>	127
5.2	Wind Data Preparation and Analysis	128
5.2.1	<i>3Tier Data (Wind-Rose for 2007 and 2008)</i>	129
5.2.2	<i>Luqa Data (Wind-Rose for 2007 and 2008)</i>	129
5.2.3	<i>Sectorial Analysis</i>	130
5.2.4	<i>LiDAR Data</i>	131
5.3	Econometric Data	133
5.4	Demographic Data	133
5.5	Energy (Electricity Generation) Demand Data	135
5.6	Conclusion	135
6	Design of Windfarm and Energy Storage System Models.....	137
6.1	Design of Windfarms using WindPRO®	137
6.1.1	<i>First Windfarm Design (WF1) using 5 MW Wind Turbines</i>	137
6.1.2	<i>Second Windfarm Design (WF2) using 8 MW Wind Turbines</i>	139
6.2	The Design of the Energy Storage System in Matlab® and Simulink®	140
6.2.1	<i>The Floating Offshore Windfarm</i>	145

6.2.2	<i>Energy Demand</i>	145
6.2.3	<i>The Windfarm Controller</i>	146
6.2.4	<i>The Energy Storage System (ESS)</i>	147
6.3	<i>Conclusion</i>	148
7	Results – Part 1 – Measure-Correlate-Predict Methodology	150
7.1	Results with 3Tier and Luqa Data for the Years 2007 and 2008	150
7.1.1	<i>Simple and Multivariate Linear Regression – 3Tier-Luqa Data Sectorial Analysis</i>	151
7.1.2	<i>Artificial Neural Networks 3Tier Data – Luqa Data Sectorial Analysis</i>	152
7.1.3	<i>Decision Trees – 3Tier-Luqa Data Sectorial Analysis</i>	153
7.1.4	<i>Support Vector Regression – 3Tier-Luqa Data Sectorial Analysis</i>	154
7.1.5	<i>Comparing the Overall Results for the 3Tier Sectorial Analysis</i>	154
7.1.6	<i>Conclusion</i>	157
7.2	LiDAR Data Height Analysis for the Years 2015 and 2016	157
7.2.1	<i>Linear Regression – LiDAR Data</i>	158
7.2.2	<i>Artificial Neural Networks (ANN) – LiDAR Data</i>	158
7.2.3	<i>Decision Trees (DT) – LiDAR Data</i>	159
7.2.4	<i>Support Vector Regression (SVR)– LiDAR Data</i>	160
7.2.5	<i>Comparing the Results from the LiDAR Data</i>	160
7.2.6	<i>Conclusion</i>	162
7.3	Applying Measured Wind Speed and Direction to the Hypothetical Windfarm Model Designed in windPRO®	163
7.3.1	<i>5 MW Wind Turbines (WF1)</i>	163
7.3.2	<i>8 MW Wind Turbines (WF2)</i>	165
7.4	Applying Predicted Wind Speed and Direction to the Hypothetical Windfarm Model Designed in WindPRO® (WF1)	166
7.4.1	<i>Wind Speed and Direction with Regression Technique</i>	167
7.4.2	<i>Hypothetical Windfarm Power Output with Regression Technique</i>	171
7.4.2	<i>Conclusions from the Analysis of the Power Output from the Hypothetical Offshore Windfarm</i>	174
8	Results - Part 2- Econometric, Demographic and Energy Demand Forecasting	176
8.1	Econometric and Demographic Forecasts	176
8.1.1	<i>Econometric Forecasts</i>	176
8.1.2	<i>Demographic Forecasts</i>	179
8.2	Energy Demand Forecasting	179
8.3	Conclusions for Econometric, Demographic and Energy Demand Forecasting	189
9	Results – Part 3 – Determining the Optimal Combination of MCP and Energy Demand Forecasting Methodologies	190
9.1	Results with Measured Wind Speed and Actual Energy Demand	190
9.2	Establishing a Matrix from Combinations of MCP and Energy Forecasting for the Different Regression Techniques	194
9.2.1	<i>An Offshore Windfarm with an Installed Capacity of 250 MW</i>	195
9.2.2	<i>Results for an Offshore Windfarm with an Installed Capacity of 200 MW and 150 MW</i>	204
9.3	Dimension Reduction from Results of the Matrix Analysis	204
9.3.1	<i>Energy Discharged from the ESS to the Electricity Grid</i>	207
9.3.2	<i>Curtailed Energy from the Windfarm</i>	208
9.3.3	<i>Energy from the Windfarm Transferred to the Electricity Grid</i>	209
9.4	Results from the Optimal Combination of Regression Techniques	211

9.5	Conclusions from the Determination of the Optimum Combination of MCP and Energy Demand Forecasting Methodologies.	214
10	Results – Part 4 - Determining the Optimum ESS Capacity	216
10.1	The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 250 MW	217
10.1.1	<i>Using Optimal MCP and Energy Demand Methodology Combination (DT_DT).</i>	217
10.1.2	<i>Using Measured Wind Speed and Direction and Energy Demand</i>	222
10.2	The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 200 MW	227
10.2.1	<i>Using the Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodology (DT_DT).</i>	227
10.2.2	<i>Using Measured Wind Speed and Direction and Energy Demand</i>	229
10.3	The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 150 MW	231
10.3.1	<i>Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)</i>	231
10.3.2	<i>Using Measured Wind Speed and Direction and Energy Demand</i>	233
10.4	Using the Energy Discharged to the Electricity Grid from the ESS.	235
10.4.1	<i>Windfarm with an Installed Capacity of 250 MW</i>	236
10.4.2	<i>Windfarm with an Installed Capacity of 200 MW</i>	239
10.4.3	<i>Windfarm with an Installed Capacity of 150 MW</i>	243
10.5	Establishing an Optimal Capacity for the ESS using the Rate of Change of Curtailed Energy and Energy Discharged from the ESS	248
10.6	Conclusions from the Analysis to Determine the Optimal ESS Capacity	252
11	Results – Part 5- Determining the LCOE and the LCOS	254
11.1	System Behaviour	256
11.2	The Costs Associated with an Offshore Floating Windfarm	260
11.2.1	<i>CAPEX</i>	260
11.2.2	<i>OPEX</i>	261
11.2.3	<i>DECEX</i>	262
11.3	The Costs Associated with a Lithium-Ion and Vanadium Redox Battery Energy Storage Systems	262
11.3.1	<i>Lithium-Ion Energy Storage Systems CAPEX</i>	263
11.3.2	<i>Lithium-Ion Energy Storage Systems OPEX</i>	264
11.3.3	<i>Lithium-Ion Energy Storage Systems DECEX</i>	264
11.3.4	<i>Vanadium Redox Battery Energy Storage Systems CAPEX</i>	264
11.3.5	<i>Vanadium Redox Battery Energy Storage Systems OPEX</i>	265
11.3.6	<i>Vanadium Redox Battery Energy Storage Systems DECEX</i>	265
11.3.7	<i>Physical Sizing</i>	265
11.4	LCOE for the Offshore Floating Windfarm	266
11.4.1	<i>Conclusions from the LCOE Calculations for the Floating Windfarm</i>	269
11.5	Levelised Cost of Storage for the Energy Storage System	270
11.5.1	<i>Lithium-Ion Battery Energy Storage System</i>	272
11.5.2	<i>Vanadium Redox Battery Energy Storage System</i>	273
11.6.3	<i>Levelised Cost of Storage Results</i>	274
11.6	Conclusions from the Levelised Cost of Storage Calculations	276
12	Discussion and Conclusions	278
12.1	Addressing the Knowledge Gap	279

Addressing the Research Questions	281
12.3 Main Conclusions	282
12.3.1 Regression techniques for MCP	282
12.3.2 Econometric, Demographic and Energy Demand Forecasting	282
12.3.3 The Ideal Combination of Regression Techniques for the MCP and Energy Forecasting Methodologies.	283
12.3.4 Conclusions from the Analysis to Determine the Optimal ESS Capacity	283
12.3.5 Conclusions from the LCOE and LCOS	284
12.4 Opportunities for Further Research	285
12.5 Implications for the Wind Energy Industry	286
References.....	288
A. Filtering the LiDAR data.....	301
A.1 2015 LiDAR Data	301
A.2 2016 LiDAR Data	301
A.3 2017 LiDAR Data	302
B. Quarterly Economic Data.....	303
C. Measure-Correlate-Predict Results – 3Tier Data.....	305
C.1 Regression Techniques for the MCP methodology.	305
C.2 Results from Decision Trees Regression and Support Vector Regression Techniques	309
C.1.1 Decision Trees	310
C.1.2 Support Vector Regression	312
D. Forecasted Quarterly Economic Data using ARIMA and SARIMA Methodology.	314
E. Econometric and Demographic Forecasts.....	315
F. Energy Demand Forecasting	319
G. Matrix Results for Windfarms with Installed Capacities of 200 MW and 150 MW	326
G.1 Results for a Windfarm with an Installed Capacity of 200 MW	326
G.2 Results with a Windfarm with an Installed Capacity of 150 MW	335
H. Curtailed Energy as a Criterion for Establishing the Optimal Capacity of the Energy Storage System.....	341
H.1 An Offshore Windfarm with an Installed Capacity of 200 MW	341
H.1.1 Using the Optimal Combination of Regression Techniques for MCP and EDF Methodology (DT_DT).	341
H.1.2 Using Measured Wind Speed and Direction and Energy Demand	344
H.2 An Offshore Windfarm with an Installed Capacity of 150 MW	347
H.2.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)	347
H.2.2 Using Measured Wind Speed and Direction and Energy Demand	349
I. Discharged Energy as a Criterion for Establishing the Optimal Capacity of the Energy Storage System.....	353
I.1 An Offshore Windfarm with an Installed Capacity of 250 MW	353
I.1.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)	353
I.1.2 Using Measured Wind Speed and Direction, and Energy Demand	356
I.2 Windfarm of 200 MW Capacity	359

I.2.1	Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)	359
I.2.2	Using Measured Wind Speed and Energy Demand	362
I.3	An Offshore Windfarm with an Installed Capacity of 150 MW	365
I.3.1	Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)	365
I.3.2	Using Measured Wind Speed and Direction and Energy Demand.	368
J.	LCOE and LCOS Calculations	371
J.1	LCOE Calculations for a Floating Offshore Windfarm	371
J.1.1	Installed Capacity of 240 MW	371
J.1.2	Installed Capacity of 320 MW	372
J.1.3	Installed Capacity of 400 MW	372
J.2	Energy Storage System	373
J.2.1	Lithium-Ion Battery ESS	373
J.2.2	Vanadium Redox Battery ESS	375

List of Figures

Figure 1-1: Establishing a relationship between MCP methodologies, energy demand prediction, offshore windfarms, energy storage facilities and economic factors.	43
Figure 1-2: Organisation of Work (Part 1).	45
Figure 1-3: Organisation of Work (Part 2)	46
Figure 1-4: Organisation of Work (Part 3)	47
Figure 2-1: Applying the MCP methodology.	49
Figure 2-2: Three different floating windfarm concepts, from left to right, Spar-buoy, Semi-Submersible and Tension Leg Platform [90, 96].	56
Figure 2-3: Breakdown of CAPEX, OPEX and DECEX components for LCOE calculation for offshore floating windfarms [3].	58
Figure 2-4: Offshore wind energy integrated with pumped hydroelectric energy storage [108].	61
Figure 2-5: ORES concept, with containers for ES serving as anchorage points for a floating windfarm [112].	62
Figure 2-6: Underground pumped hydroelectric generation integrated with an offshore windfarm [117].	62
Figure 2-7: Compressed Air Energy Storage System for offshore wind [121].	63
Figure 2-8: Different technologies for different purposes [44].	69
Figure 2-9: A classification of ESS technologies according to Discharge Time at Rated Power, Power Rating and Application [44].	69
Figure 2-10: Energy demand forecasting methodology [8].	73
Figure 2-11: Creating an ARIMA model for forecasting of a time-series [40, 149].	74
Figure 3-1: Typical structure of a multilayer perceptron [17].	83
Figure 3-2: Difference between the meteorological wind direction, the mathematical wind direction, and the component of the wind vector [39].	88
Figure 3-3: Calculating the value of θ_{metip} according to the value of uip and vip [39].	89
Figure 3-4: Application of regression methodologies to wind direction [39].	90
Figure 3-5: Predicting the wind direction [39]	90
Figure 4-1: Integrating MCP with EDF for the optimisation of an ESS capacity coupled to a windfarm [175].	102
Figure 4-2: Possible combinations resulting from coupling different regression techniques for the MCP and energy demand forecasting methodology [175].	103
Figure 4-3: Utilisation of the available data to establish the model for the behaviour of the ESS [175].	103
Figure 4-4: STEP 1 and STEP 2 – constructing the regression model and prediction of wind speed at the candidate site.	105
Figure 4-5: Model used for Artificial Neural Network for regression between the reference site and the candidate site.	106
Figure 4-6: Applied methodology to determine the behaviour of the hypothetical windfarm and to compute the error due to the MCP methodology.	108
Figure 4-7: First methodology used to forecast energy demand for the year 2017, using ARIMA to forecast the input variables for MLR, ANN, DT and SVR regression techniques.	111
Figure 4-8: Second methodology used to forecast energy demand for the year 2017, using ARIMA to forecast the input variables for MLR, ANN, DT and SVR regression techniques.	112
Figure 4-9: Energy demand forecast methodology based on quarterly data used to forecast energy demand for the year 2017.	112
Figure 4-10: Energy demand forecast methodology based on quarterly data used to forecast energy demand for the years 2016-2020.	113

Figure 4-11: A block diagram showing the integration of the wind farm, the conventional thermal generation and the energy store to the power grid as defined in Simulink® [29].	114
Figure 4-12: Total energy demand, including baseload for the period 24 to 30 November 2015 [29].	114
Figure 4-13: Combination of regression techniques for MCP and EDF.	116
Figure 4-14: Methodology used to determine the optimal combination of regression techniques for the MCP and EDF methodology.	118
Figure 4-15: Dimension reduction algorithm (Part 1).	120
Figure 4-16: Dimension reduction algorithm (Part 2).	121
Figure 4-17: Calculation of LCOE and LCOE sensitivity to predicted wind speed and direction and forecasted energy demand.	124
Figure 5-1: A satellite Map of Malta showing relative locations of the LiDAR Unit at Qalet Marku, the Luqa Weather Station and the source location of the 3Tier Reference Time-series.	126
Figure 5-2: LiDAR system situated at Qalet Marku Tower, Malta.	128
Figure 5-3: Satellite imagery of the Qalet Marku Coastal Watch Tower, located on a promontory at Baħar iċ-Cagħaq.	128
Figure 5-4: 12-Sector Wind Rose for 3Tier Wind Data for 2007.	129
Figure 5-5: 12-Sector Wind Rose for 3Tier Wind Data for 2008 Luqa Data (Wind Rose for 2007 and 2008)	129
Figure 5-6: 12-Sector Wind Rose for Luqa Wind Data for 2007.	129
Figure 5-7: 12-Sector Wind Rose for Luqa wind Data for 2008.Sectorial Analysis.	129
Figure 5-8: Plot of wind veer against time, following removal of the points which had a veer which is greater than 180°. The plots are for the ‘all sectors’ data’.	130
Figure 5-9: Comparison of time-series and distributions, with 3Tier data serving as reference site and Luqa site serving as the candidate site.	131
Figure 5-10: Averaged hourly wind speed for the various LiDAR measurement heights and concurrent wind speed data measured at the Luqa meteorological station for the first week of 2016.	132
Figure 5-11: Averaged hourly wind direction for the various LiDAR measurement heights and concurrent wind direction data measured at the Luqa meteorological station for the first week of 2016.	132
Figure 5-12: Energy Demand and Quarterly Gross Domestic Product, in kEuro/hour for the year 2016.	135
Figure 6-1: View of the wind farm with 5 MW wind turbines rendered onto an image of the area and also showing the LiDAR unit.	138
Figure 6-2: Satellite image of the location of the hypothetical windfarm, using 50 5 MW wind turbines.	138
Figure 6-3: Power curve for the RE Power 5 MW offshore wind turbine [180].	139
Figure 6-4: View of the wind farm with 50 8 MW wind turbines rendered onto an image of the area, also showing the LiDAR unit.	139
Figure 6-5: Satellite image of the location of the hypothetical windfarm, using 50 8 MW wind turbines.	139
Figure 6-6: Power curve for the Vestas V-164 8 MW wind turbine [179, 181].	140
Figure 6-7: Block diagram representation of the ESS integrated with Energy Demand (Thermal Generation), the Wind Farm and the Controller.	144
Figure 6-8: Diagram showing how the floating windfarm power output is converted for use in the Simulink® model.	145
Figure 6-9: The energy demand, which was split into two components, Generation Baseload and Energy Demand in excess of Generation Baseload.	146

Figure 6-10: The windfarm and the ESS controller. This controlled the windfarm power output, the charging and the discharge of the ESS and the transfer of energy from the windfarm to the grid or curtailment of wind energy.	147
Figure 6-11: Block showing the ESS, with charging represented by an integrator and discharge into the grid occurring at a constant rate.	149
Figure 7-1: A comparison of the coefficient of determination, R , obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.	156
Figure 7-2: A comparison of coefficient of determination, R , obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.	156
Figure 7-3: A comparison of the MSE obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.	156
Figure 7-4: A comparison of the MSE obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.	156
Figure 7-5: A comparison of the MAE obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.	156
Figure 7-6: A comparison of the MAE obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.	156
Figure 7-7: Coefficient of determination, R , at different LiDAR measurement heights with the regression model based on wind data from the year 2016.	161
Figure 7-8: Coefficient of determination, R , at various LiDAR measurement heights for wind data for the year 2015 predicted with the regression model based on 2016 wind data.	161
Figure 7-9: MSE of residuals, at the various LiDAR measurement heights and with the regression model based on wind data for the year 2016.	161
Figure 7-10: MSE of residuals, at the various LiDAR measurement heights for wind data for the year 2015 predicted with the regression model based on wind data for the year 2016.	161
Figure 7-11: MAE of residuals, at the various LiDAR measurement heights and with the regression model based on wind data for the year 2016.	162
Figure 7-12: MAE of residuals, at the various LiDAR measurement heights for wind data for the year 2015 predicted with the regression model based on wind data for the year 2016.	162
Figure 7-13: A time-series of the measured wind-speed at a LIDAR measurement height of 80 m applied to a windfarm with an installed capacity of 250 MW (WF1) and the corresponding power output from the windfarm for the year 2016.	164
Figure 7-14: A time-series of measured wind speed and direction at a LiDAR measurement height of 80 m, at Qalet Marku as applied to the offshore windfarm (WF1) with an installed capacity of 250 MW (WF1) for the year 2016.	164
Figure 7-15: Weibull and wind direction statistics for measured wind speed and direction, at a LiDAR measurement height of 80 m, at Qalet Marku as applied to a hypothetical offshore windfarm with an installed capacity of 250 MW (WF1), for the year 2016.	165
Figure 7-16: A time-series of the measured wind-speed at a LIDAR measurement height of 150 m applied to a windfarm with an installed capacity of 400 MW (WF2) and the corresponding power output from the windfarm for the year 2016.	165
Figure 7-17 A time-series of measured wind speed and direction at a LiDAR measurement height of 150 m, at Qalet Marku as applied to the offshore windfarm with an installed capacity of 400 MW (WF2) for the year 2016.	166
Figure 7-18: Weibull and wind direction statistics for measured wind speed and direction, at a LiDAR measurement height of 150 m, at Qalet Marku as applied to a hypothetical offshore windfarm with an installed capacity of 400 MW (WF2), for the year 2016.	166

Figure 7-19: Comparing measured wind speed and wind speed predicted by MLR technique based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	168
Figure 7-20: Comparing measured wind speed and wind speed predicted by ANN regression technique based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	168
Figure 7-21: Comparing actual wind speed and wind speed predicted by DT regression technique based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	168
Figure 7-22: Comparing actual wind speed and wind speed predicted by SVR technique based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	168
Figure 7-23: Comparing measured and predicted wind direction predicted by MLR technique, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	169
Figure 7-24: Comparing measured and predicted wind direction predicted by ANN regression technique, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	169
Figure 7-25: Comparing measured and predicted wind direction predicted by DT regression technique, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.	169
Figure 7-26: Comparing measured and predicted wind direction predicted by SVR technique, based on wind for the year 2015 at a LiDAR measurement height of 80 m.	169
Figure 7-27: Weibull and wind direction statistics using wind data measured by the LiDAR at a height of 80 m for the year 2015.	170
Figure 7-28: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an MLR technique for wind data measured at a height of 80 m, for the year 2015.	170
Figure 7-29: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an ANN regression technique for wind data measured at a height of 80 m, for the year 2015.	171
Figure 7-30: Weibull and wind direction statistics for wind data predicted by the MCP methodology using a DT regression technique for wind data measured at a height of 80 m, for the year 2015.	171
Figure 7-31: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an SVR technique for wind data measured at a height of 80 m, for the year 2015.	171
Figure 7-32: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a MLR technique applied to the MCP methodology.	172
Figure 7-33: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by an ANN regression technique applied to the MCP methodology.	172
Figure 7-34: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a DT regression technique applied to the MCP methodology.	172
Figure 7-35: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a SVR technique applied to the MCP methodology.	172
Figure 8-1: Actual GDP trend for the years 2011-2019 and forecasted GDP for the years 2016 – 2020 using the ARIMA methodology.	177
Figure 8-2: Population trends on 1 January for the years 2011-2019 and forecasted results for the years 2016-2020.	179
Figure 8-3: Population trends on 31 December for the years 2011-2019 and forecasted results for the years 2016-2020.	179
Figure 8-4: Hourly EDF with MLR technique and actual energy demand for Q1 2017.	182
Figure 8-5: Hourly EDF with MLR technique and actual energy demand for Q2 2017.	182
Figure 8-6: Hourly EDF with MLR technique and actual energy demand for Q3 2017.	182
Figure 8-7: Hourly EDF with MLR technique and actual energy demand for Q4 2017.	182

Figure 8-8: Hourly EDF with ANN regression technique and actual energy demand for Q1 2017.	183
Figure 8-9: Hourly EDF with ANN regression technique and actual energy demand for Q2 2017.	183
Figure 8-10: Hourly EDF with ANN regression technique and actual energy demand for Q3 2017.	183
Figure 8-11: Hourly EDF with ANN regression technique and actual energy demand for Q4 2017.	183
Figure 8-12: Hourly EDF with DT regression technique and actual energy demand for Q1 2017.	184
Figure 8-13: Hourly EDF with DT regression technique and actual energy demand for Q2 of 2017.	184
Figure 8-14: Hourly EDF with DT regression technique and actual energy demand for Q3 2017.	184
Figure 8-15: Hourly EDF with DT regression technique and actual energy demand for Q4 2017.	184
Figure 8-16: Hourly EDF with SVR technique and actual energy demand for Q1 2017.	185
Figure 8-17: Hourly EDF with SVR technique and actual energy demand for Q2 2017.	185
Figure 8-18: Hourly EDF with SVR technique and actual energy demand for Q3 2017.	185
Figure 8-19: Hourly EDF with SVR technique and actual energy demand for Q4 2017.	185
Figure 8-20: Hourly EDF with ANN regression technique and actual energy demand for Q1 2016.	186
Figure 8-21: Hourly EDF with ANN regression technique and actual energy demand for Q2 2016.	186
Figure 8-22: Hourly EDF with ANN regression technique and actual energy demand for Q3 2016.	186
Figure 8-23: Hourly EDF with ANN regression technique and actual energy demand for Q4 2016.	186
Figure 8-24: Hourly EDF with DT regression technique and actual energy demand for Q1 2016.	187
Figure 8-25: Hourly EDF with DT regression technique and actual energy demand for Q2 2016.	187
Figure 8-26: Hourly EDF with DT regression technique and actual energy demand for Q3 2016.	187
Figure 8-27: Hourly EDF with DT regression technique and actual energy demand for Q4 2016.	187
Figure 9-1: Variation of energy output from the offshore windfarm to the electricity grid with different generation baseloads.	191
Figure 9-2: Variation of energy output from the ESS to the electricity grid with different baseloads.	192
Figure 9-3: Curtailed energy from the offshore windfarm with different baseloads.	192
Figure 9-4: Time-series for output power from the windfarm, energy demand and ESS output, and charging and discharging energy for the period 4 to 11 January 2017 based on measured wind data and energy demand.	193
Figure 9-5: Time-series of curtailed windfarm output power from for the period 4 to 11 January 2017, based on measured wind data and energy demand.	194
Figure 9-6: Variation of energy output from the offshore windfarm to the electricity grid with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.	211
Figure 9-7: Variation of energy discharges from the ESS the electricity grid with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.	212
Figure 9-8: Variation of curtailed energy from the offshore windfarm with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.	212

- Figure 9-9: Time-series of output power from the windfarm, energy demand, ESS output, and charging and discharging energy for the period 4 to the 11 of January 2017, from predicted wind speed and direction, and forecasted energy demand. 213
- Figure 9-10: Time sequence of curtailed energy from the offshore windfarm from predicted wind speed and wind direction and forecasted energy demand for the period 4 till 11 of January 2017. 214
- Figure 10-1: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 250 MW with predicted wind speed and direction and forecasted energy demand. 218
- Figure 10-2: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand. 219
- Figure 10-3: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings of 10MW to 50 MW for predicted wind speed and direction and forecasted energy demand. 219
- Figure 10-4: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand. 220
- Figure 10-5: Rate of change of curtailed energy with ESS capacity, for an offshorewindfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 220
- Figure 10-6: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW, with a generation baseload of 150 MW for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 221
- Figure 10-7: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand. 222
- Figure 10-8: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 250 MW, with measured wind speed and direction and energy demand. 222
- Figure 10-9: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand. 223
- Figure 10-10: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand. 224
- Figure 10-11: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand. 225
- Figure 10-12: Rate of change of curtailed energy with ESS capacity, for a 250 MW offshore windfarm with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand. 225
- Figure 10-13: Curtailed energy from an offshore wind farm with an installed capacity of 250 MW and a generation baseload of 250 MW, for ESS power ratings from 10 MW to 50 MW for measured wind speed and direction, and energy demand. 226
- Figure 10-14: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand. 226
- Figure 10-15: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity 200 MW with predicted wind speed and direction and forecasted energy demand. 227

- Figure 10-16: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for a 200 MW offshore windfarm with measured wind speed and direction, and energy demand. 229
- Figure 10-17: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150 MW, for predicted wind speed and direction and forecasted energy demand. 232
- Figure 10-18: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with a capacity of 150 MW, for predicted wind speed and direction and forecasted energy demand. 234
- Figure 10-19: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for a 250 MW offshore windfarm with predicted (MCP) wind speed and forecasted energy demand. 236
- Figure 10-20: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm of with an installed capacity of 250MW, with measured wind speed and forecasted energy demand. 238
- Figure 10-21: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 200 MW for predicted wind speed and direction and forecasted energy demand. 240
- Figure 10-22: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 200 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand. 242
- Figure 10-23: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150 MW with predicted wind speed and direction (MCP) and forecasted energy demand. 244
- Figure 10-24: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150MW for measured wind speed and direction and energy demand. 246
- Figure 10-25: Distribution for the various optimal ESS capacities shown in Table 10-65 and Table 10-66. 250
- Figure 10-26: Distribution for the various optimal ESS capacities shown in Table 10-68 and Table 10-69. 252
- Figure 11-1: Power Generation by Source using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016 (Li-Ion Battery ESS). 258
- Figure 11-2: Level of energy in the ESS showing charging and discharging cycles for a Lithium-Ion Battery Energy Storage System using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016. 258
- Figure 11-3: Curtailed energy from the offshore windfarm integrated with a Lithium-Ion Energy Storage System using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016. 258
- Figure 11-4: Power Generation by Source using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016 (VRB ESS). 259
- Figure 11-5: Level of energy in the ESS showing charging and discharging cycles for a VRB ESS using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016. 259
- Figure 11-6: Curtailed energy from the offshore windfarm integrated with a VRB ESS using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016. 259
- Figure 11-7: Hypothetical offshore windfarm with 400 MW installed capacity - energy output used for generation, baseline and with predicted wind data (MCP) and forecasted energy demand. 268

Figure 11-8: Hypothetical offshore windfarm with 320 MW installed capacity - energy output used for generation, baseline and with predicted wind data (MCP) and forecasted energy demand.	268
Figure 11-9: 240MW hypothetical offshore windfarm energy output used for generation.	268
Figure 11-10: LCOE with predicted wind speed and direction and forecasted energy demand and LCOE from the baseline power output (measured wind speed and direction and energy demand).	269
Figure 11-11: Energy discharged to the grid for an ESS capacity of 600 MWh Li-Ion and a 500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	271
Figure 11-12: Energy discharged to the grid for an ESS capacity of 3600 MWh Li-Ion and a 3000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	271
Figure 11-13: Energy discharged to the grid for an ESS capacity of 4200 MWh Li-Ion and a 3500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	272
Figure 11-14: Energy discharged to the grid for an ESS capacity of 4800 MWh Li-Ion and a 4000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	272
Figure 11-15: Energy discharged to the grid for an ESS capacity of 5400 MWh Li-Ion and a 4500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	272
Figure 11-16: Energy discharged to the grid for an ESS capacity of 6000 MWh Li-Ion and a 5000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240 MW, 320 MW and 400 MW.	272
Figure 11-17: LCOS obtained from predicted wind speed and direction and forecasted energy demand, baseline LCOS and percentage error for a Li-Ion Battery ESS, with increasing ESS capacity.	275
Figure 11-18: Absolute and percentage error in LCOS for a Li-Ion battery ESS, with increasing ESS capacity.	275
Figure 11-19: LCOS obtained from predicted wind speed and direction and forecasted energy demand, baseline LCOS and percentage error for a VRB ESS, with increasing ESS capacity.	275
Figure 11-20: Absolute and percentage error in LCOS for a VRB ESS, with increasing ESS capacity.	275
Figure C-1: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the SLR regression model with the 2008 data and then predicting the 2007 wind data.	305
Figure C-2: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the MLR model with the 2008 data and then predicting the 2007 wind data.	306
Figure C-3: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the ANN model with the 2008 data and then predicting the 2007 wind data.	307
Figure C-4: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the DT regression model with the 2008 data and then predicting the 2007 wind data.	308
Figure C-5: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the SVR regression model with the 2008 data and then predicting the 2007 wind data.	309
Figure C-6: Results from the DT regression technique, comparing different model parameters, number of Trees and Leafs.	311
Figure C-7: Results from the SVR technique, comparing different hyperparameter values.	313
Figure E-1: Actual Agriculture, Forestry and Fishing trends for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	315
Figure E-2: Actual Manufacturing trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	315

Figure E-3: Actual Construction trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	315
Figure E-4 : Actual Mining, Quarrying and Water Supply trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	316
Figure E-5: Actual Information and Communication trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	316
Figure E-6: Actual Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	316
Figure E-7: Actual Financial and Insurance Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	317
Figure E-8 Actual Real Estate Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	317
Figure E-9: Actual Arts, Entertainment and Recreation, Repair of Household Goods and other Services trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	317
Figure E-10: Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	318
Figure E-11: Professional, Scientific and technical Activities trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.	318
Figure F-1: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.	319
Figure F-2: Residuals time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.	319
Figure F-3: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.	320
Figure F-4: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.	320
Figure F-5: Residuals time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.	320
Figure F-6: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.	321
Figure F-7: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.	321
Figure F-8: Residuals time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.	321
Figure F-9: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.	322
Figure F-10: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.	322
Figure F-11: Residuals time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.	322
Figure F-12: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.	323
Figure F-13: Analysis of residuals for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using ANN regression technique for EDF.	323
Figure F-14: Residuals time-series for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using ANN regression technique for EDF.	323

Figure F-15: Time-series for actual energy demand and forecast, carried out for the year 2016, using the years 2011-2015 to create the models using the ANN regression technique for EDF.	324
Figure F-16: Analysis of residuals for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using DT regression technique for EDF.	324
Figure F-17: Residuals time-series for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using DT regression technique for EDF.	324
Figure F-18: Time-series for actual energy demand and forecast, carried out for the year 2016, using the years 2011-2015 to create the models using the DT regression technique for EDF.	325
Figure H-1: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.	341
Figure H-2: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.	342
Figure H-3: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW, and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.	342
Figure H-4: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.	343
Figure H-5: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.	343
Figure H-6: Rate of change of curtailed energy with ESS capacity, for a 200 MW offshore windfarm with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	344
Figure H-7: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.	344
Figure H-8: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 M and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.	345
Figure H-9: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW, with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.	345
Figure H-10: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.	346
Figure H-11: Curtailed energy from an offshore winffarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.	346
Figure H-12: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.	347
Figure H-13: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 100 MW generation baseload and ESS power ratings of 10 MW to 50 MW.	347
Figure H-14: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.	348

- Figure H-15: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW, using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 150 MW generation baseload, for ESS power ratings of 10 MW to 50 MW. 348
- Figure H-16: Curtailed energy from a 150 MW offshore wind farm with a generation baseload of 150 MW, for ESS power rating of 10 MW, for predicted wind speed and direction, and forecasted energy demand. 349
- Figure H-17: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for an ESS power rating of 10 MW, for predicted wind speed and direction and forecasted energy demand. 349
- Figure H-18: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW offshore windfarm using measured wind speed and direction, and energy demand for the year 2017, with a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW. 350
- Figure H-19: Curtailed energy from a 125 MW offshore windfarm using measured wind speed and direction, together with energy demand for the year 2017, for a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW. 350
- Figure H-20: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW, using measured wind speed and direction, and energy demand for the year 2017, with a 150 MW generation baseload, for ESS power ratings of 10 MW to 50 MW. 351
- Figure H-21: Curtailed energy for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power rating of 10 MW and 20 MW, for predicted wind speed and direction, and forecasted energy demand. 351
- Figure H-22: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 150 MW windfarm with a generation baseload of 150 MW, for an ESS power rating of 10 MW and 20 MW, for predicted wind speed and direction and forecasted energy demand. 352
- Figure I-1: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, using predicted wind speed and direction and forecasted energy demand. 353
- Figure I-2: Rate of change of energy discharged from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW¹ with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, using predicted wind speed and direction and forecasted energy demand. 354
- Figure I-3: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 354
- Figure I-4: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand. 355
- Figure I-5: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand. 355
- Figure I-6: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW. for predicted wind speed and direction and forecasted energy demand. 356
- Figure I-7: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW with measured wind speed and direction and energy demand. 356

Figure I-8: Rate of change of Energy output from the ESS to the electricity grid, for a 250 MW offshore windfarm with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW. 357

Figure I-9: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW offshore windfarm with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 357

Figure I-10: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for measured wind speed and direction and energy demand. 358

Figure I-11: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW for measured wind speed and direction and energy demand. 358

Figure I-12: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand. 359

Figure I-13: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW for ESS power ratings from 10 MW to 50 MW for a generation baseload of 100 MW, for predicted wind speed and direction and forecasted energy demand. 360

Figure I-14: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity 200 MW with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 360

Figure I-15: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 361

Figure I-16: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 361

Figure I-17: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 362

Figure I-18: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 362

Figure I-19: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 363

Figure I-20: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand. 363

Figure I-21: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 364

Figure I-22: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand. 364

Figure I-23: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 365

Figure I-24: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand. 365

Figure I-25: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 366

Figure I-26: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW offshore windfarm, with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 367

Figure I-27: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 367

Figure I-28: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand. 368

Figure I-29: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 369

Figure I-30: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 369

Figure I-31: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand. 370

Figure I-32: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand. 370

List of Tables

Table 2-1: Battery properties [127].	66
Table 2-2: A comparison of capital cost for the various energy storage technologies [109, 127, 132, 133].	67
Table 2-3: A comparison of the various energy storage technologies available, regarding advantages, disadvantages and existing facilities [44].	68
Table 2-4: A comparison of the different methodologies for forecasting of energy demand.	72
Table 4-1: Type of regression techniques applied to the data.	105
Table 4-2: Description of the regression techniques used for the Measure-Correlate-Predict Methodology.	106
Table 4-3: Summary of combinations of methodologies, LiDAR measurement heights and amount of wind turbines used in the analysis.	108
Table 4-4: Input variables, used as independent variables for the regression used to forecast energy demand.	110
Table 5-1: 3Tier data set parameters.	126
Table 5-2: Luqa Weather Station equipment parameter data.	127
Table 5-3: LiDAR equipment parameter list [37].	128
Table 5-4: Number of hourly samples obtained after removing veer values which are greater than 180° for the twelve segments.	130
Table 5-5: Number of hourly samples by LiDAR measurement height.	133
Table 5-6: Population trends for the Island of Malta for the years 2011-2019, together with calculated values T and the calculated values of m and c .	134
Table 6-1: RE Power 5 MW Wind Turbine Parameters [179, 180].	138
Table 6-2: Vestas V-164 8 MW Wind Turbine Parameters used in the study [179, 181].	140
Table 7-1: Results of the sectorial analysis using SLR, using 2008 data to generate the model and predicting the 2007 wind data, Coefficient of Determination, MSE and MAE, and the weighted average of all sectors.	152
Table 7-2: Results of the sectorial analysis using MLR, using 2008 data from the year 2008 to create the model and to predict the wind data for the year 2007, coefficient of determination, MSE and MAE, and the weighted average of all sectors.	152
Table 7-3: Results of the sectorial analysis using ANNs, using wind speed from the year 2008 data to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all sectors.	153
Table 7-4: Results of the sectorial analysis using DTs, using the wind speed from the year 2008 to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all the sectors.	154
Table 7-5: Results of the sectorial analysis using SVR, using wind speed from the year 2008 data to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all sectors.	154
Table 7-6: A comparison of the weighted averages from a sectorial analysis for the coefficient of determination, R , the MSE and the MAE for the different regression techniques for the MCP methodology.	155
Table 7-7: A comparison of results without a sectorial breakdown for the Coefficient of Determination, R the MSE and the MAE for the different regression techniques used for the MCP methodology.	155
Table 7-8: Regression results at the various LiDAR measurement heights obtained with a SLR technique with one input.	158
Table 7-9: Regression results at the various LiDAR measurement heights obtained	158

Table 7-10: Regression results at the various LiDAR measurement heights obtained with an ANN regression technique using two inputs.	159
Table 7-11: Regression results at the various LiDAR measurement heights with a DT regression technique using two inputs.	159
Table 7-12: Regression results obtained at the various LiDAR measurement heights with a SVR regression technique using two inputs.	160
Table 7-13: Summarised results for NMAE by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.	173
Table 7-14: Summarised results for the NMSE by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.	173
Table 7-15: Summarised results for the percentage error in overall energy yield by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.	173
Table 8-1: Parameters used ARIMA methodology to forecast GDP and other end-use parameters for the years 2016-2020	177
Table 8-2: Percentage Error by Quarter for GDP and End-User Forecast for the Years 2016-2019 (Part 1).	178
Table 8-3: Percentage Error by Quarter for GDP and End-User Forecast for the Years 2016-2019 (Part 2).	178
Table 8-4: Population trends for the years 2011-2019, together with forecasts obtained using ARIMA model for the years 2016-2020.	179
Table 8-5: Coefficient of determination 'R', MSE and MAE for EDF using the first methodology for the year 2017.	180
Table 8-6: Coefficient of determination 'R', MSE and MAE for EDF using the second methodology for the year 2017.	180
Table 8-7: Coefficient of determination 'R', MSE and MAE for EDF using the second methodology. The forecasted results are for the year 2016.	188
Table 9-1: Percentage error for the total energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.	196
Table 9-2: Percentage error in curtailed energy from the windfarm for a wind farm with an installed capacity of 250 MW.	197
Table 9-3: Percentage error in energy from the windfarm transferred to the electricity grid for a windfarm capacity of 250 MW and a generation baseload of 100 MW.	198
Table 9-4: Percentage error in energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.	199
Table 9-5: Percentage error in curtailed energy from a windfarm with an installed capacity of 250 MW.	200
Table 9-6: Percentage error in energy transferred to the electricity grid from a windfarm with an installed capacity of 250 MW.	201
Table 9-7: Percentage error for the energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.	202
Table 9-8: Percentage error in curtailed energy from a windfarm with an installed capacity of 250 MW.	203
Table 9-9: Percentage error in energy transferred to the electricity grid from an offshore windfarm with an installed capacity of 250 MW.	204
Table 9-10: Mean Percentage Error (MPE) for energy discharged into the grid by the ESS, by EDF methodology for a windfarm of 250 MW capacity and a baseload of 100 MW.	205
Table 9-11: Mean Percentage Error (MPE) for energy discharged by the ESS into the grid, by MCP methodology for a windfarm of 250 MW capacity and a baseload of 100 MW.	206

Table 9-12: Matrix of Product of MPE (PMPE) for energy discharged to the grid by the ESS, for various conditions of windfarm capacity and generation baseload.	208
Table 9-13: Final iteration of a 4x4 matrix for the percentage error of energy discharged to the grid by the ESS.	208
Table 9-14: Matrix of percentage error for curtailed energy from the windfarm, for various conditions of windfarm capacity and generation baseload.	209
Table 9-15: Final iteration of a 4x4 matrix for the percentage error of curtailed energy from the windfarm.	209
Table 9-16: Matrix of percentage error for energy transferred to the electricity grid from the windfarm, for various conditions of windfarm capacity and generation baseload.	210
Table 9-17: Final iteration of a 4x4 matrix for the percentage error for the energy transferred from the windfarm to the energy grid.	210
Table 10-1: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW capacity and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	218
Table 10-2: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	218
Table 10-3: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	220
Table 10-4: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	220
Table 10-5: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	221
Table 10-6: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a 150 MW generation baseload for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	221
Table 10-7: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for measured wind speed and direction and energy demand.	223
Table 10-8: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	223
Table 10-9: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for measured wind speed and direction and energy demand.	224
Table 10-10: Coefficients for fitted 3 rd order polynomials for curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	224
Table 10-11: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for measured wind speed and direction and energy demand.	226
Table 10-12: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	226

Table 10-13: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	228
Table 10-14: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a 100 MW generation baseload, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	228
Table 10-15: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	228
Table 10-16: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a 125 MW generation baseload, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	228
Table 10-17: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	229
Table 10-18: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW capacity and a 150 MW generation baseload, for predicted wind speed and direction and forecasted energy demand.	229
Table 10-19: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	230
Table 10-20: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	230
Table 10-21: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	230
Table 10-22: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	230
Table 10-23: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	230
Table 10-24: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	231
Table 10-25: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	232
Table 10-26: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	232
Table 10-27: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	232

Table 10-28: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.	233
Table 10-29: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	234
Table 10-30: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	234
Table 10-31: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.	234
Table 10-32: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	235
Table 10-33: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	237
Table 10-34: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a 100 MW generation baseload, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	237
Table 10-35: Energy discharged by the ESS into the electricity grid for an offshore windfarm of with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	237
Table 10-36: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a 125 MW generation baseload, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	237
Table 10-37: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	237
Table 10-38: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	238
Table 10-39: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	238
Table 10-40: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	239
Table 10-41: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	239
Table 10-42: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	239

Table 10-43: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	239
Table 10-44: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm of with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.	239
Table 10-45: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	240
Table 10-46: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	240
Table 10-47: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	241
Table 10-48: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	241
Table 10-49: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	241
Table 10-50: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.	241
Table 10-51: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	242
Table 10-52: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	242
Table 10-53: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	243
Table 10-54: Coefficients for fitted 3 rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	243
Table 10-55: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	243
Table 10-56: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.	243
Table 10-57: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	244

Table 10-58: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	244
Table 10-59: Energy discharged by the ESS into the electricity grid for an offshore windfarm of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	245
Table 10-60: Coefficients for fitted 3 rd order polynomials for energy discharged into the electricity grid for an offshore windfarm of with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.	245
Table 10-61: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW capacity and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.	246
Table 10-62: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.	247
Table 10-63: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.	247
Table 10-64: Coefficients for fitted 3 rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.	247
Table 10-65: Optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using predicted wind speed and direction and forecasted energy demand.	248
Table 10-66: Optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using measured wind speed and direction and energy demand.	249
Table 10-67: Percentage error in optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using measured wind speed and direction and energy demand.	249
Table 10-68: Optimal ESS Capacities using rate of change of ESS energy discharged to the electricity grid to establish the optimal point, using predicted wind speed and direction and forecasted energy demand.	250
Table 10-69: Optimal ESS Capacities using rate of change of ESS energy discharged to the energy grid to establish the optimal point, using measured wind speed and direction and energy demand.	251
Table 10-70: Percentage error in optimal ESS capacities using rate of change of ESS energy discharged to the electricity grid to establish the optimal point, using measured wind speed and direction and energy demand.	251
Table 11-1: Unit CAPEX for a floating windfarm, based on data for the Mediterranean Sea [3].	260
Table 11-2: CAPEX for a 400 MW floating offshore windfarm.	261
Table 11-3: CAPEX for a 320 MW floating offshore windfarm.	261
Table 11-4: CAPEX for a 240 MW floating offshore windfarm.	261
Table 11-5: OPEX for the offshore floating windfarm [95].	262
Table 11-6: DECEX for a floating offshore windfarm with an installed capacity of 400 MW.	262
Table 11-7: DECEX for a floating offshore windfarm with an installed capacity of 320 MW.	262
Table 11-8: DECEX for a floating offshore windfarm with an installed capacity of 240 MW.	262
Table 11-9: CAPEX for a Li-Ion Battery ESS.	263
Table 11-10: OPEX for a Li-Ion Battery ESS.	264
Table 11-11: DECEX for a Li-Ion Battery ESS.	264
Table 11-12: CAPEX for a Vanadium Redox Battery ESS.	264

Table 11-13: OPEX for a Vanadium Redox Battery ESS.	265
Table 11-14: DECEX for a Vanadium Redox Battery ESS.	265
Table 11-15: Average wind speed at the candidate site.	266
Table 11-16: Total power generated by the hypothetical offshore windfarm.	266
Table 11-17: Capacity factor for the hypothetical offshore windfarm.	266
Table 11-18: Power output component used for generation, percentage error due to predicted and forecasted values, and baseline output output for hypothetical offshore windfarms of installed capacity of 400 MW, 320 MW and 240 MW.	267
Table 11-19: LCOE results for the hypothetical offshore floating windfarm (WF2).	269
Table 11-20: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 600 MW, 3600 MW and 4200 MW capacity Li-Ion Battery ESS.	273
Table 11-21: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 4800 MW, 5400 MW and 6000 MW capacity Li-Ion Battery ESS.	273
Table 11-22: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 500 MW, 3000 MW and 3500 MW capacity VRB ESS.	274
Table 11-23: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 4000 MW, 4500 MW and 5000 MW capacity VRB ESS	274
Table 11-24: LCOS Results for a Li-Ion Battery and VRB ESS.	275
Table A-1: LiDAR missing and duplicate for 2015.	301
Table A-2: LiDAR missing and duplicate for 2016 (Part 1).	301
Table A-3: LiDAR missing and duplicate for 2016 (Part 2)	302
Table A-4: LiDAR missing and duplicate for 2017.	302
Table B-1: Malta's quarterly econometric data for the years 2011-2020 (Part 1) [41]	303
Table B-2: Malta's quarterly econometric data for the years 2011-2020 (Part 2) [41]	304
Table D-1: Forecast scenario for the years 2016-2020 with ARIMA methodology (Part 1).	314
Table D-2: Forecast scenario for the years 2016-2020 with ARIMA methodology (Part 2)	314
Table G-1: Percentage error in the total energy discharged from the ESS into the electricity grid, for an offshore windfarm with capacity of 200 MW and a generation baseload of 100 MW.	326
Table G-2: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW.	327
Table G-3: Percentage error in energy from transferred to the electricity grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW.	328
Table G-4: Percentage error in the total energy discharged from the ESS into the electricity grid, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.	329
Table G-5: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.	330
Table G-6: Percentage error in energy transferred to the electricity grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.	331
Table G-7: Percentage error in the total energy discharged from the ESS into the electricity grid for an offshore windfarm of an installed capacity of 200 MW and a baseload of 150 MW.	332
Table G-8: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a baseload of 150 MW.	333
Table G-9: Percentage error in energy from the windfarm transferred to the grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW.	334
Table G-10: Percentage error in energy yield for the total energy discharged from the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW.	335

Table G-11: Percentage error in energy from the windfarm transferred to the grid from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW.	336
Table G-12: Percentage error in energy yield for the total energy discharged from the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW.	337
Table G-13: Percentage error in energy from the windfarm transferred to the grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW.	338
Table G-14: Percentage error for the energy discharged from the ESS into the electricity grid for an offshore windfarm of an installed capacity of 150 MW and a generation baseload of 150 MW.	339
Table G-15: Percentage error in energy from the windfarm transferred to the grid with an offshore windfarm with and installed capacity of 150 MW and a generation baseload of 150 MW.	340
Table J-1: Values of $1 + rt$ for a WACC of 8%.	371
Table J-2: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using Spar Buoy.	371
Table J-3: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using a Semi-Submersible Platform.	371
Table J-4: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using a Tension Leg Platform.	372
Table J-5: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using Spar Buoy.	372
Table J-6: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using a Semi-Submersible Platform.	372
Table J-7: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using a Tension Leg Platform.	372
Table J-8: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using Spar Buoy.	373
Table J-9: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using a Semi-Submersible Platform.	373
Table J-10: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using a Tension Leg Platform.	373
Table J-11: LCOE calculation for a Lithium-Ion ESS with 600 MWh capacity.	373
Table J-12: LCOE calculation for a Lithium-Ion ESS with 3600 MWh capacity.	374
Table J-13: LCOE calculation for a Lithium-Ion ESS with 4200 MWh capacity.	374
Table J-14: LCOE calculation for a Lithium-Ion ESS with 4800 MWh capacity.	374
Table J-15: LCOE calculation for a Lithium-Ion ESS with 5400 MWh capacity.	374
Table J-16: LCOE calculation for a Lithium-Ion ESS with 6000 MWh capacity.	375
Table J-17: LCOS calculation for a Vanadium Redox Battery ESS with 500 MWh capacity.	375
Table J-18: LCOS calculation for a Vanadium Redox Battery ESS with 3000 MWh capacity.	375
Table J-19: LCOS calculation for a Vanadium Redox Battery ESS with 3500 MWh capacity.	375
Table J-20: LCOS calculation for a Vanadium Redox Battery ESS with 4000 MWh capacity.	376
Table J-21: LCOS calculation for a Vanadium Redox Battery ESS with 4500 MWh capacity.	376
Table J-22: LCOE calculation for a Vanadium Redox Battery ESS with 5000 MWh capacity.	376

List of Abbreviations

ACF	Autocorrelation Factor
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BOS	Balance of System
BWES	Buoyancy Work Energy Storage
CAES	Compressed Air Energy Storage
CACO	Continuous Ant Colony Optimisation
CAPEX	Capital expenditure,
CF	Capacity Factor
CFD	Computational Fluid Dynamics
DECEX	Decommissioning expenditure,
DoD	Depth of charge of a battery system,
DT	Decision Trees
DWMM	Dynamic Wake Meandering Model
EDF	Energy Demand Forecasting
EM UPHS	Energy Membrane Underground Pumped Hydro Storage
ES	Energy Storage
ESS	Energy Storage System
EU	European Union
FE	Feature Extraction
FR	Frequency Response
FOWT	Floating Offshore Wind Turbine
GA	Genetic Algorithms
GDP	Gross Domestic Product
IREA	International Renewable Energy Agency
KPCA	Kernel Principal Component Analysis
LCOE	Levelised Cost of Energy
LCOS	Levelised Cost of Storage
LDA	Linear Discriminant Analysis
LES	Large Eddy Simulation
LiDAR	Light Direction and Ranging
Li-Ion	Lithium Ion
MIA	Malta International Airport
MAE	Mean Absolute Error
MCP	Measure-Correlate-Predict
MDS	Multi-Dimensional Scaling
ML	Machine Learning,
MLP	Multilayer Perceptron
MLR	Multivariate Linear Regression
MPE	Mean Percentage Error
MSE	Mean Squared Error
NMAE	Normalised Mean Absolute Error
NMSE	Normalised Mean Squared Error
Na-S	Sodium Sulphur
NSO	National Statistics Office
ORES	Ocean Renewable Energy Storage
OPEX	Operating and Maintenance Costs
PACF	Partial Autocorrelation Function

PCA	Principal Component Analysis
PLS	Partial Least Squares
PMPE	Product of Mean Percentage Error
PS	Particle Swarm
PHEs	Pumped Hydro Energy Storage
RE	Renewable Energy
RES	Renewable Energy Source
ROI	Return on Investment
SA	Simulated Annealing
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SB	Spar Buoy
SLR	Simple Linear Regression
SoDAR	Sonic Detection and Ranging
SSP	Semisubmersible Platform
STEnSea	Stored Energy in the Sea
SVD	Singular Value Decomposition
SVR	Support Vector Regression,
T&D	Transmission and Distribution
TLP	Tension Leg Platform
UPHEs	Underground Pumped Hydroelectric Energy Storage
UPS	Uninterrupted Power Supply
VRB	Vanadium Redox Battery
WACC	Weighted Average Capital Cost

List of Symbols

$E(y/x)$	Mean of y (dependent variable) given x (independent variable)
$Var(y/x)$	Variance of y (dependent variable) given x (independent variable)
$\mathbb{R}^n$	Feature space of dimension n
$\mathbb{R}^d$	Feature space of dimension d , used in Support Vector Regression,
$\hat{y}$	Estimate of the variable y
$\bar{y}$	Mean of the variable y
a, d, c, d	3 rd order polynomial coefficients,
$b_m(x)$	Decision function at node m of a Decision Tree,
b_k	Coefficient in autoregression (AR),
B	Backshift operator,
c	Overall component in a time-series,
c	Number of cycles in an Energy Storage System,
C	Cost function in Support Vector Regression
C_{ESS}	Energy Storage System Capacity [MWh]
$C_{ESS_{OPT}}$	Optimal Energy Storage System Capacity [MWh]
d	Number of dimensions of input regressor
d	Number of inputs to the hidden layer in Artificial Neural Networks
d_k	Partial autocorrelation coefficient in time-series
D	Wind turbine rotor diameter [m]
D	Decommissioning cost of the windfarm [€]
D_{ESS}	Decommissioning cost of the Energy Storage System [€]
e, f, g, h	3 rd order polynomial coefficients
E_C	Total Curtailed Energy from the windfarm [MWh]
E_S	Level of energy in the Energy Storage System [MWh]
E_m	Mean Squared Error at Decision Tree node m
E_{ESS_G} or E_G	Energy discharged from the ESS to the grid [MWh]
$E_{S_{MAX}}$	Maximum storage capacity of the Energy Storage System [MWh]
$E_{S_{OPT}}$	Optimal storage capacity of the Energy Storage System [MWh]
E_t	Energy generated in year t [MWh]
F_t	Fuel cost in year t [€]
g_m	Estimated value of x at node m
h	Dimension of new feature space
H	Dimension of the hidden layer
I_S	Investment cost for Energy Storage System [€]
I_W	Investment cost for the windfarm [€]
I_t	Investment cost in year t [€]
$I_{RESS}, I'_{RESS}, I''_{RESS}$	Replacement cost of the Energy Storage System [€]
J	Number of distinct and overlapping regions in a decision tree regression
k	Kernel function in Support Vector Regression
k	Number of outputs from the hidden layer
k	Counter used for dimension reduction algorithm
L	Likelihood of a set of data
L, L_d, L_p	Lagrangian
$\ell_{p,\epsilon}$	Loss function in Support Vector Regression
$LCOS_{Li-Ion}$	Levelised Cost of Storage for Li-Ion Battery Energy Storage System
$LCOS_{VRB}$	Levelised Cost of Storage for Vanadium Redox Battery Energy Storage System [€/kWh]

MS_{RES}	Residual mean square of a regression [$(ms^{-1})^2$]
m	Set of possible values in a decision tree
m	Population hourly growth rate [$hours^{-1}$]
$M + 1$	Number of dimensions of a reduced space in dimension reduction
M_t	Maintenance and operating cost in year t [€]
n	Number of observations (for example, wind speed readings), or dimension of feature space, or number of observations in a time-series
n	Expected lifetime of the windfarm and Energy Storage System [$years$]
n	Number of regression techniques for Measure-Correlate-Predict
m	Number of regression techniques for Energy Demand Forecasting
p	Loss function parameter
$p + 1$	Number of dimensions of a space in dimension reduction
p, d, q	ARIMA parameters
p, M	Matrix dimension
P_C	Charging cost of the Energy Storage System [€]
P_i	Power output from windfarm (timeseries) [MW]
P_B	Generation baseload [MW]
P_D	Electrical energy demand [MW]
$\bar{P}_i$	Average power output from windfarm [MW]
$\hat{P}_i$	Predicted power output from windfarm [MW]
$\tilde{P}_i$	Average predicted power output from windfarm [MW]
P, D, Q	Seasonal ARIMA parameters
P_T	Energy demand in excess of the established generation baseload [MW]
P'_T	Total thermal (fossil fuel) power generated after using power from the windfarm and the Energy Storage System [MW]
P_W	Windfarm power output [MW]
P'_W	Windfarm power output compensated for windfarm efficiency and losses from power cables [MW]
P_{WC}	Curtailed power from the windfarm [MW]
P_{WG}	Component of power transferred to the electricity grid directly from the windfarm [MW]
r	Parameter representing Weighted Average Capital Cost
r_k	Autocorrelation Factor (ACF)
R	Coefficient of determination, of a regression
$R_i,$	Distinct and non-overlapping regions in the Decision Tree, $i = 1, 2, \dots, J$
RC	Rated capacity of the Energy Storage System [MW]
S	Support vectors in Support Vector Regression
s	Seasonal parameter in SARIMA
SS_{RES}	Residual sum of squares [$(ms^{-1})^2$]
SS_T	Sum of squares of the observations [$(ms^{-1})^2$]
T	Number of hours in a year [$hours$]
v_{ij}	Weights in second layer of perceptron
v_t	Wind velocity [ms^{-1}]
v_i	Measured wind speed [ms^{-1}]
$\hat{v}_i$	Predicted wind speed [ms^{-1}]
V_i	Wind velocity vector
V_{RES}	Residual value of the windfarm and the Energy Storage System at end of life [€]
u_i, v_i	Wind velocity vector component [ms^{-1}]

$\mathbf{u}_{i_{ref}}, \mathbf{v}_{i_{ref}}$	Wind velocity vector components at the reference site [ms^{-1}]
$\mathbf{u}_{i_{can}}, \mathbf{v}_{i_{can}}$	Wind velocity vector components at the candidate site [ms^{-1}]
w_{hj}	Weights in first layer of perceptron
$\mathbf{w}$	Regression coefficient matrix in Support Vector Regression
w_{dir_t}	Wind direction, [$degrees$]
x, y	Regressor x and response y in a regression model
$\mathbf{x}$	Input vector to the model, consisting of the wind speed x_1 in [ms^{-1}] and x_2 , the wind direction in [$degrees$], such that $\mathbf{x} = \langle x_1, x_2 \rangle$
x, x_i, x_1, x_{1i}	Wind speed at the reference site [ms^{-1}]
X_i	Subsets of the input x in a Decision Tree, $i = 1, 2, \dots, m$
x_2, x_{2i}	Wind direction at the candidate site [$degrees$]
$X_1, X_2, \dots, X_p$	Explanatory variables in a time-series (for example, GDP or end-user data)
y_1	population on 1 January
y_2	population on 31 December
Y	Forecast variable
Y'_t, Y''_t	Differentiated time-series
Y_t, Y_{t-k}	Observations at time t , and $t - k$ in a time-series
z_h	Sigmoid function of the hidden layer, $h = 1, 2, \dots, H$
$\beta_0, \beta_1, \beta_2$	Regression coefficients
$\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2$	Least squares estimators of the regression coefficients
$\beta_0, \beta_1, \dots, \beta_p$	coefficients of a multidimensional space $p + 1$ in dimension reduction
$\hat{\sigma}^2$	Unbiased estimate of σ^2
Θ_i	i^{th} Moving Average (MA) operator, for SARIMA (Seasonal ARIMA)
Φ_i	i^{th} Autoregressive operator (AR), for SARIMA (Seasonal ARIMA)
dE_s/dt	Rate of discharge of the Energy Storage System, equal to the power rating [MW]
α_k	Partial Autocorrelation Function (PACF)
ε_t	Random error at time t in a time-series
η_w	Windfarm efficiency
θ_i	i^{th} Moving Average (MA) operator, for ARIMA
θ_{math}	Mathematical Wind Direction [$degrees$]
θ_{met}	Meteorological Wind Direction [$degrees$]
θ_r	Level of acceptable error at a node
$\theta_0, \theta_1, \dots, \theta_M$	coefficients of a reduced multidimensional space $M + 1$ in dimension reduction
σ^2	Variance of residuals [$(ms^{-1})^2$]
ϕ_i	i^{th} Autoregressive operator (AR), for ARIMA
α	Dual variable or Lagrange Multiplier
ε	Residual error [ms^{-1}]
η	Dual variable or Lagrange Multiplier
ξ, ξ^*	Slack variables in Support Vector Regression
σ	Characteristic parameter in the Gaussian Radial Basis Function kernel
σ	Standard deviation of residuals [ms^{-1}]
ϵ	Predefined maximum tolerated error in Support Vector Regression
ϕ	Kernel function in Support Vector Regression

1. Introduction

As the penetration of renewable energy (RE) increases, system flexibility becomes essential to manage the intermittency in electricity supply networks and to facilitate a cost-effective shift towards a low-carbon electricity supply. The utilisation of Energy Storage (ES) is an opportunity that can result in a substantial and important monetary benefit [1]. The additional flexibility offered by ES reduces the dependence on investment in baseload generation capacity, which is presently based on fossil fuels. Moreover, ES facilitates the management of uncertainty in future system development [1].

A recent technological achievement in offshore windfarms has seen the introduction of floating platforms. The cost of wind turbines is decreasing, while wind turbines are also becoming larger, hence capturing more wind [2]. Placing windfarms in deep waters, rather than close to the shore in shallow waters will enable the exploitation of the vast wind resources which are available offshore. Recent studies are showing that this is also feasible in the Mediterranean Sea [3, 4].

Advances in ESS have enabled the increase in the penetration of energy from such RE sources. This increases the value of such energy by allowing it to be stored when there is low energy demand and high renewable energy availability instead of curtailing it. Energy in storage can be used in times of high energy demand and low availability of renewable energy.

The increased penetration of RE will facilitate CO₂ reduction and the achievement of European Union (EU) goals for 2050 in achieving a secure, competitive and decarbonised energy system in an effort to tackle climate change. The targets include a renewable energy share of 75% in the total consumption of energy and up to a 97% share of RES in electricity consumption [5]. This roadmap defines the importance of ESS in reaching these targets [6].

This study dealt with the numerical modelling of an ESS coupled to an offshore windfarm with the former being used to utilise the stored energy at times of high energy demand and low wind resource availability. In such a system, the use of renewable energy is prioritised by consuming first the windfarm's energy output, then the ESS's output and finally energy from fossil fuel sources, hence reducing the carbon footprint. However, the integration of a windfarm with the electricity grid and the use of an ESS gives rise to questions and challenges due to a series of knowledge gaps. Amongst the questions to be answered are: how will the system behave? Can its behaviour be predicted by predicting wind availability and forecasting the energy demand? What error could be introduced due to prediction and forecasting methods used?

The wind behaviour at a prospective candidate site can be predicted by means of a MCP methodology [7] and energy demand can also be forecasted [8, 9]. Recent advances in statistical learning [10] have

improved both the MCP and EDF methodologies. Prediction and forecasting have become more accurate and powerful.

The study starts with a description of MCP and EDF methodologies, and the possible outcomes when combining the two methodologies. The use of prediction and forecasting gives rise to errors and the least possible error is sought by applying different combinations of regression techniques for MCP and EDF to a model of an offshore windfarm, which is implemented in WindPRO®, and a model of an ESS which is implemented in Matlab® and Simulink®. By analysing the behaviour of the windfarm and the ESS, an optimal ESS capacity can be calculated. This can be achieved with both predicted wind data and forecasted energy demand data and measured data. In this way the error in capacity could be estimated.

The long-term predictions, which are possible with MCP and energy forecasting methodologies, and their application to the windfarm model in windPRO® and the ESS model in Simulink® enable both the LCOE and the LCOS to be calculated. The combined error in the use of the MCP and EDF on the LCOE and the LCOS is also evaluated.

This introductory chapter starts with an introduction to MCP, offshore floating windfarms, ESS, and EDF methodologies. A description of the research problem is then presented together with a list of objectives and the project challenges.

1.1 Measure-Correlate-Predict Methodology

An estimation of long-term wind behaviour at a prospective candidate site requires the availability of more than 10 years of data to be able to assess the economic feasibility of a windfarm with an acceptable degree of reliability. This is because wind varies in the temporal domain (diurnal, seasonal, inter-annual variability) [11, 12, 13]. A historical time-series of wind data at a candidate site is required to enable a site-specific evaluation of such variability. However, in most cases, such data is unavailable and statistical tools, referred to as MCP techniques, are used to derive long-term wind characteristics at the candidate site based on short-term measurements (normally of not less than 12 months) and longer-term wind data from a suitable reference site. Detailed descriptions of the general MCP methodology were presented by Jain et al. [7] and Burton et al. [11]. The MCP methodology uses historical wind data series from nearby weather stations, such as airports, which are dubbed the reference sites. MCP assumes that a correlation between the wind speed at the candidate and reference sites exists and creates a statistical model with which the long-term wind behaviour at the candidate site can be predicted. The short-term measuring period for the wind data of the reference site must also coincide in date and time with the measuring period at the candidate site.

The methodologies have improved with the use of modern statistical methodologies [10, 14], which take advantage of ever-improving computational power. MCP can be carried out using regression techniques such as Linear Regression (LR) [15], Artificial Neural Networks (ANNs) [16], Decision Trees (DT) [17] and Support Vector Regression (SVR) [18, 19, 20]. Moreover, the use of modern statistical learning tools, such as ANN, DT and SVR as regression techniques for MCP analysis is a recent development [21]. The wind speed and direction data enable models to be developed and used to predict the wind speed at a reference site. An assessment of the suitability of the models for predicting the wind speed is performed through an analysis of the Coefficient of Determination and residuals by means of established metrics such as the Mean Squared Error (MSE) and the Mean Absolute Error (MAE). Residual analysis plays an important role in detecting any departure from the underlying assumptions. The study also established a relationship between the coefficient of determination with measurement for the various LiDAR measurements and the different regression techniques [22].

1.2 Offshore Floating Windfarms

Although the research could be applied to various scenarios, which include both onshore and offshore windfarms (both shallow water and floating), the study used the costings of a floating windfarm to calculate the LCOE. The study focused on the Maltese Islands, where space on land is severely restricted and where the bathymetric conditions surrounding the islands are too deep for shallow water foundation technologies. This scenario is described in detail in Section 2.4.

New developments in offshore windfarm foundations' technology show that large-scale wind turbines can be supported on floating structures such as Tension Leg Platforms (TLP), Semi-submersible platforms (SSP) and Spar Buoy (SB) platforms. Typical examples are *Hywind*, a prototype floating windfarm positioned off the Scottish coast and *Windfloat*, a semi-submersible platform prototype positioned off the Portuguese coast [3]. Due to the increasing RE targets and because much of the coastline is already occupied by windfarms having fixed foundations, it is necessary to move further offshore. Noise from floating windfarms will not affect the nearby population, due to the increased distance from the shore and, for the same reason, there will be lower visual impact. Floating windfarms can also capture more wind due to the stronger wind found offshore, apart from harnessing wind which is undisturbed by terrain. They can also be constructed wherever necessary and can even be moved to accommodate changing circumstances [23].

1.3 Energy Storage Systems

Several forms of ESS exist, with a few of these being described in the literature review in Section 2.6.2. These include Pumped Hydraulic Energy Storage (PHES), Underground Pumped

Hydraulic Energy Storage system (UPHES), Compressed Air Energy Storage (CAES) and Battery Energy Storage [24].

Battery storage systems can be of several types amongst which are Lead Acid, Nickel-Cadmium (Ni-Cd), Lithium-Ion, Sodium Sulphur (NaS) and Redox Flow systems [24, 25]. Recent developments such as Tesla's Massive Energy Storage system at the Hornsdale Power Reserve [26] in Australia and the recent announcement of New York State's plans to reach 1500 MWh of battery energy storage by 2025 and 3000 MWh by 2030 [27], show that large-scale battery energy storage is becoming feasible.

Research on ESS involves the determination of the optimal capacity and power rating, with the primary use of the ESS being that of storing surplus energy during off-peak hours [28]. Various studies have been conducted in this regard and this current research attempted to optimise the size of an ESS coupled to an offshore wind farm, based on wind speed and energy demand data for the Maltese Islands [29].

1.4 Energy Demand Forecasting

Energy demand forecasting takes the form of long-term demand, peak demand, and load duration, such as daily or weekly demand. In the long term, energy demand can change due to climatic conditions, economic growth, and lifestyle [30]. Various regression techniques such as ANNs [31], DT, and SVR [8, 32] can be applied to forecast the energy demand. Energy Demand Forecasting (EDF) methodologies involve the analysis of trends, end-use of energy and econometric analysis, with each technique having its advantages and disadvantages.

Recent developments are using regression methodologies for long-term energy demand prediction, rather than the traditional ARIMA and Seasonal Autoregressive Integrated Moving Average (SARIMA) methodologies [33]. Several studies show that regression techniques such as SVR, which utilise evolutionary algorithms such as Genetic Algorithms (GA) and Simulated Annealing (SA), together with other algorithms such as Particle Swarm (PS) and Continuous Ant Colony Optimisation (CACO) for minimisation, provide a better estimation of energy demand [8, 9].

Energy Demand Forecasting is the most important technique that is used in the management of energy and is based upon historical data. The mathematical models utilised in this study forecast the energy demand, based on past behaviour. Also, an analysis of the characteristics and patterns in the available data is also necessary for EDF. For example, patterns depend on the hour of the day, on day of the week, such as a weekday or a weekend, public holidays, and season. Other factors include meteorological conditions, such as cloud-cover, and even special events such as sporting events [8].

1.5 Data Acquisition.

Rather than the traditional cup anemometer and wind vane for wind measurement, a wind resource assessment can now be carried out by means of a LiDAR system, which is being applied successfully in the renewable energy industry to measure wind speed, turbulence, veer and shear [34]. A ZephIR 300 remote sensing unit was used for the present study [35]. This was used to measure wind speed and direction at various heights above ground level.

Two sets of data were made available by the University of Malta for this research. The first set of data were the 3Tier [36] wind speed and direction data from the years 1980 till 2000. 3Tier data is a computational dataset. The second set of measured data were from June 2015 till July 2017. The latter data was measured by means of a LiDAR unit located on a coastal tower at Qalet Marku [37, 38]. Other wind data sets, for the periods 2007-2009, and 2013-2019, were acquired from Malta International Airport (MIA) Meteorological Office. The data from MIA's Luqa Weather Station site were measured with a mast-mounted cup anemometer and wind direction vane, at a fixed height above ground level.

Although various studies concerning different MCP methodologies have been conducted, ones showing the behaviour of the various methodologies based on measurement heights attainable by means of a LiDAR system for the Mediterranean Island of Malta were non-existent. The procurement of the LiDAR unit therefore created an opportunity to study this behaviour, and this is described in subsequent chapters [22]. Hourly energy demand data for the Island of Malta for the years 2011-2019, was provided by Enemalta Corporation Plc, the state provider for energy.

1.6 Problem Statement

The use of ESS facilities coupled with offshore windfarms relies on the accurate prediction of wind resources and the energy demand over the entire project lifetime. The research arises from the need to integrate the MCP methodology, which is used to predict wind behaviour at a candidate site with EDF. Measure-Correlate-Predict and EDF are normally performed independently, and this becomes problematic when one considers that the increased penetration of renewable energy sources has become more important.

Feasibility studies of ESS integrated with offshore windfarms and the electricity grid, and the analysis of their interdependent behaviour, are not available nor are studies of their predicted behaviour. Moreover, the predicted long-term behaviour and the extension of the study to the optimisation of the ESS capacity also made the calculation of the LCOE of the windfarm and the LCOS of the ESS possible. In this case the LCOS was carried out at the optimised value of the ESS and the use of predicted wind values and forecasted energy demand enabled the margin of error in the ESS capacity, LCOE and LCOS to be calculated.

The research analysed the accuracy of the models at the various steps of the research. These steps include determination of the optimal regression technique for the MCP methodology and the EDF methodology following which, the optimal regression technique for the MCP methodology was determined after applying the predicted wind speed and direction to the hypothetical windfarm. The best combination of regression techniques to be used for MCP and EDF was also determined by using the energy yield from the windfarm, the amount of curtailed energy and the energy discharged from the ESS to the electricity grid. The reliability of the results from the methodology determined the accuracy of the estimation for the ESS capacity, that of the LCOE and that of the LCOS.

1.7 Objectives.

The main objectives of this research were as follows:

- the integration of MCP with EDF methodologies,
- developing a model for an offshore windfarm integrated with an ESS,
- the optimisation of energy storage capacity, and,
- the establishment of the minimum LCOE for the windfarm and the LCOS for the ESS system coupled to the offshore wind farm, taking into consideration the lifetime of the windfarm and ESS infrastructure.

The relationship between MCP methodologies, ESS and EDF methodologies is shown in Figure 1-1.

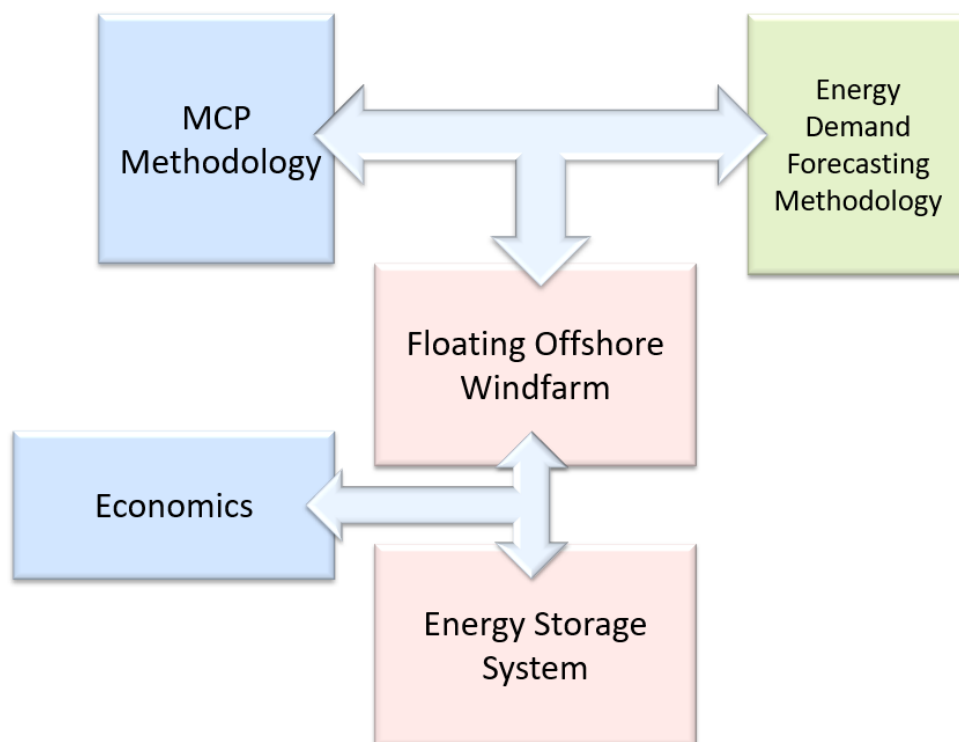


Figure 1-1: Establishing a relationship between MCP methodologies, energy demand prediction, offshore windfarms, energy storage facilities and economic factors.

The objectives of this research were achieved by using the methodology described in the next section which describes the organisation of the work carried out.

1.8 Organisation of Work

This Section describes how the objectives of this research were achieved and how the research was organised. Figure 1-2 to Figure 1-4 show the methodology applied. This was divided into three parts, while the objectives of the research were achieved in eight steps, as described below:

- Part 1 (Figure 1-2)
 - The literature review was carried out in Chapter 2 and this involved topics such as:
 - Measure-Correlate-Predict (MCP) methodologies,
 - Wind turbine wake models,
 - Energy storage technologies,
 - Energy Demand Forecasting (EDF) methodologies,
 - Dimension reduction
 - Levelised Cost of Energy,
 - Levelised Cost of Storage,
 - Establish the knowledge gaps, and,
 - Establishing the research aims.
 - The mathematical review was conducted in Chapter 3, and this included:
 - regression techniques for MCP and EDF methodologies, including a review of Simple and Multivariate Linear Regression, Artificial Neural Networks (ANN), Decision Trees (DT) and Support Vector Regression (SVR).
 - the Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) techniques.
 - the ESS model, which was applied in Matlab® and Simulink®,
 - dimension reduction techniques,
 - the LCOE and the LCOS, and,
 - the measurement metrics such as MAE and MSE.
 - Chapter 4 described the methodology used in this research.
 - Chapter 5 described the data acquisition and preparation.
 - Chapter 6 describes the design of the windfarm in WindPRO® and the ESS model in Matlab® and Simulink®.
 - The behaviour of the MCP methodology was established in Chapter 7 where the results obtained from using this methodology were also described. This was done in three steps as follows:

- **STEP 1** – A comparison of various regression techniques which could be applied to MCP methodologies was performed. This was achieved by using 3Tier (reference site) datasets and the Luqa (candidate site) Meteorological Office wind data to establish the validity of the regression technique to the MCP methodology.
- **STEP 2** – A comparison of various regression techniques applied to the MCP methodology using wind speed data measured at various heights with the LiDAR system located at Qalet Marku.
- **STEP 3** – the behaviour of a hypothetical offshore windfarm was established by applying actual and predicted wind time-series from the various regression techniques to the hypothetical offshore windfarm and the residuals compared to obtain the best regression technique for the MCP methodology [39]. Wind data from the Qalet Marku LiDAR site were used as the candidate site data, while concurrent wind data from Luqa were used as the reference site.

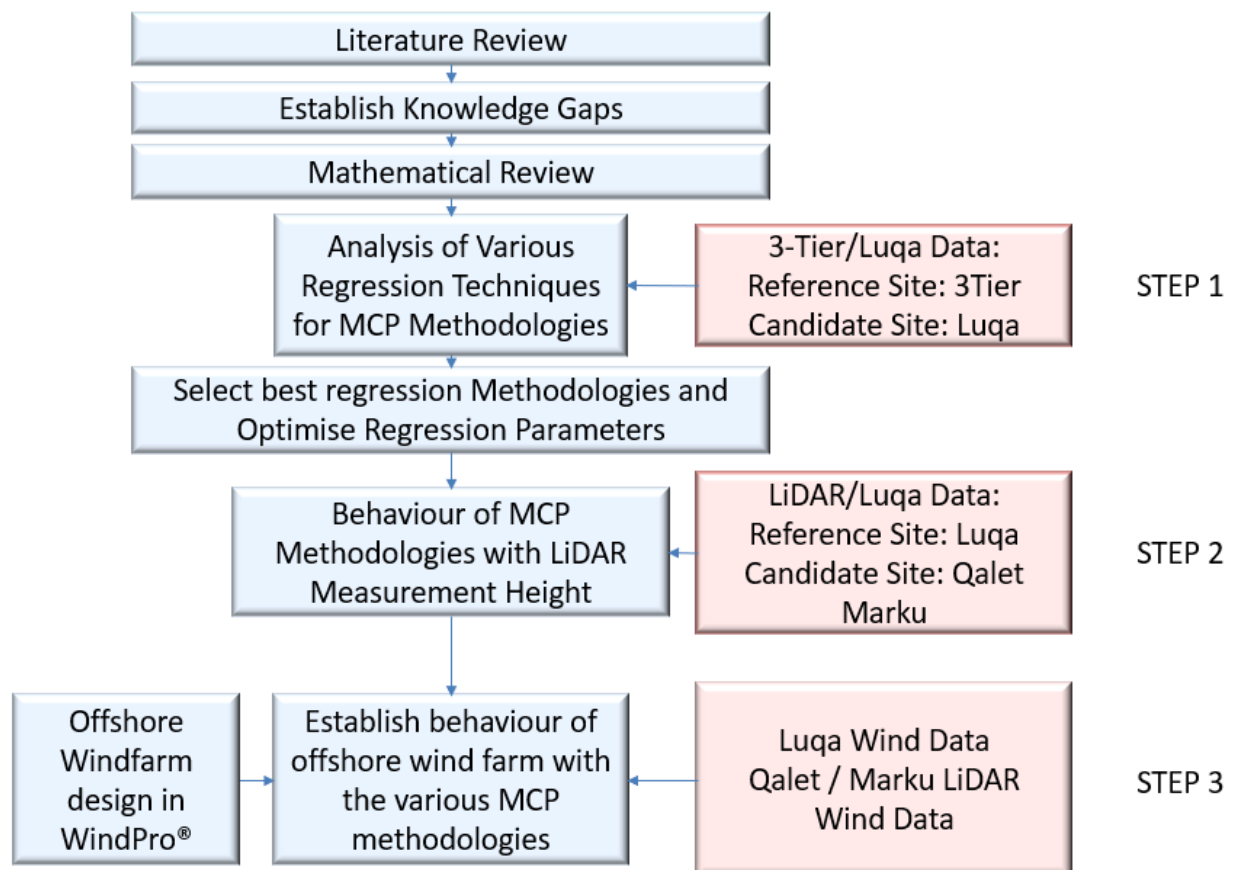


Figure 1-2: Organisation of Work (Part 1).

- Part 2 (Figure 1-3):
 - Chapter 8 presents the results from **STEPS 4** and **5**,

- where in **STEP 4**, ARIMA and SARIMA were used [33] to predict Gross Domestic Product (GDP), econometric end-use data and demographic trends, by using data from Malta's National Statistics Office, (NSO) web site [40], and,
- in **STEP 5**, various regression techniques were applied to EDF using the predicted GDP, end user and demographic data, together with other seasonal parameters such as season and time of day as the independent inputs of the regression. The suitability of the methodology was assessed by comparing the time-series of the EDF to the measured energy demand, and,
- Chapter 9 presents the results from **STEP 6**, where the best combination of regression techniques for MCP and EDF was established. In this case, a matrix of combinations of regression techniques for the MCP and EDF methodologies was produced to establish the combination which produced the least percentage error in energy yield from the windfarm and the ESS, together with curtailed energy from the windfarm. Dimension reduction was required to analyse the results from the matrix which resulted from the combinations of the regression techniques for the MCP and EDF methodologies.

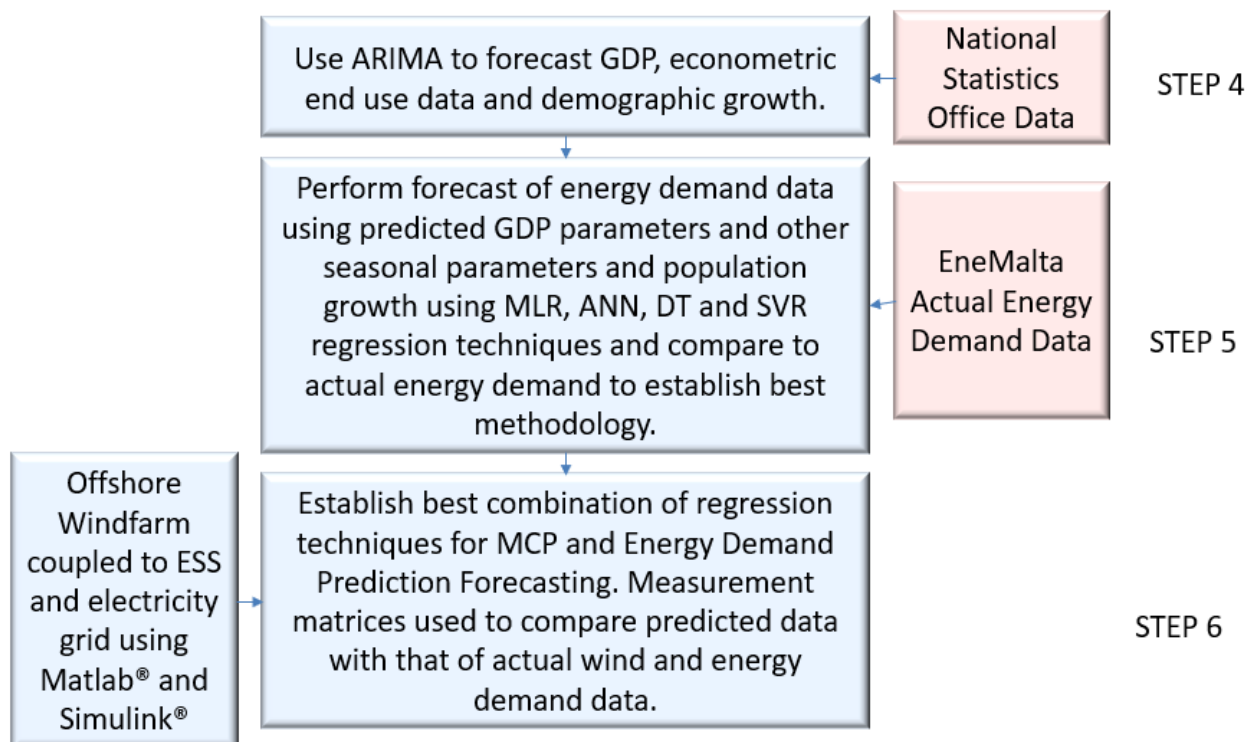


Figure 1-3: Organisation of Work (Part 2)

- Part 3 (Figure 1-4):
 - Chapter 10 describes the results from **STEP 7**, where the optimum size of the ESS was determined, using actual data, and predicted and forecasted data to establish the error in the ESS capacity.

- Chapter 11 presents the results from **STEP 8**, where the long-term behaviour of the offshore windfarm and the ESS was analysed, using the predicted data for wind speed and direction and the forecasted energy demand. The sensitivity of the LCOE against different floating windfarm scenarios and the LCOS against different battery-operated energy storage systems, namely Lithium-Ion (Li-Ion) and Vanadium Redox Battery (VRB) storage systems, was determined [3, 41, 42]. Several sources of windfarm and battery storage costing reports and other sources were used to obtain this information [3, 4, 43, 44, 45].
- A discussion of the results and the conclusions are presented in Chapter 12, which also recommends further recommended research, and describes the implications for the windfarm and energy storage industry.

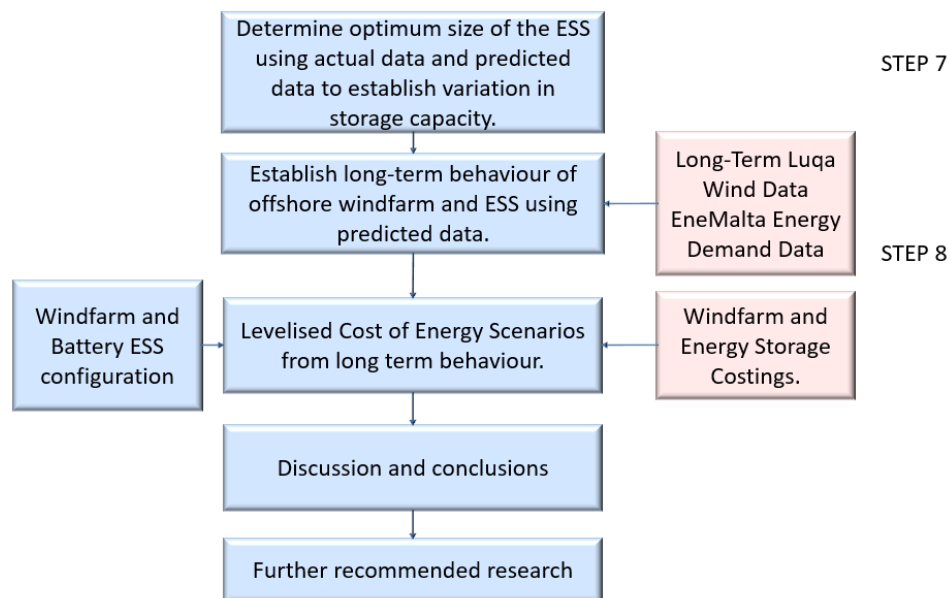


Figure 1-4: Organisation of Work (Part 3)

1.9 Conclusion

When using the above methodologies for wind prediction and EDF in isolation, one can predict wind behaviour and project energy demand independently. The study of the behaviour of an ESS to changing wind patterns and energy demand in the short- and the longer-term requires integrating the two projections. With the current need to integrate an ESS to offshore wind generation technologies and the existing electricity grid, the independent use of these tools becomes limited in scope. This is also especially true in calculating the feasibility of any proposed project which involves an ESS.

The knowledge gap identified in the literature review of Chapter 2, showed that there is no methodology which integrates wind prediction and EDF into a single model and which can predict the behaviour of a large-scale ESS. Such a methodology has therefore been proposed in this research. This model was tested by using the same mathematical techniques which are used to test MCP and EDF models for reliability and uncertainty. The extent of cumulative uncertainty in estimating the

optimal size of the ESS was also analysed. Uncertainty should be minimised, as the size of the ESS will have an impact on the LCOE and LCOS. A literature review which involves MCP methodologies, ESS for offshore windfarms, EDF, LCOE and LCOS will follow in the next chapter.

2 Literature Review

This chapter presents a literature review which identified the knowledge gaps and established the basis for this research. This also leads to the mathematical theory which establishes the regression techniques used for MCP and EDF methodologies, ESS models, forecasting, dimension reduction, LCOE and LCOS. These were used to obtain the results shown in Chapters 7 to 11. The literature review is followed by a list of identified knowledge gaps. A brief description of the methodology being adopted through the present research to address these gaps was presented in Chapter 1.

2.1 An Overview the Measure-Correlate-Predict Methodology

The first MCP methods introduced by the wind industry, which were described by Rogers et al., estimated the mean long-term annual wind speed [46]. In another study, Rogers et al. made use of SLR to establish a relationship between hourly wind characteristics of the candidate and the reference sites [47]. The MCP methodology is described in Figure 2-1, where the data to be correlated consists of two concurrent data sets, one at the reference site and one at a candidate site.

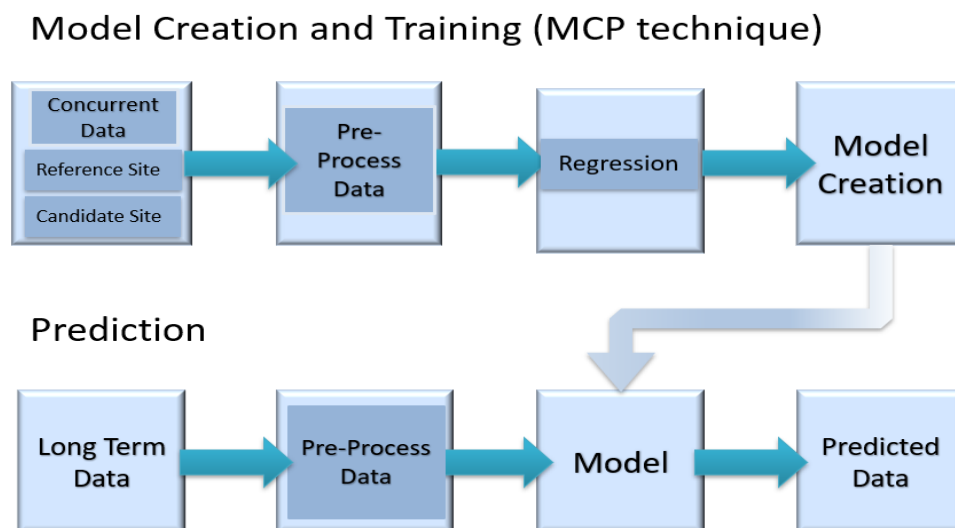


Figure 2-1: Applying the MCP methodology.

In the MCP methodology, data is first analysed for consistency and filtered from possible errors in measurements following which, a regression between the two concurrent data sets is performed, hence creating the model. When the model is created, a relationship between the wind speed at both sites is established. The long-term wind data at the reference can then be used to predict the long-term wind speed at the candidate site. The reference site is normally the closest meteorological station, e.g., airports, and the candidate site is the location chosen for the windfarm.

Montgomery et al. described several linear regression techniques, amongst which was the Multivariate Linear Regression (MLR) [15]. This regression technique involves more than one regressor variable. In the current research the regression was carried out using concurrent wind speed and wind direction data at the reference and the candidate sites. More recent models established non-

linear type relationships [48, 49]. These employ statistical learning [10]. Amongst these are Artificial Neural Networks (ANNs) [50, 51] and the more recent regression techniques which are based on Machine Learning (ML). These include Decision Trees (DTs) [14, 17] and Support Vector Regression (SVR) [17, 18, 52, 53].

A study by Carta et al. reviewed many MCP methodologies [46]. These included the method of ratios, first-order linear regression, higher than first-order linear, non-linear, probabilistic methods such as the use of Bayesian classifiers [54]. The authors were also concerned with the uncertainties associated with the MCP methodology and argued that users of the MCP methodology had little information on which to determine the uncertainty. According to the authors one way to measure this uncertainty was to use the full set of data from the concurrent period to train the model and assess its quality.

Further studies by Rogers et al. compared four different MCP methodologies [47]. These included a linear regression model, the distributions of ratios of the wind speeds at the two sites, an SVR model and another method based on the ratio of the standard deviations of the two data sets. The authors concluded that SVR gave the best results. In a different study, Rogers et al. also analysed the uncertainties introduced with the use of the MCP methodology [55]. They concluded that the use of linear regression techniques could seriously underestimate uncertainties due to serial correlation of data. Another study by Lackner et al. showed that a proper assessment of uncertainty is critical for judging the feasibility and risk of a potential wind farm development, and the authors described the risks of oversimplifying and assuming uncertainties [56].

Zhang et al. applied a hybrid MCP method [57]. This involved adding different weights, which depended on the distance and elevation of the candidate site with respect to the reference sites. This was applied to five different regression techniques for the MCP methodology. The techniques consisted of the LR, Variance Ratio, Weibull scale, ANNs and SVR methods. The ability of ANNs to recognise patterns in complex data sets meant that they could be used to correlate and predict wind speed and wind direction [57]. The results were assessed in terms of metrics such as the MSE and the MAE. Perea et al. [58] evaluated three techniques for MCP. One method included a LR, which was derived from the bivariate normal joint distribution and the Weibull regression technique. Another method was based on conditional probability density functions applied to the joint distributions of the reference and the candidate sites. The results from these two methodologies were in turn compared to SVR. Although the conclusion was that the SVR method predicted all the parameters very accurately, the probability density function based on the Weibull distribution was better in terms of prediction accuracy.

A neural network contains an input layer, one or more hidden layers of neurons and an output layer. A learning process updates the weights of the interconnections and biases between the neurons in the

various layers. The Levenberg-Marquardt [16] algorithm may be used for this purpose. The regression is performed by means of feedforward networks [17] with *multilayer perceptrons* (MLP).

Velasquez et al. utilised wind speed and direction from various reference stations. These were introduced into the input layer of an ANN [59]. It was concluded that when wind direction was used as an angular magnitude to the input signal, the model gave better results. Estimation errors also decreased as the number of reference stations was increased. The authors hence concluded that ANNs are superior to other methods for predicting long-term wind data.

The use of ANNs for long-term predictions was also investigated by Bechrakis et al. [60]. In this case the authors used wind speed and direction measurements from just one reference station and compared results to those from standard techniques used for the MCP methodology. This resulted in an improved prediction accuracy of 5 to 12%. Unfortunately, many models that use various reference stations use only the recorded wind speeds as input. The topologies of the ANNs used in this case have only a single neuron in the input layer, with the output signal being the wind speed at the candidate site [51, 52, 61].

Data from meteorological stations which possess long-term measurement periods provides many potential inputs for MCP. Apart from wind speed and direction, inputs can also include other climatological variables such as air temperature, relative humidity, and atmospheric pressure. Due to this Patane et al. utilised a multivariate MCP methodology [62]. This technique considers all the inputs and extracts the maximum amount of information at the sites. The methodology is a two-stage process since some input variables may be inter-correlated or may not provide any additional information about the candidate site's wind characteristics. Input variables were analysed and those that contained little or redundant information about the candidate site wind characteristics were discarded, following which, a multivariate regression was performed. The results led to the conclusion that this methodology was more accurate than standard techniques used for MCP. The quality of the estimation of the long-term wind resource increased by 19%.

SVR is the adaptation of Support Vector Machines (SVM) to the regression problem. The SVM technique was developed by Vapnik to solve classification problems [19, 20]. SVR is popular within the RE community because it is a unique way to construct both smooth and nonlinear regression approximations [17]. Diaz et al. considered the use of SVR for the analysis of MCP as one which best represented state-of-the-art ML [63]. This was not only due to its prediction capability, but also to its property of universal approximation to any continuous function. It was also considered to be an efficient and stable algorithm that provided a unique solution to the estimation problem. In this current research different hyperparameters were used to study the performance of the SVR methodology

when applied to MCP. Other studies by Zhao et al. described how SVR may be adapted to wind speed prediction [53].

Another recent study by Diaz et al. [64] demonstrated the importance of DTs in improving the regression results for MCP. The study applied five different regression techniques to mean hourly wind speed, wind direction and air density, using data from ten weather stations in the Canary Islands. The study showed that the models using SVR, and DTs provided better results than ANNs. A DT is a hierarchical data structure which implements the ‘divide and conquer’ rule, which may also be applied to the regression problem [10, 14, 17].

According to Probst et al. [65] the use of LiDAR for wind resource assessment has a distinct advantage over the traditional cup and wind vane measurements. This was demonstrated by Probst by carrying out a study using different regression techniques for MCP such as SLR and ratio analysis. However, this study did not utilise ANNs, DTs or SVR to predict wind speed. Nor did it predict wind direction, as described in Section 2.1.1. Part of this current research also investigated the accuracy of different regression techniques and to measure their reliability against the LiDAR measurement height [22]. The study concluded that the MCP accuracy depended on both the regression technique and the measurement height at the candidate site. Other studies using LiDAR at the same measurement site were also carried out by Cordina et al. [37]. These analysed the flow of the wind at the different measurement heights.

2.1.1 A Measure-Correlate-Predict Methodology for Wind Direction

It was established that the MCP methodology is based on regression techniques, which can be SLR or more powerful techniques, amongst which are MLR, ANNs, SVR and DT. Also, while the MCP methodology has been developed for wind speed, they cannot be used directly for predicting wind direction. According to Bossart and Papin this is due to the reason that while a wind direction of 1° should appear strongly correlated with a wind direction of 359° , this will not be the case when using a regression technique for wind direction [66]. Nothing has been found in literature on MCP techniques which explicitly mentions prediction of wind direction at a candidate site. Wind velocity may be negative (if one considers it as a vector) and the MCP methodology normally only considers the positive value of the wind, i.e., its magnitude. The use of wind speed vectors was therefore an innovative way of using a regression methodology to predict the wind direction [39]. This was achieved by splitting the wind velocity vector into its respective components. This innovative methodology was used to create a regression model which used the wind velocity vector components to predict the respective wind vector components at the candidate site as described in Section 3.1.5.

2.2 Wake Models for Windfarms

The issue of wake losses in a wind farm has been described by several authors. Manwell et al. [67] showed that wake losses can be minimised by optimising the layout of the wind farm. A short literature review of wake models is now presented.

Manwell et al. classified wake models into four categories, namely [67]: Surface roughness models [68], semi-empirical models [69, 70], eddy viscosity models [71], and Navier-Stokes solutions [72, 73]. In a review of wind turbine wake models Sanderse showed the effects of reduced power production due to lower incident wind speed and the effect on the wind turbine rotors due to increased turbulence [74]. Sanderse also showed that numerical simulation is preferred to experimentation; mainly due to the use of Computational Fluid Dynamics (CFD) [74]. Another study by Gonzales-Longatt et al. presented the mathematical theory behind a simple wake model and that for a multiple wake model, while another study by Churchfield described a hierarchy of wake models ranging from the empirical to Large-Eddy Simulation (LES) [75, 76]. Some of the models compared include Ainslie's Model [71], Frandsen's model [77], and the N.Ø. Jensen's model [78], with the latter being a simple model with results which were comparable to experimental results. The Dynamic Wake Meandering Model (DWMM) is another method which is described by Larsen et al. [79]. This was also validated by Larsen et al. in a study carried out on the Egmond aan Zee offshore wind farm [80]. In another study, Barthelmie et al. compared wake model simulations for offshore wind farms, with the wake profiles being measured with Sonic Detection and Ranging (SoDAR) [81]. In this case, the models gave a wide range of predictions, and it was not possible to identify a model with superior projections with respect to measurements.

In some studies, it is necessary for the wake model to be straightforward. This means that they are dependent on relatively few wake measurements and are also economical in terms of the computing power. Simple models were found to be in reasonable agreement with the available data in the case of a single wake within a small wind farm in a simple meteorological environment. In addition, a comparison of different wake models by Manwell et al. did not suggest any difference in terms of accuracy, between the sophisticated and simple wake models [67].

Katic et al. showed that the use of wake models could also be illustrated by considering a semi-empirical model [82]. This model attempted to characterise the energy content in the flow field whilst ignoring the details of the exact nature of the flow field, which is assumed to consist of an expanding wake with uniform velocity deficit that decreases with downstream distance.

2.3 Dimension Reduction

As a part of the analysis required in STEP 6 (Figure 1-3), dimension reduction will be required. This is because of the multidimensional data which was generated when defining the optimum

combination of regression techniques for the MCP and EDF methodologies. This resulted in a complex dataset which involved the offshore windfarm capacity, generation baseload, ESS capacity as well as the various combinations of regression techniques which were applied to the MCP and EDF methodologies. In a comparative review of dimension reduction, van der Maaten et al. defined dimension reduction as the transformation of a space with a large number of dimensions into space with a lower number of dimensions, which will represent the high-dimensional space with the least possible loss of information [83].

According to an assessment of dimension reduction techniques carried out by Fodor [84], the best dimension reduction algorithm is the Principal Component Analysis (PCA) technique. This technique reduces the dimensions of the data by identifying a few orthogonal linear combinations of the original variables with the largest variance. It is considered as a second-order linear dimension reduction technique.

Anowar et al. performed a conceptual and empirical comparison of various dimensionality reduction techniques [85]. The authors focused on Feature Extraction (FE) algorithms, because of their ability to represent real-life datasets. The authors concluded that following the application of FE algorithms, the quality and accuracy of the data increased.

In a further review of dimension reduction algorithms Ma and Zhu provided a description of the dimension reduction problem [86]. They mentioned the growth in complexity of scientific data, which makes it very difficult to identify a relationship between the many variables. They indicated that this problem could be approached in two ways. This first method was related to the fact that only a few of the variables were significant, with the rest having no real effect on the result. The second methodology was to reduce the data, hence applying the approach of data reduction. This assumed that the data could be represented by a few linear combinations. Dimension reduction attempts to identify these few linear combinations.

Dimension reduction methods were also described by James et al. [14]. In this definition of dimension reduction, $p + 1$ coefficients $\beta_0, \beta_1, \dots, \beta_p$ which define a high-dimensional space, are reduced to smaller number of $M + 1$ coefficients $\theta_0, \theta_1, \dots, \theta_M$, where $M < p$, hence reducing the dimension size from $p + 1$ to $M + 1$.

Algorithms for dimension reduction were categorised into Linear or Nonlinear type. Linear types such as PCA [14, 84, 85], Partial Least Squares (PLS) [14], Singular-Value Decomposition (SVD) [85] and Linear Discriminant Analysis (LDA) [85] techniques mapped a high-dimensional space into a lower space using a linear algorithm. Nonlinear types such as Multi-Dimensional Scaling (MDS)

and Kernel PCA (KPCA) [83] utilised a non-linear algorithm to map a high-dimension space into a lower dimension space [83, 85].

In this research STEP 6 resulted in a matrix with 5 dimensions ($p = 4$), with the dimensions being equivalent to the installed capacity of the windfarm, the generation baseload, the capacity of the ESS, and the regression techniques, which when applied to the MCP and EDF methodologies resulted in another two dimensions. This was reduced to 2 dimensions, equivalent to the regression techniques applied to the MCP and EDF methodologies.

2.4 Floating Wind Farm Concepts

The coastline around the Maltese Islands consists mostly of special protected areas [87]. Amongst the several sites proposed for offshore wind, one of the most attractive shallow water sites suitable for a monopole windfarm was the area known as is-Sikka il-Bajda, on the Northwest side of the island [88]. A wind energy project installed here was expected to provide 40% of the Islands' total 10% European Union target for 2020, as given in EU directive 2009/28/EC. At the time, wind energy was therefore seen as an essential part of the Island of Malta's National Renewable Energy Action Plan (NREAP) [89] for reaching the 2020 targets. This project was not deemed feasible by the Maltese Government, mainly due to its vicinity to a Natura 2000 [90] site, which is home to a large breeding colony of sea birds. This was apart from other environmental concerns such as being visible from one of the most popular beaches on the islands. It was also in the vicinity of a major shipping lane and close to a bunkering area. One option was therefore to place the wind farm elsewhere. However, the bathymetry, which exceeds 50 m within a few hundred metres of the shoreline, showed that there are few areas which support shallow water windfarms [88]. However, since then, technology has evolved, and the concept of a floating windfarm can now be considered for the purpose this research project.

As already highlighted in the Section 1.2, floating wind is a developing new technology, which enables windfarms to be placed in deeper waters. According to the International Renewable Energy Agency (IREA), the technology could be a potential game changer in the industry [91] and is one of the fundamental pillars which according to Adam et al. enables the supply of energy, while meeting environmental restrictions [92]. According to Wind Europe the technology for floating windfarms has reached maturity and costs are expected to plunge soon [93]. Floating windfarms can be of three types:

- Spar-Buoy (SB), such as the Hywind concept, developed by StatoilHydro, Siemens and Technip [94]. This is installed and moored to the seabed around 30 km off the coast of Aberdeenshire in Scotland,
- Tension Leg Platform (TLP), such as Golsten's Pelastar [95], or,
- Semi-submersible platform (SSP), such as that developed by Principle Power [91, 96].

Jonkman et al. described the above three different floating windfarm concepts, which are shown in Figure 2-2 [97]. The SB is ballast stabilised, the TLP is mooring line stabilised and the SSP is buoyancy stabilised.

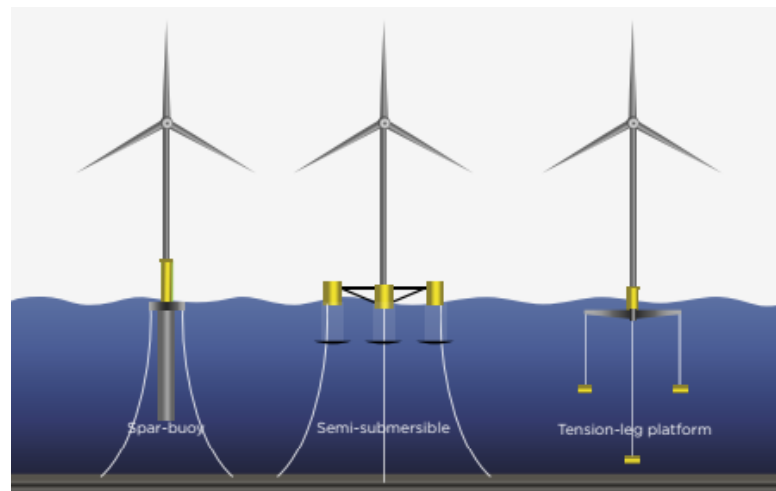


Figure 2-2: Three different floating windfarm concepts, from left to right, Spar-buoy, Semi-Submersible and Tension Leg Platform [91, 97].

In the SB configuration, an enormous cylindrical buoy stabilises the turbine by using ballast. The lower parts of the foundation are heavy, resulting in a centre of gravity which is low in the water. This gives rise to a very simple and stable structure with low installation cost. The simple structure makes it simple to manufacture. However, the draft of the structure makes it unsuitable for near shore applications, and it has to be deployed in depths of more than 100 m. This makes maintenance of the system difficult [91, 96, 98].

According to Heidari, a TLP requires tensioned mooring lines which are kept in place by means of heavy steel rods anchored to the seabed [96]. The TLP structure is submerged and keeps the wind turbine up above the water surface while the mooring lines pull the structure downwards, in the direction of the seabed. Gicon SOF [92] is a TLP offshore floating windfarm, while Golsten's Pelastar is another concept in TLPs [95]. This structure has low production costs and can be installed onshore and transported to its destination. It suffers from the disadvantage of having a complex installation and maintenance [91, 96, 98].

In an SSP stability is achieved by means of distributed buoyancy. The foundations consist of several columns which are connected to one other. This structure provides both stability and buoyancy. The structure is secured and kept in position by means of the mooring lines. The most mature concept in semi-submersible technology is WindFloat, which was developed by Principal Power. WindFloat 1 reaches a hub height of 70 m, while WindFloat 2 reaches a hub height of 100 m. In October 2011, Principal Power deployed a full-scale 2 MW prototype wind turbine 5 km off the coast of Portugal [98]. This structure has the advantage that it can be towed to shore for maintenance or repairs, and its

shallow draft means it can be deployed in shallow waters. However, its complex structure makes it difficult to manufacture.

2.5 The Levelised Cost of Energy of Floating Offshore Windfarms

In 2018, it was estimated that the LCOE for shallow offshore wind was around € 124/MWh, with a decreasing trend for the coming years [2]. The LCOE for Floating Offshore Wind Turbine (FOWT), is greater, due to larger and more complex foundations. A study by Myhr et al. considered various concepts of floating wind [41]. The study showed that Hywind's SB system had an average LCOE of € 164.6/MWh, which varied between € 243.4/MWh and € 109.3/MWh, while again according to Myhr et al. that for Windfloat's semisubmersible varied between € 189.2/MWh and € 120.5/MWh [41].

According to the Offshore Wind Market Report for 2021, offshore wind LCOE has declined by 28-51% between 2014 and 2020, currently being at levels of between € 69/MWh and € 111/MWh, and it is predicted that by 2030 levels will fall to approximately € 50/MWh, declining further to a range of between € 39/MWh to € 64/MWh by the year 2050 [99].

Other studies by Maienza et al. and Myhr et al. also compared the LCOE of the various floating windfarm platform configurations [3, 41]. LCOE studies included installation, operational and decommissioning costs [3]. In another study by Muisal et al. installations included the costs of wind turbine, harbour space rentals, ship, tug and crane rentals, mooring cables, anchors, platforms, substations, transformers and export cables [100]. The study by Maienza et al. also described LCOE methodologies and established the net present value costs for offshore floating windfarms [3]. The study focused on an offshore floating windfarm located in Southern Italy, where the Weibull parameters for wind speed are $a = 7.7 \text{ ms}^{-1}$ and $k = 1.574$, which are values similar to the Weibull distribution for the wind speed at the Qalet Marku LiDAR site ($a = 7.5 \text{ ms}^{-1}$ and $k = 1.86$) at a LiDAR measurement height of 80 m and ($a = 8.03 \text{ ms}^{-1}$ and $k = 1.84$) at a LiDAR measurement height of 150 m.

The study by Maienza et al. showed that floating windfarms have become economically feasible, with the LCOE being in the range of € 94.71/MWh for a Spar Buoy (SB) windfarm to € 106.70/MWh for the Tension Leg Platform (TLP) [3]. Castro-Santos et al. also described the methodology used to calculate the installation costs of offshore windfarms and provided an itemised list of requirements for floating windfarms situated in deep waters [101]. The study used a windfarm situated in the region of Galicia in the North-West region of Spain. A study by Musial et al. [100] on the cost of a windfarm which uses semisubmersible technology which is located off the shore in the state of Maine in the United States, showed that such windfarms can be placed in waters which are deeper than 60 m. The

study shows that the cost of the technology will continue to decline and by the year 2032 could be as low as € 48.63/MWh for a floating windfarm with a 600 MW installed capacity.

A recent study conducted by Ghigo et al. for a floating windfarm around the Mediterranean island of Pantelleria, shows that for a 10 MW wind farm, a capacity factor ranging from 41.7% to 42.8% was possible, depending on wind farm type and location [4]. Ghigo et al. also predicted an LCOE in the range of € 136.6/MWh to € 179.4/MWh, again depending on wind farm location and type of mooring [4]. Another study by Ahmed [102] considered the technical and economic feasibility of a windfarm on the coast of the Mediterranean Sea. Here the capacity factor of the windfarm varied from a minimum 12.9% to a maximum of 30% depending on the month of the year, with an annual capacity factor of 22%. The farm was located a few hundred metres from the coast outside the town of Sidi Barrani, in Egypt.

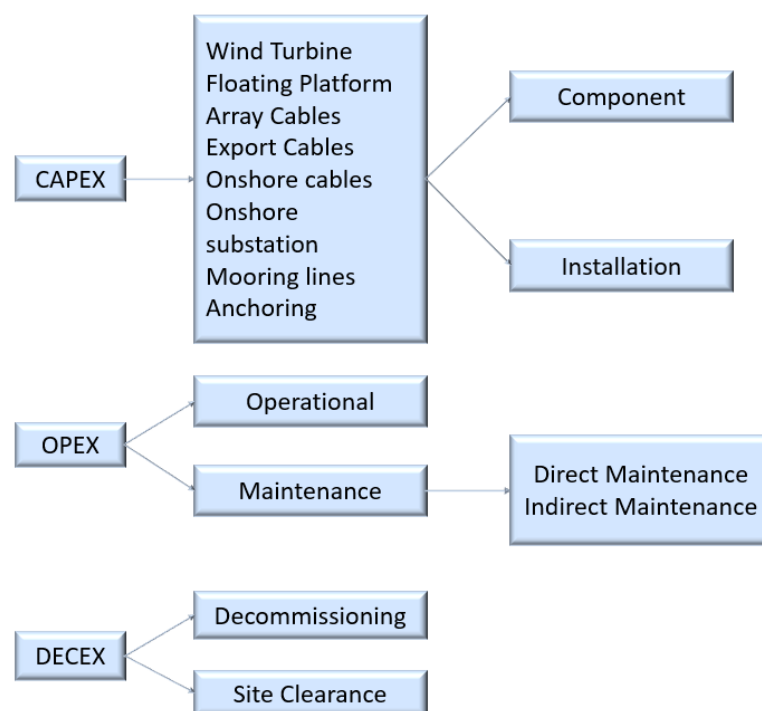


Figure 2-3: Breakdown of CAPEX, OPEX and DECEX components for LCOE calculation for offshore floating windfarms [3].

The study by Myhr et al. showed that LCOE studies typically assume a life cycle of twenty years for an offshore windfarm [41]. The authors showed that the LCOE fell off exponentially with windfarm size. Figure 2-3 shows typical components considered for the calculation of the LCOE for a floating windfarm. Costs include Capital Expenditure (CAPEX), Operating Expenditure (OPEX) and Decommissioning Expenses (DECEX) [3].

2.6 Energy Storage Systems for Offshore Wind

Various countries throughout the world have embarked on an era of distributed generation and non-dispatchable electrical energy systems. The ability to manage increased levels of variable generation

will therefore become critical. To manage this increased variability, Barnes and Levine stated that electricity grids need to become flexible in the management of both load and generation [24]. For example, when a system has more wind energy available than it can absorb, output power from wind farms needs to be curtailed. It is therefore desirable to locate an ESS near an offshore windfarm. This will absorb unneeded power from the windfarm and will supply peak loads when required.

The operating level of coal-fired and nuclear power plants cannot be reduced below a set minimum without causing serious problems to their operations. It will take several hours to start a coal-fired system and several days to restart a nuclear generator. Generation is also limited to allowable ramping rates. On the other hand, natural gas is susceptible to supply shortfalls and price variation, while operating gas-turbines intermittently to balance fluctuations in wind power generation will lead to higher inefficiencies in the operation of the gas-turbine, as well as higher emissions.

The management of increased variability by the utility companies will depend on the type of ESS available. The ESS system must therefore exhibit a profile which is complementary to standard generation. An ESS can result in considerable system cost savings. However, investors always require a viable business case [1]. Other contributing factors to be considered when deploying an ESS are energy arbitrage, frequency response (FR), balancing services, network support, and the removal of under-utilised fossil-fuel generation sources. Last but not least is the reduction of carbon emissions.

Further studies on the integration of an ESS with windfarms by Saadat et al. present a model for controlling an open accumulator system for a CAES and wind turbine [103]. The model utilises a non-linear controller and demonstrates how the system can be used to downsize the electrical system and maximise revenues. Saadat et al. showed how wind energy with an integrated ESS can become a dispatchable base power and replace fossil fuel sources.

In another study, Saadat and Li [104] presented an ESS concept for offshore windfarms which took the form of a mathematical model. This envisaged the storage of excess energy from the wind turbines. Saadat and Li also concluded that ESS would turn windfarms into a dispatchable power source that can replace conventional generation and that further studies were necessary to optimise such systems.

Optimal sizing was further analysed by Xia et al. who described a cost-benefit analysis model for power system planning with uncertain wind conditions [28]. This study optimised storage capacities for windfarms. It described the behaviour of four ESS types and shows how ESS size can be optimised while taking uncertainties in wind generation into account. This study also took the lifetime of the system and the charging and discharging efficiencies into account. Similar research by Aghajani et al. discussed optimal energy storage sizing, in view of proposing a strategy for the introduction of battery storage systems to increase the cost benefits [105]. Moghaddan et al. proposed a model for

optimising profits from a battery storage system by analysing purchased and curtailed wind power against an optimised storage capacity [106]. Du and Lu described other ESSs, such as super capacitors, flywheels, hydrogen storage and fuel production systems [25].

Pumped Hydraulic Energy Storage (PHES), Underground Pumped Hydroelectric Energy Storage (UPHES), CAES and Battery Storage systems support the utilisation and penetration of RES with the electricity grid. Figure 2-4 to Figure 2-7 show possible configurations with an offshore wind farm for such ES facilities [24, 107].

2.6.1 The Challenges for Energy Storage for Offshore Wind Farms

Barnes and Levine argued that if RES are to provide an alternative to fossil fuel generation, they must provide a means to replace baseload generation capacity [24]. This is very challenging since baseload generation is the cheapest form of generation. When RE generation comes online coincident with a low energy demand, it will not be possible to ramp down the baseload fossil fuel-based generation systems. Energy Storage Systems, specifically PHES, UPHES, CAES and battery systems can address this hurdle and help in balancing generation and loads. Energy storage can also be utilised to manage peaks in energy demand, and this is the case with a low ESS capacity such as that provided by battery systems as shown by Beaudin et al. [108]. The authors also showed that growth of RE penetration favours the expansion of ESS and vice-versa. Therefore, the ESS must be managed carefully, and different management scenarios should be analysed to find out which strategy would result in the best LCOE and LCOS.

On the one hand, it should be mentioned that the availability of a large capacity of offshore wind energy increases the possibility to utilise an ESS, with the windfarm being its main source of energy. This will require more flexibility in ESS management. On the other hand, a lower penetration of offshore wind energy increases the risk that the ESS will be charged from fossil-fuel based sources.

The kind of ESS to be installed depends on the power required to meet transient needs, on the total energy required to match the output of the renewable sources to loads over the times of interest, and the chosen strategy. Another item to be considered is the site's topography, for example, hills which could serve as reservoirs in the case PHES, or underground caves which might be necessary in the case of CAES, or an adequate aquifer in the case of UPHES. If it is feasible to use battery storage, one should consider the various battery technologies available.

2.6.2 Energy Storage Systems

With the increase in penetration of wind energy, the inclusion of an ESS becomes an option that utilities might want to use to increase reliability and reduce the cost of providing power. The kind of ESS to be installed depends on the power required to meet transient needs, the total energy required to match the output of the renewable sources to loads, the chosen strategy, and site topography [24].

A few types of ESS which could be integrated with offshore windfarms are now described in the following sections.

Pumped Hydraulic Energy Storage (PHES)

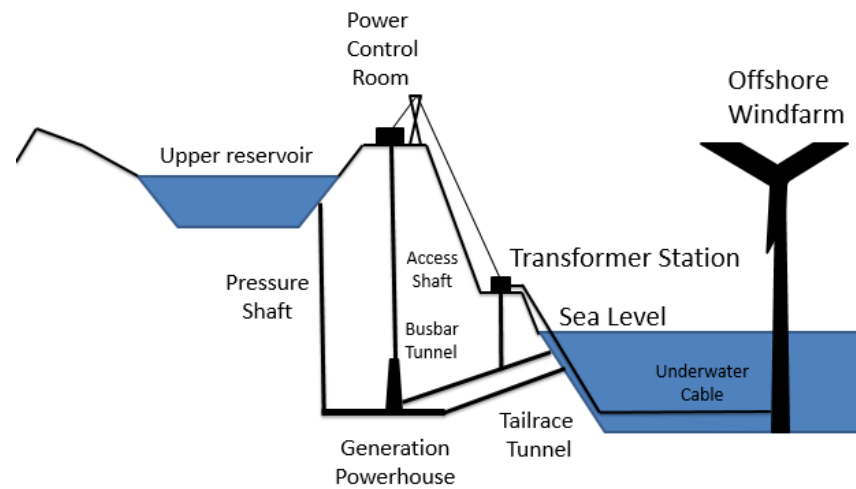


Figure 2-4: Offshore wind energy integrated with pumped hydroelectric energy storage [107].

Donalek described pumped storage as having deep historic roots [109]. Levine shows that a PHES facility is different from normal hydroelectric energy generation [107]. Water is pumped, via a pump/turbine which is driven by means of the excess energy from a windfarm. Figure 2-4 shows how such a system could derive energy from an offshore windfarm. Water flows from a reservoir at a low level to a higher-level reservoir, hence storing energy as potential energy. When it is necessary to release the stored energy, the water flows through the turbine from the high-level reservoir to the low-level reservoir. In 2015, an approximate 250 existing PHES plants had a cumulative 125 GWh of generation capacity and Beaudin et al. [96] claimed that this capacity was increasing at the rate of 5 GW per annum. This represented 3% of the world's energy generation capacity and 97% of the world's storage capacity. At the time of writing, the US Department of Energy's (DOE) Energy Storage Database reported that the world's global PHES capacity for 2020 stood at 185 GWh with a total of 352 pumped storage facilities worldwide [110].

Farrugia et al. investigated the use of pumped hydroelectric energy integrated with wind energy resources by considering the potential use of limestone quarries on the Island of Malta as a store for hydroelectric energy [111]. They proposed their integration with deep offshore wind. Brown et al. [112] analysed different scenarios to optimise reservoir capacities in isolated systems which have a large RE penetration, while Tuchy and O'Malley [113] considered different scenarios to optimise the hydroelectric storage capacity for the Republic of Ireland. Another interesting type of hydroelectric storage was suggested by Slocum et al. [114] as an undersea storage concept known as Ocean Renewable Energy Storage (ORES), shown in Figure 2-5. This was especially suited for floating wind farms as the storage spheres could also serve as anchorage points. Another project, also based on the

concept of underwater energy storage known as Stored Energy in the Sea (STEnSea), is currently being developed by the Fraunhofer Institute [115].

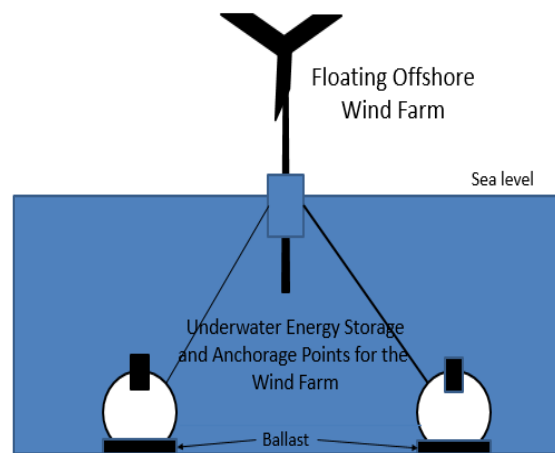


Figure 2-5: ORES concept, with containers for ES serving as anchorage points for a floating windfarm [114].

Underground Pumped Hydraulic Energy Storage (UPHES)

Martin described a UPHES as a variation of the surface PHES. This utilised an underground storage location as the lower reservoir, while the upper reservoir is at the surface. The design and construction of large UPHES is a difficult task. The lower reservoir has to be excavated. It can also utilise an existing naturally occurring underground aquifer or cavern [116]. To date, no UPHES system, commercial or otherwise, has been installed and used. However, Olsen et al. proposed an interesting variation which takes the form of an Energy Membrane Underground Pumped Hydro Storage (EM UPHS) system [117].

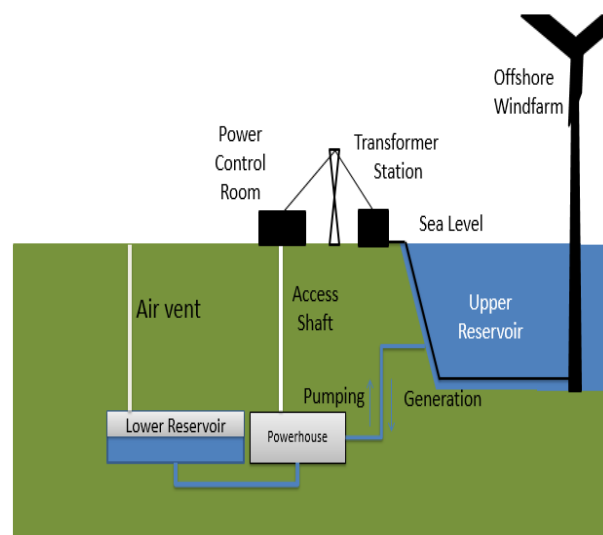


Figure 2-6: Underground pumped hydroelectric generation integrated with an offshore windfarm [116].

UPHES has the advantage of overcoming the dependence of PHES installations on surface topography. However, the disadvantage is that suitable naturally occurring underground geologies

and structures are rarely available. Figure 2-6 shows how this can be integrated with an offshore wind farm.

Compressed Air Energy Storage (CAES)

Compressed Air Energy Storage (CAES) is a technology whereby energy is stored in the form of pressurised air [118]. In a review of CAES for offshore applications Vella et al. described the challenges for integrating CAES with offshore wind turbines [119]. The combination of offshore wind energy with CAES was also described by Wang et al. [120]. CAES was also described by Succar as an ES technology which can be applied for long duration and large utility applications, and as being particularly suitable for incorporation with windfarms [118]. The two existing CAES plants, Huntorf in Germany and McIntosh in the USA, have demonstrated very high reliability and economic feasibility [108].

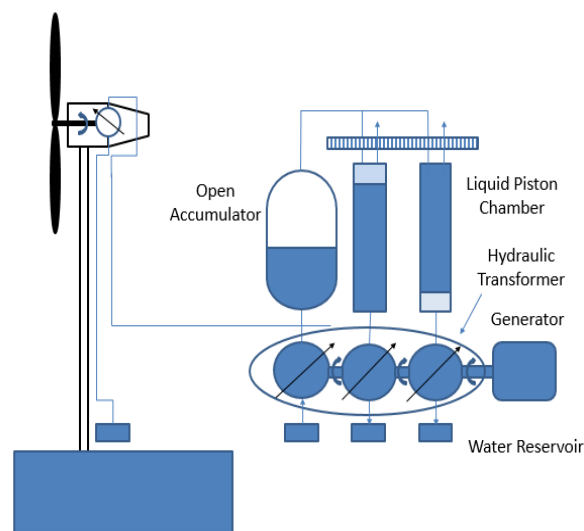


Figure 2-7: Compressed Air Energy Storage System for offshore wind [120].

CAES is especially suited for electrical grid balancing, which requires large-scale and long duration ES together with, fast output storage times, fast response times, and suitable siting [118]. Furthermore, CAES can ramp output at short notice, making it effective for countering the variation in the energy output from the windfarm. A CAES also has a low greenhouse gas emission level. Ramadan et al. analysed such a system which is integrated with large-scale wind energy and presented a model which demonstrated the effectiveness of such a system [121].

Research into CAES which was carried out by Carson et al. resulted in the evaluation of the possibility of the underwater CAES potential in the Gulf of Maine [122]. Alami also showed the possibility of integrating CAES with Buoyancy Work Energy Storage (BWES), which is a novel concept that is also applicable for direct coupling with offshore wind farms, especially if appropriate anchoring provisions are integrated in the foundations of the wind turbines while they are being built [123].

A novel concept in energy storage has also suggested by the Institute for Sustainable Energy of the University of Malta by Buhagiar et al. [124]. This consisted of a hydro-pneumatic energy storage device which was used to store energy in the form of compressed air. The model was tested in the Central Mediterranean climate with positive results. This is an offshore system concept which benefits primarily from the fact that it is based in sea water [125].

Battery Energy Storage

One of the main advantages of a battery ESS is grid stability. It also aids RE integration by balancing demand and supply in real time. This is due to its high efficiency and quick response time. Another important factor is that it is very suited for densely populated areas, such as the Island of Malta, where storage systems such as PHES and CAES are not feasible [42, 126]. The operation of battery storage ESS was described by Akhavan-Hwjazi and Mohsenian-Rad [127], who proposed a novel approach for the management of large battery ESS. Types of battery ESS are listed as follows:

- **Lead acid batteries** – A description of lead acid batteries is provided by Beaudin et al. [108]. These batteries come at a low cost and are very reliable with strong surge capabilities. They are also highly efficient with a good power quality. However, they have short life span, and their management can be problematic. They require continuous maintenance and also have a low energy density, emit explosive gasses, and possess very poor thermal properties and a usable storage capacity of 50% (or Depth of Discharge, *DoD*), and suffer from a yearly degradation in storage capacity of 3.7% [45, 128].
- **NiMH** – consist of a nickel-oxyhydroxide-based positive electrode, a metallic cadmium based negative electrode, and an alkaline electrolyte. When compared to Ni-Cd batteries, NiMH batteries have a higher energy density and are more environmentally friendly. However, according to Hu et al. [126] they also suffer from a high self-discharge rate, and they have a short lifetime.
- **Sodium-Sulphur Batteries (NaS)** – are an attractive emerging technology for use in the wind energy industry. According to Beaudin et al. [108] they have a high energy density and are very efficient and could therefore be the most economically feasible battery ESS for use with RE sources. There is no limitation with the availability of raw materials. The authors stated that the materials of the battery are 99% recyclable and are relatively inexpensive. However, their operation requires a heat source [128] and they have issues with thermal management and safety [42, 108]. A 34 MW (204 MWh) Na-S battery facility has been in operation since 2008 at Rokkasho, Japan [42], together with several other installations in Japan and in the USA [128].

- **Lithium-ion batteries** – these batteries have a high efficiency and a long life cycle. High energy density and fast discharge capabilities make them ideal for electronic applications [129]. However, these are expensive when used in high energy applications such as ESS for RES and need a complex management system, which is required to prevent overcharging and thermal runaway and they have a usable storage capacity (or Depth of Discharge, *DoD*) of 80% and suffer from a yearly 2% degradation in storage capacity [45]. Moreover, lithium reserves are extremely limited [129]. A recent addition has been a 100 MWh Li-Ion battery storage facility built by Tesla and located in South Australia, which is coupled with the Neoen's Hornsdale Wind Farm [130]. The facility utilises Tesla Megapack® storage units [131]. The state of New York, one of the most densely populated states in the USA, is planning to reach 1500 MWh of battery energy storage by 2025 and 3000 MWh by 2030 [27]. The Victorian Big Battery, located in Geelong, Victoria Australia, provides 450 MWh of energy storage which can discharge at a rated power of 300 MW [132]. This facility, which is also owned by Neoen, also utilises Tesla Megapack® storage units [131]. This facility came online in December of 2021. A larger Li-Ion battery storage facility is the Moss Landing Battery Storage Project in California, USA, which is currently the world's largest facility. This has a capacity of 1200 MWh, with a 100 MW output [133]. This is also powered with Tesla Megapack®.
- **Vanadium Redox Batteries (VRB)** – are a type of electromechanical flow batteries which are appropriate for small- and medium-scale functions. Their design allows energy to be stored inside two chemical solutions which provide an electromotive force [42]. VRB are modular, and power output can be increased by expanding the capacity of the storage tanks [42]. They have a high efficiency and a long life cycle and a *DoD* of 100% and have a negligible degradation in storage capacity [45]. However, these batteries are disadvantaged by having a low energy density (see Table 2-1) and could take up a considerable amount of space. However, this will eventually be overcome as the batteries benefit from the advantage that rated power and stored energy are independent [134]. VRBs are suitable for energy storage applications and integration with RES [128]. Commercial applications which are already in existence include a 4 MW (6 MWh) installation in Tomamae Wind Villa, Japan, while other applications have been developed by a German company called Cellstrom [42]. Other installations include the Dalian Battery in China, with a final capacity of 800 MWh and a power rating of 200 MW. The batteries were manufactured by Rongke Power and the installation was completed in May of 2021 and is one of the several sites being built in China [135, 136].

Table 2-1: Battery properties [126].

Type	Lead-Acid	NiMH	Li-ion	NaS	VRB
Energy density ($Whkg^{-1}$)	25-50	60-120	75-200	150-240	10-30
Power density (Wkg^{-1})	75-300	250-1000	500-2000	150-230	80-150
Cycle Life (100% depth of discharge)	200-1000	180-2000	1000-10000	2500-4000	>12000
Capital cost [$USD(kWh)^{-1}$]	100-300	900-3500	300-3500	300-500	150-1000
Round-trip efficiency (%)	75-85	65	85-97	75-90	75-90
Self-discharge	Low	High	Medium		Negligible

Batteries technologies which can be used as ESS can be classified according to energy density, power density, life cycle, capital cost, round-trip efficiency and self-discharge [126], as shown in Table 2-1. The most important factors are efficiency, pricing, and number of cycles as these have a direct effect on the LCOS. A battery with a low number of cycles might not be feasible for long-term grid applications.

Battery Energy Storage System Physical Size

The physical size of a battery ESS used for grid applications may be understood from applications and installations in current use. Most modern Li-Ion applications, namely Hornsdale [26, 130], Victorian Big Battery [132] and the Moss Landing [133] project are utilising the Tesla Megapack® Li-Ion battery [131]. Each Megapack® module has a 3 MWh capacity with a 1.5 MW inverter. Thus, a typical 450 MWh plant takes up an area of 219 m by 112 m ($24,528 m^2$) and consists of a total 183 battery packs stacked in rows next to each other [137]. An analysis of the layout at the Victorian Big Battery site shows that $5,992 m^2$ or 24% of the area consists of passageways and service zones which are used to access the battery containers [137].

Vanadium Redox Battery systems are an alternative to Li-Ion systems for grid applications because they are considered safer and made from common materials. According to the Energy Storage Association, the floor area occupied by VRB storage system is less than $46 m^2(MWh)^{-1}$ [138]. Other manufacturers such as Vinox specify an 8 MWh VRB battery as having a footprint of $195 m^2$ [139].

2.7 Advantages and Disadvantages of Energy Storage Systems and Capacity Ranges

Table 2-2 shows a comparison of the costs involved in the most common ESS technologies. A cost analysis for ESS was carried out by Sabihuddin et al. [140]. The analysis showed that PHES was the most viable contender for an ESS. However, PHES had the highest capital costs and very long pay-back periods, together with a high environmental impact. According to the analysis, the next most viable option for an ESS was CAES. CAES had a high storage capacity, duration, and low capital cost. This was again coupled with the choice of suitable land area, such as the location of underground caverns, or being situated in the sea or being set-up as an anchorage point for a floating windfarm [122], which is a more expensive alternative. This was followed by VRB ESS. Response time and capacity ranges were also compared.

Table 2-2: A comparison of capital cost for the various energy storage technologies [108, 126, 140, 141].

Technology	Capacity Range	Efficiency	Storage Duration	Initial investment cost (€/kW)	Energy Capital Cost (€/kWh)
Pumped Hydroelectric Energy Storage (PHES)	10 – 8000 MW	65-87%	10 hrs	262-4631	0.88-254
Underground Pumped Hydro Electric Energy Storage (UPHES)	Small 10 kW – 0.5 MW (small installations) Large 0.5 MW – 3000 MW (large installations)				
Compressed Air Energy Storage (CAES)	High power capacity (0.01-3000 MW), large storage capacity (2-50 hours)	60-89%	2-50 hrs	350-1970	0.88-122
Battery Energy Storage	20 – 40 MW for lead acid batteries Up to 40 MW for NiCd batteries 0.05 – 34 MW for Na-S batteries, 0 – 100 MW for Li-Ion batteries, 0 – 3 MW for VRB.	65% (NiMh)- 90% (VRB)	5-9 hrs	153-3500	43 (Lead Acid) – 3500 (Li-ion)

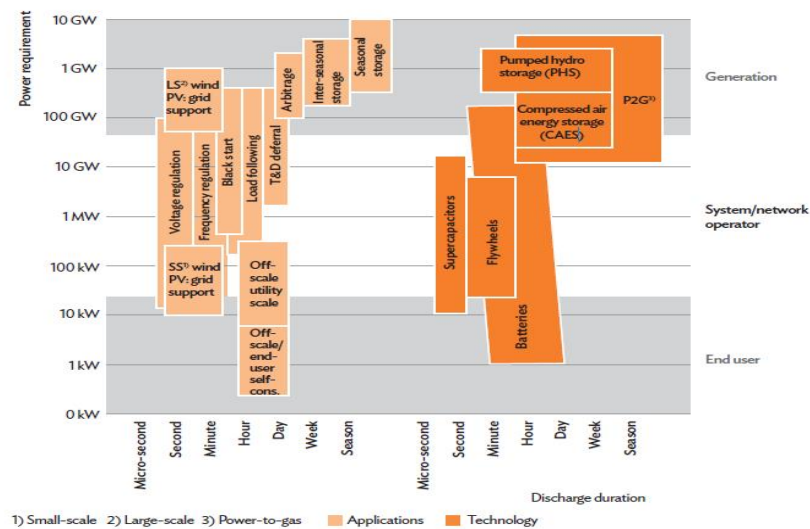
In Table 2-2 the performance of an ESS was characterized by its capacity, storage duration, efficiency, and cost. An ESS can also be distinguished as shown in Figure 2-8 where ESS applications were categorised according to power requirement, discharge duration, and type of system and/or network operation [43].

Table 2-3 shows the advantages and disadvantages of the various technologies together with a list of currently existing facilities [43]. While the most established technology was PHES, Hu et al. described battery storage as a rapidly emerging technology [126]. The research performed by Wang et al. together with that by Ramadan et al. also described CAES as very suited for integration with offshore wind energy [120, 121].

According to Figure 2-8, the technologies that have been mentioned in the above paragraphs, namely PHES, CAES and battery storage, all fall within the scope of energy generation and are thus suitable for integration with an electricity grid. Figure 2-9 also shows that Li-Ion and flow batteries are suitable for transmission and distribution purposes [43]. Thus, in addition to their capability to be used for energy arbitrage, the capacity market and carbon savings (As described in Section 2.6), the above paragraphs also lead to the conclusion that these battery technologies fall within the scope of this research.

Table 2-3: A comparison of the various energy storage technologies available, regarding advantages, disadvantages and existing facilities [43].

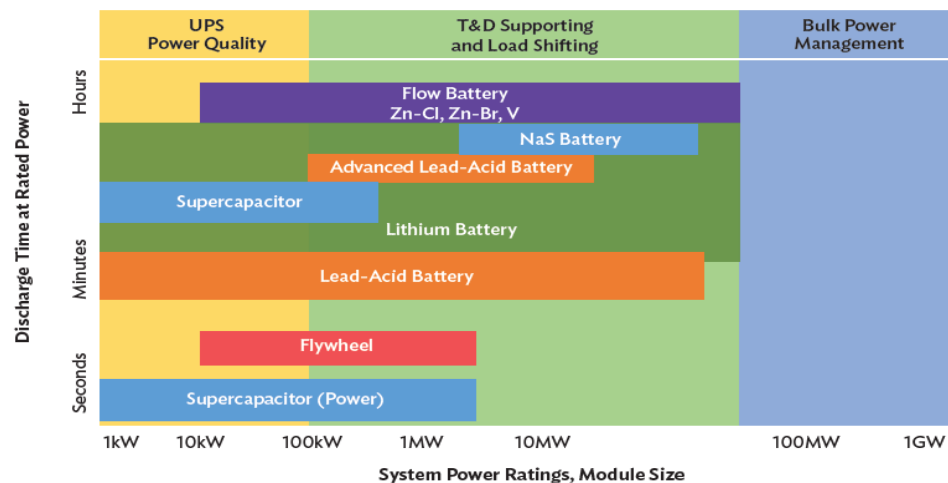
Technology	Advantages	Disadvantages	Existing Facilities
Pumped Hydroelectric Energy Storage (PHES)	Very popular due to a high energy efficiency.	Generally limited to high energy applications due to a high capital cost	Cabin Creek, Colorado, US Bath County, US Gordon Butte Pumped Storage Project, Montana, USA. Seneca Pumped Storage Generating Station, Warren, Pennsylvania, US. Ohira, Japan Raccoon Mountain, US Bajina Basta, Serbia La Coche, France Edolo, Italy Chiotas, Italy San Fiorano, Italy Rottau, Austria Hornburg, Germany Rosshag, Austria
Underground Pumped Hydro Electric Energy Storage (UPHES).	Small environmental impact and minimal wildlife habitat disruption. Potentially smaller underground installation when compared to PHES. Eliminates surface reservoirs, river dams, surface power houses. Vertical flow path reduces losses associated with transversal flow	Locations limited to geological formations. Could potentially destabilise the aquifer, if an underground aquifer is used as storage.	
Compressed Air Energy Storage (CAES)	Especially suited for integration with wind energy Very reliable and economically feasible. Ability for quick ramping and operates efficiently under partial load conditions. Significantly lower capital costs than PHS.	Relies on geological formations	McIntosh plant, Alabama, United States Huntorf Plant, Germany
Battery Energy Storage.	Depends on the technology used. Location does not depend on geological and topological conditions. Recent developments in flow batteries with a high life-cycle and deep discharge capabilities. Sodium Sulphur batteries very suitable for renewable energy applications	Suppliers of Na-S batteries are limited. Supplies of Lithium is very limited Storage capacity is limited by life cycles and energy density	100 MW built by Tesla in South Australia, coupled with Neoen's Hornsdale Wind Farm. 34 MW /245 MWh system in Japan used for stabilising a 51MW wind farm. 32 MWh system in Santa Rita Jail Smart Grid Advanced Energy Storage System used for load balancing. 25 MWh system in Anchorage Area Battery Energy Storage System used for spinning reserve capacity and load levelling. 2500 MWh Li-Ion facility in New York State, USA. 450 MWh Storage facility in Victoria, Australia (Victorian Big Battery). Moss Landing Project, California, USA with 1200MWh capacity. 800 MWh VRB facility in Dailan, China.



GW = gigawatt, kW = kilowatt, MW = megawatt, P2G = power to gas, PV = photovoltaic, SS = small-scale, T&D = transmission and distribution.

Source: ROLAND BERGER GMBH (2017). R. Berger, "Business models in energy storage – Energy Storage can bring utilities back into the game," May.

Figure 2-8: Different technologies for different purposes [43].



GW = gigawatt, kW = kilowatt, MW = megawatt, T&D = transmission and distribution, UPS = uninterruptible power supply, V = vanadium, Zn-Br = zinc-bromine, Zn-Cl = zinc-chlorine.

Note: With nominal discharge time ranging from seconds to hours. Both power output and energy consumption are expressed in logarithmic scales.

Source: Korea Battery Industry Association 2017 "Energy storage system technology and business model".

Figure 2-9: A classification of ESS technologies according to Discharge Time at Rated Power, Power Rating and Application [43].

2.8 Levelised Cost of Storage

Research carried out by Jülich [142] compared the LCOS of various ESS. The author analysed both long-term and short-term storage systems and concluded that long-term ESS such as PHES, had the lowest LCOS among the technologies which were available at that time. PHES also showed the lowest LCOS for short-term storage. The author also concluded that battery storage systems had a high LCOS, but this was expected to be offset by expected sharp cost decreases. The author also stated that costs should be minimised by optimising the size of the ESS, with the amount of energy discharged to the electricity grid from the ESS being an influential factor in the determination of the LCOS. In the investigation of battery storage systems, the author also listed the input data for the

calculation of the LCOS for a large-scale battery storage system, which included the system efficiency, the Depth of Discharge (DoD), number of cycles, lifetime, and the self-discharge rate. Amongst other parameters CAPEX and OPEX were also analysed. The author also listed cost of batteries, inverters, and Balance of System (BoS).

In a study of the economics of electric ES for the Western Balkans, Topalovic et al. mentioned the ambitious targets of the European Commission for increasing the share RE sources in the supply of electric energy [143]. They stated that due to the Paris Agreement [144]¹, ES would not only play a crucial role in introducing stability and security for the energy supply but will also support the integration of windfarms to the electricity grid [145].

More recent cost projections for utility scale battery storage systems were analysed by Cole and Frazier who projected the costings for Li-Ion battery systems till the year 2050. They predicted that capital costs reduction in 2030 will be at 26-63% of today's market prices, and the year 2050 battery system capital cost reduction will be at between 44% to 78% of today's market prices [146].

Another study by Zakeri and Syri described the costs associated with several ESS technologies [147]. The authors compared costs for PHES, CAES and several battery ESS including Li-Ion, Pb-Acid, Na-S and Ni-Cd battery systems. PHES with a discharge time of 8 hrs had a capital cost of € 596/kW while an above ground CAES system with a discharge time of 8 hrs had a capital cost of € 955/KW. A Pb-Acid ESS with a DoD of 80% and a discharge time of 4 hrs had an average capital cost of € 1085/kW. An Na-S battery ESS with a DoD of 80% and a discharge time of 4 hr had an average capital cost of € 644/kW, while a Li-Ion battery ESS with a DoD of 80% and a discharge time of 2 hrs had an average capital cost of € 2102/kW. Moreover, a VRB ESS with a rated DoD of 80% and a discharge time of 8 hrs had an average capital cost of € 957/kW. Other authors such as Fu et al. also describe a cost model for a 240 MWh (discharge time of 4 hrs) Li-Ion battery ESSs giving a system cost of €335 €/kWh [148].

In another study Pawel [45] described a methodology to calculate the LCOS and described how it could be applied to RE systems. The author concluded that the LCOS for an a VRB is € 338/MWh, that of a Li-Ion battery ESS is € 1,687/MWh while that of a Pb-Acid battery ESS is € 3,072/MWh. It turns out that even if a VRB system has the highest investment cost, it turns out to be the most economic system.

Another study by Lazard showed that a 48 MWh standalone battery ESS situated in Nantucket, Massachusetts (USA) had an LCOS of € 1663/MWh, calculated with a WACC of 8% [149].

¹ The Paris Agreement is a legally binding international treaty on climate change adopted by 119 countries on 12 December 2015. It entered into force on 4 November 2016.

In a more recent study, Topalovic et al. [143] concluded that PHES had the lowest LCOS with € 125/MWh, while the LCOS for Ni-Cd batteries was € 912/MWh, € 876/MWh for Li-Ion batteries, € 673 €/MWh for Pb-Acid batteries, and € 339/MWh for Na-S batteries.

2.9 Energy Demand Forecasting

With a growing requirement to increase the efficiency in the provision of electrical energy, both from an economic and environmental perspective, accurate EDF is crucial if generating capacity is to be in line with the future demand. Ringwood and Bofelli [150] estimated that an improvement in forecasting accuracy of 1% was estimated to yield a savings in operating costs of approximately € 12 million per annum. Dannecker [8] also described how the deregulation of the electricity markets and the increasing utilisation of RES has changed the electricity market from a static one-day ahead market to a flexible real-time market. Energy demand profiles may therefore be defined as daily, medium-term, or long-term.

Knowledge of the daily demand profile allows for the reduction of the total cost of supply and the optimal scheduling of generation. Medium-term forecasts are used to plan maintenance and to establish policies for the purchase of fuel. Islam and Al-Alawi [151] described the importance of long-term forecasts in the strategic planning of generating plant.

Long-term EDF is dependent on several factors. Hor et al. suggested that the long-term energy demand pattern depends on changing climatic patterns [30]. Due to this, the authors established a correlation between the demand and climatic variables such as temperature, degree days and enthalpy latent days to produce a long-term forecast. Islam and Al-Alawi [151] showed that demand values displayed a strong cyclic pattern which reflected the change in temperature throughout the year and the prevailing weather conditions. In a further study, Islam and Al-Alawi [152] demonstrated that in addition to climate, weather and holidays patterns and economic parameters also altered the demand. Studies by Swider and Weber [153] also showed that energy demand depended on season, working days and weekends, holidays, etc. Table 2-4 compares the various EDF techniques' advantages and limitations. Any chosen technique will need to be analysed for its level of uncertainty.

Table 2-4: A comparison of the different methodologies for forecasting of energy demand.

Method	Description	Advantages	Limitations	References
Trend	Is performed in terms of one day to a week. It plays a very important role in the basic operation of a generation system.	Tools are commercially available.	This is only suitable for short-term forecasting.	[8, 33, 154, 155]
Similar Day	Analyses patterns in energy demand and the forecasting day's weather to define a model which can be used to compare previous days with weather patterns.	This technique is very accurate for short-term forecasts. Several computational tools (ANNs, Fuzzy logic, etc.) can be utilised.	The accuracy decreases with increased duration. The quality of the data (training sets) has a strong effect on the model's behaviour.	[8, 16, 30, 31, 150, 152, 153, 156, 157]
End-use	The method uses the influence of energy patterns of the various sources or components of energy consumption.	Suitable for long-term forecasting. Can simulate demand changes if new technologies are introduced or consumption patterns change.	Model's accuracy is highly dependent on the information from the consumers. If the consumer's sample is too limited, the model cannot simulate large-scale demand forecasting	[157]
Econometric	These models combine the economic theory and statistical analysis for forecasting electricity demand, by establishing the relationship between energy consumption and the factors that influence it.	Suitable for long-term forecasting and simulation of different demand scenarios, technologies implementation	Historical electrical data, economic and behavioural components for the same consumer's population sample is required for building the model. Otherwise, extrapolation is required and this lower's the model's accuracy.	[30, 156, 157]

Ringwood and Bofelli [150] showed that EDF can be performed by using a range of modelling methodologies. These included univariate methods as described by Taylor et al. [154], those which are regression based as described by Hong [9], Papalexopoulos and Hesterberg [155], and by the Box-Jenkins methodology [8, 33]. The use of computational intelligence techniques included the use of Fuzzy Logic as described by Tzefestas and Tzefestas [31]. Ganbari et al. described how ANN could be used forecast energy trends in Iran [156]. ANNs were also applied by Ringwood and Bofelli [150] to forecast energy demand in the short-, medium- and long-terms. Table 2-4 shows a summary of available methodologies for EDF. Not all methodologies can be used for long-term forecasting. For example, ANNs are mostly used for forecasting daily demand profiles or daily peaks.

Other studies by Ocgu et al. compared the use of ANNs and SVR for the EDF of a developing country with a rapidly growing economy, such as Turkey [158]. In this case, the authors used the Mean Absolute Percentage Error (MAPE) to compare the forecasted results with real data, concluding that SVR was a better methodology. However, the study only used univariate data to achieve the results, whereas other forecasting studies by Papalexopoulos and Hesterberg [155] and Kavaklioglu [159] utilised multivariate data. These studies used economic and seasonal variables. The study by Kavaklioglu utilised SVR with multivariate inputs, such as population size, GDP, and manufacturing data (end-user) such as imports and exports as variables to the forecasting model, concluding that socio-economic variables can be used to predict energy consumption.

Other studies utilised more complex models to forecast electricity demand in the state of New South Wales, Australia. One such model described by An et al. based on an empirical model such as decomposition-based signal filtering which was used to filter noise and seasonal components, also utilised feedforward ANNs [160]. The model improved forecasting accuracy when compared to

existing models. Another model by Wang et al. combined Particle Swarm Optimisation (PSO) and trend adjustment to overcome limitations of models which depended on the accuracy and reliability of independent variables over the forecasting period [161].

Dannecker [8] extensively described the current state of EDF. In his work, he described a methodology which was based on an iterative approach. The forecasting methodology was divided into two phases; actual forecasting and the maintenance of the model. This is shown in Figure 2-10. As in the case of the MCP methodology, the decision on the adequacy of the model depended on the metrics chosen to determine the uncertainty or the forecasting error. Again, in this case these were the MSE and the MAE.

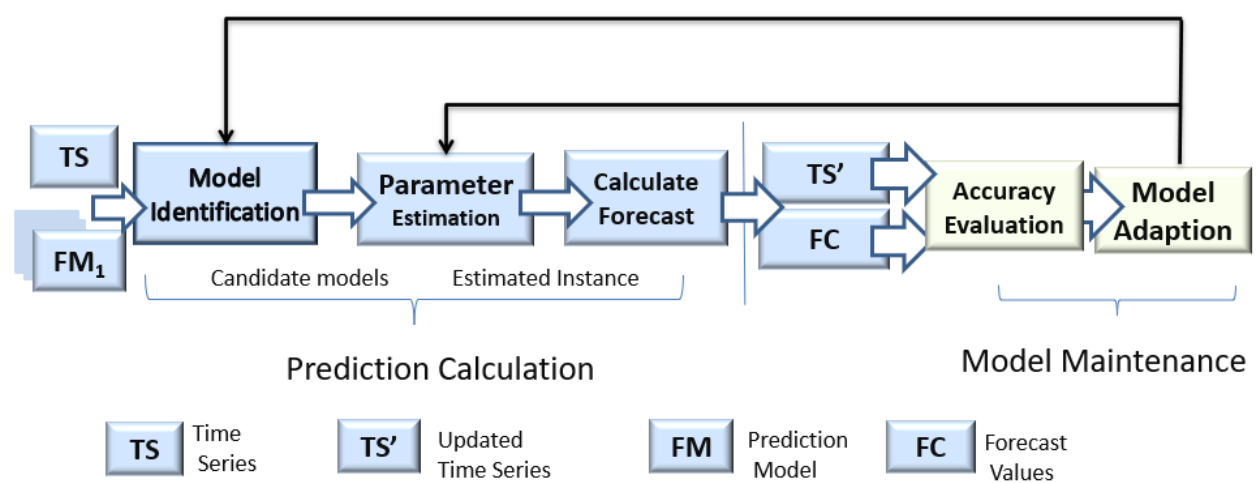


Figure 2-10: Energy demand forecasting methodology [8].

2.10 Forecasting of Economic Trends

The economic growth of a country is measured by its GDP. Gellings described economic growth as a factor which contributes to an increase in energy demand [162]. Chatfield described GDP as a time-series [163]. Time-series forecasts are used for a wide range of economic activities. According to Stock these models relied on past patterns to forecast the future [164] while according to Box et al. one way to predict economic trends was to use the Auto-Regressive Integrated Moving Average (ARIMA) or Seasonal ARIMA (SARIMA) models [33]. Again, according to Stock, ARIMA models extended the AR models by introducing a MA term in the error [164]. This had the effect of generating long lags in the forecast which is a function of both current and past values.

Several texts on the use of ARIMA and SARIMA to predict future trends exist [33, 163, 165, 166]. These texts described time-series analysis in detail. The methodology used parameters such as Auto-Correlation Factors (ACF) and the Partial Autocorrelation Function (PACF) to establish the order of the Autoregressive (AR), Integral (I) and Moving Average (MA), (p, d, q) in ARIMA notation or (P, D, Q) in SARIMA notation [33, 157]. Tests on the residuals and the confirmation that the residuals are white noise or otherwise, then established the suitability of the model [33, 157]. The ARIMA

methodology uncovers lags, trends, and seasonality (repeated patterns) in a time-series. Indeed, some economic factors are in fact seasonal and at the same time show either a positive or a negative trend. Studies by Abonazel and Abd-Elftah showed that ARIMA can be used to create models to forecast the GDP of countries such as Egypt [167], while Razak et al. applied ARIMA to create forecast models for Malaysia [168]. Other authors such as Wei et al. [169] applied the ARIMA model to the GDP for the region of Shaanxi in China. The methodology for the creation of forecasting models using ARIMA has been standardised as shown in Figure 2-11 [33, 157].

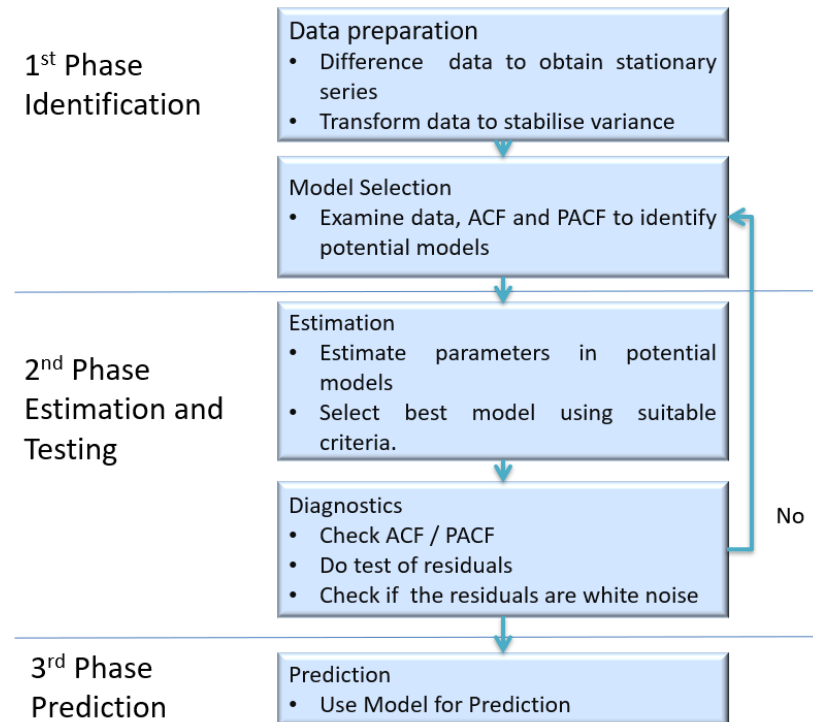


Figure 2-11: Creating an ARIMA model for forecasting of a time-series [33, 157].

2.11 Operating Scenarios for Energy Storage Integrated with the Electricity Grid

Dannecker [8] stated that energy demand, generation and storage must be carefully balanced if the electricity grid is to remain stable. Various operating scenarios are possible with offshore windfarms and ESSs, which are integrated to the electricity grid. These scenarios were described in detail by Barton and Infield [170]. The authors showed that the selected ESS technology, its capacity, power rating and efficiency depended on several factors. Apart from the available terrain and topography, the requirements of the operator also needed to be considered. These included load balancing, power levelling or frequency compensation.

All possible operating scenarios required some level of *power curtailment* from the offshore windfarm. The power exported from the windfarm to the electricity grid was always limited to the maximum power that did not cause the voltage of the electricity grid to exceed its limit. According to Barton and Infield, this depended upon the time of day and season [170]. Even if an ESS was utilised, there were instances when curtailment was necessary because the accumulated power output

exceeded the capacity of the ESS. There were also times of low energy demand during which it was not possible to dispatch energy from offshore windfarm.

When choosing a strategy which maximised energy export, energy was only stored when the power generation from the offshore windfarm exceeded the demand. Again, the maximum power exported by the offshore windfarm was set by the limitations of the grid. Energy was exported as soon as the power from the windfarm dropped below the maximum power allowed by the electricity grid. The application of this strategy minimised the total amount of energy entering and leaving the ESS and so reduced the losses due to the round-trip efficiency of the ESS according to Barton and Infield [170].

When choosing a power levelling strategy, the sum of local generation was kept as constant as possible. The exported power from the offshore windfarm was set to either the average net power during the period under assessment or by the maximum, which was determined from the energy demand, whichever was lower. According to Barton and Infield the net power was determined by the difference between the power from the offshore windfarm and the maximum power that the electricity grid could absorb [170].

Another study by Garvey [171] described several configurations for the integration of energy storage and RE generation and prescribed a metric whereby the costs of any solution to the grid balancing problem can be compared. Hence analysing the different possible scenarios when utilising ESS was considered by the author to be very important. The author also suggested that the optimal size of the ESS and therefore the costs will depend upon these various scenarios.

2.12 Measurement Metrics

Authors such as Santamaria-Bonfil et al. and Shcherbakov et al. showed the importance of employing more than one metric to evaluate a statistical model. Each metric had disadvantages that could lead to inaccurate evaluation of the results [172, 173].

The measurement metrics that were used to establish the suitability of the regression techniques for the MCP and EDF models were the MAE and the MSE [15] of the residuals, together with the Coefficient of Determination, R , which was used to measure the effectiveness of a regression model. Various authors such as Carta et al. [46] and various studies carried out by Diaz et al. [63, 64], investigated the MCP methodology and used the above-mentioned metrics to assess the adequacy of the regression techniques used in the MCP methodology. Similar utilisation of these metrics was made by Rogers et al. [47] and Velazquez et al. [59]. The lower the value of the MAE and MSE, the better was the performance of the model.

Other metrics such as the Normalised Mean Absolute Error (NMAE) and the Normalised Mean Squared Error (NMSE) can also be used to quantify the uncertainties due to the various MCP methodologies. According to Masden et al. the use of normalised values provided results which are independent of windfarm capacities [174]. Hu et al. showed that the NMAE was suitable to describe errors which were uniformly distributed round the mean, thus exposing the average variance between the measured and the predicted value [175]. The NMAE also applied an equal weight to the errors. A definition of NMSE was defined by Poli et al., who also described the usefulness of the NMSE in appraising model performance [176]. According to Santamaria-Bonfil et al. the NMSE was a measure of the extent of the dispersion of the errors about the mean and gives a higher weight to larger errors [172]. It was assumed that the errors formed a normal distribution. The percentage error of the energy yield gave an estimate of the accuracy of the model for predicting the total energy generated by the wind farm over the period of evaluation.

According to Makridakis et al. the above mentioned metrics were also adequate for measuring the suitability of ARIMA models for the forecasting of the GDP and according to Dannecker and Hong the regression techniques which are used to forecast energy demand can be also be analysed by using MAE and MSE [8, 9, 157].

According to Du, there is a set of metrics which can be used to assess the suitability of an ESS system [25]. According to Manwell et al, apart from metrics which included the usefulness of ESS for the regulation of energy markets and attractiveness to the generation utility due to power quality improvement, regulation and load following, other relevant metrics included the quantity of energy stored, the discharge rate of the energy system, energy discharged to the grid and the curtailed energy from the windfarm [67]. These metrics were utilised in this current research to analyse the behaviour of the hypothetical offshore windfarm and the ESS, which will be described in Chapter 6.

2.13 Identification of Knowledge Gaps

Following the literature review, which shows several studies conducted on MCP, ESS and energy demand modelling, it became clear that a connection was needed to be established between the three topics. The literature review served to prompt further research on the use of prediction methods to analyse the operation of ES systems coupled to offshore wind farms. It also highlighted the need to define the following exploratory questions in the field of regression techniques for MCP, EDF, and ES:

- Which regression technique for MCP best suits integration of offshore wind energy and energy storage?
- Which regression technique for EDF methodology is best suited for use with energy storage modelling?

- How can the MCP methodology be integrated numerically with EDF and energy storage models?
- How can MCPs and EDF methodologies be combined to predict the long-term overall performance of offshore wind farms which are integrated to the electricity grid and ES?
- What is the role of such models in optimising the sizing and utilisation of energy storage?

The review for MCP and EDF methodologies showed that both have uncertainty issues. The combination of the two models will therefore increase the uncertainty, and it is not known if and to what extent will this affect the optimal ESS capacity requirements, and how this uncertainty effects the LCOE of the windfarm and the LCOS of the ESS. Therefore, the following research questions will also need to be addressed:

- Which are the most reliable regression techniques for MCP and EDF methodology?
- What is the level of uncertainty resulting from the different coupled regression techniques for MCP and EDF methodologies?
- How will the level of uncertainty of the combined methodologies influence the optimal size of the ES system?
- How does this impact the LCOE and LCOS of the offshore windfarm and the ESS, respectively?

2.14 Conclusion

The literature review conducted above has addressed several topics. The topics included the MCP methodology for wind prediction at a candidate site, the ARIMA methodology, which is used for forecasting, and the various EDF methodologies available. The utilisation of an of RES which is integrated into the electricity grid may be improved by using an ESS.

Although the MCP methodology is capable of predicting the long-term behaviour at a candidate site, and energy demand can be forecasted, nothing was found that describes a combination of the two methodologies. The integration of an RES with an ESS and the electricity grid certainly requires the combination of the MCP and EDF methodologies. to be able to predict the behaviour of the ESS and optimise its capacity.

The scope of the research is to seek a methodology which couples MCP methodology which is used for the prediction of wind behaviour at a candidate site with an energy demand forecasting methodology to establish an optimal capacity for an ESS integrated with an offshore wind farm.

Statistical learning methods such as ANNs, DTs and SVR have been described and these techniques can be applied to both the prediction of the wind speed and direction at the candidate site, and to the forecast of energy demand. However, these techniques introduce an error both in the prediction and

in the forecasting. The combination of the methodologies will result in a greater uncertainty in the behaviour of the windfarm and the ESS. This uncertainty will in turn influence the optimal size of the ESS, the LCOE of the windfarm and the LCOS of the ESS. The uncertainty is defined by means of an analysis of residuals and the use of measurement metrics such as the coefficient of determination, MAE and MSE.

Levelised Cost of Energy and LCOS are also described in the review, with the scope of comparing the results from this research with those from similar studies carried out on windfarms which operate in the Mediterranean Sea.

The use of ARIMA and SARIMA as forecasting techniques for economic and demographic trends has also been described. Economic and demographic trends influence the energy demand and are used as independent parameters in EDF.

The review also analyses the concept of floating windfarms. This is due to the limitation of the shoreline in the Maltese islands. The use of an offshore windfarm which is close to the shore has not been deemed feasible for the Maltese islands, therefore floating offshore windfarms are a viable option, given the developments of the technology and falling costs.

The review considers various options for ESS which can be used in conjunction with offshore wind. The lack of natural formations, which do not permit the use of PHES or natural underground formations which do not permit the use of CAES, lead to the analysis and consideration of battery energy storage, where recent technological developments and falling costs, have permitted this technology to be considered for electrical grid applications. The advantages and disadvantages of various storage systems are presented in the literature review, and these show that a battery ESS is the most suited storage technology for the Maltese islands.

Following the review, a set of knowledge gaps and research questions are drawn up. To answer the above research questions, the theoretical background necessary to address the knowledge gap is described in Chapter 3, while the methodology described in Chapter 4 is proposed.

3 Theoretical Background

The following chapter deals with the theoretical background of the regression techniques used for MCP and EDF, namely SLR, MLR, ANN, DT and SVR. The Box-Jenkins ARIMA methodology which is used in the forecast of the GDP, econometric trends, and demographic data is also described [33]. Dimension reduction is also addressed. The equations used for calculating the LCOE for the windfarm and the LCOS of the ESS are also described. This theoretical background forms the basis for addressing the knowledge gap identified in Section 2.13.

3.1 Measure-Correlate-Predict Methodology

The MCP methodology is based on regression techniques. Regression can be performed by using a SLR or MLR technique or the more powerful ANNs, SVR and DT. Several techniques for regression are presented in Table 4-1 (next chapter), but only the regression techniques which gave adequate results when applied to the MCP methodology will be described.

3.1.1 Simple and Multivariate Linear Regression

SLR is a regression technique with a single regressor x and a response, y . In the MCP methodology, the wind speed at the reference site has a relationship with the wind speed at the candidate site that is assumed to a straight line. For $(y_i|x_i) \in \mathbb{R}^n$ the simple regression model is therefore,

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \quad i = 1, 2, \dots, n \quad (3-1)$$

where the intercept β_0 and the slope β_1 (*regression coefficients*) are unknown constants and ε is a random error component. The errors, or *residuals*, are assumed to have zero mean and an unknown variance σ^2 . Hence, the probability distribution for y at each value of x , has a mean which is given by:

$$E(y|x) = \beta_0 + \beta_1 x = 0 \quad (3-2)$$

and whose variance is given by,

$$Var(y|x) = Var(\beta_0 + \beta_1 x + \varepsilon) = Var(\varepsilon) = \sigma^2 \quad (3-3)$$

The values of β_0 and β_1 are estimated using the *least-squares criterion*. For Eq. (3-1) the criterion is given by the function S , minimised with respect to β_0 and β_1 , such that,

$$\min_{\beta_0, \beta_1} S(\beta_0, \beta_1) = \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \quad (3-4)$$

The least-squares estimators of β_0 and β_1 , $\hat{\beta}_0$ and $\hat{\beta}_1$ satisfy the conditions:

$$\left. \frac{\partial S}{\partial \beta_0} \right|_{\hat{\beta}_0, \hat{\beta}_1} = -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

$$\left. \frac{\partial S}{\partial \beta_1} \right|_{\hat{\beta}_0, \hat{\beta}_1} = -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) x_i = 0$$

Simplifying the above two equations yields:

$$\begin{aligned} n\hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^n x_i &= \sum_{i=1}^n y_i \\ \hat{\beta}_0 \sum_{i=1}^n x_i + \hat{\beta}_1 \sum_{i=1}^n x_i^2 &= \sum_{i=1}^n y_i x_i \end{aligned} \quad (3-5)$$

The solution to the normal equations given in Eqs. (3-5) is:

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad (3-6)$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n y_i x_i - \frac{(\sum_{i=1}^n y_i)(\sum_{i=1}^n x_i)}{n}}{\sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n x_i)^2}{n}} \quad (3-7)$$

where,

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i \quad \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

are the respective averages of y_i and x_i . The fitted SLR model is given by Eq. (3-8), which is also the estimate of the mean of y for a given value of x :

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \quad (3-8)$$

The i^{th} residual, ε_i is the difference between the observed value y_i and the corresponding fitted value $\hat{y}_i$, given by,

$$\varepsilon_i = y_i - \hat{y}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i) \quad i = 1, 2, \dots, n \quad (3-9)$$

Residual analysis is an important tool for analysing the suitability of the model. The residuals should have a mean of zero and be normally distributed around the mean, with variance σ^2 . The distribution should be Gaussian with the estimate of σ^2 being given by the *residual or error sum of squares*, SS_{RES} . such that [15]:

$$SS_{RES} = \sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3-10)$$

A convenient way for computing the SS_{RES} may be found by substituting Eq. (3-8) into Eq. (3-10) yielding,

$$\begin{aligned}
SS_{RES} &= \sum_{i=1}^n y_i^2 - n\bar{y}^2 - \hat{\beta}_1 S_{xy} \\
\sum_{i=1}^n y_i^2 - n\bar{y}^2 &= \sum_{i=1}^n (y_i - \bar{y})^2 \equiv SS_T \\
SS_{RES} &= SS_T - \hat{\beta}_1 S_{xy}
\end{aligned} \tag{3-11}$$

where SS_T is the corrected sum of squares of the response observations. The residual sum of squares, SS_{RES} has $n - 2$ degrees of freedom and the expected value is therefore $E(SS_{RES}) = (n - 2)\sigma^2$, so an *unbiased estimator* of σ^2 is,

$$\hat{\sigma}^2 = \frac{SS_{RES}}{n - 2} = MS_{RES}$$

The quantity MS_{RES} is defined as the *residual mean square*, and $\hat{\sigma}$ is the *standard error of regression*, and it has the same units as the variable y . The quantity R , in Eq. (3-12) is called the *coefficient of determination* of the regression.

$$R = \sqrt{1 - \frac{SS_{RES}}{SS_T}} \tag{3-12}$$

Suppose now, that apart from the wind speed at the candidate site, the wind direction is also used as a regressor, then Eq. (3-1), becomes:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i = \beta_0 + \sum_{j=1}^2 \beta_j x_{ij} + \varepsilon_i, \quad i = 1, 2, \dots, n \tag{3-13}$$

where x_{i2} , is the wind direction at reference site. The relationship becomes a MLR model [15] with two regressors, where β_0 is now the intercept of the regression plane, β_1 represents the predicted response in y per unit change in x_1 when x_2 is held constant while, β_2 represents the predicted change in y per unit change in x_2 when x_1 is kept constant [15].

The method of least-squares is used to estimate the regression coefficients in Eq. (3-13). Suppose that n observations (number of hourly wind observations) are available and let y_i denote the i^{th} observed response and x_{ij} denote the i th observation of the regressor x_j . (In this case, $j = 1, \dots, d$ and $d = 2$.) Again, it is assumed that the error term ε in the model has zero mean $E(\varepsilon) = 0$, that the residuals are normally distributed with $Var(\varepsilon) = \sigma^2$ and that the errors are uncorrelated. From Eq. (3-13), the least-squares function is the function S minimised with respect to β_0, β_1 and β_2 ,

$$\min_{\beta_0, \beta_1, \beta_2} S(\beta_0, \beta_1, \beta_2) = \min_{\beta_0, \beta_1, \beta_2} \sum_{i=1}^n \varepsilon_i^2 = \min_{\beta_0, \beta_1, \beta_2} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^2 \beta_j x_{ij} \right)^2 \quad (3-14)$$

Hence, the least-squares estimators $\hat{\beta}_0, \hat{\beta}_1$ and $\hat{\beta}_2$ must satisfy the following conditions.

$$\begin{aligned} \left. \frac{\partial S}{\partial \beta_0} \right|_{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2} &= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2}) = 0 \\ \left. \frac{\partial S}{\partial \beta_1} \right|_{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2} &= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2}) x_{i1} = 0 \\ \left. \frac{\partial S}{\partial \beta_2} \right|_{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2} &= -2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2}) x_{i2} = 0 \end{aligned} \quad (3-15)$$

Simplifying Eq. (3-15), one obtains three *least-squares normal equations*, as follows:

$$\begin{aligned} n\hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^n x_{i1} + \hat{\beta}_2 \sum_{i=1}^n x_{i2} &= \sum_{i=1}^n y_i \\ \hat{\beta}_0 \sum_{i=1}^n x_{i1} + \hat{\beta}_1 \sum_{i=1}^n x_{i1}^2 + \hat{\beta}_2 \sum_{i=1}^n x_{i1} x_{i2} &= \sum_{i=1}^n x_{i1} y_i \\ \hat{\beta}_0 \sum_{i=1}^n x_{i2} + \hat{\beta}_1 \sum_{i=1}^n x_{i2} x_{i1} + \hat{\beta}_2 \sum_{i=1}^n x_{i2}^2 &= \sum_{i=1}^n x_{i2} y_i \end{aligned} \quad (3-16)$$

the solutions to which, $\hat{\beta}_0, \hat{\beta}_1$ and $\hat{\beta}_2$ are the least-squares estimators of β_0, β_1 and β_2 [15]. As in SLR, an estimator of σ^2 is derived from the residual sum of squares, which is:

$$SS_{RES} = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \varepsilon_i^2$$

The sum of the squares of the residuals has $n - 3$ degrees of freedom associated with it, since 3 parameters are estimated in the model. The residual mean square is:

$$MS_{RES} = \frac{SS_{RES}}{(n - 3)} = \hat{\sigma}^2 \quad (3-17)$$

Since the predicted value of MS_{RES} is σ^2 , it is also an *unbiased estimator* of σ^2 [15].

3.1.2 Artificial Neural Networks (Multilayer Perceptrons)

Artificial Neural Network (ANN) techniques can be used to correlate and predict wind conditions due to their ability to recognise patterns in complex data sets [57]. A neural network contains an input layer, one or more hidden layers of neurons and an output layer. It is developed by means of a learning process which updates the weights of the interconnections and biases between the neurons

in the various layers. In Figure 3-1, the Levenberg-Marquardt [16] algorithm is used to adjust the weights and biases during the learning process. The regression is performed by applying feedforward networks [17] with *multilayer perceptrons* (MLP).

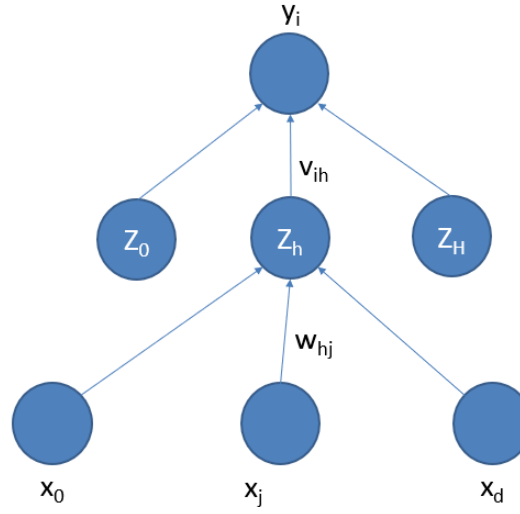


Figure 3-1: Typical structure of a multilayer perceptron [17].

Figure 3-1 shows the structure of a MLP. In this figure, $\mathbf{x}_j$, ($j = 0, \dots, d$) are the inputs to the hidden layer and $\mathbf{z}_h$, ($h = 0, \dots, H$) are hidden units, where H is the dimension of the hidden layer, $\mathbf{z}_0$, is the bias of the hidden layer, $\mathbf{y}_i$, ($i = 1, \dots, K$) are the output units, $\mathbf{w}_{hj}$ are weights in the first layer, while $\mathbf{v}_{ih}$ are the weights in the second layer. As the input $\mathbf{x}$ is serially fed into the input layer, the activation propagates in the forward direction of the network and the values of the hidden units are calculated. Each hidden unit applies the nonlinear sigmoid function $\mathbf{z}$, given by Eq. (3-18), to its weighted sum, such that:

$$z_h = \text{sigmoid}(\mathbf{w}_h^T \mathbf{x}) = \frac{1}{1 + \exp[-(\sum_{j=1}^d w_{hj} x_j + w_{h0})]}, h = 1, \dots, H \quad (3-18)$$

The outputs y_i are those of the perceptrons of the second layer. Taking the hidden units as their inputs, as shown in Eq. (3-19).

$$y_i = \mathbf{x}_i^T \mathbf{z} = \sum_{h=1}^H v_{ih} z_h + z_0 v_{i0} \quad (3-19)$$

where the hidden layer is biased by a unit denoted by z_0 , v_{i0} being the bias weight. The output is a linear combination of the nonlinear basis function values, each computed by the hidden units. Other hidden layers can be placed after the first hidden layer. Equation (3-20) is a nonlinear regression with z_h being computed by Eq. (3-18):

$$y^T = \sum_{h=1}^H v_h z_h^t + v_0 \quad (3-20)$$

During the learning phase, the weights, w_{hj} and v_h are initiated as small random values. The values of the weights are adjusted after each pass, using the Levenberg-Marquardt algorithm. A complete pass over all the patterns in the learning phase is defined as an *epoch*. As learning continues, with consecutive passes, the MLP fit gets closer to the underlying function and the error decreases.

3.1.3 Decision Trees

DTs are hierarchical data structures which employ the divide and conquer rule [10, 17]. Tree-based regression methods split the feature space unto a set of rectangles, and then fit a simple model in each one [10]. This is a nonparametric method, which can be used for regression [14]. The *regression tree* is built using a set of learning algorithms that are based on a simple set of rules. The tree is grown in two steps:

1. The predictor space is divided into subsets, i.e., the set of m possible values for x , i.e., $X_1, X_2, \dots, X_m$, are divided into J distinct and non-overlapping regions, $R_1, R_2, \dots, R_J$.
2. For every observation that falls into region R_j , the same prediction is made. This prediction is the mean of the response values for the training observations in R_j .

At a decision node, X_m is the subset of x which reaches node m ; namely, it is the set of all $x \in X$ satisfying all the conditions in the decision nodes on the path from the root up till node m . Each decision node implements a test function, $b_m(x)$, as defined below:

$$b_m(x) = \begin{cases} 1 & \text{if } x \in X_m: x \text{ reaches node } m \\ 0 & \text{otherwise} \end{cases} \quad (3-21)$$

The goodness of the split is measured by the MSE, E_m from the estimated value g_m at a node m ,

$$E_m = \frac{1}{N_m} \sum_t (r^t - g_m)^2 b_m(x^t) \quad (3-22)$$

where $N_m = \sum_t b_m(x^t)$. The estimated value at a node is the mean of the required outputs of instances reaching this node,

$$g_m = \frac{\sum_t b_m(x^t) r^t}{\sum_t b_m(x^t)} \quad (3-23)$$

Equation (3-23) corresponds to the variance at m . If the error is acceptable at a node, that is, $E_m < \theta_r$, then a leaf node is created, and it stores the value of g_m generating a piecewise constant estimate with discontinuities at leaf boundaries.

If the error is not acceptable, data reaching node m is split further, such that the sum of errors in the branches is a minimum. A DT will look for a split threshold for a numeric attribute that minimises the error, before continuing recursively.

The design of the model is specified by the size of the tree and a minimum number of leaf nodes. Care is to be taken in determining the size of the tree to avoid over- or under-fitting the data [10]. The variation of these two parameters will give different results and the best combination of these two parameters is sought as shown in the later Section 7.1.

A decision tree can also be multivariate. In this case, the paths down the different nodes can be written as a set of IF-THEN rules. Once the model is created, the coefficient of determination R can be calculated, together with the MSE and the MAE in the analysis of the residuals.

3.1.4 Support Vector Regression

SVR is the adaptation of Support Vector Machines (SVM) to the regression problem. The technique was developed by Vapnik [19, 20] to solve the classification problem. SVR [17] has gained acceptance within the RE community as a unique way of creating smooth and nonlinear regression approximations [63]. SVR is one of the techniques which best represents the ML state-of-the-art, due to its prediction capability. This is not only due to its property of universal approximation to any continuous function, but also due to an efficient and stable algorithm that provides a unique solution [63]. The approach is expressed as:

$$\bar{y}_i = \langle \mathbf{w}, \mathbf{x}_i \rangle + b \quad (3-24)$$

where $\langle \mathbf{w}, \mathbf{x}_i \rangle = \sum_{j=1}^d w_j x_{ij}$ denotes the inner product in the feature space, $\mathbb{R}^d$ and $\mathbf{w}$ is a set of coefficients to be determined [17]. To solve for the coefficients, one allows a predefined maximum tolerated error ϵ at each data point, given by:

$$|\bar{y}_i - y_i| \leq \epsilon \quad (3-25)$$

where y_i is the function to be approximated. By including slack variables, ξ to the constraint and a cost function C , the regression model is the solution to the optimisation problem given by Eq. (3-26) [18, 63]:

$$\min_{\mathbf{w}, b, \xi_i, \xi_i^*} \frac{1}{2} \|\mathbf{w}\|^2 + \frac{C}{n} \sum_{i=1}^n (\xi_i + \xi_i^*) \quad (3-26)$$

subject to the conditions,

$$\begin{cases} (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) - y_i \leq \epsilon + \xi_i \\ y_i - (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1, \dots, n \end{cases} \quad (3-27)$$

where n is the number of samples. The parameter $C > 0$ represents the trade-off between flatness and the amount up to which errors larger than ϵ are tolerated. In most cases, the dual form with fewer constraints is easier to solve and is widely used to define the final form of the approximation [17].

The described SVR design is commonly used and is called the ϵ -insensitive loss function or ϵ -SVR [18]. The optimisation problem is resolved by constructing the *Lagrangian* and through the corresponding *dual* problem, the Lagrangian, L_p , is defined as:

$$\begin{aligned}
 L_p = & \frac{1}{2} \|\mathbf{w}\|^2 + \frac{C}{n} \sum_{i=1}^n (\xi_i + \xi_i^*) \\
 & - \sum_{i=1}^m \alpha_i [\epsilon + \xi_i + y_i + (\langle \mathbf{w}, \mathbf{x}_i \rangle + b)] - \sum_{i=1}^n \alpha_i^* [\epsilon + \xi_i^* - y_i \\
 & + (\langle \mathbf{w}, \mathbf{x}_i \rangle + b)] - \sum_{i=1}^n (\eta_i \xi_i + \eta_i^* \xi_i^*)
 \end{aligned} \quad (3-28)$$

where the dual variables, $\alpha_i, \alpha_i^*, \eta_i, \eta_i^*$ must satisfy the constraints,

$$\alpha_i, \alpha_i^*, \eta_i, \eta_i^* \geq 0 \quad (3-29)$$

At the optimal point, the partial derivatives of L_p with respect to the variables w, b, ξ_i, ξ_i^* must be equal to zero [18], hence:

$$\begin{aligned}
 \frac{\partial L_p}{\partial b} &= \sum_{i=1}^n (\alpha_i - \alpha_i^*) = 0 \\
 \frac{\partial L_p}{\partial \mathbf{w}} &= \mathbf{w} - \sum_{i=1}^n (\alpha_i - \alpha_i^*) \mathbf{x}_i = 0 \\
 \frac{\partial L_p}{\partial \xi_i^{(*)}} &= \frac{C}{n} - \alpha_i^{(*)} - \eta_i^{(*)} = 0
 \end{aligned} \quad (3-30)$$

from which by substituting Eq. (3-30) into Eq. (3-28), yields the dual optimisation problem,

$$L_d = -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) \langle \mathbf{x}_i, \mathbf{x}_j \rangle - \epsilon \sum_{i=1}^n (\alpha_i^* + \alpha_i) + \sum_{i=1}^n (\alpha_i^* - \alpha_i) \quad (3-31)$$

subject to:

$$0 \leq \alpha_i \leq \frac{C}{n}, 0 \leq \alpha_i^* \leq \frac{C}{n}, \sum_{i=1}^n (\alpha_i - \alpha_i^*) = 0$$

The result is a linear combination $\mathbf{w} = \sum_{\mathbf{x}_i \in S} \beta_i \mathbf{x}_i$ of a subset S of sample points which saturate the constraints and are therefore relevant to the regression function. The points $\mathbf{x}_i \in S$ are defined as *support vectors* [18].

To illustrate the correlation between SVRs and the least-squares MLR, the optimisation problem in Eq. (3-31) permits the following interpretation as a regularised regression problem:

$$\min_{\mathbf{w}, b, \xi_i, \xi_i'} \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + \frac{C}{n} \sum_{i=1}^n \ell_{1,\epsilon}(y_i f(\mathbf{x}_i)) \right\} = \min_{\mathbf{w}, b, \xi_i, \xi_i'} \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + \frac{C}{n} \sum_{i=1}^n |y_i - f_{\mathbf{w},b}(\mathbf{x}_i)|_{\epsilon} \right\} \quad (3-32)$$

When the ϵ -insensitive loss function is applied:

$$\ell_{p,\epsilon}(y_i, f(\mathbf{x}_i)) = |y_i - f_{\mathbf{w},b}(\mathbf{x}_i)|_{\epsilon}^p \quad (3-33)$$

with $p = 1$.

However, when the regression function, $f(\mathbf{x}) = E(Y|\mathbf{X} = \mathbf{x})$ [176] is assumed to be sufficiently complex, it becomes necessary to use a non-linear model obtained a priori from a transformation of the input space through a non-linear function $\phi = \phi(\mathbf{x}) \in \mathbb{R}^h$ and subsequently applying the above technique in the new feature space of dimension h (usually larger than d) [53]. It is common for this transformation to be made by selecting a positive definitive kernel function k , which represents the inner product in the feature space (known as the kernel trick) [17], hence:

$$k(\mathbf{x}_i, \mathbf{x}_j) = \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}_j) \rangle \quad (3-34)$$

With this transformation, it is only necessary to replace $\mathbf{x}$ with $\phi(\mathbf{x})$ in Eq. (3-26), obtaining:

$$\min_{\mathbf{w}, b, \xi_i, \xi_i'} \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + \frac{C}{n} \sum_{i=1}^n (\xi_i + \xi_i') \right\} \quad (3-35)$$

subject to:

$$\begin{cases} \langle \mathbf{w}, \phi(\mathbf{x}_i) \rangle + b - y_i \leq \epsilon + \xi_i \\ y_i - \langle \mathbf{w}, \phi(\mathbf{x}_i) \rangle + b \leq \epsilon + \xi_i' \\ \xi_i, \xi_i' \geq 0, i = 1, \dots, n \end{cases} \quad (3-36)$$

and so, analogously, its solution is $\mathbf{w} = \sum_{\mathbf{x}_i \in S} \beta_i \phi(\mathbf{x}_i)$ with S being the set of support vectors in the feature space. The regression function then becomes:

$$\begin{aligned} f_{\mathbf{w},b}(\mathbf{x}) &= \langle \mathbf{w}, \phi(\mathbf{x}) \rangle + b = \left\langle \sum_{\mathbf{x}_i \in S} \beta_i \phi(\mathbf{x}_i), \phi(\mathbf{x}) \right\rangle + b \\ &= \sum_{\mathbf{x}_i \in S} \beta_i \langle \phi(\mathbf{x}_i), \phi(\mathbf{x}) \rangle = \sum_{\mathbf{x}_i \in S} \beta_i k(\mathbf{x}_i, \mathbf{x}) \end{aligned} \quad (3-37)$$

The robustness of the solution lies within the properties of the kernel k and different kernels result in different regression models. However, the final model always possesses the property of universal approximation and therefore the Gaussian kernel was selected due to its generally good properties in all applications [63]. The Gaussian kernel is given by:

$$k(x, x_i) = \exp\left\{-\frac{1}{2\sigma^2}\|x - x_i\|^2\right\} \quad (3-38)$$

where the parameter σ defines the level of complexity of the solution. The selection of the *hyperparameters* requires considerable work, i.e., ϵ of the ϵ -insensitive loss, Eq. (3-33), the parameter C in Eqs. (3-26) and (3-35), and the parameter σ which defines the Gaussian kernel function in Eq. (3-38).

3.1.5 MCP Methodology Applied to Wind Direction

As established in Section 2.1.1, nothing was found in literature which explicitly establishes a relationship between the wind direction at the reference site and the candidate site. Thus, the use of wind vectors is a way of applying a regression technique to predict the wind direction [66]. The methodology was based upon a simple relationship between the meteorological wind direction θ_{met} and the mathematical wind direction θ_{math} , such that:

$$\theta_{math} = 90 - \theta_{met} \quad (3-39)$$

in which the wind velocity vector $\mathbf{V}_i$ can be broken down into its vector components such that,

$$\mathbf{u}_i = |\mathbf{V}_i| \cos \theta_{math} = |\mathbf{V}_i| \cos(90 - \theta_{met}) \quad (3-40)$$

$$\mathbf{v}_i = |\mathbf{V}_i| \sin \theta_{math} = |\mathbf{V}_i| \sin(90 - \theta_{met}) \quad (3-41)$$

in which case the values of $\mathbf{u}_i$ and $\mathbf{v}_i$ may be either positive or negative, depending on the direction from where the wind is blowing (the value of θ_{met}). This results in wind velocity components from the North (y) and from the East (x) directions (axes). The relationship is shown in Figure 3-2.

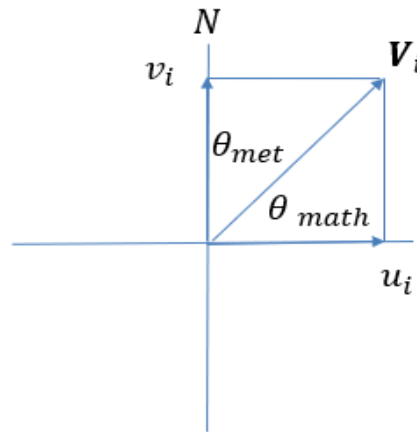


Figure 3-2: Difference between the meteorological wind direction, the mathematical wind direction, and the component of the wind vector, which is made of two components of wind coming from the north and the east [39].

Also,

$$|V_i| = (u_i^2 + v_i^2)^{\frac{1}{2}} \quad (3-42)$$

The regression was carried out between the respective components of the wind velocity in the y and x directions, hence establishing a relationship between the components at both sites. The predicted wind direction at the candidate site was then obtained from the predicted wind components using the relationship in Eq. (3-43):

$$\theta_{met_{ip}} = 90 - \tan^{-1} \frac{v_{ip}}{u_{ip}} \quad (3-43)$$

The value of the angle $\theta_{met_{ip}}$ depended on the direction of u_{ip} and v_{ip} , as shown in Figure 3-3 and in accordance with the relationships shown in Eq. (3-44):

$u_{ip} > 0$ and $v_{ip} > 0$	NE winds	$0^\circ < \theta_{met_{ip}} < 90^\circ$	(3-44)
$u_{ip} > 0$ and $v_{ip} < 0$	SE winds	$90^\circ < \theta_{met_{ip}} < 180^\circ$	
$u_{ip} < 0$ and $v_{ip} < 0$	SW winds	$180^\circ < \theta_{met_{ip}} < 270^\circ$	
$u_{ip} < 0$ and $v_{ip} > 0$	NW winds	$270^\circ < \theta_{met_{ip}} < 360^\circ$	

and Eq. (3-45):

$u_{ip} = 0$ and $v_{ip} > 0$	(North Wind)	$\theta_{met_{ip}} = 0^\circ$	(3-45)
$u_{ip} = 0$ and $v_{ip} < 0$	(South Wind)	$\theta_{met_{ip}} = 180^\circ$	
$u_{ip} > 0$ and $v_{ip} = 0$	(East Wind)	$\theta_{met_{ip}} = 90^\circ$	
$u_{ip} < 0$ and $v_{ip} = 0$	(West Wind)	$\theta_{met_{ip}} = 270^\circ$	

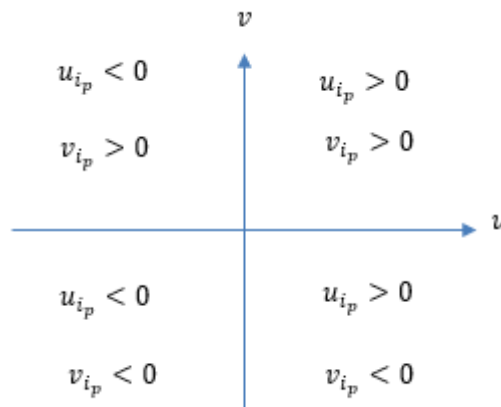


Figure 3-3: Calculating the value of $\theta_{met_{ip}}$ according to the value of u_{ip} and v_{ip} [39].

The above was applied to MCP methodology as shown in Figure 3-3 and Figure 3-5. Figure 3-4 shows that two regressions are carried out using both vector components at the reference site and each corresponding component at the reference site. The use of Eqs. (3-44) and (3-45) compensated

for possible rotations in the wind direction, ensuring that the wind direction was derived correctly from the vector components.

The methodology resulted in two regression models: one for the magnitude of the wind component from the North direction and another for the wind component from the East direction. The two models were then used to predict the wind direction at the candidate site as shown in Figure 3-5. Hence the values of the magnitude of the wind velocity from the North direction and from the East direction were first predicted, and the wind direction at the candidate site for θ_{met_p} , was then derived from the mathematical relationships given in Eqs. (3-44) and (3-45).

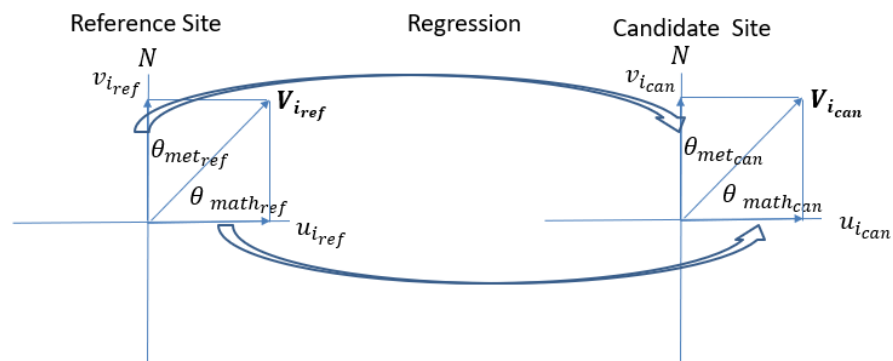


Figure 3-4: Application of regression methodologies to wind direction [39].

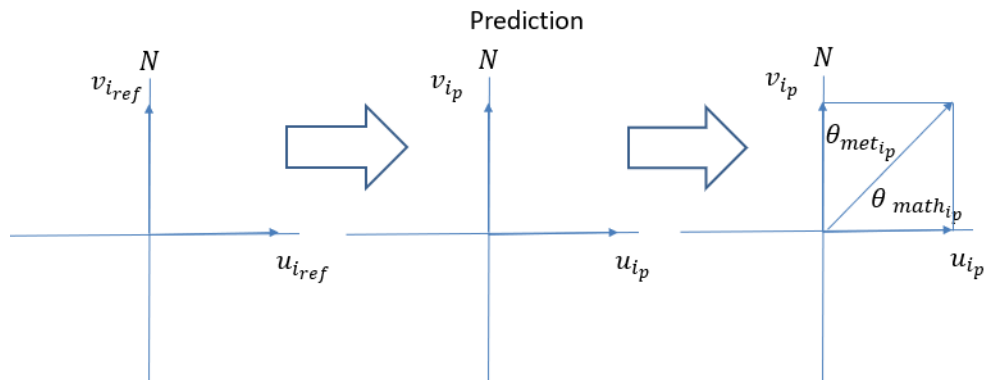


Figure 3-5: Predicting the wind direction [39]

3.2 The Basis of ARIMA – the Box-Jenkins Methodology

The ARIMA methodology was used to forecast the economic data of the Islands of Malta. As shown in Section 4.3, the economic forecasts were used as independent inputs to the regression model that was used to forecast energy demand. This section shows the theory behind the use of ARIMA for econometric forecasting.

The standard methodology for forecasting a time-series is the ARIMA or the Box-Jenkins methodology [33, 157]. The Box-Jenkins methodology for modelling a time-series is summarised in Figure 2-11. Each step of this method is reviewed in the following paragraphs, starting with the Autocorrelation Factor (ACF), which measures the correlations in the time-series, and the Partial Autocorrelation Function (PACF).

3.2.1 Phase 1: Data Preparation and Model Selection

The methodology for selecting the ARIMA model parameters is now defined, with a description of the ACF and the PACF, together with methodologies for analysing the data for stationarity and seasonality. This is done to assess the potential models as required in the 1st Phase of the ARIMA methodology shown in Figure 2-11.

Representing the Time-Series

A time-series can be represented in either of two ways i.e., the *white noise* model or the *random walk* model [157]. Equation (3-46) represents a white noise model where observation Y_t is made up of two components: an average value, c , and a random error component, ε_t .

$$Y_t = c + \varepsilon_t \quad (3-46)$$

In a random walk model, the time-series Y_t , is defined by Eq. (3-47), where:

$$Y_t - Y_{t-1} = \varepsilon_t \quad (3-47)$$

or,

$$Y_t = Y_{t-1} + \varepsilon_t \quad (3-48)$$

Random walk models are suitable for non-stationary data and are frequently used for analysing economic trends [157].

The Autocorrelation Function

The Autocorrelation Function (ACF) is the correlation within the time-series, lagged by 1, 2 or more time periods. This has the formula:

$$r_k = \frac{\sum_{t=k+1}^n (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^n (Y_t - \bar{Y})^2} \quad (3-49)$$

The value of r_1 indicates how the consecutive values of Y correlate to each other while r_2 indicates how values of Y which are two time periods apart correlate to each other, and so on. The autocorrelations at lags 1, 2, etc., constitute the ACF.

The Sampling Distribution of Autocorrelations

The properties of the ACF from a white-noise time-series model can be analysed from the values of r_k . This problem is analysed by using the values of r_k for developing a test which decides whether a particular r_k is significantly different from zero.

In theory, all values of r_k for a series of random numbers must be zero. In reality, the autocorrelations will not be exactly zero. The autocorrelation coefficients of white noise data should have a distribution that can be represented by a normal distribution with a mean of zero and a

standard error $1/\sqrt{n}$, where n is the number of observations in the series [177, 178, 179]. It is therefore expected that 95% of the values of r_k be within $\pm 1.96/\sqrt{n}$, otherwise the probability of the time-series being white noise is very low.

The Partial Autocorrelation Function

Partial autocorrelation is used to determine the degree of association between Y_t and Y_{t-k} , at the same time ignoring the influence of the other time lags $-1, 2, 3, \dots, k-1$. The partial autocorrelation coefficient of order k is calculated by the regression of Y_t against $Y_{t-1}, \dots, Y_{t-k}$:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \dots + b_k Y_{t-k} \quad (3-50)$$

The variables on the right-hand side of Eq. (3-50) are the time-lagged values of the variable to be forecasted, Y_t . The term *autoregression* (AR) is consequently used to define Eq. (3-50).

The Partial Autocorrelation Function (PACF), α_k , is therefore the coefficient b_k which is estimated from this AR. Changing the number of terms on the right-hand side of Eq. (3-50) will give the partial autocorrelation for the values of k .

As was the case with the ACF, if the time-series is white noise, then the estimated partial autocorrelations are expected to be normally distributed, with a standard error of $1/\sqrt{n}$ [179]. Hence in the case of the ACF, the values of $\pm 1.96/\sqrt{n}$ can be used to evaluate if the data are white noise.

Seasonality in a Time-series

Patterns in a time-series that repeat themselves at fixed time intervals, such as once every twelve months or every four quarters, give rise to *seasonality*. If the pattern is a consistent one, the existence of seasonality will be indicated by the ACF at 12 months or every fourth quarter having a high positive value. If the autocorrelation factor is not significantly different from zero, this would indicate that the time-series is not seasonal [157, 163].

Stationarity in a Time-Series

A time-series is stationary if there is no growth or decline with time. The data roughly lie along the horizontal time axis. The data fluctuate around a constant mean and the fluctuation has a variance that does not change with time [33]. Stationarity is generally assessed by means of a time plot. If there is no change over time in the mean and the variance of the time-series, then the time-series is stationary in mean and variance.

Trends in a non-stationary time-series result in autocorrelations that dominate the autocorrelation diagram. It is therefore essential to eliminate the non-stationarity. Non-stationarity is eliminated

from a time-series by means of *differentiating*, where the differentiated time-series is defined as the change between the successive observations in the original time-series. The differentiated time-series is defined in Eq. (3-51) and the time-series will have $n - 1$ values, so that:

$$Y'_t = Y_t - Y_{t-1} \quad (3-51)$$

Sometimes the differenced data itself might also be non-stationary, and therefore differentiating the time-series a second time would be necessary, forming the relationship shown in Eq. (3-52),

$$Y''_t = Y'_t - Y'_{t-1} = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2} \quad (3-52)$$

where Y''_t is a time-series second-order difference of $n - 2$ values [157].

Seasonal Differencing

When a seasonal time-series is non-stationary, *seasonal differences* are used. A seasonally differenced series, Y'_t , is therefore the change in observations which are separated by s time periods. When, for example $s = 4$ in the case of quarterly data, the relationship is shown in Eq. (3-53):

$$Y'_t = Y_t - Y_{t-4} \quad (3-53)$$

Any other non-stationarity in the seasonal time-series can be removed with a first difference.

If $Y'_t = Y_t - Y_{t-4}$ denotes the seasonally differenced series, the first difference of a seasonal time-series would be denoted as in Eq. (3-54),

$$\begin{aligned} Y_t^* &= Y'_t - Y'_{t-1} \\ &= (Y_t - Y_{t-4}) - (Y_{t-1} - Y_{t-5}) \\ &= Y_t - Y_{t-1} - Y_{t-4} + Y_{t-5} \end{aligned} \quad (3-54)$$

3.2.2 Phase 2: Estimation of the ARIMA Model Parameters for Time-Series Data

A regression model may be expressed in the form given by Eq. (3-55),

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_pX_p + \varepsilon \quad (3-55)$$

where Y is the forecast variable, $X_1, \dots, X_p$ are explanatory variables, $b_0 \dots b_p$, are linear coefficients, and ε is the error term. In Eq. (3-55), $X_1, X_2, \dots, X_p$, can represent the GDP or any other end-user data described in Table 4-4. If these variables are defined as $X_1 = Y_{t-1}$, $X_2 = Y_{t-2}$, $X_3 = Y_{t-3}$, $\dots$, $X_p = Y_{t-p}$, then Eq. (3-55) becomes:

$$Y_t = b_0 + b_1Y_{t-1} + b_2Y_{t-2} + \dots + b_pY_{t-p} + \varepsilon_t \quad (3-56)$$

Equation (3-56) is still a regression model but differs from Eq. (3-55) in that the right-hand side consist of time-lagged values of the forecast variable, Y_t , while those of Eq. (3-55) are different

explanatory variables. An equation of the form of Eq. (3-56) is known as an *AutoRegression* (AR) function. Refer also to Eq. (3-50).

Equation (3-57) shows a time-series that employs past errors as explanatory variables:

$$Y_t = b_0 + b_1\varepsilon_{t-1} + b_2\varepsilon_{t-2} + \cdots + b_q\varepsilon_{t-q} + \varepsilon_t \quad (3-57)$$

Equation (3-57) is a dependence relationship between the successive error terms in a time-series. Thus, Eq. (3-57) represents a *moving average* (MA) model of the error series, ε_t .

In order to simplify the mathematical equations, the Backshift Operator [8, 33, 157] is used. The Backshift Operator, B is defined by Eqs. (3-58) and (3-59), where:

$$BY_t = Y_{t-1} \quad (3-58)$$

and for any time $t - k$,

$$B^k Y_t = Y_{t-k} \quad (3-59)$$

Both the AR and MA models can be merged into the Autoregressive Moving Average (ARMA) model, which is useful when the time-series is stationary. The ARMA model will need to be extended in the case of a non-stationary time-series by differencing, giving rise to the AutoRegressive Integrated Moving Average (ARIMA) model [33]. This non-seasonal model is known as ARIMA(p, d, q), where p is the order of the AR, d is the degree of the differencing, and q is the order of the MA part. Thus, an AR model of order p can be expressed as shown in Eq. (3-60) [8, 157],

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t = \sum_{i=1}^p \phi_i Y_{t-i} + \varepsilon_t \quad (3-60)$$

where ϕ_i is the i^{th} AR parameter, where $i = 1, 2, \dots, p$, and ε_t is the error at time t . There are constraints on the acceptable values of the AR parameters ϕ_i . For $p = 1$, $-1 < \phi_1 < 1$, while for $p = 2$, the limitations in Eq. (3-61) hold true:

$$-1 < \phi_1 < 1 \quad \phi_2 + \phi_1 < 1 \quad \phi_2 - \phi_1 < 1 \quad (3-61)$$

With the help of the backshift notation Eq. (3-60) may be re-written as shown in Eq. (3-62) [8]:

$$\varepsilon_t = \left(1 - \sum_{i=1}^p \phi_i B^i \right) Y_t \quad (3-62)$$

In a similar manner, the MA model of order q can be expressed as shown in Eq. (3-63) [8, 157]:

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} = \varepsilon_t + \sum_{i=1}^q \theta_i \varepsilon_{t-i} \quad (3-63)$$

where θ_i is the i^{th} MA parameter, and ε_{t-i} is the error term at time $t - i$, where $i = 1, 2, \dots, q$. Again, the same constraints that were necessary for the AR model are also necessary for the MA model. Therefore, for $q = 1$, $-1 < \theta_1 < 1$, while for $q = 2$, the limitations in Eq. (3-64) hold true:

$$-1 < \theta_2 < 1 \quad \theta_2 + \theta_1 < 1 \quad \theta_2 - \theta_1 < 1 \quad (3-64)$$

With the help of the backshift notation Eq. (3-63) may be re-written as shown in Eq. (3-65) [8]:

$$Y_t = \left(1 + \sum_{i=1}^q \theta_i B^i \right) \varepsilon_t \quad (3-65)$$

The AR and MA models are then merged into the ARMA model [33]. Using the backshift notation, an ARMA model of order p, q or ARMA(p, q) may be expressed as shown in Eq. (3-66):

$$\left(1 - \sum_{i=1}^p \phi_i B^i \right) Y_t = \left(1 + \sum_{i=1}^q \theta_i B^i \right) \varepsilon_t \quad (3-66)$$

The same parameter restrictions for AR and MA in Eqs. (3-61) and (3-64) also apply for the ARMA model.

If non-stationarity, or a trend component, is introduced to the ARMA model, then the ARIMA(p, d, q) model in Eq. (3-67) is obtained [8].

$$\left(1 - \sum_{i=1}^p \phi_i B^i \right) (1 - B)^d Y_t = \left(1 + \sum_{i=1}^q \theta_i B^i \right) \varepsilon_t \quad (3-67)$$

where the trend component of the ARIMA model is denoted by $(1 - B)^d$.

Seasonality and ARIMA models.

Just as a time-series may have AR, MA, ARMA, or ARIMA properties, data which are separated by a season (for example, a year, whether by months or quarters) may present the same characteristics. Hence, the ARIMA notation can be expanded to manage seasonality in a time-series, and the general notation in this case is given by Eq. (3-68) [157]:

$$\text{ARIMA} \quad \underbrace{(p, d, q)}_{\substack{\text{Non-seasonal} \\ \text{part of the} \\ \text{model}}} \quad \underbrace{(P, D, Q)}_{\substack{\text{Seasonal} \\ \text{part of the} \\ \text{model}}} \quad (3-68)$$

where S is the number of periods per season. The SARIMA model is therefore the merger of two ARIMA models where one describes the basic time-series while the another describes the seasonality. In backshift notation the seasonal part is described by Eq. (3-69) [8]:

$$\left(1 - \sum_{i=1}^p \Phi_i B^i\right)^S (1 - B^S)^D Y_t = \left(1 + \sum_{i=1}^q \Theta_i B^i\right)^S \varepsilon_t \quad (3-69)$$

where Φ_i and Θ_i are coefficients of the seasonal model. The seasonal ARIMA is merged with the basic ARIMA model given in Eq. (3-66), resulting in the model shown in Eq. (3-70) [8]:

$$\begin{aligned} & \left(1 - \sum_{i=1}^p \phi_i B^i\right) \left(1 - \sum_{i=1}^p \Phi_i B^i\right)^S (1 - B)^d (1 - B^S)^D Y_t \\ &= \left(1 + \sum_{i=1}^q \theta_i B^i\right) \left(1 + \sum_{i=1}^Q \Theta_i B^Q\right)^S \varepsilon_t \end{aligned} \quad (3-70)$$

When the coefficients ϕ_i , θ_i , Φ_i and Θ_i have been estimated from the time-series, Eq. (3-70) may be used as a model for forecasting the future values of the given time-series [157]. The seasonal part of an AR or MA model may be derived from the seasonal lags observed in the ACF or the PACF of the time-series.

Estimating the Model Parameters.

The validity of the forecasting model depends on the careful selection of the seasonal and non-seasonal AR and MA parameters [157]. Another methodology is the *maximum likelihood* where, as in the least-squares methodology, iterations are used to estimate the parameters. Computer programs for fitting ARIMA models use successive iterations to obtain the optimum values. For this purpose, Matlab® was used in this research to estimate the parameters for the GDP and other end-user forecasts, after analysing the resulting ACF and PACF plots.

The assumptions in the ARIMA model allow for a statistical analysis to be carried out to assess the suitability of the estimated parameter values. Therefore, an analysis of residuals, the standard error, or other variances will allow the model to be improved. A residual analysis should always form a part of the algorithm for the estimation of an ARIMA model [157, 163].

3.2.3 Phase 3: Forecasting with ARIMA Model

Since ARIMA equations can get quite complicated, the forecasting of quarterly GDP values (or other end-use data shown in Table 4-4) can be described by using a typical model as an example. A typical model can be described as ARIMA(1,1,1)(1,1,1)₄. Equation (3-70) is therefore used to forecast Y_{t+1} , or one period ahead thus becoming:

$$\begin{aligned} (1 - \phi_1 B)(1 - \Phi_1 B)^4(1 - B)(1 - B)Y_t \\ = (1 + \theta_1 B)(1 + \Theta_1 B)^4 \varepsilon_t \end{aligned} \quad (3-71)$$

which can be expanded into the original notation and expressed as Eq. (3-72):

$$\begin{aligned} Y_{t+1} = c + (1 + \phi_1)Y_t - \phi_1 Y_{t-1} + (1 + \Phi_1)Y_{t-3} - (1 + \phi_1 + \Phi_1 + \phi_1 \Phi_1)Y_{t-4} \\ + (\phi_1 + \phi_1 \Phi_1)Y_{t-5} - \Phi_1 Y_{t-6} + (\Phi_1 + \phi_1 \Phi_1)Y_{t-7} - \phi_1 \Phi_1 Y_{t-8} \\ + \varepsilon_{t+1} - \theta_1 \varepsilon_t + \Theta_1 \varepsilon_{t-3} + \theta_1 \Theta_1 \varepsilon_{t-4} \end{aligned} \quad (3-72)$$

The term ε_{t+1} will not be known and must be taken as zero, but the residuals for times t , $t - 3$ and $t - 4$ will be used as the values ε_t , ε_{t-3} and ε_{t-4} respectively. As the forecast progresses, the expected values for ε terms will be zero. The values Y_t , Y_{t-3} and Y_{t-4} are initially known, but, after a while, as the forecast evolves, the past Y values in Eq. (3-72) will themselves become the forecasted values [157].

3.3 Dimension Reduction

As described in Section 2.3, dimension reduction methodologies require a reduction in the number of predictors. All dimension reduction methods are characterised by the original predictors, $X_1, X_2, \dots, X_p$. A methodology that transforms the original predictors and fits a least squares model using transformed variables is required. Thus let $Z_1, Z_2, \dots, Z_M$ correspond to $M < p$ linear combinations of the original p predictors, such that:

$$Z_m = \sum_{j=1}^p \phi_{jm} X_j \quad (3-73)$$

for the constants $\phi_{1m}, \phi_{2m}, \dots, \phi_{pm}$, where $m = 1, \dots, M$. The LR model can be applied as shown in Eq. (3-74) by using the least squares algorithm,

$$y_i = \theta_0 + \sum_{m=1}^M \theta_m z_{im} + \varepsilon_i \quad i = 1, \dots, n \quad (3-74)$$

The dimension reduction algorithm reduces the problem of approximating the $p + 1$ coefficients $\beta_0, \beta_1, \dots, \beta_p$ to the simpler problem of approximating $M + 1$ coefficients $\theta_0, \theta_1, \dots, \theta_M$, where $M < p$, hence reducing the dimension of the problem from $p + 1$ to $M + 1$. Therefore, from Eq. (3-73),

$$\sum_{m=1}^M \theta_m z_{im} = \sum_{m=1}^M \theta_m \sum_{j=1}^p \phi_{jm} x_{ij} = \sum_{j=1}^p \sum_{m=1}^M \theta_m \phi_{jm} x_{ij} = \sum_{j=1}^p \beta_j x_{ij} \quad (3-75)$$

where,

$$\beta_j = \sum_{m=1}^M \theta_m \phi_{jm} \quad (3-76)$$

Dimension reduction limits the estimated coefficients β_j by forcing them to take the form shown in Eq. (3-76). The limitation on the form of the coefficients could bias the coefficient estimates. In situations where $p \gg n$, choosing a value of $M \ll p$ can have a considerable influence on the variance of the fitted constraints. If $M = p$ and all the Z_m values are linearly independent, then Eq. (3-76) will not impose any constraints. Thus, the newly transformed predictors $Z_1, Z_2, \dots, Z_M$ are estimated and the model is fitted to these M new predictors. As described in Section 2.3, the choice of the transformed predictors or the selection of ϕ_{jm} , can be achieved by a variety of methodologies, such as PCA or PLS.

3.4 Metrics

As described in Section 2.12, various measurement metrics were used to evaluate the suitability of the various regression techniques used for MCP and the EDF methodologies. In the case of the MCP methodology, the coefficient of determination, R , [Eq. (3-12)] is an especially important metric, which is used to determine the suitability of the model. This is applicable for every regression technique used. Other metrics include the Mean Absolute Error (MAE) and the Mean Squared Error (MSE) of the residuals, which are described in Section 3.4.1.

As also described in Section 2.12, when analysing the power output from a windfarm it is best to use the normalised values of the MAE and the MSE. These are the Normalised Mean Absolute Error (NMAE) and the Normalised Mean Squared Error (NMSE) respectively. The percentage error in energy yield can also be used as a measurement metric.

3.4.1 Measurement Metrics for Wind Speed

The residual error at any defined time is given by ε_i . This is the difference between the measured wind speed and the predicted wind speed at the candidate site. Hence,

$$\varepsilon_i = v_i - \hat{v}_i \quad (3-77)$$

where v_i is the measured wind speed and $\hat{v}_i$ is the predicted wind speed. The performance metrics MAE and the MSE are defined by Eqs. (3-78) and (3-79) [53] respectively, such that:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |v_i - \hat{v}_i| \quad (3-78)$$

and,

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (v_i - \hat{v}_i)^2 \quad (3-79)$$

where n is the number of observations.

3.4.2 Measurement Metrics for Windfarm and Energy Storage System Power Output

As described earlier, the results of the power output from the windfarm obtained using the measured wind speed and wind direction can be compared with those obtained by using the concurrent predicted wind speed and direction at the candidate site by calculating the NMAE and the NMSE of the residuals. The residuals, ε_i are the errors between the predicted and the actual output power values from the windfarm,

$$\varepsilon_i = \hat{P}_i - P_i \quad (3-80)$$

The formula which can be used to calculate the NMAE is shown in Eq. (3-81), whereby the errors are normalised by dividing by the average power production over the whole period of evaluation [174]:

$$NMAE = \frac{\sum_{i=1}^n |\varepsilon_i|}{\sum_{i=1}^n P_i} \quad (3-81)$$

and the NMSE, is given by [176]:

$$NMSE = \frac{\frac{1}{N} \sum_{i=1}^n (\varepsilon_i)^2}{\bar{P} \cdot \bar{P}} \quad (3-82)$$

where,

$$\bar{P} = \frac{1}{n} \sum_{i=1}^n \hat{P}_i \quad (3-83)$$

and

$$\bar{P} = \frac{1}{n} \sum_{i=1}^n P_i \quad (3-84)$$

The percentage error in overall energy yield can be applied to the both the energy output from the windfarm and the ESS, such that ε_{ene} is given by Eq. (3-85), where:

$$\varepsilon_{ene} = \left(\frac{\sum_{i=1}^n \hat{P}_i - \sum_{i=1}^n P_i}{\sum_{i=1}^n P_i} \right) \cdot 100\% \quad (3-85)$$

3.5 Levelised Cost of Energy and Levelised Cost of Storage

In mathematical terms the LCOE for a wind farm is defined by Eq. (3-86), where [3]:

$$\begin{aligned} LCOE &= \frac{\text{Sum of costs over lifetime}}{\text{sum of electrical energy produced over lifetime}} \\ &= \frac{\sum_{t=1}^n \frac{I_t + M_t + F_t + D_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_t}{(1+r)^t}} \end{aligned} \quad (3-86)$$

and where I_t is the investment expenditure in year t . M_t are the operations and maintenance expenditures (OPEX) in year t , F_t are the fuel expenditures in year t , E_t is the energy generated in year t , D_t is the decommissioning cost (DECEX) in year t , r is the Weighted Average Cost of

Capital (WACC) and n is the expected lifetime of the windfarm. As described in Section 2.3, a floating windfarm may have one of three types of floating platforms, SB, Semi-Submersible or TLP. The costings for a floating windfarm with such platforms will be described in Section 11.2.

In this case, apart from generating energy for the grid, the floating windfarm also charged an ESS, at times when energy demand is low, and when wind energy was available. For this research the ESS was only charged from the floating windfarm. Thus, there was a reduction in the instances where energy from the windfarm was curtailed. This however is not to be considered to be a part of the calculation for the LCOE of the windfarm because the windfarm does not charge a cost to the ESS. The windfarm does not have any fuel cost, hence in Eq. (3-82), $F_t = 0$ and E_t is the energy fed directly to the electricity grid. Moreover, the windfarm will have a one-time investment cost, I_w at year $t = 1$, while the windfarm also starts operating. The decommissioning cost (DECEX) D will only be incurred at the end of the lifetime in year n . Hence, Eq. (3-86) becomes:

$$\text{LCOE} = \frac{I_w}{(1+r)} + \frac{\sum_{t=1}^n \frac{M_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_G}{(1+r)^t}} + \frac{D}{(1+r)^n} \quad (3-87)$$

Equation (3-87) is useful in computing the LCOE of the offshore windfarm, however energy storage lacks a universally acceptable metric for calculating costs [180]. To solve this a version of LCOE, known as Levelised Cost of Storage (LCOS) is used for a battery ESS, as shown in Eq. (3-88).

$$\text{LCOS} = \frac{I_B + M \sum_{t=1}^n \frac{1}{(1+r)^t} - \frac{v_{\text{res}}}{(1+r)^{n+1}}}{c \cdot \text{DoD} \cdot \text{RC} \sum_{t=1}^n \frac{1 - \text{DEG} \cdot t}{(1+r)^t}} + \frac{P_c}{\eta} \quad (3-88)$$

Where I_B are the investment expenses for the ESS (CAPEX), M are the operating and maintenance expenses (OPEX), DoD is the Depth of Discharge, c is the number of cycles, RC is the rated capacity, P_c is the charging cost, η is the round-trip efficiency and v_{res} is the residual value of the ESS.

For an ESS which is charged directly from the windfarm without any cost to the ESS, $P_c = 0$. Depth of Discharge (DoD) and RC are incorporated into the Simulink® model, described in Section 6.6 and the ESS system has no residual value at the end of its life. Moreover, D_{ESS} is the decommissioning cost (DECEX) for the ESS. For a Li-Ion system, Eq. (3-88) may therefore be rewritten as Eq. (3-89), which incorporates a battery replacement cost of I_{RESS} which occurs twice (during years t_1 and t_2)

$$LCOS_{Li-Ion} = \frac{I_{ESS}}{(1+r)} + \frac{I'_{RESS}}{(1+r)^{t_1}} + \frac{I''_{RESS}}{(1+r)^{t_2}} + \frac{\sum_{t=1}^{n-1} \frac{M_{ESS_t}}{(1+r)^t}}{\sum_{t=1}^{n-1} \frac{E_{ESS_G}}{(1+r)^t}} + \frac{D_{ESS}}{(1+r)^n} \quad (3-89)$$

and as Eq. (3-90) for a VRB system, where no battery changes are necessary.

$$LCOS_{VRB} = \frac{I_{ESS}}{(1+r)} + \frac{\sum_{t=1}^{n-1} \frac{M_{ESS_t}}{(1+r)^t}}{\sum_{t=1}^{n-1} \frac{E_{ESS_G}}{(1+r)^t}} + \frac{D_{ESS}}{(1+r)^n} \quad (3-90)$$

In both Eqs. (3-89) and (3-90) E_{ESS_G} is the energy discharged by the ESS into the electricity grid.

3.6 Conclusion

This chapter explained the mathematical theory which was applied in this research. The mathematical theory complements the literature review carried out in Chapter 2, where the knowledge gaps were identified. The theoretical background covers:

- regression techniques, which are used in MCP and EDF,
- ARIMA and SARIMA forecasting (Box-Jenkins) technique,
- Forecasting of Energy Demand,
- Dimension Reduction,
- Measurement metrics, and,
- LCOE and LCOS.

The mathematical background leads to the next chapter, which describes the methodology in this current research.

4 Methodology

An overview of the methodology adopted for this present study is presented in this chapter. The methodology was based on the brief description of the work carried out in Section 1.8 and shown in Figure 1-2 to Figure 1-4. This methodology was structured to answer the research questions posed in Section 2.13. It starts with a description of the MCP and the EDF methodologies. It is then followed by a description of how the MCP and the EDF methodologies were integrated.

Following the determination of the optimal combination of regression techniques for MCP and EDF, the methodology used to establish the optimal ESS capacity is described. This methodology was also used to establish the error in the ESS capacity estimation. This error was introduced due to the use of statistical tools to predict wind speed and direction, and the forecast of energy demand. The merger of the regression techniques used for prediction and forecasting methodologies resulted in an accumulation of the error. This chapter concludes with a description of the methodology used to calculate the LCOE of the offshore floating windfarm and the LCOS of the ESS.

4.1 Addressing the Research Questions

A methodology for combining the MCP and EDF methodologies was developed to optimise the integration of a large-scale offshore windfarm with an ESS. This methodology served to determine the behaviour of an ESS vis-à-vis wind behaviour, energy demand, generation baseload and storage capacity. It also provided a model for the feasibility analysis of an offshore windfarm which supplied dispatchable energy, and charged an ESS, which in turn discharged the stored energy into the grid. The aspects on which the methodology was based are shown in Figure 4-1, which also serves as a high-level depiction of the approach undertaken for this research.

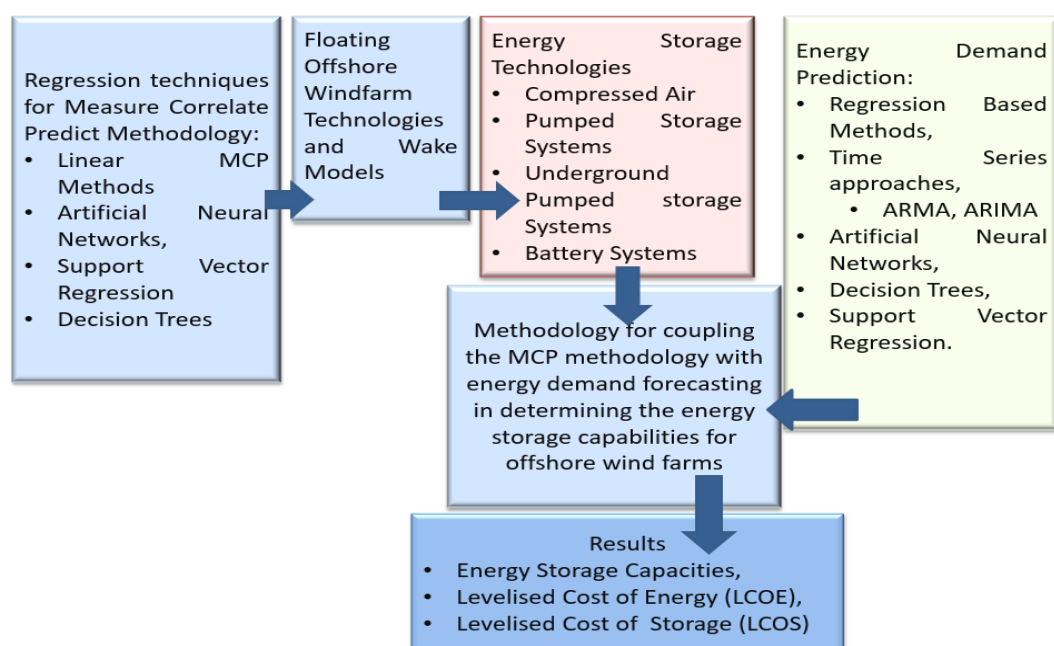


Figure 4-1: Integrating MCP with EDF for the optimisation of an ESS capacity coupled to a windfarm [181].

Different combinations of regression techniques for MCP and EDF models to estimate the ESS capacity for a given windfarm were considered (Figure 4-2). Every combination had to be analysed and tested for its specific level of percentage error. This determined the best combination of regression techniques, which will provide the least percentage error in energy yield.

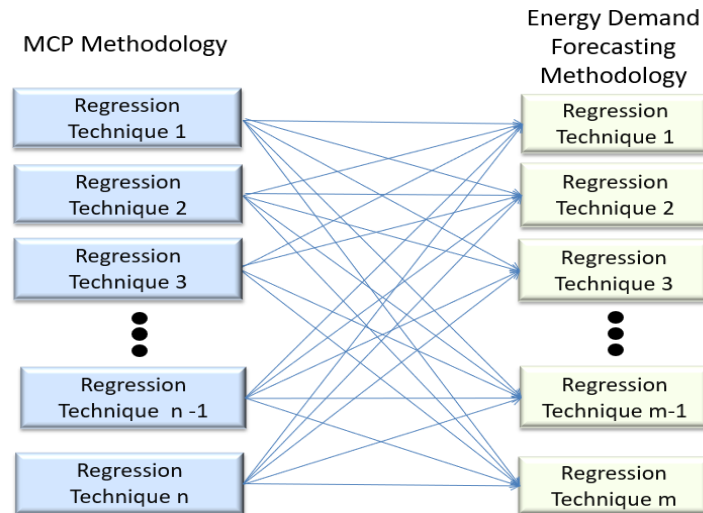


Figure 4-2: Possible combinations resulting from coupling different regression techniques for the MCP and energy demand forecasting methodology [181].

Figure 4-3 shows how the available data were utilised. In the case of the MCP methodology, the long-and short-term data were used to project the wind data at the candidate site. The energy demand data were used to build the energy demand forecast model.

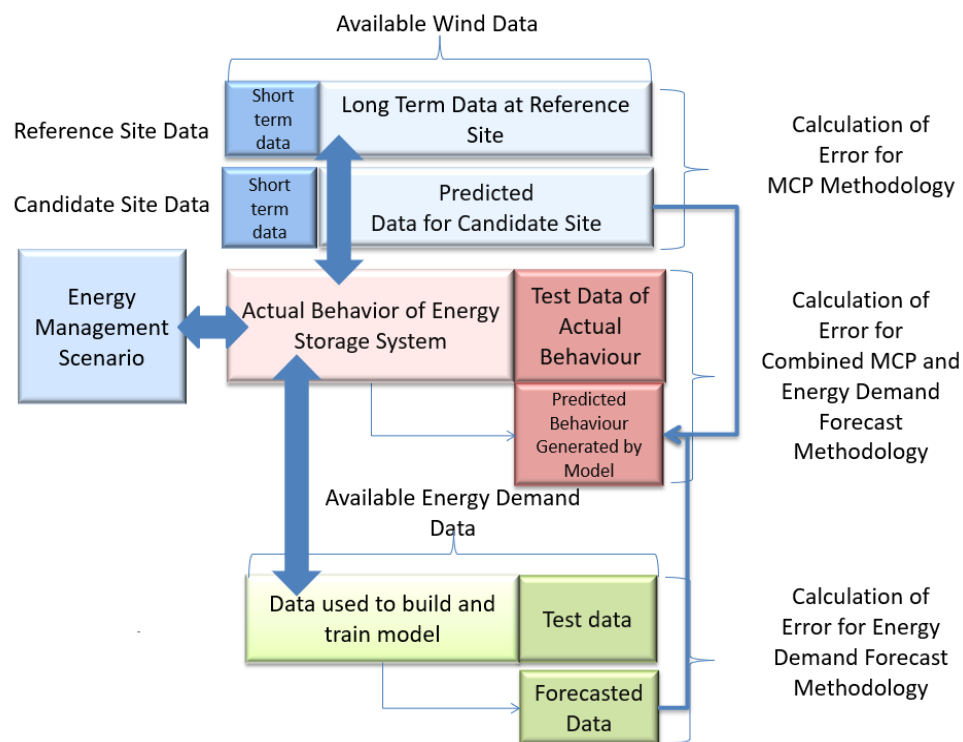


Figure 4-3: Utilisation of the available data to establish the model for the behaviour of the ESS [181].

The comparison of energy yields from actual data to those from predicted and forecasted data was used to estimate the error from the model. Once the optimal combination of regression techniques

for MCP and EDF methodologies was established, the available data were used to determine the behaviour of the ESS. The comparison between the actual behaviour and that obtained by applying the predicted and forecasted values established the error from the model which coupled MCP and EDF. The overall methodology can be subdivided into seven steps, as already summarised in Figure 1-2 to Figure 1-4. These steps are described in more detail the following sections.

4.2 Prediction of Wind Speed

This section describes how the wind speed at the candidate site was predicted by the MCP methodology.

4.2.1 Determining the Adequate Regression Techniques for the MCP Methodology

This section describes the methodology used to select the best regression techniques for MCP. Various possible regression techniques have been applied to the MCP methodology which was depicted in Figure 2-1.

Three sets of wind data were made available for this research. These are:

- **Data Set A:** 3Tier data, from the period 1 January 1980 till 31 January 2010,
- Malta International Airport (Luqa) Meteorological station, from the following periods:
 - **Data Set B:** 1 January 2007 till 31 January 2008, and,
 - **Data Set C:** 1 January 2013 till 31 January 2019, and,
- **Data Set D:** from a LiDAR system situated on a coastal tower at Qalet Marku, from the period, 25 June 2015 to 18 July 2017. This consisted of wind speed and direction measured at several heights above the coastal tower's rooftop.

The acquisition of these four data sets will be described in detail in Section 5.1 The data were also initially pre-processed to remove erroneous data points as shown in Appendix A.

In STEP 1, using concurrent wind data, from the Data Sets A and B, several regression techniques, (tabulated in Table 4-1) were analysed by using the metrics described in Section 2.12. The results from this analysis are shown in Section 7.1. In this case, the Luqa Site was used as the candidate site while the 3Tier dataset represented the reference site. Results were compared on a sector-by-sector basis. The best regression techniques from the list given in Table 4-1 were selected. The best parameters for the chosen techniques were also identified. In STEP 1, the scope was to show the behaviour of the various regression methodologies with a sectorial analysis using Data Set A and Data Set B.

Table 4-1: Type of regression techniques applied to the data.

Linear Regression	Artificial Neural Networks	Machine Learning
Simple Linear Regression	Multilayer Perceptrons with feedforward networks.	Decision Trees
Robust Regression	Exact Radial Basis Networks	Support Vector Machines
Stepwise Regression	Radial Basis Network (Bayesian)	Gaussian Process Regression
Multivariate Linear Regression.	Generalised Regression Neural Network	

The regression techniques which were considered adequate for the MCP methodology were SLR, MLR, ANNs, SVR and DTs. The mathematical background of the technique which have been deemed to be adequate for use with the MCP methodology was described in Section 3.1.

In STEP 2, the scope was to show how the regression model identified in STEP 1 behaved with data from various measurement heights by using Data Set C and Data Set D i.e., another data set. The selected regression techniques were applied to Data Set C and D and the results from this step will be presented in Section 7.2.

With the exception of the SLR technique, all the regression techniques used the hourly average of the wind speed in ms^{-1} and the wind direction in *degrees* from the reference site as input, while the wind speed in ms^{-1} at the candidate site was used as the output of the models. In the case of the SLR technique, only the wind average hourly wind speed from the reference site was used as input to the model. In order to evaluate the effectiveness of the models, which were created with Matlab®, the coefficient of determination R , the MSE and the MAE of the residuals between the actual wind values and those predicted by the regression model, were computed. The best model was deemed to be that having the highest coefficient of determination and the least error. The methodology used in STEP 1 and STEP 2 is shown in Figure 4-4.

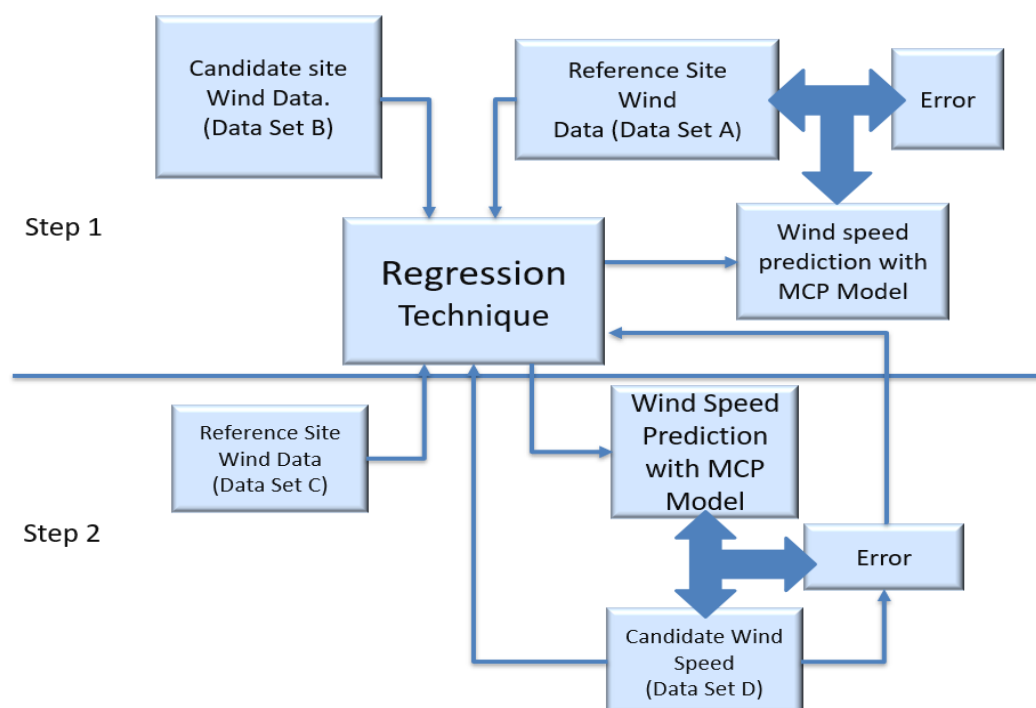


Figure 4-4: STEP 1 and STEP 2 – constructing the regression model and prediction of wind speed at the candidate site.

The regression models allowed the wind data from the reference site to be used to predict the concurrent data at the candidate site. The regression models could predict both wind speed and direction at the candidate site as will be shown in the methodology described in Section 4.2.2.

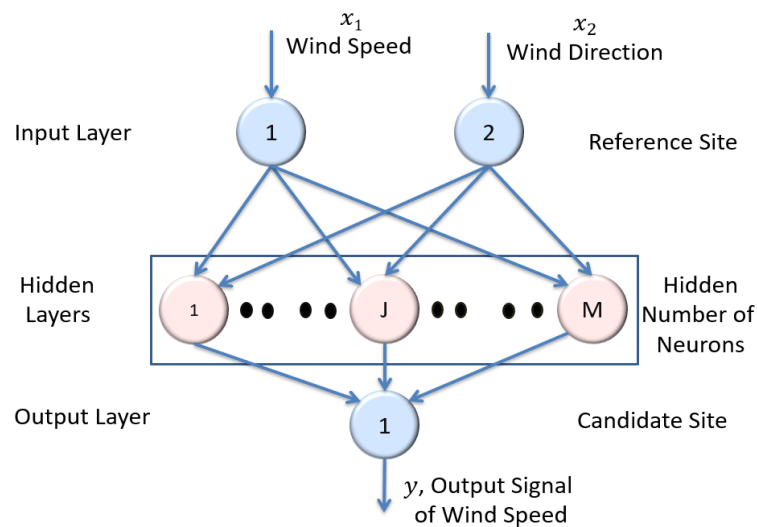


Figure 4-5: Model used for Artificial Neural Network for regression between the reference site and the candidate site.

For STEP 1 and STEP 2, the feedforward ANN regression technique shown in Figure 4-5, was constructed by applying the characteristics shown in Table 4-2. In this case, 70% of the data was used to train the model, 15% was used for verification of the model and 15% was used for testing the model. The model was constructed using Matlab® [182] by setting these specific parameters in the program commands.

Table 4-2: Description of the regression techniques used for the Measure-Correlate-Predict Methodology.

MCP methodology	Wind Speed	Wind Direction
MLR	Independent variables: 2 (Wind speed magnitude, wind direction at the reference site). Dependent variables: Wind Speed magnitude at candidate site. Methodology: Least Squares	Independent variable: Wind velocity vector in North and East direction at reference site. Dependent variable: Wind velocity vector in North and East direction at candidate site.
ANN	Number of inputs: 2 – Wind speed magnitude, wind direction at the reference site) Number of outputs: 1 – Wind speed magnitude at candidate site. Number of layers: 3 Number of neurons in layer: 30,30,10 Training Methodology: Levenberg-Marquardt Algorithm Percentage of points used for training: 70% Percentage of points used for verification: 15% Percentage of points used for testing: 15%	Number of inputs: 1 – Wind velocity vector in North and East direction at reference site) Number of outputs: 1 – Wind velocity vector in North and East direction at candidate site.
DT	Number of inputs: 2 – wind speed magnitude, wind direction at reference site. Number of outputs: 1 – wind speed at candidate site. Number of Trees: 200 Minimum Number of Leafs: 5 Methodology: Tree Bagger Ensemble	Number of inputs: 1 – Wind velocity vector in North and East direction at reference site. Number of outputs: 1 – Wind velocity vector in North and East direction at candidate site.
SVR	Number of inputs: 2 – wind speed magnitude, wind direction at reference site. Number of outputs: 1 – wind speed magnitude at candidate site. Methodology: Hyperparameter optimisation, Kernel: Gaussian Solver: Sequential Minimal Optimisation	Number of inputs: 1 – Wind velocity vector in North and East direction at reference site. Number of outputs: 1 – Wind velocity vector in North and East direction at candidate site.

Table 4-2 also presents the data inputs and the regression parameters which were used to train the respective models, both for wind speed and wind direction. It also tabulates the parameters of the regression techniques and the algorithms which were used to train the regression model, such as Least-Squares for MLR and the Levenberg-Marquardt algorithm for ANNs.

As described in Sections 3.1.3 and 3.1.4, for case of the DT regression technique, the number of trees was set at 200, while the minimum number of leafs was set to 5, while for the SVR technique the hyperparameters were optimised iteratively by Matlab®, with the kernel function in the model being set to Gaussian. Results from STEP 1 and STEP 2 are presented and discussed in Sections 7.1 and 7.2.

4.2.2 Applying the Predicted Wind Data to the Hypothetical Windfarm

Following the determination and the analysis of the behaviour of the regression techniques and their application to the MCP methodology, in STEP 1 and STEP 2, in STEP 3 the predicted wind data (wind speed and direction) were applied to an offshore hypothetical windfarm. The windfarm model was created in windPRO® and will be described in Section 6.1. Figure 4.6 describes the methodology applied for this part of the research.

As wind direction was crucial for determining the power output from a windfarm, the MCP methodology was also applied to the wind direction as described in Section 3.1.5. For the wind direction the input training data were the wind velocity vector component in the North or East directions at the candidate site, while the output of the model was the respective component at the candidate site. The same regression models described in Section 4.2.1, were also applied for wind direction, and these were summarised in Table 4.2.

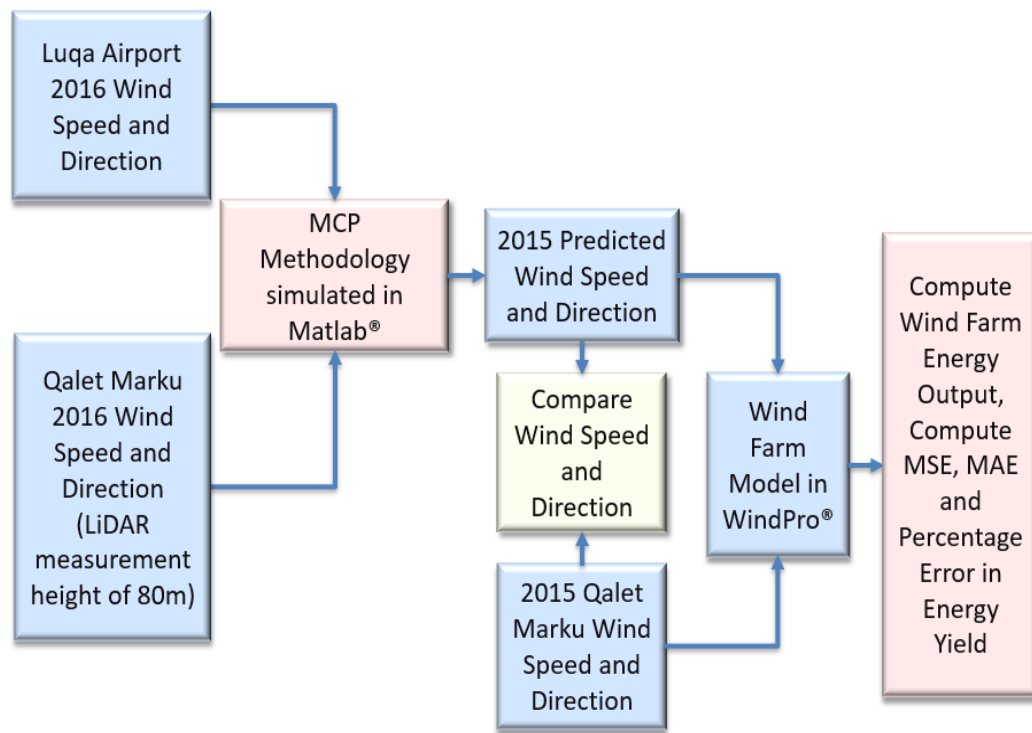


Figure 4-6: Applied methodology to determine the behaviour of the hypothetical windfarm and to compute the error due to the MCP methodology.

The wind data at the LiDAR measurement height of 80 m was used to create the models in STEP 3. This height corresponded to the hub-height of the wind turbines used in the hypothetical windfarm, as shown in Table 4-3.

Table 4-3: Summary of combinations of methodologies, LiDAR measurement heights and installed capacities of the offshore windfarm used in the analysis.

80 m Measurement Height (equivalent to an offshore 100m hub height)	MCP Methodology			
	Simple Linear Regression (SLR)	Artificial Neural Networks (ANN)	Decision Trees (DT)	Support Vector Regression (SVR).
	Wind Speed, Wind Direction, predicted for the year 2015. Actual and predicted sequences fed into wind farm model, comparisons of wind farm power output made for a capacity of 250, 200, 150, 100 and 50 MW.			

Regression models were created using the SLR, ANN, DT and SVR techniques for the MCP methodology by using the reference and candidate wind speed and direction data for the year 2016. Models were created for both wind speed and direction. The wind speed and wind direction for the year 2015 were then predicted with the models by feeding the speed and direction values from the reference site from the year 2015 to the model. Thus, a sequence of predicted wind speeds time-series could be compared to the actual speed measured at the candidate site for the year 2015.

To predict the wind direction, the MCP methodology was applied as shown in Figure 3-4 and Figure 3-5. Figure 3-4 shows that two regressions were carried out: one for the magnitude of the wind component in the North direction and one for the wind component in the East direction. Thus, two models were created using the wind speed and direction data of the reference and the candidate site for 2016. The two models were then used to derive the predicted wind direction for 2015 at the candidate site, as shown in Figure 3-5. This was performed by using the wind components at the

reference site for 2015 as inputs to the respective models. The values of the wind speed in the North direction and the in the East direction were first predicted, and the wind direction at the candidate site for 2015, θ_{met_p} , was then derived from the mathematical relationships given in Eqs. (3-44) and (3-45).

Sequences of wind speed and wind directions (both actual and those predicted by the MCP methodology), were fed into the windPRO® hypothetical offshore windfarm model. This was done for different combinations of regression technique and windfarm installed capacity configuration (i.e., for 250, 200, 150, 100 and 50 MW). The results were compared to determine which regression technique used for the MCP methodology and windfarm capacity, would give the lowest prediction error. The prediction error for the power output from the wind farm was analysed using the NMSE, the NMAE and the percentage error in the Overall Energy Yield for the timeframe of the analysis. The results are shown in Section 7.4.2.

4.3 Econometric and Demographic Forecasting

STEP 4 involved the use of the Box-Jenkins [33] methodology for forecasting econometric and demographic data for the Island of Malta. The results for the forecast of econometric trends are shown in Section 8.1.1, while Section 8.1.2 describes the results for the forecast of demographic data. Both econometric and demographic data were used as independent inputs for the regression used to forecast the energy demand. Econometric and demographic data were forecasted using the ARIMA or Seasonal ARIMA methodologies [33, 157]. Other independent variables were the seasons, time of day, public holidays, and the weekends. The models used for predicting the electricity demand were regression models based on MLR, ANN, DT and SVR.

4.4 Energy Demand Forecasting

The energy demand was forecasted in STEP 5. The forecast was carried out by means of the regression techniques described in Section 3.1.1 to 3.1.4. The parameters shown in Table 4-4, which included the results from STEP 4 were used as the regression's independent variables. The energy demand was the dependent variable [9, 183]. As described above, the GDP, other econometric trends and population parameters shown in Table 4-4 were predicted using the ARIMA methodology described in Section 3.2.

Table 4-4: Input variables, used as independent variables for the regression used to forecast energy demand.

Time Dependent Variables	Time of day	Hour (1 to 24)
	Weekday	Yes/No
	Public Holiday	Yes/No
	Season	1 – Winter 2 – Spring 3 – Summer 4 – Autumn
Econometric data [40]	Gross Domestic Product (GDP) [40]	Economic Value in Euros
	Agricultural Activities	
	Manufacturing Activities	
	Mining Quarrying and Water Supply.	
	Construction Activities	
	Wholesale retail and trade, repair of motor vehicles and motorcycles, transportation and storage, accommodation and food service activities,	
	Information and communication services.	
	Finance and insurance services.	
	Real Estate Activities	
	Professional, Scientific and Technical Activities	
	Public Administration and defence, compulsory social security, education, human health and social work activities.	
	Art entertainment and recreation, repair of household goods and other services.	
Demographic Factors [40]	Population growth.	

In this current research, energy demand was dependent on the time of the day, with the demand decreasing during the hours of day and reaching a minimum during the hours of the night. Another factor was whether the day was a weekday, on a weekend or a public holiday; in this case, the energy demand being less during weekends and public holidays. Energy demand also depended on the season, where trends showed a higher demand for energy during the summer months.

The independent variables were made up of three groups of data. These were the time dependent variables, such as time of the day, season, etc., which were easily forecasted, econometric data [162] and demographic factors or population growth. The econometric data, which included the GDP, were made up of the different sectors of economic activity as shown in Table 4-4 [40].

As explained in Figure 1-2 to Figure 1-4, the energy demand was forecasted in STEP 5. The models were created and trained using the actual energy demand, season, time of day, public holidays, weekends, and econometric and demographic data for the years 2011-2016. This established a model which described the relationship between the energy demand, econometric, demographic and the other variables described in Table 4-4. Two methodologies were used for EDF, as described in Sections 4.4.1 and 4.4.2. In both methodologies, the MLR, ANN regression, DT regression and SVR techniques were first used to create a regression model. This was then used to forecast the energy demand. The models from the two methodologies were used to forecast the energy demand for 2017, with the results shown in Section 8.2. In both methodologies, the econometric and demographic data were assumed to increase at a constant hourly rate. Thus, the econometric data and demographic growth are calculated on a per hour basis, i.e., the quarterly value of the GDP was divided by the number of hours in the quarter to find the hourly growth rate for GDP in € hr^{-1} . The population was also considered to grow at a constant rate hourly rate, as given by Eqs. (5-3) and (5-4).

4.4.1 First Methodology used to Forecast Energy Demand

Figure 4-7 shows the first methodology which was used to create the model which enabled the energy demand for the year 2017 to be forecasted. As opposed to the second methodology, which splits the data into the four yearly quarters thus creating a regression model for every quarter, the forecast in the first methodology was carried out by creating a single model which incorporated the data of the whole year.

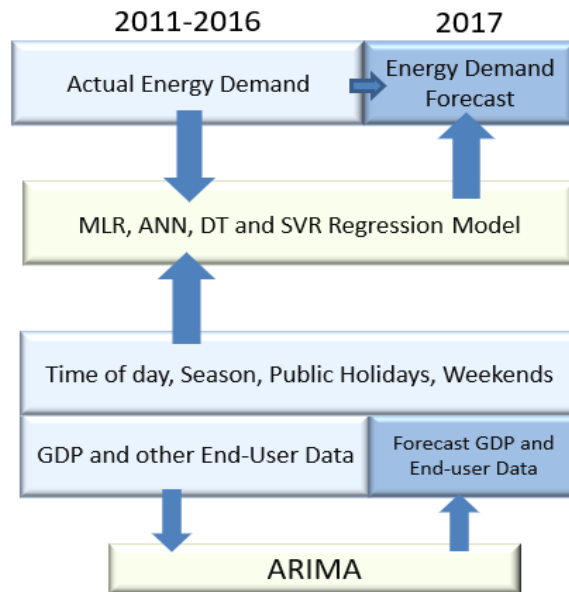


Figure 4-7: First methodology used to forecast energy demand for the year 2017, using ARIMA to forecast the input variables for MLR, ANN, DT and SVR regression techniques.

4.4.2 Second Methodology used to Forecast Energy Demand

The second methodology was based on the use of quarterly data. In this methodology, the data was split into four parts, each corresponding to the four respective quarters of the year. Hence, the forecast for Q1 of the year 2017 was made on the basis of the Q1 data for the years 2011-2016. A similar methodology was used for Q2, Q3 and Q4. Due to this, Figure 4-7 was modified as shown in Figure 4-8. Better results were obtained using this methodology. The four models were created with the same numerical techniques defined in Section 4.4.1 and were integrated as shown in Figure 4-9.

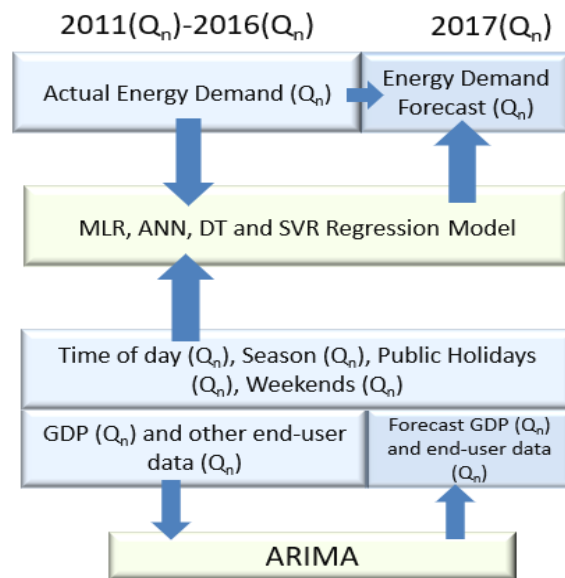


Figure 4-8: Second methodology used to forecast energy demand for the year 2017, using ARIMA to forecast the input variables for MLR, ANN, DT and SVR regression techniques.

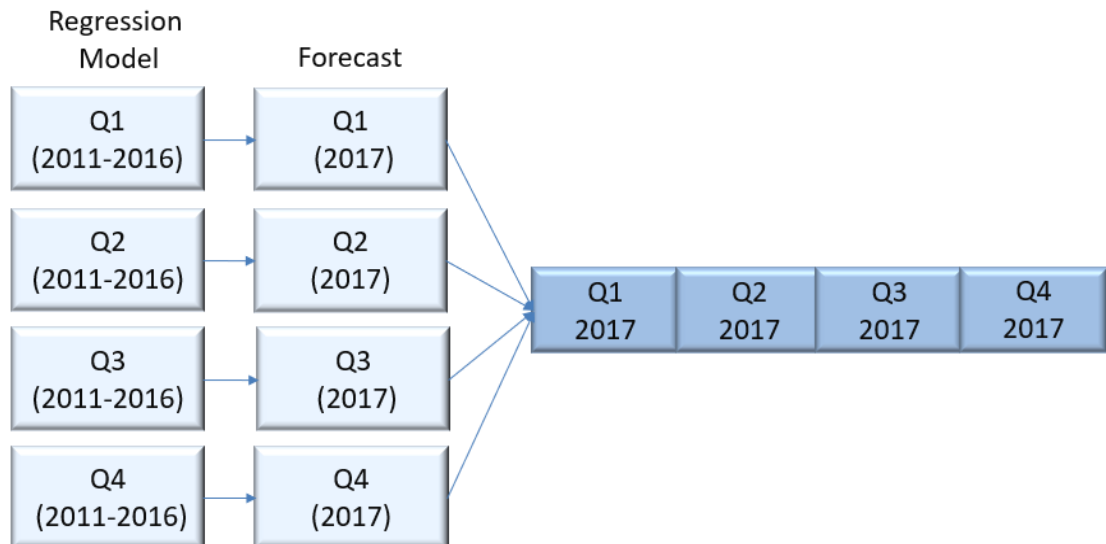


Figure 4-9: Energy demand forecast methodology based on quarterly data used to forecast energy demand for the year 2017.

4.4.3 Forecasting Energy Demand for the Years 2016-2020

Since the second methodology produced better results in terms of the coefficient of determination, R , the MAE and the MSE, this second methodology was used to forecast the energy demand for the years 2016-2020, as shown in Figure 4-10. Using the forecasted econometric data, demographic forecasts, and the other variables as input data, the energy demand was forecasted for the years 2016 to 2020. The EDF results from the second methodology were used in Sections 11.4 and 11.5 for the long-term analysis of the energy demand in establishing the sensitivity of the LCOE and LCOS to the error introduced by the forecasting methodology.

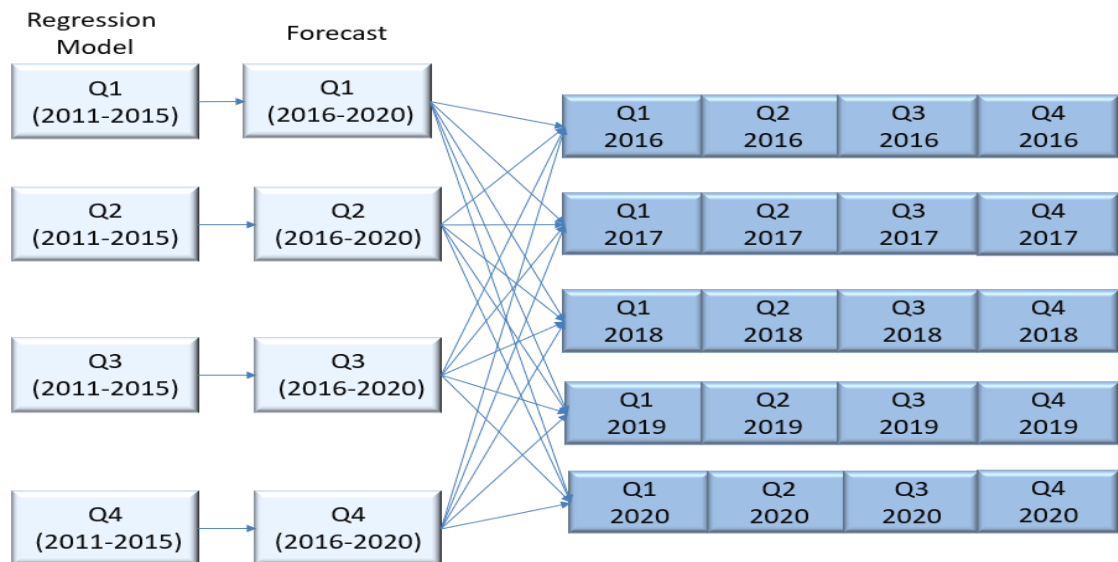


Figure 4-10: Energy demand forecast methodology based on quarterly data used to forecast energy demand for the years 2016-2020.

4.5 Energy Storage Model in Matlab® and Simulink®

The ESS model design in Simulink® was based on simple mathematical equations and conditions. It modelled a battery ESS and considered the battery's depth of discharge and discharging efficiencies. Transmission efficiencies were also included. Two types of battery-based ESS were considered for this research, namely Li-Ion and VRB. A block diagram of the Matlab® model, which shows the integration of the ESS with the wind farm and the electricity grid as shown in Figure 4-11. The model included the ESS, a controller and the inputs and outputs to and from the ESS. Energy sources to the grid are either from the generation baseload, generation from fossil fuel sources above baseload, the windfarm and the ESS. The controller checked the status of all sources and decided how the supply to the grid would be provided. As energy from the windfarm fed the ESS, the controller responded to the input conditions. It decided on whether the energy from the offshore wind farm would charge the store, be fed to the grid, or whether it had to be curtailed. It also decided when the ESS discharged energy to the grid.

System operation depended on wind availability, energy demand and the state of charge of the ESS. One basic and important assumption was that the baseload generation, P_B , would remain constant, and that the wind power output, P_W , and power output, P_S , from the energy store would replace fossil fuel energy generation above the baseload, when available. In addition, both energy from the windfarm and the ESS took priority over generation from fossil fuel sources above the baseload [29].

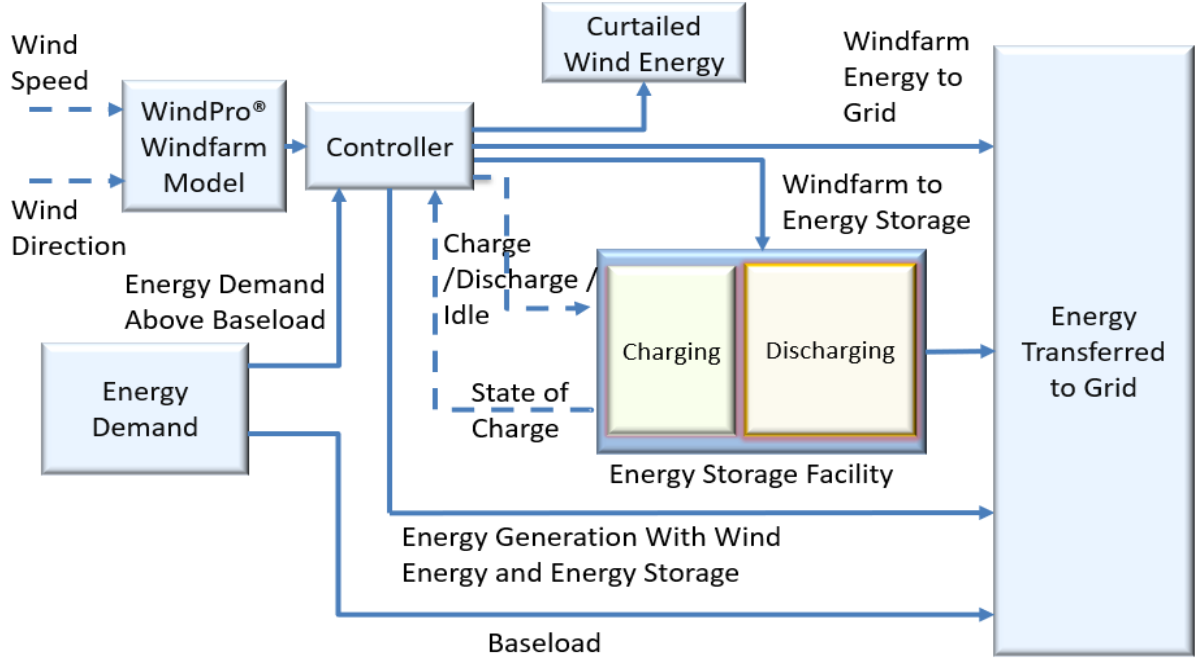


Figure 4-11: A block diagram showing the integration of the wind farm, the conventional thermal generation and the energy store to the power grid as defined in Simulink® [29].

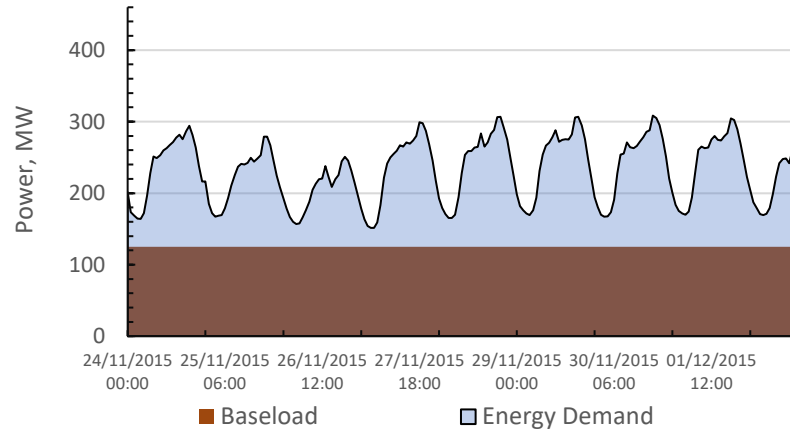


Figure 4-12: Total energy demand, including baseload for the period 24 to 30 November 2015 [29].

A typical time sequence of the energy demand, from the 24 till the 30 of November 2015, is shown in Figure 4-12. This shows the total energy demand P_D , as being made up of two components, i.e., the generation baseload P_B , and the energy demand above baseload, P_T . This relationship was established as Eq. (4-1). Without the windfarm and the ESS, P_T would be entirely dispatched from fossil-fuel sources.

$$P_T = P_D - P_B \quad (4-1)$$

At any given instant, the effective power output from the wind farm P'_W , was composed of three parts: the part used for generation P_{WG} (fed directly into the grid), the part used for energy storage P_{WS} , and the curtailed energy P_{WC} , such that:

$$\eta_W P_W = P'_W = P_{WG} + P_{WS} + P_{WC} \quad (4-2)$$

While the ESS is charging, at any given time t , the level of energy was given by:

$$E_s = \int_0^t P_{W_s} + E_{S_{t=0}}, \text{ for } E_s < E_{S_{MAX}} \text{ and } P'_W > P_T \quad (4-3)$$

and $t = 0, 1, 2, 3, \dots$ until $E_s < E_{S_{MAX}}$. The variable t was a counter which started at $t = 0$ (on commencement of a charging cycle). The value $E_{S_{t=0}}$ was the level of energy in the store at the beginning of the charging cycle. Charging of the ESS commenced if the wind farm energy output was greater than the difference between the energy demand and the base load, i.e., when:

$$P'_W > P_T$$

and continued until either the ESS was saturated, such that:

$$E_s = E_{S_{MAX}}$$

or the power output from the wind farm decreased below P_T , this being the difference between the energy demand and the generation baseload. The power output from the windfarm at this point continued to be used for generation, such that:

$$P'_W = P_{W_G} < P_D - P_B = P_T \quad (4-4)$$

In this case, the wind farm power output allowed for a reduction in fossil energy generation as the energy demand could be met by a combination of wind farm and the fossil fuel energy generation. During the charging cycle the part P_{W_G} , which under these conditions would be equal to P_T , was fed to the grid replacing the fossil fuel generation.

The energy store discharged with a constant discharge rate $\left(\frac{dE_s}{dt}\right)$ which was the rated power of the ESS in MW. As the store discharged from an initial energy level $E_{S_{t=0}}$, the resulting level of energy in the store was given by:

$$E_s = \left[E_{S_{t=0}} - \left(\frac{dE_s}{dt} \right) t \right] \eta_D \quad (9-5)$$

where η_D was the efficiency of the energy discharge from the ESS. The energy store discharged if $E_s > 0$, i.e., if the store contained energy and if the power output from the wind farm was less than the component of the energy demand which was above the generation baseload, such that $0 < P'_W < P_T$.

Hence, the component of the generation from fossil fuel sources was reduced, such that the energy demand above baseload, P'_T , was then made up of three components as follows:

$$P'_T = P_D - P_{W_G} - \frac{dE_s}{dt} \quad (4-6)$$

Under certain conditions windfarm energy output had to be curtailed. This occurred when the output from the wind farm, P'_W exceeded P_T , and the ESS was fully charged, i.e., $E_S = E_{S_{MAX}}$. Therefore, the power from the wind farm is curtailed when the conditions in Eq. (4-7) are satisfied:

$$P'_W > P_T \text{ and } E_S = E_{S_{MAX}} \quad (4-7)$$

In such conditions, the curtailed energy from the windfarm is given by, P_{W_C} , where,

$$P_{W_C} = P'_W - P_{W_G} - P_{W_S} \quad (4-8)$$

4.6 Applying the Wind Farm Power Output and Energy Demand Time-Series to the Model

The creation of a matrix which enabled the comparison of the results from all the combinations regression techniques used for the MCP and EDF methodologies presents a novel approach. The results from the optimal combination of regression techniques for MCP and the EDF were used to determine the optimal size of the ESS and to compute the LCOE and the LCOS.

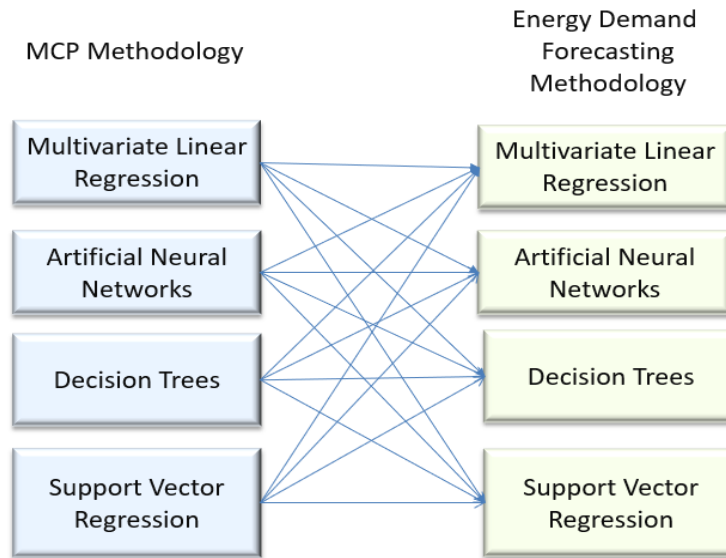


Figure 4-13: Combination of regression techniques for MCP and EDF.

STEP 6 defined the matrix described in Section 4.1 (Figure 4.2). The matrix was obtained by comparing the percentage error in energy yields from the ESS and the levels of curtailed energy from the offshore windfarm from each combination of regression techniques for MCP and EDF methodologies and comparing these to the concurrent energy yields and curtailed energy obtained with measured wind speed and direction and actual energy demand. This was given by Eq. (3-85). Figure 4-13 shows the possible combinations of regression techniques for MCP and EDF.

The applied methodology is shown in Figure 4-14. The generation of the predicted wind speed and direction time-series using the MCP methodology, was described in Section 4.2, with the results being presented in Section 7.2. The regression models used for the MCP methodology were created

using hourly wind data from the year 2016, with the predicted wind speed and wind direction data being those for the year 2017.

The energy yield time-series from the windfarm was obtained from the model of the hypothetical wind farm, which will be described in Section 6.1, with the results being presented in Section 7.3. The wind data used for this step were that for the 80 m LiDAR measurement height since this was equivalent to the hub height of the 5 MW wind turbines in an offshore environment. The wind speed and direction data for the year 2017 were predicted with the MCP methodology by using the concurrent wind speed and direction data from the reference site. Energy demand forecasting was described in Section 4.3, with the results shown in Chapter 8. Thus, the combinations of energy yield time-series from the combinations of regression techniques for the MCP and EDF methodologies were applied to the Simulink® model shown in Figure 6-7.

The optimal combination of regression techniques for MCP and EDF was established by analysing the percentage error in the energy yield for various windfarm and ESS parameters. This was done by varying the installed capacity of the windfarm (from 50 to 250 MW) in 50 MW increments, using a variable ESS capacity from 500 to 5000 MWh, together with baseload conditions of 100, 125 and 150 MW, for all the MCP methodologies. The ESS was rated at a power of 10 MW. These ranges are derived from the Maltese energy scenario. The maximum energy demand is around 500 MW, and occurs during the summer months, when wind energy is at a minimum. The minimum energy demand is of around 200 MW and occurs while the available wind energy is at a maximum. The generation baseload is normally in the range of between 100 MW and 150 MW. Results will also indicate that the ESS power rating will not influence the optimal ESS capacity, as demonstrated in Chapter 10. The results in Chapter 10 also demonstrated that a larger ESS power rating will result in lesser amount of curtailed energy from the windfarm, hence favouring the LOCE, while a large ESS rating results in a lesser amount of energy being discharged to the grid. This also increases the LCOS of the storage system.

Results from STEP 6 are shown and discussed in Chapter 9 and these results required dimension reduction, as was described in the literature review of Section 2.3 and the theoretical description given in Section 3.3. The data derived from the combination of the regression techniques for MCP and EDF resulted in a multi-dimensional array of data, making it difficult to obtain a clear optimal combination. The 4 regression techniques resulted in 16 combinations. Each combination had a three-dimensional set of results for the percentage error, with the axis set as ESS capacity (from 0 to 5000 MWh in steps of 500 MWh), offshore windfarm installed capacity (of 150, 200 and 250 MW) and the generation baseload (set at 100, 125 and 150 MW).

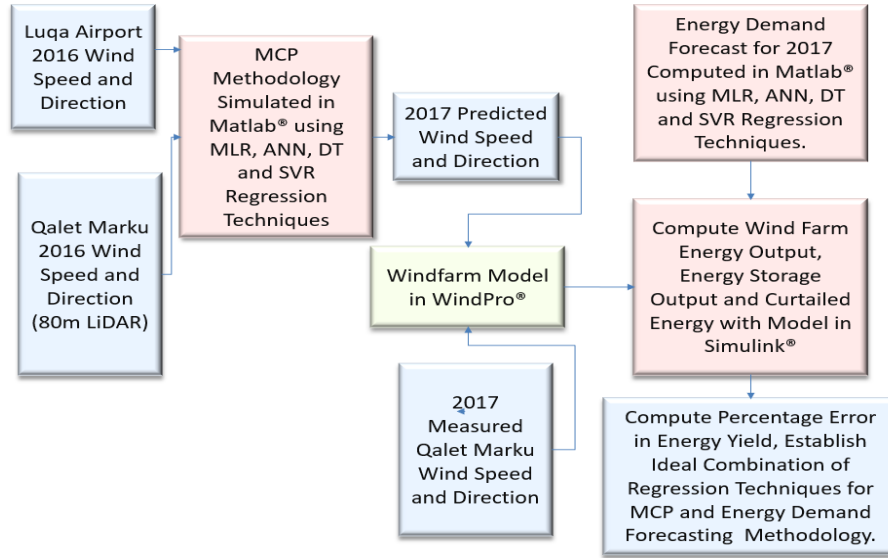


Figure 4-14: Methodology used to determine the optimal combination of regression techniques for the MCP and EDF methodologies.

The dimension reduction algorithm is shown in Figure 4-15 and Figure 4-16, and is performed for the energy discharged from the ESS to the electricity grid, the curtailed energy from the offshore windfarm and the energy transferred from the offshore windfarm which is transferred to the electricity grid.

The first parameter (or dimension) to be eliminated was the capacity of the ESS. This was done by calculating the Mean of the Percentage Error (MPE) for every combination of offshore windfarm installed capacity and generation baseload. In this process Eqs. (4-8) and (4-9) are used. Equation (4-9) is the transposition of Eq. (4-8).

$$MPE_{(M,N)} = \frac{1}{n} \sum_{k=1}^n PE_{(ESS)_n} \Big|_{\text{Windfarm Capacity, Generation Baseload}} \quad (4-8)$$

$$MPE'_{(N,M)} = \frac{1}{m} \sum_{k=1}^m PE_{(ESS)_m} \Big|_{\text{Windfarm Capacity, Generation Baseload}} \quad (4-9)$$

where, M is the number of regression techniques used for the MCP methodology, N is the number of regression techniques used for the EDF methodology, n is the number of combinations of ESS capacity and regression techniques and MCP methodologies, m is the number of combinations of ESS capacity and regression techniques used for EDF methodologies and k represents a counter. Therefore, Eq. (4-10) represents the result of the product of the various combinations generated from Eqs (4-8) and (4-9). This is reflected in Figure 4-15.

$$\begin{aligned} & PMPE_{(m,n)} \Big|_{\text{Windfarm Capacity, Generation Baseload}} \\ &= \frac{[Mean Percentage Error_{(MCP Methodology)_m} \times Mean Percentage Error_{(EDF Methodology)_n}]/10}{\Big|_{\text{Windfarm Capacity, Generation Baseload}}} \end{aligned} \quad (4-10)$$

The next two dimensions to be eliminated were the installed capacities of the offshore windfarm and the generation baseload and thus a further multiplication of the products of the PMPE (represented by Eq. (4-11)) was performed. This created the final matrix of results where the product with the lowest value represents the optimal combination of regression methodologies for the MCP and the EDF methodologies. This is reflected in Figure 4-16.

$$\text{Product of PMPE}_{(m,n)} = \begin{pmatrix} \text{mean}(\text{PMPE}_{\text{MCPmethodology}_1}) \cdot \text{mean}(\text{PMPE}_{\text{EDFMethodology}_1}) & \cdots & \text{mean}(\text{PMPE}_{\text{MCPmethodology}_1}) \cdot \text{mean}(\text{PMPE}_{\text{EDFMethodology}_N}) \\ \vdots & \ddots & \vdots \\ \text{mean}(\text{PMPE}_{\text{MCPmethodology}_M}) \cdot \text{mean}(\text{PMPE}_{\text{EDFMethodology}_1}) & \cdots & \text{mean}(\text{PMPE}_{\text{MCPmethodology}_M}) \cdot \text{mean}(\text{PMPE}_{\text{EDFMethodology}_N}) \end{pmatrix} \quad (4-11)$$

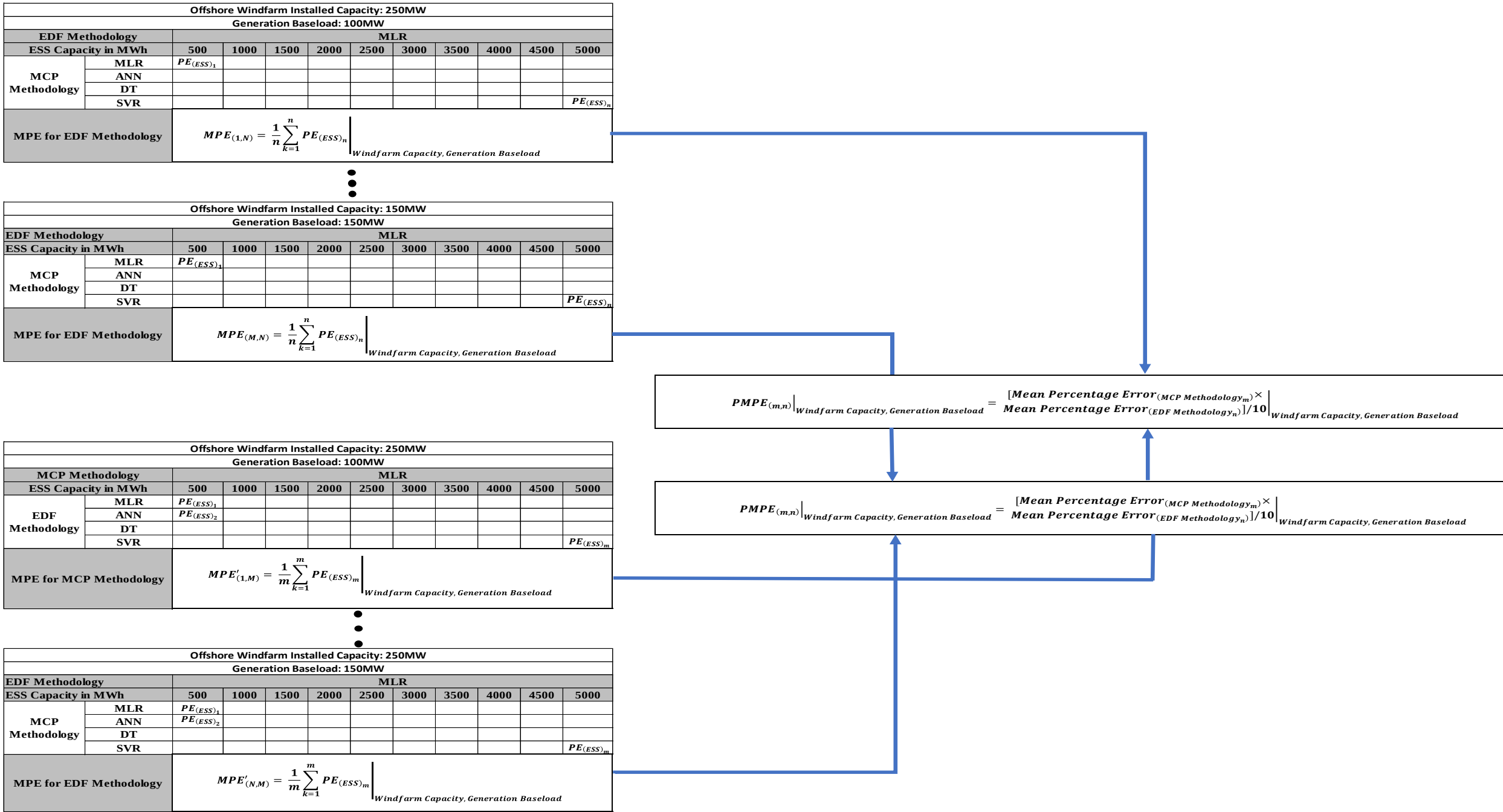


Figure 4-15: Dimension reduction algorithm (Part 1).

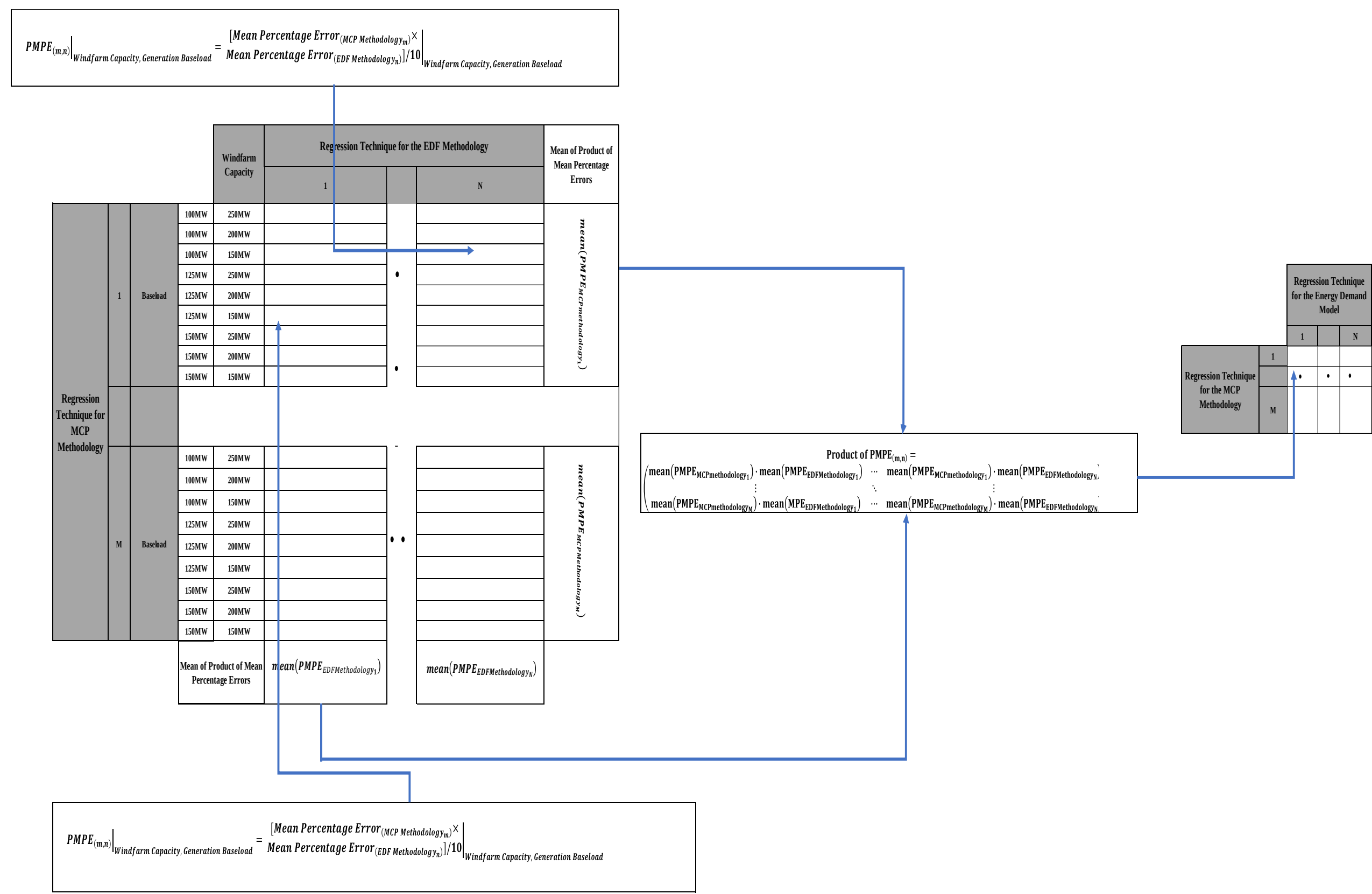


Figure 4-16: Dimension reduction algorithm (Part 2).

4.7 Defining the Optimal Storage Capacity

As described in Figure 1-4, the optimal storage capacity of the ESS was estimated in STEP 7. This was done by analysing the rate of change in curtailed power output from the windfarm and the energy discharged from the ESS to the electricity grid for increasing ESS capacity and power rating. The application of the optimal combination of regression techniques for the MCP and EDF methodologies resulted in an error in the estimation of the optimal size of the ESS when compared with the result obtained from measured values of wind speed and direction and energy demand. Hence, the error in the size of the ESS could be estimated.

The optimal ESS capacity was achieved when the rate of change of curtailed energy with the ESS capacity equalled zero, i.e., when any further increase in ESS capacity did not result in any further decrease in curtailed energy from the windfarm. This condition was observed by plotting graphs for the curtailed energy from the windfarm against ESS capacity for various conditions of installed capacity of the offshore windfarm, generation baseload and ESS power rating.

The optimal ESS capacity was estimated both with measured wind speed and direction, and the energy demand in conjunction with the results obtained from the ideal combination of regression techniques for the MCP and EDF methodologies. The results from the various conditions were compared and the percentage error for each condition was then be calculated.

By using a curve fitting methodology, it was established that the relationship between the curtailed energy and the ESS capacity could be approximated by a third order polynomial, where a differentiation with the ESS capacity resulted in a polynomial of the second order which peaked at the value of the optimal ESS capacity. Thus, if the total curtailed energy from the windfarm is defined as E_C , then the relationship with the ESS capacity, C_{ESS} , is defined as:

$$E_C = -a(C_{ESS})^3 + b(C_{ESS})^2 - c(C_{ESS}) + d \quad (4-12)$$

where the coefficients a , b , c and d are defined by the curve fitting analysis which is carried out in Sections 10.1 to 10.3. On differentiating Eq. (4-12) with respect to C_{ESS} , the following relationship is obtained.

$$\frac{dE_C}{dC_{ESS}} = -3a(C_{ESS})^2 + 2b(C_{ESS}) - c \quad (4-13)$$

From which the optimal ESS capacity is defined as the point where:

$$\frac{d^2E_C}{d(C_{ESS})^2} = -6a(C_{ESS_{OPT}}) + 2b = 0 \quad (4-14)$$

or,

$$C_{ESS_{OPT}} = \frac{b}{3a} \quad (4-15)$$

giving a value for the optimal ESS capacity, $C_{ESS_{OPT}}$.

Results are shown and discussed in Chapter 10, with Section 10.5 showing the results of applying Eqs. (4-12) to (4-15), i.e., the optimal ESS capacity for various conditions of installed capacity of the windfarm, generation baseload and ESS power rating. This was done both for predicted wind speed and direction as well as for forecasted energy demand, together with the optimal ESS capacity obtained with the measured wind speed and direction and energy demand for the various operating conditions.

An alternative methodology for establishing the optimal size of the ESS was to apply the same methodology described above to the amount of energy discharged by the ESS to the grid, with the optimal ESS capacity being defined as that at which the rate of change of energy discharge to the grid equals zero. Therefore, if the total energy discharged to the grid is defined as E_G , then similarly to the above case, the relationship with the ESS capacity could be defined in a manner expressed by to Eq. (4-16), giving:

$$E_G = e(C_{ESS})^3 + f(C_{ESS})^2 - g(C_{ESS}) + h \quad (4-16)$$

where the coefficients e , f , g and h are defined by the curve fitting analysis which is shown in Section 10.4 and Appendix H. On differentiating Eq. (4-16) with respect to C_{ESS} , the following relationship is obtained:

$$\frac{dE_G}{dC_{ESS}} = -3e(C_{ESS})^2 + 2f(C_{ESS}) - g \quad (4-17)$$

from which the optimal ESS capacity is defined as the point where:

$$\frac{d^2E_G}{d(C_{ESS})^2} = -6e(C_{ESS_{OPT}}) + 2f = 0 \quad (4-18)$$

or

$$C_{ESS_{OPT}} = \frac{f}{3e} \quad (4-19)$$

giving a value for the optimal ESS capacity, $C_{ESS_{OPT}}$. As above, the results of applying Eqs. (4-16) to (4-19) are shown and discussed in Section 10.4 and Appendix I.

4.8 Establishing the LCOE of the Offshore Windfarm and the LCOS of the ESS

In Section 2.3, it was established that due to the bathymetry of the Maltese Islands, the offshore windfarm will be of the floating type. In order to obtain an acceptable capacity factor, the hypothetical offshore windfarm model was based on a windfarm made up of 8 MW floating wind turbines which will be described in Section 6.1.2. Levelised Cost of Energy and LCOS were described in Sections 2.5 and 2.8 respectively. In Section 3.5 it was also shown that the costings

which affected the LCOE and LCOS were made up of CAPEX, OPEX and DECEX components. The methodology which was used to estimate the LCOE and the LCOS, together with sensitivity of the LCOE and the LCOS to the error introduced by the choice of the optimal combination of regression techniques for the MCP and EDF methodologies is described in Figure 4-17.

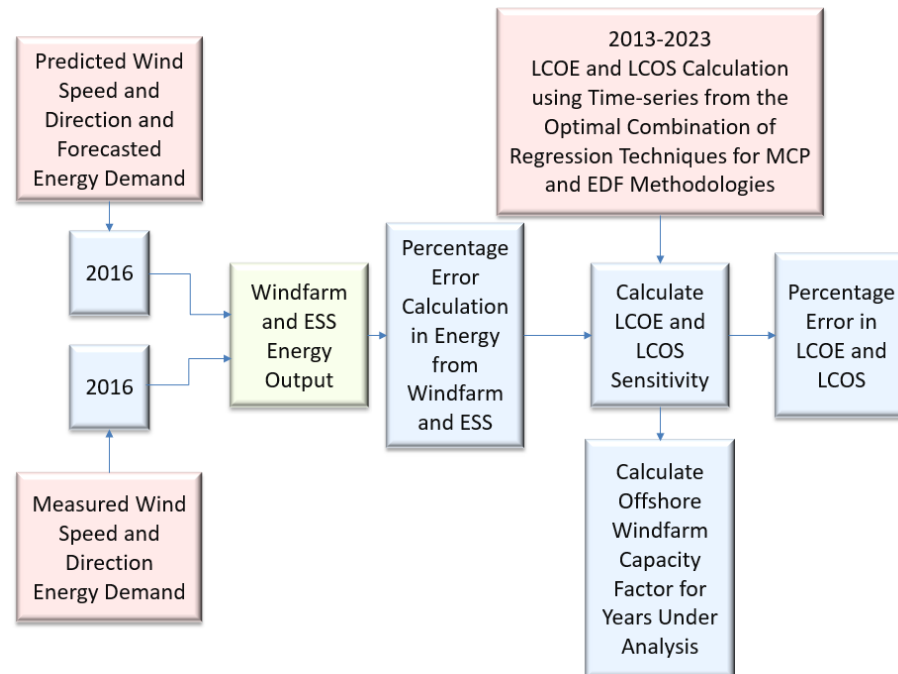


Figure 4-17: Calculation of LCOE and LCOE sensitivity to predicted wind speed and direction and forecasted energy demand.

The actual wind speed and direction together with the energy demand for the year 2016 were used to calculate the power output from the windfarm and the ESS. The year 2016 was used as a baseline for the calculation of the error of the LCOS and LCOE. The error in the energy yields of the year 2016 were calculated from the comparison of the energy yields from the actual wind speed and direction and energy demand to those from the predicted and forecasted values. This percentage error for 2016 was assumed to be the same for the successive years of the project duration of the project, and therefore an estimate of the baseline energy for the successive years was estimated by applying the percentage error to the energy estimated from windfarm and the ESS using predicted and forecasted time-series. The error in LCOE and LCOS could therefore be estimated. The results are shown in Section 11.4 and 11.5.

The LCOE of the floating offshore windfarm and the LCOS of the ESS were therefore established in STEP 8. The methodology for the calculation of the LCOE and the LCOS was as described in Section 3.5. The LCOE for a floating windfarm was calculated using Eq. (3-82), while Eqs. (3-85) and (3-86) were used to calculate the LCOS for the Li-Ion and the VRB ESSs respectively. In all the cases, a WACC of 8% [2] was applied. In Eqs. (3-82), (3-85) and (3-86) this was the parameter r .

4.9 Conclusion

The methodology shows how the knowledge gap identified in Section 2.13 and the research questions described in Section 4.1 were addressed. It also defines the method by which the research objectives were reached, and challenges overcome. Each of the eight steps used in the methodology was described in detail with the use of flow charts and block diagrams at every stage. The acquisition of data used to reach the objectives is now described in Chapter 5.

The optimal ESS capacity could be established with the use of simple equations which described the relationship between ESS capacity and curtailed energy from the windfarm, together with the energy discharge from the ESS to the grid. This was done with both measured wind speed and wind direction and energy demand and from predicted wind speed and wind direction using the MCP and EDF methodologies. Due to this, the level of error in optimal ESS capacity could be established, and the optimal ESS capacity could also be used to establish the LCOE of the offshore windfarm and the LCOS of the ESS, following which the error in the LCOE and LCOS due to the use of the MCP and EDF methodologies could be estimated.

5 Data Acquisition and Preparation

This chapter describes the acquisition of data for this current research which consisted of wind data, econometric data, demographic data, and energy demand data. This chapter is a detailed description of these sources of data. Data preparation will also be described.

5.1 Wind Data

As highlighted in Section 4.2, three sources of wind data were used. These included the 3Tier wind data, the Luqa Weather station situated at Malta International Airport, and that from a coastal LiDAR unit. The latter was located on the roof of a coastal tower situated at Qalet Marku on the Northwest coast of island of Malta. Figure 5-1 shows the positions of the three different sites. These sources provided 4 data sets of wind speed and wind direction.



Figure 5-1: A satellite Map of Malta showing relative locations of the LiDAR Unit at Qalet Marku, the Luqa Weather Station and the source location of the 3Tier Reference Time-series².

5.1.1 The 3Tier Wind Data

The 3Tier wind data from the years 1980 till 2010 were provided by the University of Malta. The 3Tier reference time-series parameters are described in Table 5-1. These wind data were an atmospheric simulation from data taken from high quality datasets, which included real observed data³. These data (designated as Data Set A in Section 4.2) were used to analyse various regression techniques, to determine which ones would prove to be more suitable to predict the data at a potential candidate site. This was described in Section 4.2.1.

Table 5-1: 3Tier data set parameters.

Data Set	3Tier Reference Time-series
Geographical Coordinates	36.017°N, 14.542°E
Height	80m
Temporal Resolution	Hourly average
Data Range	1 January 1980 – 31 January 2010 (Data Set A)

² Source: Google Earth, Accessed 17 July 2021

³ www.3Tier.com (accessed June 2021)

5.1.2 The Malta International Airport (Luqa) Meteorological Station

The meteorological station was situated at Malta International Airport (MIA), Luqa, in the south-eastern part of the island. Table 5-2 shows the parameters for the weather station at the MIA. The wind speed and direction at this weather station were measured using a standard cup and vane system.

The data which were acquired from this weather station consisted of two blocks of data, which are also shown in Table 5-2. These data were in two groups, and these were designated as Data Set B and Data Set C in Section 4.2. Data Set B data were used in conjunction with Data Set A to define adequate regression techniques for the MCP methodology, while Data Set C were used in conjunction with Data Set D, to define the predicted wind speed and wind direction time-series to be used as input to the hypothetical wind farm.

Table 5-2: Luqa Weather Station equipment parameter data⁴.

Data Set	Luqa Data.
Station Name	Luqa MIA Weather Station.
Data	Hourly wind speed and wind direction data.
Mast height	10 m above ground level.
Geographical Location	35.85657°N, 14.47676°E
Data Range	1 January 2007 – 31 December 2009 (Data Set B) 1 January 2013 – 31 December 2019 (Data Set C)

5.1.3 The University of Malta's LiDAR Station at Qalet Marku

Qalet Marku was considered as a potential candidate site for a hypothetical offshore windfarm. Wind measurements were carried out by means of a LiDAR unit. The measurement campaign started on 25 June 2015 and ended on 18 July 2017. The LiDAR unit was located on the rooftop of an historic coastal watchtower, at a height of 10 m above ground level [37]. Figure 5-2 shows an image of the installed LiDAR system, while Figure 5-3 illustrates a satellite image of the site. The LiDAR unit was configured with the parameters shown in Table 5-3. These data were designated as Data Set D.

⁴ Source: Malta International Airport



Figure 5-2: LiDAR system situated at Qalet Marku Tower, Malta⁵.



Figure 5-3: Satellite imagery of the Qalet Marku Coastal Watch Tower, located on a promontory at Bahar iċ- Ċagħaq⁶.

Table 5-3: LiDAR equipment parameter list [37].

Data Set	LiDAR Data.
Cone Angle, LiDAR aperture height above the tower rooftop.	60°, 1m
User defined heights, in m above the aperture window	10, 20, 30, 40, 50, 60, 80, 100, 150, 200
Data	Averaged 10 min data converted averaged to hourly data
Data range	25 June 2015 – 18 July 2017 (Data Set D)
Geographical Coordinates	35.946252°N, 14.45329°E
Average tower rooftop height above surrounding ground level.	10 m
Average tower rooftop height above sea level.	10 m

5.2 Wind Data Preparation and Analysis

Wind speed and direction data were not provided in the required format and therefore needed to be prepared. Data Sets A and B were split into sectors, according to the wind direction to perform a sectorial MCP analysis. Data Set D was provided in 10-minute intervals and therefore had to be transformed into hourly intervals by averaging the wind speed and wind direction. These data were also analysed for erroneous data points and corrections made accordingly, as shown in Appendix A.

⁵ Image provided by the University of Malta.

⁶ Source Google Earth Accessed 01 March, 2022

5.2.1 3Tier Data (Wind-Rose for 2007 and 2008)

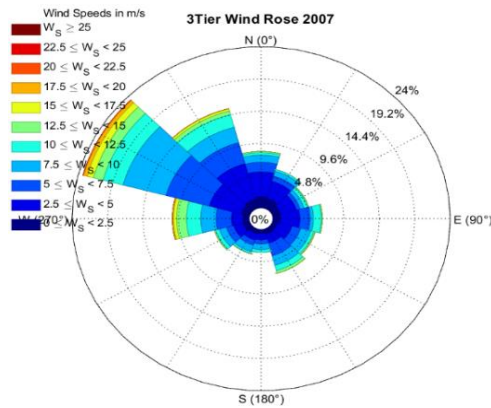


Figure 5-4: 12-Sector Wind Rose for 3Tier Wind Data for 2007.

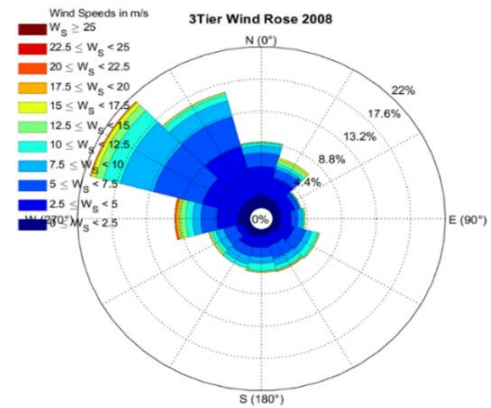


Figure 5-5: 12-Sector Wind Rose for 3Tier Wind Data for 2008.

The 3Tier (Data Set A) data for the year 2007 and 2008 were divided into 12 sectors as shown in the wind direction distribution or wind-rose, shown as Figure 5-4 and Figure 5-5 respectively. The division of the hourly wind data into 12 sectors permitted the use of a sectorial analysis to compare various regression techniques for MCP. The wind-rose showed a prevailing wind direction from the North-West both for the years 2007 and 2008.

5.2.2 Luqa Data (Wind-Rose for 2007 and 2008)

In a similar analysis, Figure 5-6 represents the wind-rose for the Luqa data for the year 2007, while that for 2008 is shown in Figure 5-7. The roses show a prevailing direction of winds blowing from the North-West to West which agrees with the wind rose plotted from the 3Tier data, as was the case for the wind-rose for the 3Tier data, for the years 2007 and 2008 (see Figure 5-4 and Figure 5-5).

More data in the sectorial analysis was therefore expected in the west-north-westerly direction with the bulk of sectorial readings falling in these sectors, as shown in Table 5-4. However, in the case of 3Tier data there were less readings from the westerly direction than there were in the Luqa data, while the Luqa wind-rose shows hardly any wind from the north direction as seen in Figure 5-6 and Figure 5-7.

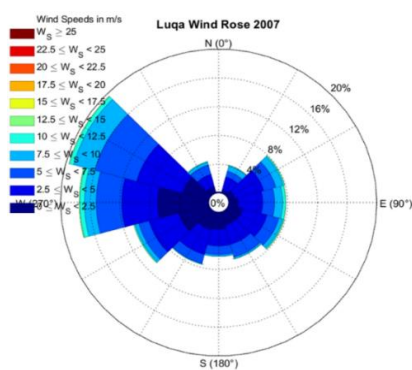


Figure 5-6: 12-Sector Wind Rose for Luqa Wind Data for 2007.

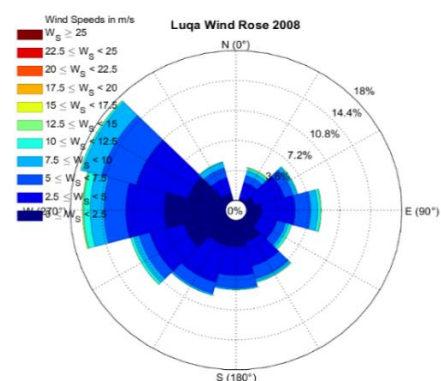


Figure 5-7: 12-Sector Wind Rose for Luqa wind Data for 2008.

5.2.3 Sectorial Analysis

Due to the reasons explained in Sections 5.2.1 and 5.2.3, a detailed sectorial analysis was carried out on Data Sets A and B, for the years 2007 and 2008. As explained above, the wind data was sorted out into 12 directional sectors. Points having a directional veer which was greater than 180° were removed from the dataset, following the sectorial MCP methodology applied by Jain et al. [7].

The number of points remaining were those shown in Table 5-4. The wind veer distribution for the ‘all sectors’ data is as shown in Figure 5-8, which showed the veer in degrees against time and a frequency distribution. The analysis of the behaviour of various MCP techniques was based on this sectorial analysis, and results will be shown in Section 7.1.

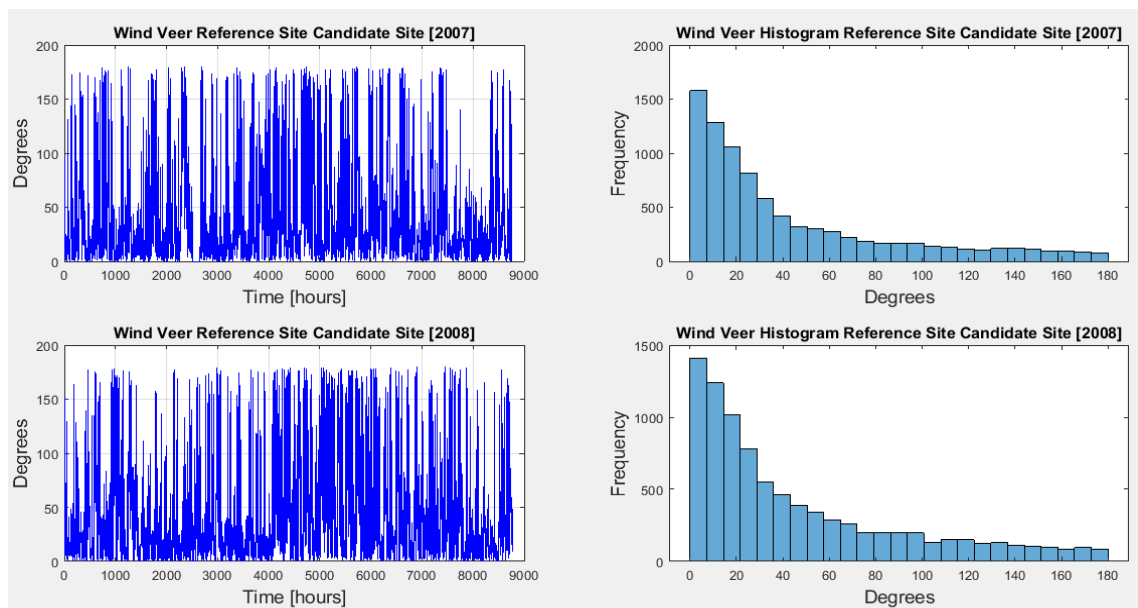


Figure 5-8: Plot of wind veer against time, following removal of the points which had a veer which is greater than 180° . The plots are for the ‘all sectors’ data’.

Table 5-4: Number of hourly samples obtained after removing veer values which are greater than 180° for the twelve segments.

Sector	Number of Hourly Samples	
	2007 – Number of Data Samples	2008 – Number of Data Samples
All Sectors (all data)	8760	8784
345 – 015	420	520
015 – 045	345	413
045 – 075	357	220
075 – 105	520	337
105 – 135	504	520
135 – 165	565	515
165 – 195	279	515
195 – 225	319	457
225 – 255	426	458
255 – 285	812	819
285 – 315	1945	1730
315 – 345	981	1020
Total	7473	7524

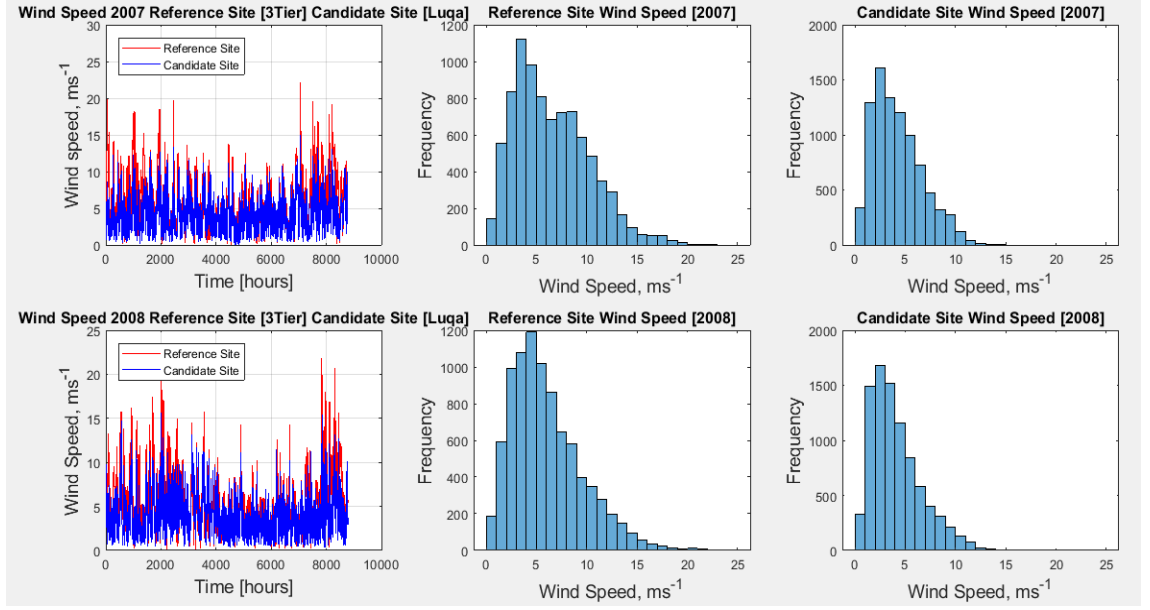


Figure 5-9: Comparison of time-series and distributions, with 3Tier data serving as reference site and Luqa site serving as the candidate site.

In the first set of experiments, which served to establish which regression methodologies were best suited for MCP, the Luqa Weather station served as the candidate site (Data Set B), while the 3Tier data served as the data (Data Set A) for the long-term reference site. Figure 5-9 shows a comparison of the data for the years 2007 and 2008 for both these sites. These are a plot of wind speed in ms^{-1} against time in hours and the frequency distribution of the wind speed.

5.2.4 LiDAR Data

The wind speed and direction data were measured in 10 min intervals by the LiDAR equipment. Data files with daily data were integrated into monthly data and then into yearly data. The six 10 min intervals for wind speed were converted to hourly averages by using a simple averaging formula as shown in Eq. (5-1),

$$v_t = \frac{1}{6} \sum_{i=1}^6 v_{t_i} \quad (5-1)$$

while wind direction was averaged with the formula shown in Eq. (5-2) which considered the circular nature of wind direction values. All values were considered to lie on a unit circle and were converted to complex numbers. Then the mean of the complex numbers was computed, following which the means were transformed back to polar coordinates to find the average wind direction using Eq. (5-2) [184]. The function $\arctan2$ returns the arctangent of the specified x and y coordinates and hence, the wind direction.

$$\bar{w}_{dir_t} = \arctan2 \left[\frac{1}{6} \sum_{i=1}^6 \sin w_{dir_{t_i}}, \frac{1}{6} \sum_{i=1}^n \cos w_{dir_{t_i}} \right] \quad (5-2)$$

Figure 5-10 shows a sequence of hourly averaged wind data using Eq. (5-1), which is compared to the concurrent wind speed at the Luqa meteorological station for the first week of 2016. Figure 5-11 shows the sequence for wind direction.

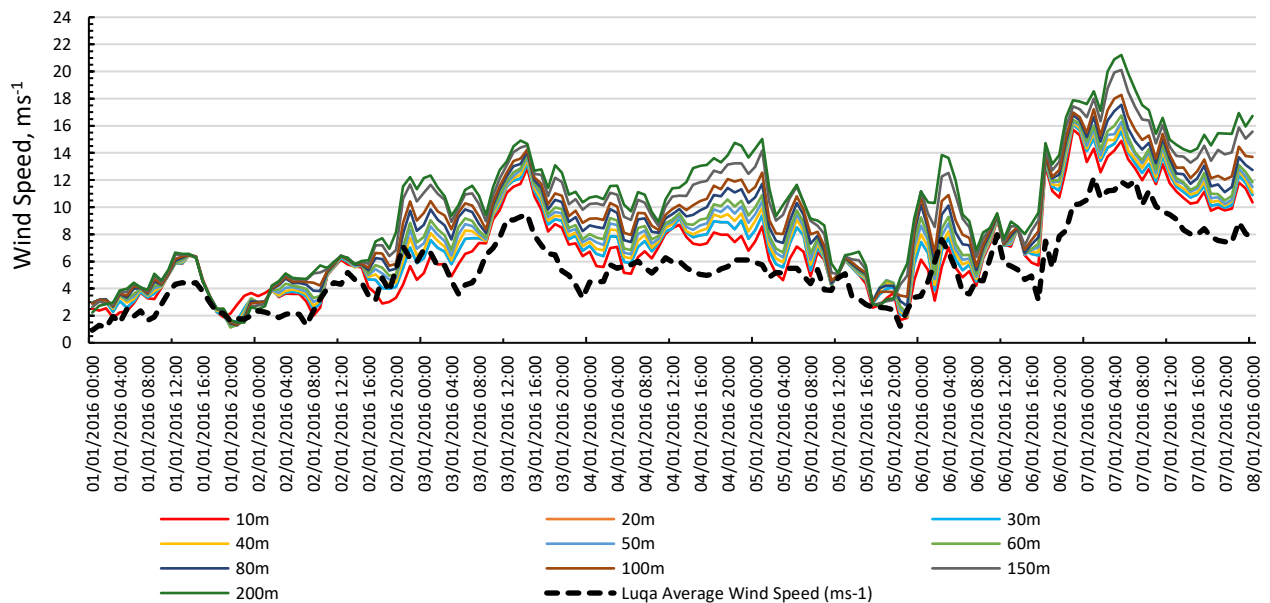


Figure 5-10: Averaged hourly wind speed for the various LiDAR measurement heights and concurrent wind speed data measured at the Luqa meteorological station for the first week of 2016.

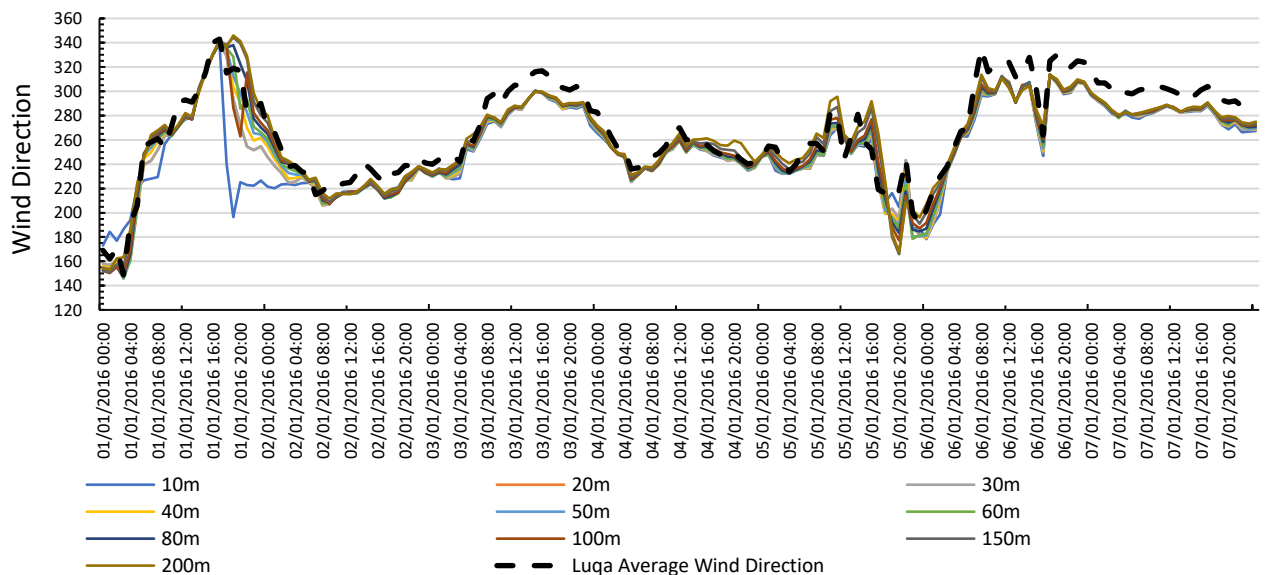


Figure 5-11: Averaged hourly wind direction for the various LiDAR measurement heights and concurrent wind direction data measured at the Luqa meteorological station for the first week of 2016.

The LiDAR data (Data Set D) for the years 2015, 2016 and 2017 were checked for erratic readings, duplicate and missing data. Table 5-5 shows the number of valid data points remaining after filtering and averaging the LiDAR data. Other missing data were extrapolated as described in Appendix A, where Table A-1 to Table A-4 show the errors (duplicate and missing data) encountered, together with, the date, time of occurrence, and the measurement.

Table 5-5: Number of hourly samples by LiDAR measurement height.

LiDAR measurement height above window	Number of Hourly Samples								
	2015 – Number of Data Samples (hrs)	2015 – Valid Data Samples (hrs)	2015 – Percentage of Valid Data Samples	2016 – Number of Data Samples (hrs)	2016 – Valid Data Samples (hrs)	2016 – Percentage of Valid Data Samples	2017 – Number of Data Samples (hrs)	2017 – Valid Data Samples (hrs)	2017 – Percentage of Valid Data Samples
10m	4561	4557	99.91%	8784	8710	99.16%	4776	4752	99.49%
20m	4561	4557	99.91%	8784	8709	99.16%	4776	4750	99.46%
30m	4561	4557	99.91%	8784	8709	99.16%	4776	4750	99.46%
40m	4561	4558	99.93%	8784	8709	99.16%	4776	4748	99.41%
50m	4561	4558	99.93%	8784	8709	99.16%	4776	4750	99.46%
60m	4561	4558	99.93%	8784	8708	99.13%	4776	4748	99.41%
80m	4561	4558	99.93%	8784	8711	99.17%	4776	4747	99.39%
100m	4561	4558	99.93%	8784	8707	99.12%	4776	4744	99.33%
150m	4561	4556	99.89%	8784	8706	99.11%	4776	4742	99.29%
200m	4561	4556	99.89%	8784	8712	99.18%	4776	4745	99.35%

5.3 Econometric Data

The quarterly econometric data shown in Table 4-4 were available from the National Statistics Office (NSO) [40]. The available data trends were those from the years 2011 to 2019. The data are shown in Appendix B, where Table B-1 and

Table B-2 show quarterly figures for the various econometric parameters for the Maltese Islands.

As described in Section 3.2, the Box-Jenkins Methodology (ARIMA or SARIMA) was used to forecast the econometric trends for the Maltese Islands [33]. These were then used as independent inputs to the regression model which was used to derive the EDF. This method, used for forecasting the econometric data, was described in Section 4.3 and the results from applying the ARIMA or SARIMA are shown in Section 8.1.1.

5.4 Demographic Data

According to the NSO reports, at the end of the year 2011, the population of Malta stood at 417,546 persons [40]. At the end of 2019, the population stood at 514,564 persons. Demographic growth was identified as one of the factors which increased overall energy consumption, and directly impacted the demand for electrical energy [162]. In forecasting the population growth, a hypothetical hourly growth value was calculated. It was assumed that the population grew at a linear hourly rate. Hence, using a simple linear equation of the form $y = mx + c$, and taking values of y_1 and y_2 from as shown in Table 5-6, then:

$$m = \frac{y_2 - y_1}{T} \quad (5-3)$$

and

$$c = y_1 \quad (5-4)$$

where m is the hourly population growth, T is the number of hours in the year, y_1 was the population on the 1 January, and y_2 was the population size on the 31 December of the same year. Values of y_1 , y_2 , m , c , and T are shown in Table 5-6.

Table 5-6: Population trends for the Island of Malta for the years 2011-2019, together with calculated values T and the calculated values of m and c .

	Population on 1 st January, y_1	Population on 31 st December, y_2	T	m	c
2011	414,989	417,546	8760	0.2919	414,989
2012	417,546	422,509	8784	0.5650	417,564
2013	422,509	429,424	8760	0.7894	422,509
2014	429,424	439,691	8760	1.1720	429,424
2015	439,691	450,691	8760	1.2557	439,691
2016	450,691	460,297	8784	1.0936	450,691
2017	460,297	475,701	8760	1.7584	460,297
2018	475,701	496,559	8760	2.3811	475,701
2019	496,559	514,564	8760	2.0554	496,559
2020	514,564		8784		

The following algorithm was then used to forecast the population growth for the years 2016-2020:

- For the year 2016:
 - Compute ARIMA model based on the years 2011-2015,
 - Forecast 2016 population trend.
- For the year 2017:
 - Append forecasted 2016 data to population trend for 2011-2015,
 - Compute ARIMA model based on the appended trend for 2011-2016,
 - Forecast 2017 population trend.
- For the year 2018:
 - Append forecasted 2017 data to population trend 2011-2016,
 - Compute ARIMA model based on the appended trend for 2011-2017,
 - Forecast 2018 population trend.
- For the year 2019:
 - Append forecasted 2018 data to population trend 2011-2017,
 - Compute ARIMA model based on the appended trend for 2011-2018,
 - Forecast 2019 population trend.
- For the year 2020:
 - Append forecasted 2019 data to population trend 2011-2018,
 - Compute ARIMA model based on the appended trend for 2011-2019,
 - Forecast 2020 population trend.

Results for demographic forecasts will be shown in Section 8.1.2 where the forecasted results will be shown in Table 8-4 together with the population growth trends in Figure 8-2 and Figure 8-3.

5.5 Energy (Electricity Generation) Demand Data

Energy demand data (or electricity generation) were provided by Enemalta Corporation. Hourly data were made available for the years 2013 to 2019. Figure 5-12 shows the hourly energy demand for the year 2016 and the quarterly GDP value. It was observed that the energy demand was also dependent on the time of the day, where energy demand was lower during the night-time hours. A dependence on whether the day was a public holiday, a normal working day or a weekend was also noted. A seasonal dependence was also noted, with energy demand peaking during the summer months, while also being lowest during spring. These dependencies were noted for every year.

Also shown in Figure 5-12 is the hourly GDP (see Section 4.3), where it was also evident that the GDP was seasonal. It was lowest during the winter months and highest during the summer months which coincided with a peak in electricity demand.

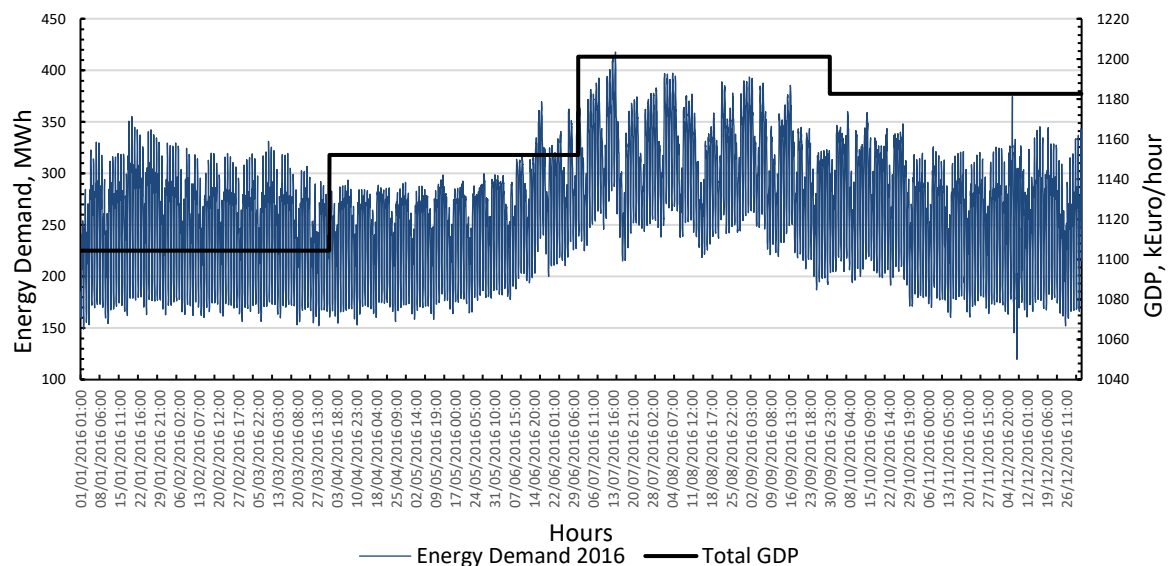


Figure 5-12: Energy Demand and Quarterly Gross Domestic Product, in kEuro/hour for the year 2016.

5.6 Conclusion

This chapter described the data sources used in this research, where:

- The data consisted of wind data necessary to generate the MCP model and to predict the behaviour of the wind speed at the candidate site. The predicted wind data was used to study the behaviour of a hypothetical windfarm which was located offshore, opposite the wind measurement site at Qalet Marku.
- The chapter also described the econometric trends for the Maltese Islands. Econometric data for the Maltese Islands were available from the national statistics provider, the National Statistics Office (NSO).

- The GDP, end use data and the demographic data were used as independent variables to predict energy demand after establishing the model which described the relationship between these time-series and the energy demand.
- A description of the energy demand data for the Maltese Islands was provided. The energy demand showed distinct patterns, which show a dependency on day/night patterns, public holidays, weekends, season, and economic activity.

6 Design of Windfarm and Energy Storage System Models

This chapter describes the models used to address the knowledge gap identified in Section 2.13. The models consisted of two hypothetical windfarms developed in windPRO®. The first windfarm utilised a 5 MW wind turbine which was used in the first part of the analysis namely, to determine the optimal combination of MCP and EDF techniques as well as the optimal capacity of the ESS. The second model consisted of 8 MW wind turbines and was used to determine the LCOE and the LCOS of the ESS.

A detailed description of the model implemented in Simulink® simulating the ESS coupled to a windfarm will be presented. The inputs to this model were time-series data of power output from the hypothetical windfarms and the EDF models. Actual measured data was also fed to the model to define a baseline against which the error of the predictions and forecasts could be measured. The model was used to analyse the behaviour due to the integration of the hypothetical windfarm, the ESS and the electricity grid according to the behaviour described in Section 4.5.

6.1 Design of Windfarms using WindPRO®

The design of the two offshore windfarm models in windPRO® Ver. 2.7 [185] follows. The first windfarm design was used to determine which MCP technique yielded the lowest error when estimating the energy yield. This also enabled the determination of the optimal combination of MCP and EDF techniques and the associated ESS capacity requirements. The second offshore windfarm design was used to determine the LCOE, the LCOS and the associated errors.

The offshore site where the two windfarms were considered is approximately 5 km away from the costal watch tower of Qalet Marku [14.452498°E, 35.945892°N]. Both windfarms faced the North-West direction, which is the prevailing wind direction, as explained earlier in Section 5.2. The windPRO® software was used to model the energy yield from this wind farm, taking wake losses into account. Although many wake models exist, the N. Ø. Jensen [78] model was used in both windfarm designs, mainly due to its simplicity and because results are comparable to experimental results as described previously in Section 2.2.

6.1.1 First Windfarm Design (WF1) using 5 MW Wind Turbines

WindPRO® was used to render an image of the windfarm onto an image of the LiDAR unit as positioned on the watch tower's rooftop. This was indicative as to the extent of the wind farm. The rendering is shown in Figure 6-1, while Figure 6-2 shows the satellite imagery of the wind farm. These figures show the windfarm, with an installed capacity of 250 MW.



Figure 6-1: View of the wind farm with 5 MW wind turbines rendered onto an image of the area and also showing the LiDAR unit⁷.



Figure 6-2: Satellite image of the location of the hypothetical windfarm, using 50 5 MW wind turbines⁸.

Table 6-1: RE Power 5 MW Wind Turbine Parameters [186, 187].

Wind Turbine Parameter	
Manufacturer	RE Power (Germany)
Rated Power	5075 kW
WEC Concept	3-stage Spur/Planetary Gearbox, Double-Fed Induction Generator
Power Control	Pitch
Rotor orientation	Upwind
Number of blades	3
Rotor Diameter	126 m
Swept Area	12469 m ²
Blade Type	LM 61.5
Cut in speed	3.5 ms ⁻¹
Rated Wind Speed	14 ms ⁻¹
Cut out speed (for off-shore)	30 ms ⁻¹
Hub-height, z	90 m min., 120 m max.

The wind turbine selected for use in windPRO® was the RE Power's 5 MW wind turbine [186, 187], whose parameters are summarised in Table 6-1. The windfarm was modelled to include up to 50 turbines. There were 10 wind turbines in a row. Thus, considering that the RE Power 5 MW wind turbines had a rotor diameter, D , of 126 m, the distance between the turbines in the crosswind direction with respect to the prevailing direction was set to 630 m (5D). The distance between two successive rows of turbines was set to 1008 m (8D) [67]. The RE Power 5 MW wind turbine had a minimum hub height of 90 m. The power curve of this wind turbine is shown in Figure 6-3.

⁷ Photograph taken by author during a visit to the LiDAR station at Qalet Marku on 12 May 2017.

⁸ Source: Google Earth with image of windfarm rendered using windPRO®.

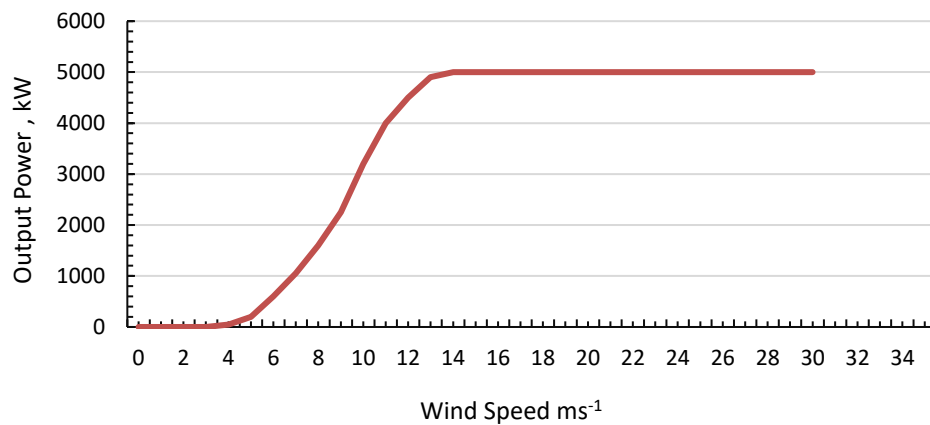


Figure 6-3: Power curve for the RE Power 5 MW offshore wind turbine [187].

6.1.2 Second Windfarm Design (WF2) using 8 MW Wind Turbines

The second windfarm utilised 8 MW wind turbines. The wind turbine was manually created in the windPRO® database from manufacturer's data. This was the Vestas v164 8.0 MW offshore wind turbine [186, 188], which had a rotor diameter, D , of 164 m and a hub height of 150 m. windPRO® was again used to render an image of the windfarm onto an image of the LiDAR unit. This is shown in Figure 6-4, while Figure 6-5 which shows a satellite image of the windfarm.



Figure 6-4: View of the wind farm with 50 8 MW wind turbines rendered onto an image of the area, also showing the LiDAR unit⁹.



Figure 6-5: Satellite image of the location of the hypothetical windfarm, using 50 8 MW wind turbines¹⁰.

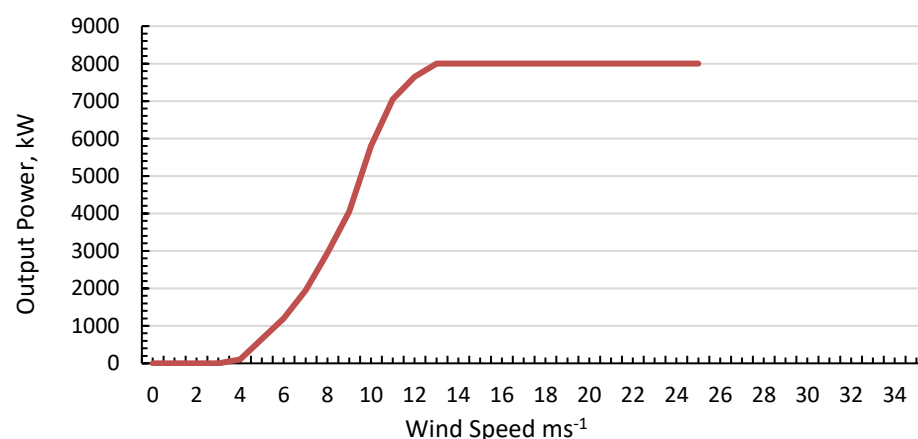
⁹ Photograph taken by author during a visit to the LiDAR station at Qalet Marku on 12 May 2017.

¹⁰ Source: Google Earth with image of windfarm rendered using windPRO®.

Table 6-2: Vestas V-164 8 MW Wind Turbine Parameters used in the study [186, 188].

Wind Turbine Parameter	
Manufacturer	Vestas (Denmark)
Model	V-164
Wind Class	IEC S
Rated Power	8000 kW
Rotor orientation	Upwind
Number of blades	3
Rotor Diameter	164 m
Swept Area	21,124 m ²
Blade Type	LM
Electrical	Full scale converter, Permanent Magnet
Power Regulation	Pitch regulated with variable speed
Cut in speed	4.0 ms ⁻¹
Rated Wind Speed	13 ms ⁻¹
Cut out speed (for off-shore)	25 ms ⁻¹
Hub-height, z	150 m

The parameters of the wind turbine are shown in Table 6-2 while its power curve is shown in Figure 6-6. In order to increase power output and to minimise wake losses, the windfarm was conceived as consisting of two rows with an equal number of 25 wind turbines. The turbines were placed at a crosswind distance of 820 m (5D) with the downwind distance being 1312 m (8D) [67]. The windfarm faced the prevailing north-westerly wind direction. The turbine characteristics permitted an improvement in the capacity factor of the wind farm, and hence contribute to a lower LCOE when compared with the windfarm described in Section 6.1.1. The configuration of the windfarm also reduces wake losses, overcoming the disadvantage that the simulations performed with the windfarm shown in Figure 6-2, which resulted in the wind turbines in the fifth row producing a negligible amount of energy. This was the cause of the lower capacity factor for the first windfarm (WF1). The first windfarm (WF1) was deemed uneconomic due to the resulting capacity factor and therefore a new design with larger capacity wind turbines was considered. The results for LCOE from this second windfarm configuration will be discussed in Section 11.4.

**Figure 6-6: Power curve for the Vestas V-164 8 MW wind turbine [186, 188].**

6.2 The Design of the Energy Storage System in Matlab® and Simulink®

A brief description of the how the ESS was integrated with the windfarm and the electricity grid was given in Section 4.5. A detailed description of how Simulink® was used to create the model is now

presented. The model was used by several Matlab® programs, which were utilised in several steps of the analysis. The model was used to determine the best combination of the regression techniques for MCP and EDF methodologies. It was also used to determine the optimum capacity of the ESS and the error in the predicted capacity by comparing the capacity estimated from the use of the predicted wind time-series and the forecasted energy demand to that obtained by using actual wind time-series and energy demand values. Finally, it was also used to determine the LCOE of the hypothetical offshore windfarm and the LCOS of the ESS.

The model was governed by Eqs. (4-1) to (4-7). The design was based on simple mathematical equations which used integration [Eq. (4-3) represents the charging of the energy store] and differentiation [Eq. (4-5) represents the discharge of the energy store at a constant rate into the electricity grid]. The ESS retained a memory of the level of energy in the storage, such that charging and discharging always started from the level of energy contained in the store. The model is shown in Figure 6-7 and consisted of four main building blocks:

- A block which represented the power output from the offshore windfarm. The power output from the offshore windfarm was generated by windPRO®, using the models of the windfarm described in Section 6.1. The contents of this block are shown in Figure 6-8.
- A block which represented the energy demand, which could be either actual or forecasted data. The contents of this block are shown in Figure 6-9.
- A block which represented the controller which according to the conditions described in Section 4.4, decided whether the ESS was to be charged, discharged or kept idle. The level of energy in the store was monitored by the controller, which curtailed energy from the windfarm when the store was full and energy demand was low. The controller decided whether the energy from the wind farm was supplied to the grid, charged the ESS or had to be curtailed. The contents of this block are shown in Figure 6-10.
- A block which represented the ESS, consisting of an integrator, which represented the charging from the windfarm and a differentiator which represented the discharging of power at a constant rate (power rating) into the grid. The contents of this block are shown in Figure 6-11.
- The model also contained summation nodes, which represented power generation from fossil fuel sources with wind generation, with the total energy demand above the established baseload, P_T , [given by Eq. (4-1)], windfarm output and energy store output energy level, E_S [given by Eq. (4-3) during charging, and Eq. (4-5) on discharging], and total power generated from fossil fuel sources, windfarm power output, P_W and ESS power output.

- The losses in energy from the windfarm due to the transformation of output energy to energy storage and transfer of energy to the grid were assumed to be 5% while the ESS discharge losses in the transformation of storage energy to electric energy dispatched to the electricity grid depended on the type of energy storage used. These were integrated as fixed constants in the model. The energy store discharged at a constant rate $\left(\frac{dE_s}{dt}\right)$, which was set at values which ranged from 10 MW to 50 MW (incremented in steps of 10 MW).

These input variables to the model could be changed according to the required conditions. These were inputted through a Matlab® program which was used to drive the model. The inputs to the model (shown in light blue colour in Figure 6-7) were as follows:

- The floating offshore windfarm power output time-series (from windPRO®), in MW.
- The total energy demand, P_D , time-series. This was either actual energy demand or forecasted energy demand in MW.
- The maximum storage capacity of the ESS, $E_{s_{max}}$ in MWh.
- The power rating $\left(\frac{dE_s}{dt}\right)$ of the ESS in MW, which was a variable which ranged from 10 to 50 MW. This rated output was constant, with discharging efficiency of the ESS being defined as given by Eq. (4-5), and,
- The generation baseload, P_B in MW, which was a variable ranging from 100 MW to 150 MW, in steps of 25 MW for the case of WF1 and ranging from 50 MW to 100 MW in the case of WF2.

The inputs were transferred from the Matlab® workspace to the model during the simulations. The outputs from the model, which were transferred to the Matlab® workspace at the end of the simulations were the following:

- The energy demand, P_T above the generation baseload, P_B [Eq. (4-1)], in MW,
- The floating offshore windfarm power output, P_W , which became $P'_W = \eta_w P_W$ [Eq. (4-2)] in MW,
- The total level of energy in the ESS, E_s , in MWh, during the charging of the ESS [Eq. (4-3)], and the discharging of the ESS [Eq. (4-5)],
- The output from the cumulative discharge counter,
- The total power generated from fossil fuel sources, P'_T in MW [Eq. (4-6)], after using power from the windfarm and the ESS,

- The curtailed power from the offshore windfarm P_{W_c} , in MW,
- The output from the ESS in MW,
- The floating offshore windfarm power output component P_{W_G} , which was transferred directly to the electricity grid, in MW.

Each block is now described in detail.

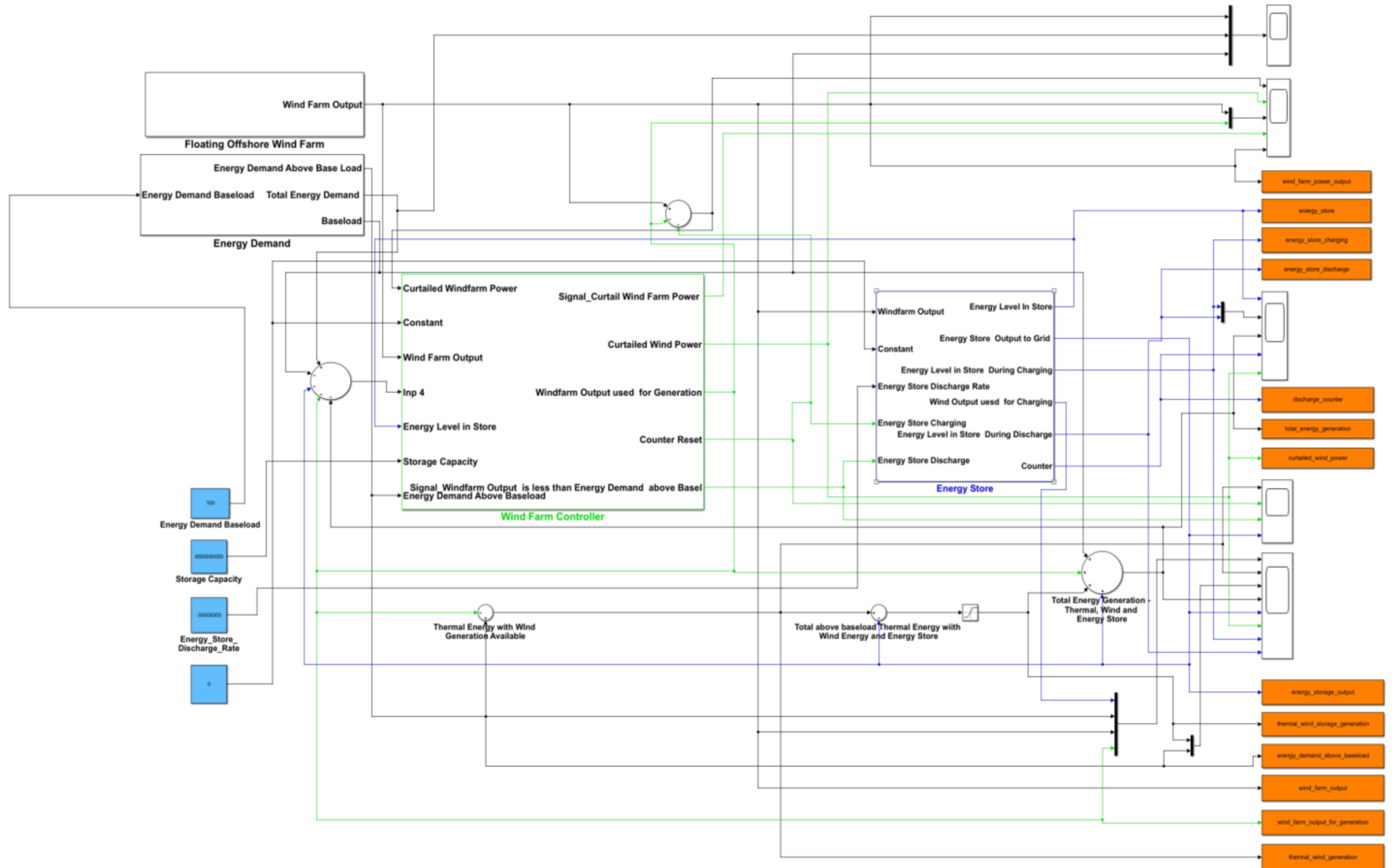


Figure 6-7: Block diagram representation of the ESS integrated with Energy Demand (Thermal Generation), the Wind Farm and the Controller.

6.2.1 The Floating Offshore Windfarm

The block shown in Figure 6-8 converted the time-series which represented the power output from the windfarm (wind_farm_output) from MW to Watts (W), by means of a simple multiplication. The input to this block is stored in the Matlab® workspace and was transferred to the Simulink® model by means of the Matlab® code, which drove the model. The windfarm output was directed to the ESS, to the electricity grid or curtailed according to the electricity demand and the energy levels in the store.

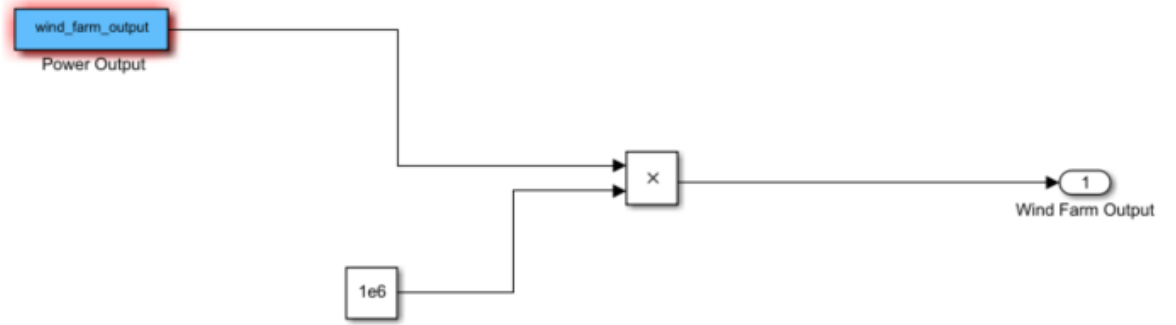


Figure 6-8: Schematic showing how the floating windfarm power output is converted for use in the Simulink® model.

6.2.2 Energy Demand

The block shown in Figure 6-9 converted the time-series (energy_demand) P_D from MW to Watts and split the time-series in two components; the Energy Demand above the Generation Baseload, P_T , and the baseload P_B as given in Eq. (4-1). The baseload power P_B went directly to the electricity grid, while the energy demand above baseload was fed to the controller. At any point in time, this component of the energy demand, was composed of three elements, i.e., electricity generated from fossil fuel sources, from the windfarm, and the power output from the ESS $\left(\frac{dE_s}{dt}\right)$. Electricity generated from fossil fuel sources P_T' , was calculated as the difference between the energy demand, P_D and the sum of the power output from the windfarm, P_{W_G} and the ESS [Eq. (4-6)].

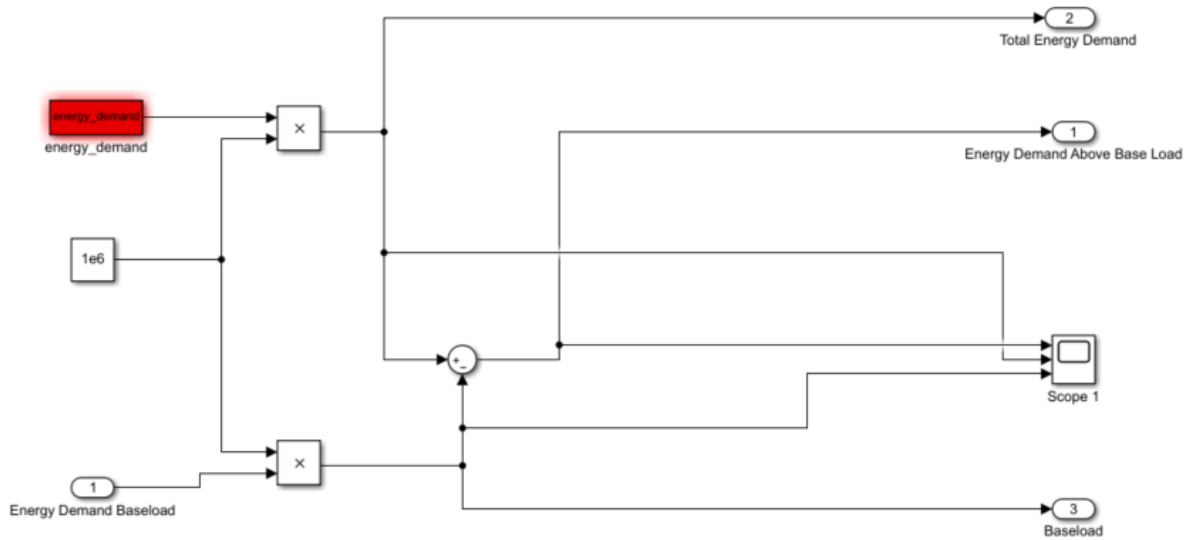


Figure 6-9: Schematic showing the Energy Demand, which was split into two components, Generation Baseload and Energy Demand in excess of Generation Baseload.

6.2.3 The Windfarm Controller

The windfarm and ESS controller compared levels of energy demand, wind energy from the windfarm and the state of charge of the ESS and directed the transfer of power accordingly. The controller is shown in Figure 6-10, and is explained below:

Windfarm Power Output Curtailment

Windfarm power output curtailment occurred when the following conditions were satisfied:

- The energy level in the store E_S was equal to the storage capacity $E_{S_{max}}$, hence implying that no more charging was possible, and,
- The total power output, P'_W , from the offshore windfarm was greater than the sum of power generated from fossil fuel sources $P_T + P_B$, the power discharged from the ESS to the grid $\left(\frac{dE_S}{dt}\right)$ and the component of power from the windfarm transmitted to the electricity grid P_{W_G} , and the ESS was fully charged, thus satisfying the conditions given by Eq. (4-7). The amount of curtailed power from the windfarm P_{W_c} is given by Eq. (4-8).

When these conditions were satisfied, the output signal *Signal_Curtail Windfarm Power* in Figure 6-10 was set to '1', signalling the windfarm to curtail its output.

Windfarm Power Output used for Generation or Charging of the ESS

Windfarm power output was used for generation when the following conditions were satisfied:

- The windfarm power output, P_W was less than or equal to the energy demand in excess of the generation baseload, P_T . During this period the discharge counter was being incremented.

Discharge of energy from the ESS to the grid was also possible if there was enough energy available in the ESS. Any available windfarm power output was transmitted to the electricity grid. In this case the value of the *Signal_Windfarm Output is Less than Energy Demand Above Baseload* in Figure 6-10 was set to '1', and this signalled the windfarm to transfer all its output power to the grid.

- When the windfarm power output was greater than the energy demand above the generation baseload, the discharge counter was reset, and the windfarm charged the energy store, provided that it was not saturated. If it was fully charged, power output from the windfarm was curtailed. During the charging period the ESS did not discharge any energy to the electricity grid.

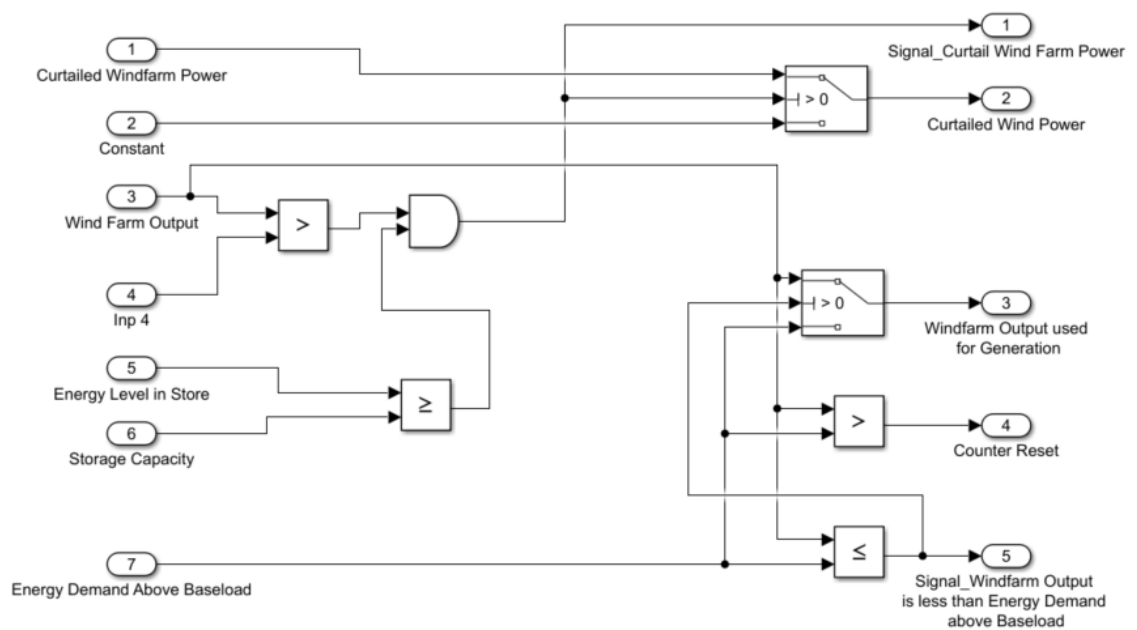


Figure 6-10: Schematic showing the windfarm and the ESS controller. This controlled the windfarm power output, the charging and the discharge of the ESS, the transfer of energy from the windfarm to the grid or the curtailment of wind energy.

6.2.4 The Energy Storage System (ESS)

Figure 6-11 shows the implementation of the charging and discharging of the ESS as mathematically described by Eqs. (4-3) and (4-5). The charging or discharging of the ESS was driven by signals from the controller. The ESS was charged [output from the integrator (Energy Storage)], starting from the initial condition which was the level of the energy in the store at time $t = 0$ (commencement of charging). Charging stopped when the level of energy in the ESS was equal to $E_{S_{max}}$ (the ESS maximum energy storage capacity) or when the level of wind energy from the offshore wind farm dropped to a value which was less than the energy demand above baseload, P_T . When charging or discharging stopped, the sample-and-holds retained the level of energy in the energy store and used it as the initial conditions when the charging or discharging restarted.

The ESS discharged energy at a constant rate $\left(\frac{dE_s}{dt}\right)$ to the grid. The ESS discharged energy to the grid only when there was not enough power from the windfarm to cover the energy demand above baseload, thus avoiding unnecessary curtailment. The discharge counter was reset when the ESS was being charged, and again started counting from zero, when the charging stopped. When the ESS discharged its energy to the grid, the energy level in the store was reduced by an amount equal to the product of the discharge rate and the duration of the discharge, taking the inefficiencies of ESS into account according to Eq. (4-5).

6.3 Conclusion

The acquisition of data, as described in Chapter 5, analysing and filtering it and developing a model which utilises commands in Matlab® and Simulink® as shown in this chapter was fundamental to predicting the wind speed and direction at the candidate site.

The outcome of the results depended on a predicted time-series and a forecasted time-series, which was inputted to the hypothetical windfarm and the Simulink® model shown in Figure 6-7. The error due to the prediction and forecasting will need to be kept to a minimum. This minimisation of this error was obtained by applying the time-series from the different combinations of the regression techniques for the MCP and EDF methodologies and applying them to the hypothetical windfarm and the model described in Figure 6-7.

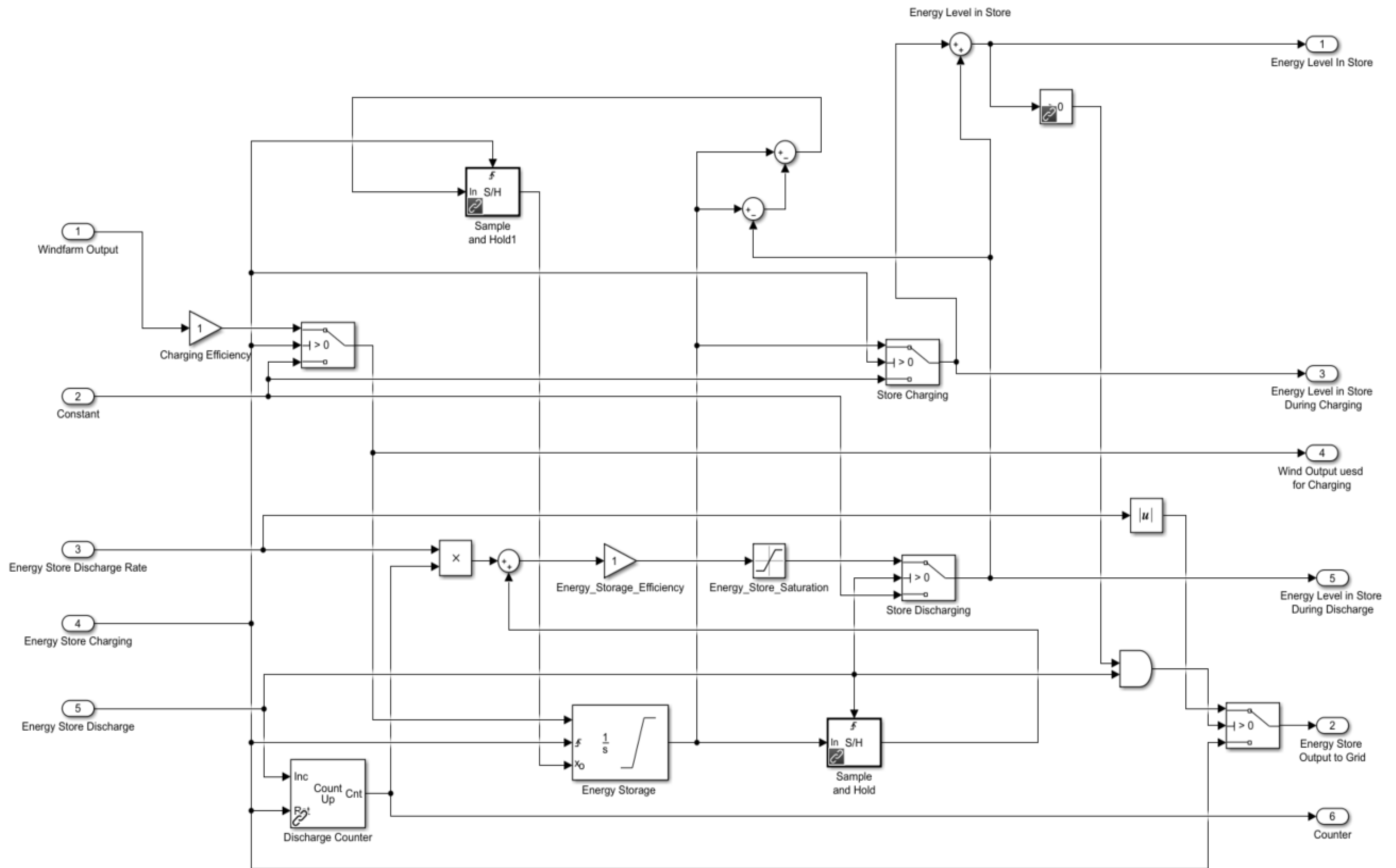


Figure 6-10: Schematic showing the ESS, with charging represented by an integrator and discharging into the grid occurring at a constant rate.

7 Results – Part 1 – Measure-Correlate-Predict Methodology

This chapter presents the results derived from STEPS 1 to 3 of the methodology described earlier in Sections 4.2.1 and 4.2.2. The following sections start with the identification of regression techniques which were adequate for use with the MCP methodology, as described for STEP 1, in Section 4.2.1. This will be followed by a presentation of the results from STEP 2, where the regression methodologies were applied to the wind data from the LiDAR system at Qalet Marku. In STEP 3, which was described in Section 4.2.2, the predicted wind speed and direction time-series from the different regression techniques for the MCP methodology were applied to the hypothetical offshore windfarm model (WF1) to obtain the power output from the windfarm model. This windfarm was described in Section 6.1.1. Measured wind speed and direction time-series were also applied to the windfarm model and the results were used to compare the error in power output from the different regression techniques which were applied to the MCP methodology.

7.1 Results with 3Tier and Luqa Data for the Years 2007 and 2008

The results from the STEP 1 of the methodology, which was described in Section 4.2.1 are now presented. Once adequate regression techniques for the MCP methodology were determined, they were used in STEP 2 to identify the best regression technique for the MCP analysis by using data from a LiDAR situated on a coastal watch tower at Qalet Marku.

The two data sets which were used for STEP 1 are Data Set A and Data Set B. The acquisition of these data sets was described in Sections 5.1.1 and 5.1.2. The data from the 3Tier data set were designated as Data Set A, while those for the years 2007 and 2008 obtained from the Luqa Meteorological Station were designated as Data Set B. A sectorial analysis was applied to the two data sets, and data points having a wind direction veer which was greater than 180° were removed from the data as shown in the sectorial analysis carried out in Section 5.2.3.

Various regression techniques (shown in Table 4-1), were applied to the two datasets. Only the regression techniques with the best results were retained. This was determined by analysing the coefficient of determination, R , from the regressions. Regression techniques which gave a low value of R (< 0.50) were no longer considered as suitable for the MCP methodology. The techniques which resulted in a higher value of R were the SLR, MLR, ANN, DT and SVR techniques.

As described in Section 3.1, each regression technique had a set of model parameters, such as number of layers and perceptrons in an ANN, the number of trees and leafs for a DT, or hyperparameters for SVR. The results shown below were those obtained with the optimised model parameters. The regression models were optimised with the variation of the various parameters.

Concurrent wind data for the year 2008 (in Data Set A and B) were used to create the regression models, while the data for 2007 were used to validate the models. Results were analysed for a range of parameters to optimise the models, and results obtained through variation of the various parameters are shown in Appendix C. Once the optimal model parameters were determined, they were used throughout the current research. The optimised parameters for the regression models are described in Table 4-2.

The residuals were computed by using Eq. (3-77), while the MAE and the MSE were computed by using Eqs. (3-78) and (3-79) respectively. Table 7-1 to Table 7-5 tabulate the results from the regression techniques used for MCP for each of the 12 sectors under consideration and by weighted average. The weighted average was computed according to the number of valid samples per segment. The SLR model utilised the wind speed (measured in ms^{-1}) at the reference site as input to the model and the wind speed at the candidate site as the output of the model, while the MLR, ANN, DT and SVR techniques utilised the wind speed and wind direction (measured in *degrees*) at the reference site as input and the wind speed at the candidate site as output of the regression model.

The theoretical background for the regression techniques for the MCP methodology was described in Section 3.1. The MCP methodology was outlined in Figure 2-1, while the methodology used in STEP 1 was mapped out in Figure 4-4. The methodology was used to predict the wind speed for the year 2007 at the candidate site. The results from the optimised regression techniques are now presented.

7.1.1 Simple and Multivariate Linear Regression – 3Tier-Luqa Data Sectorial Analysis

Table 7-1 and Table 7-2 tabulate the Coefficient of Determination, R , the MSE and the MAE of the residuals, obtained for the SLR and MLR techniques, respectively. For both the SLR and MLR techniques, the values of R , MSE and MAE for the year 2008 were those from the residuals generated by the model for the 2008 wind speed, while those for the year 2007 are those of the residuals of the prediction model when applying the wind speed data for the year 2007 at the reference site.

Simple Linear Regression

The results obtained with a SLR technique are presented in Table 7-1. Meanwhile, Figure C-1 presents a graph of wind speed against time for the actual wind data and the time-series predicted with using the regression model for the year 2008. It also shows a time domain plot and a frequency distribution of the residuals. The predicted wind data for the year 2007 is shown in the lower half

of Figure C-1, where again the time domain plot and the frequency distribution of the residuals are shown.

Table 7.1: Results of the sectorial analysis using SLR, using 2008 data to generate the model and predicting the 2007 wind data, Coefficient of Determination, MSE and MAE, and the weighted average of all sectors.

Sector degrees	Simple Linear Regression					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2008 Model	2007 Prediction	2008 Model	2007 Prediction	2008 Model	2007 Prediction
345 – 015	0.556	0.493	2.367	2.403	1.193	1.226
015 – 045	0.756	0.625	4.360	4.086	1.572	1.519
045 – 075	0.675	0.785	2.736	2.665	1.260	1.289
075 – 105	0.805	0.787	2.440	3.270	1.234	1.407
105 – 135	0.798	0.738	2.712	3.269	1.343	1.439
135 – 165	0.705	0.664	2.385	2.575	1.216	1.262
165 – 195	0.705	0.744	2.385	1.642	1.216	1.004
195 – 225	0.699	0.634	2.142	2.365	1.109	1.214
225 – 255	0.792	0.597	2.884	4.032	1.359	1.602
255 – 285	0.799	0.705	2.944	3.557	1.334	1.504
285 – 315	0.742	0.672	2.766	3.632	1.349	1.534
315 – 345	0.652	0.584	2.371	3.269	1.188	1.475
Weighted value	0.724	0.666	2.690	3.247	1.287	1.428

Multivariate Linear Regression

As was case for the SLR technique, the results obtained from the MLR technique are shown in Table 7-2. An increase of 0.8% over the value obtained with the SLR technique could be observed for the weighted value of the coefficient of determination, R , from the 2008 model. The coefficient of determination from the prediction of the wind speed for the year 2007, remained equal. A slight improvement in MSE, and a slight deterioration in MAE could be observed when comparing the results from the two regression techniques. Graphical results are shown in Figure C-2 in Appendix C, which is similar to Figure C-1.

Table 7-2: Results of the sectorial analysis using MLR, using 2008 data from the year 2008 to create the model and to predict the wind data for the year 2007, coefficient of determination, MSE and MAE, and the weighted average of all sectors.

Sector degrees	Multivariate Linear Regression					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2008 Model	2007 Prediction	2008 Model	2007 Prediction	2008 Model	2007 Prediction
345 – 015	0.561	0.488	2.350	2.420	1.190	1.239
015 – 045	0.769	0.652	4.168	3.793	1.554	1.474
045 – 075	0.678	0.776	2.714	2.775	1.265	1.311
075 – 105	0.806	0.785	2.432	3.274	1.229	1.414
105 – 135	0.816	0.733	2.497	3.321	1.284	1.456
135 – 165	0.712	0.669	2.338	2.540	1.213	1.265
165 – 195	0.712	0.757	2.338	1.910	1.213	1.050
195 – 225	0.701	0.626	2.132	2.413	1.101	1.230
225 – 255	0.799	0.591	2.799	4.201	1.327	1.632
255 – 285	0.804	0.698	2.881	3.623	1.328	1.515
285 – 315	0.745	0.668	2.742	3.668	1.337	1.544
315 – 345	0.658	0.594	2.343	3.211	1.175	1.466
Weighted value	0.730	0.666	2.634	3.271	1.273	1.436

7.1.2 Artificial Neural Networks 3Tier Data – Luqa Data Sectorial Analysis

The results obtained for the sectorial analysis using the ANN regression technique described in Sections 3.1.2 and 4.2.1, are shown in Table 7.3. An increase of 5.9% over the weighted value

obtained with the SLR technique could be observed in the coefficient of determination, R , for the 2008 model. The coefficient of determination for the prediction of the wind speed for year 2007 decreased. Improvements were also observed in the MSE and the MAE, and again a deterioration of these values for the wind prediction of the year 2007. Figure C-3 in Appendix C shows the graphical results, which are again similar to those presented in Figure C-1. Appendix C also shows results from various parameter models applied to the ANN regression technique.

Table 7-3: Results of the sectorial analysis using ANNs, using wind speed from the year 2008 data to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all sectors.

Sector Degrees	Artificial Neural Networks					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2008 Model	2007 Prediction	2008 Model	2007 Prediction	2008 Model	2007 Prediction
345 – 015	0.624	0.449	2.100	2.779	1.112	1.325
015 – 045	0.866	0.476	2.551	5.670	1.162	1.731
045 – 075	0.751	0.573	2.219	7.064	1.088	2.550
075 – 105	0.870	0.718	1.698	6.105	0.971	1.890
105 – 135	0.806	0.711	2.848	3.612	1.368	1.566
135 – 165	0.797	0.614	1.730	3.052	1.014	1.361
165 – 195	0.769	0.646	1.952	2.315	1.072	1.235
195 – 225	0.626	0.427	2.556	3.365	1.241	1.464
225 – 255	0.783	0.511	2.995	4.553	1.396	1.724
255 – 285	0.833	0.607	2.501	4.679	1.228	1.677
285 – 315	0.788	0.589	2.341	4.613	1.210	1.695
315 – 345	0.698	0.531	2.124	3.747	1.115	1.553
Weighted value	0.767	0.579	2.311	4.823	1.177	1.650

7.1.3 Decision Trees – 3Tier-Luqa Data Sectorial Analysis

The results from the sectorial analysis obtained from the DT regression technique as described in Sections 3.1.3, are tabulated in Table 7-4. An increase of 18.8% over the weighted value obtained with the SLR technique could be observed in the coefficient of determination, R , for the 2008 model. The results from the prediction for the wind speed for the year 2007 also showed a decrease in the weighted result of the coefficient of determination, the MSE and the MAE. The graphical results are presented in Figure C-4 in Appendix C, which also presents results for various combinations for number of trees and leafs which were applied to the DT regression technique.

Table 7-4: Results of the sectorial analysis using DTs, using the wind speed from the year 2008 to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all the sectors.

Sector Degrees	Decision Trees					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2008 Model	2007 Prediction	2008 Model	2007 Prediction	2008 Model	2007 Prediction
345 – 015	0.783	0.506	1.412	2.515	0.899	1.255
015 – 045	0.895	0.546	2.087	4.928	1.086	1.677
045 – 075	0.849	0.734	1.547	3.160	0.927	1.380
075 – 105	0.899	0.712	1.379	4.041	0.872	1.599
105 – 135	0.898	0.708	1.486	3.585	0.960	1.497
135 – 165	0.859	0.614	1.301	2.872	0.896	1.339
165 – 195	0.861	0.723	1.289	1.907	0.891	1.134
195 – 225	0.851	0.571	1.202	2.781	0.815	1.348
225 – 255	0.904	0.576	1.450	4.696	0.920	1.688
255 – 285	0.889	0.617	1.759	4.540	1.023	1.673
285 – 315	0.863	0.612	1.627	4.192	1.014	1.644
315 – 345	0.812	0.559	1.452	3.521	0.909	1.509
Weighted value	0.860	0.616	1.523	3.764	0.950	1.531

7.1.4 Support Vector Regression – 3Tier-Luqa Data Sectorial Analysis

The results of the sectorial analysis from the SVR technique described in Section 3.1.4 are shown in Table 7-5. An increase of 5.4% could be observed in the coefficient of determination, R , on comparing the weighted results with those of the SLR for the 2008 model. An improvement in MSE and MAE could also be observed. The results of the prediction of the wind speed for the year 2007 showed a slight decrease in the coefficient of determination, the MSE and the MAE. Graphical results are presented in Figure C-5 in Appendix C, which also presents results obtained from using a variation of hyperparameters.

Table 7-5: Results of the sectorial analysis using SVR, using wind speed from the year 2008 data to create the model and to predict the wind speed for the year 2007. Coefficient of determination, MSE and MAE, and the weighted average of all sectors.

Sector	Support Vector Regression					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2008 Model	2007 Prediction	2008 Model	2007 Prediction	2008 Model	2007 Prediction
345 – 015	0.799	0.166	1.893	3.102	0.832	1.369
015 – 045	0.830	0.533	3.179	5.357	1.370	1.698
045 – 075	0.677	0.784	2.763	2.626	1.234	1.259
075 – 105	0.804	0.778	2.483	3.220	1.219	1.408
105 – 135	0.817	0.725	2.507	3.440	1.266	1.491
135 – 165	0.714	0.668	2.327	2.570	1.198	1.264
165 – 195	0.710	0.751	2.358	1.626	1.203	0.980
195 – 225	0.699	0.613	2.152	2.511	1.105	1.266
225 – 255	0.997	0.115	0.070	6.032	0.192	2.057
255 – 285	0.806	0.699	2.871	3.606	1.315	1.505
285 – 315	0.745	0.666	2.751	3.695	1.333	1.548
315 – 345	0.668	0.614	2.293	3.206	1.157	1.444
Weighted value	0.763	0.616	2.382	3.483	1.160	1.473

7.1.5 Comparing the Overall Results for the 3Tier Sectorial Analysis

Table 7-6 and Table 7-7 present a comparison of the results of the different regression techniques for the MCP methodology. Table 7-6 compares the weighted averages, where the DT regression technique produced the best coefficient of determination, R and the least MSE and MAE from the residuals. Table 7-7 compares the results from a regression carried out without a sectorial

breakdown. It could again be observed that the DT regression technique produced the best coefficient of determination, R and the least MSE and MAE. The best values for the predictions were obtained with the MLR in using both the weighted average from both the sectorial analysis and a regression performed without the sectorial breakdown.

Table 7-6: A comparison of the weighted averages from a sectorial analysis for the coefficient of determination, R , the MSE and the MAE for the different regression techniques for the MCP methodology.

	Weighted Average for Sectorial Breakdown of Wind Speed Data									
	Simple Linear Regression		Multivariate Linear Regression		Decision Tree		Artificial Neural Network		Support Vector Regression	
	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data
Coefficient of Determination, R	0.724	0.666	0.730	0.666	0.860	0.616	0.767	0.579	0.763	0.616
Mean Squared Error, $[\text{ms}^{-1}]^2$	2.690	3.247	2.634	3.271	1.523	3.764	2.311	4.823	2.382	3.483
Mean Absolute Error $[\text{ms}^{-1}]$	1.287	1.428	1.273	1.436	0.950	1.531	1.177	1.650	1.160	1.473

Table 7-7: A comparison of results without a sectorial breakdown for the Coefficient of Determination, R the MSE and the MAE for the different regression techniques used for the MCP methodology.

	Results without sectorial breakdown of wind speed data									
	Simple Linear Regression		Multivariate Linear Regression		Decision Tree		Artificial Neural Network		Support Vector Regression	
	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data	2008 Model	Predicted 2007 Wind Data
Coefficient of Determination, R	0.723	0.673	0.728	0.680	0.882	0.661	0.781	0.669	0.777	0.680
Mean Squared Error, $[\text{ms}^{-1}]^2$	2.937	3.324	2.898	3.253	1.400	3.568	2.397	3.518	2.482	3.452
Mean Absolute Error $[\text{ms}^{-1}]$	1.339	1.439	1.329	1.430	0.906	1.481	1.212	1.467	1.196	1.445

Figure 7-1 and Figure 7-2 are a comparison of the Coefficient of Determination, R , obtained from the various regression techniques. Figure 7-1 is a comparison obtained with the wind data of 2008, while Figure 7-2 is a comparison obtained by predicting the wind data for the year 2007, by using the regression model from the data of the year 2008. Figure 7-3 and Figure 7-4 are a comparison of the MSE of the residuals, while Figure 7-5 and Figure 7-6 are a comparison of the MAE of the residuals.

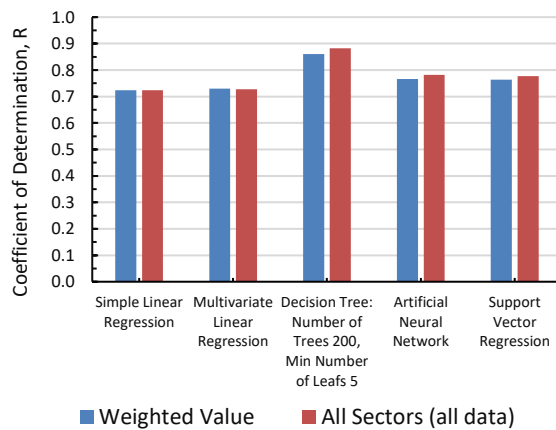


Figure 7-1: Comparison of the coefficient of determination, R , obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.

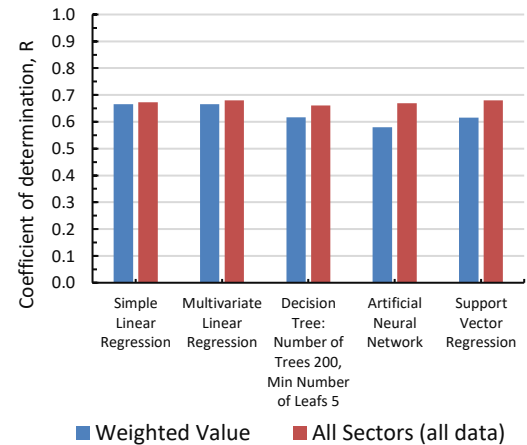


Figure 7-2: Comparison of coefficient of determination, R , obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.

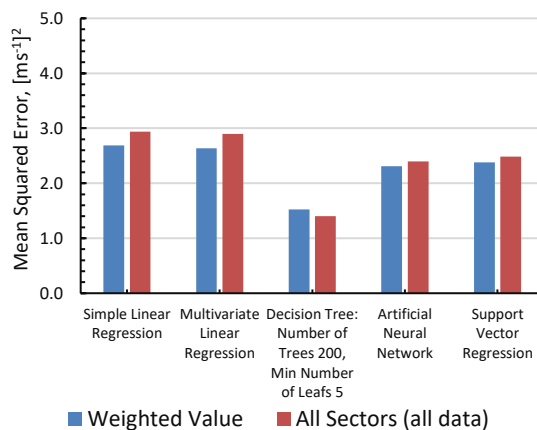


Figure 7-3: Comparison of the MSE obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.

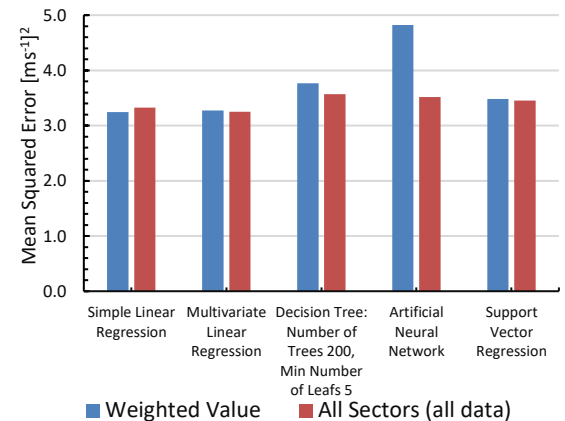


Figure 7-4: Comparison of the MSE obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.



Figure 7-5: Comparison of the MAE obtained with the wind data for the year 2008 with the various regression techniques for the MCP methodology.

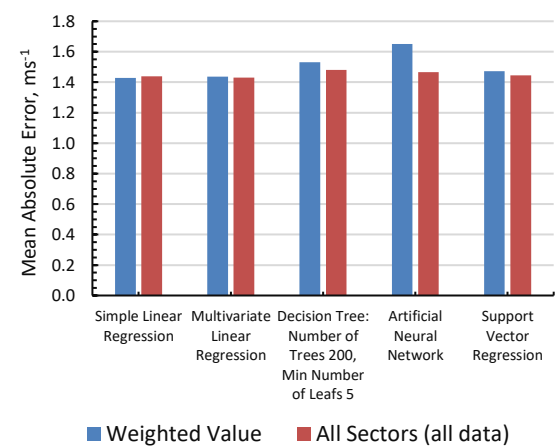


Figure 7-6: Comparison of the MAE obtained from the prediction of the wind data for the year 2007 from the various regression techniques using the regression models from the wind speed for the year 2008.

7.1.6 Conclusion

The regression models developed from the 2008 wind data were used to predict the wind speed for the year 2007 at the candidate site. From this prediction, the best coefficient of determination, R , MSE and MAE were obtained with the SLR and the SVR techniques. This means that while the model with the best results was that which utilised the DT regression technique, the best prediction results were obtained by a different model. This shows that the regression model and the prediction model could be different, hence concluding that the various regression techniques available must be analysed before the best regression technique for the MCP methodology is determined. Thus, the above methodology determined a set of regression techniques which could be used for the MCP methodology but did not determine a single technique which could be considered as the best.

Results with other model parameters are shown in Appendix C. The tables presented in this chapter show results with optimised parameters for the regression models which were applicable to the MCP methodology.

The parameters of the SLR, MLR, ANN, DT and SVR regression models obtained using 3Tier data were also applicable to the LiDAR measurements from Qalet Marku. Therefore, the model parameters identified in STEP 1 were carried over to STEP 2, thus constructing an analysis for the coefficient of determination R , the MAE and the MSE with the Data Sets C and D. This confirmed the portability of the models with a different data set and for different LiDAR measurement heights.

7.2 LiDAR Data Height Analysis for the Years 2015 and 2016

STEP 2 of the methodology was described in Section 4.2.1. In STEP 1, the adequate regression techniques in Section 7.1 and the model parameters were determined. In STEP 2 the models determined in STEP 1 were applied to the second pair of data sets, namely Data Set C and Data Set D. These datasets were described in Section 5.2.4.

In STEP 2 the reference site was the Luqa Meteorological Station (Data Set C), while the candidate site was the LiDAR site (Data Set D). In the methodology described in Figure 4-4, the concurrent wind and direction data for year 2016 was used to define the regression models, while the data from the year 2015 was used to test the prediction capability of the model with the same methodology utilised in Section 7.1. The results from STEP 2 are presented in the following sections.

An analysis of the residuals was conducted by comparing the time-series of the predicted wind speed with that from the actual wind speed time-series of that period. Equations (3-77), (3-78) and (3-79) were used in this process. The following tables show the Coefficient of Determination, R , and the MSE and MAE from the regression techniques applied at the various LiDAR measurement heights.

7.2.1 Linear Regression – LiDAR Data

Simple Linear Regression

The results from the SLR technique are shown in Table 7-8. The best results were obtained for a LiDAR measurement height of 30 m¹¹.

Table 7-8: Regression results at the various LiDAR measurement heights obtained with a SLR technique with one input.

Measurement Height above LiDAR Window (m)	Simple Linear Regression					
	Coefficient of Determination, <i>R</i>		Mean Squared Error (<i>ms</i> ⁻¹) ²		Mean Absolute Error (<i>ms</i> ⁻¹)	
	2016 Model	2015 Prediction	2016 Model	2015 Prediction	2016 Model	2015 Prediction
10	0.867	0.869	2.896	1.880	1.293	1.059
20	0.868	0.871	3.045	1.979	1.339	1.106
30	0.886	0.870	2.642	1.990	1.235	1.109
40	0.825	0.870	4.034	2.061	1.554	1.138
50	0.824	0.869	4.170	2.147	1.585	1.170
60	0.862	0.868	3.434	2.213	1.439	1.193
80	0.818	0.866	4.656	2.410	1.679	1.259
100	0.819	0.863	4.879	2.591	1.717	1.311
150	0.816	0.855	5.554	3.089	1.833	1.441
200	0.809	0.846	6.251	3.578	1.945	1.556

Multivariate Linear Regression

The results from the MLR technique are shown in Table 7-9. As with the case of the SLR technique, the best results with the MLR technique were again obtained at a LiDAR measurement height of 30 m. When this result was compared with the result from the SLR technique, there was a slight improvement in *R* of 0.1% at a height of 30 m.

Table 7-9: Regression results at the various LiDAR measurement heights obtained with a MLR technique using two inputs.

Measurement Height above LiDAR Window (m)	Multivariate Linear Regression					
	Coefficient of Determination, <i>R</i>		Mean Squared Error (<i>ms</i> ⁻¹) ²		Mean Absolute Error (<i>ms</i> ⁻¹)	
	2016 Model	2015 Prediction	2016 Model	2015 Prediction	2016 Model	2015 Prediction
10	0.867	0.869	2.886	1.886	1.289	1.061
20	0.868	0.871	3.033	1.975	1.334	1.106
30	0.887	0.871	2.631	1.991	1.229	1.111
40	0.826	0.871	4.012	2.044	1.546	1.136
50	0.825	0.870	4.143	2.125	1.575	1.167
60	0.863	0.869	3.410	2.200	1.431	1.191
80	0.820	0.867	4.617	2.377	1.666	1.252
100	0.821	0.864	4.836	2.556	1.705	1.303
150	0.818	0.856	5.500	3.046	1.819	1.429
200	0.811	0.848	6.188	3.528	1.930	1.543

7.2.2 Artificial Neural Networks (ANN) – LiDAR Data

The results obtained by using the ANN methodology are presented in Table 7-10. The best results with the ANN regression technique were obtained at a LiDAR measurement height of 30 m, with *R*

¹¹ Above the LiDAR window, i.e., at 40 m above ground level, or 50 m above sea level.

having a value of 0.912. This was an improvement of 2.9% over the value of R obtained with SLR. The MSE and the MAE were also at a minimum at this measurement height.

Table 7-10: Regression results at the various LiDAR measurement heights obtained with an ANN regression technique using two inputs.

Measurement Height above LiDAR Window (m)	Artificial Neural Networks					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2016 Model	2015 Prediction	2016 Model	2015 Prediction	2016 Model	2015 Prediction
10	0.898	0.884	2.268	1.675	1.156	1.005
20	0.892	0.881	2.533	1.822	1.225	1.062
30	0.912	0.878	2.078	1.917	1.093	1.079
40	0.857	0.868	3.367	2.118	1.421	1.153
50	0.851	0.879	3.575	2.011	1.462	1.130
60	0.884	0.879	2.912	2.071	1.315	1.156
80	0.846	0.872	4.006	2.266	1.543	1.198
100	0.846	0.864	4.209	2.573	1.583	1.299
150	0.843	0.863	4.818	2.892	1.712	1.370
200	0.843	0.864	5.234	3.203	1.785	1.465

When the data at the reference site for the year 2015 was used to predict the behaviour of the wind at the candidate site, an R value of 0.878 was obtained. This was approximately the same as for the R values as that obtained with the SLR and the MLR techniques.

7.2.3 Decision Trees (DT) – LiDAR Data

The results for the model which used the DT regression technique are shown in Table 7-11. Again, the best results with the wind data for the year were obtained for a measurement a height of 30 m¹², with R having the highest value of 0.941, from all the applied regression techniques. This was an improvement of 6.2% over the result obtained with SLR technique. Again, the MSE and the MAE were a minimum for the 30 m height.

Table 7-11: Regression results at the various LiDAR measurement heights with a DT regression technique using two inputs.

LiDAR Measurement Height Above Window (m)	Tree Bagger: Number of Trees 200, Min Number of Leafs 5					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2016 Model	2015 Prediction	2016 Model	2015 Prediction	2016 Model	2015 Prediction
10	0.932	0.877	1.541	1.760	0.944	1.035
20	0.930	0.874	1.671	1.947	0.987	1.107
30	0.941	0.875	1.426	1.909	0.901	1.087
40	0.904	0.872	2.333	2.063	1.171	1.147
50	0.903	0.871	2.422	2.160	1.191	1.179
60	0.925	0.873	1.942	2.132	1.065	1.165
80	0.899	0.869	2.740	2.369	1.264	1.238
100	0.899	0.868	2.877	2.516	1.295	1.280
150	0.899	0.862	3.217	2.976	1.377	1.405
200	0.898	0.857	3.566	3.364	1.458	1.499

¹² Above the LiDAR window, i.e. at 40m above ground level.

The DT regression technique attained the best overall results, in not only having the best performance for a measurement height of 30 m, but it also had the best results for all the LiDAR measurement heights, when the results for the various measurement heights were compared. When the model based on the DT regression technique, was used to predict the wind speed at the candidate site (using the wind data for the year 2015), results indicated that this regression technique also had a good performance in predicting the wind speed at the candidate site. This indicated that an MCP methodology which utilised DT as a regression technique gave the best overall results.

7.2.4 Support Vector Regression (SVR)– LiDAR Data

The results obtained with the SVR technique are shown in Table 7-12. The best results were again obtained at a LiDAR measurement height of 30 m, where the value of the coefficient of determination, R , was of 0.888, which was an improvement of 0.2% over the value obtained with the SLR technique.

Table 7-12: Regression results obtained at the various LiDAR measurement heights with a SVR regression technique using two inputs.

LiDAR Measurement Height Above Window (m)	Support Vector Regression: Optimised Model					
	Coefficient of Determination, R		Mean Squared Error (ms^{-1}) ²		Mean Absolute Error (ms^{-1})	
	2016 Model	2015 Prediction	2016 Model	2015 Prediction	2016 Model	2015 Prediction
10	0.873	0.870	2.782	1.858	1.258	1.050
20	0.868	0.870	3.185	1.977	1.351	1.098
30	0.888	0.871	2.611	1.990	1.225	1.113
40	0.828	0.869	3.989	2.041	1.534	1.129
50	0.829	0.868	4.082	2.122	1.557	1.162
60	0.862	0.868	3.438	2.179	1.427	1.180
80	0.823	0.863	4.582	2.374	1.647	1.244
100	0.822	0.863	4.857	2.484	1.695	1.276
150	0.818	0.855	5.722	3.020	1.830	1.419
200	0.812	0.846	6.197	3.405	1.917	1.512

7.2.5 Comparing the Results from the LiDAR Data

Figure 7-7 to Figure 7-12 compare the results from the various regression techniques at the various LiDAR measurement heights which are shown in Section 7.2.1 to 7.2.4.

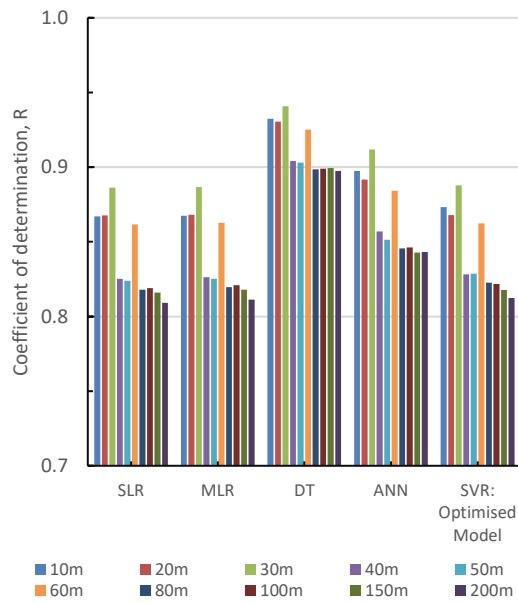


Figure 7-7: Coefficient of determination, R , at different LiDAR measurement heights with the regression techniques based on wind data from the year 2016.

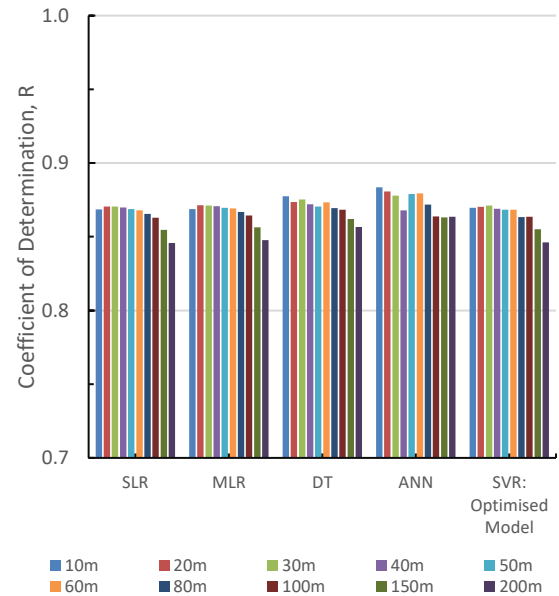


Figure 7-8: Coefficient of determination, R , at various LiDAR measurement heights for wind data for the year 2015 predicted with the regression techniques based on 2016 wind data.

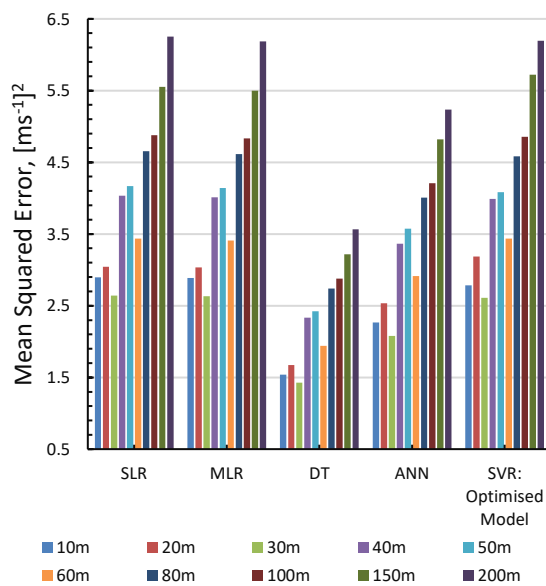


Figure 7-9: MSE of residuals at the various LiDAR measurement heights with the different regression techniques based on wind data for the year 2016.

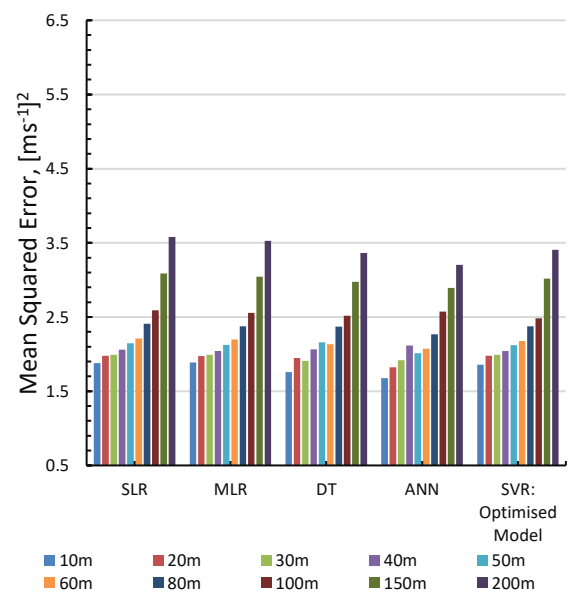


Figure 7-10: MSE of residuals, at the various LiDAR measurement heights for wind data for the year 2015 predicted with the different regression techniques based on wind data for the year 2016.

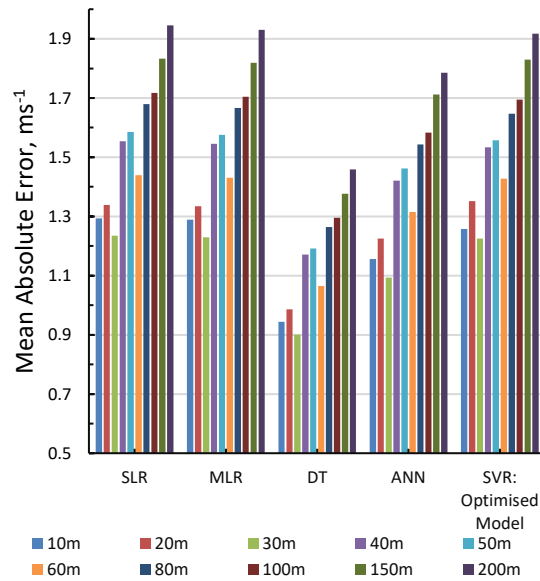


Figure 7-11: MAE of residuals, at the various LiDAR measurement heights and with the different regression techniques based on wind data for the year 2016.

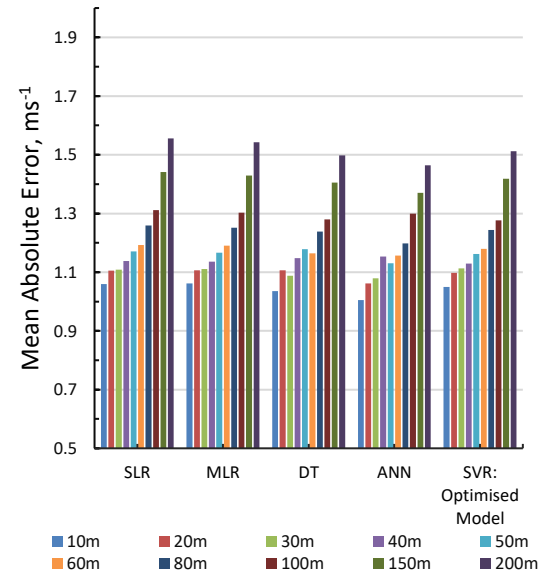


Figure 7-12: MAE of residuals, at the various LiDAR measurement heights for wind data for the year 2015 predicted with the different regression techniques based on wind data for the year 2016.

7.2.6 Conclusion

It was observed that for the regression models created from the wind data for the year 2016, the best values for the coefficient of determination, R , MSE and MAE were obtained with the DT regression technique. This also showed the best improvement when compared to the SLR technique. The best results for all regression techniques were obtained at a measurement height of 30 m above the LiDAR window.

Except for the results at 30 m and 60 m height, the coefficient of determination, R , showed a decreasing trend with measurement height, irrespective of the model used. For the year 2016, the least error was obtained at the 30 m height, while the error continued to increase with height, irrespective of the technique used.

An aspect for further research is the effect of the different topographical conditions of the candidate and the reference site. This may have had an impact on the residual error. The reference site and the candidate site were at a distance of 10.3 km from each other, and the terrain was very rough. The LiDAR was positioned at a height of 20 m above sea level, while the anemometers and the wind vane at the reference site were at 79 m above sea level. The topography of the two sites did not permit a direct line-of-sight. When considering the variation in heights, one would have expected that the measurements taken at a height of 60 m to have the best results, but, however, the best results are obtained at a measurement height of 30 m, for all the applied regression techniques. The

reason why the results obtained at 30 m and 60 m deviate from those at the other heights could be due to the topography of the terrain and this could be the topic of further research.

For the case of the predicted wind speed for the year 2015, the best results occurred at a height of 10 m for all the models while the Coefficient of Determination R , decreased with height.

The MSE and the MAE showed an increasing trend with height, for all the regression techniques used. The overall error in the residuals was less than that obtained with the model generated with the data for the year 2016. The least error was obtained with the ANN model. Leading to the conclusion that the ANN regression technique generated the least error in predicting the 2015 wind speed at the candidate site. At a 10 m measurement height the ANN model generated the best Coefficient of Determination and the least MSE and MAE for the predicted data of 2015.

Therefore, one should consider the use of DTs and ANNs as opposed to the use of SLR, MLR and SVR due to their better overall performance at all LiDAR measurement heights. These were the two regression techniques which had the highest overall Coefficient of Determination and lowest residual error values. This showed again that one cannot rely on a single model but must analyse many regression techniques to obtain the best possible results.

Section 7.3 deals with the application and the effect of the MCP methodologies in predicting the energy output from the hypothetical windfarm arrays (WF1) and (WF2) described in Section 6.1.1 and 6.1.2 respectively. Section 7.3 shows the behaviour of the windfarm (WF1) when applying measured wind speed and direction for the year 2016, while Section 7.4 shows the behaviour of the windfarm when predicted wind speed and wind direction were applied to the model.

7.3 Applying Measured Wind Speed and Direction to the Hypothetical Windfarm Model Designed in windPRO®

7.3.1 5 MW Wind Turbines (WF1)

The measured wind speed and direction were applied to the model of the hypothetical windfarm (WF1). Figure 7-13 shows a time-series of windfarm power output generated from the windPRO® windfarm model when wind speed and direction, at a LiDAR measurement height of 80 m, for the year 2016 were applied to the model (WF1). This LiDAR measurement height was equivalent to a 100 m height; since the LiDAR was at a height of 20 m above the sea level which, according to Table 6-1, was equivalent to the hub height of the wind turbine when placed out at sea.

Figure 7-14 shows the time-series for wind speed and direction at a LiDAR measurement height of 80 m which are applied to the hypothetical offshore model (WF1). Figure 7-15 shows the Weibull and wind direction statistics from windPRO®. The measured wind speed and wind direction at

150 m are applied to the 400 MW windfarm model (WF2) and the results are shown in the following section.

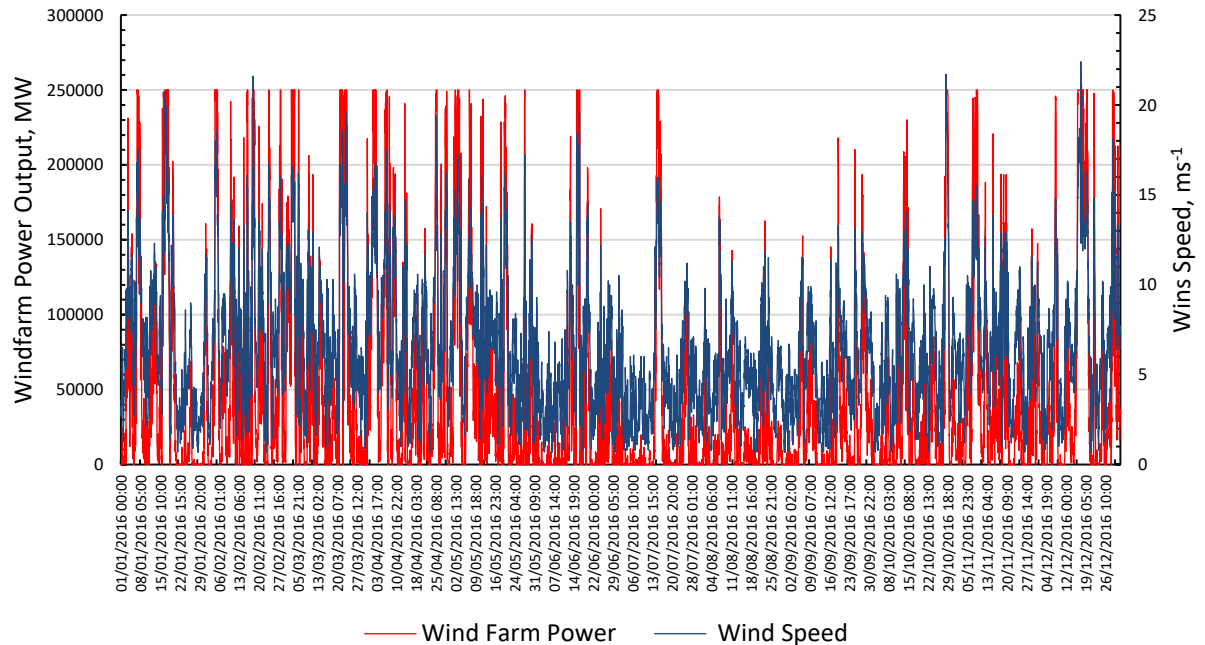


Figure 7-13: Time-series of the measured wind-speed at a LiDAR measurement height of 80 m applied to a windfarm with an installed capacity of 250 MW (WF1) and the corresponding power output from the windfarm for the year 2016.

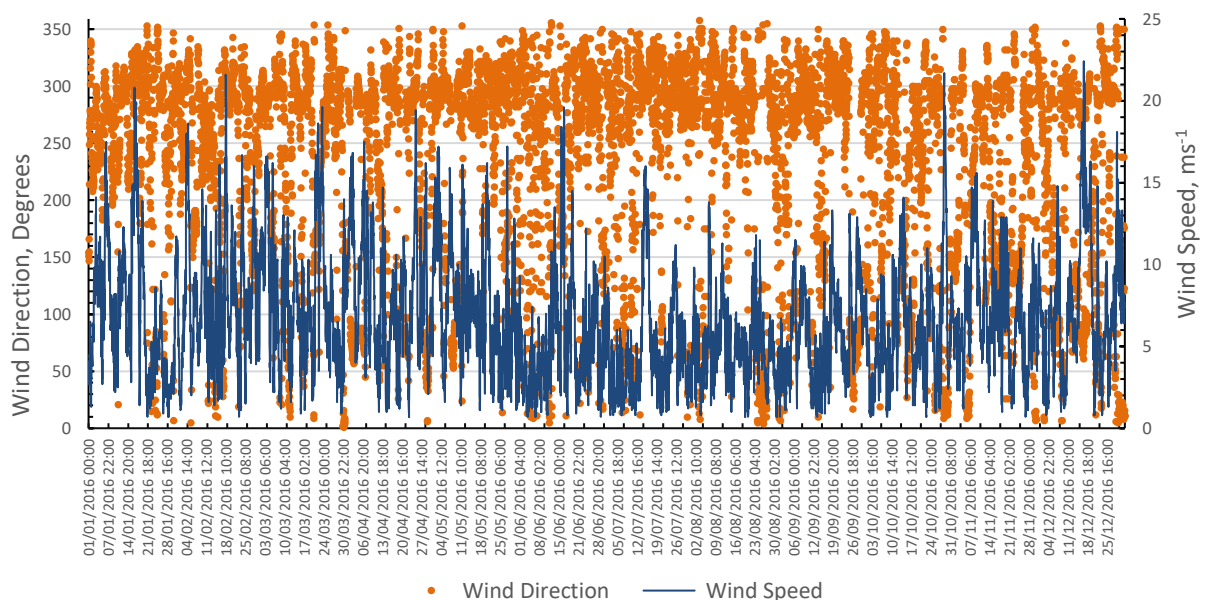


Figure 7-14: Time-series of measured wind speed and direction at a LiDAR measurement height of 80 m, at Qalet Marku as applied to the offshore windfarm (WF1) with an installed capacity of 250 MW (WF1) for the year 2016.

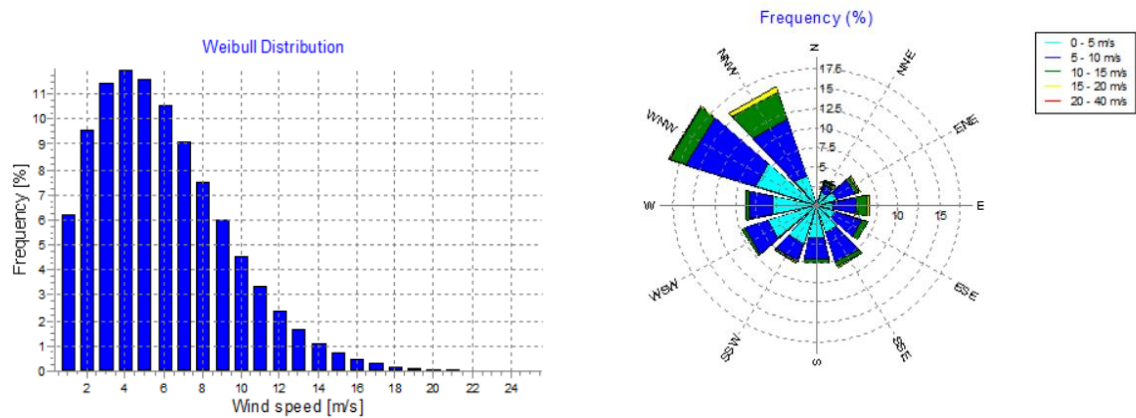


Figure 7-15: Weibull and wind direction statistics for measured wind speed and direction, at a LiDAR measurement height of 80 m, at Qalet Marku as applied to a hypothetical offshore windfarm with an installed capacity of 250 MW (WF1), for the year 2016.

7.3.2 8 MW Wind Turbines (WF2)

The measured wind speed and wind direction from the LiDAR measurement height of 150 m were applied to the windfarm model (WF2) in windPRO®, obtaining the time-series' shown in Figure 7-16 and Figure 7-17. The LiDAR measurements at 150 m (actual height was 170 m, with the LiDAR being at a height of 20 m above sea level), were closest to the hub height of 150 m. Figure 7-18 shows the Weibull and wind direction statistics from windPRO®.

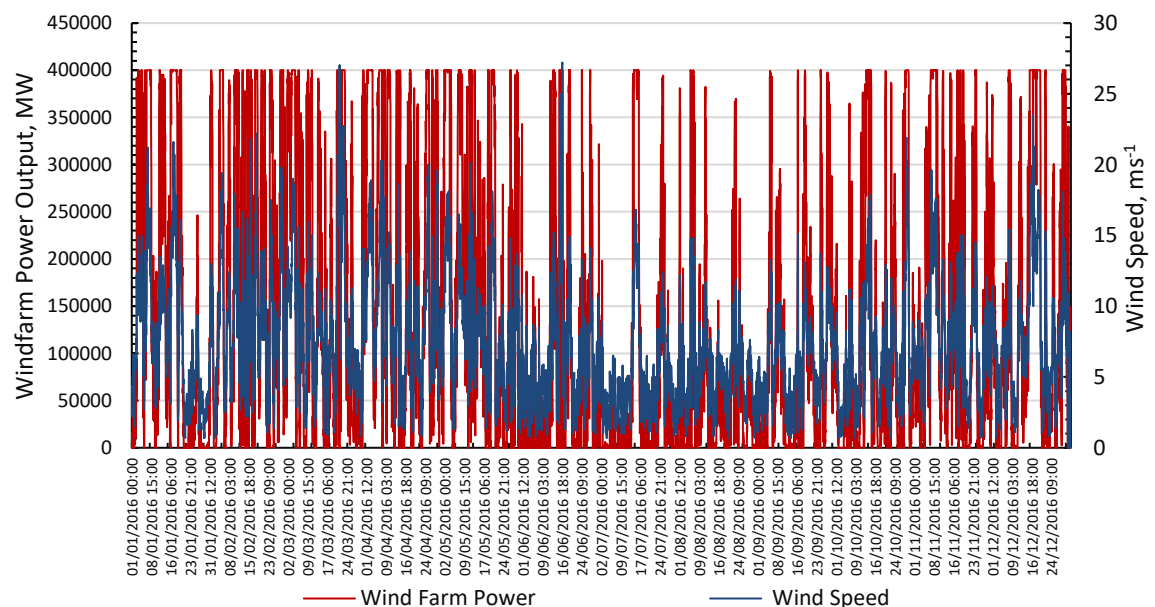


Figure 7-16: Time-series of the measured wind-speed at a LiDAR measurement height of 150 m, at Qalet Marku, applied to a windfarm with an installed capacity of 400 MW (WF2) and the corresponding power output from the windfarm for the year 2016.

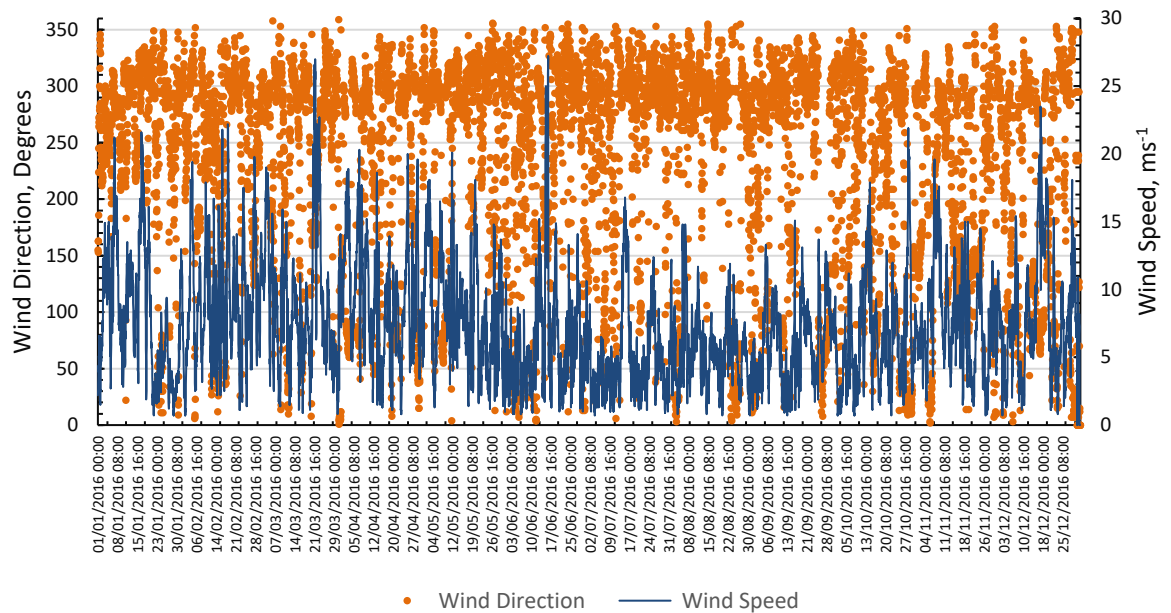


Figure 7-17: Time-series of measured wind speed and direction at a LiDAR measurement height of 150 m, at Qalet Marku as applied to the offshore windfarm with an installed capacity of 400 MW (WF2) for the year 2016.

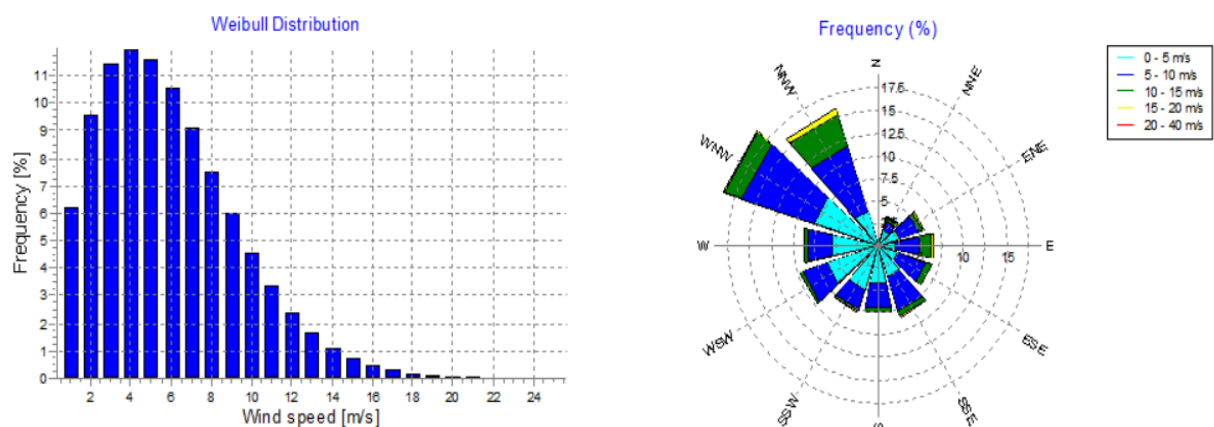


Figure 7-18: Weibull and wind direction statistics for measured wind speed and direction, at a LiDAR measurement height of 150 m, at Qalet Marku as applied to a hypothetical offshore windfarm with an installed capacity of 400 MW (WF2), for the year 2016.

7.4 Applying Predicted Wind Speed and Direction to the Hypothetical Windfarm Model Designed in WindPRO® (WF1)

The next step in the methodology described in Section 4.2.2. STEP 3 consisted of applying the predicted wind speed and direction to the hypothetical windfarm model (WF1). As discussed earlier in Sections 4.2.2 and 7.2, the reference site employed in STEP 3 was the Luqa Weather Station (Date Set C), while the candidate site was at Qalet Marku (Data Set D). This time, the MCP methodology was applied using both wind speed and wind direction as described in Section 3.1.5. The models for wind speed and wind direction were created by using the wind data for the year 2016, following which the wind data at the reference site was used to create the time-series for the

predicted wind speed and direction at the candidate site for the year 2015. The models were based on the measured data at the reference site and that from a LiDAR measurement height of 80 m for the year 2016. The predicted wind speed and direction were then applied to the windfarm model (WF1) and the power output compared to that obtained when the measured wind speed and direction.

A summary of the results from STEP 3 is now presented. Sequences of data for a specific period of the year 2015 were compared. These sequences are for wind speed, wind direction and windfarm power output. The NMAE, NMSE [using Eqs. (3-81) and (3-82) respectively] and percentage error in energy yield [using Eq. (3-85)] were then calculated, with the results shown in Sections 7.4.1 and 7.4.2. The advantages for using NMAE and NMSE were described earlier in Section 3.4.2.

7.4.1 Wind Speed and Direction with Regression Technique

The wind speed and direction predicted by the MLR, ANN, DT and SVR techniques were compared to the wind speed and direction measured at the candidate site. Since wind direction at the candidate site was also predicted by using various regression techniques, which are applied to the MCP methodology (as described Section 3.1.5), the actual wind direction at the candidate site is also compared to that predicted by the regression techniques.

Figure 7-19 to Figure 7-22 show the wind speed from the period 23 to 30 November 2015, while Figure 7-23 to Figure 7-26 show the wind direction from the same period. The period was chosen because of high wind speeds. The predicted values closely followed the measured values, for all the regression techniques applied to the MCP methodology.

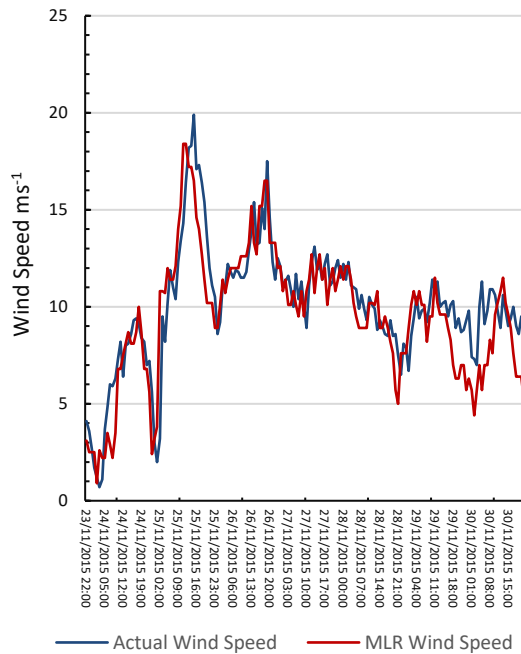


Figure 7-19: Comparing measured and MLR predicted wind speed, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

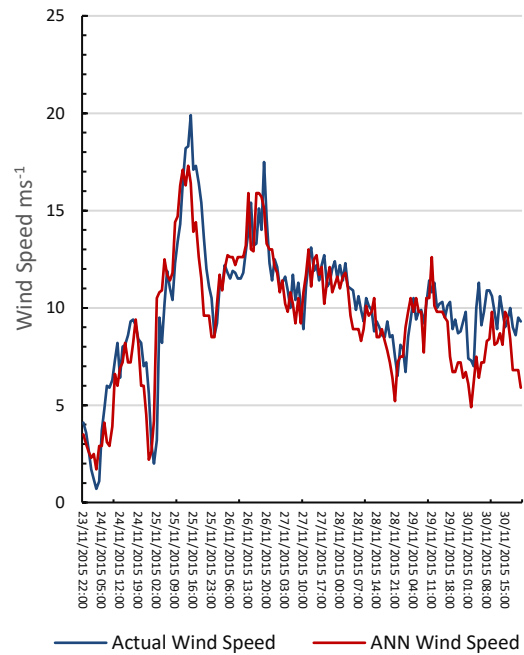


Figure 7-20: Comparing measured and ANN predicted wind speed, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

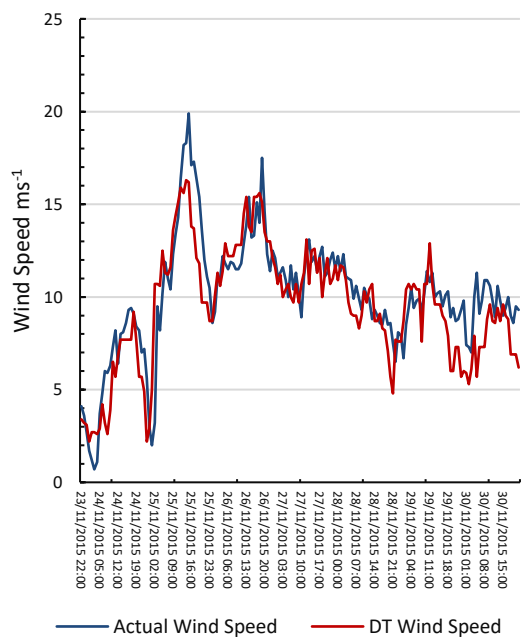


Figure 7-21: Comparing measured and DT predicted wind speed, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

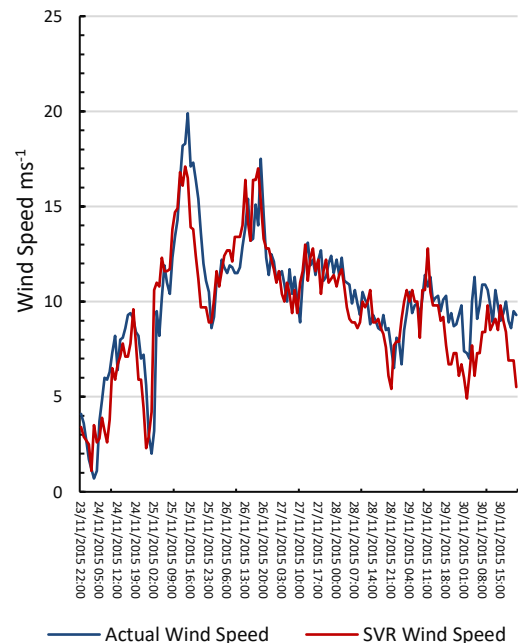


Figure 7-22: Comparing measured and SVR predicted wind speed, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

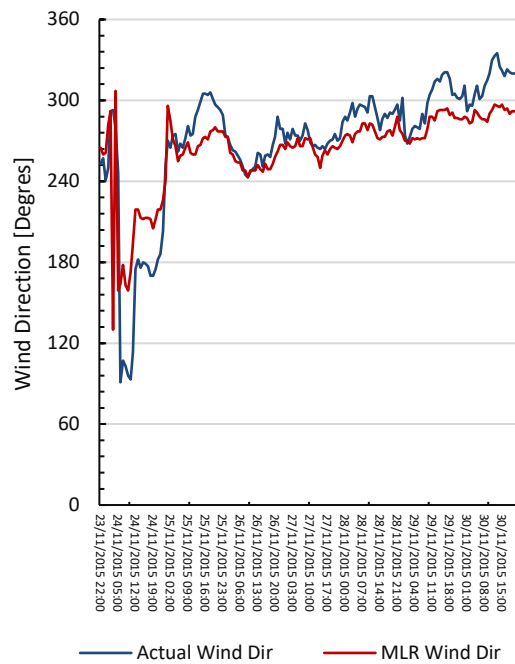


Figure 7-23: Comparing measured and MLR predicted wind direction, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

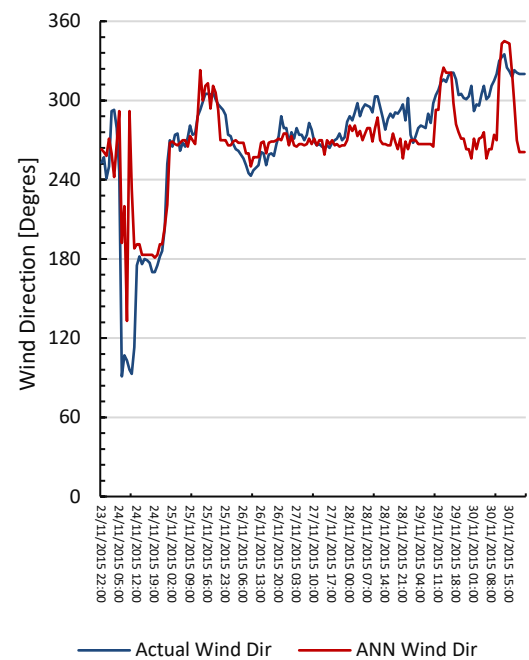


Figure 7-24: Comparing measured and ANN predicted wind direction, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

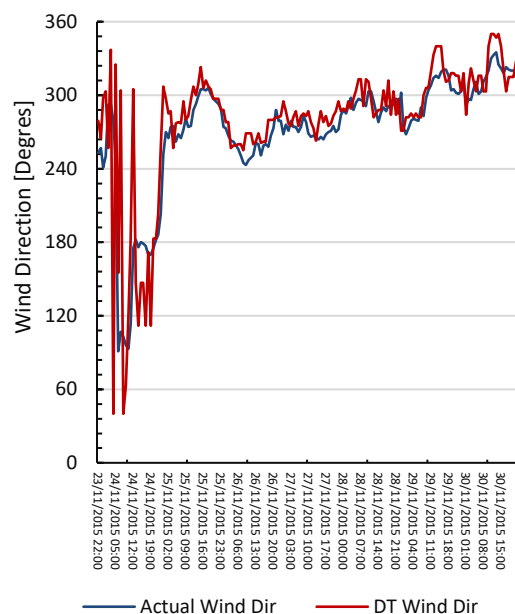


Figure 7-25: Comparing measured and DT predicted wind direction, based on wind data for the year 2015 at a LiDAR measurement height of 80 m.

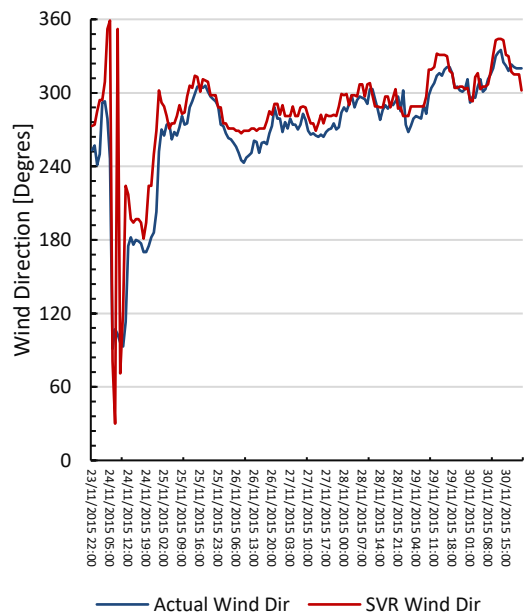


Figure 7-26: Comparing measured and SVR predicted wind direction, based on wind for the year 2015 at a LiDAR measurement height of 80 m.

A wind data analysis using windPRO® was also carried out. The results presented here are a Weibull distribution for wind speed and the wind direction frequency distribution, or wind-rose. These charts were computed from the wind speed and direction which were predicted by using the different regression techniques. Figure 7-27 represents a Wind Data Analysis Report from WindPRO® for LiDAR wind data measured at an 80 m level height for the year 2015. These reports were compared to those from the predicted wind data.

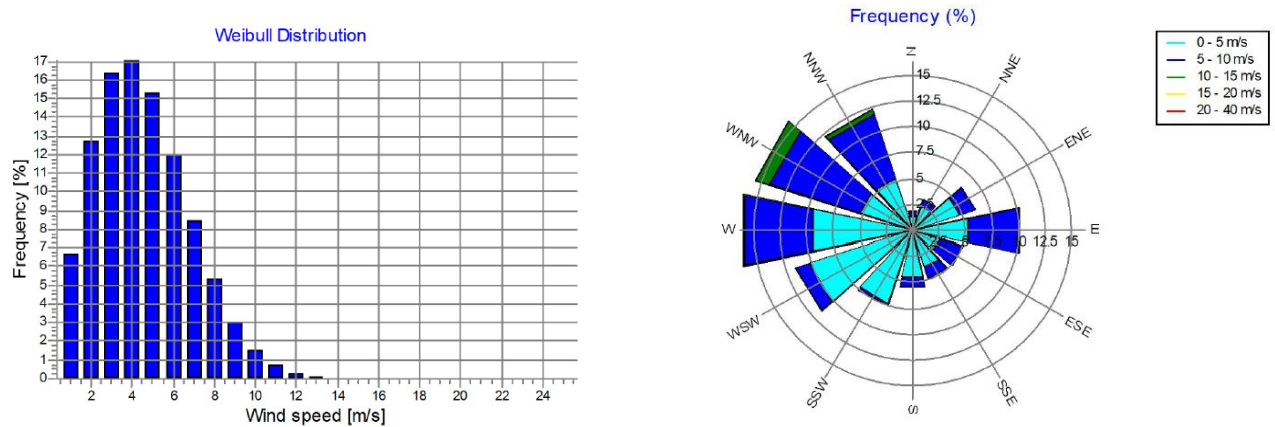


Figure 7-27: Weibull and wind direction statistics using wind data measured by the LiDAR at a height of 80 m for the year 2015.

Figure 7-28 to Figure 7-31 represent the Weibull distribution and the wind-roses for the wind speed and direction predicted for the year 2015, resulting from the regression techniques applied to the MCP methodology. There existed a similarity between the Weibull plots for the measured wind data and those for the predicted wind speed. The wind direction predicted by the ANN and DT regression techniques showed a higher resemblance to that of the measured wind direction than that predicted by the MLR or SVR techniques. Hence it was expected that the ANN and the DT regression techniques would yield the least error in the predicted power output from the wind farm.

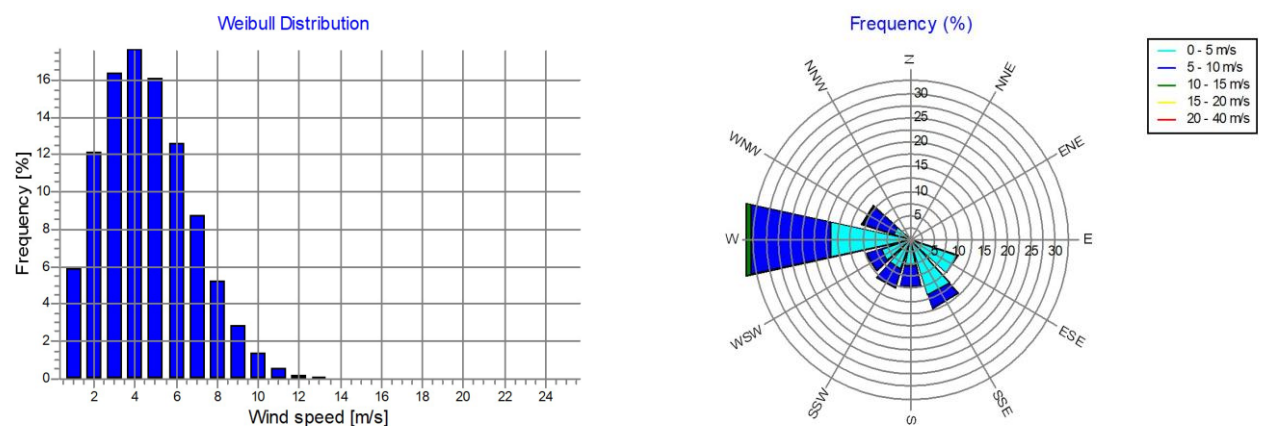


Figure 7-28: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an MLR technique for wind data measured at a height of 80 m, for the year 2015.

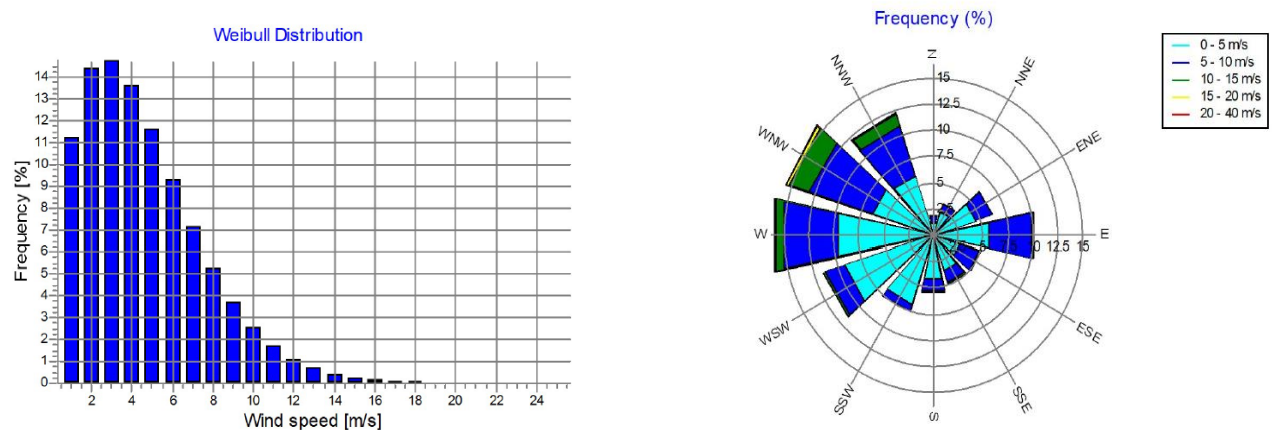


Figure 7-29: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an ANN regression technique for wind data measured at a height of 80 m, for the year 2015.

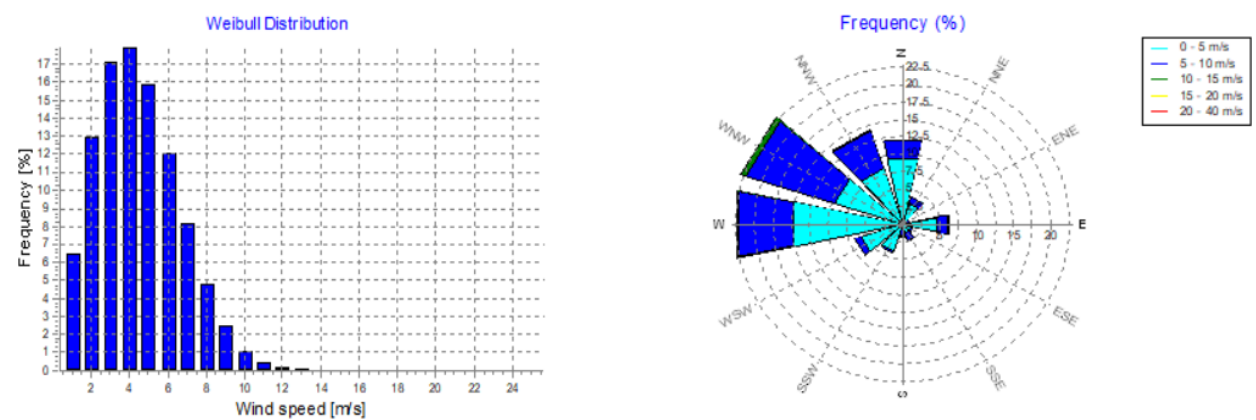


Figure 7-30: Weibull and wind direction statistics for wind data predicted by the MCP methodology using a DT regression technique for wind data measured at a height of 80 m, for the year 2015.

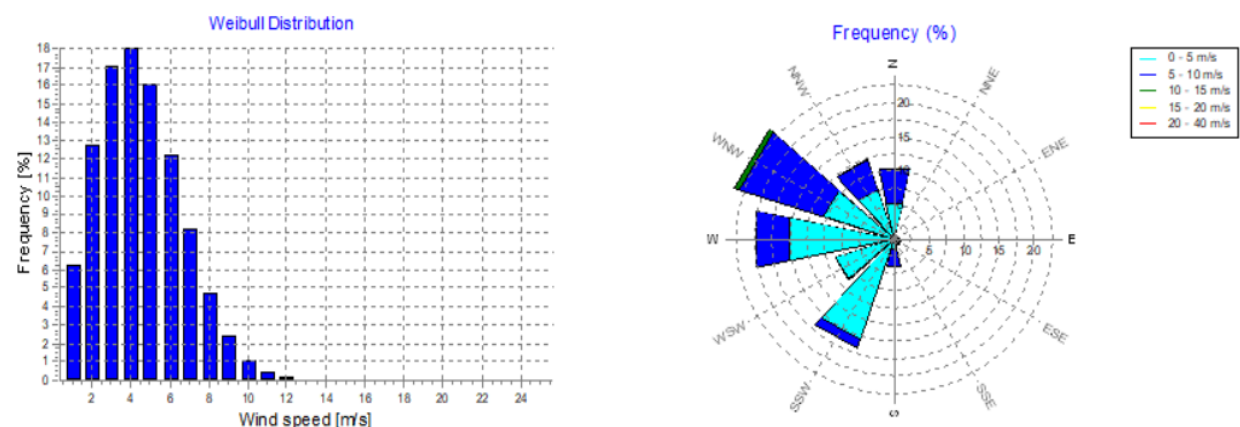


Figure 7-31: Weibull and wind direction statistics for wind data predicted by the MCP methodology using an SVR technique for wind data measured at a height of 80 m, for the year 2015.

7.4.2 Hypothetical Windfarm Power Output with Regression Technique

Figure 7-32 to Figure 7-35 compare the output power from the windPRO® model of the offshore windfarm (WF1) described in Section 6.1.1 which was derived from the measured wind speed and direction to that derived from the predicted wind speed and direction from the period 23 to the 30 November 2015. This comparison was carried out for the MLR, ANN, DT and SVR methodologies.

The results for a windfarm with an installed capacity 250 MW (WF1) are being shown. As in the case for the results shown in Section 7.4.1, the predicted power output from the windfarm model with the predicted wind speed and direction closely followed that obtained with the actual wind speed and direction.

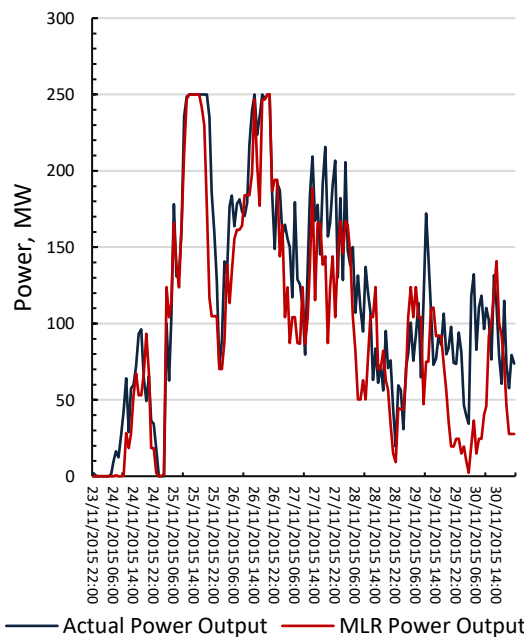


Figure 7-32: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a MLR technique applied to the MCP methodology.

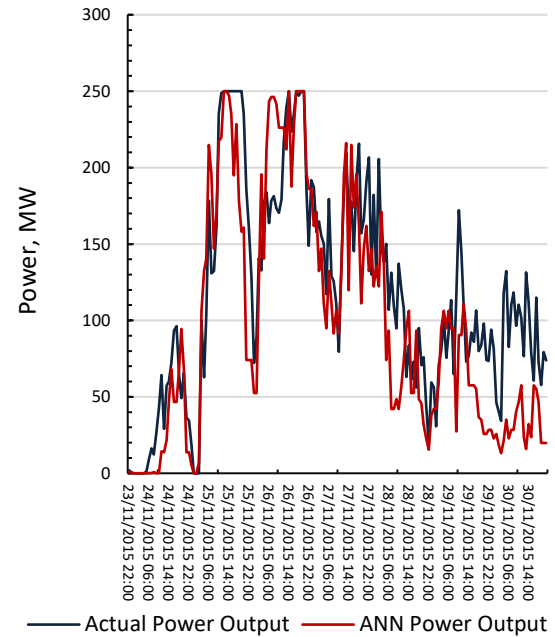


Figure 7-33: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by an ANN regression technique applied to the MCP methodology.

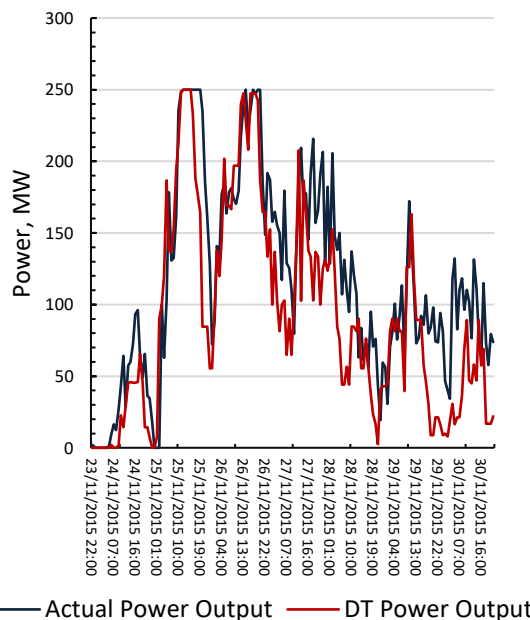


Figure 7-34: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a DT regression technique applied to the MCP methodology.

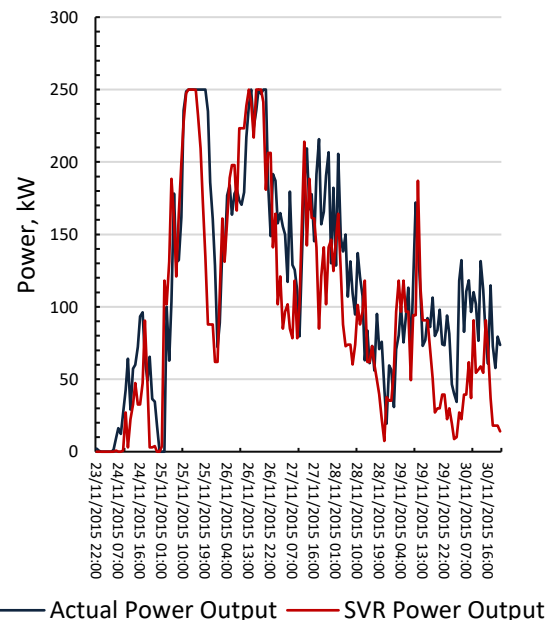


Figure 7-35: Comparing actual and predicted power output from the hypothetical offshore windfarm, from measured wind data for 2015, and that predicted by a SVR technique applied to the MCP methodology.

Table 7-13: Summarised results for NMAE by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.

Normalised Mean Absoluter Error (NMAE)				
Wind Farm Capacity (MW)	MLR	ANN	DT	SVR
250	0.505	0.502	0.572	0.544
200	0.502	0.499	0.565	0.539
150	0.492	0.482	0.545	0.532
100	0.484	0.472	0.537	0.515
50	0.510	0.547	0.573	0.558

Table 7-14: Summarised results for the NMSE by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.

Normalised Mean Squared Error (NMSE)				
Wind Farm Capacity (MW)	MLR	ANN	DT	SVR
250	0.977	1.004	1.170	1.082
200	0.956	0.979	1.123	1.052
150	0.912	0.938	1.056	1.002
100	0.834	0.868	0.960	0.917
50	0.789	0.884	0.930	0.890

Table 7-15: Summarised results for the percentage error in overall energy yield by regression technique as applied to the MCP methodology and the installed capacity of the hypothetical offshore windfarm.

Percentage Error in Overall Energy Yield				
Wind Farm Capacity (MW)	MLR	ANN	DT	SVR
250	4.63	4.54	18.83	9.44
200	4.80	4.90	18.40	9.34
150	4.92	5.40	17.78	9.23
100	4.78	5.70	16.92	8.71
50	3.65	7.03	14.73	8.23

The NMAE, the NMSE and the percentage error in the overall yield were then used to analyse the residuals from the time-series of the power output from the hypothetical offshore windfarm, derived from the measured wind speed and that predicted by the MCP methodology for the year 2015. The NMAE and the NMSE were obtained by using Eqs. (3-81) to (3-84), while the percentage error in energy yield was calculated by means of Eq. (3-85). This analysis was performed for a windfarm with an installed capacity which ranged from 50 MW to 250 MW (in 50 MW increments). The results are summarised in Table 7-13 to Table 7-15. The tabulated results show that the MLR and ANN techniques had the best performance in NMAE, NMSE and percentage error in energy yield. The lowest values have been highlighted in red, while the highest values have been highlighted in green. The results were consistent for all windfarm capacities under consideration. The ANN approach was found to perform better than MLR for the case of NMAE, while MLR was slightly better than ANN in the case of a windfarm with a 50 MW capacity. The MLR technique was superior to ANN in the case on NMSE, for all windfarm capacities. However, the differences between MLR and the ANN techniques were minimal, and both showed a better performance than the DT or SVR techniques, especially in the case of the overall energy yield shown in Table 7-15.

The ANN methodology also showed the best similarity to the measured wind speed and wind direction, as seen in Figure 7-29. In the case of the overall energy yield, the MLR and ANN

methodologies showed a significant improvement in percentage error over the DT and SVR methodologies. The ANN methodology was only better than the MLR methodology for a windfarm with an installed capacity of 250 MW. The MLR methodology had better results in the case of windfarms with installed capacities of 200, 150, 100 and 50 MW, with the percentage error being 3.65% at a windfarm capacity of 50 MW, when compared to an error of 7.3% obtained with the ANN methodology. Thus, the metrics show that the best regression technique for predicting the output power from the windfarm was therefore that which used the MLR technique, closely followed by that which uses the ANN regression technique.

7.4.2 Conclusions from the Analysis of the Power Output from the Hypothetical Offshore Windfarm

The above sections have combined the use of various regression techniques for the MCP methodology for wind speed and additionally used a novel methodology for predicting the wind direction at a candidate site.

The wind direction at the candidate site was predicted with the MCP methodology, which utilised MLR, ANN, DT and SVR as regression techniques. This was performed by breaking down the wind velocity vector into its respective North and East direction components, as described in Sections 3.1.5 and 4.2.2. The regression technique was carried out on the respective components at the reference and the candidate sites. The wind speed was predicted by using the magnitude of the wind speed at the respective sites.

The projected wind speed and direction time-series were then applied to a hypothetical wind farm. Thus, the error introduced by the four regression techniques could be measured. This was done by calculating the NMAE, the NMSE and the percentage error in wind farm's energy yield. The results show that the NMAE, NMSE and the percentage error in energy yield depended upon the regression technique and windfarm capacity. The results also showed that an optimal regression technique for the MCP methodology could be identified.

The best regression technique was that which used MLR. Although other techniques gave larger errors, they cannot be disregarded. It is always best to compare methodologies, comparing results by analysing residuals and errors and then choosing the best regression technique on a case-by-case basis. In this case, the results from the ANN regression technique gave results which were close to the MLR technique, while the DT regression and SVR techniques gave larger errors.

Unless actual wind data is available, one cannot carry out this analysis with the same level of confidence, as the error in prediction was obtained in comparing the energy from the windfarm with predicted and measured wind data. The above analysis could only be conducted because 18 months

of data were available, rather than the normal 12 months, which is usual for a wind resource assessment which uses MCP methodologies.

The above study was limited to using the same regression technique for predicting wind speed and direction. Thus, a regression model was created for wind speed, and two more regression models were created for the wind speed components, which were then used to calculate the wind direction. The advantage of having three regression models, afforded the possibility of using different combinations of techniques, i.e., MLR for wind speed and ANN for wind direction. This was performed for a limited number of combinations and is being suggested for further research.

8 Results - Part 2- Econometric, Demographic and Energy Demand Forecasting

The results for STEP 4, the forecasting of econometric and demographic data, and those of STEP 5, the forecasting of energy demand, are now presented. The methodologies used in STEPS 4 and 5 were described in Section 4.3 and 4.4, respectively. Econometric data consisted of both of GDP and end-user data. Section 8.1.1 shows the ARIMA and SARIMA parameters which were used to forecast the GDP and the end-user data, together with the derived results while Section 8.1.2 describes the results from the demographic forecasts. The econometric and demographic forecasts were then used as independent inputs for the regression models which were used to obtain the EDF. The theoretical background for the ARIMA and SARIMA methodologies was described in Section 3.2. The methodology requires the identification of the parameters (p, q, d) in the case of the ARIMA and the seasonal parameter S and (P, Q, D) in the case of a SARIMA. The results for the EDF are also shown in Section 8.2.

8.1 Econometric and Demographic Forecasts

The data for GDP and end-user data for the years 2011 to 2019 were obtained from the National Statistics Office (NSO) as described in Section 5.3 [40]. The forecasted trends were those for the years 2016 to 2020. The forecasted results were compared to the actual data and the percentage error in the forecasts was also calculated to evaluate the accuracy of the forecast. The forecasted trends were obtained by analysing the PCF and PACF for the GDP and each end-use parameter, following the approach described in Section 3.2, and by applying the Box-Jenkins methodology graphically depicted in Figure 2-11. Matlab® built-in commands were used to perform the forecasts.

8.1.1 Econometric Forecasts

The ARIMA (p, d, q) , SARIMA (P, D, Q) and S parameters (see Eq. (3-70)) are listed in Table 8-1. Table 8-2 presents the percentage error achieved for the forecasted results when comparing the actual GDP and the other end user data to the forecasted data. When seasonality was observed, S was set to 4, since the data was quarterly. The best results were obtained with the parameters shown in Table 8-1. The column ‘Distribution’ describes the nature of the error distribution as described in Eq. (3-46) with the Gaussian distribution being equivalent to white noise. The t –distribution, which is another method for representing the error ε_t in Eq. (3-46), was also used. The parameters were chosen by following the theoretical background described in Sections 3.2.1 to 3.2.3, and the analysis of the ACF [Eq. (3-49)], PACF [Eq. (3-50)], stationarity [Eq. 3-52)] and the seasonality of the end-user time-series. An analysis of the residuals was also carried out to assess the suitability of the parameters. This analysis is not being presented as part of this research.

Table 8-1: Parameters used ARIMA methodology to forecast GDP and other end-use parameters for the years 2016-2020.

End-Use parameter	Constant	(p, d, q)	Seasonal ARIMA		Distribution
			S	(P, D, Q)	
Gross Domestic Product	0	(1,1,1)	4	(4,0,4)	Gaussian
Manufacturing	1	(1,1,1)	4	(4,0,4)	Gaussian
Agriculture, Forestry and Fishing.	1	(2,1,2)	4	(4,0,4)	t
Information and Communication.	0	(1,1,2)	4	(4,0,4)	Gaussian
Construction	NA	(2,1,2)	4	(0,0,0)	t
Mining, Quarrying and Water Supply	1	(2,1,2)	4	(0,0,0)	Gaussian
Finance and Insurance Activities	0	(2,1,2)	4	(0,0,1)	Gaussian
Real Estate Activities	1	(2,1,2)	NA	NA	t
Art, Entertainment and Recreation, Repair of Household Goods and other Services.	0	(3,1,3)	4	(4,0,4)	t
Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities.	0	(4,1,0)	NA	NA	Gaussian
Professional, Scientific and Technical Activities.	0	(2,1,2)	4	(0,0,4)	Gaussian
Wholesale Retail and Trade, Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service Activities.	1	(2,2,2)	4	(0,0,4)	Gaussian

Appendix D shows the resulting forecasts of econometric data, using the ARIMA model described in Section 3.2. Table D-1 and Table D-2 present the results obtained for the forecasted trends by means of the ARIMA methodology. The actual trends and forecasts for the GDP are shown in Figure 8-1, while similar diagrams for the other end-user parameters listed in Table 4-4 are also represented in Figure E-1 to Figure E-11 of Appendix E.

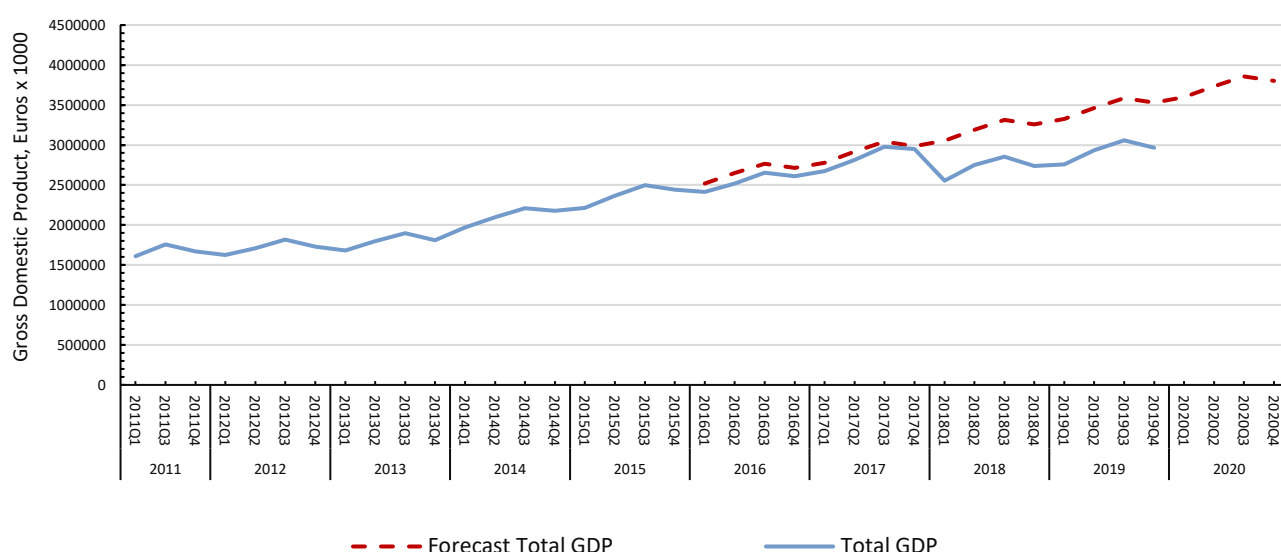
**Figure 8-1: Actual GDP trend for the years 2011-2019 and forecasted GDP for the years 2016 – 2020 using the ARIMA methodology.**

Table 8-2: Percentage Error by Quarter for GDP and End-User Forecast for the Years 2016-2019 (Part 1).

Year	Quarter	Forecast Data (% Error)					
		Forecast Total GDP	Forecast Agriculture, Forestry and Fishing	Forecast manufacturing	Mining and quarrying, Water supply	Forecast Construction	Forecast Wholesale and retail trade; repair of motor vehicles and motorcycles, transportation and storage, accommodation and food service activities.
2016	2016Q1	-4.41	1.37	2.21	34.09	-11.33	-19.73
	2016Q2	-5.28	15.23	-6.77	21.49	-10.89	-21.88
	2016Q3	-4.31	-0.74	-6.42	21.17	-8.30	-22.65
	2016Q4	-4.00	-6.95	-6.83	0.37	-6.89	-27.24
2017	2017Q1	-3.88	2.92	6.31	32.02	-10.17	-45.36
	2017Q2	-3.69	9.94	4.51	18.54	-8.29	-37.80
	2017Q3	-2.09	-10.51	8.33	28.88	-7.75	-35.60
	2017Q4	-1.29	-19.57	2.82	52.95	-7.89	-51.17
2018	2018Q1	-19.64	-12.59	8.96	46.28	-10.52	-74.49
	2018Q2	-16.06	-15.03	9.37	22.54	-9.35	-62.46
	2018Q3	-16.07	-32.81	10.46	44.50	-10.03	-60.82
	2018Q4	-18.99	-41.85	10.45	55.75	-6.60	-81.72
2019	2019Q1	-20.54	-33.60	8.70	51.57	-12.06	-103.81
	2019Q2	-18.06	-53.36	10.41	45.25	-5.42	-92.57
	2019Q3	-17.22	-74.96	16.40	50.23	-2.98	-85.04
	2019Q4	-19.13	-78.78	19.26	63.41	0.83	-107.23

Table 8-3: Percentage Error by Quarter for GDP and End-User Forecast for the Years 2016-2019 (Part 2).

Year	Quarter	Forecast Data (% Error)				
		Forecast Information and Communication	Financial and Insurance Activities	Real Estate Activities	Professional, Scientific and Technical Activities	Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities.
2016	2016Q1	-7.8%	2.2%	-5.5%	-7.9%	0.4%
	2016Q2	-6.0%	1.2%	-5.0%	-9.0%	1.2%
	2016Q3	-3.3%	-3.6%	-4.6%	-7.5%	1.7%
	2016Q4	-6.1%	0.2%	-2.7%	-9.5%	-0.3%
2017	2017Q1	-11.9%	2.6%	-7.1%	-8.3%	1.6%
	2017Q2	-11.2%	-0.4%	-9.7%	-6.6%	2.7%
	2017Q3	-12.2%	-5.3%	-7.9%	-12.4%	4.4%
	2017Q4	-10.7%	1.8%	-7.8%	-8.8%	-5.7%
2018	2018Q1	-13.8%	-1.7%	-3.3%	-19.8%	6.6%
	2018Q2	-15.3%	1.3%	-3.4%	-16.2%	4.8%
	2018Q3	-11.8%	-7.7%	-4.6%	-17.0%	6.0%
	2018Q4	-14.6%	-1.7%	-2.4%	-18.7%	6.2%
2019	2019Q1	-16.8%	1.4%	-0.5%	-27.7%	9.5%
	2019Q2	-18.3%	-4.1%	-1.3%	-25.7%	8.2%
	2019Q3	-18.9%	-10.4%	0.4%	-28.1%	9.8%
	2019Q4	-18.8%	-9.2%	4.5%	-9.5%	10.5%

Table 8-2 represents the percentage error obtained for the forecasts. It was observed that the percentage error increased with time. This was expected as described in Eq. (3-72) in Section 3.2.3. As the forecast evolves in time, with past values of Y becoming the forecasted values. This was because the ARIMA methodology eventually starts to use forecasted values to calculate the AR and MA components of the sequence. This was one factor which could have influenced the prediction of energy demand and the choice the regression technique for the EDF methodology. From Table 8-2 and Table 8-3 it was also observed that, some end user forecasts were more erratic than others. These were *Wholesale and Retail Trade, Repair of Motor Vehicles, Transportation and Storage, Accommodation and Food Service Activities, Agriculture, Forestry and Fishing* and *Mining, Quarrying and Water Supply*.

Results from the forecasting of econometric data were used as input parameters to the regression which is used to forecast the electricity demand. The following section deals with the demographic data, or population growth.

8.1.2 Demographic Forecasts

Demographic forecasts were conducted using the methodology described in Section 4.3. The demographic data was forecasted for the years 2016-2020 with the results being shown in Table 8-4. The last two (on the right) columns show the forecasted population. The forecasted results may also be seen in Figure 8-2 and Figure 8-3. The econometric and demographic forecasts were then used as independent variables to forecast the energy demand as shown in Section 8.2.

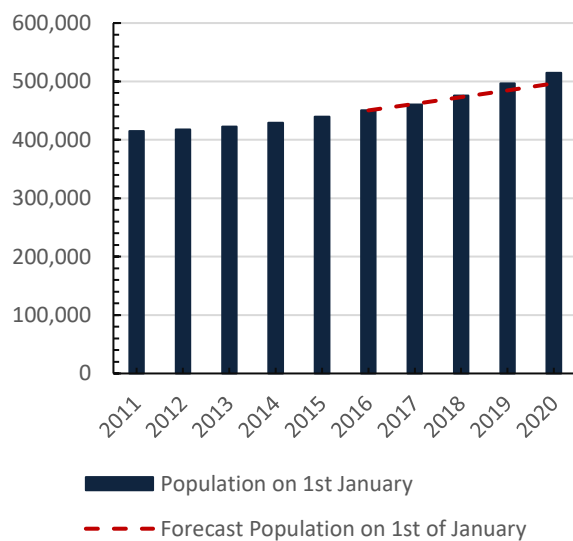


Figure 8-2: Population trends on 1 January for the years 2011-2019 and forecasted results for the years 2016-2020.

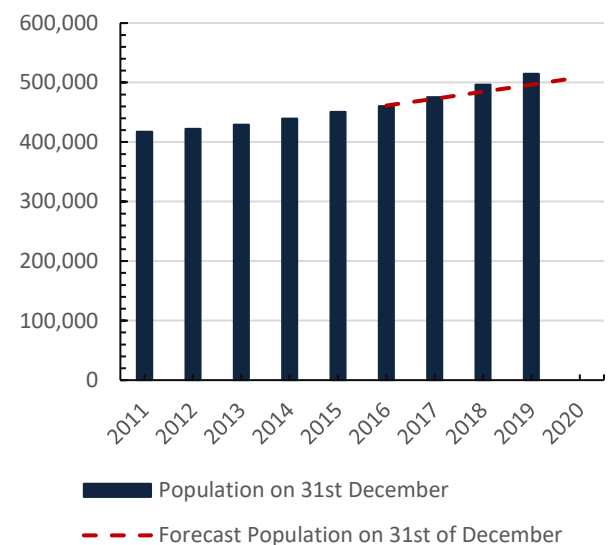


Figure 8-3: Population trends on 31 December for the years 2011-2019 and forecasted results for the years 2016-2020.

Table 8-4: Population trends for the years 2011-2019, together with forecasts obtained using ARIMA model for the years 2016-2020.

	Population on 1 st January, y_1	Population on 31 st December, y_2	T	m	c	Forecasted value for 1 January	Forecasted value for 31 December
2011	414,989	417,546	8760	0.2919	414,989		
2012	417,546	422,509	8784	0.5650	417,564		
2013	422,509	429,424	8760	0.7894	422,509		
2014	429,424	439,691	8760	1.1720	429,424		
2015	439,691	450,691	8760	1.2557	439,691		
2016	450,691	460,297	8784	1.0936	450,691	450,415	461,446
2017	460,297	475,701	8760	1.7584	460,297	461,448	472,897
2018	475,701	496,559	8760	2.3811	475,701	472,899	484,684
2019	496,559	514,564	8760	2.0554	496,559	484,685	496,723
2020	514,564		8784			496,725	508,985

8.2 Energy Demand Forecasting

The results of STEP 5 of the methodology, as described earlier in Sections 1.8 and 4.4 are now presented. Two methodologies were described for forecasting the energy demand. The first part of this work was described in Section 4.4.1 and Figure 4-9. All the data was used to create one model

which was then used to forecast the energy demand (time-series) for the entire year. The second part was described in Section 4.4.2 and Figure 4-10. The data was split according to the four quarters of the year. This resulted in the creation of four models. These were used to forecast the energy demand for the individual quarters of the years under analysis.

The results from the two EDF methodologies are now presented. The coefficient of determination R , the MSE and the MAE of the residuals are shown in Table 8-5 and Table 8-6. The results indicated that the forecasting model which utilised the DT regression technique yielded better results than the other three regression techniques. Table 8-5 shows the coefficient of determination R , the MSE and the MAE obtained by utilising the first EDF methodology while Table 8-6 shows the results from the second EDF methodology.

Table 8-5: Coefficient of determination ‘ R ’, MSE and MAE for EDF using the first methodology for the year 2017.

	MLR	ANN	DT	SVR
Coefficient of determination ‘ R ’	0.71	0.63	0.86	0.72
Mean Squared Error (MW) ²	5910.6	2799.3	1248.4	1902.3
Mean Absolute Error MW	64.6	43.5	26.1	34.1

Table 8-6: Coefficient of determination ‘ R ’, MSE and MAE for EDF using the second methodology for the year 2017.

Multivariate Linear Regression (MLR)				
	Q1	Q2	Q3	Q4
Coefficient of determination ‘ R ’	0.76	0.75	0.63	0.69
Mean Squared Error (MW) ²	1242.9	1220.6	1568.3	2022.3
Mean Absolute Error MW	28.8	27.8	35.7	32.8
Artificial Neural Networks (ANN)				
	Q1	Q2	Q3	Q4
Coefficient of determination ‘ R ’	0.85	0.86	0.72	0.87
Mean Squared Error (MW) ²	1373.6	2390.6	7436.0	1269.9
Mean Absolute Error MW	28.9	43.6	77.2	29.7
Decision Trees (DT)				
	Q1	Q2	Q3	Q4
Coefficient of determination ‘ R ’	0.91	0.78	0.83	0.92
Mean Squared Error (MW) ²	1315.6	1397.0	666.4	3132.8
Mean Absolute Error MW	27.6	31.8	46.4	20.5
Support Vector Regression (SVR)				
	Q1	Q2	Q3	Q4
Coefficient of determination ‘ R ’	0.76	0.72	0.71	0.72
Mean Squared Error (MW) ²	1477.3	1072.2	1216.4	1444.7
Mean Absolute Error MW	31.7	26.2	31.2	28.1

Table 8-5 and Table 8-6 show that the second methodology presented an improved coefficient of determination, R , especially for the ANN regression technique. In most cases, especially for the MLR and SVR techniques, better results for the MAE and MSE were obtained. Figure 8-4 to Figure 8-19 show the hourly time-series’ for the forecasts obtained for the year 2017, using both forecasting methodologies. The plots also show a direct comparison with the actual energy demand. Four charts which represent every quarter of the year are shown for every regression technique, as follows:

- Figure 8-4 to Figure 8-7 show the time-series’ when applying the MLR technique,
- Figure 8-8 to Figure 8-11 show the time-series’ using the ANN regression technique,
- Figure 8-12 to Figure 8-15 show the time-series’ when applying the DT regression technique, and,

- Figure 8-16 to Figure 8-19 show the time-series' data using the SVR technique.

More results concerning the analysis of residuals from the MLR, ANN, DT and SVR techniques, as applied to the above methodologies, for the year 2017 are shown in Appendix F, where:

- Figure F-1, Figure F-4, Figure F-7 and Figure F-10 show a histogram of residuals for the MLR, ANN, DT and SVR techniques respectively,
- Figure F-2, Figure F-5, Figure F-8 and Figure F-11 show the time-series of the residuals, for every quarter, for the MLR, ANN, DT and SVR forecasting methodologies, respectively, and,
- Figure F-3, Figure F-6, Figure F-9 and Figure F-12 show the time-series of the actual and forecasted energy demand.

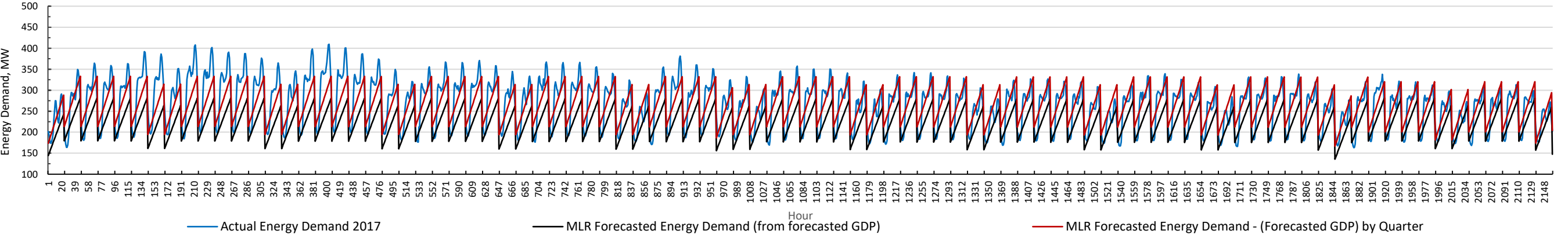


Figure 8-4: Hourly EDF with MLR technique and actual energy demand for Q1 2017.

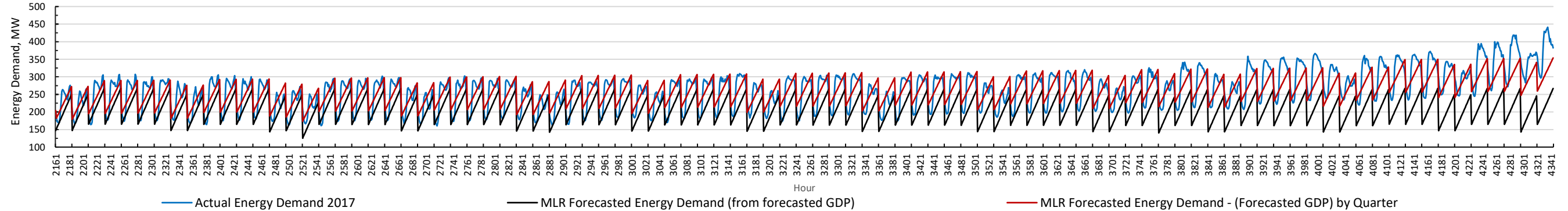


Figure 8-5: Hourly EDF with MLR technique and actual energy demand for Q2 2017.

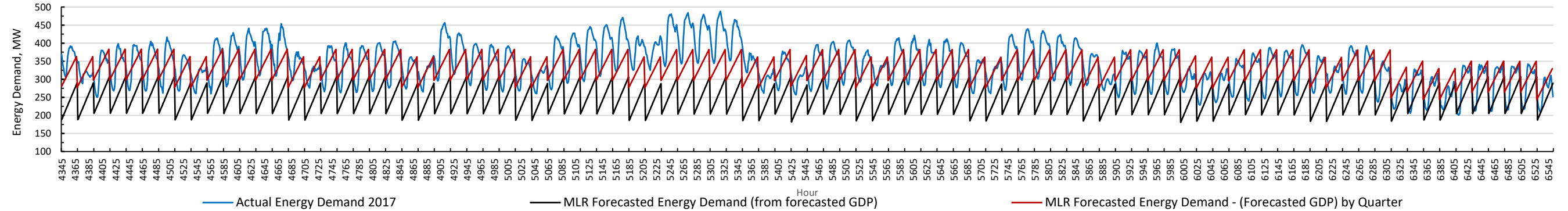


Figure 8-6: Hourly EDF with MLR technique and actual energy demand for Q3 2017.

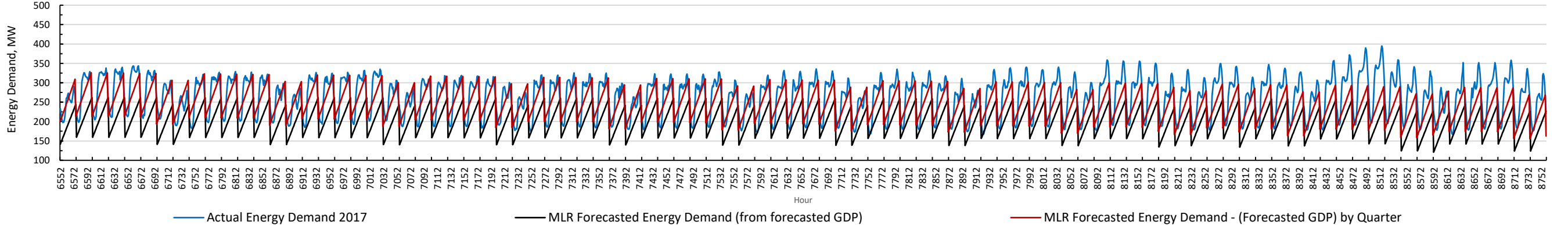
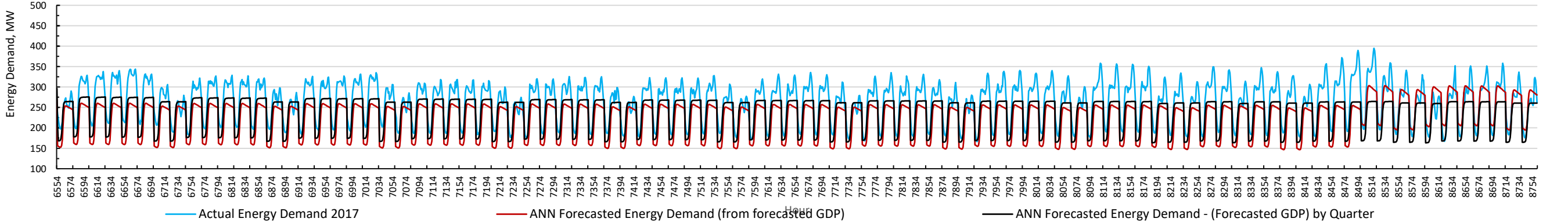
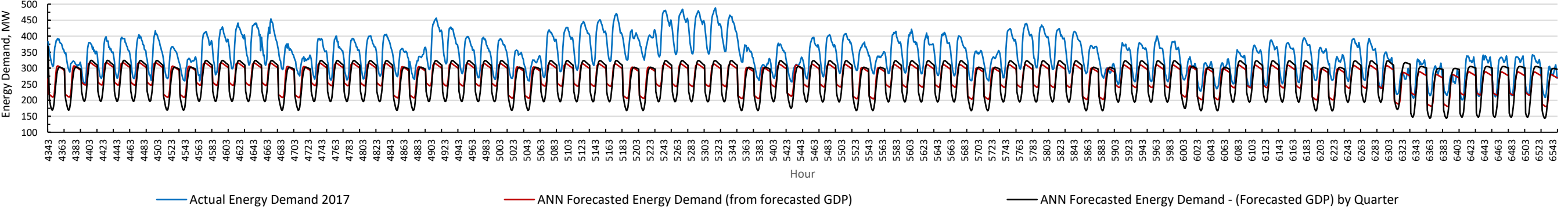
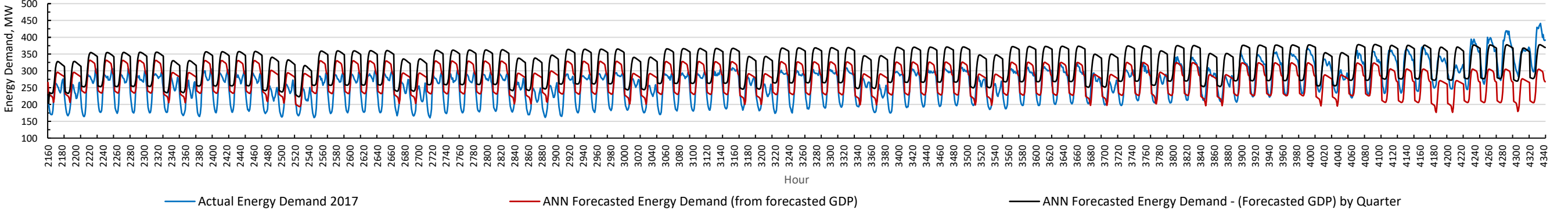
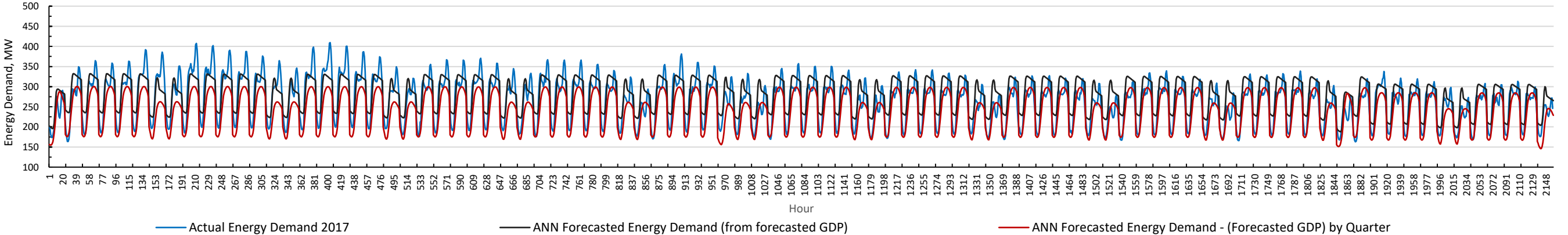


Figure 8-7: Hourly EDF with MLR technique and actual energy demand for Q4 2017.



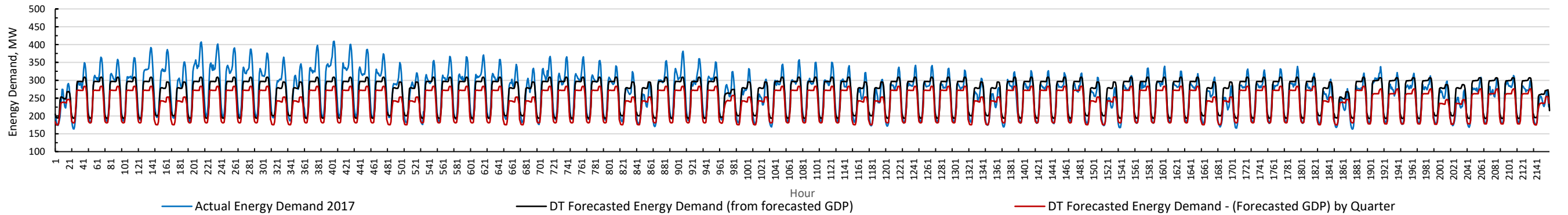


Figure 8-12: Hourly EDF with DT regression technique and actual energy demand for Q1 2017.

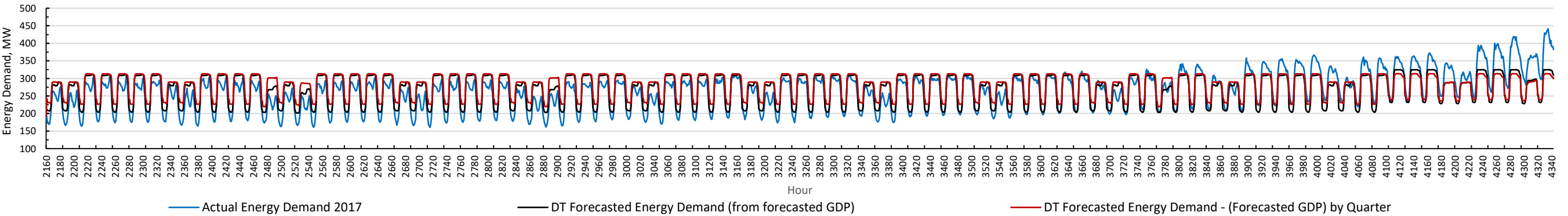


Figure 8-13: Hourly EDF with DT regression technique and actual energy demand for Q2 of 2017.

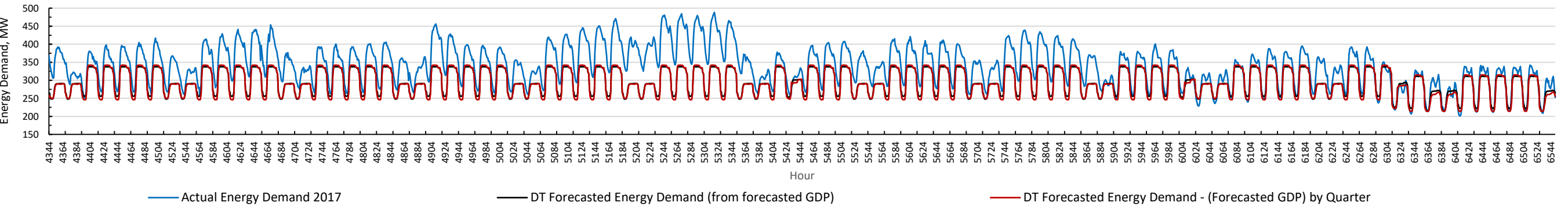


Figure 8-14: Hourly EDF with DT regression technique and actual energy demand for Q3 2017.

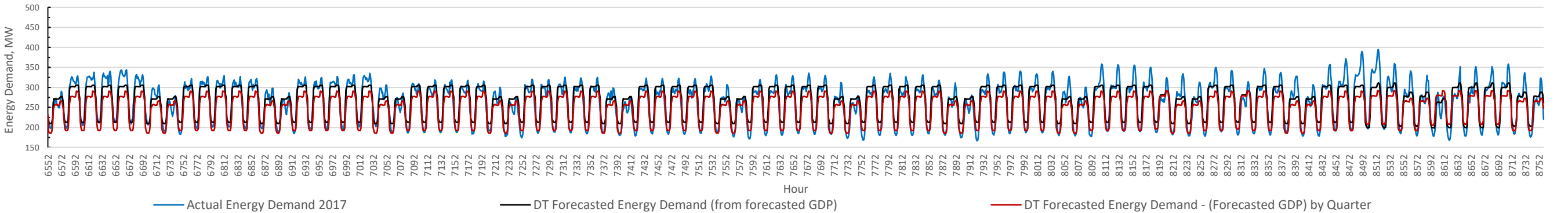


Figure 8-15: Hourly EDF with DT regression technique and actual energy demand for Q4 2017.

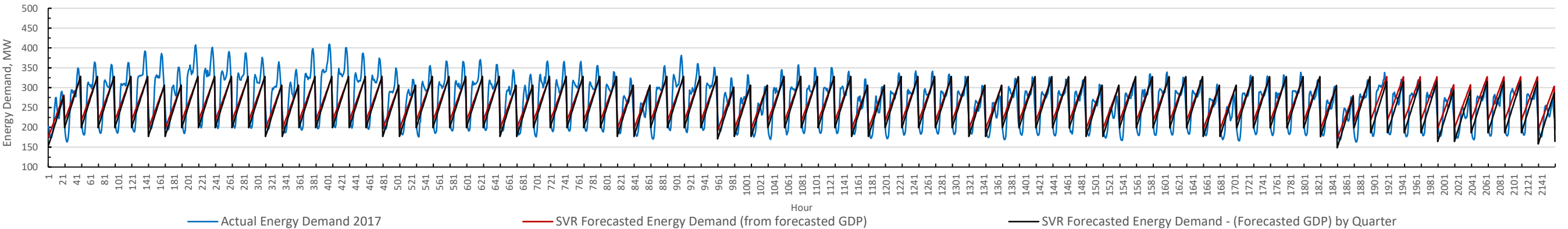


Figure 8-16: Hourly EDF with SVR technique and actual energy demand for Q1 2017.

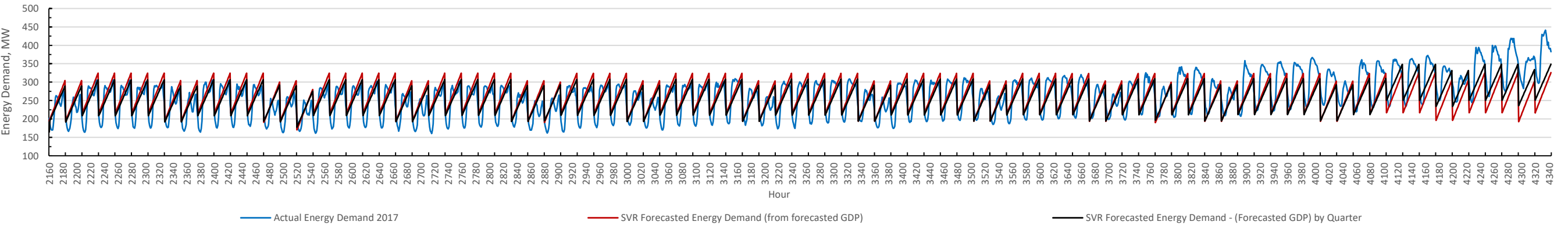


Figure 8-17: Hourly EDF with SVR technique and actual energy demand for Q2 2017.

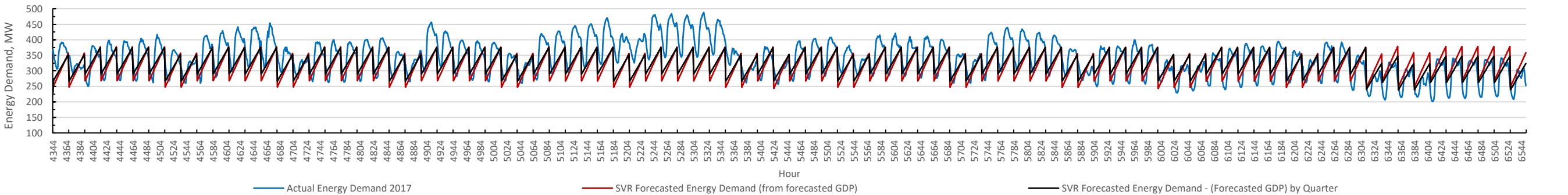


Figure 8-18: Hourly EDF with SVR technique and actual energy demand for Q3 2017.

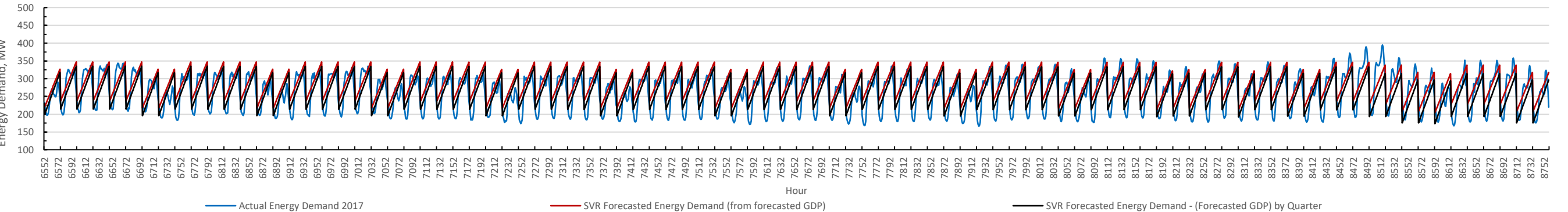


Figure 8-19: Hourly EDF with SVR technique and actual energy demand for Q4 2017.

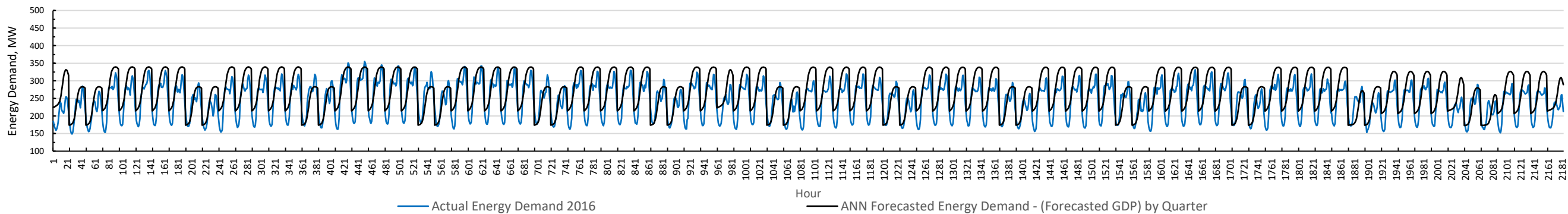


Figure 8-20: Hourly EDF with ANN regression technique and actual energy demand for Q1 2016.

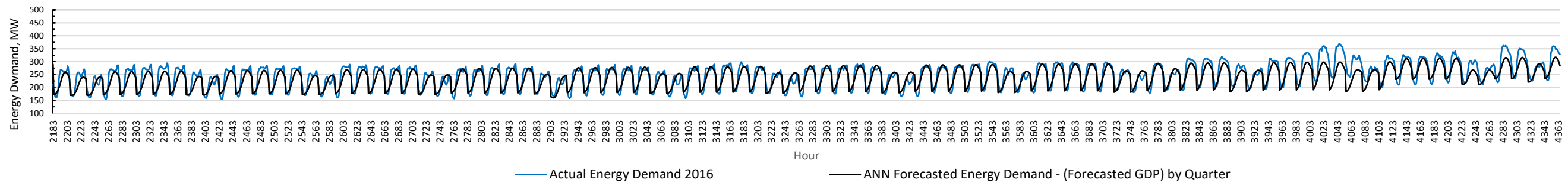


Figure 8-21: Hourly EDF with ANN regression technique and actual energy demand for Q2 2016.

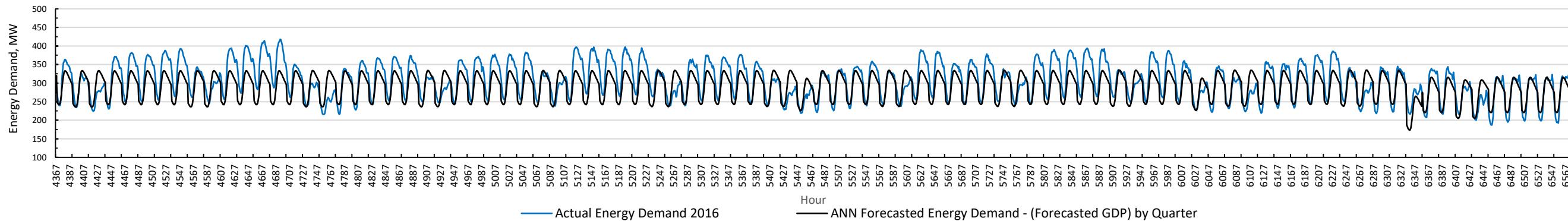


Figure 8-22: Hourly EDF with ANN regression technique and actual energy demand for Q3 2016.

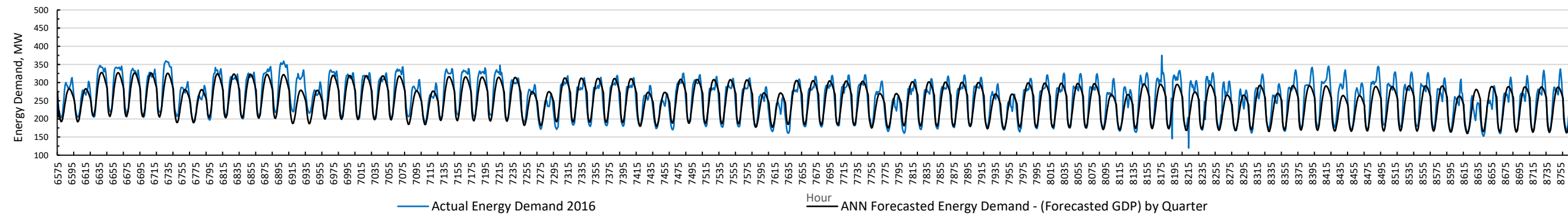


Figure 8-23: Hourly EDF with ANN regression technique and actual energy demand for Q4 2016.

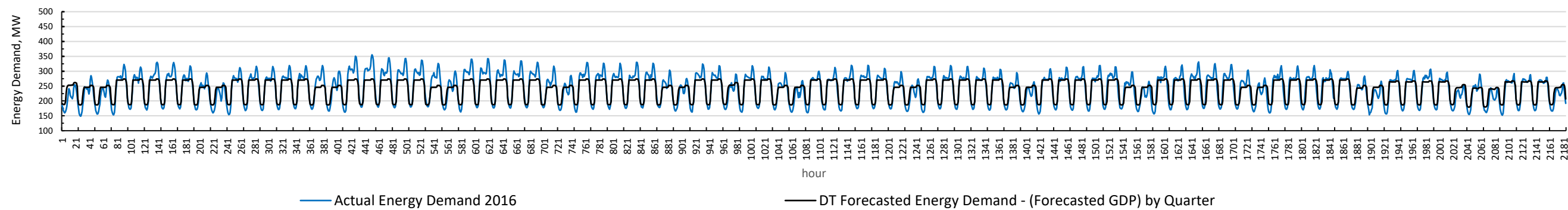


Figure 8-24: Hourly EDF with DT regression technique and actual energy demand for Q1 2016.

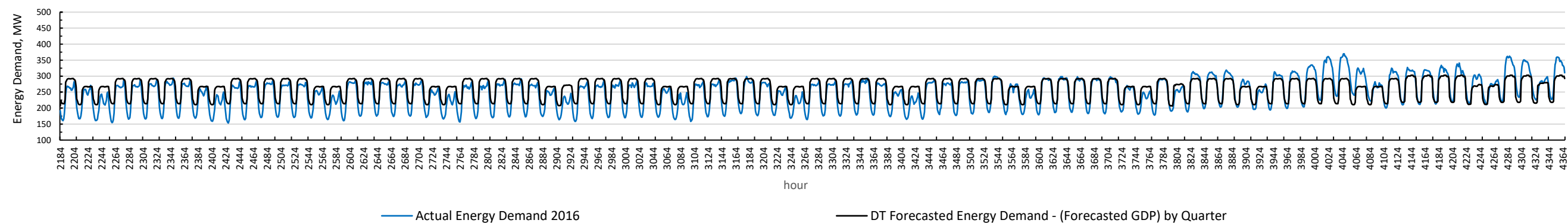


Figure 8-25: Hourly EDF with DT regression technique and actual energy demand for Q2 2016.

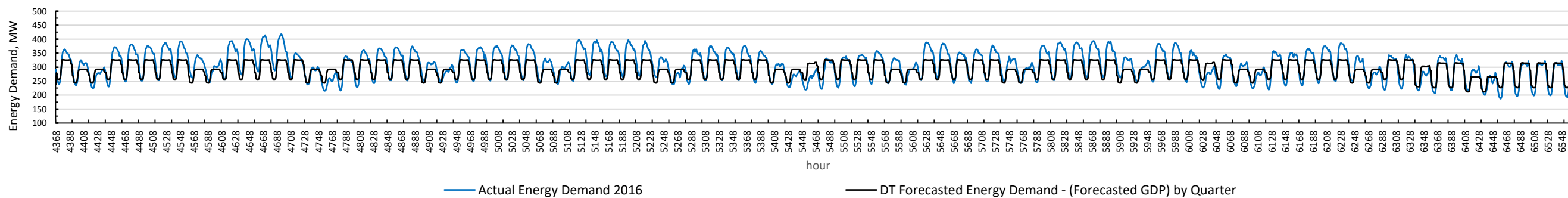


Figure 8-26: Hourly EDF with DT regression technique and actual energy demand for Q3 2016.

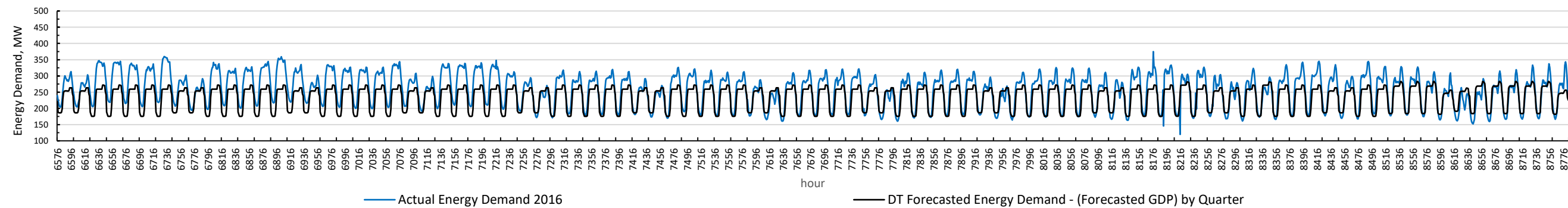


Figure 8-27: Hourly EDF with DT regression technique and actual energy demand for Q4 2016.

The hourly energy demand for the years 2016 to 2020 which were used for the long-term analysis of the windfarm and the ESS were forecasted using the second EDF methodology. The second forecasting methodology was used due to its better performance when compared to the first methodology as shown in Table 8-6. Table 8-7 shows the coefficient of determination, R , the MSE and the MAE from the analysis of the residuals for the year 2016.

Table 8-7: Coefficient of determination ‘ R ’, MSE and MAE for EDF using the second methodology. The forecasted results are for the year 2016.

Multivariate Linear Regression (MLR)				
	Q1	Q2	Q3	Q4
Coefficient of determination, R	0.75	0.76	0.68	0.73
Mean Squared Error, (MW) ²	1619.5	910.8	1328.1	1307.7
Mean Absolute Error, (MW)	33.7	25.1	29.9	29.2
Artificial Neural Networks (ANN)				
	Q1	Q2	Q3	Q4
Coefficient of determination, R	0.81	0.88	0.80	0.90
Mean Squared Error, (MW) ²	1717.7	592.0	1145.6	559.6
Mean Absolute Error, (MW)	34.3	19.0	27.80	18.31
Decision Trees (DT)				
	Q1	Q2	Q3	Q4
Coefficient of determination, R	0.93	0.87	0.89	0.86
Mean Squared Error, (MW) ²	465.2	729.7	1285.9	840.5
Mean Absolute Error, (MW)	16.7	22.6	23.1	29.0
Support Vector Regression (SVR)				
	Q1	Q2	Q3	Q4
Coefficient of determination, R	0.75	0.73	0.68	0.71
Mean Squared Error, (MW) ²	1697.9	997.4	1361.1	1384.4
Mean Absolute Error, (MW)	31.9	25.2	30.6	30.3

The results shown in Table 8-7, where the energy demand for the year 2016 was forecasted using a regression model built on the years 2011-2015, were consistent with those in Table 8-6 for the year 2017. This model was based on energy demand data, econometric and demographic data from the years 2011-2016. It is evident that the best methodologies are those based on the DT and ANN regression techniques. Therefore Figure 8-20 to Figure 8-23 show the quarterly results for 2016 using the ANN regression technique, while Figure 8-24 to Figure 8-27 show the time-series with the DT regression technique.

More results concerning the analysis of residuals from the ANN and DT regression techniques when applied to the above methodologies (as applied to the year 2016), are shown in Appendix F, where:

- Figure F-13 and Figure F-16 illustrate histograms of residuals for the ANN and DT regression techniques respectively,
- Figure F-14 and Figure F-17 show the time-series of the residuals, for every quarter, for the ANN and DT regression techniques for the year 2016, respectively, and,
- Figure F-15 and Figure F-18 show the time-series of the actual and energy demand forecasted by the ANN and DT regression techniques for the year 2016.

8.3 Conclusions for Econometric, Demographic and Energy Demand Forecasting

The forecasting of econometric and demographic trends was conducted by using the Box-Jenkins methodology. The forecasted hourly data obtained by applying this methodology were then used as inputs (or independent variables) for the regression models which were used to forecast the energy demand. The following conclusions may be drawn from this analysis:

- The forecasting of energy demand on an hourly basis over a long-term period is not normally performed. Hourly forecasts are normally limited to a day ahead.
- When a long-term forecast of energy demand is carried out, it is normally carried out daily, monthly, or on a quarterly basis. The use of GDP, end-user and hour of the day, season, weekend or public holiday as independent variables is a standard methodology.
- The model needs further analysis and improvement, especially to forecast sudden increases in energy demand, as seen in the third quarter of the year 2017. This effect is not seen in 2016 where the energy demand for Q3 was more stable than that for the year 2017.
- Two further independent variables upon which energy demand depends are temperature and relative humidity. The Maltese Islands have hot summers, with high temperatures and sometimes even high relative humidity depending on the wind direction. This was evidenced in the results of the third quarter of the year 2017, where it was noted that the increase in temperature during the summer months resulted in an increase in energy demand. The latter was not detected by the forecasting model. However, the forecast of temperature and humidity will necessitate further study as the forecast of temperature and humidity on an hourly basis over the period of several years requires forecasting methodologies which are more complex than the ones used in the current work.
- Two methodologies for EDF were used, with the second methodology giving better results for coefficient of determination, R , MAE and MSE.
- The results shown in Table 8-7 indicate that, using the second method, two regression techniques, namely ANN and DT, gave better results than the MLR and SVR techniques. This was evident in the results for the coefficient of determination and the analysis of residuals as was shown in the MAE and the MSE from the forecasted hourly values and the measured hourly values of energy demand.
- These results were affirmed in both the analysis of the residuals for both the years 2016 and 2017.

9 Results – Part 3 – Determining the Optimal Combination of MCP and Energy Demand Forecasting Methodologies

The results from STEP 6 are now presented. The methodology for STEP 6 was described in Section 4.6. In STEP 6 the results from the combinations of regression techniques for the MCP and EDF methodologies are analysed. This methodology resulted in a matrix of results which allowed the results from the different combinations of regression techniques for MCP and EDF to be compared to establish the best possible combination. Results from the actual measured wind speed, wind direction and the actual energy demand for the year 2017 are shown in Section 9.1. These results were used to calculate the percentage error from the various combinations of regression techniques.

The conditions for establishing the results matrix were described in Section 4.6, namely that the results were obtained using the measured wind data at a LiDAR measurement height of 80 m, and predicted wind data from the MCP methodology at the candidate site, wind farm capacities ranging from 50 MW to 250 MW in steps of 50 MW, an ESS capacity, $E_{S_{MAX}}$ of up to 5000 MWh in steps of 500 MWh starting without an ESS. An ESS power rating $\left(\frac{dE_s}{dt}\right)$ of 10 MW was assumed. The generation baseload, P_B was considered to vary from 100 MW to 150 MW in steps of 25 MW. The windfarm model WF1 described in Section 6.1.1 was used together with the Matlab® and Simulink® ESS model described in Section 6.2.

Three measurement metrics were analysed, namely the ones which were most important in calculating the optimal size of the ESS. The first metric was the amount of curtailed energy from the windfarm. The other metrics, which were also considered necessary to calculate the LCOE of the offshore windfarm and the LCOS of the ESS, are the energy from the windfarm which is transmitted directly into the electricity grid and the energy discharged by the ESS into the electricity grid.

The above conditions produced a substantial number of results which needed to be reduced to a size that presented a clear and simple combination of the ideal regression techniques for the MCP and EDF methodologies. Dimension reduction was thus applied to reduce the data to a simple matrix. Dimension reduction was described in Sections 2.3 and 3.3 while the methodology was also described in Section 4.6.

9.1 Results with Measured Wind Speed and Actual Energy Demand

STEP 6 provided an opportunity to analyse and describe the behaviour of the offshore windfarm and the ESS when connected to the electricity grid. Results obtained by applying measured wind

speed and direction to the windfarm model WF1 and the ESS model described in Section 6.2 are shown in Figure 9-1 to Figure 9-3. Figure 9-1 shows the wind farm output power which was transferred directly to the electricity grid. This was independent of the ESS capacity and depended only on the installed capacity of the windfarm and the generation baseload. The energy dispatched to the grid decreased with a larger baseload as more energy from the windfarm was curtailed during periods of low energy demand.

Figure 9-2 shows the energy output from the ESS to the electricity grid, where the output increased with ESS capacity and generation baseload. This was because with a larger generation baseload, more energy from the windfarm was available to charge the ESS. Figure 9-3 shows the curtailed energy from the windfarm, where curtailed energy increased with generation baseload and decreased with ESS capacity.

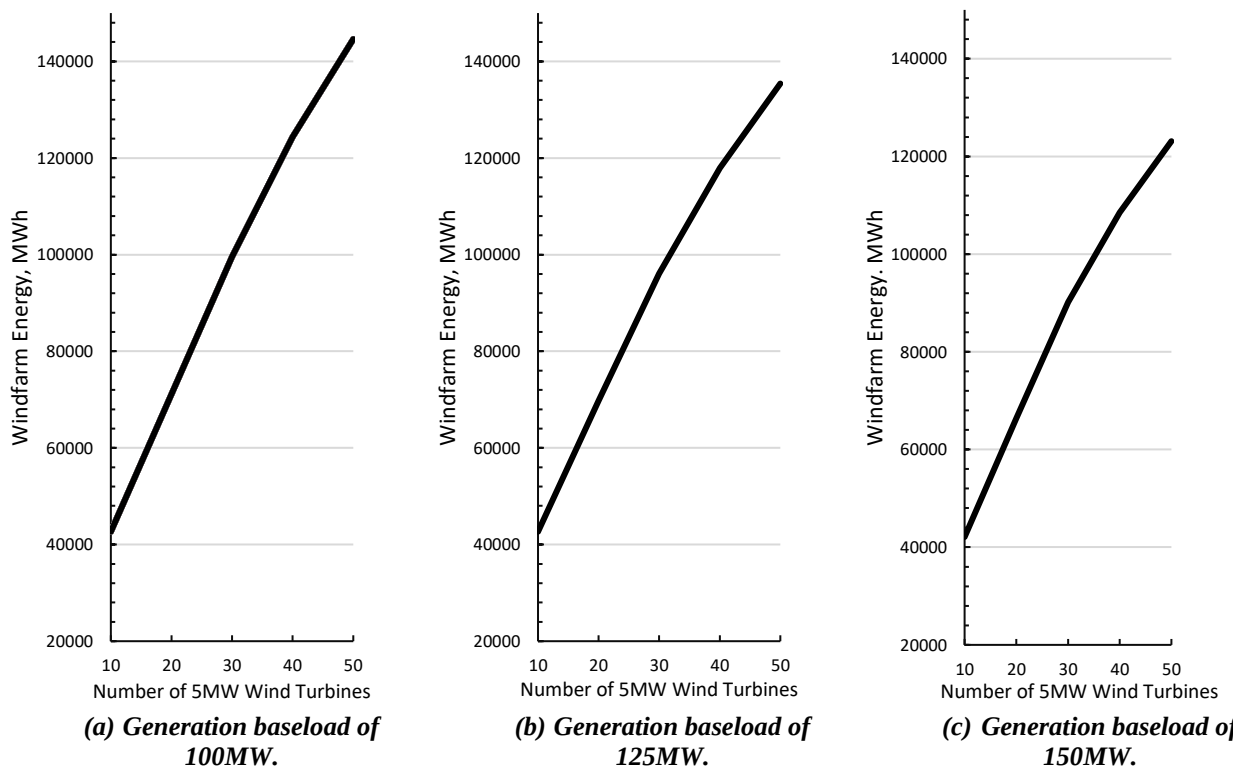


Figure 9-1: Variation of energy output from the offshore windfarm to the electricity grid with different generation baseloads.

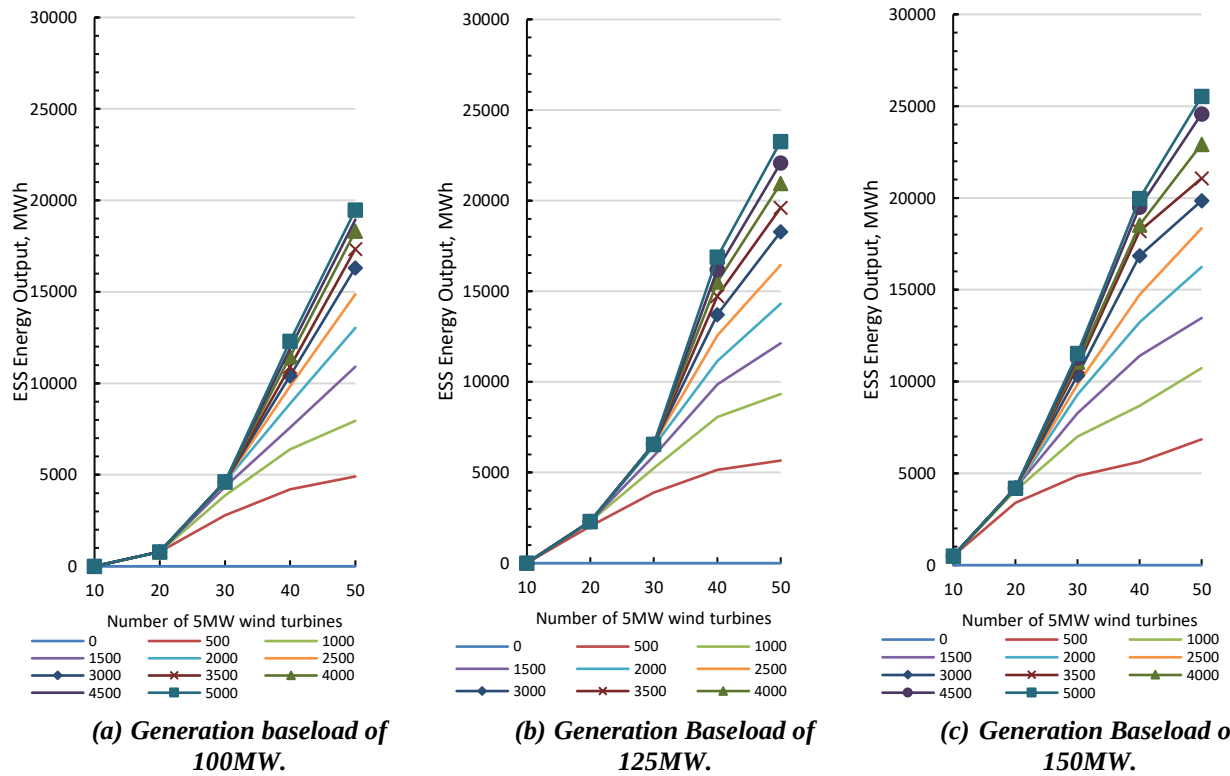


Figure 9-2: Variation of energy output from the ESS to the electricity grid with different generation baseloads for increasing capacities of the ESS.

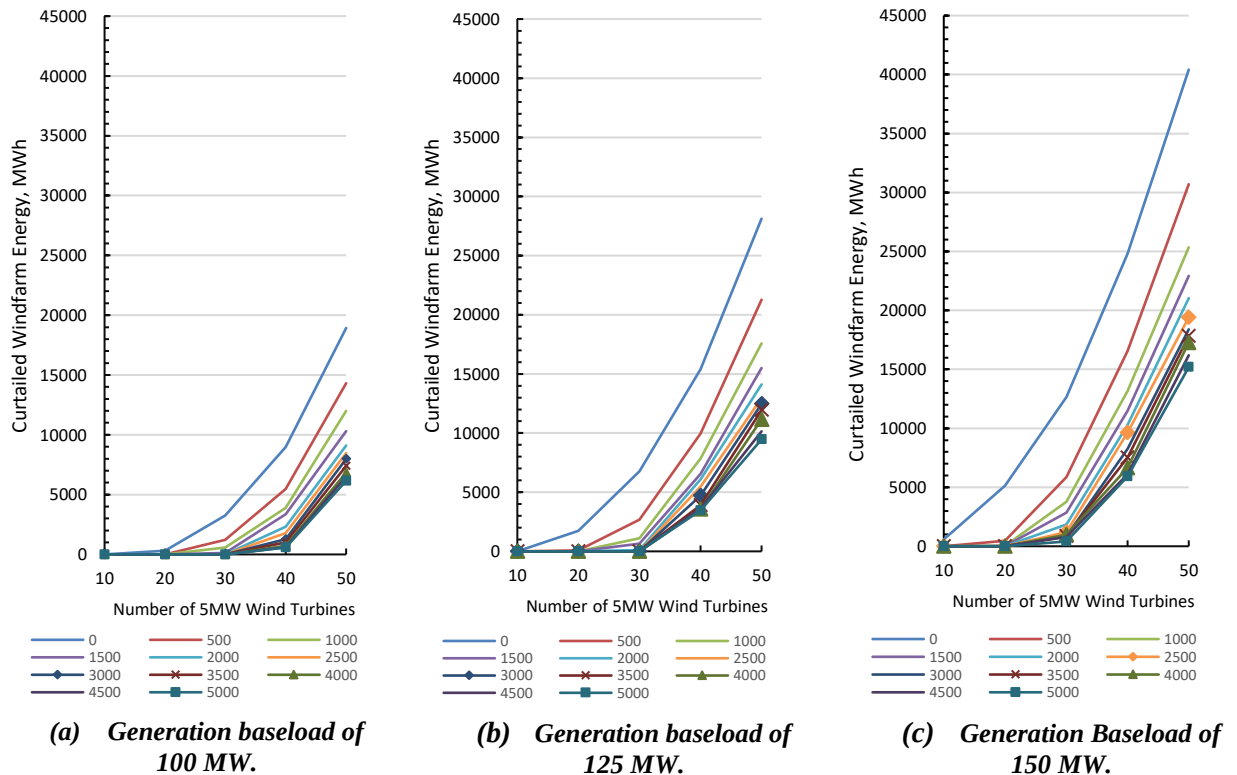
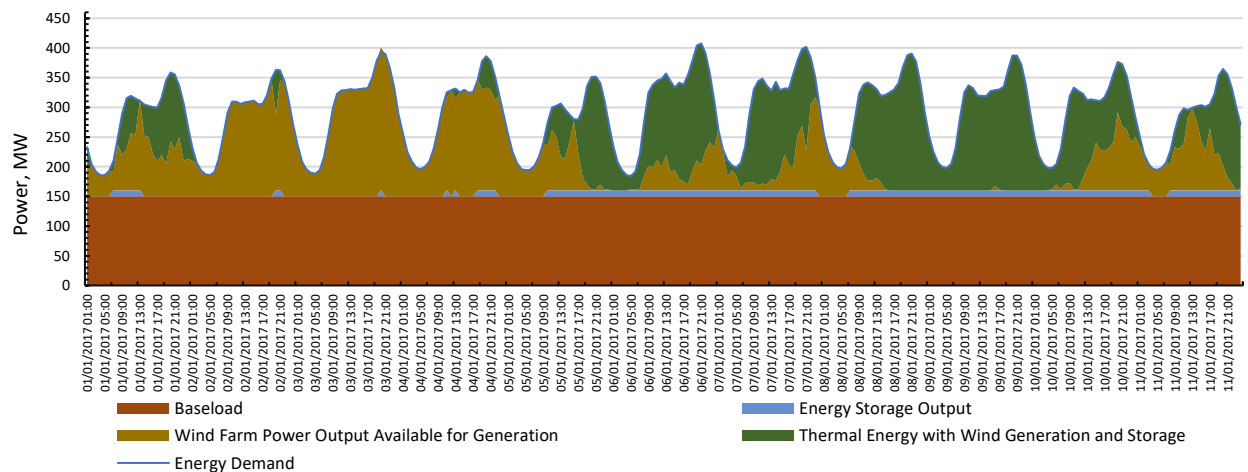


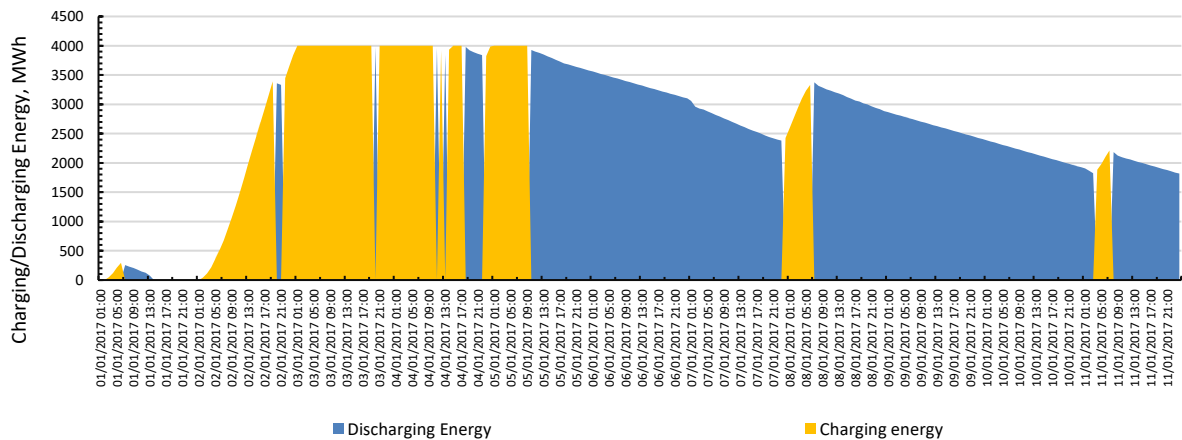
Figure 9-3: Curtailed energy from the offshore windfarm with different generation baseloads for increasing capacities of the ESS.

Figure 9-4 shows time-series plots of electricity demand, generation baseload, power output from fossil-fuel generation, the offshore windfarm and the ESS generated from measured wind data and energy demand for the period 4 to 11 of January 2017. The figure also indicates the state of charge

of the ESS, with a distinction between the charging and the discharging sequences. The transfer of power from the ESS to the electricity grid which occurred at a constant rate of 10 MW is also shown. Conventional fossil-fuel sources, other than the generation baseload, were used when there was not enough power from the windfarm to meet the electricity demand. The windfarm installed capacity was of 250 MW and the ESS capacity was set at 4000 MWh while the baseload was set at 150 MW. A similar time-series is shown in Figure 9-5 for the curtailed energy from the windfarm.



(a) Output power from the windfarm, energy demand, thermal generation, and ESS output.



(b) Charging and discharging energy from the ESS.

Figure 9-4: Time-series for output power from the windfarm, energy demand and ESS output, and charging and discharging energy from the ESS for the period 1 to 11 January 2017 based on measured wind data and energy demand.

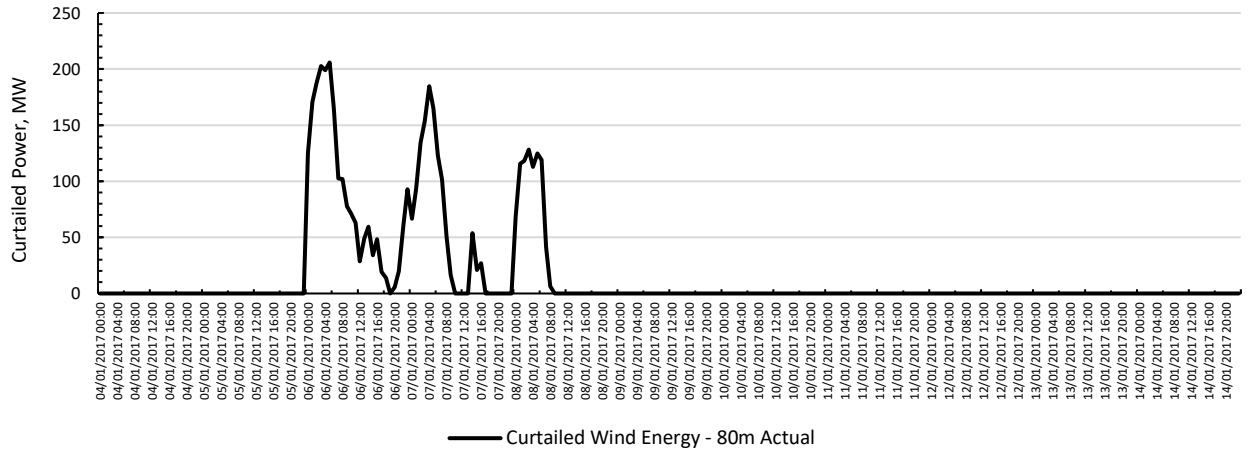


Figure 9-5: Time-series of curtailed windfarm output power from for the period 4 to 11 January 2017, based on measured wind data and energy demand.

Results were compared again in Section 9.4, following the determination of the ideal combination of regression techniques for the MCP and EDF shown in Section 9.2.

9.2 Establishing a Matrix from Combinations of MCP and Energy Forecasting for the Different Regression Techniques

As described in Section 4.6, a matrix of results was established to determine the best combination of regression techniques used for the MCP and EDF methodologies. The matrix was based on the analysis of the percentage error of the metrics identified in Section 9.1. The percentage error was defined in Eq. (3-85) and was the error between the results obtained with the application of measured wind and energy demand data and the results obtained with applying the wind data which was predicted by the MCP methodology and energy demand forecasted with the EDF methodology. The measured wind data was that measured at the LiDAR measurement height of 80 m, as described in Section 5.1.3, for the year 2017. The wind data were those predicted by applying the MCP methodology. These were applied to the windfarm model WF1 to obtain the output power from the windfarm, as described in Section 7.3. The matrix was established for variations in the windfarm capacity, ESS capacity and the generation baseload.

The results with least percentage error for every given condition were highlighted in green for errors which were less than 20%, blue for errors less than 10%, orange for errors which were less than 5% and red for percentage errors which were less than 2%.

As highlighted in Section 4.5, dimension reduction was used to simplify the data into a format where the ideal combination of regression techniques could be easily identified. Therefore, the tables show the average percentage error obtained when averaging the results by EDF methodology for the given conditions of windfarm capacity and generation baseload. These averaged percentage values

provided an indication as to which combination of regression techniques provided the least overall error.

The analysis for the percentage error on energy discharged to the electricity grid by the ESS, curtailed energy and the energy transferred by the offshore windfarm to the grid was carried out next. The analysis was carried out for generation baseloads of 100, 125 and 150 MW for wind farms with installed capacities of 250, 150 and 100 MW, and an ESS capacity which ranges from zero to 5000 MWh, in steps of 500 MW. The calculation of the MPE for every condition eliminates the ESS capacity from the data, as described in Section 4.6. The calculation of the product of the MPE (PMPE) eliminates the installed windfarm capacity and the generation baseload from the data matrix hence reducing the dimensions in the data matrix. The energy from the windfarm was independent of the storage capacity of the ESS, as discussed in Section 9.1. The ESS capacity did not influence the energy transferred from the windfarm to the electricity grid, but it did reduce the curtailed energy from the windfarm, with the extra wind energy being used to charge the ESS.

9.2.1 An Offshore Windfarm with an Installed Capacity of 250 MW

The results presented are those obtained for a windfarm with an installed capacity of 250 MW for the various conditions of generation baseload and ESS capacity for the 16 combinations of regression techniques for the MCP and the EDF methodologies.

100 MW Generation Baseload

Table 9-1 represents the percentage error obtained for the energy yield from the ESS for a generation baseload of 100 MW.

Table 9-2 represents the percentage error for the total curtailed energy from the offshore windfarm, while Table 9-3 represents the percentage error for the energy transferred to the electricity grid from the windfarm.

Table 9-1: Percentage error for the total energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.

		Percentage Error in total energy discharged from the ESS for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	16.9	14.3	6.9	5.1	2.7	1.1	1.7	1.9	0.8	4.1
	ANN	36.3	30.6	25.6	22.5	21.3	21.0	24.7	19.7	27.2	42.1
	DT	19.0	22.6	14.8	13.3	10.0	8.1	9.1	10.6	14.0	16.9
	SVR	15.9	11.6	17.6	20.2	21.7	22.0	20.4	19.4	15.9	13.5
Mean Percentage Error		16.0%									
		Percentage Error in total energy discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	43.2	44.3	50.4	48.9	48.8	46.6	44.5	41.6	37.5	33.8
	ANN	21.4	19.0	17.4	20.0	20.6	19.6	16.7	15.7	13.9	13.0
	DT	26.3	24.0	27.5	31.7	34.2	35.3	34.4	32.6	30.2	28.8
	SVR	33.4	25.2	28.4	29.3	32.6	31.7	30.1	27.9	27.7	26.8
Mean Percentage Error		30.4%									
		Percentage Error in total energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	38.9	38.4	44.1	45.4	45.6	45.2	42.0	40.1	35.3	31.5
	ANN	13.44	10.2	12.5	11.7	11.8	11.8	9.1	7.8	8.3	5.1
	DT	21.00	18.1	21.3	19.7	16.7	16.7	14.5	14.3	13.1	11.8
	SVR	27.7	26.5	27.0	25.9	27.3	27.0	24.8	23.9	19.6	23.0
Mean Percentage Error		23.2%									
		Percentage Error in total energy discharged from the ESS for a SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.3	29.8	41.3	42.4	43.0	41.9	39.1	36.5	32.9	31.8
	ANN	5.5	5.7	10.7	10.2	11.6	9.6	6.1	7.8	6.1	4.9
	DT	10.2	10.8	14.7	11.1	10.3	8.4	6.3	6.4	6.4	2.3
	SVR	28.5	24.5	25.5	24.4	27.2	26.4	24.6	23.1	21.3	20.6
Mean Percentage Error		19.5%									

Table 9-2: Percentage error in curtailed energy from the windfarm for a wind farm with an installed capacity of 250 MW.

		Percentage Error in Curtailed Energy for a MLR EDF Methodology									
		80m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	48.7	54.5	66.0	80.1	84.6	90.0	99.7	108.9	103.9	107.7
	DT	68.4	75.3	83.4	92.7	102.7	103.4	114.3	124.2	125.8	136.5
	SVR	32.7	40.7	53.0	60.1	55.7	63.2	66.5	63.7	69.3	85.0
Mean Percentage Error		76.3%									
		Percentage Error in Curtailed Energy for an ANN EDF Methodology									
		80m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	52.7	51.8	48.7	46.2	46.5	46.8	47.6	48.7	50.6	52.7
	DT	53.2	52.3	53.8	53.4	52.4	54.4	54.3	54.1	57.2	56.7
	SVR	32.0	34.4	38.5	40.2	44.6	46.5	57.9	66.6	68.2	77.8
Mean Percentage Error		56.4%									
		Percentage Error in Curtailed Energy for a DT EDF Methodology									
		80m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	27.3	23.9	16.6	10.4	9.8	13.0	15.8	18.5	22.9	23.0
	DT	24.8	25.3	24.1	19.8	24.9	22.9	18.5	17.3	19.9	20.1
	SVR	47.4	48.4	46.5	47.0	46.4	47.7	48.2	46.0	47.6	51.8
Mean Percentage Error		34.1%									
		Percentage Error in Curtailed Energy for a SVR EDF Methodology									
		80m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	29.3	26.1	19.8	13.8	13.3	16.2	14.4	15.7	20.9	16.8
	DT	20.4	19.0	19.7	18.3	19.2	21.0	16.5	6.5	8.0	0.3
	SVR	44.8	44.7	45.0	44.3	50.2	51.1	51.4	50.7	48.4	46.3
Mean Percentage Error		31.1%									

Table 9-3: Percentage error in energy from the windfarm transferred to the electricity grid for a windfarm capacity of 250 MW and a generation baseload of 100 MW.

		Percentage error in windfarm energy transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.1									
	ANN	3.2									
	DT	10.2									
	SVR	10.3									
Mean Percentage Error		6.5%									
		Percentage error in windfarm energy transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	10.6									
	ANN	12.1									
	DT	3.4									
	SVR	2.3									
Mean Percentage Error		7.1%									
		Percentage error in windfarm energy transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	3.0									
	ANN	5.4									
	DT	4.1									
	SVR	4.9									
Mean Percentage Error		4.3%									
		Percentage error in windfarm energy transferred to the grid for a in SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	7.8									
	ANN	8.2									
	DT	0.1									
	SVR	1.0									
Mean Percentage Error		4.3%									

125 MW Generation Baseload

Table 9-4 presents the results for the percentage error in the energy discharged from the ESS into the electricity grid, for a generation baseload of 125 MW. Table 9-5 presents the percentage error for the total curtailed energy from the offshore windfarm, while Table 9-6 presents the percentage error in energy from the windfarm transferred to the electricity grid.

Table 9-4: Percentage error in energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.

		Percentage Error in energy yield for the total energy discharged from the ESS for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	19.1	14.0	9.6	8.6	5.9	1.5	3.7	1.1	6.1	2.2
	ANN	22.1	22.0	20.0	18.9	14.8	12.0	10.4	10.0	10.3	13.2
	DT	13.4	11.0	11.2	12.9	9.7	4.5	3.6	5.9	10.1	12.2
	SVR	16.3	9.7	5.9	4.8	3.8	1.8	3.1	4.0	6.2	8.0
Mean Percentage Error		10.7%									
		Percentage Error in energy yield for the total energy discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	38.3	37.3	36.6	37.7	35.1	33.6	30.7	27.9	27.5	33.7
	ANN	15.6	16.8	16.6	14.7	12.8	10.8	5.5	10.5	12.1	8.6
	DT	22.3	16.6	16.3	14.8	15.3	17.5	16.3	18.1	20.0	22.4
	SVR	31.5	28.9	27.1	24.0	25.2	27.0	26.7	26.0	28.2	36.4
Mean Percentage Error		21.4%									
		Percentage Error in energy yield for the total energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	25.3	27.0	32.4	32.2	35.0	36.1	36.2	36.4	35.6	35.4
	ANN	7.6	6.2	5.2	6.4	9.2	12.1	13.0	13.3	12.82	12.6
	DT	17.7	14.6	12.1	11.5	13.5	16.3	17.1	16.8	14.2	13.6
	SVR	25.3	22.4	21.0	18.1	16.6	19.1	20.6	21.8	22.4	22.9
Mean Percentage Error		19.2%									
		Percentage Error in energy yield for the total energy discharged from the ESS for a SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	20.0	20.9	24.6	25.7	28.6	27.5	27.9	28.9	28.7	28.8
	ANN	6.0	1.1	0.7	3.1	7.2	10.5	10.8	10.3	9.4	8.7
	DT	13.8	10.2	13.1	11.7	12.5	14.0	16.7	14.4	13.4	13.1
	SVR	18.4	21.8	21.5	19.6	20.7	20.6	17.6	17.4	18.3	23.9
Mean Percentage Error		15.4%									

Table 9-5: Percentage error in curtailed energy from a windfarm with an installed capacity of 250 MW.

		Percentage error in curtailed energy for an MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	48.7	54.5	66.0	80.1	84.6	90.0	99.7	108.9	103.9	107.7
	ANN	68.4	75.3	83.4	92.7	102.7	103.4	114.3	124.2	125.8	136.5
	DT	32.7	40.7	53.0	60.1	55.7	63.2	66.5	63.7	69.3	85.0
	SVR	38.0	48.1	53.2	59.0	65.5	66.5	63.8	68.2	75.4	79.3
Mean Percentage Error		76.3%									
		Percentage error in curtailed energy for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	52.7	51.8	48.7	46.2	46.5	46.8	47.6	48.7	50.6	52.6
	ANN	53.2	52.3	53.8	53.4	52.4	54.4	54.3	54.1	57.2	56.7
	DT	32.0	34.4	38.5	40.2	44.6	46.5	58.0	66.6	68.2	77.8
	SVR	56.2	55.3	57.0	60.7	62.6	65.0	66.8	65.6	64.6	65.2
Mean Percentage Error		56.4%									
		Percentage error in curtailed energy for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	27.3	23.9	16.6	10.4	9.8	13.0	15.8	18.5	22.9	23.0
	ANN	24.8	25.3	24.1	19.8	24.9	22.9	18.5	17.3	19.9	20.1
	DT	47.4	48.4	46.5	47.0	46.4	47.7	48.2	46.0	47.6	51.8
	SVR	35.8	36.6	35.1	35.8	38.9	38.6	37.0	38.4	31.7	30.2
Mean Percentage Error		34.1%									
		Percentage error in curtailed energy for a SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.3	26.1	19.8	13.8	13.3	16.2	14.44	15.7	20.9	16.8
	ANN	20.4	19.0	19.7	18.3	19.2	21.0	16.51	6.5	8.0	0.3
	DT	44.8	44.7	45.0	44.3	50.2	51.1	51.37	50.7	48.4	46.3
	SVR	34.3	32.8	34.0	34.8	36.0	36.9	36.84	36.5	30.0	26.8
Mean Percentage Error		31.1%									

Table 9-6: Percentage error in energy transferred to the electricity grid from a windfarm with an installed capacity of 250 MW.

		Percentage error in windfarm energy transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	4.9									
	ANN	6.5									
	DT	13.2									
	SVR	13.0									
Mean Percentage Error		9.4%									
		Percentage error in windfarm energy transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	14.1									
	ANN	14.9									
	DT	6.2									
	SVR	5.4									
Mean Percentage Error		10.1%									
		Percentage error in windfarm energy transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	3.0									
	ANN	5.4									
	DT	4.1									
	SVR	4.9									
Mean Percentage Error		4.3%									
		Percentage error in windfarm energy transferred to the grid for an SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	10.1									
	ANN	9.6									
	DT	1.7									
	SVR	0.9									
Mean Percentage Error		5.6%									

150 MW Generation Baseload

Table 9-7 presents the results for the percentage error in the energy discharged from the ESS for a generation baseload of 150 MW, Table 9-8 presents the percentage error for the total curtailed energy from the offshore windfarm while Table 9-9 presents the percentage error in energy from the windfarm transferred to the electricity grid.

Table 9-7: Percentage error for the energy discharged from the ESS into the electricity grid for a windfarm with an installed capacity of 250 MW.

		Percentage error in energy discharged from the ESS for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	19.9	18.6	18.4	17.6	17.5	16.7	16.4	17.0	17.5	16.1
	ANN	9.9	8.1	3.1	5.4	5.9	5.3	5.0	3.8	2.2	3.1
	DT	11.4	11.2	7.7	9.0	8.0	6.6	4.1	2.0	1.6	0.5
	SVR	16.8	16.0	12.8	15.3	17.6	15.8	15.1	17.0	17.3	14.9
Mean Percentage Error		9.6%									
		Percentage error in energy discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	18.5	17.0	18.0	13.1	12.9	14.5	19.3	11.8	8.3	8.2
	ANN	18.4	21.0	21.3	18.7	21.3	20.9	18.7	14.0	10.7	10.7
	DT	5.6	6.3	8.0	6.1	8.7	13.3	9.2	5.5	3.0	4.9
	SVR	12.7	12.0	12.7	9.5	8.6	9.3	9.1	5.1	2.4	2.6
Mean Percentage Error		12.9%									
		Percentage error in energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.3	27.4	27.6	30.3	30.7	29.8	29.5	31.8	32.75	32.7
	ANN	22.9	17.2	13.7	15.5	16.0	16.6	15.5	17.0	19.28	17.1
	DT	26.0	22.5	19.3	16.6	15.2	16.2	13.3	14.4	14.69	13.2
	SVR	32.9	26.9	20.7	21.2	20.9	21.3	22.5	25.8	27.54	27.0
Mean Percentage Error		21.5%									
		Percentage error in energy discharged from the ESS for an SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	23.5	24.1	20.8	24.6	25.9	24.3	22.3	25.1	25.3	25.8
	ANN	9.6	7.8	5.1	6.6	10.5	8.9	9.4	11.5	12.5	11.1
	DT	19.0	18.9	15.6	13.4	11.7	14.2	13.0	14.9	13.2	12.7
	SVR	20.7	16.7	14.2	17.6	19.7	19.6	19.4	22.2	22.8	21.2
Mean Percentage Error		16.0%									

Table 9-8: Percentage error in curtailed energy from a windfarm with an installed capacity of 250 MW.

		Percentage error in curtailed energy for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	46.7	60.2	63.7	66.4	71.00	78.6	91.8	101.1	118.8	125.9
	ANN	14.5	11.6	14.2	14.2	11.1	9.3	11.1	11.9	12.9	6.2
	DT	47.0	48.9	49.0	46.9	53.5	54.2	51.5	55.9	59.0	60.6
	SVR	31.0	28.9	31.0	31.2	31.4	34.0	37.5	39.4	38.3	35.1
Mean Percentage Error		45.1%									
		Percentage Error in curtailed energy for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	44.6	42.0	41.7	40.2	37.9	38.3	37.5	37.7	37.4	32.9
	ANN	60.4	71.9	76.6	79.9	87.1	98.4	106.2	115.6	130.9	144.3
	DT	32.7	40.7	53.0	60.1	55.7	63.2	66.5	63.7	69.3	85.0
	SVR	37.2	46.4	47.6	52.1	58.7	65.9	78.2	85.8	96.1	106.3
Mean Percentage Error		65.7%									
		Percentage Error in curtailed energy for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	25.3	18.7	16.3	12.8	7.5	5.2	3.2	3.7	2.0	3.5
	ANN	37.6	35.7	39.0	37.3	34.4	32.4	31.9	31.8	31.1	29.6
	DT	32.0	34.4	38.5	40.2	44.6	46.5	57.9	66.6	68.2	77.8
	SVR	49.6	49.4	51.6	53.4	53.1	53.5	54.0	53.3	53.5	51.1
Mean Percentage Error		36.7%									
		Percentage Error in curtailed energy for a SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	25.1	18.8	15.4	11.9	7.8	5.8	5.4	5.5	6.7	4.6
	ANN	16.8	14.3	14.7	15.4	13.7	15.0	15.9	19.9	22.5	25.1
	DT	47.4	48.4	46.5	47.0	46.4	47.7	48.2	46.0	47.7	51.8
	SVR	32.7	29.8	30.6	27.3	24.6	20.1	22.0	24.8	23.6	22.6
Mean Percentage Error		25.4%									

Table 9-9: Percentage error in energy transferred to the electricity grid from an offshore windfarm with an installed capacity of 250 MW.

		Percentage error for energy from windfarm transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	11.1									
	ANN	13.2									
	DT	19.2									
	SVR	19.0									
Mean Percentage Error		15.6%									
		Percentage Error for energy from windfarm transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	19.3									
	ANN	19.3									
	DT	10.5									
	SVR	10.1									
Mean Percentage Error		14.8%									
		Percentage Error for energy from windfarm transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	3.0									
	ANN	5.4									
	DT	4.1									
	SVR	4.7									
Mean Percentage Error		4.3%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height – Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	13.1									
	ANN	11.9									
	DT	4.1									
	SVR	3.7									
Mean Percentage Error		8.2%									

9.2.2 Results for an Offshore Windfarm with an Installed Capacity of 200 MW and 150 MW

The results for the matrix results for windfarms with an installed capacity of 200 MW and 150 MW are presented in Appendix G. This presents the detailed results for percentage error of energy discharged from the ESS, curtailed energy from the windfarm and energy transferred from the windfarm to the electricity grid for 100, 125 and 150 MW generation baseloads. The measured and predicted wind data used for the MCP methodology was also that at a LiDAR measurement height of 80 m at the Qalet Marku candidate site. The measured and predicted wind data were used to obtain these results, together with the actual and forecasted energy demand data for the year 2017.

9.3 Dimension Reduction from Results of the Matrix Analysis

From above analysis it was inferred that results obtained from the matrix analysis are complex. There was no evident conclusion as to which was the best combination of regression techniques for the MCP and the EDF methodologies. The results showed that several combinations and conditions

of windfarm capacity, baseload and ESS capacity could provide an adequate combination of MCP and EDF methodologies. It was therefore necessary to use dimension reduction. As described in Sections 2.3 and 3.3, dimension reduction is a technique used when a large amount of multi-dimensional data are available and a decision which is based on this data needs be taken. The methodology is described in Section 4.6 and depicted in Figure 4-15 and Figure 4-16. Dimension reduction eliminated the dependence of the results on the different parameters such as windfarm capacity, generation baseload and ESS capacity.

This was done as described in the example below for the energy discharged into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW. This was performed by calculating the mean percentage error (MPE) from the various regression techniques with the results tabulated in Table 9-10 which presents the energy discharged from the ESS to the electricity grid. This was done by applying Eq. (4-8), as shown in Figure 4-15.

Table 9-10: Mean Percentage Error (MPE) for energy discharged into the grid by the ESS, by EDF methodology for a windfarm of 250 MW capacity and a baseload of 100 MW.

EDF Methodology		MLR									
ESS Capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	16.9	14.3	6.9	5.1	2.7	1.1	1.7	1.1	0.8	4.1
	ANN	36.3	30.6	25.6	22.5	21.3	21.0	24.7	19.7	27.2	42.1
	DT	18.9	22.6	14.8	13.3	10.0	8.1	9.1	10.6	14.0	17.0
	SVR	16.0	11.6	17.6	20.2	21.7	22.0	20.4	19.4	16.0	13.5
MPE for EDF Methodology		Mean _(MLR) = 16.0%									
EDF Methodology		ANN									
ESS capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	43.2	44.3	50.4	48.9	48.8	46.6	44.5	41.6	37.5	33.8
	ANN	21.4	19.0	17.4	20.0	20.6	19.6	16.7	15.7	13.9	13.0
	DT	26.3	24.0	27.5	31.7	34.2	35.3	34.4	32.6	30.2	28.8
	SVR	33.4	25.2	28.2	29.3	32.6	31.6	30.1	27.9	27.7	26.8
MPE for EDF Methodology		Mean _(ANN) = 30.4%									
EDF Methodology		DT									
ESS capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	38.9	38.4	44.1	45.4	45.6	45.2	42.1	40.1	35.3	31.5
	ANN	13.4	10.2	12.5	11.7	11.8	11.8	9.1	7.8	8.3	5.1
	DT	21.0	18.1	21.3	19.7	16.7	16.7	14.5	14.3	13.1	11.8
	SVR	27.7	26.5	27.0	25.9	27.3	27.0	24.8	23.9	19.6	23.0
MPE for EDF Methodology		Mean _(DT) = 23.2%									
EDF Methodology		SVR									
ESS capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.3	29.8	41.3	42.4	43.0	41.9	39.1	36.5	32.9	31.8
	ANN	5.5	5.7	10.7	10.2	11.6	9.6	6.1	7.8	6.1	4.9
	DT	10.2	10.8	14.7	11.1	10.3	8.4	6.3	6.4	6.4	2.3
	SVR	28.5	24.5	25.5	24.4	27.2	26.4	24.6	23.1	21.3	20.6
MPE for EDF Methodology		Mean _(SVR) = 19.5%									

The information shown in Table 9-10 was then transposed to show the average percentage error by MCP methodology. The MPE for this transposition was also calculated as is shown in Figure 4-15, by applying Eq. (4-9), with the results being shown in Table 9-11.

Using the results from the various combinations of windfarm capacities, generation baseload values, Table 9-12 was prepared listing the energy discharged from the ESS to the electricity grid. This eliminated the dependency of the data on the capacity of the ESS, thereby reducing the data by a dimension.

Table 9-11: Mean Percentage Error (MPE) for energy discharged by the ESS into the grid, by MCP methodology for a windfarm of 250 MW capacity and a baseload of 100 MW.

MCP Methodology		MLR									
ESS Capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
EDF Methodology	MLR	16.9	14.3	6.9	5.1	2.7	1.1	1.6	1.1	0.8	4.1
	ANN	43.2	44.3	50.4	48.9	48.8	46.6	44.5	41.6	37.5	33.8
	DT	38.9	38.4	44.1	45.4	45.6	45.2	42.1	40.1	35.3	31.5
	SVR	29.3	29.8	41.3	42.4	43.0	41.9	39.1	36.5	32.9	31.8
MPE for MCP Methodology.		Mean _(MLR) = 31.7%									
MCP Methodology		ANN									
ESS Capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
EDF Methodology	MLR	36.3	30.6	25.6	22.5	21.3	21.0	24.7	19.7	27.2	42.1
	ANN	21.4	19.0	17.4	20.0	20.6	19.6	16.7	15.7	13.9	13.0
	DT	13.4	10.2	12.5	11.7	11.8	11.8	9.1	7.8	8.3	5.1
	SVR	5.5	5.7	10.7	10.21	11.6	9.6	6.1	7.8	6.1	4.9
MPE for MCP Methodology.		Mean _(ANN) = 15.7%									
MCP Methodology		DT									
ESS Capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
EDF Methodology	MLR	18.9	22.6	14.8	13.3	10.0	8.1	9.1	10.6	14.0	17.0
	ANN	26.3	24.0	27.5	31.7	34.2	35.3	34.4	32.6	30.2	28.8
	DT	21.0	18.1	21.3	19.7	16.7	16.7	14.5	14.3	13.1	11.8
	SVR	10.2	10.8	14.7	11.1	10.3	8.4	6.3	6.4	6.4	2.3
MPE for MCP Methodology.		Mean _(DT) = 17.4%									
MCP Methodology		SVR									
ESS Capacity in MWh		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
EDF Methodology	MLR	15.9	11.6	17.6	20.2	21.7	22.0	20.4	19.4	15.9	13.5
	ANN	33.4	25.2	28.2	29.3	32.6	31.6	30.1	27.9	27.7	26.8
	DT	27.7	26.5	27.0	25.9	27.3	27.0	24.8	23.9	19.6	23.0
	SVR	28.5	24.5	25.5	24.4	27.2	26.4	24.6	23.1	21.3	20.6
MPE for MCP methodology.		Mean _(SVR) = 24.2%									

The results shown in Table 9-12, Table 9-14 and Table 9-16 therefore eliminated the ESS capacity by averaging the values of percentage error and multiplying according the algorithm shown in Figure 4-15 and utilising Eq. (4-8) and (4-9). The algorithm was applied again to obtain a second matrix which shows the product of the MPE, (PMPE) without the ESS capacity, by utilising Eq. (4-10). The best combination of regression techniques for MCP and EDF was obtained by applying Eq. (4-11), to calculate the mean of the PMPE obtained from the first transformation. This last transformation eliminated the dependency of the data on the generation baseload and the windfarm capacities hence reducing the data by a further two dimensions.

This process was repeated for all conditions of installed windfarm capacities and generation baseloads, using:

- For an offshore windfarm with and installed capacity of 250 MW, using the results in:
 - Table 9-4 to Table 9-6 for a 125 MW generation baseload, and,
 - Table 9-7 to Table 9-9 for a 150 MW generation baseload.
- For an offshore windfarm with an installed capacity of 200 MW, using the results in:
 - Table G-1 to Table G-3 for a generation baseload of 100 MW,
 - Table G-4 to Table G-6 for a generation baseload of 125 MW, and,
 - Table G-7 to Table G-9 for a generation baseload of 150 MW.

- For an offshore windfarm with an installed capacity of a 150 MW, using the results in:
 - Table G-10 and Table G-11 for a generation baseload of 100 MW,
 - Table G-12 and Table G-13 for a generation baseload of 125 MW, and,
 - Table G-14 and Table G-15 for a generation baseload of 150 MW.

Therefore, results which were obtained for all conditions or installed windfarm capacities and generation baseloads the MPE for the energy discharged from the ESS to the electricity grid, the curtailed energy from the offshore windfarm and the energy transferred directly from the offshore windfarm directly to the electricity grid are presented in Sections 9.3.1 to 9.3.3 respectively.

9.3.1 Energy Discharged from the ESS to the Electricity Grid

A matrix of MPE results for the energy discharged from the ESS for the various values of installed windfarm capacity and generation baseload is shown in Table 9-12. This table shows the MPE results from Table 9-1 for an offshore windfarm with an installed capacity of 250 MW. The results of the PMPE from Table G-1, Table G-4 and Table G-7 for an offshore windfarm with an installed capacity of 200 MW, are also shown in Table 9-12, together with those for a windfarm with an installed capacity of 150 MW, which were obtained from Table G-10, Table G-12 and Table G-14.

A further multiplication, shown in Table 9-12 [according to Eq. (4-11)], finally resulted in the final results for energy discharged to the grid by the ESS, shown in Table 9-13. This final iteration averages out the values of windfarm capacity and generation baseload leaving a final matrix of results which only involved the regression techniques.

Table 9-12: Matrix of Product of MPE (PMPE) for energy discharged to the grid by the ESS, for various conditions of windfarm capacity and generation baseload.

				Windfarm Capacity	Regression Technique for the EDF Methodology				Mean of Product of Mean Percentage Errors
					MLR	ANN	DT	SVR	
Regression Technique for the MCP methodology	MLR	Baseload	100MW	250MW	50.8	96.3	73.6	61.8	172.4
			100MW	200MW	124.5	207.5	124.3	77.8	
			100MW	150MW	782.6	472.1	425.9	472.1	
			125MW	250MW	26.7	53.7	48.2	38.6	
			125MW	200MW	66.1	158.4	99.6	85.3	
			125MW	150MW	465.0	394.0	347.6	305.7	
			150MW	250MW	20.8	27.8	46.2	34.5	
			150MW	200MW	31.6	23.4	73.9	53.5	
			150MW	150MW	183.2	239.2	229.7	183.9	
	ANN	Baseload	100MW	250MW	25.2	47.7	36.4	30.6	519.3
			100MW	200MW	99.5	165.9	99.3	62.2	
			100MW	150MW	4147.9	2502.4	2257.4	2501.9	
			125MW	250MW	11.8	2.4	2.1	1.7	
			125MW	200MW	36.8	88.2	55.4	47.5	
			125MW	150MW	1422.0	1205.1	1063.1	934.8	
			150MW	250MW	11.8	15.9	26.4	19.7	
			150MW	200MW	16.9	23.4	39.5	28.6	
			150MW	150MW	365.1	476.9	457.7	366.5	
	DT	Baseload	100MW	250MW	28.0	52.9	40.4	33.9	190.3
			100MW	200MW	128.6	214.4	128.4	80.4	
			100MW	150MW	1091.1	658.3	593.8	658.1	
			125MW	250MW	14.8	29.7	26.7	21.3	
			125MW	200MW	46.5	111.5	70.1	60.0	
			125MW	150MW	529.7	448.9	396.0	348.2	
			150MW	250MW	10.9	14.6	24.2	18.1	
			150MW	200MW	19.9	27.7	46.6	33.8	
			150MW	150MW	184.9	241.4	231.8	185.7	
	SVR	Baseload	100MW	250MW	38.9	73.6	56.2	47.2	185.1
			100MW	200MW	113.9	189.8	113.7	71.1	
			100MW	150MW	1048.7	632.7	570.8	632.6	
			125MW	250MW	20.1	40.4	36.3	29.0	
			125MW	200MW	33.8	81.1	50.9	43.7	
			125MW	150MW	524.4	444.4	392.0	344.7	
			150MW	250MW	16.5	22.1	36.7	27.4	
			150MW	200MW	24.3	33.7	56.8	41.1	
			150MW	150MW	170.2	222.1	213.3	170.6	
			Mean of Product of Mean Percentage Errors		331.5	270.5	238.6	226.5	

Table 9-13: Final iteration of a 4x4 matrix for the percentage error of energy discharged to the grid by the ESS.

		Regression Technique for the Energy Demand Model			
		MLR	ANN	DT	SVR
Regression Technique for the MCP Methodology	MLR	5713	4663	4113	3904
	ANN	17213	14049	12392	11762
	DT	6308	5148	4541	4310
	SVR	6137	5008	4418	4193

9.3.2 Curtailed Energy from the Windfarm

As for the energy discharged from the grid to the ESS, Table 9-14 shows the results for the curtailed energy from the windfarm. The results for the windfarm capacity of 150 MW are omitted as here, the amount of curtailed energy is small and hence an assessment based on percentage cannot be made.

Therefore, Table 9-14 represents the PMPE results from

Table 9-2, Table 9-5 and Table 9-8 for an offshore windfarm with an installed capacity of 250 MW. The results of the PMPE from Table G-2, Table G-5 and Table G-8, for an offshore windfarm with an installed capacity of 200 MW are also represented in Table 9-14. This leads to the final iteration for the curtailed energy as shown in Table 9-15.

Table 9-14: Matrix of percentage error for curtailed energy from the windfarm, for various conditions of windfarm capacity and generation baseload.

				Windfarm Capacity	Regression Technique for the Energy Demand Model				Mean of Product of Mean Percentage Errors
					MLR	ANN	DT	SVR	
Regression Technique for the MCP Methodology	MLR	Baseload	100MW	250MW	324.8	272.7	145.0	132.4	732.9
			100MW	250MW	4049.8	879.0	900.8	739.4	
			125MW	250MW	321.8	218.4	117.9	115.9	
			125MW	200MW	2835.4	1595.3	705.2	596.1	
			150MW	200MW	160.1	232.9	130.2	90.0	
			150MW	200MW	573.0	1249.5	882.2	320.9	
	ANN	Baseload	100MW	250MW	368.9	272.7	164.7	150.4	716.2
			100MW	250MW	4666.1	1838.0	1037.9	851.9	
			125MW	250MW	299.2	203.1	109.6	107.8	
			125MW	200MW	1562.3	879.0	388.5	328.5	
			150MW	200MW	180.8	263.0	147.0	101.7	
			150MW	200MW	651.3	1249.5	1002.8	364.7	
	DT	Baseload	100MW	250MW	390.9	288.9	174.5	159.4	975.6
			100MW	250MW	5134.0	2022.3	1141.9	937.3	
			125MW	250MW	387.3	262.9	141.9	139.5	
			125MW	200MW	3594.6	2022.3	893.9	755.7	
			150MW	200MW	237.0	344.7	192.7	133.2	
			150MW	200MW	768.6	1676.0	1183.3	430.4	
	SVR	Baseload	100MW	250MW	423.8	313.2	189.2	172.8	614.1
			100MW	250MW	3638.7	1433.3	809.3	664.3	
			125MW	250MW	365.1	247.9	133.8	131.6	
			125MW	200MW	1535.5	863.9	381.9	322.8	
			150MW	200MW	124.0	294.2	164.5	113.7	
			150MW	200MW	457.2	997.0	703.9	256.0	
			Mean of Product of Mean Percentage Errors		1377.1	830.0	493.4	338.2	

Table 9-15: Final iteration of a 4x4 matrix for the percentage error of curtailed energy from the windfarm.

		Regression Technique for the Energy Demand Model			
Regression Technique for the MCP Methodology	MLR	MLR	ANN	DT	SVR
	ANN	23738	14307	8506	5830
	DT	71514	43102	25624	17562
	SVR	26206	15795	9390	6436
		25495	15366	9135	6261

9.3.3 Energy from the Windfarm Transferred to the Electricity Grid

Results for the MPE for the energy from the windfarm transferred to the grid are tabulated in Table 9-16, which leads to the final iteration presented in Table 9-17. Table 9-16 therefore shows the MPE results from Table 9-3, Table 9-6 and Table 9-9 for an offshore windfarm with an installed capacity of 250 MW.

The results of the MPE from Table G-3, Table G-6, and Table G-9 for an offshore windfarm with an installed capacity of 200 MW, are also shown in Table 9-16, together with those for a windfarm with an installed capacity of 150 MW, which were obtained from Table G-11, Table G-13 and Table G-15.

Table 9-16: Matrix of percentage error for energy transferred to the electricity grid from the windfarm, for various conditions of windfarm capacity and generation baseload.

				Windfarm Capacity	Regression Technique for the Energy Demand Model				Mean of Products of Mean Percentage Error
					MLR	ANN	DT	SVR	
Regression Technique for the MCP Methodology	MLR	Baseload	100MW	250MW	3.8	4.2	3.4	2.5	7.5
			100MW	200MW	2.1	2.5	1.5	1.9	
			100MW	150MW	4.6	6.3	6.7	5.7	
			125MW	250MW	7.5	8.1	3.5	4.4	
			125MW	200MW	5.0	5.0	5.0	5.0	
			125MW	150MW	5.5	8.8	8.8	7.5	
			150MW	250MW	18.2	17.2	5.1	9.7	
			150MW	200MW	14.0	13.9	3.5	8.2	
			150MW	150MW	10.8	18.6	15.6	14.5	
	ANN	Baseload	100MW	250MW	4.7	5.1	3.6	3.1	35.2
			100MW	200MW	2.9	3.5	2.1	2.6	
			100MW	150MW	74.7	102.0	108.2	93.3	
			125MW	250MW	8.6	9.2	4.0	5.1	
			125MW	200MW	6.1	6.1	6.1	6.1	
			125MW	150MW	64.2	101.7	102.3	87.4	
			150MW	250MW	12.2	18.4	5.4	10.3	
			150MW	200MW	15.7	15.6	4.0	9.2	
			150MW	150MW	66.4	114.0	95.6	89.4	
	DT	Baseload	100MW	250MW	2.9	3.2	1.9	1.9	6.0
			100MW	200MW	1.8	2.1	1.3	1.6	
			100MW	150MW	2.9	3.9	4.1	3.6	
			125MW	250MW	5.9	6.4	2.7	3.5	
			125MW	200MW	4.0	4.0	4.0	4.0	
			125MW	150MW	4.5	7.1	7.1	6.1	
			150MW	250MW	14.8	14.0	4.1	7.8	
			150MW	200MW	11.7	11.7	3.0	6.9	
			150MW	150MW	9.3	16.0	13.4	12.5	
	SVR	Baseload	100MW	250MW	3.0	3.3	2.0	2.0	6.0
			100MW	200MW	1.68	2.0	1.2	1.5	
			100MW	150MW	4.54	6.2	6.6	5.7	
			125MW	250MW	5.70	6.1	2.6	3.4	
			125MW	200MW	3.79	3.8	3.8	3.8	
			125MW	150MW	4.20	6.6	6.7	5.7	
			150MW	250MW	14.68	13.9	4.1	7.7	
			150MW	200MW	11.45	11.4	2.9	6.8	
			150MW	150MW	8.73	15.0	12.6	11.7	
			Mean of Products of Mean Percentage Error		12.4	16.6	13.0	12.7	

Table 9-17: Final iteration of a 4x4 matrix for the percentage error for the energy transferred from the windfarm to the energy grid.

		Regression Technique for the Energy Demand Model			
		MLR	ANN	DT	SVR
Regression Technique for the MCP Methodology	MLR	9.2	12.4	9.7	9.6
	ANN	16.4	18.0	12.5	10.8
	DT	7.8	7.7	7.8	7.7
	SVR	7.5	10.0	7.8	7.7

The results from Table 9-13, Table 9-15 and Table 9-17 showed the following:

The best combinations of regression techniques for MCP and EDF methodologies were combinations of the DT and SVR techniques. These combinations gave the lowest MPE product for all the measurement metrics under consideration.

- ANN should not be used as a regression technique for MCP nor EDF, due to the very large MPE product for combinations which involved the ANN regression technique.

- The MLR technique was also ruled out since it also exhibited large MPE errors for most of the metrics under consideration.
- The results from Chapter 8, determined that the best regression technique for the EDF methodology was the DT regression technique.
- Results from Section 7.2.5, also established that the DT regression technique presented the best results for the MCP methodology.
- When considering also the above results, it can be deduced that the optimal combination of regression techniques for MCP and EDF methodologies was one which used the DT regression for both the MCP and the EDF methodologies.

9.4 Results from the Optimal Combination of Regression Techniques

As mentioned in Section 9.1, results from the DT_DT combination are now compared to those from the measured wind speed and direction and the actual energy demand. Figure 9-6 shows the energy transferred to the electricity grid from the offshore windfarm for different generation baseloads. Figure 9-7 presents the energy discharged from the ESS to the electricity grid for various ESS capacities and generation baseloads. Figure 9-8 presents the variation of curtailed energy from the offshore windfarm for the various ESS capacities and generation baseloads. All results refer to predicted wind data and forecasted energy demand using the DT regression technique.

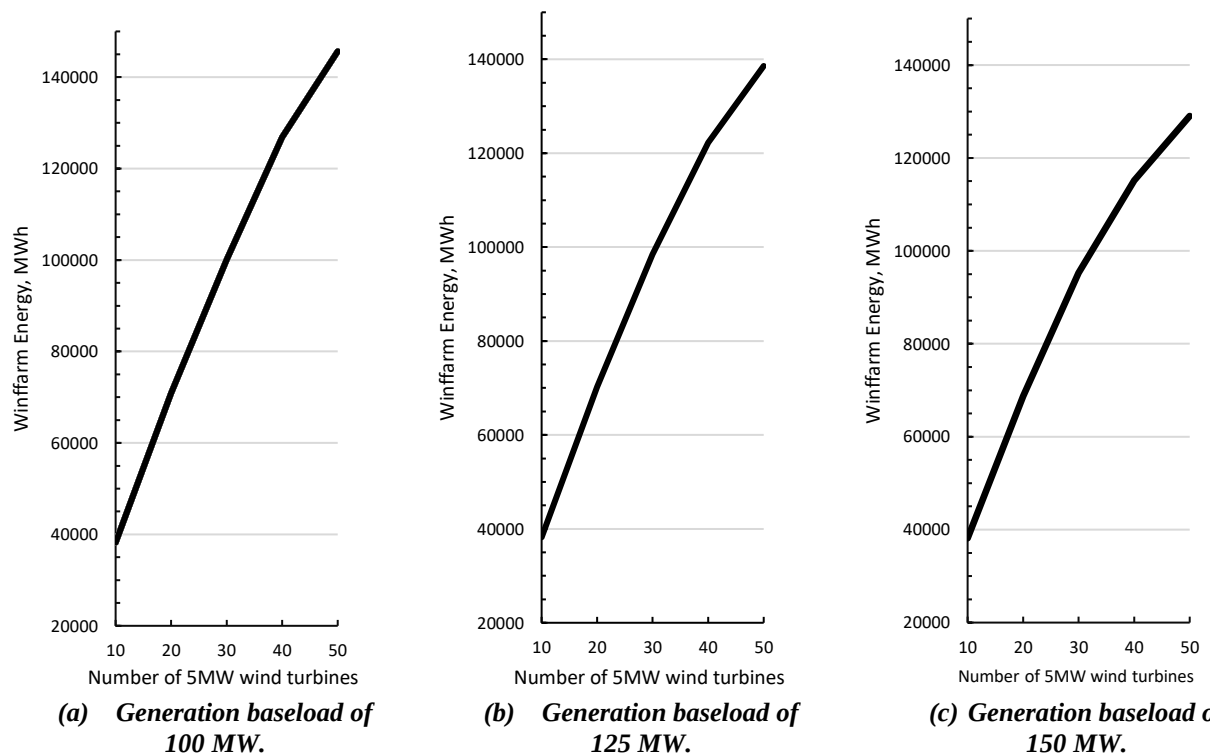


Figure 9-6: Variation of energy output from the offshore windfarm to the electricity grid with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.

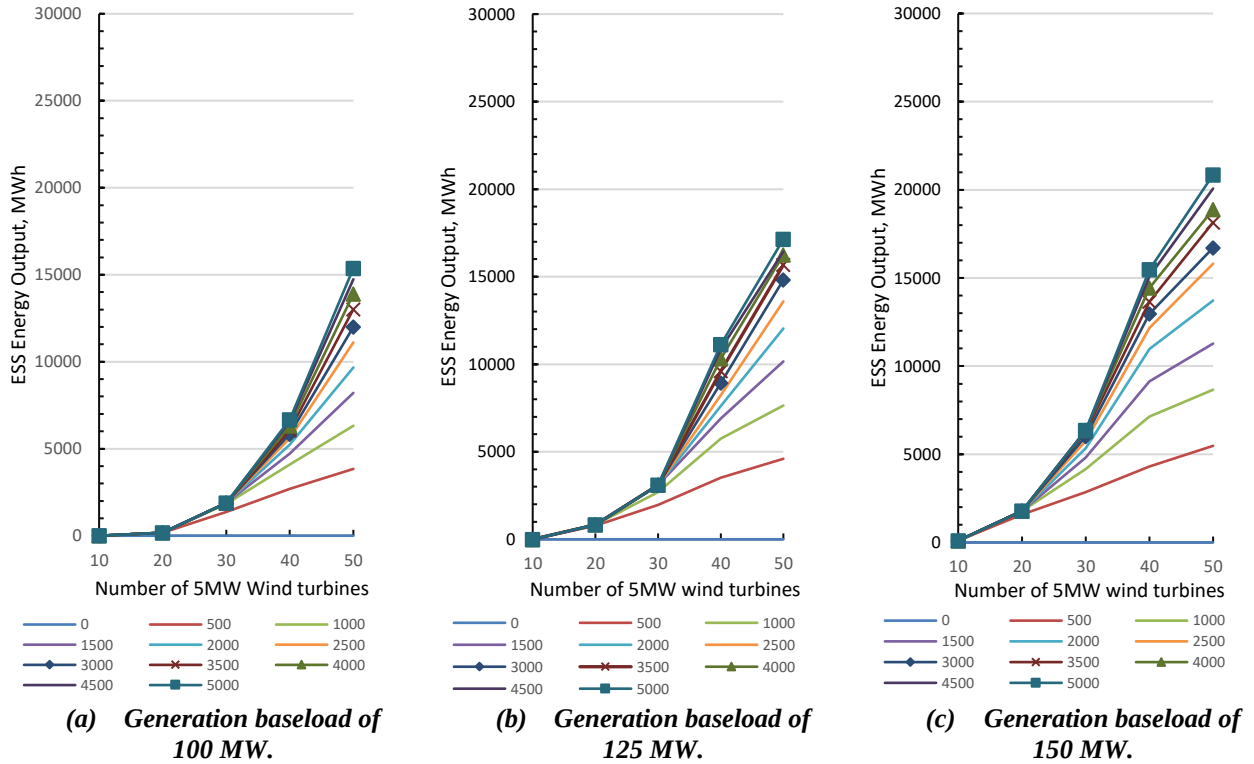


Figure 9-7: Variation of energy discharges from the ESS the electricity grid with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.

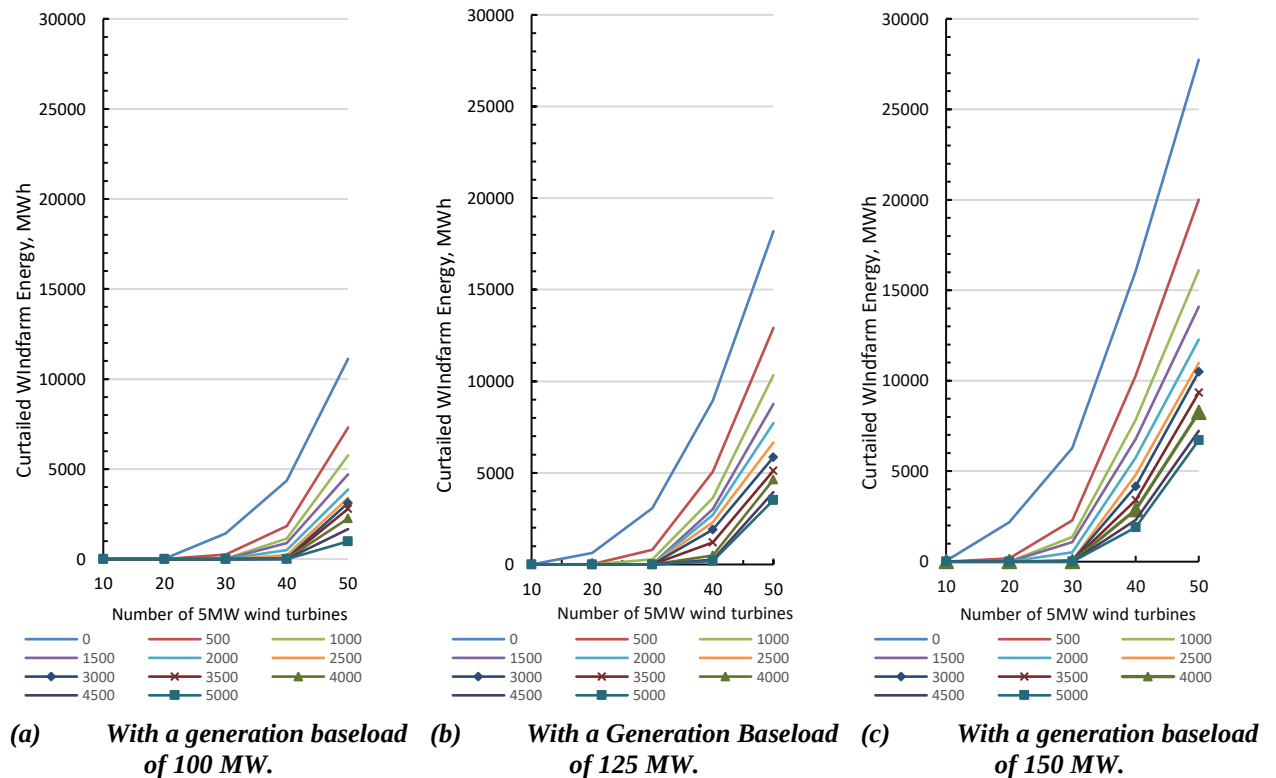
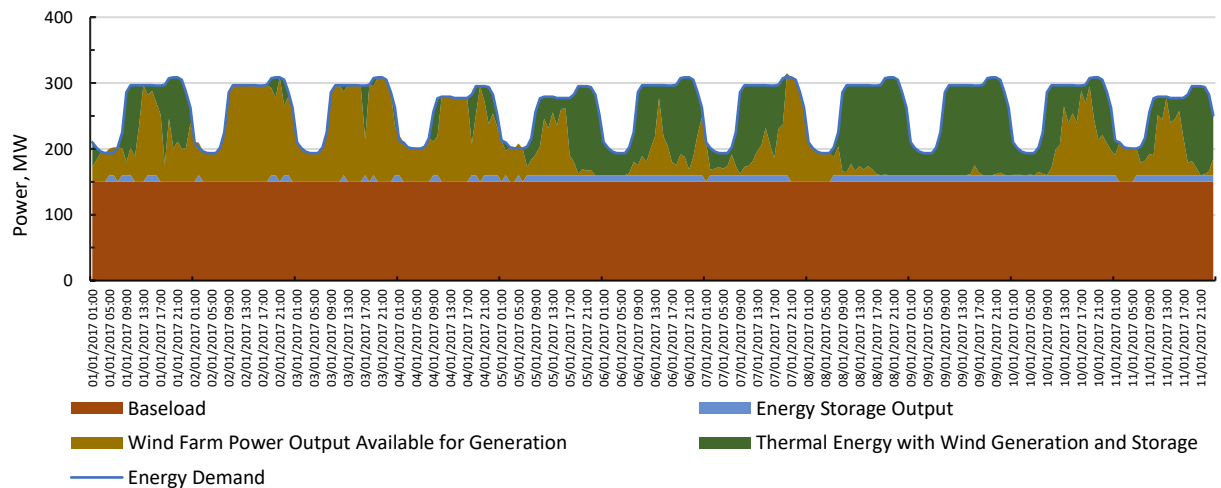


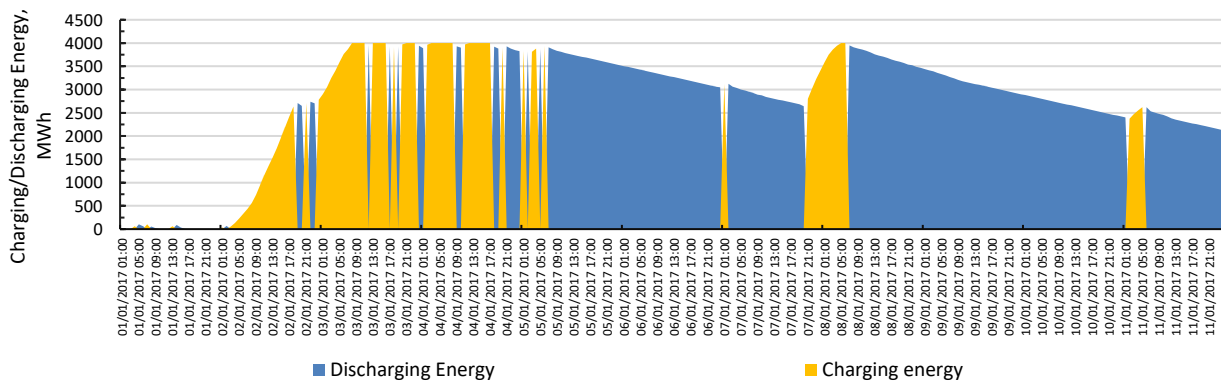
Figure 9-8: Variation of curtailed energy from the offshore windfarm with different generation baseloads, predicted using wind speed and direction and forecasted energy demand from a DT_DT combination of regression techniques.

As in the case of Section 9.1,

Figure 9-9 presents a time-series with predicted wind speed and direction and forecasted energy demand for the period 4 till 11 of January 2017. The predictions and forecasts utilised the DT regression technique. The discharge of power from the ESS to the electricity grid which occurred at a constant rate of 10 MW is shown in Figure 9-10. The windfarm capacity was set at 250 MW and the ESS capacity at 4000 MWh while the generation baseload was set at 150 MW. A time-series for the curtailed energy from the windfarm is shown in Figure 9-10.



(a) Output power from the windfarm, energy demand, thermal generation, and ESS output.



(a) Charging and discharging energy from the ESS.

Figure 9-9: Time-series of output power from the windfarm, energy demand, ESS output, and charging and discharging energy for the period 1 to the 11 of January 2017, from predicted wind speed and direction, and forecasted energy demand.

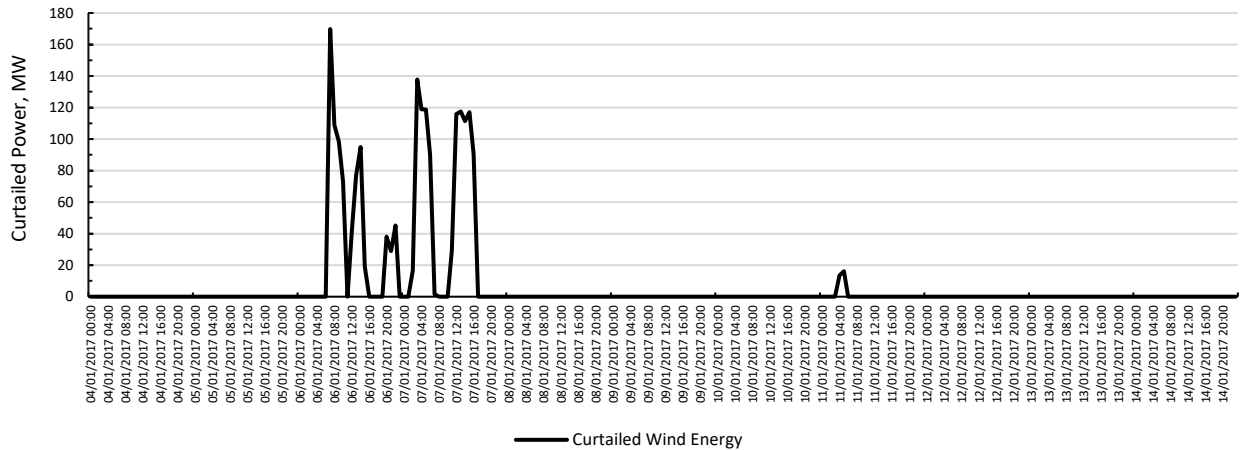


Figure 9-10: Time sequence of curtailed energy from the offshore windfarm from predicted wind speed and wind direction and forecasted energy demand for the period 4 till 11 of January 2017.

9.5 Conclusions from the Determination of the Optimum Combination of MCP and Energy Demand Forecasting Methodologies.

This analysis was conducted for an 80 m LiDAR measurement height and for the various capacities of windfarm, generation baseload and ESS storage capacities. The following conclusions could be drawn from the above analysis:

- The results presented in Table 9-13, Table 9-15 and Table 9-17 indicated that the best combinations of regression techniques for MCP and EDF were combinations of the DT regression and SVR techniques.
- The ANN and MLR techniques were ruled out as a regression technique for both the MCP and EDF methodologies, since they gave a large MPE product.
- Considering the results of Chapter 8, the DT regression technique provided the best results for EDF. This result was independent of the behaviour of the windfarm and the ESS. The matrix analysis carried out in Section 9.2 showed that the use of the DT regression technique was also adequate when used in the context of the windfarm and ESS combined with the electricity grid, although in this context, SVR performed slightly better.
- The results from Section 7.4 indicated that after considering the error in the energy yield obtained from a stand-alone hypothetical offshore windfarm, MLR was the best regression technique. This was followed by the ANN regression technique, while the DT and SVR techniques gave a larger error in energy yield. This result seemed to contradict the result obtained in Section 9.3, which determined that DT and SVR were the best regression techniques for MCP when it comes to combining the hypothetical offshore windfarm to the ESS and the electricity grid.
- The results from Section 7.2.5 also determined that, at an 80 m LiDAR measurement height, the DT regression technique was the best regression technique for the MCP methodology. Due to this, it was therefore safe to state that a DT_DT combination for MCP and EDF methodology

can be used to perform the analysis to determine the optimal ESS capacity and to determine the error in LCOE of the windfarm and LCOS of the ESS, as shown in Chapters 10 and 11.

- The investigation carried out in Section 9.3 where several tables showed the percentage error for various conditions of windfarm capacities, generation baseload and ESS capacities for the various combinations of regression techniques for the MCP and EDF methodologies presents an in-depth analysis of the percentage error variation under the various conditions.

The above results were then used to determine the optimum capacity of the ESS, when coupled to an offshore windfarm and to the electricity grid, as shall be presented in Chapter 10.

10 Results – Part 4 - Determining the Optimum ESS Capacity

This chapter presents the results from STEP 7, which was the determination of the optimal size of the ESS capacity, $C_{ESS_{OPT}}$, based on the optimal combination determined in STEP 6 (Chapter 9). As described in Section 2.6 and Section 4.7, the ESS stored energy from the offshore windfarm when there was a surplus of energy output from the RE source or when the energy demand was low. The energy stored in the ESS was discharged to the grid when the conditions described in Section 4.5 were met. As seen in Section 9.1, the ESS reduced the amount of energy curtailed from the windfarm as the extra energy was transferred to the ESS for later use.

The first aim of this chapter was to show how the size of the ESS was optimised according to the equations described in Section 4.7. A small sized ESS would not adequately increase the utilisation of the offshore windfarm, while an ESS which is too large would be underutilised. The optimal capacity of the ESS, $C_{ESS_{OPT}}$, was defined as the size beyond which the amount of curtailed energy, E_C , from the windfarm no longer decreased at an acceptable rate, and was no longer economically viable to increase the ESS capacity. It was also defined as the size beyond which there was no further increase in the energy, E_G discharged from the ESS to the grid.

The analysis presented in this chapter was carried out according to Eqs. (4-12) to (4-15) for curtailed energy, E_C from the offshore windfarm and Eqs. (4-16) to (4-19) for the energy discharged, E_G by the ESS to the grid. As described in Section 4.7, $C_{ESS_{OPT}}$ was estimated by fitting the relationship between E_C and C_{ESS} to a 3rd order polynomial and establishing the point, $C_{ESS_{OPT}}$ at which, $\frac{d^2 E_C}{d(C_{ESS})^2}$ was equal to zero.

The second aim of this chapter was to establish the error in $C_{ESS_{OPT}}$ due to the application of the MCP methodology to predict the wind behaviour at the candidate site and the use of EDF methodology to forecast the energy demand. This determined how the uncertainty introduced due to the optimal combination of regression techniques influenced the optimum size of the ESS. Determining $C_{ESS_{OPT}}$ enabled the LCOS of the ESS to be calculated.

The results shown are for the same windfarm conditions of Chapter 9 namely, an offshore windfarm with installed capacities of 250, 200 and 150 MW and a generation baseload set at 100, 125 and 150 MW. Wind data from the LiDAR measurement for a height of 80 m, at the candidate site during the year 2017 were used, as shown in Section 5.2.4. The wind behaviour predicted by the MCP methodology described Section 4.2.2 and presented in Section 7.4.1, utilised a DT regression technique. Energy demand was that measured for the year 2017 and that forecasted with the DT regression technique as described in Section 4.4.3 and presented in Section 8.2. The charts which

follow show the results with a variation of an ESS power rating in the range from 10 MW to 50 MW, which is incremented in steps of 10 MW. ESS capacity varies in the range of 0 (i.e., no ESS) to 5000 MWh in 500 MWh increments.

The ranges chosen to calculate the optimal size of the ESS were the same as those used to calculate the optimal combination of regression techniques for MCP and EDF methodologies. The ranges of ESS capacity and power rating depended on the maximum value of the energy demand for the Island of Malta. This has a peak value of around 500 MW [189]. The maximum availability of the wind resource, which occurs during the winter months, did not coincide with the maximum energy demand, which occurred during the summer period. In this research, it was also assumed that the generation baseload always had a constant value throughout the whole year. The presence of the offshore windfarm and the ESS also allowed for a reduction of the generation baseload. The reduction of the baseload permitted a greater use of the energy from the windfarm, and this was coupled with a reduction in the utilisation of the ESS as shown in Section 9.1.

The error in the optimal size of the ESS capacity was calculated by comparing results for optimal capacity obtained with measured wind speed and direction and actual energy demand for the year 2017, to those for the wind speed and direction predicted with the MCP methodology using DT regression technique and EDF using the DT regression technique for the year 2017. All charts were generated using the Matlab® and Simulink® model described in Section 6.2.

10.1 The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 250 MW

The optimal ESS capacity at an offshore windfarm with an installed capacity of 250 MW was estimated using the curtailed energy from the windfarm as given by Eqs. (4-12) to (4-15).

10.1.1 Using Optimal MCP and Energy Demand Methodology Combination (DT_DT).

The following results are for predicted wind speed and direction (MCP) and forecasted energy demand for the year 2017. Figure 10-1 shows the variation of the curtailed energy with generation baseload, ESS capacity and ESS power rating.

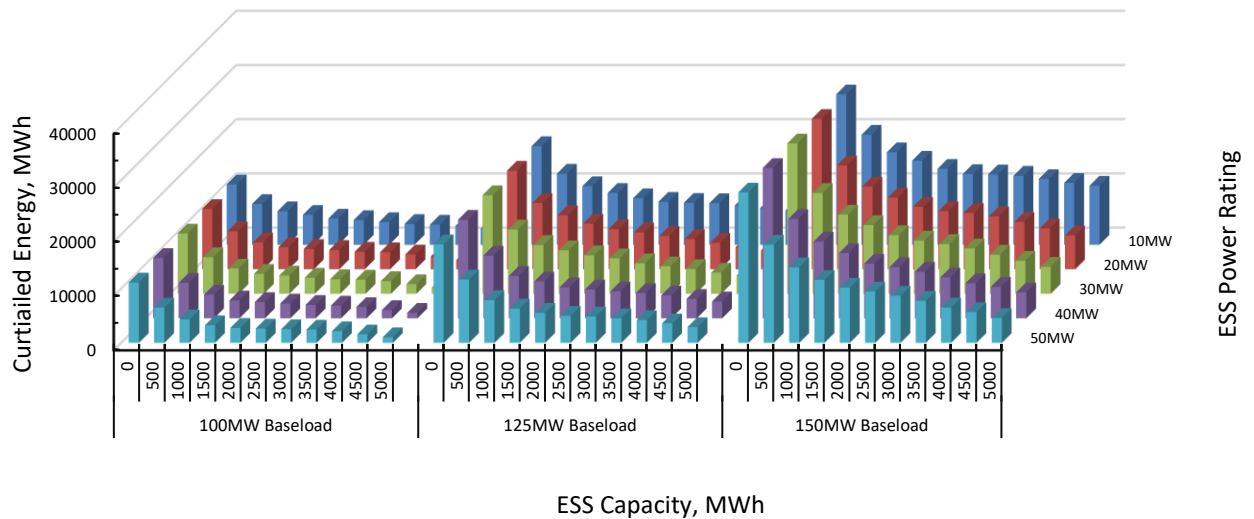


Figure 10-1: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 250 MW with predicted wind speed and direction and forecasted energy demand.

100 MW Generation Baseload

Table 10-1, Table 10-2, Figure 10-2 and Figure 10-3 present the results for an electricity grid with a generation baseload of 100 MW. Table 10-1 and Figure 10-2 show the relationship between the curtailed energy and the ESS capacity for different ESS power ratings. Table 10-2 presents the coefficients, a , b , c , and d of the fitted 3rd order polynomials as described by Eq. (4-12), while Figure 10-3 shows the plots for the 2nd order polynomials of the differentiated fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-1: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW capacity and a generation baseload of 100 MW, for ESS power ratings form 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	11,124	7,527	6,187	5,509	4,824	4,538	4,171	3,833	3,695	3,415	2,964
20	11,124	6,995	4,954	4,086	3,746	3,563	3,234	3,147	2,734	2,343	1,706
30	11,124	6,761	4,659	3,683	3,376	2,971	2,695	2,613	2,345	1,779	1,126
40	11,124	6,544	4,362	3,303	3,007	2,735	2,482	2,347	2,086	1,526	1,005
50	11,124	6,499	4,342	3,250	2,766	2,642	2,523	2,439	2,148	1,556	1,036

Table 10-2: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficients			
	a	b	c	d
10	-22.838	509.8	-3869.3	14063
20	-34.379	734.14	-5164.3	15160
30	-35.933	770.16	-5445.9	15399
40	-37.691	810.43	-5710.3	15591
50	-39.363	843.83	-5889.2	15772

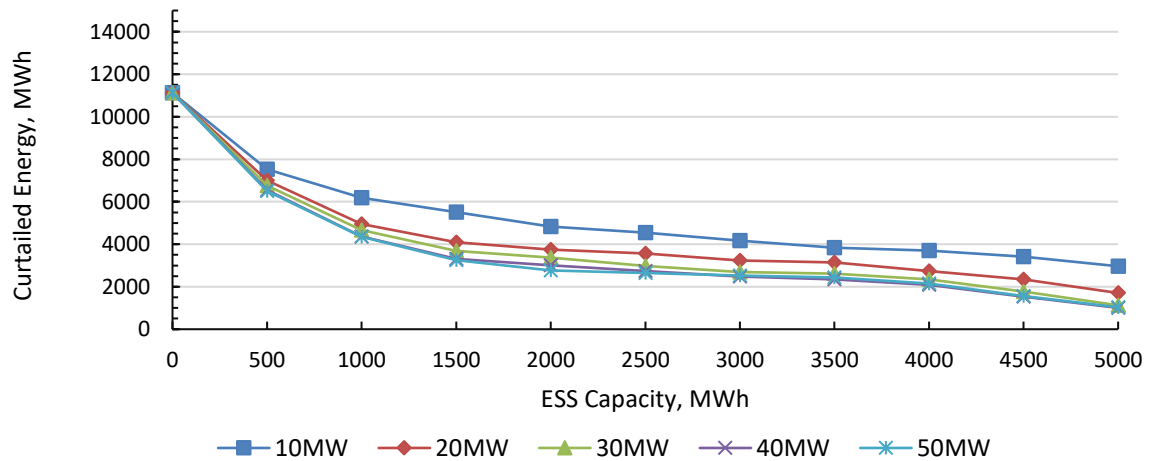


Figure 10-2: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

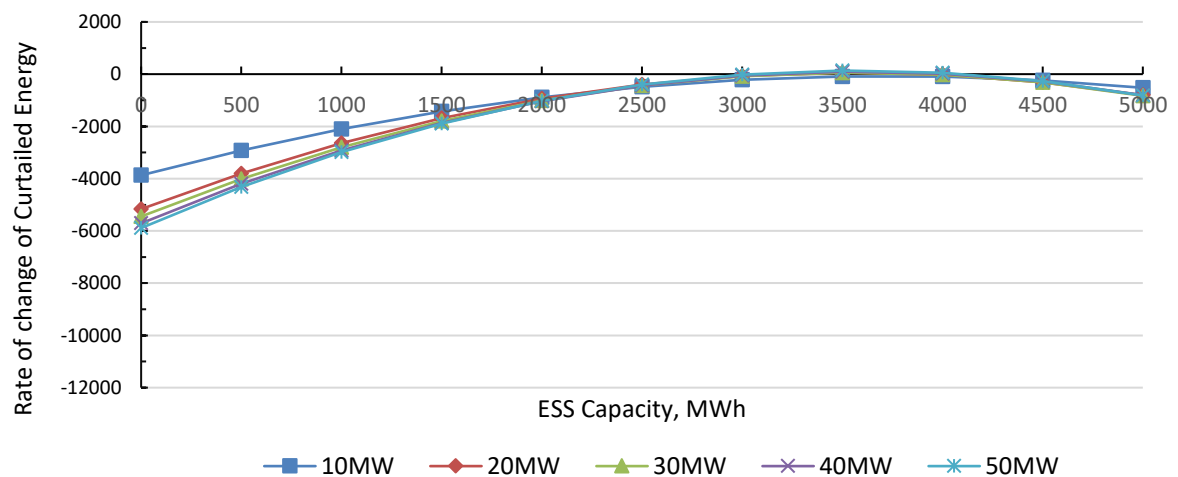


Figure 10-3: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

125 MW Generation Baseload

Table 10-3, Table 10-4, Figure 10-4 and Figure 10-5 represent the results for an electricity grid with a generation baseload of 125 MW. An increase in the levels of curtailed energy was noted when comparing with the same conditions for offshore windfarm capacity and ESS capacity. The increase in generation baseload restricted the transfer of energy from the windfarm to the electricity grid, hence although there was more energy available to charge the ESS, more energy was curtailed. Figure 10-4 represents the relationship between the curtailed energy and the ESS capacity for different ESS power ratings. Table 10-4 presents the coefficients, a , b , c , and d of the fitted 3rd order polynomials as described by Eq. (4-12) while Figure 10-5 shows the plots of the differentiated 2nd order polynomials of the fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-3: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	18,189	13,110	10,804	9,568	8,585	7,911	7,724	7,666	7,232	6,751	6,312
20	18,189	12,235	9,975	8,417	7,398	6,802	6,154	5,596	4,886	4,079	3,456
30	18,189	11,857	8,998	8,018	7,087	6,546	5,622	5,060	4,573	3,907	3,363
40	18,189	11,563	7,823	6,814	5,717	5,314	4,968	4,681	4,222	3,595	3,123
50	18,189	11,685	7,882	6,329	5,531	4,976	4,867	4,544	4,200	3,595	2,907

Table 10-4: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-35.693	804.89	-6079.4	23027
20	-38.618	850.86	-6519.8	23198
30	-41.022	908.53	-6892.5	23373
40	-51.551	1138.1	-8289.8	24713
50	-54.105	1192.4	-8629.6	25146

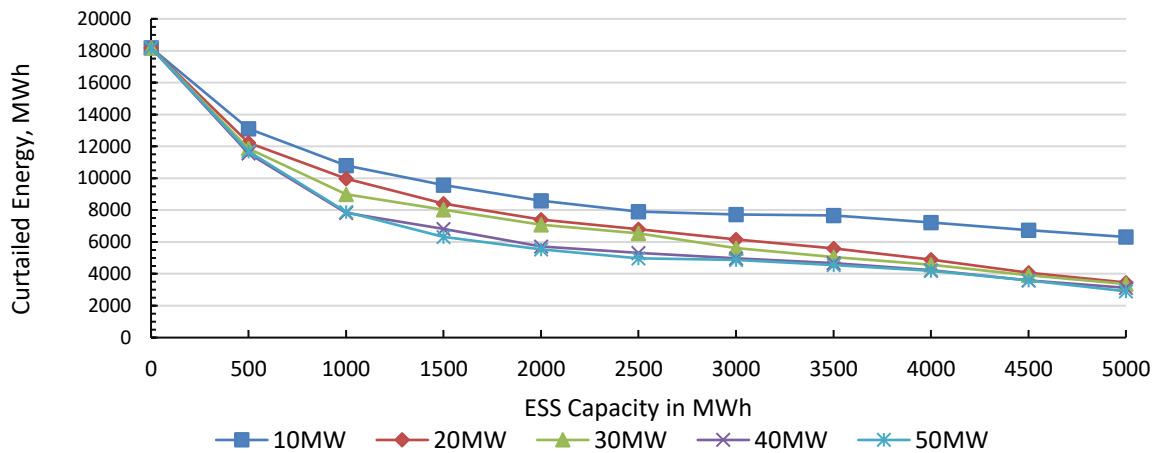


Figure 10-4: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

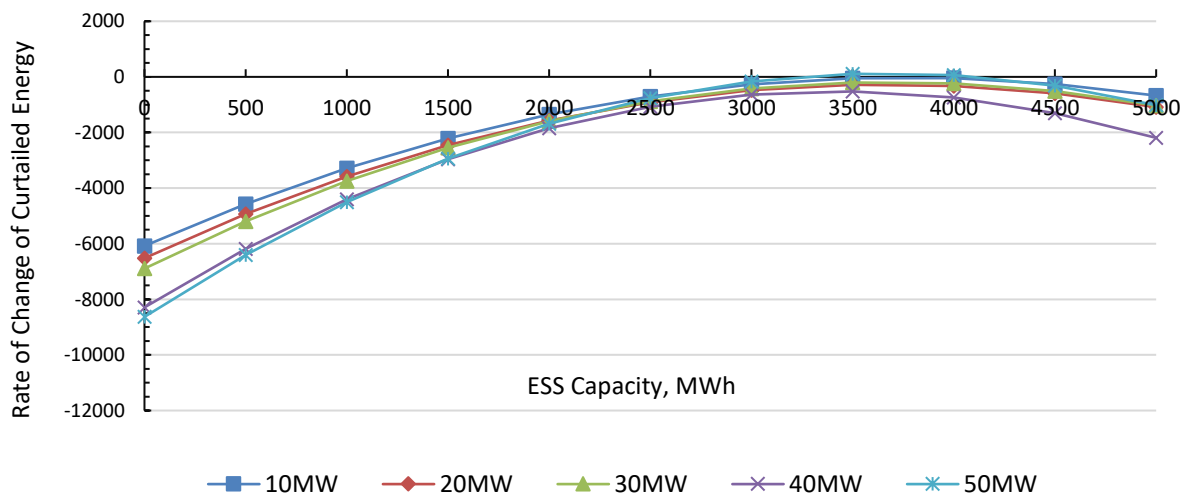


Figure 10-5: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

150 MW Generation Baseload

Table 10-5, Table 10-6, Figure 10-6 and Figure 10-7 represent the results for an electricity grid with a generation baseload of 150 MW. A further increase in the levels of curtailed energy was again observed when comparing the results in this section. Table 10-5 and Figure 10-6 show the relationship between the curtailed energy and ESS capacity for different ESS power ratings. Table 10-6 presents the coefficients, a , b , c , and d of the fitted 3rd order polynomials as described by Eq. (4-12) while Figure 10-7 shows the plots of the differentiated 2nd order polynomials of the fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-5: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

	Curtailed Energy in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	27,740	20,298	17,059	15,519	14,011	13,049	12,970	12,728	12,122	11,415	10,895
20	27,740	19,166	15,265	13,216	11,523	10,716	10,400	9,754	8,721	7,532	6,240
30	27,740	18,616	14,614	12,685	10,817	9,824	9,178	8,370	7,220	6,100	4,988
40	27,740	18,312	14,150	12,030	10,077	9,434	8,603	7,521	6,471	5,803	4,786
50	27,740	18,111	13,949	11,625	10,187	9,458	8,696	7,762	6,519	5,662	4,595

Table 10-6: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a 150 MW generation baseload for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-51.408	1155.9	-8687.3	34567
20	-62.24	1411.6	-10384	35958
30	-62.66	1376	-10414	35831
40	-62.21	1390.5	-10622	36005
50	-67.3	1475.2	-11027	36256

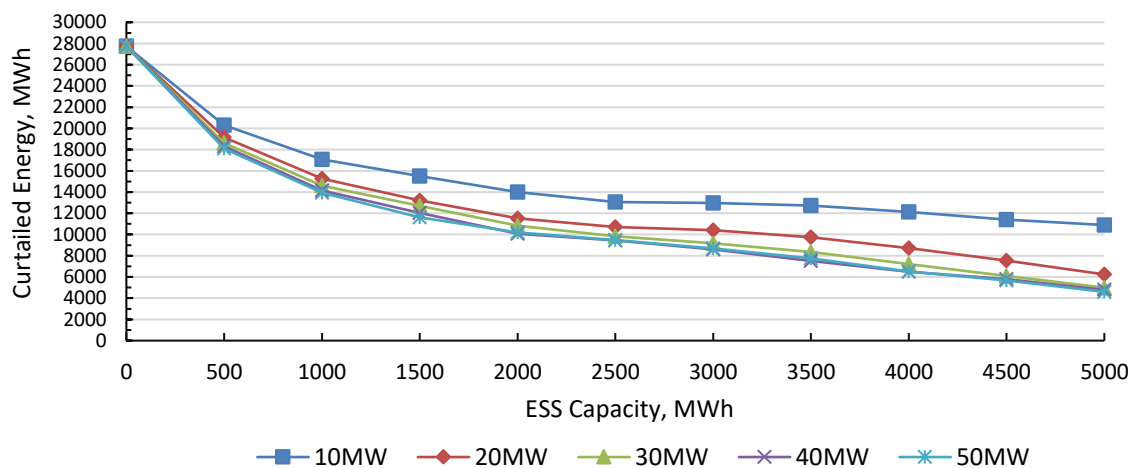


Figure 10-6: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW, with a generation baseload of 150 MW for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

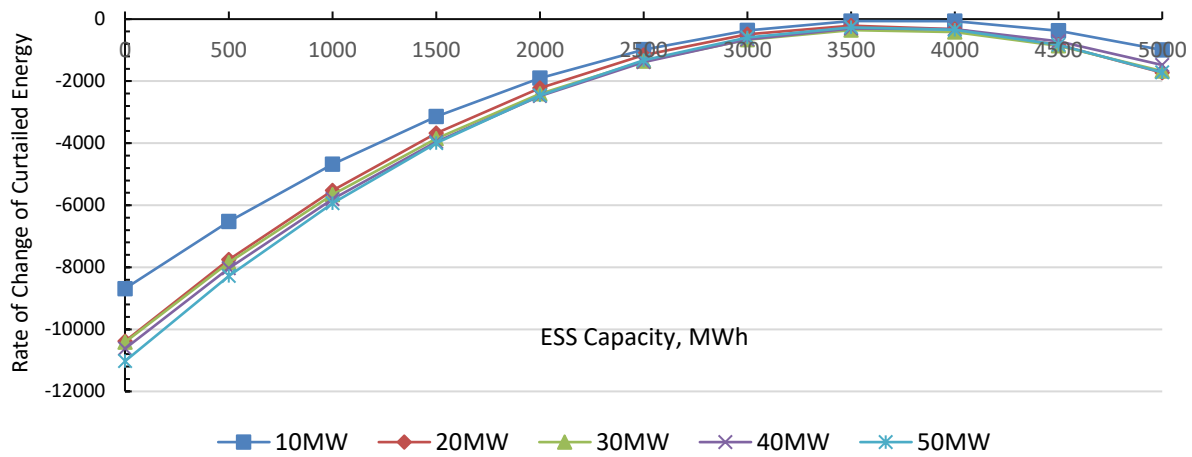


Figure 10-7: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

10.1.2 Using Measured Wind Speed and Direction and Energy Demand

The results presented here are those for measured wind speed and direction and energy demand for an offshore windfarm with an installed capacity of 250 MW. As mentioned previously, the wind speed and direction were those measured for the year 2017 at the candidate site and at a LiDAR measurement height of 80 m. The energy demand was that measured for the year 2017. Generation baseloads of 100, 125 and 150 MW were used to obtain the result. Figure 10-8 shows the variation of curtailed energy from the offshore windfarm baseload, ESS capacity and power rating.

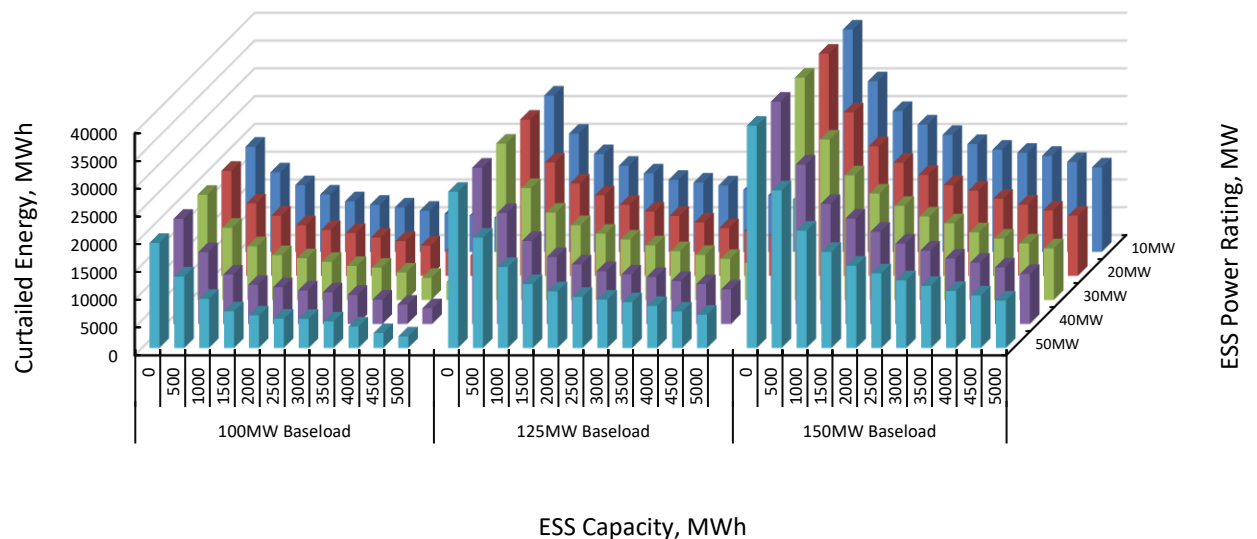


Figure 10-8: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 250 MW, with measured wind speed and direction and energy demand.

100 MW Generation Baseload

Table 10-7, Table 10-8, Figure 10-9 and Figure 10-10, show the results for an electricity grid with a generation baseload of 100 MW. Table 10-7 and Figure 10-9 show the relationship between the curtailed energy and the ESS capacity. Table 10-8 shows the coefficients, a , b , c , and d for the fitted

3rd order polynomials as described by Eq. (4-12), while Figure 10-10 shows the plots of the differentiated 2nd order polynomials of the fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-7: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	18,923	14,309	11,997	10,304	9,102	8,470	7,977	7,398	6,843	6,512	6,149
20	18,923	13,042	10,812	9,117	8,247	7,709	6,893	6,254	5,433	4,501	3,646
30	18,923	12,976	9,650	8,058	7,509	6,863	6,124	5,794	4,939	3,971	3,187
40	18,923	12,918	8,898	7,058	6,603	6,013	5,705	5,248	4,371	3,471	2,813
50	18,923	12,883	8,849	6,595	5,853	5,283	5,242	4,785	3,849	2,684	2,080

Table 10-8: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-27.28	651.4	-5452.5	23371
20	-39.62	855.2	-6495.3	23916
30	-47.19	1017.6	-7499.7	24857
40	-52.99	1147.8	-8347.1	25727
50	-55.15	1196.4	-8730.3	26189

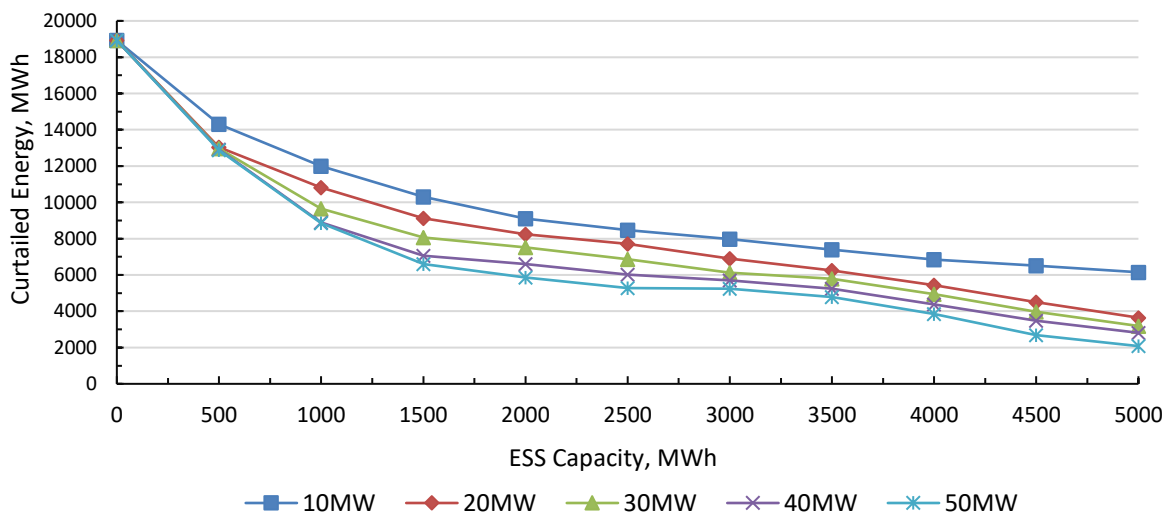


Figure 10-9: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

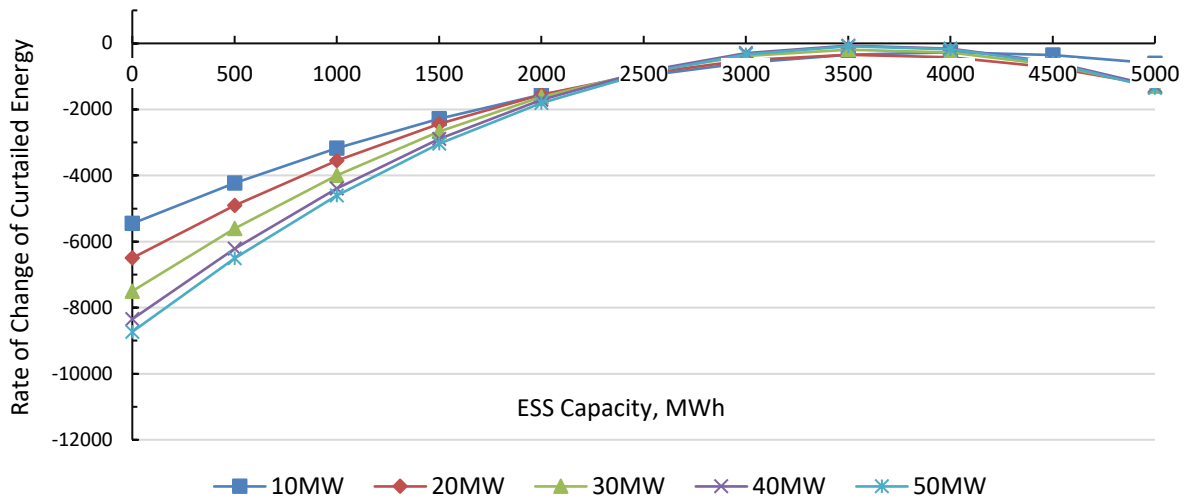


Figure 10-10: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

125 MW Generation Baseload

Table 10-9, Table 10-10, Figure 10-11 and Figure 10-12 present the results for an electricity grid with a generation baseload of 125 MW. Table 10-9 and Figure 10-11 show the relationship between the curtailed energy and the ESS capacity. Figure 10-12 shows the 2nd order differentiated polynomials for the fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-9: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	28,124	21,270	17,579	15,497	14,108	12,959	12,467	11,948	11,157	10,142	9,464
20	28,124	20,405	16,599	14,498	12,777	11,575	10,768	9,610	8,588	8,029	7,245
30	28,124	20,133	15,703	13,451	11,910	10,877	9,807	8,773	8,102	7,386	6,624
40	28,124	19,973	14,937	12,043	10,705	9,507	8,916	8,433	7,736	7,160	6,218
50	28,124	19,866	14,581	11,519	10,190	9,213	8,699	8,248	7,588	6,565	5,978

Table 10-10: Coefficients for fitted 3rd order polynomials for curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Generation Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-48.00	1085.7	-8496.7	35022
20	-45.72	1060.2	-8696.4	34989
30	-51.33	1186.2	-9528.8	35774
40	-60.92	1401.2	-10885	37157
50	-65.00	1481.5	-11355	37590

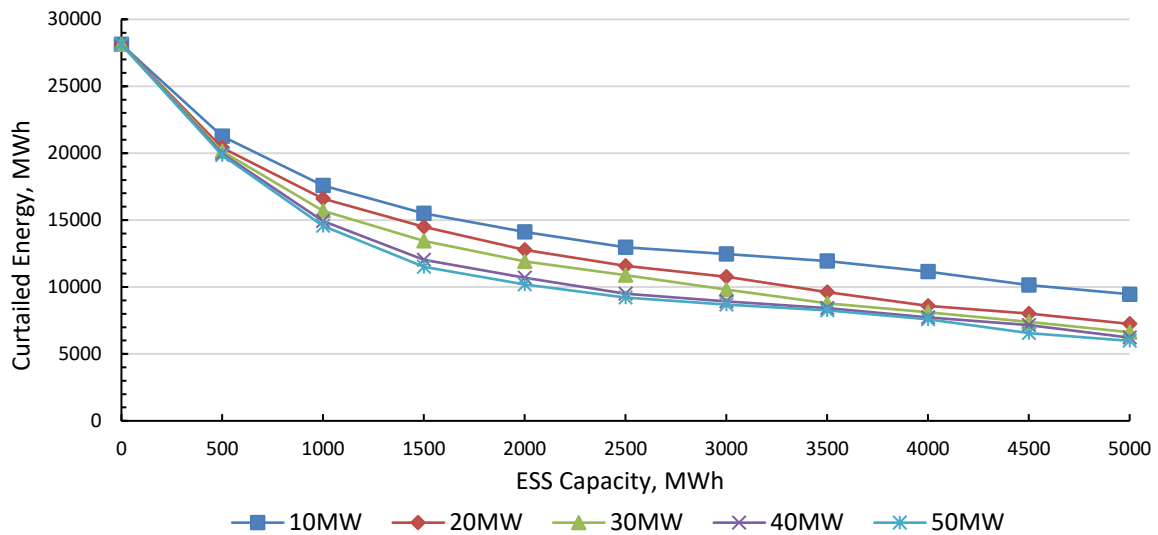


Figure 10-11: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

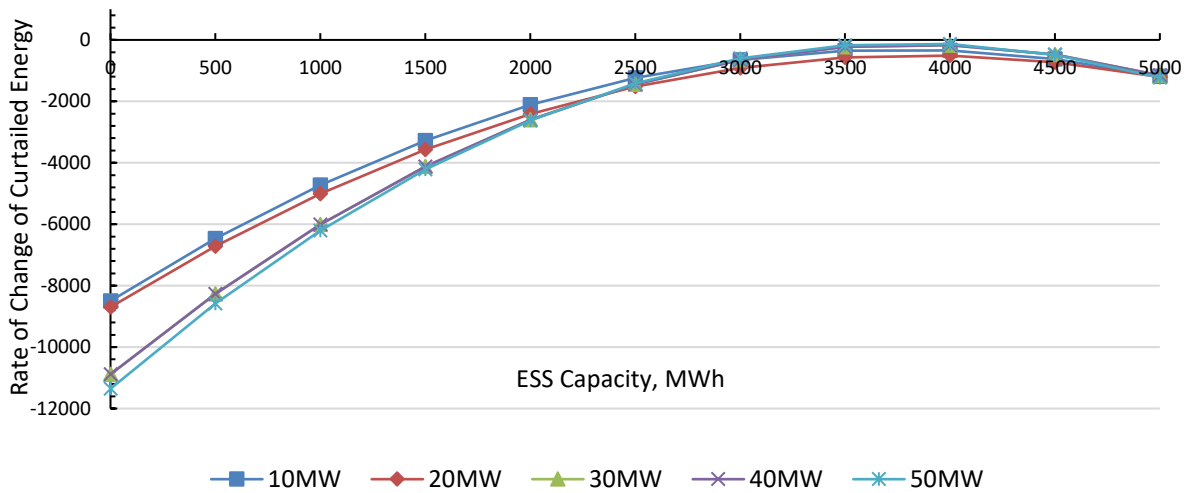


Figure 10-12: Rate of change of curtailed energy with ESS capacity, for a 250 MW offshore windfarm with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

150 MW Generation Baseload

Table 10-11, Table 10-13, Figure 10-13 and Figure 10-14 present the results for an electricity grid with a generation baseload of 150 MW. Table 10-11 and Figure 10-13 show the relationship between the curtailed energy and the ESS capacity. Figure 10-14 shows the 2nd order differentiated polynomials for the fitted 3rd order polynomials, according to Eq. (4-13).

Table 10-11: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	40,419	30,698	25,347	22,924	21,033	19,412	18,389	17,831	17,278	16,190	15,191
20	40,419	29,417	23,324	20,370	18,170	16,314	15,324	13,888	12,836	11,770	10,832
30	40,419	28,851	22,421	19,141	16,947	15,012	13,791	12,161	11,041	10,161	9,285
40	40,419	28,684	21,606	18,974	16,607	14,462	13,194	11,791	11,023	10,170	8,996
50	40,419	28,374	21,113	17,296	14,811	13,437	12,179	11,190	10,271	9,462	8,542

Table 10-12: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Generation Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-65.68	1507.9	-11843	49952
20	-70.33	1626.7	-13090	50892
30	-71.25	1669.0	-13625	51305
40	-74.94	1750.1	-14126	51739
50	-82.94	1938.0	-15389	53041

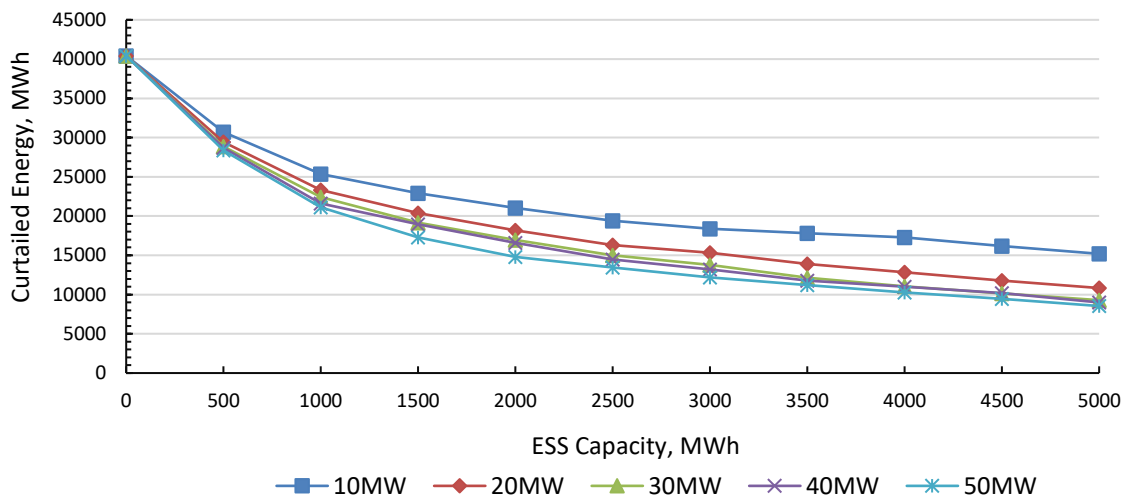


Figure 10-13: Curtailed energy from an offshore wind farm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW for measured wind speed and direction, and energy demand.

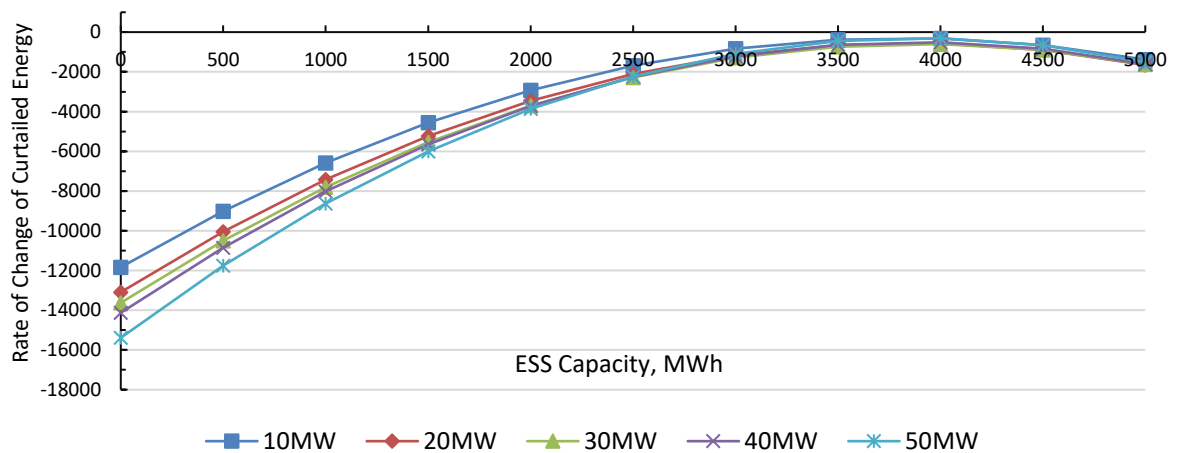


Figure 10-14: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

The results obtained from offshore windfarms with an installed capacity of 200 MW and 150 MW are now discussed. The results for the curtailed energy from these offshore windfarms are summarised in Sections 10.2 and 10.3, with the complete results being shown in Appendix H. Results for these conditions were similar to those obtained for an offshore windfarm of 250 MW generation capacity.

10.2 The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 200 MW

The behaviour for an offshore windfarm with an installed capacity of 200 MW was then analysed. Results included those from the optimal combination of regression techniques for MCP and EDF methodologies, which were compared to those from measured wind speed and direction and energy demand. As shown in Figure 9-3 and Figure 9-8, a reduction in the level of curtailed energy was expected, since the windfarm had a lower installed capacity.

10.2.1 Using the Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodology (DT_DT).

The results for predicted wind speed and direction and forecasted energy demand for the *DT_DT* combination for the regression techniques applied to the MCP and EDF methodologies are now presented. The results which follow are for predicted wind speed and direction and forecasted energy demand for the year 2017, for an offshore windfarm with an installed capacity of 200 MW and generation baseloads of 100, 125 and 150 MW respectively. There were instances when the curtailed energy was zero, especially in cases of large ESS capacities and a lower generation baseload. Figure 10-15 shows the relationship between curtailed energy, generation baseload, ESS capacity and ESS power rating.

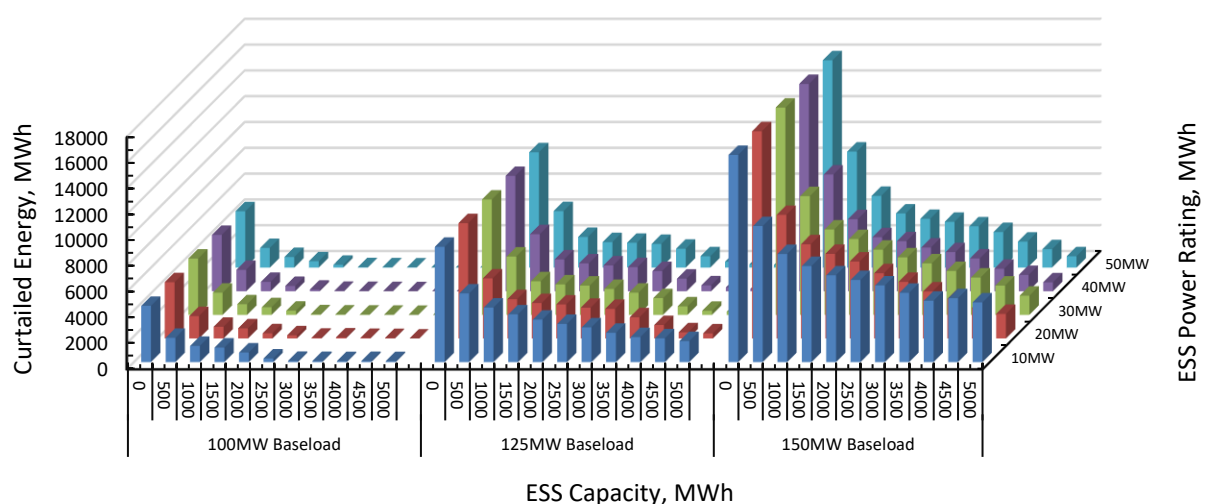


Figure 10-15: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity 200 MW with predicted wind speed and direction and forecasted energy demand.

The results shown in Figure 10-15 were tabulated in Table 10-13, Table 10-15 and

Table 10-17. These tables present the amount of curtailed energy from an offshore windfarm with a generation capacity of 200 MW for generation baseloads of 100, 125 and 150 MW respectively. The results were those obtained for an ESS with rated power in the range of 10 to 50 MW, in steps of 10 MW. A 3rd order polynomial was then fitted to the results [given by Eq. (4-12)], with the respective coefficients a , b , c and d being shown in Table 10-14, Table 10-16 and Table 10-18. Detailed results may be seen in Appendix H, in Figure H-1 to Figure H-6.

Table 10-13: Curtailed energy variation with ESS capacity for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	4,364	1,883	1,258	1,131	747	280	94	87	77	89	82
20	4,364	1,734	909	785	404	251	65	84	48	37	0
30	4,364	1,716	821	591	323	44	24	17	7	0	0
40	4,364	1,655	725	407	119	27	21	10	3	0	0
50	4,364	1,521	821	489	217	31	24	14	3	0	0

Table 10-14: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a 100 MW generation baseload, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-11.38	274.18	-2175.6	5865.3
20	-15.716	356.53	-2600.7	6216.5
30	-16.57	377.17	-2737.7	6357.0
40	-18.38	413.07	-2931.6	6531.4
50	-17.51	394.81	-2821.0	6380.2

Table 10-15: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	8,937	5,323	4,233	3,705	3,295	2,965	2,695	2,273	1,940	1,851	1,633
20	8,937	4,655	3,049	2,746	2,634	2,384	2,297	1,643	1,043	483	398
30	8,937	4,518	2,605	2,364	2,268	2,007	1,722	1,295	661	317	247
40	8,937	4,422	2,466	2,155	2,001	1,868	1,564	973	455	296	171
50	8,937	4,376	2,374	1,971	1,921	1,831	1,462	876	455	256	199

Table 10-16: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a 125 MW generation baseload, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-20.69	461.02	-3481.4	11408
20	-30.47	632.69	-4376.4	11974
30	-31.17	660.82	-4633.6	12197
40	-31.22	669.66	-4737.7	12284
50	-31.78	684.07	-4834.7	12366

Table 10-17: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	16,061	10,544	8,384	7,448	6,729	6,366	5,947	5,377	4,760	4,955	4,628
20	16,061	9,578	7,305	6,561	5,963	5,056	4,392	3,647	3,082	2,362	1,904
30	16,061	9,199	6,618	5,874	5,054	4,454	3,990	3,398	2,890	2,270	1,487
40	16,061	9,045	5,583	4,190	3,875	3,384	3,028	2,539	1,741	1,260	689
50	16,061	8,989	5,554	4,192	3,773	3,548	3,196	2,752	2,008	1,421	877

Table 10-18: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW capacity and a 150 MW generation baseload, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-33.25	756.39	-5760.6	20318
20	-38.76	844.18	-6342.8	20565
30	-46.98	1009.9	-7279.7	21399
40	-54.41	1176.9	-8401.8	22494
50	-56.51	1214.3	-8555.9	22618

10.2.2 Using Measured Wind Speed and Direction and Energy Demand

The results presented next are those with measured wind speed and direction and energy demand for an offshore windfarm with an installed capacity of 200 MW. The wind speed and direction were those measured at the candidate site at a LiDAR measurement height of 80 m, and the measured energy demand for the year 2017. Generation baseloads of 100, 125 and 150 MW were assumed. Figure 10-16 presents the relationship between curtailed energy, generation baseload, ESS capacity and ESS rated power.

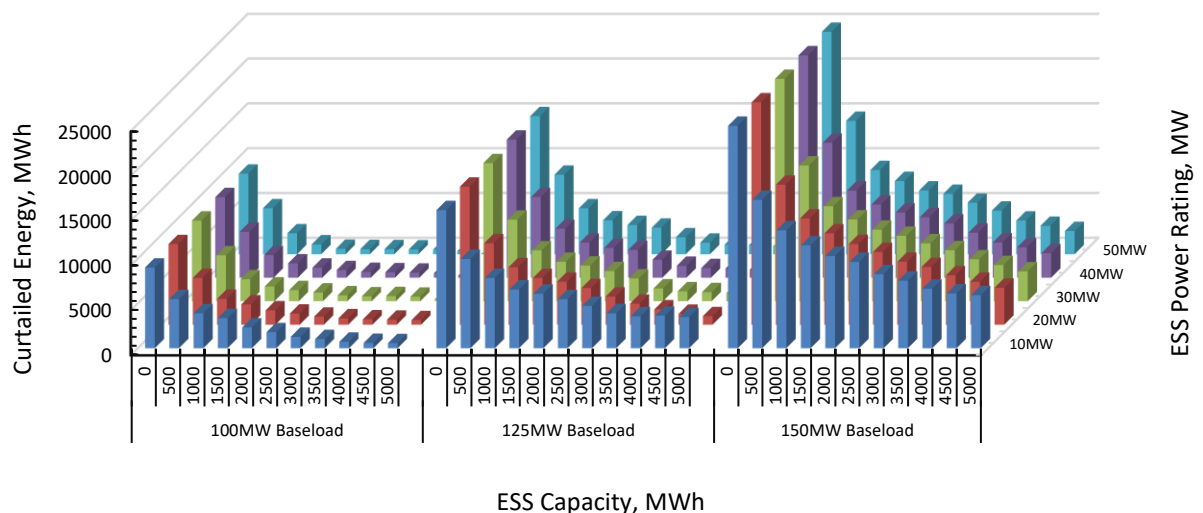


Figure 10-16: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for a 200 MW offshore windfarm with measured wind speed and direction, and energy demand.

The results shown in Figure 10-16 were tabulated as shown in Table 10-19, Table 10-21 and Table 10-23. These show the curtailed energy for an offshore windfarm with an installed capacity of 200 MW for generation baseloads of 100, 125 and 150 MW respectively. The results are those

achieved for an ESS rated power in the range of 10 MW to 50 MW in steps of 10 MW. The results were then fitted into a 3rd order polynomial as given by Eq. (4-12), with the respective coefficients a , b , c and d being shown in Table 10-20, Table 10-22 and Table 10-24. More results may be seen in Appendix H, in Figure H-7 to Figure H-12.

Table 10-19: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	8,991	5,479	3,894	3,360	2,319	1,779	1,267	1,017	722	593	564
20	8,991	5,212	2,886	2,257	1,610	1,245	897	712	592	552	500
30	8,991	5,123	2,450	1,646	1,236	963	656	546	571	500	236
40	8,991	5,120	2,522	1,601	1,119	841	639	597	564	500	236
50	8,991	5,120	2,333	1,088	603	565	555	529	500	343	56

Table 10-20: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-16.54	412.79	-3572.8	11722
20	-25.41	597.95	-4631.7	12660
30	-31.11	710.70	-5257.4	13255
40	-31.48	720.04	-5322.3	13344
50	-36.04	811.71	-5847.5	13897

Table 10-21: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	15,403	9,960	7,842	6,549	6,086	5,479	4,719	3,898	3,562	3,634	3,475
20	15,403	9,089	6,411	5,211	4,798	4,087	3,139	2,348	1,713	1,220	951
30	15,403	9,089	5,666	4,398	3,971	3,354	2,536	1,423	1,102	1,013	909
40	15,403	9,010	5,457	3,915	3,313	3,098	1,997	1,334	1,070	1,013	909
50	15,403	8,872	5,123	3,785	3,252	2,960	1,893	1,281	1,070	9,85	875

Table 10-22: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	a	b	c	d
10	-28.28	670.61	-5439.2	19405
20	-37.66	842.69	-6512.8	20170
30	-38.35	890.16	-7001.6	20691
40	-41.28	962.22	-7481.6	21204
50	-43.27	1001.20	-7686.9	21337

Table 10-23: Curtailed energy variation with ESS capacity and power rating for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	24,814	16,556	13,155	11,474	10,300	9,630	8,251	7,534	6,642	6,112	5,920
20	24,814	15,619	11,850	10,198	9,000	8,119	7,026	6,441	5,516	4,790	4,122
30	24,814	15,152	10,589	9,114	7,973	7,294	6,453	5,679	4,677	4,027	3,325
40	24,814	15,066	9,726	8,161	7,282	6,749	6,047	5,026	3,935	3,389	2,742
50	24,814	14,881	9,391	8,163	7,105	6,737	5,739	4,865	3,756	3,166	2,583

Table 10-24: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
10	-46.92	1077.5	-8534.6	31165
20	-58.74	1306.5	-9882.6	32227
30	-67.51	1483.7	-10930	33075
40	-72.91	1596.5	-11641	33723
50	-73.37	1606.1	-11706	33701

10.3 The Curtailed Energy from an Offshore Windfarm with an Installed Capacity of 150 MW

Finally, the behaviour for an offshore windfarm with an installed capacity of 150 MW was analysed. Results included those from the optimal combination of regression techniques for MCP and EDF methodologies which, in a similar fashion to the above, were compared to those from measured wind speed and direction, and energy demand. As shown in Figure 9-3 and Figure 9-8, a further reduction in curtailed energy was expected since the offshore windfarm had a lesser installed capacity. Curtailed energy from the windfarm become significant with a larger generation baseload. The results from the predicted wind speed and direction and forecasted energy demand for the (DT_DT) combination are therefore presented next.

10.3.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)

The results which follow are for predicted wind speed and direction and forecasted energy demand, for the year 2017, for generation baseloads of 100, 125 and 150 MW respectively. There were several instances when the curtailed energy was zero, especially for increasing ESS capacities. Figure 10-17 shows the relationship between the curtailed energy, the generation baseload, the ESS capacity and power rating. The results shown in Figure 10-17 were tabulated in Table 10-25, Table 10-26 and Table 10-27.

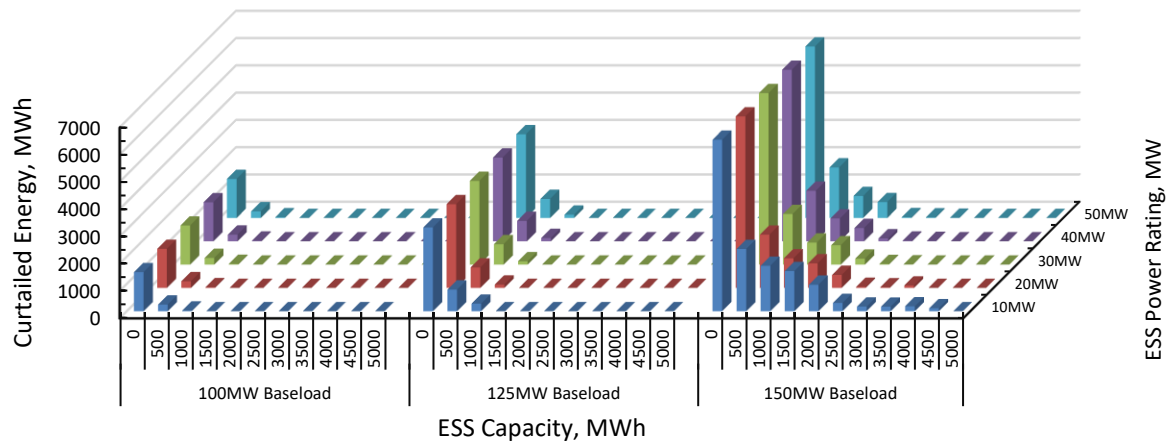


Figure 10-17: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150 MW, for predicted wind speed and direction and forecasted energy demand.

Table 10-25: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	1,431.29	244.87	24.80	0	0	0	0	0	0	0	0
20	1,431.29	244.87	24.80	0	0	0	0	0	0	0	0
30	1,431.29	244.87	24.80	0	0	0	0	0	0	0	0
40	1,431.29	244.87	24.80	0	0	0	0	0	0	0	0
50	1,431.29	244.87	24.80	0	0	0	0	0	0	0	0

Table 10-26: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Energy in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	3,069.73	793.89	276.80	0	0	0	0	0	0	0	0
20	3,069.73	749.82	122.30	0	0	0	0	0	0	0	0
30	3,069.73	748.08	122.30	0	0	0	0	0	0	0	0
40	3,069.73	748.08	122.30	0	0	0	0	0	0	0	0
50	3,069.73	698.28	122.30	0	0	0	0	0	0	0	0

Table 10-27: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	6,286.5	2,281.4	1,665.0	1,470.7	970.7	303.8	171.0	166.7	181.5	110.9	0.0
20	6,286.5	1,952.1	1,084.7	902.1	478.5	39.6	22.1	88.9	0.0	0.0	0.0
30	6,286.5	1,854.2	807.8	708.8	218.4	22.7	6.5	0.0	0.0	0.0	0.0
40	6,286.5	1,853.9	837.5	486.9	107.7	23.9	10.4	0.0	0.0	0.0	0.0
50	6,286.5	1,853.9	807.5	582.8	30.6	20.5	6.5	0.0	0.0	0.0	0.0

Table 10-28: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Generation Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
10	-11.38	274.18	-2175.6	5865.3

For an offshore windfarm with an installed capacity of 150 MW capacity and a generation baseload of 100 MW, the amount of curtailed energy was drastically reduced, as can be observed in Table 10-25. At all values of ESS power rating, the amount of curtailed energy was zero for ESS capacities of 1000 MWh or greater. With these conditions it was not viable to have an ESS with a capacity larger than 1000 MWh.

The results shown in Table 10-26 are those for an offshore windfarm with an installed capacity of 150 MW coupled to an ESS and an electricity grid which has a generation baseload of 125 MW. The results showed that the amount of curtailed energy was zero for values of ESS capacity which was greater or equal to 1000 MWh. This value of ESS capacity was therefore considered to be the optimal ESS capacity for these conditions. Hence, for the above two scenarios, it was not necessary to apply Eqs. (4-12) to (4-15) to obtain the optimum ESS capacity, as the curtailed energy was zero in most of the combinations of ESS capacity and power rating.

The results shown in Table 10-27 are those obtained for a 150 MW offshore windfarm with an installed capacity of 150 MW, coupled to an ESS and an electricity grid with a generation baseload of 150 MW. The results again showed that the amount of curtailed energy was zero for values of ESS capacity which was greater or equal to 3500 MWh and for ESS power ratings which were greater or equal to 20 MW. The curtailed energy was also equal to zero for capacities greater than 3000 MWh and for ESS power ratings which were equal or greater than 30 MW.

It was observed, from Table 10-27, that a 3rd order polynomial could be fitted to the curtailed energy from the offshore wind farm, coupled to an ESS with a power rating of 10 MW, and hence a 2nd order polynomial could be derived by differentiating the 3rd order polynomial, according to Eq. (4-13). The coefficients for this polynomial are presented in Table 10-28. More results may be seen in Appendix H in Figure H-18 to Figure H-22.

10.3.2 Using Measured Wind Speed and Direction and Energy Demand

The results which follow are for measured wind speed and direction and energy demand for an offshore windfarm with an installed capacity of 150 MW. Figure 10-18 shows the relationship between the curtailed energy, the generation baseload, the ESS capacity and the ESS power rating. The results shown in Figure 10-18 were tabulated in Table 10-29, Table 10-30 and Table 10-31.

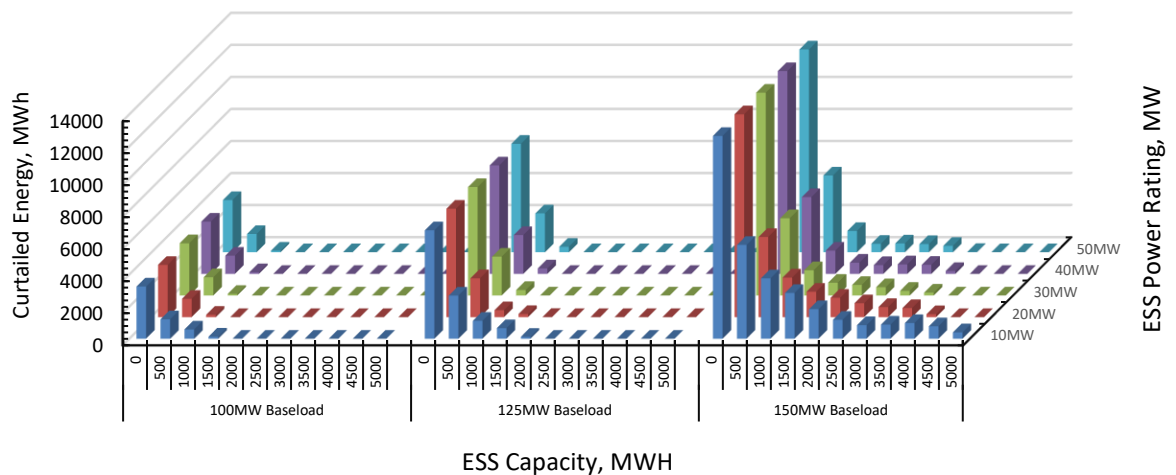


Figure 10-18: Curtailed energy variation with baseload, ESS capacity and ESS power rating, for an offshore windfarm with a capacity of 150 MW, for predicted wind speed and direction and forecasted energy demand.

Table 10-29: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	3,258.8	1,208.4	578.3	130.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	3,258.8	1,144.1	146.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30	3,258.8	1,136.6	99.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
40	3,258.8	1,136.6	99.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
50	3,258.8	1,136.6	99.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 10-30: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	6,768.0	2,689.9	1,119.5	657.6	119.0	0.0	0.0	0.0	0.0	0.0	0.0
20	6,768.0	2,423.4	430.3	190.8	8.1	0.0	0.0	0.0	0.0	0.0	0.0
30	6,768.0	2,423.4	341.6	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0
40	6,768.0	2,423.4	341.6	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0
50	6,768.0	2,423.4	341.6	0.00	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 10-31: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Curtailed Wind Farm Power Output in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	12,656.4	5,856.3	3,767.6	2,859.9	1,845.1	1,184.7	848.6	883.2	982.0	779.2	399.7
20	12,656.4	4,997.6	2,468.7	1,585.1	1,205.5	865.1	628.7	565.0	180.8	0.0	0.0
30	12,656.4	4,822.2	1,575.7	792.7	657.4	517.6	289.3	180.8	0.0	0.0	0.0
40	12,656.4	4,790.2	1,450.4	697.5	548.3	593.3	565.0	180.8	0.0	0.0	0.0
50	12,656.4	4,790.3	1,326.6	524.1	548.3	508.3	398.0	18.5	0.0	0.0	0.0

Table 10-32: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 150 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
10	-42.06	958.01	-7067.4	17907
20	-52.03	1145.3	-8041.3	18455

The amount of curtailed energy for an electricity grid with a generation baseload of 100 MW, is shown in Table 10-29. For an ESS with a power rating of 10 MW, the amount of curtailed energy was zero for an ESS capacity which was greater than 1500 MWh. Hence, this was the optimal ESS capacity at these conditions. For ESS power ratings equal to or greater than 20 MW, the amount of curtailed energy was zero for ESS capacities of 1000 MWh or greater, therefore this was the optimal ESS capacity at these particular conditions.

The results shown in Table 10-30 are those for an electricity grid with a generation baseload of 125 MW. The results showed that the amount of curtailed energy was zero for values of ESS capacity which was greater than 2000 MWh for an ESS power rating of 10 MW, greater than 1500 MWh for an ESS rating of 20 MWh, and greater than 1000 MWh for ESS power ratings of 30 MW or more. These ESS capacities were therefore considered to be the optimal ESS capacity at these conditions.

The results shown in Table 10-31 are for a generation baseload of 150 MW. These results showed that the amount of curtailed energy was zero for values of ESS capacity which was greater or equal to 4000 MWh, for an ESS power rating less than 30 MW and equal to 3500 MWh for an ESS power rating of 30 MW or more. In this case, a 3rd order polynomial could be fitted to the curtailed energy for an ESS power rating of 10 MW and 20 MW, and thus a 2nd order polynomial could be derived according to Eq. (4-13). The coefficients of the 3rd order polynomial are presented in Table 10-32. More results may be seen in Appendix H in Figure H-13 to Figure H-17.

As described in Section 4.6, a further criterion which was used to establish the optimal ESS capacity was the amount of energy discharged by the ESS to the grid. The results for an offshore windfarm with an installed capacity of 250 MW are shown below, while further results for offshore windfarms with installed capacities of 200 MW and 150 MW installed capacities are shown in Appendix I. This approach produced results which were similar to those derived using the above methodology which was used for curtailed energy from the offshore windfarm. A summary of the results is presented in Section 10.4.

10.4 Using the Energy Discharged to the Electricity Grid from the ESS.

In this case, due to the similarity of the methodology to the results presented in Sections 10.1 to 10.3, more detailed results concerning the discharge of energy from the ESS to the electricity grid are shown Appendix I. As in the previous analysis, results for offshore windfarms with installed

capacities of 250, 200 and 150 MW, together with generation base loads of 100, 125 and 150 MW were analysed. Again, the ESS capacity was in the range of 0 (i.e., no ESS) to 5000 MWh, in steps of 500 MWh, and the ESS power rating was in the range of 10 to 50 MW, varied in steps of 10 MW.

As in the previous cases, results which were obtained by using the optimal combination of regression techniques for MCP and energy demand forecasting, as seen in Chapter 9, and the results obtained by using the measured values of wind speed and direction and energy demand are compared. The result of the comparison is shown in Section 10.5. As presented previously, the measured wind speed and direction were those measured at the candidate site at a LiDAR measurement height of 80 m, and the measured energy demand, for the year 2017.

10.4.1 Windfarm with an Installed Capacity of 250 MW

The results for energy discharged from the ESS to the electricity grid which was coupled to an offshore windfarm having an installed capacity of 250 MW, are now presented. The results below are for predicted wind speed and direction (MCP) and forecasted energy demand.

Using the Optimal Combination of Regression Techniques for the MCP and Energy Demand Forecast Methodology (DT_DT)

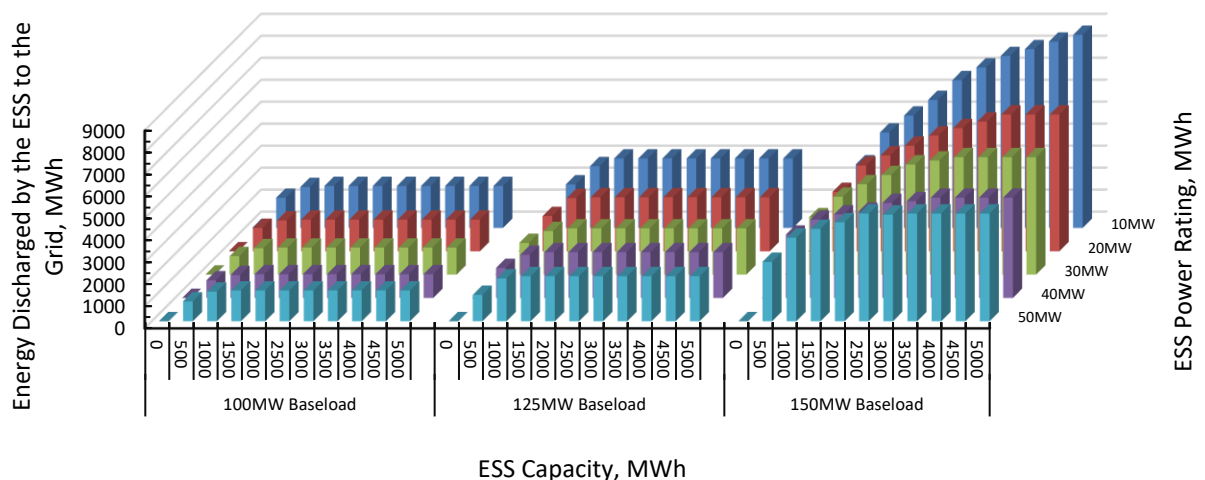


Figure 10-19: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for a 250 MW offshore windfarm with predicted (MCP) wind speed and forecasted energy demand.

Figure 10-19 shows the variation of energy discharged by the ESS to the electricity grid with baseload, ESS capacity and ESS power rating. The results shown in Figure 10-19 are presented in Table 10-33, Table 10-35 and Table 10-37, while Table 10-34, Table 10-36 and Table 10-38 show the coefficients *e*, *f*, *g* and *h* for the 3rd order polynomial which were fitted to the relationship between energy discharged from the ESS to the grid and the ESS capacity for various ESS power ratings. Further results are shown in Appendix I in Figure I-1 to Figure I-6.

Table 10-33: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	3,880	6,510	8,590	1,0470	12,390	13,600	14,840	15,710	16,460	17,180
20	0	3,420	6,720	8,920	9,880	10,720	11,480	12,220	12,920	13,840	14,700
30	0	3,210	6,000	7,530	8,430	8,970	9,480	10,440	11,070	11,730	12,600
40	0	2,800	5,400	7,280	7,720	8,440	9,080	9,800	9,880	10,760	11,360
50	0	3,350	5,650	7,200	7,950	8,650	9,100	9,650	10,200	10,550	10,950

Table 10-34: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a 100 MW generation baseload, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 250 MW Generation Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	9.71	-318.69	4235.1	3717.4
20	27.93	-644.76	5514.3	-4957.9
30	25.97	-580.73	4784.7	-4146.8
40	22.821	-529.18	4465.6	-3986.1
50	21.90	-251.56	4442.1	-3765.1

Table 10-35: Energy discharged by the ESS into the electricity grid for an offshore windfarm of with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	4,660	7,970	10,660	12,670	14,230	15,310	16,250	17,440	18,950	20,110
20	0	4,140	7,140	9,360	11,420	13,180	14,300	15,520	16,340	17,160	18,000
30	0	3,840	7,110	8,940	10,890	11,880	12,600	13,800	14,700	15,360	16,200
40	0	3,960	7,080	8,920	10,880	11,960	12,640	13,560	14,200	15,200	15,720
50	0	3,750	6,200	8,450	10,150	10,950	11,500	12,050	12,700	13,350	13,800

Table 10-36: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 150 MW and a 125 MW generation baseload, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 250 MW Generation Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	27.91	-662.88	6260.9	-5557.7
20	15.05	-462.03	4971.7	-4411.5
30	22.18	-551.05	5288.6	-4682.7
40	22.56	-565.45	5364.7	-4738.2
50	21.70	-549.83	5099.7	-4543.9

Table 10-37: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	5,550	8,700	11,360	14,060	16,210	17,030	18,340	19,520	21,340	22,280
20	0	4,980	8,300	10,840	12,700	14,480	15,800	16,900	18,160	20,060	20,920
30	0	4,560	7,590	9,570	11,850	13,290	13,950	15,210	16,350	17,250	18,360
40	0	4,440	7,920	10,160	11,760	13,160	13,920	15,120	15,840	16,600	17,520
50	0	4,100	7,500	9,950	11,200	12,400	13,150	13,950	15,100	15,550	16,250

Table 10-38: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 250 MW Generation Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	25.93	-644.86	6511.9	-5641.8
20	26.69	-632.19	6134.8	-5285.8
30	23.86	-582.66	5647.1	-4893.6
40	26.04	-642.61	5999.2	-5254.6
50	25.70	-634.5	5833.7	-5160.6

Using Measured Wind Speed and Direction, and Energy Demand

The results that follow were those obtained for measured wind speed and direction energy demand. Figure 10-20 shows the variation of energy discharged by the ESS to the electricity grid with baseload, ESS capacity and ESS power rating for an offshore windfarm capacity with an installed capacity of 250 MW.

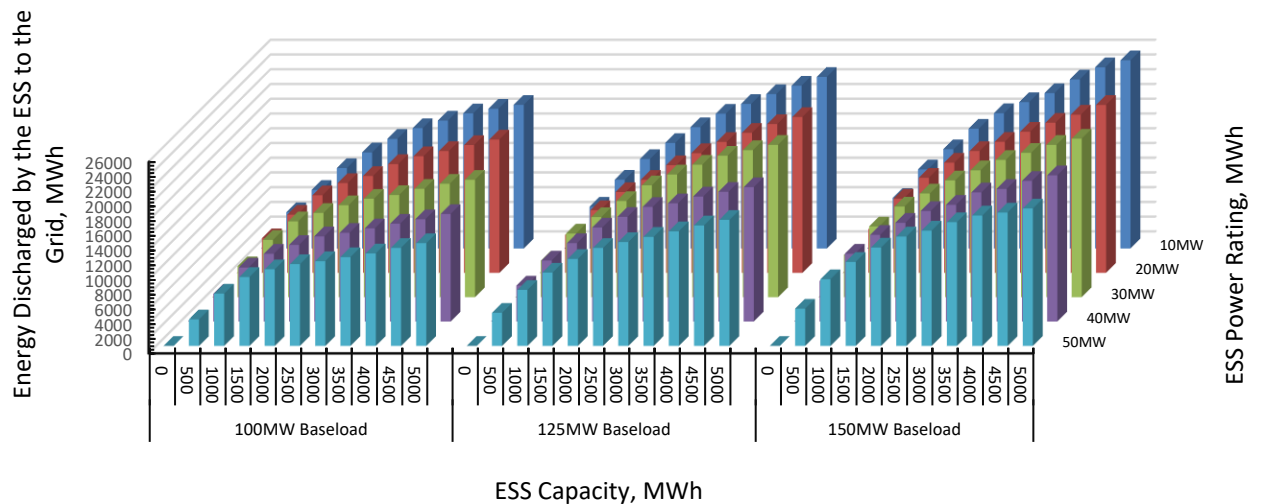


Figure 10-20: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm of with an installed capacity of 250MW, with measured wind speed and forecasted energy demand.

The results presented in Figure 10-20 are presented in Table 10-39, Table 10-41 and Table 10-43, while Table 10-40, Table 10-42 and Table 10-44 present the coefficients *e*, *f*, *g* and *h* for the 3rd order polynomials which have been fitted to the relationships between energy discharged from the ESS to the grid and the ESS capacity for the various ESS power ratings, according to Eq. (4-16). Further results are also given in Appendix I in Figure I-7 to Figure I-12.

Table 10-39: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	4,910	7,950	10,910	13,030	14,870	16,320	17,350	18,320	18,950	19,480
20	0	4,700	7,880	10,520	12,180	13,140	14,760	15,820	16,520	17,340	18,080
30	0	4,200	7,770	10,290	11,430	12,480	13,350	13,860	14,700	15,390	15,930
40	0	3,760	7,320	9,200	10,400	11,560	12,040	12,640	13,280	13,880	14,600
50	0	3,600	7,100	9,350	10,400	11,100	11,500	12,050	12,550	13,300	13,950

Table 10-40: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 250 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	15.12	-474.17	5613.7	-4940.9
20	23.01	-592.35	5850.4	-5062.7
30	29.03	-707.03	6238.1	-5535.9
40	27.99	-672.03	5815.1	-5180.6
50	31.64	-739.16	6083.7	-5495.5

Table 10-41: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	5,660	9,330	12,130	14,310	16,450	18,280	19,610	20,950	22,080	23,270
20	0	5,140	8,500	10,960	12,620	14,600	16,240	17,760	19,000	20,180	21,140
30	0	4,920	8,640	10,860	13,050	15,180	16,650	17,970	19,200	19,950	20,670
40	0	4,880	8,280	10,640	12,760	14,200	15,560	16,040	16,960	17,600	18,240
50	0	4,500	7,600	9,950	11,800	13,300	14,100	14,800	15,550	16,350	17,100

Table 10-42: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 250 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	22.56	-596.74	6462.2	-5537.3
20	20.57	-529.35	5715.5	-4802.4
30	16.25	-479.79	5649.0	-4887.7
40	22.63	-609.88	6123.2	-5360.6
50	23.94	-612.94	5877.5	-5182.6

Table 10-43: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 150 MW for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	6850	10730	13460	16240	18350	19850	21070	22930	24580	25530
20	0	5900	10060	12900	14940	16520	17780	19140	20360	21460	22780
30	0	5730	9600	12300	14070	15840	17220	18630	19590	20670	21510
40	0	5480	9200	11760	13400	15000	15840	17520	18000	19080	19840
50	0	5050	9050	11400	13350	14850	15650	16800	17700	18100	18650

Table 10-44: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm of with an installed capacity of 250 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for measured wind speed and direction and energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 250 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	32.16	-785.86	7693.9	-6422.3
20	34.99	-835.62	7646.4	-6585.3
30	28.39	-713.64	6928.4	-5883.2
40	29.79	-735.62	6843.1	-5824.2
50	26.13	-688.00	6646.5	-5795.5

10.4.2 Windfarm with an Installed Capacity of 200 MW

Using the Optimal Combination of Regression Techniques for the MCP and Energy Demand Forecast Methodology (DT_DT)

The following results are for predicted wind speed and direction (MCP) and forecasted energy demand. Figure 10-21 presents the variation of energy discharged by the ESS to the electricity grid,

with generation baseload, ESS capacity and ESS power rating for an offshore windfarm capacity of 200 MW.

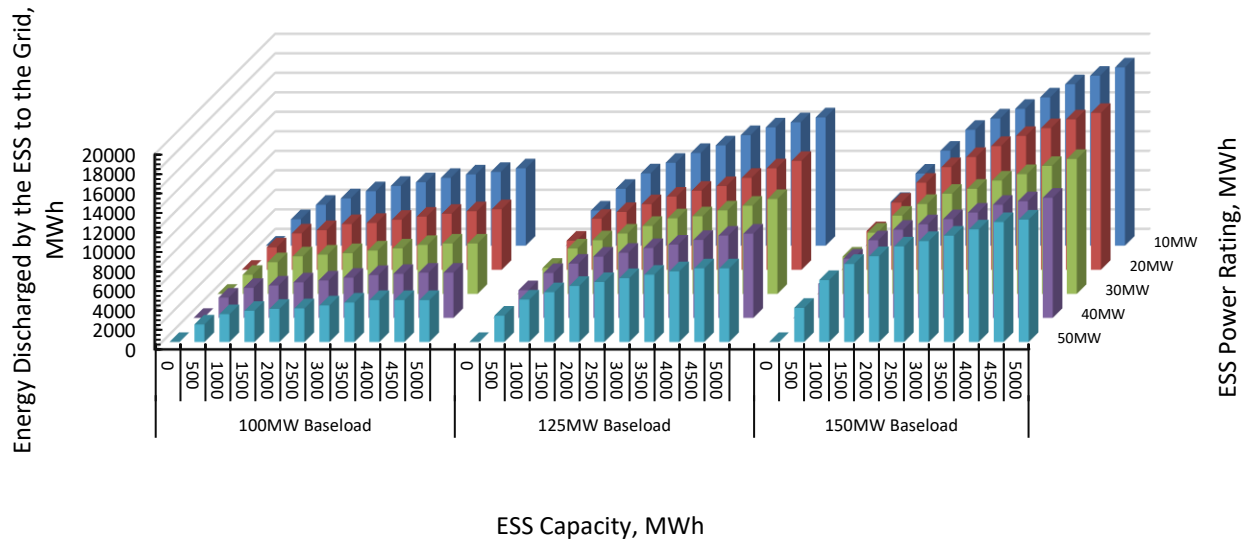


Figure 10-21: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 200 MW for predicted wind speed and direction and forecasted energy demand.

The results presented in Figure 10-21 are also tabulated in Table 10-45, Table 10-47 and Table 10-49, while Table 10-47, Table 10-48 and Table 10-50 give the coefficients e , f , g and h for the 3rd order polynomials which have been fitted to the relationships between energy discharged from the ESS to the grid and the ESS capacity for the various ESS power ratings, according to Eq. (4-16). Further results are also presented in Appendix I, in Figure I-13 to Figure I-18.

Table 10-45: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	2,710	4,190	4,850	5,580	6,130	6,500	6,950	7,300	7,560	7,930
20	0	2,300	3,720	4,060	4,680	4,800	5,120	5,440	5,740	6,000	6,200
30	0	1,950	3,240	3,840	4,020	4,170	4,440	4,650	5,010	5,160	5,160
40	0	2,080	3,080	3,320	3,640	3,840	4,120	4,400	4,520	4,640	4,640
50	0	1,800	2,850	3,200	3,400	3,450	3,750	4,050	4,300	4,300	4,300

Table 10-46: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	100 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	e	f	g	h
10	15.39	-360.54	3059.2	-2435.8
20	15.82	-354.59	2765.0	-2176.1
30	14.00	-318.46	2478.0	-1978.6
40	11.77	-272.77	2159.7	-1592.1
50	10.11	-257.98	2031.6	-1538.6

Table 10-47: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	3,600	5,830	7,410	8,500	9,500	10,280	11,330	12,120	12,650	13,150
20	0	2,980	5,220	5,920	6,720	7,500	8,100	8,580	9,420	10,400	11,160
30	0	2,670	4,650	5,490	6,180	6,960	7,740	7,950	8,550	9,030	9,720
40	0	2,840	4,600	5,560	6,280	6,680	7,160	7,520	8,000	8,440	8,640
50	0	2,700	4,350	5,100	5,750	6,150	6,550	6,900	7,250	7,550	7,550

Table 10-48: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	16.85	-419.44	4099.5	-3395.8
20	22.80	-483.08	3881.1	-3185.2
30	17.33	-396.71	3418.9	-2859.1
40	18.14	-421.63	3509.9	-2874.5
50	15.73	-377.38	3191.4	-2565.2

Table 10-49: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	3,880	6,510	8,590	10,470	12,390	13,600	14,840	15,710	16,460	17,180
20	0	3,420	6,720	8,920	9,880	10,720	11,480	12,220	12,920	13,840	14,700
30	0	3,210	6,000	7,530	8,430	8,970	9,480	10,440	11,070	11,730	12,600
40	0	2,800	5,400	7,280	7,720	8,440	9,080	9,880	9,880	10,760	11,360
50	0	3,350	5,650	7,200	7,950	8,650	9,100	9,650	10,200	10,550	10,950

Table 10-50: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 200 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	22.00	-594.53	5496.3	-4775.5
20	20.38	-551.56	5037.8	-4378.1
30	23.79	-556.05	4890.2	-4169.1
40	22.74	-550.40	4822.6	-4169.1
50	23.48	-560.96	4879.2	-4198.5

Using Measured Wind Speed and Direction, and Energy Demand

The results that follow are those achieved for measured wind speed and direction energy demand. Figure 10-22 illustrates the relationship between energy discharged by the ESS to the grid, with the generation baseload, ESS capacity and ESS rated power.

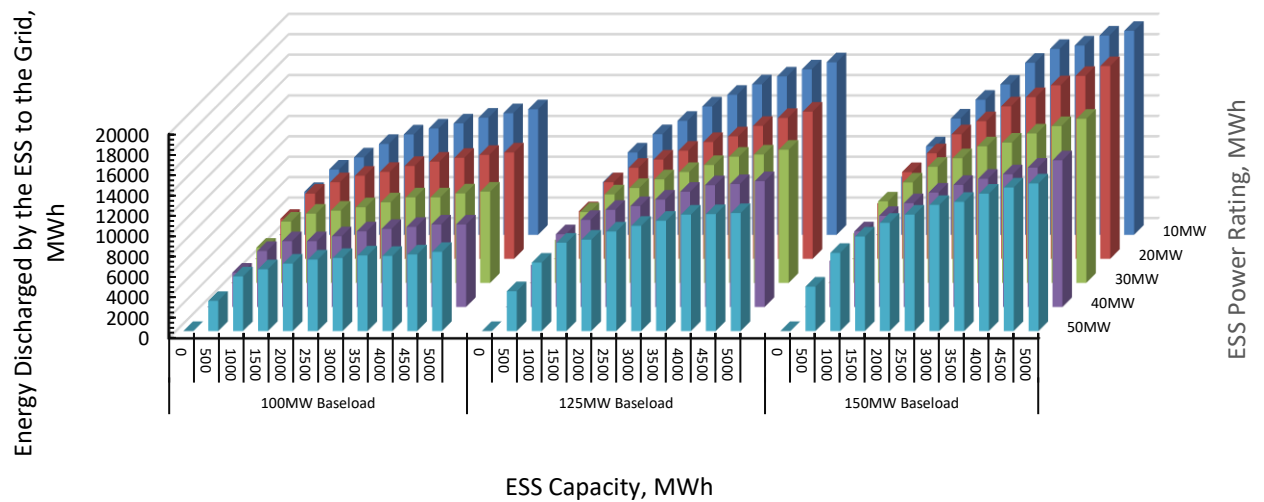


Figure 10-22: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 200 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

The results shown in Figure 10-22 are also presented in Table 10-51, Table 10-53 and Table 10-55, while Table 10-52, Table 10-54 and Table 10-56 present the coefficients e , f , g and h for the 3rd order polynomials which have been fitted to the relationships between energy discharged from the ESS to the electricity grid and the ESS capacity for various the ESS power ratings, according to Eq. (4-16). Further results are also included in Appendix I, in Figure I-19 to Figure I-24.

Table 10-51: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	4,850	7,010	8,270	9,290	9,840	10,340	10,830	11,060	11,290	11,530
20	0	4,660	6,540	7,340	7,800	8,340	8,580	8,940	9,140	9,300	9,300
30	0	4,050	6,210	6,780	7,350	7,620	7,800	7,950	8,100	8,100	8,100
40	0	4,000	6,040	6,280	6,880	7,360	7,400	7,760	7,760	7,760	7,760
50	0	3,850	6,100	6,600	6,950	7,300	7,350	7,350	7,450	7,450	7,450

Table 10-52: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 200 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	e	f	g	h
10	22.00	-535.52	4711.1	-3807.7
20	26.75	-618.83	4903.8	-3950.6
30	26.47	-600.94	4581.2	-3686.8
40	23.53	-542.05	4178.7	-3301.8
50	23.79	-554.25	4260.6	-3568.9

Table 10-53: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	5,140	8,060	9,860	11,160	12,570	13,710	14,740	15,510	16,200	16,900
20	0	4,660	7,500	8,920	9,720	10,600	11,440	12,000	13,020	13,800	14,420
30	0	4,170	6,930	8,670	9,300	10,140	10,860	11,550	12,360	12,570	13,050
40	0	4,080	7,120	8,520	9,520	9,880	10,520	11,280	11,920	12,040	12,320
50	0	3,900	6,700	8,650	8,950	9,750	10,300	10,800	11,400	11,450	11,550

Table 10-54: Coefficients for fitted 3rd order polynomials for curtailed energy for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	125 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	25.02	-612.54	5688.5	-4602.7
20	31.35	-698.86	5652.2	-4537.6
30	25.94	-615.31	5233.3	-4314.5
40	26.95	-643.08	5365.7	-4450.3
50	25.15	-616.03	5208.1	-4373.5

Table 10-55: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	5,630	8,670	11,390	13,230	14,720	16,850	18,200	18,530	19,510	19,980
20	0	5,400	8,500	10,340	12,200	13,480	14,940	15,840	17,000	17,920	18,880
30	0	4,830	7,980	9,840	11,370	12,210	13,380	13,740	14,640	15,360	16,080
40	0	4,480	7,400	8,920	10,160	11,200	11,960	12,560	13,000	13,640	14,360
50	0	4,350	7,650	9,250	10,600	11,400	12,350	12,650	13,450	14,050	14,450

Table 10-56: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW and measured wind speed and direction and energy demand.

ESS Power Rating in MW	Offshore Windfarm with 200 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	17.85	-521.9	5855.9	-4858.9
20	27.08	-648.9	6050.4	-4948.8
30	30.08	-712.34	6148.5	-5178.2
40	27.92	-661.3	5644.7	-4714.5
50	28.17	-677.04	5826.6	-4951.5

10.4.3 Windfarm with an Installed Capacity of 150 MW

Using the Optimal Combination of Regression Techniques for the MCP and Energy Demand Forecast Methodology (DT_DT)

The results that follow are those for predicted wind speed and direction (MCP) and forecasted energy demand. Figure 10-23 shows the variation of energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating for an offshore windfarm with an installed capacity of 150 MW.

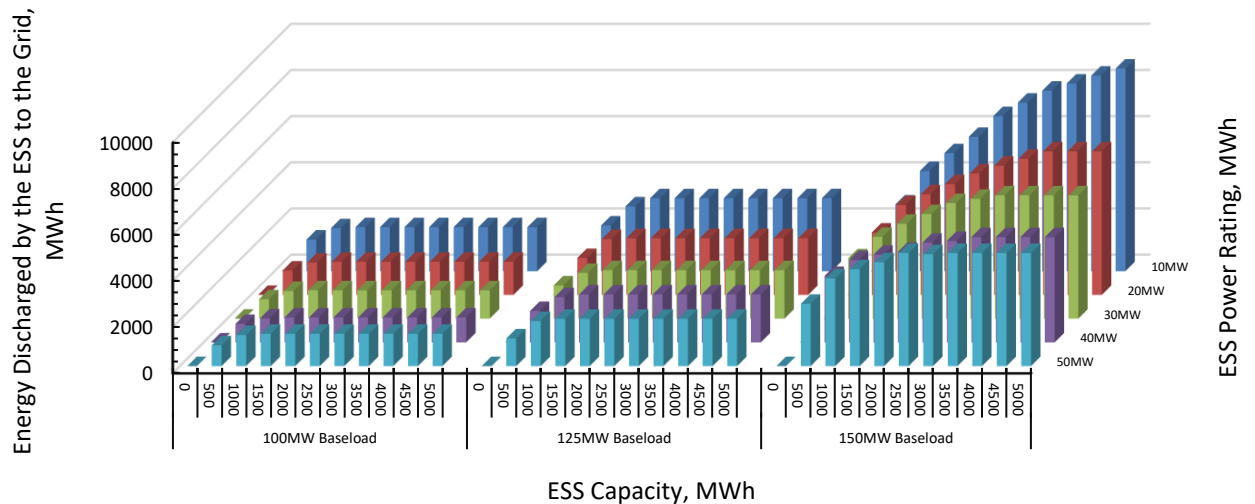


Figure 10-23: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150 MW with predicted wind speed and direction (MCP) and forecasted energy demand.

The results presented in Figure 10-23 are presented in, Table 10-57 to Table 10-59, while Table 10-60 presents the coefficients e , f , g and h for the 3rd order polynomial which have been fitted to the relationships between energy discharged from the ESS to the grid and the ESS capacity for various ESS power ratings, according to Eq. (4-16).

Table 10-57: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	1,370	1,860	1,910	1,910	1,910	1,910	1,910	1,910	1,910	1,910
20	0	1,060	1,400	1,440	1,440	1,440	1,440	1,440	1,440	1,440	1,440
30	0	840	1,230	1,230	1,230	1,230	1,230	1,230	1,230	1,230	1,230
40	0	800	1,080	1,080	1,080	1,080	1,080	1,080	1,080	1,080	1,080
50	0	900	1,350	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400

Table 10-58: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	1,980	2,810	3,160	3,160	3,160	3,160	3,160	3,160	3,160	3,160
20	0	1,600	2,420	2,460	2,460	2,460	2,460	2,460	2,460	2,460	2,460
30	0	1,440	1,980	2,100	2,100	2,100	2,100	2,100	2,100	2,100	2,100
40	0	1,360	1,960	2,080	2,080	2,080	2,080	2,080	2,080	2,080	2,080
50	0	1,200	1,950	2,050	2,050	2,050	2,050	2,050	2,050	2,050	2,050

Table 10-59: Energy discharged by the ESS into the electricity grid for an offshore windfarm of 150 MW capacity and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	2,890	4,340	5,110	5,820	6,720	7,300	7,820	8,130	8,470	8,780
20	0	2,700	3,900	4,360	4,800	5,260	5,600	5,900	6,220	6,220	6,220
30	0	2,610	3,540	4,110	4,530	5,010	5,190	5,340	5,340	5,340	5,340
40	0	2,880	3,560	3,800	3,920	4,320	4,400	4,560	4,560	4,560	4,560
50	0	2,700	3,800	4,200	4,500	4,900	4,850	4,900	4,900	4,900	4,900

Table 10-60: Coefficients for fitted 3rd order polynomials for energy discharged into the electricity grid for an offshore windfarm of with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 150 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	12.33	-309.95	2936.0	-2298.6
20	13.17	-319.95	2691.1	-1994.8
30	13.00	-321.01	2641.9	-2001.4
40	17.21	-399.94	2982.8	-2265.2
50	15.64	-355.34	2610.0	-1771.5

For the case of an offshore windfarm of 150 MW capacity with a generation baseload of 100 MW, the amount of energy discharged by the ESS to the grid was drastically reduced, as can be observed in Table 10-57. This was also coupled with the amount of curtailed energy from the wind farm being zero for ESS capacities of 1000 MWh or greater. With these conditions, it was not considered viable to have an ESS with a capacity larger than 1000 MWh.

The results shown in Table 10-58 were those for an offshore windfarm with a capacity of 150 MW coupled to an ESS and an electricity grid which had an assumed generation baseload of 125 MW. The results demonstrate that there is no increase in the amount of energy discharged from the ESS to the electricity grid for values of ESS capacity which was equal or greater than 1500 MWh for all ESS power ratings. The value of 1500 MWh was deemed to be the optimal ESS capacity for these conditions. Again, this was coupled to the fact that at these conditions the amount of curtailed energy from the windfarm was zero. Hence, in the above two scenarios it was not necessary to apply Eqs. (4-16) to (4-19) in order to obtain the optimum ESS capacity.

The results represented in Table 10-59 are those obtained for a 150 MW offshore windfarm with an installed capacity of 150 MW coupled to an ESS and an electricity grid with a generation baseload of 150 MW. In this case the results demonstrated that the amount energy discharged from the ESS to the electricity grid continued to increase with ESS capacity. Hence, Eqs. (4-16) to (4-19) could be applied to obtain the optimum ESS capacity.

Table 10-62 presents the coefficients *e*, *f*, *g* and *h* of the 3rd order polynomials that could be fitted to the energy discharged to the electricity grid. A 2nd order polynomial could be derived by differentiating the 3rd order polynomial, according to Eq. (4-17).

Further results may be seen in Appendix I, in Figure I-25 to Figure I-27, while Figure I-28 presents the 2nd order relationship $\frac{d^2 E_c}{d(C_{ESS})^2}$ derived from the 3rd order polynomials according to Eq. (4-17).

Using Measured Wind Speed and Direction, and Energy Demand

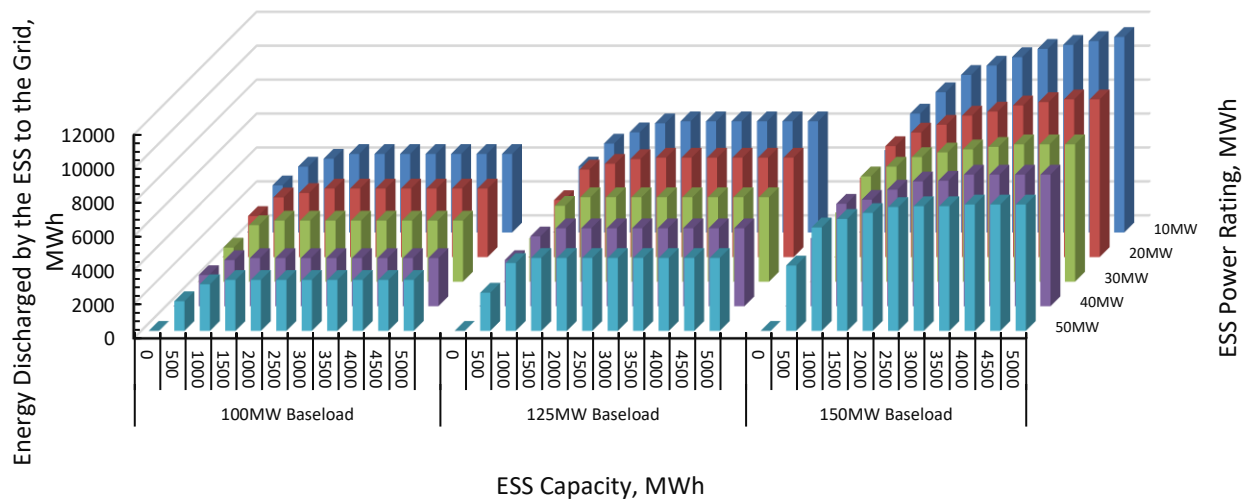


Figure 10-24: Energy discharged by the ESS to the electricity grid with generation baseload, ESS capacity and ESS power rating, for an offshore windfarm with an installed capacity of 150MW for measured wind speed and direction and energy demand.

The following results were those obtained for measured wind speed and direction and energy demand. Figure 10-24 presents the relationship between the energy discharged by the ESS to the grid, the generation baseload, ESS capacity and ESS rated power.

The results presented in Figure 10-24 are also tabulated in Table 10-61 to Table 10-63, while Table 10-64 shows the coefficients e , f , g and h for the 3rd order polynomials which have been fitted to the relationships between energy discharged from the ESS to the grid and the ESS capacity for various ESS power ratings.

Table 10-61: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW capacity and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	100 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	2,780	3,880	4,350	4,630	4,630	4,630	4,630	4,630	4,630	4,630
20	0	2,420	3,520	3,780	4,040	4,040	4,040	4,040	4,040	4,040	4,040
30	0	2,010	3,330	3,600	3,600	3,600	3,600	3,600	3,600	3,600	3,600
40	0	1,840	2,720	2,840	2,840	2,840	2,840	2,840	2,840	2,840	2,840
50	0	1,750	2,750	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000

Table 10-62: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.

ESS Power	Energy Discharged into the Electricity Grid by the ESS in MWh										
	125 MW Generation Baseload										
	ESS Capacity in MWh										

Rating in MW	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	3,890	5,240	5,910	6,440	6,560	6,560	6,560	6,560	6,560	6,560
20	0	3,360	5,160	5,500	5,780	5,860	5,860	5,860	5,860	5,860	5,860
30	0	2,550	4,470	4,980	4,980	4,980	4,980	4,980	4,980	4,980	4,980
40	0	2,720	4,120	4,600	4,600	4,600	4,600	4,600	4,600	4,600	4,600
50	0	2,250	4,000	4,300	4,300	4,300	4,300	4,300	4,300	4,300	4,300

Table 10-63: Energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.

ESS Power Rating in MW	Energy Discharged into the Electricity Grid by the ESS in MWh										
	150 MW Generation Baseload										
	ESS Capacity in MWh										
	0	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
10	0	4,850	7,010	8,270	9,290	9,840	10,340	10,830	11,060	11,290	11,530
20	0	4,660	6,540	7,340	7,800	8,340	8,580	8,940	9,140	9,300	9,300
30	0	4,050	6,210	6,780	7,350	7,620	7,800	7,950	8,100	8,100	8,100
40	0	4,000	6,040	6,280	6,880	7,360	7,400	7,760	7,760	7,760	7,760
50	0	3,850	6,100	6,600	6,950	7,300	7,350	7,350	7,450	7,450	7,450

Table 10-64: Coefficients for fitted 3rd order polynomials for energy discharged by the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW for measured wind speed and direction and energy demand.

ESS Power Rating (MW)	Offshore Windfarm with 150 MW Installed Capacity			
	150 MW Generation Baseload			
	3 rd Order Polynomial Coefficient			
	<i>e</i>	<i>f</i>	<i>g</i>	<i>h</i>
10	28.09	-666.31	5387.4	-4222.4
20	28.41	-652.26	4952.1	-3690.3
30	27.96	-644.02	4803.9	-3717.7
40	25.46	-590.26	4447.9	-3346.1
50	29.01	-661.36	4810.4	-3759.8

From the results presented in Table 10-61 for the case of an offshore windfarm with a 150 MW generation capacity coupled to an ESS and an electricity grid with a generation baseload of 100 MW, it was not considered viable to have an ESS with a capacity larger than 2500 MWh for an ESS at a power rating of 10 MW, 2000 MWh at an ESS power rating of 20 MW and 1500 MW or at a power rating of 30 MW and greater.

The results presented in Table 10-62 are those for a generation baseload of 125 MW. The results demonstrate that there was no increase in the amount of energy discharged from the ESS to the electricity grid for values of ESS capacity which were equal or greater than 2500 MWh at ESS power ratings of 20 MW and less. There was also no increase in energy discharge for ESS capacities which were equal to or greater than 1500 MWh at ESS power ratings which were equal to or greater than 30 MW. These values of ESS capacity were therefore considered to be the optimal ESS capacity at these conditions. Again, this was coupled to the fact that at these conditions, the amount of curtailed energy from the windfarm was also zero. Hence, in the above two scenarios it was not deemed necessary to apply Eqs. (4-12) to (4-15) in order to obtain the optimum ESS capacity.

The results tabulated in Table 10-63 are those obtained with a generation baseload of 150 MW. In this case results demonstrated that the amount energy discharged from the ESS to the electricity grid continued to increase with ESS capacity. Hence Eqs. (4-16) to (4-19) could be applied to obtain the optimum ESS capacity. Therefore, Table 10-64 shows the coefficients of the 3rd order polynomials that could be fitted to the relationship for the energy discharged to the electricity grid with ESS

capacity and hence a 2nd order polynomial could be derived by differentiating the 3rd order polynomial, according to Eq. (4-17).

More results are presented in Appendix I, in Figure I-29 to Figure I-31, while Figure I-32 shows the 2nd order relationship $d^2E_C/d(C_{ESS})^2$ derived from the 3rd order polynomials according to Eq. (4-17).

10.5 Establishing an Optimal Capacity for the ESS using the Rate of Change of Curtailed Energy and Energy Discharged from the ESS

To conclude this Chapter, Table 10-65 presents the optimal ESS capacity, C_{ESSOPT} , for the various conditions of ESS power rating, offshore windfarm capacity and generation baseload for the predicted wind speed and direction and forecasted energy demand. Table 10-66 shows the optimal ESS capacity obtained for measured wind speed and direction and energy demand. According to Eqs. (4-12) to (4-15), C_{ESSOPT} occurs when $d^2E_C/d(C_{ESS})^2 = 0$, and has the value $C_{ESSOPT} = b/3a$. Thus, the values for the optimal capacity were calculated from the coefficients a and b which are shown in Section 10.3. This result was based on the level of curtailed energy from the windfarm.

The results from Section 10.3 also established that, for an offshore windfarm with the lowest installed capacity, of 150 MW, which was coupled to an ESS and an electricity grid, the curtailed energy was negligible under most conditions. This result was obtained in conjunction with the results from Section 10.4, which showed that for the same conditions of baseload, ESS capacity and rated power the energy discharged from the ESS to the electricity grid was also negligible. This implied that in these conditions all available windfarm energy was transferred to the electricity grid. These instances are presented as the greyed-out cells Table 10-65 and Table 10-66, and the use of an ESS was in these conditions was not considered feasible.

Table 10-65: Optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using predicted wind speed and direction and forecasted energy demand.

Baseload		Windfarm Capacity								
		250 MW			200 MW			150 MW		
		150 MW	125 MW	100 MW	150 MW	125 MW	100 MW	150 MW	125 MW	100 MW
ESS Power Rating (MW)	10	3774	3758	3720	3792	3713	4009	3769	2000.00	1500
	20	3604	3672	3559	3630	3460	3780	3667	2000.00	1000
	30	3662	3688	3571	3582	3533	3793	3500	1000.00	1000
	40	3723	3679	3583	3605	3575	3745	3500	1000.00	1000
	50	3652	3673	3569	3581	3588	3758	3500	1000.00	1000

Table 10-66: Optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using measured wind speed and direction and energy demand.

		Windfarm Capacity								
		250 MW			200 MW			150 MW		
Baseload		150 MW	125 MW	100 MW	150 MW	125 MW	100 MW	150 MW	125 MW	100 MW
ESS Power Rating (MW)	10	4139	3958	5473	4161	4149	4057	4189	1500	1500
	20	3947	4784	3847	4183	3531	3855	4048	1500	1000
	30	4070	4071	3726	3898	3815	3783	4116	1500	1000
	40	4112	4177	3864	4033	3873	3839	3874	1500	1000
	50	4115	4229	3969	3981	4000	3884	3787	1500	1000

Table 10-67: Percentage error in optimal ESS capacities using rate of change of curtailed energy to establish the optimal point, using measured wind speed and direction and energy demand.

		Percentage Error								
		Windfarm Capacity								
		250 MW			200 MW			150 MW		
Baseload		150 MW	125 MW	100 MW	150 MW	125 MW	100 MW	150 MW	125 MW	100 MW
ESS Power Rating (MW)	10	1.4	0.3	6.5	0.9	6.0	3.7	0.7		
	20	6.5	5.0	1.1	2.1	7.3	3.7	0.1		
	30	6.2	4.3	0.6	2.2	8.7	0.4			
	40	4.4	4.0	0.8	1.2	8.0	1.8			
	50	6.2	3.3	1.3	1.8	7.0	-0.1			

Table 10-67 presents the percentage error obtained using the curtailed energy from the offshore windfarm to obtain the optimal ESS capacity. The absolute value of the error varies between 0.05% and 8.7% depending on the conditions of windfarm capacity, generation baseload and ESS power rating.

If the optimal ESS capacities shown in Table 10-65 and Table 10-66 were to be plotted in the form of a histogram (normalised distribution), then the plots of the optimal ESS capacity for predicted wind speed and direction and forecasted energy demand and from measured wind speed and direction and energy demand would yield the results shown in Figure 10-25. In such a case, the mean optimal ESS capacity would be 3651 MWh for the predicted and forecasted values, while that obtained from the measured values would be 3801 MWh, hence a percentage error of 3.94% between the two capacities would result. This error, together with the range of errors shown in Table 10-67, shows that the estimated ESS capacity was within an acceptable tolerance.

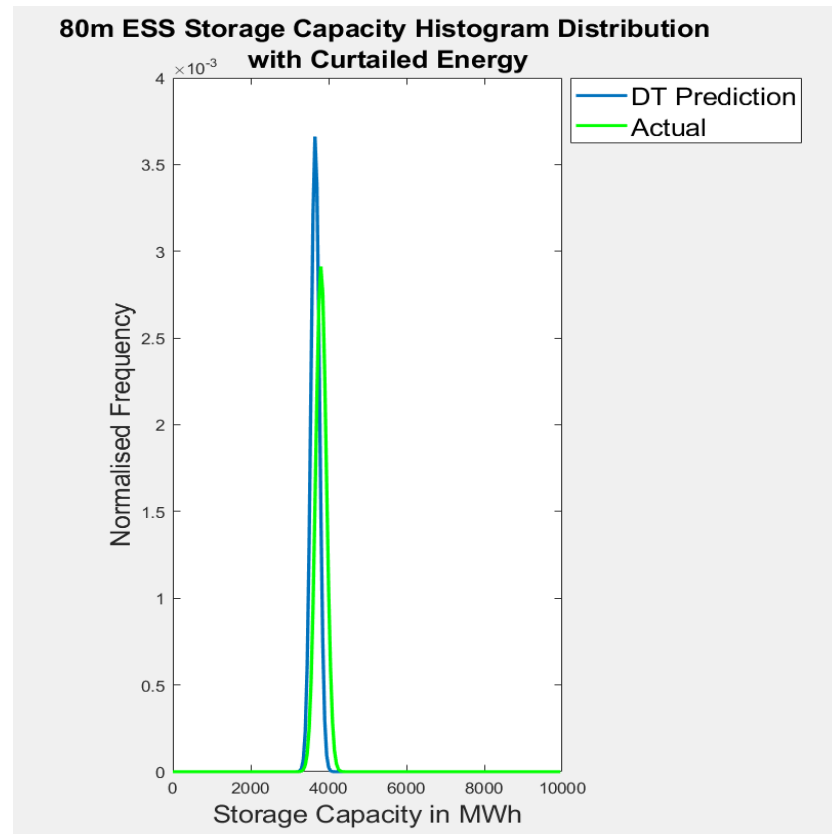


Figure 10-25: Distribution for the various optimal ESS capacities shown in Table 10-65 and Table 10-66.

From the results presented in Section 10.4 and Appendix I, Table 10-68 and Table 10-69 again present the optimal ESS capacity ($C_{ESS_{opt}}$) for various conditions of offshore windfarm capacity and ESS capacity, using the amount of energy discharged by the ESS into the grid, E_G . As described by Eqs. (4-5) to (4-8), $C_{ESS_{opt}}$ occurs when $d^2 E_G / d(C_{ESS})^2 = 0$ and has the value $C_{ESS_{opt}} = f/3e$. These results were similar to the ones shown previously when using the curtailed energy, but this time the greyed-out results are less frequent. This is because even with zero curtailed energy, the ESS may still receive charging energy from the windfarm, and thus be able to discharge energy to the electricity grid. This shows that the discharge of energy from the ESS may be used for a larger number of conditions of windfarm capacity, generation baseload and ESS rated power than the previous method. It thus gave a wider range of conditions for which the optimal capacity could be determined.

Table 10-68: Optimal ESS Capacities using rate of change of ESS energy discharged to the electricity grid to establish the optimal point, using predicted wind speed and direction and forecasted energy demand.

Baseload		Windfarm Capacity								
		250MW			200MW			150MW		
		150MW	125MW	100MW	150MW	125MW	100MW	150MW	125MW	100MW
ESS Power Rating	10	3774	3758	3720	3792	3713	4009	3769	2000	1500
	20	3604	3672	3559	3630	3460	3780	3667	2000	1000
	30	3662	3688	3571	3582	3533	3793	3500	1000	1000
	40	3723	3679	3583	3605	3575	3745	3500	1000	1000
	50	3652	3673	3569	3581	3588	3758	3500	1000	1000

Table 10-69: Optimal ESS Capacities using rate of change of ESS energy discharged to the energy grid to establish the optimal point, using measured wind speed and direction and energy demand.

		Windfarm Capacity								
		250MW			200MW			150MW		
Baseload		150MW	125MW	100MW	150MW	125MW	100MW	150MW	125MW	100MW
ESS Power Rating	10	3774	3758	3720	3792	3713	4009	3769	2000	1500
	20	3604	3672	3559	3630	3460	3780	3667	2000	1000
	30	3662	3688	3571	3582	3533	3793	3500	1000	1000
	40	3723	3679	3583	3605	3575	3745	3500	1000	1000
	50	3652	3673	3569	3581	3588	3758	3500	1000	1000

Table 10-70 presents the percentage error obtained using the energy discharged from the ESS to the electricity grid required to obtain the optimal ESS capacity. The absolute value of the error ranges between 0 and 17.3% depending on the actual combination of windfarm capacity, generation baseload and ESS power rating. There are many instances when the percentage error was almost equal to zero, but the variation in error is greater than that obtained when using the previous method.

Table 10-70: Percentage error in optimal ESS capacities using rate of change of ESS energy discharged to the electricity grid to establish the optimal point, using measured wind speed and direction and energy demand.

		Windfarm Capacity								
		250 MW			200 MW			150 MW		
Baseload		100 MW	125 MW	150 MW	100 MW	125 MW	150 MW	100 MW	125 MW	150 MW
ESS Power Rating	10	-1.6	10.1	-4.7	14.6	-1.7	0.00	-6.0		
	20	0.8	-11.5	10.3	-7.6	5.0	0.02	-5.8		
	30	2.8	17.3	8.3	1.3	3.5	0.01	-7.2		
	40	3.4	7.0	3.5	-2.2	2.6	0.00	-0.3		
	50	6.2	0.9	-2.0	0.6	2.0	0.00	-0.2		

If the various optimal ESS capacities shown in Table 10-68 and Table 10-69 were to be plotted in the form of a histogram (normal distribution), then the plots of the optimal ESS capacity with predicted wind speed and direction and forecasted energy demand, together with those from measured wind speed and direction and energy demand, would result in Figure 10-26, with a mean optimal ESS capacity of 4051 MWh for the predicted and forecasted values while that obtained from the measured values is of 4101 MWh, i.e. a percentage error of 1.2%. Although the mean percentage error is less than that resulting from the first methodology, Figure 10-26 also demonstrates the wider variation in percentage error than that shown in Figure 10-25 as demonstrated by the values shown in Table 10-67 and Table 10-70.

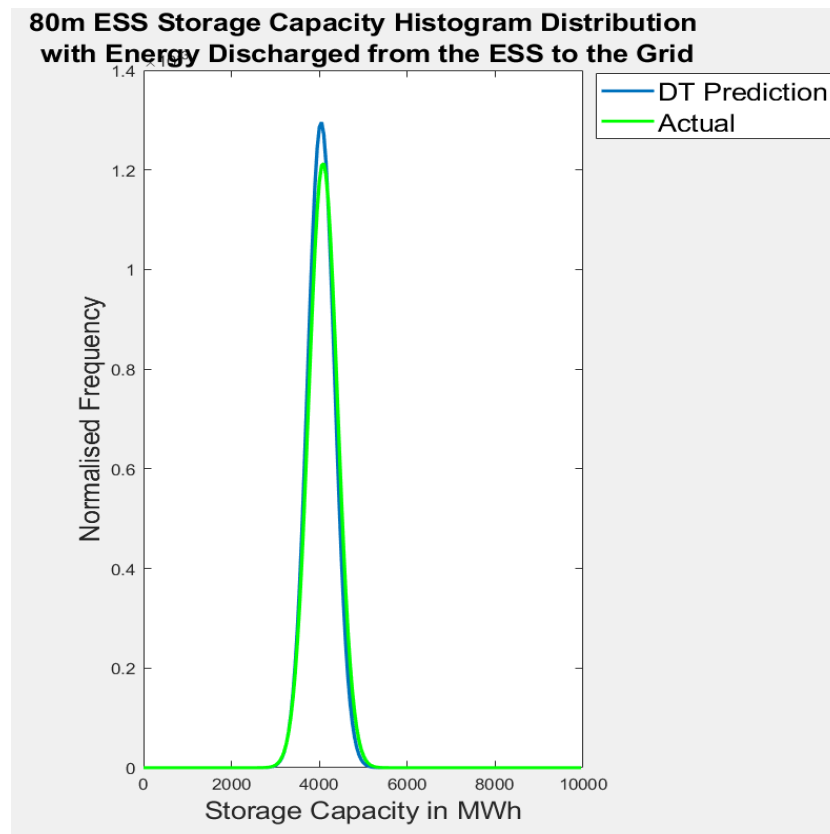


Figure 10-26: Distribution for the various optimal ESS capacities shown in Table 10-68 and Table 10-69.

10.6 Conclusions from the Analysis to Determine the Optimal ESS Capacity

A methodology was developed to obtain the optimal ESS capacity, $C_{ESS_{OPT}}$ and to measure the percentage error obtained due to using predicted wind speed and wind direction and forecasted energy demand by comparing it to $C_{ESS_{OPT}}$ obtained from measured wind speed and direction and energy demand. The following conclusions may be drawn from this analysis:

- The ESS power rating does not influence the optimal ESS capacity.
- Two metrics were used to estimate the optimal ESS capacity, namely, the curtailed energy from the offshore windfarm and the energy discharged from the ESS to the electricity grid.
- Both metrics produced similar results, with an optimal ESS capacity which has a mean value for all conditions of 3651 MWh for predicted and forecasted values when using curtailed energy, E_C , as a metric and a mean value of 4051 MW when using the energy discharged from the ESS to the grid, E_G when compared to an $C_{ESS_{OPT}}$ of 3801 MWh and 4101 MWh, respectively when using measured values.
- A large ESS capacity could be justified for windfarms with a larger installed capacity and a reduced generation baseload.
- If a smaller windfarm capacity and/or a larger generation baseload is selected, the optimal ESS capacity should be decreased or even omitted, because according to the results large ESS capacities will not be utilised effectively.

- The use of curtailed energy as a metric yielded a lower percentage error, but in a narrower range of combinations of windfarm capacities, ESS capacities, generation baseload and ESS power ratings (see Table 10-67). The absolute percentage error was in the range of 0.05% to 8.67%, with a percentage error of 3.94% when considering the mean value of the estimated ESS size (see Figure 10-25).
- The use of energy discharged to the grid from the ESS as a metric yielded a larger percentage error, but permitted a wider range of combinations of windfarm capacities, ESS capacities, generation baseload and ESS power ratings (see Table 10-70). This is because even though curtailed energy from the wind farm was zero, the ESS was still receiving energy from the windfarm and discharging it to the grid.
- The use of energy discharged from the ESS as a metric resulted in an absolute error in the range of 0 to 17.25% and a percentage error of 1.21%, when considering the mean values of the estimated ESS size (see Figure 10-26).
- The use of a 3rd order polynomial showed a strong correlation between the results and the fitted polynomial. The derivative of the 3rd order polynomial enabled the optimal capacity of the ESS to be estimated. The result clearly indicates that the range of the optimum ESS capacity, which is limited to a narrow range, is independent of the size of the windfarm. The optimum ESS capacity is dependent on the energy demand. The same result is obtained when considering the energy discharged from the ESS to the grid. The charging of the ESS from the windfarm occurs when there is excess wind energy with the ESS being charged rather than the wind energy being curtailed. This also depends on the energy demand.
- Other management scenarios other than the one described in Section 4.5 exist, as shown in Section 2.11. These management scenarios may have produced different results, and could be the scope of further research.
- Other methodologies exist which can be used to optimise the ESS capacity. These methodologies are based on the optimal unit cost of the ESS. It was not the scope of the current research to use a financial methodology, but this can be the scope of future research.

11 Results – Part 5- Determining the LCOE and the LCOS

As shown in Section 1.8 and Figure 1-4, the LCOE of the floating offshore windfarm and the LCOS of the ESS were determined in STEP 8. Moreover, due to the error introduced due to the use of MCP and EDF methodologies, it was also necessary to estimate the corresponding error in the estimate of the LCOE and the LCOS. The estimation of this error will provide the industry with a clearer assessment of the risk involved with the investment. The analysis was based on the costings of a floating offshore windfarm which was integrated with an ESS and an electricity grid. This was possible following the determination of the optimal combination of regression techniques for MCP and EDF methodologies which was carried out in Chapter 9, where it was determined that the optimal combination was that which used a DT regression for both methodologies.

The optimal capacity for the ESS was determined in Chapter 10. This was determined with the use of two methodologies. The first methodology used the curtailed energy from the windfarm to determine the optimal size. The optimal size was considered that at which the rate of change of curtailed energy with ESS capacity is at a maximum, meaning that any increase in ESS capacity will not result in an increase in the amount of curtailed energy from the offshore windfarm. In another methodology to determine the optimal ESS size, the energy discharged by the ESS to the grid was used. The optimal size of the ESS was considered to be that at which an increase in the size of the ESS capacity did not result in any increase in the amount of energy discharged to the electricity grid. This is the point at which the rate of change of discharged energy with ESS size is at a minimum. The size of the ESS was estimated using both predicted wind speed and direction at the candidate site and forecasted energy demand, and measured wind speed and direction and actual energy demand, for the year 2017.

The optimal capacity of the ESS $C_{ESS_{OPT}}$ was selected according to the chosen windfarm size and baseload. For the case of a large windfarm and an electricity grid with a low generation baseload, this was ideally between 3000 MWh and 4200 MWh. The LCOE of the windfarm was calculated according to offshore windfarm capacity while the LCOS was calculated according to the chosen ESS capacity range.

The LCOE and the LCOS were described in Section 3.5, while the methodology applied to calculate the LCOE and the LCOS, together with the error associated with the use of the MCP and energy forecasting methodology, was described in Section 4.8. Large windfarms with installed capacities of 400, 320 and 240 MW (utilising 8 MW wind turbines) were considered, as described by the hypothetical offshore windfarm model (WF2), which was designed using the windPRO® software as explained in Section 6.1.2. The costs associated with floating windfarms and battery-based ESS were

presented in Sections 11.2 and 11.3, respectively. The LCOE analysis for the offshore windfarm and the ESS was based on the following:

- Use of the DT regression technique to predict the wind speed and direction at the Qalet Marku LiDAR ‘candidate’ site with wind data predicted for the years 2013 to 2019,
- Use of the the DT regression technique to forecast electrical energy demand. The LCOE calculation was based on actual energy demand for the years 2013 to 2015 and on the forecasted energy demand for the years 2016 – 2019,
- A moving average extrapolation was performed for the windfarm power output for the years 2020 to 2032. This was because wind data from the reference site for these years were not available, hence, an extrapolation was used, which was based on the calculations from the MCP methodology for those years,
- The offshore windfarm costings and LCOE calculations were based on an installed capacity of 400, 320 and 240 MW, using the hypothetical offshore windfarm designs based on 8 MW wind turbines outlined in Section 6.1.2 (WF2). Estimates for energy yield from these windfarm layouts were computed using windPRO® software as described in Section 6.1.2,
- The generation baseload for the electricity grid was set at 75 MW. As shown in Section 9.1, a low value for generation baseload lowers curtailed energy from the windfarm and hence increases energy output from the windfarm, hence favouring the LCOE and the LCOS.
- The LCOE was based on a WACC of 8% [190], based on a 20-year project lifetime, with a year allocated for the installation phase and another year allocated for decommissioning,
- The cost estimates for the offshore floating windfarms consider a SB, Semi-Submersible and TLP foundations as described in Section 11.2,
- Electro-chemical storage technologies (Li-Ion and VRB) are assumed, as described in Section 2.6.2.
- The cost estimates for Li-Ion battery and VRB are described in Section 11.3. Li-Ion batteries have a Usable Storage Capacity (DoD) of 80%, while that of VRB is 100% [45]. Hence 500 MWh of VRB storage is equivalent to 600 MWh of Li-Ion battery storage. This is considered in the CAPEX, OPEX and DECEX calculations and in the Simulink® model shown in Figure 6-7. Using a Li-Ion battery ESS of the same capacity of the VRB signifies that the windfarm will curtail more energy and this will reduce the penetration of wind energy from the offshore windfarm and increase the LCOE of the windfarm. Therefore, the LCOS for the ESS was analysed for energy storage capacities of values of:
 - 600, 3600, 4200, 4800, 5400 and 6000 MWh for a Li-Ion battery storage facility, and,

- The equivalent values of 500, 3000, 3500, 4000, 4500 and 5000 MWh for a VRB storage facility.

This ensured that the capacity available for charging the ESS and hence the electrical power discharged from the ESS to the grid was at approximately at same level, for both the Li-Ion battery storage and the VRB storage. The difference in the DoD of both the Li Ion battery and VRB storage system was therefore compensated with the capacity difference and thus difference in the LCOS would only be attributed to the CAPEX, OPEX and DECEX of the storage systems.

- Since the capability of the VRB ESS to be charged to full capacity permits a lower capacity ESS when compared to a Li-Ion battery system [45]. In the analysis carried out in Section 10.5, the estimated optimal value of the ESS capacity had a value ranging from 3651 MWh (when using curtailed energy from the windfarm as a metric), and a value of 4051 MWh when energy discharged from the ESS to the grid was used as a metric.
- An ESS power rating of 20 MW was used. The value of 20 MW was chosen due to the results from Chapter 10 and Appendices H and I. It was observed that for example, in a typical response of the curtailed energy with increasing ESS capacity such as that shown in Figure 10-6, the value of 10 MW for ESS power rating gave results which could be considered as outliers, when comparing them to the results obtained from the range of 20 MW to 50 MW. The results concerning the relationship between the energy discharged from the ESS and ESS capacity, presented in Chapter 10 and Appendix I showed that (Figure I-1), discharge was a maximum with an ESS power rating of 10 MW. The value of 20 MW was therefore a compromise between the minimisation of curtailed energy and the maximisation of energy discharged to the electricity grid by the ESS.
- The costings associated with floating offshore windfarms and battery storage systems are presented in Sections 11.2 and 11.3 respectively, while the results of the projected energy output from the windfarm and the ESS are presented in Sections 11.4 and 11.5.

11.1 System Behaviour

Time-series' data showing the system behaviour are now presented. In all cases, measured wind speed and direction together with energy demand data were fed into the Simulink® model described in Section 6.2. Wind data were those measured by the LiDAR unit for a height of 150 m for the year 2016. The data used were that from the year 2016. The offshore wind farm had an installed capacity of 400 MW and the generation baseload was set at 75 MW. ESS power rating was set at 20 MW.

Figure 11-1 represents the power generation by source with measured energy demand data and wind data measured with the LiDAR unit at Qalet Marku for the year 2016, with a Li-Ion Battery ESS. The

parameters set for this time-series were a Li-Ion battery with a capacity of 4200 MWh. Figure 11-2 shows the level of energy in the ESS, during the charging and discharge cycles, while Figure 11-3 shows the curtailed power from the windfarm. The Li-Ion ESS had a usable storage capacity (DoD) of 80% [45] of and an efficiency of 95% [43, 45] set into the model. Due to the usable storage capacity the 4200 MWh energy store could only be charged with a maximum of 3400 MWh, or up to 80% of the total capacity. This is seen in Figure 11-2, which shows the available level of energy in the ESS at a maximum of 3400 MWh. Similar charts are also shown for a VRB ESS in Figure 11-4, Figure 11-5 and Figure 11-6. For a VRB ESS, the ESS had a capacity of 3500 MWh which, due to an extremely high usable storage capacity (DoD) close to 100% [45], yielded an equivalent of a 4200 MWh Li-Ion ESS. On the other hand, the discharge efficiency for a VRB was set at 70% [45].

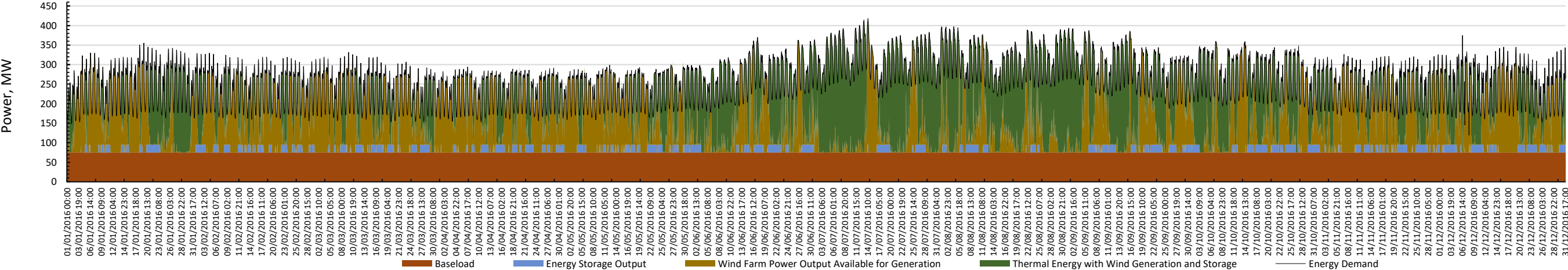


Figure 11-1: Power by generation source using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016 (Li-Ion Battery ESS).

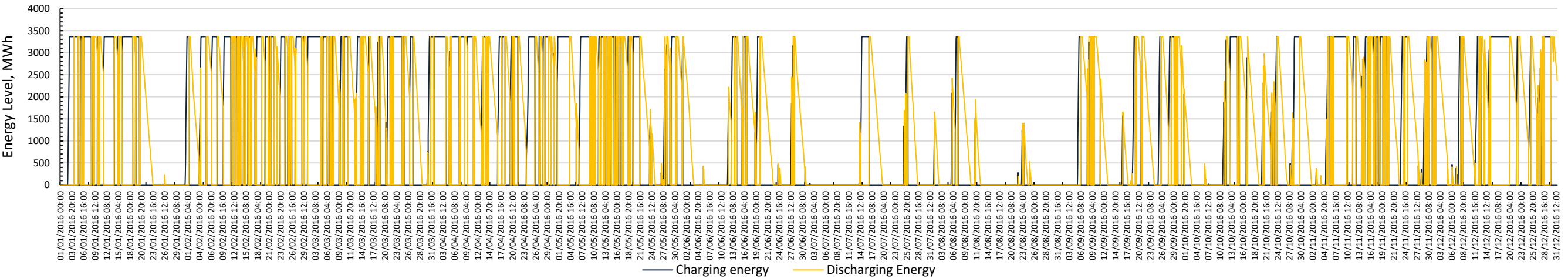


Figure 11-2: Level of energy in the ESS showing charging and discharging cycles for a Lithium-Ion Battery Energy Storage System using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016.

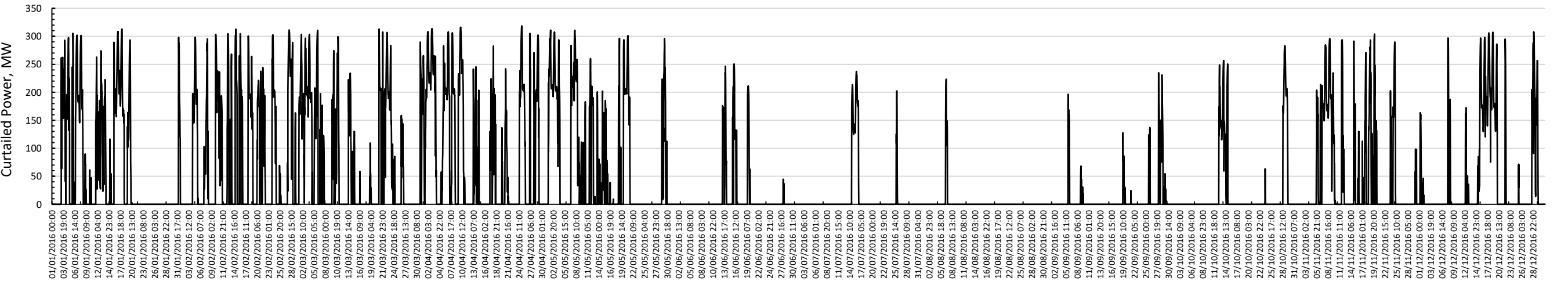


Figure 11-3: Curtailed energy from the offshore windfarm integrated with a Lithium-Ion Energy Storage System using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016.

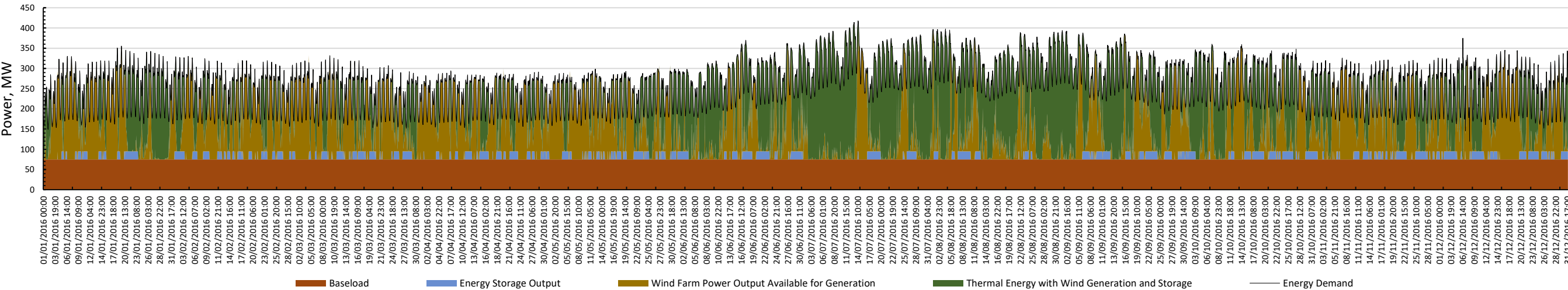


Figure 11-4: Power by generation source using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016 (VRB ESS).

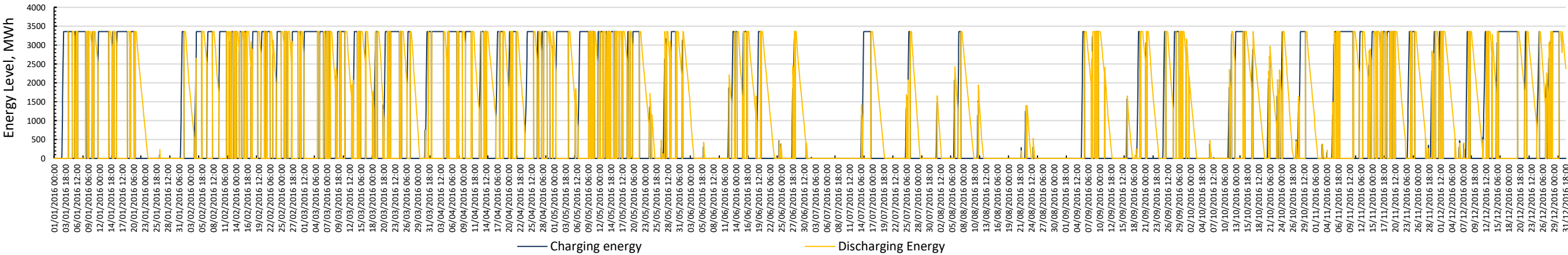


Figure 11-5: Level of energy in the ESS showing charging and discharging cycles for a VRB ESS using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016.

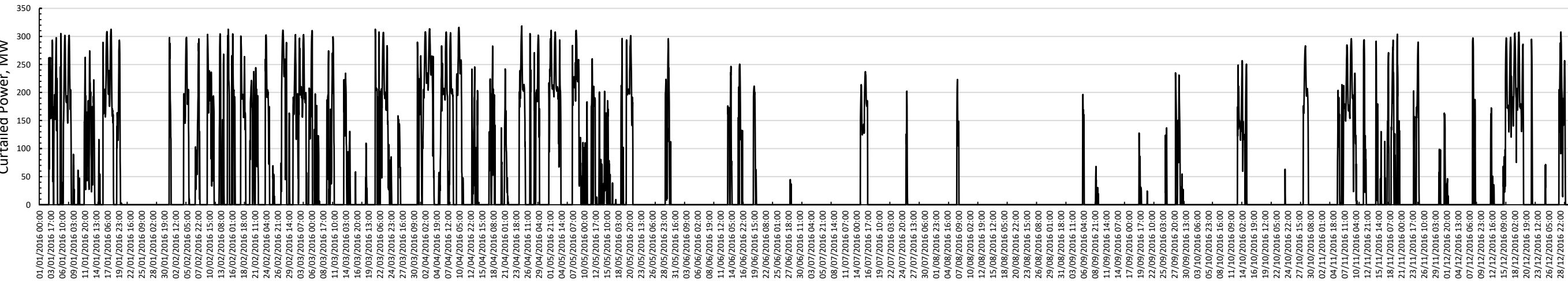


Figure 11-6: Curtailed energy from the offshore windfarm integrated with a VRB ESS using actual energy demand and windfarm power output values derived from measured wind data, for the year 2016.

11.2 The Costs Associated with an Offshore Floating Windfarm

As described in Sections 2.5 and 4.8, the costs associated with a windfarm consist of the CAPEX, OPEX and DECEX. The computation of the CAPEX for a floating windfarm is complex and requires deeper analysis. CAPEX depends on several factors, such as water depth, distance from the port, crane hire, number of voyages, number of lifts, etc. [3, 41, 100]. The figures shown are for a simplified version of the CAPEX based on data from the Mediterranean Sea [3, 4]. The OPEX costs depend on the size of the windfarm while the DECEX figures are normally considered to be a percentage of the installation costs [41].

11.2.1 CAPEX

Table 11-1 shows the per unit (number of turbines) or per MW (wind farm installed capacity), component and installation costs in Euros [3]. The costs are typical for a floating wind farm in the Mediterranean Sea with the windfarm situated at a distance of 16 km from the shore and at a water depth of between 130 and 140 m. The data from Table 11-1 were used to estimate the CAPEX of the floating wind farm. The CAPEX is shown in Table 11.2 to Table 11.4 and was based on the windfarm capacity.

Table 11-1: Unit CAPEX for a floating windfarm, based on data for the Mediterranean Sea [3].

	Component Cost (Euro)	Installation Cost (Euro)
Wind turbine (COST per MW)	1,204,134	
Tension Leg Platform (each)		288,719
Spar Buoy (each)		90,799
Semi-Submersible Platform(each)		24,999
Floating platform		
Tension Leg Platform (each)	5,240,000	943,999
Spar Buoy (each)	5,476,000	234,399
Semi-Submersible Platform(each)	3,824,000	173,600
Total Mooring Lines and Anchoring		
Tension Leg Platform (each)	180,000	452,000
Spar Buoy (each)	546,918	169,600
Semi-Submersible Platform(each)	1,249,800	338,800
Offshore substation (Cost per MW)	110,400	35,039
Onshore substation (Cost per MW)	55,120	8,319
Array cable (Cost per turbine)	263,200	800,000
Export cable (Cost per turbine)	214,800	364,800
Onshore Cable (Cost per turbine)	33,320	240,000
Port fees (per MW)		29,120
Insurance (per MW)		42,560

Table 11-1 shows Capital and Installation costs for [3]:

- Wind turbines,
- Floating Platforms, which include TLP, SB and SSP, together with mooring lines and anchoring costs,
- Offshore substation,
- Onshore substation,
- Array (inter-turbine) cables,
- Export (windfarm to shore) cables,

- Onshore cables,
- Port fees and
- Insurance fees.

The unit costs shown in Table 11-1 resulted in the following CAPEX costings for a 400 MW capacity windfarm as tabulated in Table 11-2, while Table 11-3 shows the CAPEX for a 320 MW floating offshore windfarm and Table 11-4 shows the CAPEX for a floating offshore windfarm with an installed capacity of 240 MW.

Table 11-2: CAPEX for a 400 MW floating offshore windfarm.

	Tension Leg Platform		Semi-Submersible		Spar Buoy	
	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)
50 x 8 MW Wind turbine	481.65	14.43	481.65	1.25	481.65	4.54
50 x Floating Platform	262.00	47.20	191.20	8.68	273.80	11.72
Array Cables	13.16	40.00	13.16	40.00	13.16	40.00
Export Cable	10.74	18.24	10.74	18.24	10.74	18.24
Onshore Cable	16.66	12.00	16.66	12.00	16.66	12.00
Onshore substation	22.05	3.33	22.05	3.33	22.05	3.33
Offshore substation	44.16	14.02	44.16	14.02	44.16	14.02
Mooring lines and Anchoring	9.00	22.60	6.25	16.94	27.35	8.48
Port Fees	11.65		11.65		11.65	
Insurance cost during installation	17.02		17.02		17.02	
Total CAPEX	1,044.92		970.24		1,015.57	

Table 11-3: CAPEX for a 320 MW floating offshore windfarm.

	Tension Leg Platform		Semi-Submersible		Spar Buoy	
	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)
40 x 8MW Wind turbine	385.32	11.55	385.32	1.00	385.32	3.63
40 x Floating Platform	209.60	37.76	152.96	6.94	219.040	9.38
Array Cables	10.53	32.00	10.53	32.00	10.53	32.00
Export Cable	8.59	14.59	8.59	14.59	8.59	14.59
Onshore Cable	1.33	9.56	1.33	9.56	1.33	9.56
Onshore substation	17.64	2.66	17.64	2.66	17.64	2.66
Offshore substation	35.33	11.21	35.33	11.21	35.33	11.21
Mooring lines and Anchoring	8.00	18.08	49.99	13.55	21.88	6.78
Port Fees	9.32		9.32		9.32	
Insurance cost during installation	13.62		13.62		13.62	
Total CAPEX	895.934		776.194		812.454	

Table 11-4: CAPEX for a 240 MW floating offshore windfarm.

	Tension Leg Platform		Semi-Submersible		Spar Buoy	
	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)	Component (MEuro)	Installation (MEuro)
30 x 8 MW Wind turbine	289.00	8.66	289.00	0.75	289.00	2.72
30 x Floating Platform	157.20	28.32	114.72	5.21	164.28	7.03
Array Cables	7.90	24.00	7.90	24.00	7.90	24.00
Export Cable	6.44	10.94	6.44	10.94	6.44	10.94
Onshore Cable	1.00	7.20	1.00	7.20	1.00	7.20
Onshore substation	13.23	2.00	13.23	2.00	13.23	2.00
Offshore substation	26.50	8.41	26.50	8.41	26.50	8.41
Mooring lines and Anchoring	5.40	13.56	5.40	13.56	5.40	13.56
Port Fees	7.00		7.00		7.00	
Insurance cost during installation	10.21		10.21		10.21	
Total CAPEX	626.95		582.15		609.34	

11.2.2 OPEX

OPEX for a floating offshore windfarm depends on various factors such as number of employees. Operational costs also include annual maintenance, condition-based replacement of components and

extra personnel costs which include accommodation and port facilities [41]. Hence, Table 11-5 represents the total OPEX for floating offshore windfarm capacities with three different support structure technologies. This was based on the OPEX cost of a 490 MW floating windfarm, consisting of 70×7 MW wind turbines and adjusted accordingly according to the installed capacity [96].

Table 11-5: OPEX for the offshore floating windfarm [96].

	OPEX for floating offshore windfarm annual cost in MEuro		
	Tension Leg Platform	Semi-Submersible	Spar Buoy
400MW (50 WT 8 MW)	37.86	36.43	40.71
320MW (40 WT 8 MW)	30.29	29.14	32.57
240MW (30 WT 8 MW)	22.71	21.86	24.43

11.2.3 DECEX

DECEX was estimated as a percentage of the installation cost of the floating offshore windfarm [41]. Hence, the resulting costs as presented in Table 11-6, which shows the DECEX for a 400 MW offshore windfarm, while Table 11-7 shows the DECEX for a floating offshore windfarm with an installed capacity of 320 MW. Table 11-8 represents the DECEX for a floating offshore windfarm with an installed capacity of 240 MW.

Table 11-6: DECEX for a floating offshore windfarm with an installed capacity of 400 MW.

Description	% of installation cost	Tension Leg Platform Cost (MEuro)	Semi-Submersible Cost (MEuro)	Spar Buoy Cost (MEuro)
Floating wind turbine - floating	70%	43.15	6.95	11.38
Subsea cables	10%	7.024	7.02	7.024
Substations	90%	15.61	15.61	15.61
Mooring systems	90%	20.34	15.25	7.63
Total DECEX		86.12	44.84	41.65

Table 11-7: DECEX for a floating offshore windfarm with an installed capacity of 320 MW.

Description	% of installation cost	Tension Leg Platform Cost (MEuro)	Semi-Submersible Cost (MEuro)	Spar Buoy Cost (MEuro)
Floating wind turbine - floating	70%	34.52	5.56	9.11
Subsea cables	10%	5.62	5.62	5.62
Substations	90%	12.49	12.48	12.49
Mooring systems	90%	16.27	12.20	6.11
Total DECEX		68.89	35.86	33.32

Table 11-8: DECEX for a floating offshore windfarm with an installed capacity of 240 MW.

Description	% of installation cost	Tension Leg Platform Cost (MEuro)	Semi-Submersible Cost (MEuro)	Spar Buoy Cost (MEuro)
Floating wind turbine - floating	70%	25.89	4.18	6.83
Subsea cables	10%	4.21	4.21	4.21
Substations	90%	9.37	9.37	9.37
Mooring systems	90%	12.20	9.15	4.58
Total DECEX		51.67	26.90	25.00

The costings for Li-Ion battery and VRB ESS systems are now discussed.

11.3 The Costs Associated with a Lithium-Ion and Vanadium Redox Battery Energy Storage Systems

After analysing the characteristics of various ESS types and considering the current advances in technology (as discussed in Section 2.7), Li-Ion and VRB technologies are being proposed as ESSs for the Maltese Islands. These will not take up a critical amount of space and can be spread around

several strategic locations around the island. There are obvious advantages that battery systems have against the use of underwater or underground storage and the use of reservoirs, such as lack of space and inadequate terrain. The costs considered for a Li-Ion battery ESS consist of the Li-Ion Battery Bank and the Battery Inverter. While the costs considered for a VRB ESS include the Battery Stack, Pumps, Compressors, the Electrolyte and Absorption tanks and the Vanadium. Both types of battery systems include installation costs, Balance of Plant (BoP), EPC overheads and development costs (including land lease, interconnection fees, permits, contingencies and developer profits).

Li-Ion batteries can take up to 4000 cycles (which will not be achieved during the project lifetime) and/or will need to be replaced after seven years of operation. This will not be the case for a VRB battery system. Operating costs for a Li-Ion battery ESS are 1% of CAPEX, while those of a VRB are 2% [45].

In year 7, a Li-Ion battery cost was projected to be 30% of the cost of the batteries in 2020, while for the second envisaged replacement, i.e., after 14 years, the batteries will cost 20% of what they cost in 2020 [146]. Battery reinstallation costs will be the same as those in the year 2020. VRB have a 25-year lifetime and thus will not be changed over the project's lifetime [45]. This was reflected in the LCOS costings. The discharge efficiency of a Li-Ion battery was 95% [43], while that of a VRB ESS was 70% [43, 45]. These efficiencies were incorporated in the Matlab® program and the Simulink® model shown in Figure 6-7.

11.3.1 Lithium-Ion Energy Storage Systems CAPEX

The CAPEX for a battery installation was based on the benchmarked costs of a Li-Ion standalone system with a power rating of 60 MW with a duration of 8 hrs, hence a 480 MWh system [148, 191, 192]. Using a cost per MW and considering the larger capacity systems as subsystems of a 600 MWh installation then CAPEX costs for a Li-Ion battery ESS are shown in Table 11-9.

Table 11-9: CAPEX for a Li-Ion Battery ESS.

	Energy Storage Size MWh					
	600	3600	4200	4800	5400	6000
Number of 600 MWh power banks	1	6	7	8	9	10
	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
Li-Ion battery	105.34	632.02	737.35	842.69	948.02	1,053.36
Battery central inverter	4.55	27.31	31.86	36.41	40.96	45.51
Structural BOS	5.93	35.60	41.52	47.46	53.39	59.32
Electrical BOS	14.25	85.49	99.74	113.98	128.23	142.48
Installation Cost	8.199	49.20	57.40	65.60	73.80	82.00
EPC overhead	4.798	28.79	33.60	38.39	43.19	48.00
Total cost	143.07	858.39	1,001.46	1,144.52	1,287.59	1.43
Land	0.26	1.58	1.84	2.10	2.36	2.63
Permissions	0.31	1.86	2.17	2.48	2.79	3.10
Interconnection fees	11.34	68.06	79.40	90.74	102.08	113.42
Contingency	4.54	27.22	31.75	36.29	40.82	45.36
Developer overhead	4.54	27.22	31.75	36.29	40.82	45.36
EPC/Developer net profit	19.30	115.81	135.12	154.42	173.72	193.02
Total Developer cost	40.30	241.74	282.02	322.31	362.60	402.89
Total CAPEX	183.35	1,100.13	1,283.48	1,466.84	1,650.19	1,833.55

11.3.2 Lithium-Ion Energy Storage Systems OPEX

The OPEX costings for a Li-Ion battery ESS were as presented in Table 11-10. The data were based on a maintenance cost which is equivalent to 1% of the CAPEX, and on two battery replacements during the lifetime of the project. The replacement cost was the same as that in 2020.

Table 11-10: OPEX for a Li-Ion Battery ESS.

	Energy Storage Size MWh					
	600	3600	4200	4800	5400	6000
	1	6	7	8	9	10
Number of 600MWh power banks	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
Yearly cost of maintenance is 1% of CAPEX	1.30	7.80	9.10	10.41	11.07	13.00
Year 7 (45% of cost of 2020)	47.40	284.41	331.81	379.21	426.61	474.01
Year 7 Installation cost (100% of cost of 2020)	8.20	49.20	57.40	65.60	73.80	82.00
Total replacement cost (Year 7)	55.60	333.61	389.21	444.81	500.41	556.01
Year 14 (30% of the cost of 2020)	31.60	189.61	221.21	252.81	284.41	316.01
Year 14 Installation cost (100% of the cost of 2020)	8.20	49.20	57.40	65.60	73.80	82.00
Total replacement cost (Year 14)	39.80	238.80	278.60	318.41	358.21	398.01

11.3.3 Lithium-Ion Energy Storage Systems DECEX

As with the offshore windfarm, the DECEX, or dismantling costs of the ESS are 70% of the installation costs [41]. Hence DECEX for a Li-Ion battery ESS is as shown in Table 11-11.

Table 11-11: DECEX for a Li-Ion Battery ESS.

	Energy Storage Size MWh					
	600	3600	4200	4800	5400	6000
	1	6	7	8	9	10
Number of 600MWh power banks	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
DECEX (70% of installation cost)	5.74	34.44	40.18	45.92	51.66	57.40

11.3.4 Vanadium Redox Battery Energy Storage Systems CAPEX

The CAPEX costs for a VRB [193] are shown in Table 11-12. The developer costs were the same per MW as in the case of the Li-Ion battery system. The CAPEX costs were comparable to the Li-Ion system since battery capacities were lower due the VRB's 100% usable storage capacity (DoD) when compared to 80% of the capacity for a Li-Ion ESS system [41].

Table 11-12: CAPEX for a Vanadium Redox Battery ESS.

	Energy Storage Size MWh					
	500	3000	3500	4000	4500	5000
	1	6	7	8	9	10
Number of 500 MWh power banks	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
Total cost of stack	3.78	22.68	26.46	30.24	34.02	37.80
Pump cost	1.73	10.36	12.08	13.81	15.54	17.26
Cost of compressors	21.00	126.00	147.00	168.00	189.00	210.00
Cost of electrolyte tank	12.60	75.60	88.20	100.80	113.40	126.00
Cost of absorption tank	0.69	4.13	4.82	5.51	6.20	6.89
Cost of Vanadium	24.86	149.13	173.99	198.85	223.70	248.56
Fuel cell balance of plant	40.92	245.50	286.41	327.33	368.25	409.16
Installation Cost	6.83	41.00	47.83	54.67	61.50	68.33
PCS, Transformer, etc.	22.73	136.38	159.11	181.84	204.57	227.30
EPC overhead	4.00	23.99	27.99	31.99	35.99	39.99
Total cost	139.13	834.78	973.91	1113.04	1252.17	1391.30
Land	0.22	1.31	1.53	1.75	1.97	2.19
Permissions	0.26	1.55	1.81	2.07	2.34	2.58
Interconnection fees	9.45	56.71	66.16	75.62	85.07	94.52
Contingency	3.78	22.68	26.46	30.24	34.02	37.80
Developer overhead	3.78	22.68	26.46	30.24	34.02	37.80
EPC/Developer net profit	16.09	96.51	112.60	128.68	144.77	160.85
Total Developer cost	33.57	201.45	235.02	268.56	302.17	335.74
Total Energy storage system cost	172.70	1036.23	1208.93	1381.63	1554.34	1727.04

11.3.5 Vanadium Redox Battery Energy Storage Systems OPEX

OPEX for a VRB ESS was defined as 2% of the investment cost of the ESS plant, and there will be no battery changes during the lifetime of the project [45]. OPEX was therefore as presented in Table 11-13.

Table 11-13: OPEX for a Vanadium Redox Battery ESS.

	Energy Storage Size MWh					
	500	3000	3500	4000	4500	5000
Number of 500MWh power banks	1	6	7	8	9	10
	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
Yearly cost of maintenance is 2% of CAPEX	2.11	12.69	14.78	16.89	19.00	21.11

11.3.6 Vanadium Redox Battery Energy Storage Systems DECEX

As for the case of the offshore windfarm and the Li-Ion battery ESS, DECEX was 70% of the installation cost [41]. The result is presented in Table 11-14.

Table 11-14: DECEX for a Vanadium Redox Battery ESS.

	Energy Storage Size MWh					
	500	3000	3500	4000	4500	5000
Number of 500MWh power banks	1	6	7	8	9	10
	MEuro	MEuro	MEuro	MEuro	MEuro	MEuro
DECEX (70% of installation cost)	4.78	28.70	33.48	38.27	43.05	47.83

Results for predicted power output from the offshore windfarm, energy from the ESS discharged to the grid, the capacity factor of the wind farm, LCOE of the windfarm and the LCOS of the ESS, together with the sensitivity analysis of the LCOS and ESS will be discussed in Section 11.5.

11.3.7 Physical Sizing

According to the data shown in Section 2.6.2, a 600 MWh Li-Ion battery storage system would occupy an area equivalent to 250m by 130m (32,500 m^2), assuming that 200 Megapack® modules of 3 MWh each are used [131], this area would include a service area of 7,800 m^2 . For the ESS to operate at an optimal capacity, six or seven such sites would be required if a distributed approach is adopted.

Again, according to the physical size data for VRB provided in Section 2.6.2, a 500 MWh VRB battery site consisting of 62 battery packs of 8 MWh each, would occupy an area of 230 m by 134 m (30,820 m^2). This includes 10 m passageways surrounding the battery packs, which would take up 12,760 m^2 or 41% of the total area. In this case, if the ESS were to operate at an optimal capacity seven or eight such sites would be required.

This Section listed the costs for CAPEX, OPEX and DECEX for both the hypothetical offshore windfarm (WF2), with various supporting platforms, together with two types of battery ESS. The following conclusions could be drawn from the above analyses of costs:

- The costings of the windfarm were dependent upon capacity and type of supporting platform. The availability of such costings will allow the sensitivity of the LCOE to the error introduced because the windfarm was integrated to an ESS and the electricity grid to be determined.
- Due to the integration of the ESS, the output power from the windfarm was directed to charge the ESS rather than being curtailed and wasted. The windfarm did not charge the ESS operator for the charging energy. Thus, the LCOS of the ESS will be accordingly reduced.
- the CAPEX of both ESS systems were nearly equal. This is because the usable storage capacity of the VRB ESS was 100% when compared to a usable storage capacity of 80% for the Li-Ion system. This gives an advantage to the VRB ESS, apart from the further advantage as the VRB will not need to be replaced during the lifetime of the project.

11.4 LCOE for the Offshore Floating Windfarm

Table 11-15 shows the average predicted wind speeds for the years 2013-2019 obtained with an MCP methodology which utilised the DT regression technique. The wind data model used in this case was that for a LiDAR measurement height of 150 m, which is the closest measurement height to the hub height of the Vestas V164 used in the design of WF2 (150 m, see Table 6-2). Table 11-16 shows the total electric energy generated by the hypothetical offshore windfarm (WF2).

Table 11-15: Average wind speed at the candidate site.

Average Predicted Wind Speed at the Qalet Marku Candidate Site (ms^{-1})						
2013	2014	2015	2016	2017	2018	2019
7.46	6.97	6.62	7.34	6.83	7.25	7.24

Table 11-16: Total electrical energy generated by the hypothetical offshore windfarm.

Windfarm Capacity (MW)	Total Windfarm Output Energy (GWh)						
	2013	2014	2015	2016	2017	2018	2019
240	675	578	509	640	557	637	617
320	898	770	734	851	741	848	821
400	1,122	961	916	1,063	926	1,059	1,026

The analysis continued by calculating the capacity factor of the windfarm. The capacity factor is an important tool for estimating the quality of a windfarm. Capacity factors of between 30 and 40% are expected for the Mediterranean Sea. The Mediterranean Sea exhibits wind conditions of a moderate quality at what is considered as the windiest point of the Mediterranean Sea [4] (Island of Pantelleria). The wind farm capacity factors for the years 2013-2019, using the total energy output from the offshore wind farm are shown in Table 11-17.

Table 11-17: Capacity factor for the hypothetical offshore windfarm.

Wind farm capacity (MW)	Capacity Factor of the Offshore Windfarm (percentage)						
	Year						
	2013	2014	2015	2016	2017	2018	2019
240	32.1	27.5	24.2	30.4	26.5	30.3	29.6
320	32.0	27.5	26.2	30.4	26.5	30.3	29.3
400	32.0	27.4	26.2	30.3	26.4	30.2	29.3

Table 11-18 presents the energy output from the hypothetical offshore windfarm, which was transferred to the electricity grid. Since this energy was sold to the grid, it contributes to revenue

generation for the windfarm operator. This component of windfarm energy therefore impacts the LCOE.

Table 11-18: Power output component used for generation, percentage error due to predicted and forecasted values, and baseline output for hypothetical offshore windfarms of installed capacity of 400 MW, 320 MW and 240 MW.

Year	400MW Offshore Windfarm			320MW Offshore Windfarm			240MW Offshore Windfarm		
	Energy Output used for Generation (GWh)	% Error	Baseline Energy Output (GWh)	Energy Output used for Generation (GWh)	% Error	Baseline Energy Output (MWh)	Energy Output used for Generation (GWh)	% Error	Baseline Power Output (GWh)
2013	777		809	708		750	612		657
2014	717		747	640		678	538		578
2015	672		700	603		638	471		505
2016	784	4.2%	819	702	5.9%	747	597	7.3%	644
2017	718		748	638		676	531		570
2018	786		819	709		751	601		645
2019	765		797	685		726	580		623
2020	746		777	669		709	562		603
2021	741		772	664		703	554		595
2022	745		776	667		707	557		597
2023	755		787	676		716	569		611
2024	751		782	673		713	565		606
2025	755		787	678		718	570		611
2026	751		783	673		713	565		607
2027	749		781	671		711	563		604
2028	750		781	672		712	563		605
2029	751		782	673		713	565		606
2030	752		783	674		714	566		607
2031	751		783	673		713	565		607
2032	751		783	673		713	565		607

As described in Figure 4-17, the power output component from the windfarm which was transferred to the electricity grid, from the predicted wind speed and direction and the forecasted energy demand was calculated for the years 2013-2019. As defined in Section 4.8, the baseline energy output from the windfarm was calculated from the error between the power output from the windfarm obtained by using the predicted wind speed and direction, together with forecasted energy demand, and the power output obtained by using the measured wind speed and direction and energy demand for the year 2016. The percentage error was then used to estimate the baseline energy output for all the years. The energy output calculated from the measured wind speed and direction and the energy demand is highlighted in green. The results for the years 2013-2019 are presented graphically in Figure 11-7 to Figure 11-9.

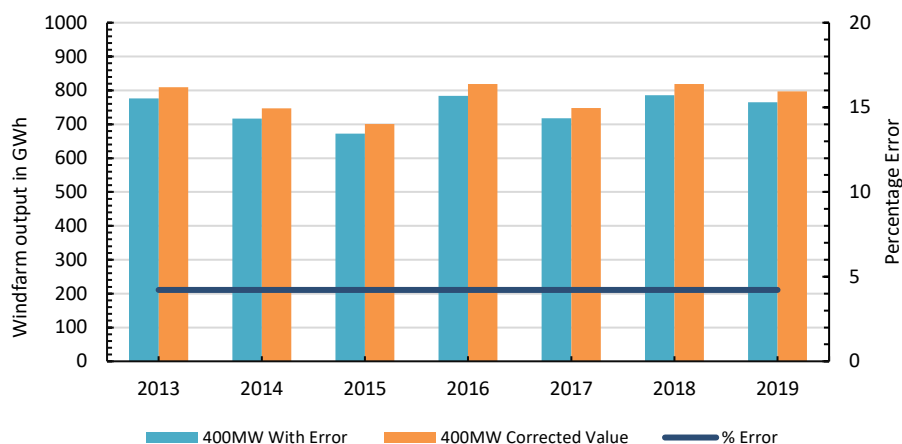


Figure 11-7: Hypothetical offshore windfarm with 400 MW installed capacity - energy output used for generation, baseline and with predicted wind data (MCP) and forecasted energy demand.

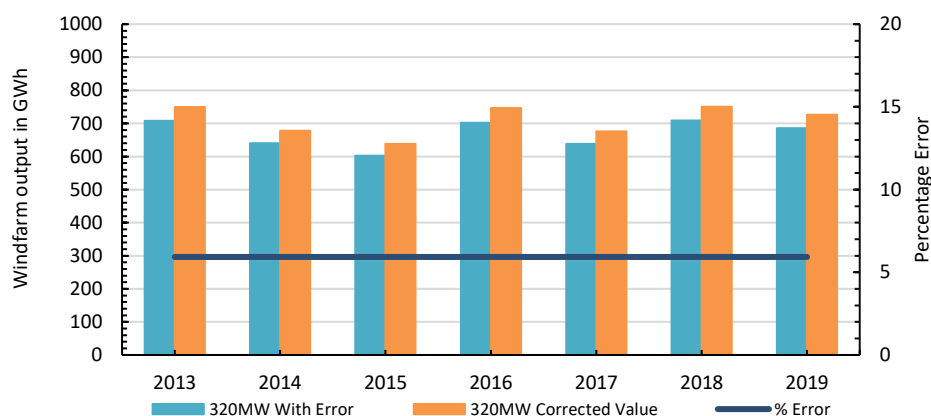


Figure 11-8: Hypothetical offshore windfarm with 320 MW installed capacity - energy output used for generation, baseline and with predicted wind data (MCP) and forecasted energy demand.

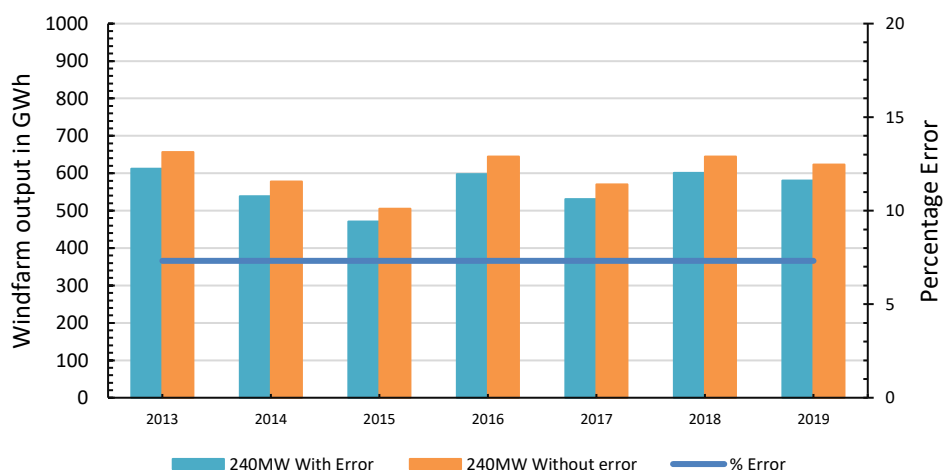


Figure 11-9: 240MW hypothetical offshore windfarm energy output used for generation.

Using the costings shown in Section 11.2, the power output for generation shown in Table 11-18, and by applying Eq. (3-89), two values of LCOE were calculated; one using the power output used for generation and another using the baseline power output used for generation. Appendix J shows LCOE cost calculations for the various windfarm installed capacities and offshore supporting platform configurations. The error between the two values of LCOE shows the sensitivity of the

LCOE to the values of output power from the predicted wind speed and direction and forecasted energy demand. The LCOE results for an offshore floating windfarm, which may utilise a SB, a Semi-submersible or a TLP foundation type, are shown in Figure 11-10 and Table 11-19.

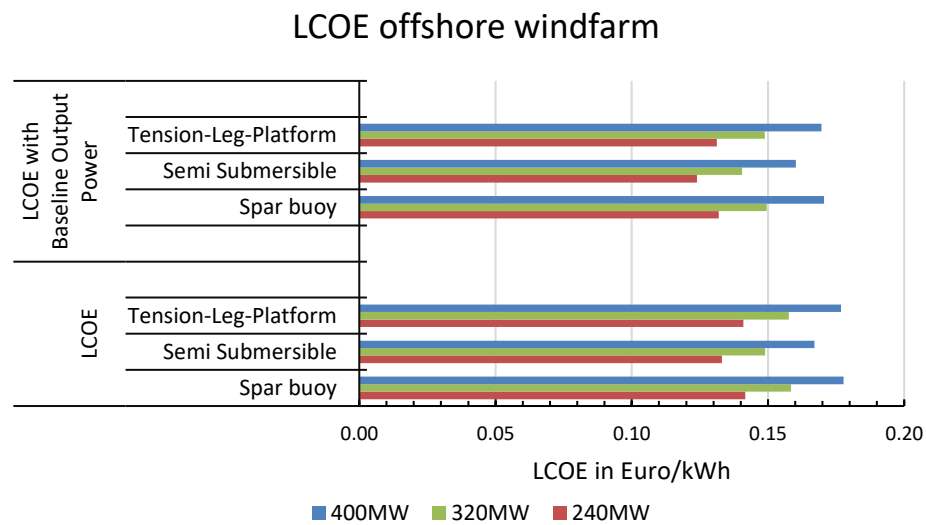


Figure 11-10: LCOE with predicted wind speed and direction and forecasted energy demand and LCOE from the baseline power output (measured wind speed and direction and energy demand).

Table 11-19: LCOE results for the hypothetical offshore floating windfarm (WF2).

Offshore Windfarm Installed Capacity (MW)	LCOE (Euros/kWh)		
	Spar buoy	Semi-Submersible	Tension-Leg-Platform
240	0.142	0.133	0.141
320	0.158	0.149	0.158
400	0.178	0.167	0.177
Offshore Windfarm Installed Capacity (MW)	LCOE with Baseline Output Power (Euro/kWh)		
	Spar buoy	Semi-Submersible	Tension-Leg-Platform
240	0.132	0.124	0.131
320	0.150	0.141	0.149
400	0.171	0.160	0.170
Offshore Windfarm Installed Capacity (MW)	Percentage Error (%)		
	Spar buoy	Semi-Submersible	Tension-Leg-Platform
240	7.4	7.4	7.4
320	6.0	6.0	6.0
400	4.2	4.2	4.2

11.4.1 Conclusions from the LCOE Calculations for the Floating Windfarm

As shown in Table 11-19, the results for LCOE for a hypothetical floating offshore windfarm (WF2) show:

- a variation of between € 0.133/kWh (€c 13.3/kWh) for a floating windfarm with a Semi-Submersible platform with an installed capacity of 240 MW to a maximum of € 0.178/kWh (€c 17.8/kWh) for a floating windfarm with a SB platform with an installed capacity of 400 MW. The analysis was carried out with for a WACC of 8% and the results agree with other studies carried out for the Mediterranean Sea for a windfarm with floating wind turbines [4].

- When one considers the sensitivity of the LCOE to the fact that an error is possible due to predicted values of wind speed and direction and forecasted energy demand, the error was limited to a maximum of 7.4% for the case of a floating offshore windfarm with an installed capacity of 240 MW and a minimum of 4.2% with an installed capacity of 400 MW.
- When including the error margin, the LCOE was estimated at € 0.124/kWh (€c 12.4/kWh) for an offshore floating windfarm with a Semi-Submersible platform having an installed capacity of 240 MW to a maximum of € 0.170/kWh (€c 17.0/kWh) for a floating windfarm, with a SB platform and an installed capacity of 400 MW.
- The results show that when considering the variation due to the error introduced by the prediction and the forecast, the LCOE was still within the expected range of typical LCOE expected for a floating windfarm in the Mediterranean Sea [4].

11.5 Levelised Cost of Storage for the Energy Storage System

The function of the ESS was explained in Section 4.5. The ESS discharged energy to the grid when the power output from the offshore windfarm was not enough to meet the electricity demand due to a high energy demand, the ESS was charged (not discharged) and was capable of delivering energy to the electricity grid and the ESS was not undergoing charging from the offshore windfarm.

The LCOS associated with two types of battery systems was analysed. Section 11.3 showed the costs for CAPEX, OPEX and DECEX associated with Li-Ion battery and VRB ESSs. The calculation of the LCOS was described in Section 3.5 and was calculated by using Eq. (3-89) for a Li-Ion battery ESS ($LCOS_{Li-Ion}$) and Eq. (3-90) for a VRB ESS ($LCOS_{VRB}$). As shown in Section 11.3 and Appendix J, the costings for a Li-Ion battery system included two replacements, each after seven years of operation over the lifetime of the project [45]. The VRB ESS did not require any battery replacement during its lifetime [45].

As was the case for LCOE calculation for the floating windfarm (WF2), the power output from the ESS was calculated from the following results, as presented in previous chapters:

- the wind speed and direction for the years 2013-2019 were predicted using the MCP methodology using a DT regression technique. The energy from the offshore windfarm was thus from the predicted values.
- The energy demand for the years 2013-2015 was the actual energy demand. Energy demand from 2016-2020 was a forecasted energy demand.
- Power output for the ESS for the years 2021 to 2032 were calculated by means of a moving average (MA) technique [33], described in Section 3.2. The MCP methodology could not be used to predict wind values for future years as it depends on a regression which assumes the availability of data from a reference site. Hourly wind speed and direction can be forecasted

using other methodologies, such as ANN using Genetic Algorithms (GA), and are at best accurate for 24 hrs [194]. The forecast of energy demand for future years can be done using the EDF methodology described in Section 4.3.3 [33], with the results shown in Chapter 8.

- The year 2016 was used to estimate the error in the LCOS calculations by calculating the output from the offshore windfarm (WF2) and the ESS using the measured wind speed and direction and the actual energy demand. This value of energy output is highlighted in green in Table 11-20 to Table 11-23. The energy values were compared to the ones obtained from predicted wind speed and direction and forecasted energy demand. In this way, a percentage error was derived.

The energy output from the ESS for the years 2013-2019 was then analysed. The analysis was carried out with the hypothetical offshore windfarm described in Section 6.1.2 (WF2). The windfarm had installed capacities of 240, 320 and 400 MW. As indicated earlier, a range of ESS capacities were used for the analysis. The results are presented in Figure 11-11 to Figure 11-16.

These results also confirmed the results from Section 10.4 for the energy discharged to the grid for values of ESS capacities which were greater than the optimal ESS capacity, and also confirmed that energy discharged to the grid increased with increasing installed windfarm capacity. The results also showed that approximately the same energy discharge was obtained with Li-Ion and the equivalent capacity of VRB, because the inefficiencies of the Li-Ion when compared to the VRB were compensated for an equivalent increase in storage capacity.

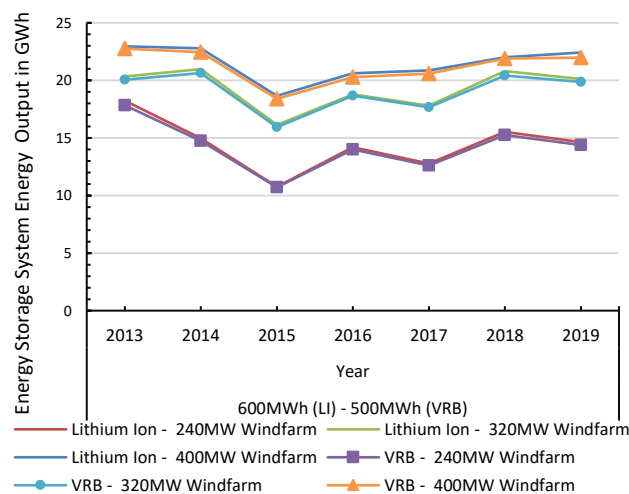


Figure 11-11: Energy discharged to the grid for an ESS capacity of 600 MWh Li-Ion and a 500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

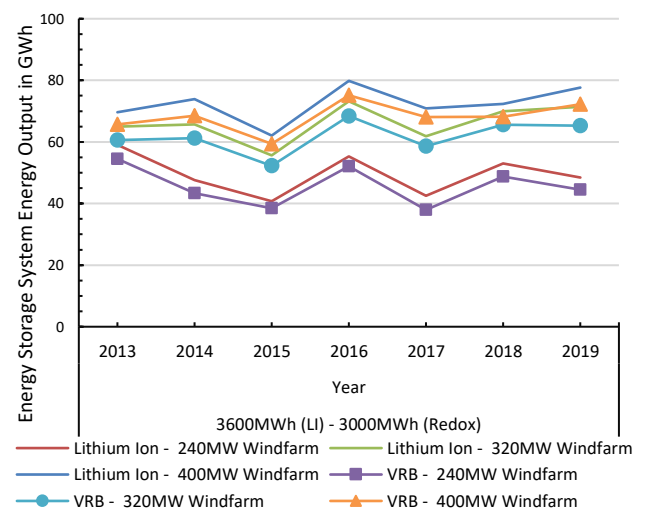


Figure 11-12: Energy discharged to the grid for an ESS capacity of 3600 MWh Li-Ion and a 3000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

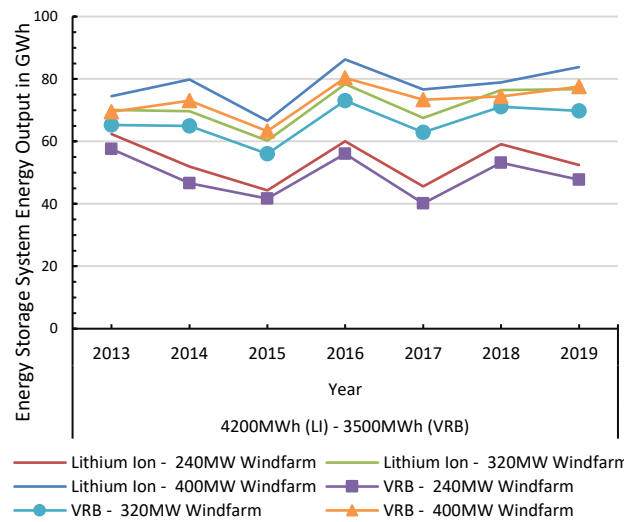


Figure 11-13: Energy discharged to the grid for an ESS capacity of 4200 MWh Li-Ion and a 3500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

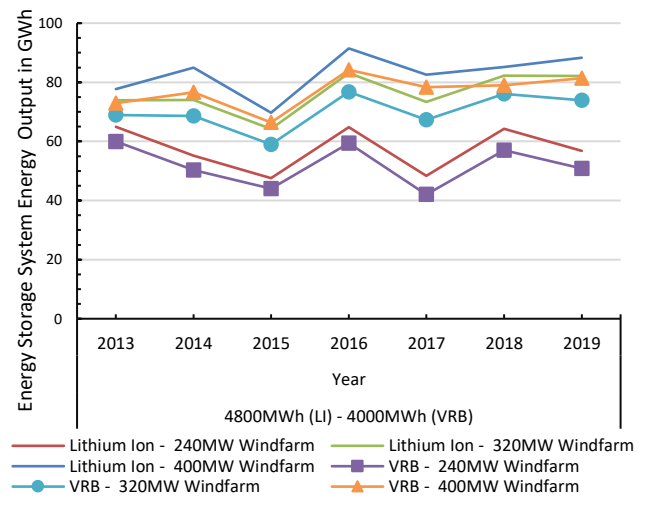


Figure 11-14: Energy discharged to the grid for an ESS capacity of 4800 MWh Li-Ion and a 4000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

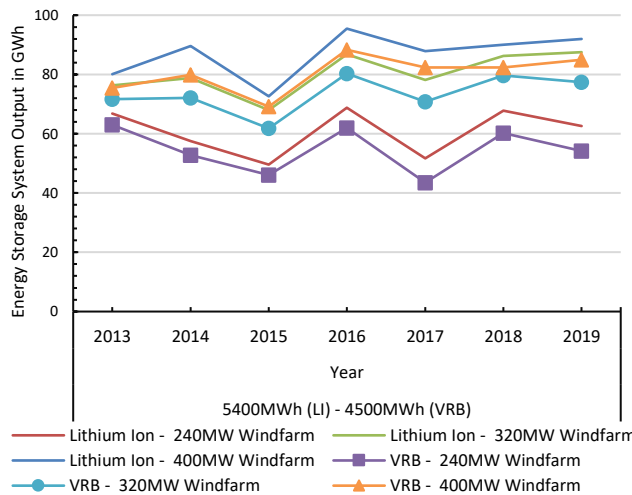


Figure 11-15: Energy discharged to the grid for an ESS capacity of 5400 MWh Li-Ion and a 4500 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

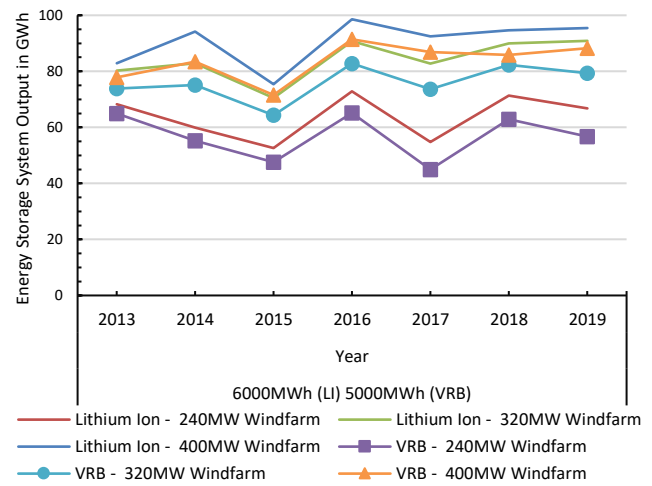


Figure 11-16: Energy discharged to the grid for an ESS capacity of 6000 MWh Li-Ion and a 5000 MWh VRB for the years 2013-2019 for windfarms with installed capacities of 240, 320 and 400 MW.

Since the conclusion from Chapter 10 and the above charts was that the transfer of energy from the battery ESS increased for increasing installed capacity of the hypothetical offshore windfarm, the analysis which follows utilised an offshore windfarm with an installed capacity of 400 MWh.

11.5.1 Lithium-Ion Battery Energy Storage System

Table 11-20 and Table 11-21 present the energy discharged to the grid for a Li-Ion battery ESS. Table 11-20 shows the energy discharged to the grid for ESS capacities of 600, 3000 and 4200 MWh. The table also shows the percentage error when comparing the results from the measured wind speed and direction and energy demand for the year 2016, and the baseline energy output as described in Sections 4.8 and 11.6. Table 11-21 shows similar results for an ESS with capacities of 4800, 5400 and 6000 MWh.

Table 11-20: Energy discharged to grid and percentage error due to predicted and forecasted values, and baseline power output for 600, 3600 and 4200 MW capacity Li-Ion Battery ESS.

Year	ESS Capacity 600 MWh			ESS Capacity 3600 MWh			ESS Capacity 4200 MWh		
	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (MWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)
2013	23.0		24.2	69.7		63.4	74.5		66.4
2014	22.8		24.1	73.9		67.2	79.8		71.2
2015	18.7		19.7	62.1		56.4	66.6		59.4
2016	21.0	5.59%	21.8	79.8	-9.04%	73.22	86.3	-10.84%	77.8
2017	20.9		22.0	70.8		64.4	76.7		68.4
2018	22.0		23.2	72.3		65.8	78.9		70.3
2019	22.4		23.7	77.7		70.6	83.9		74.8
2020	21.5		22.7	72.3		65.8	78.1		69.6
2021	21.3		22.5	72.7		66.1	78.6		70.1
2022	21.1		22.3	72.5		66.0	78.4		69.9
2023	21.5		22.7	74.0		67.3	80.1		71.4
2024	21.5		22.7	73.2		66.6	79.2		70.6
2025	21.6		22.8	73.5		66.9	79.6		71.0
2026	21.6		22.8	73.7		67.0	79.7		71.1
2027	21.5		22.7	73.1		66.5	79.1		70.5
2028	21.4		22.6	73.3		66.6	79.3		70.7
2029	21.5		22.7	73.3		66.7	79.4		70.8
2030	21.5		22.7	73.5		66.8	79.5		70.9
2031	21.5		22.7	73.4		66.7	79.4		70.8
2032	21.5		22.7	73.4		66.8	79.4		70.8

Table 11-21: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 4800, 5400 and 6000 MW capacity Li-Ion Battery ESS.

Year	ESS Capacity 4800 MWh			ESS Capacity 5400 MWh			ESS Capacity 6000 MWh		
	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (MWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)
2013	77.7		69.2	80.1		71.2	82.9		74.1
2014	84.9		75.6	89.6		79.7	94.2		84.2
2015	69.7		62.1	72.6		64.6	75.4		67.4
2016	91.5	-10.97%	82.4	95.5	-11.10%	85.9	98.6	-10.57%	89.2
2017	82.8		73.7	86.8		77.2	90.5		81.0
2018	83.6		74.4	87.8		78.0	91.6		81.9
2019	83.4		74.2	87.5		77.8	91.2		81.6
2020	85.3		76.0	89.6		79.7	93.5		83.6
2021	84.4		75.2	88.8		78.9	92.8		83.0
2022	84.7		75.4	88.9		79.1	92.8		83.0
2023	84.6		75.4	88.8		78.9	92.6		82.8
2024	84.1		74.9	88.3		78.5	92.2		82.4
2025	84.3		75.1	88.5		78.7	92.4		82.6
2026	84.4		75.2	88.6		78.8	92.5		82.7
2027	84.6		75.3	88.8		78.9	92.7		82.9
2028	84.5		75.2	88.7		78.8	92.6		82.8
2029	84.5		75.2	88.7		78.8	92.5		82.7
2030	82.8		73.7	86.8		77.2	90.5		81.0
2031	83.6		74.4	87.8		78.0	91.6		81.9
2032	83.4		74.2	87.5		77.8	91.2		81.6

11.5.2 Vanadium Redox Battery Energy Storage System

The energy discharged to the grid by a VRB ESS is presented in Table 11-22 and Table 11-23. Table 11-22 represents energy discharged to the grid for VRB ESS capacities of 500 MWh, 3000 MWh and 3500 MWh, while Table 11-23 represents the energy discharged to the grid for 4000, 4500 and 5000 MWh.

Table 11-22: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 500, 3000 and 3500 MW capacity VRB ESS.

Year	ESS Capacity 500MWh			ESS Capacity 3000MWh			ESS Capacity 3500MWh		
	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)
2013	22.8		24.1	65.7		62.0	69.5		64.3
2014	22.5		23.8	68.5		64.7	73.4		67.6
2015	18.4		19.5	59.4		56.1	63.3		58.6
2016	20.3	5.76%	21.4	75.1	-5.56%	71.0	80.3	-7.41%	74.4
2017	20.6		21.8	68.1		64.3	73.4		68.0
2018	21.9		23.2	68.1		64.4	74.4		68.9
2019	22.0		23.2	72.2		68.2	77.6		71.8
2020	21.2		22.4	68.2		64.4	73.1		67.7
2021	21.0		22.2	68.5		64.7	73.6		68.1
2022	20.8		22.0	68.5		64.7	73.7		68.2
2023	21.1		22.3	69.8		66.0	75.1		69.6
2024	21.2		22.4	69.1		65.2	74.4		68.9
2025	21.3		22.5	69.2		65.4	74.5		69.0
2026	21.2		22.4	69.4		65.5	74.7		69.0
2027	21.1		22.3	69.0		65.1	74.1		68.7
2028	21.1		22.3	69.1		65.2	74.3		68.8
2029	21.1		22.3	69.2		65.3	74.4		68.9
2030	21.2		22.4	69.2		65.4	74.5		69.0
2031	21.2		22.4	69.2		65.3	74.4		68.9
2032	21.2		22.4	69.2		65.3	74.4		68.9

Table 11-23: Energy Discharged to Grid and percentage error due to predicted and forecasted values, and baseline power output for 4000, 4500 and 5000 MW capacity VRB ESS

Year	ESS Capacity 4000MWh			ESS Capacity 4500MWh			ESS Capacity 5000MWh		
	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)	Energy Output (GWh)	%Error	Baseline Energy Output (GWh)
2013	72.9		67.9	75.5		69.6	77.9		72.0
2014	76.6		71.4	79.9		73.7	83.5		77.2
2015	66.4		61.8	69.1		63.8	71.6		66.2
2016	84.2	-6.9%	78.4	88.3	-7.8%	81.4	91.4	-7.5%	84.5
2017	78.3		72.9	82.4		76.0	86.9		80.3
2018	78.9		73.5	82.3		76.0	85.9		79.4
2019	81.4		75.8	85.0		78.4	88.2		81.6
2020	77.0		71.7	80.4		74.1	83.6		77.3
2021	77.6		72.2	81.1		74.7	84.4		78.1
2022	77.7		72.4	81.2		74.9	84.6		78.2
2023	79.3		73.9	83.0		76.5	86.4		79.9
2024	78.6		73.2	82.2		75.8	85.7		79.3
2025	78.6		73.3	82.2		75.8	85.6		79.1
2026	78.6		73.2	82.1		75.7	85.5		79.1
2027	78.2		72.8	81.7		75.4	85.1		78.7
2028	78.4		73.0	81.9		75.5	85.3		78.9
2029	78.5		73.1	82.0		75.7	85.5		79.0
2030	78.6		73.2	82.2		75.8	85.6		79.1
2031	78.5		73.1	82.0		75.7	85.5		79.0
2032	78.5		73.1	82.0		75.6	85.4		79.0

11.5.3 Levelised Cost of Storage Results

The LCOS results are presented in Figure 11-17 to Figure 11-20, where Figure 11-18 and Figure 11-20 present the error in absolute terms together with the percentage error in LCOS. The results are also tabulated in Table 11-24.

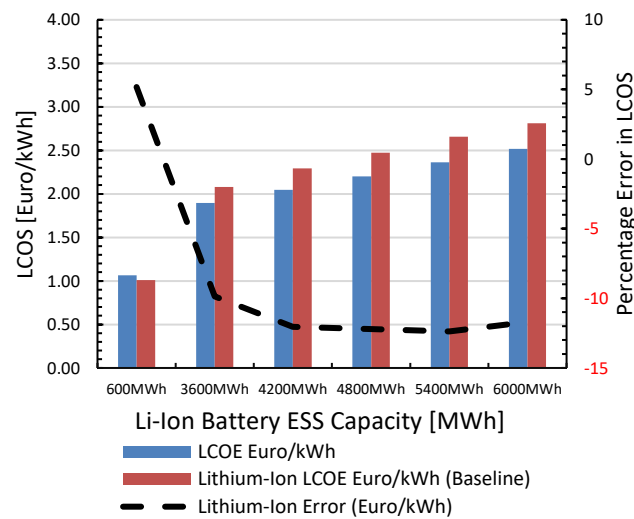


Figure 11-17: LCOS obtained from predicted wind speed and direction and forecasted energy demand, baseline LCOS and percentage error for a Li-Ion Battery ESS, with increasing ESS capacity.

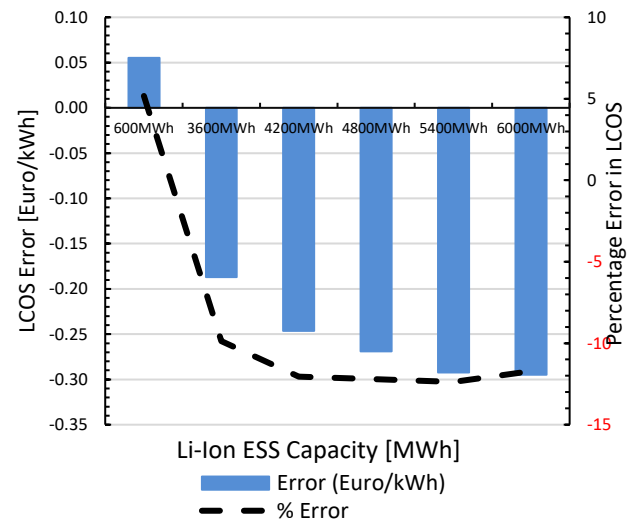


Figure 11-18: Absolute and percentage error in LCOS for a Li-Ion battery ESS, with increasing ESS capacity.

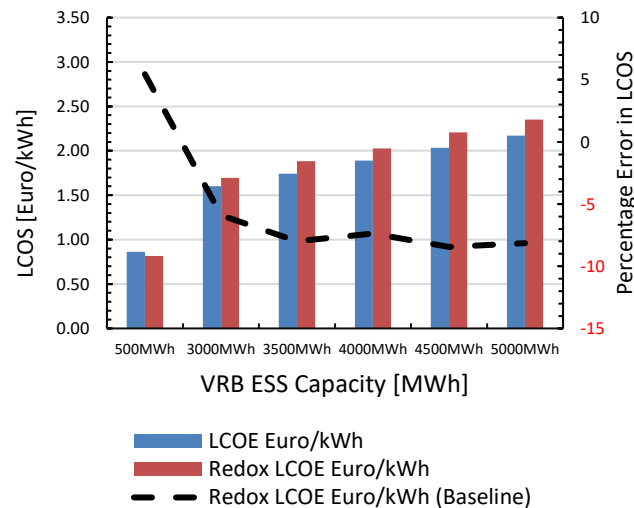


Figure 11-19: LCOS obtained from predicted wind speed and direction and forecasted energy demand, baseline LCOS and percentage error for a VRB ESS, with increasing ESS capacity.

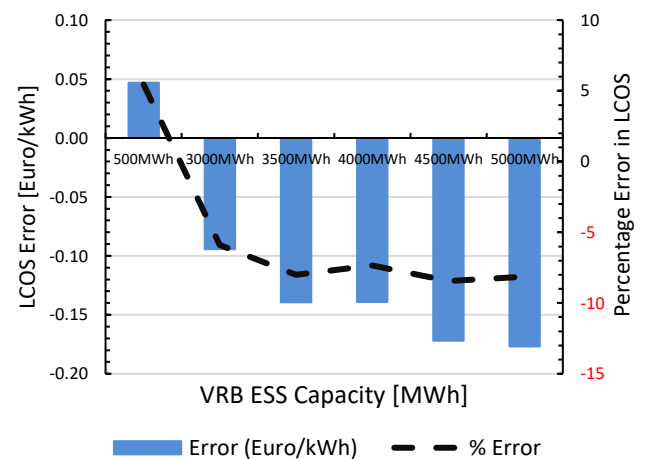


Figure 11-20: Absolute and percentage error in LCOS for a VRB ESS, with increasing ESS capacity.

Table 11-24: LCOS Results for a Li-Ion Battery and VRB ESS.

LCOS - Lithium-Ion Battery ESS				
ESS Capacity (MWh)	LCOS (Euro/kWh)	LCOS Euro/kWh (Baseline)	Error (Euro/kWh)	% Error
600	1.065	1.010	0.055	5.2%
3600	1.894	2.081	-0.187	-9.9%
4200	2.046	2.292	-0.247	-12.1%
4800	2.203	2.472	-0.269	-12.2%
5400	2.363	2.656	-0.292	-12.4%
6000	2.518	2.813	-0.295	-11.7%
LCOS - Vanadium Redox Battery (VRB) ESS				
ESS Capacity (MWh)	LCOS (Euro/kWh)	LCOS Euro/kWh (Baseline)	Error (Euro/kWh)	% Error
500	0.863	0.816	0.047	5.4%
3000	1.602	1.696	-0.094	-5.9%
3500	1.742	1.882	-0.139	-8.0%
4000	1.889	2.028	-0.139	-7.4%
4500	2.035	2.207	-0.172	-8.4%
5000	2.173	2.350	-0.177	-8.1%

The LCOS increased for increasing ESS capacity. This was expected since, as shown in Section 10.4, an ESS which is larger than the optimal size, as was determined in Section 10.5, will not discharge additional energy to the grid. The additional ESS size therefore only results in an increased CAPEX, OPEX and DECEX. It did not contribute to ROI, but only increased the LCOS.

The value of the LCOS is directly dependent on the energy discharged to the grid, as well as the cost, according to the relationship established in Eq. (3-90). Although as shown in Section 11.3, the cost increase between the different ESS configurations was linear, the increase in energy discharged to the grid was not. However, as shown in Section 10.4 and according to Eq. (4-9), it is governed by a 3rd order polynomial relationship. Hence, the relationship between the LCOS and the ESS capacity was not expected to be linear. The conclusions which were drawn from the analysis are therefore shown below.

11.6 Conclusions from the Levelised Cost of Storage Calculations

The conclusions from the results shown in Table 11-24 are therefore as follows:

- Results showed an LCOS of € 1.06/kWh for a 600MWh Li-Ion Battery ESS and an LCOS of € 0.86/kWh for a VRB ESS with a capacity of 500 MWh. The VRB system offered a lower LCOS due to the advantages described in Section 11.3.
- The LCOS increased with capacity of the ESS. This confirmed that an ESS capacity which exceeds the optimal size (Section 10.5) only increases CAPEX, OPEX and DECEX costs and unlike a windfarm does not serve to produce more energy.
- At the optimal ESS capacity of 4000 MWh, the LCOS was € 2.05/kWh for a Li-Ion Battery ESS and € 1.89/kWh for a VRB ESS.
- The results obtained for the LCOS of the ESS system were well within the range of the LCOS costings discussed in Section 2.8, where an LCOS of € 1.663/kWh was obtained for a 48 MWh stand-alone battery ESS with an WACC of 8% for an ESS in Nantucket, Massachusetts [149]. Other LCOS costings shown in Section 2.8 yielded LCOS values of € 0.338/kWh for a VRB system and a range of € 1.687/kWh [45, 149] to € 0.876/kWh [143, 149] for a Li-Ion battery system
- Table 11-24 shows the error in the calculation of the LCOS due to the use of the predicted wind speed and direction and the EDF. As in the case of the windfarm, the energy output obtained from measured wind speed and direction and energy demand for the year 2016, was used to calculate the percentage error in energy output.
- This percentage error was then used to calculate the baseline energy output which was in turn used to calculate the sensitivity of the LCOE to the prediction and forecasting models.

- The results showed a 5.3% error for a Li-Ion Battery ESS with a 600 MWh capacity and an error of 5.5% for the VRB ESS capacity of 500 MWh. At the optimal ESS capacity of 4000 MWh, the absolute error was of 12.5% and 7.4% for the respective battery ESS types. After the final step of the research has been concluded, a discussion of the conclusions is now carried out.

12 Discussion and Conclusions

A discussion now follows, and the conclusions drawn from the current research are highlighted. The research problem was described in Chapter 1. Following the literature review, which was carried out in Chapter 2, a knowledge gap could be identified. The knowledge gap was described in Section 2.13. A gap in knowledge was determined related to the regression techniques regression techniques for MCP and EDF are best suited for optimising the sizing and utilisation of an ESS, and how the uncertainties from the different combinations of regression techniques influence the determination of the LCOE and the LCOS. The knowledge gap was then addressed in the subsequent research. The mathematical theory which was needed to address the research gap was addressed in Chapter 3.

The mathematical tools included regression techniques for prediction of wind behaviour at a candidate site. Forecasting of econometric and demographic data was carried out by using the Box-Jenkins methodology. The same regression techniques which were used for the MCP methodology were also used to forecast the energy demand. Dimension reduction was also described. This was necessary to understand which combination of regression techniques gave the least error in the prediction of the behaviour of the ESS which was integrated with the offshore windfarm and the electricity grid.

Chapter 3 also described the mathematics used in the ESS model, as well as the measurement metrics which were used to assess the suitability of the regression techniques. These mainly included the use of the coefficient of determination and the analysis of residuals. The methodology was described briefly in the introductory chapter and in detail in Chapter 4. The methodology was divided into eight steps.

The sources of data needed for the research and their acquisition were described in Chapter 5. Chapter 6 described two hypothetical offshore windfarms which were designed using windPRO®. Following this, a model which integrated the hypothetical offshore wind farm which were designed in Matlab® and Simulink®. This was also described in Chapter 6.

Results were presented in Chapters 7 to 11. Chapter 7 showed the results from STEP 1 to STEP 3 of the methodology and demonstrated the results for the MCP methodology. This was divided into two parts, using two sets of data. The best regression techniques for the prediction of the wind speed and wind direction at the candidate site were identified as those which used linear regression, ANN, DT and SVR. In STEP 2 the MCP methodology was applied to the wind data as obtained from LiDAR unit measurements made at the candidate site. A methodology for predicting wind direction at the candidate site was also used in STEP 3 and the predicted wind speed and direction were

applied to the hypothetical windfarm to analyse the effect of the predicted wind data on the energy output from the hypothetical windfarm.

Chapter 8 showed the results from STEP 4, which was the application of the Box-Jenkins methodology to the econometric and demographic data of the Maltese islands. The results from this methodology were then used in STEP 5 to forecast the energy demand. The forecasting methodology applied the same regression techniques applied for the prediction of the wind data at the candidate site.

In Chapter 9, various combinations of regression techniques which were applied to the MCP and EDF methodologies were used to create a matrix of results as required in STEP 6 of the methodology. This matrix showed the error in energy discharged by the ESS to the electricity grid, the curtailed energy from the hypothetical offshore windfarm, when applying measured wind data and energy demand and predicted wind data and energy demand data to the windfarm and ESS model described in Chapter 6. Due to the complexity of the results and the multi-dimensional nature of the results, a dimension reduction methodology was applied to the data.

Following the identification of the optimal combination of regression techniques for the MCP and EDF methodology carried out in STEP 6, the optimal ESS capacity was estimated. The optimal ESS capacity was obtained by using the results from the optimal combination of the regression methodologies used in the MCP and EDF methodologies. This capacity was compared to that measured from the use of the measured wind data and energy demand. Hence the percentage error in the estimation of the optimal capacity could be estimated. The results from STEP 7 were discussed in Chapter 10.

In Chapter 11, the LCOE of the windfarm and the LCOS of the ESS were estimated. A base year (2016) was chosen to calculate the error in the LCOE and the LCOS. The energy output from the windfarm and the ESS was calculated by using actual and measured wind data and energy demand and the error in energy output calculated. The predicted wind data and energy demand data were from the optimal combination of regression techniques derived from STEP 6. The possible error in LCOE and LCOS due to the prediction and forecast was therefore calculated. Two types of battery ESS were compared in this part of the methodology, namely for a Li-Ion battery ESS and a VRB ESS. The relationship of the results with the knowledge gaps identified in Section 2.13 is now discussed.

12.1 Addressing the Knowledge Gap

Several knowledge gaps were identified from the literature review presented in Chapter 2. The knowledge gaps were addressed at various points throughout the research as follows:

- **Which regression technique for MCP best suits integration of offshore wind energy and energy storage?**

Four regression techniques were identified which could potentially provide adequate results from the MCP methodology when applied to predict the wind behaviour at a candidate site. The four regression techniques were based on Linear Regression (using both SLR and MLR), ANN, DT and SVR. The results obtained from various measurement heights confirmed that the best result was obtained when the DT regression technique was used. However, it was also observed that use of the other regression techniques should not be excluded.

- **Which regression technique for the EDF methodology is best suited for use with energy storage modelling?**

Four regression techniques were applied to the EDF methodology. The DT regression technique was found to give the best overall performance when considering the results obtained from the Coefficient of Determination and the analysis of the residuals carried out by using the MAE and MSE. The regression techniques were found suitable to analyse the behaviour of an offshore windfarm which is integrated to the electricity grid and with an ESS.

- **How can the MCP methodology be integrated numerically with energy demand forecast and energy storage models?**

This was addressed in Chapter 9 where the Simulink® model described in Chapter 6 was used to integrate the predicted wind data and the forecasted energy demand data. The results from this integration of the two methodologies was possible due to this model which simulates the behaviour of the ESS which was coupled to an offshore windfarm and the electricity grid.

- **How can MCPs and energy forecast models be combined to predict the long-term overall performance of offshore wind farms which are integrated to the electricity grid and ESS?**

The first step in predicting the long-term performance of the windfarm was to calculate the error produced from the use of the various regression techniques for MCP and EDF methodologies. This resulted in the identification of the optimal combination of regression techniques as shown in STEP 6 of the methodology. Following this, the long-term behaviour of the offshore windfarm and the ESS was determined in STEP 8 of the methodology. The determination of the long-term behaviour enabled the calculation of the LCOE of the windfarm and the LCOS of the ESS and the error in LCOE and LCOS due to the use of the MCP and EDF methodology.

Addressing the Research Questions

The methodology described in Chapter 4 also provided answers to the research questions posed in the literature review of Chapter 2. The research questions were addressed at various points throughout the research as follows:

- **Which are the most reliable regression techniques for MCP and EDF methodology?**

Throughout this research various reliable regression techniques were identified. These were SLR, MLR, ANN, DT and SVR. However, the analysis at STEP 2 identified the DT regression technique as the best technique for the MCP methodology. STEP 3 indicated that MLR was the best methodology when using NMAE and NMSE to analyse the residuals from the energy output from the windfarm, when predicted wind data was applied to the hypothetical windfarm (WF1). The analysis at STEP 5 identified the DT regression technique as the best technique for the EDF methodology.

The result of the analysis carried out in STEP 6 showed that combinations of the DT and SVR techniques may be used in the combination of regression techniques for the MCP and EDF methodologies. As the DT regression technique was already identified, from previous steps in the research, as the best regression technique for MCP and EDF, a DT_DT combination was selected to analyse the long-term behaviour of the windfarm and the ESS.

- **What is the level of uncertainty resulting from the different coupled regression techniques for MCP and EDF methodologies?**

The level of uncertainty was measured by means of the percentage error in energy yield. The lowest levels of uncertainty were obtained with combinations of the DT and SVR techniques following the utilisation of a dimension reduction methodology.

- **How will the level of uncertainty of the combined methodologies influence the optimal size of the ESS?**

The use of curtailed energy as a metric gave a more accurate result but on a narrower range of combinations than those obtained when using the energy discharged from the ESS as a metric. The absolute percentage error was in the range of 0.05% to 8.67%, with a percentage error of 3.94% when considering the mean value of the estimated ESS size.

The use of energy discharge from the ESS as a metric resulted in an error which lies in the range of 0 to 17.25%, with a percentage error of 1.21%, when considering the mean value of the estimated ESS size.

- **How does the level of uncertainty impact the LCOE and LCOS of the offshore windfarm and the ESS, respectively?**

The sensitivity of the LCOE due to predicted values of wind speed and direction and forecasted energy demand, the error was limited to a maximum of 7.4% for the case of a floating offshore windfarm with an installed capacity of 240 MW and a minimum of 4.2% with an installed capacity of 400 MW.

Results also showed a 5.31% error in the LCOS for a Li-Ion Battery ESS with a 600 MWh capacity and an error of 5.45% in the LCOS for the VRB ESS capacity of 500 MWh. At the optimal ESS capacity of 4000 MWh, the absolute errors were 12.5% and 7.37% for the respective battery ESS types.

12.3 Main Conclusions

The main conclusions from this research are summarised in the following sections.

12.3.1 Regression techniques for MCP

- The behaviour of the regression techniques, with measurement height could be analysed due to the fact that the research made use of data from a LiDAR unit remote wind measurement system.
- This research combined the use of various regression techniques for the MCP methodology for wind speed and also used a novel methodology for predicting the wind direction at a candidate site. The wind direction at the candidate site could therefore also be predicted with the MCP methodology, which utilised MLR, ANN, DT and SVR as regression techniques.
- The error in the energy yield from a hypothetical windfarm, which was introduced by the prediction from the MCP methodology utilising the four regression techniques, could be measured. This was done by calculating the NMAE, the NMSE and the percentage error in the windfarm's energy yield. The results show that the NMAE, NMSE and the percentage error in energy yield depended upon the regression technique and windfarm capacity. The results also showed that an optimal regression technique for the MCP methodology could be identified.
- Although a best regression technique was identified, and other techniques gave larger errors, they cannot be discarded. It is recommended to compare results from the various regression techniques, comparing results by analysing residuals and errors and then choosing the best regression technique on a case-by-case basis.

12.3.2 Econometric, Demographic and Energy Demand Forecasting

- The two regression techniques used for EDF, namely ANN and DT, resulted in better results than the MLR and SVR techniques. This was evident from the results for the coefficient of

determination and the analysis of residuals. This result was affirmed with two forecasting methodologies analysis of the residuals of both the years 2016 and 2017.

12.3.3 The Ideal Combination of Regression Techniques for the MCP and Energy Forecasting Methodologies.

- The results from the use of the dimension reduction methodology showed that the best combinations of regression techniques for MCP and EDF methodologies were, combinations of the DT regression and SVR techniques.
- The ANN and MLR techniques were ruled out as a regression technique for both the MCP and EDF methodologies since they resulted in a larger MPE product.
- Considering the results of Chapter 8, the DT regression technique provided the best results for EDF. This result was independent of the behaviour of the windfarm and the ESS. The matrix analysis carried out in Section 9.2 showed that the use of the DT regression technique was also adequate when used in the context of the windfarm and ESS combined with the electricity grid, although in this context SVR performance was slightly better. The results from Section 7.2.5 also determined that the DT regression technique was the best regression technique for the MCP methodology.
- It was therefore safe to state that a DT_DT combination for MCP methodology and EDF methodology can be used to continue the analysis to determine the optimal ESS capacity and to determine the error in LCOE of the offshore windfarm and LCOS of the ESS.

12.3.4 Conclusions from the Analysis to Determine the Optimal ESS Capacity

Two methodologies were developed to obtain the optimal ESS capacity. The percentage error due to the use of the MCP and EDF methodologies was estimated by comparing it to the optimal capacity obtained from measured wind speed and direction and energy demand. The following conclusions were drawn from this analysis:

- Both methodologies produced a similar result. An optimal ESS capacity with a mean value of 3651 MWh was estimated from the predicted and forecasted values when using curtailed energy as a metric. A mean value of 4051 MW was estimated when using the energy discharged from the ESS to the grid. Optimal ESS capacities of 3801 MWh and 4101 MWh, respectively, when using measured values.
- In the case where the windfarm capacity was large enough and the generation baseload was small enough, a large ESS capacity could be justified, while for smaller windfarm capacities and/or larger generation baseloads, the ESS capacity should be smaller in size or even omitted, because according to the results large ESS capacities will not be utilised effectively.

- The use of curtailed energy as a metric gave a more accurate result, but over a narrower range of combinations of offshore windfarm installed capacities, ESS capacities and power ratings.
- The use of energy discharged to the grid from the ESS as a metric gave a less accurate result, but it permitted a wider range of combinations of offshore windfarm installed capacities, ESS capacities and power ratings, due to the fact that even though curtailed energy from the wind farm was zero, the ESS still received energy from the windfarm.
- The absolute percentage error was in the range of 0.05% to 8.67%, with a percentage error of 3.94% when considering the mean value of the estimated ESS size, while the use of energy discharged from the ESS resulted in an absolute error which ranged from 0 to 17.25% with a percentage error of 1.21%, when considering the mean value of the estimated ESS size.

12.3.5 Conclusions from the LCOE and LCOS

The LCOE was computed for various installed capacities of windfarm and the use of three different platforms used for a floating windfarm. The reasons for selecting a floating windfarm were discussed in Section 2.4.

- A variation of between € 0.133/kWh (€c 13.3/kWh) for a floating windfarm with a Semi-Submersible platform for an offshore windfarm with an installed capacity of 240 MW to a maximum of € 0.178/kWh (€c 17.8/kWh) for a floating windfarm, with a SB platform and a capacity of 400 MW with a WACC of 8%.
- When one considers the sensitivity of the LCOE to the fact that an error is possible due to predicted values of wind speed and direction and forecasted energy demand, the error was limited to a maximum of 7.4% for the case of a floating offshore windfarm with an installed capacity of 240 MW and a minimum of 4.2% for one with an installed capacity of 400 MW. The results indicated that when considering the variation due to the error introduced from the prediction and the forecast, the LCOE was still comparable to the typical LCOE expected for a floating windfarm in the Mediterranean Sea [4].
- Results showed an LCOS of € 1.06/kWh for a 600 MWh Li-Ion Battery ESS and an LCOS of € 0.86/kWh for a VRB ESS with a capacity of 500 MWh. The VRB system offered a lower LCOS due to a better utilisation of the capacity and a longer lifetime of the battery which does not require any battery replacements over the operational lifetime of the ESS compared to the two necessary changes for the Li-Ion battery over the duration of the system's lifetime.
- At the optimal estimated ESS capacity, the LCOS was € 2.05 /kWh for a Li-Ion Battery ESS and € 1.89/kWh for a VRB ESS.

- Levelised Cost of Storage results confirmed that an ESS capacity which exceeded the optimal size (Section 10.5) only increased CAPEX, OPEX and DECEX costs and, unlike a windfarm does not serve to produce more energy.
- The results obtained for the LCOS were comparable to the LOCS costings discussed in Section 2.8.
- Results showed a 5.31% error for LCOS for a Li-Ion Battery ESS with a 600 MWh capacity and an error of 5.45% for the VRB ESS capacity of 500 MWh. At the optimal ESS capacity of 4000 MWh, the absolute errors were 12.5% and 7.37% for the respective battery types.

12.4 Opportunities for Further Research

Opportunities for further research are now mentioned.

- The current research was limited to using the same regression technique for predicting wind speed and wind direction. Thus, a regression model was created for wind speed, and two more regression models were created for the wind speed components, which were then used to calculate the wind direction. Having three regression models, offered the possibility of using different combinations of techniques, i.e., using MLR for wind speed and ANN for wind direction. This was performed for a limited number of combinations and is an area suggested for further research.
- Another area which warrants further study, is trying out different windfarm topologies or selecting different wind turbines and different hub heights. Development in offshore wind turbines is ongoing, with wind turbines having power ratings of 12 MW to 15 MW [99] being envisaged. It would also be of interest to study the application of different wake models as a possible means of decreasing the errors.
- The influence on the accuracy of the forecasts by the Box-Jenkins methodology on EDF was not the subject of this research. However, the ARIMA and SARIMA parameters were chosen in such a manner that the forecasting error was kept to a minimum. The influence of the ARIMA and SARIMA parameters on the forecast of econometric trends and their consequent influence on the choice of regression techniques for EDF, could therefore be analysed in further future research.
- The EDF methodology needs further analysis and improvement, especially to forecast sudden increases in energy demand, as seen in the third quarter of 2017. This effect was not seen in the year 2016, during which the energy demand for Q3 was more stable than that for 2017. Further research can also be done to test the sensitivity of the EDF to the forecasted independent variables.

- The research did not analyse the effects on energy demand due to phenomena and unexpected events such as the COVID-19 pandemic.
- Two further independent variables upon which energy demand depends are temperature and relative humidity. The Islands have hot summers, with high temperatures and sometimes even high relative humidity depending on the wind direction. This was evidenced in the results of the third quarter of the year 2017, where it was noted that the increase in temperature of the summer months resulted in an increase in energy demand, which is not detected by the forecasting model. However, the forecast of temperature and humidity will necessitate further studies as the forecast of temperature and humidity on an hourly basis over the period of several years requires more complex methodologies than the ones used above.
- Another area of research is the behaviour of the model with a varying generation baseload. The generation baseload used in this research was assumed to remain constant throughout the years of operation of the offshore windfarm and the ESS. In reality this could be variable, so this is another area worth investigating.
- An analysis of the reduction of CO₂ due to the introduction of the windfarm and the ESS can be carried out.
- The analysis carried out in Section 9.3 for the various combinations of regression techniques for the MCP and EDF methodologies was an in-depth analysis of the percentage error variation under the various conditions. Although the determination of the ESS capacity and the optimum windfarm configuration were determined using the DT-DT combination of regression techniques, it would be interesting to repeat the analysis with a different combination of regression techniques for MCP and EDF methodologies and determining if this will lower in the error. Such combinations could involve the SVR technique.
- The effect of introducing other RE sources such as PV systems also merits investigation. The research was limited to an offshore windfarm as the source for charging the ESS.

12.5 Implications for the Wind Energy Industry

The research has provided insight and generation of new knowledge in the following areas by proposing:

- A methodology for integrating MCP and EDF methodologies which utilise different regression techniques.
- A methodology for optimising ESS capacity for RE systems, hence resulting in an opportunity to increase the penetration of RE and the reduction of the dependence on fossil fuels and analysing the sensitivity to prediction and forecasting methodologies.

- A methodology for analysing the sensitivity of the LCOE and LCOS to prediction and forecasting methodologies.
- The development of a technique which will help optimise the economics of wind and energy storage.
- A reduction of generation baseload, hence reducing greenhouse gas emissions. The research permitted the analysis of the behaviour of an ESS coupled to an offshore windfarm and an electricity grid. The presence of the offshore windfarm and the ESS which permit a reduction in the baseload. The possible reduction in generation baseload permitted a greater utilisation of the windfarm energy output and also resulted in a reduction in the use of the ESS.
- The models developed are not limited to wind energy as energy from other RE sources such as PV systems can also be integrated into the model. The ESS can also be charged from excess energy from PV systems.
- Energy storage does not exclude the electrification of transportation. Studies could be carried out to analyse the effect of storing the extra energy from the offshore windfarm in the batteries of electric cars.
- The methodology is also applicable to monopole offshore windfarms and onshore windfarms.

References

- [1] G. Strbac, M. Aunedi, I. Konstantelos, R. Moriera, F. Teng, R. Morens, D. Pudjianto, A. Laguna and P. Papadopoulos, "Opportunities for Energy Storage - Assessing Whole-System Economic Benefits of Energy Storage in Future Electricity Systems," *IEEE Power and Energy*, vol. 15, no. 5, pp. 32-41, September - October 2017.
- [2] "Offshore Wind Outlook 2019," International Energy Agency, 2019.
- [3] C. Maienza, A. Avossa, F. Ricciardelli, D. Coiro, G. Troise and C. Georgakis, "A Life Cycle Model for Floating Offshore Wind Farms," *Applied Energy*, vol. 226, 2020.
- [4] A. Ghigo, L. Cottura, R. Caradonna, G. Bracco and G. Mattiazzo, "Platform Optimisation and Cost Analysis in a Floating Offshore Wind Farm," *Journal of Marine Science and Engineering*, vol. 8, 2020.
- [5] "Energy Roadmap 2050," Publications office of the European Union, Luxembourg, 2012.
- [6] "Energy Roadmap for 2050, A Euroelectric Response Paper," Euroelectric - Electricity for Europe.
- [7] P. Jain, Wind Energy Engineering, 1st ed., McGraw-Hill Companies, Inc., 2011.
- [8] L. Dannecker, Energy Time Series Forecasting: Efficient and Accurate Forecasting of Evolving Time Series from the Energy Domain, 1st ed., Wiesbaden: Springer Vieweg, 2015.
- [9] W.-C. Hong, Intelligent Energy Demand Forecasting, Springer, 2013.
- [10] T. Hastie, R. Tibshirani and J. Friedman, The Elements of Statistical Learning, Data Mining, Inference and Prediction, Second ed., New York: Springer Series in Statistics, 2009.
- [11] T. Burton, D. Sharpe, N. Jenkins and E. Bossanyi, Wind Energy Handbook, 2nd ed., Chichester, West Sussex: John Wiley & Sons, Ltd., 2011.
- [12] C. Justus, K. Mani and A. Mikhail, "Interannual and Month-to-Month Variations of Wind Speed," *Journal of Applied Meteorology*, vol. 18, pp. 913-20, 1979.
- [13] L. Landberg, L. Myllerup, O. Rathmann, E. Petersen, B. Jorgensen and B. Neils, "Wind Resource Estimation: An Overview," *Wind Energy*, vol. 6, pp. 261-71, 2003.
- [14] G. James, D. Witten, T. Hastie and R. Tibshirane, An Introduction to Statistical Learning with Applications in R, New York: Springer Texts in Statistics, 2015.
- [15] D. Montgomery, E. Peck and G. Vinning, Introduction to Linear Regression Analysis, 6th ed., John Wiley & Sons, Inc., 2021.
- [16] J. Principe, N. Euliano and W. Curt Lefebvre, Neural and Adaptive Systems: Fundamentals Through Simulations, John Wiley & Sons, Inc., 2000.
- [17] E. Alpaydin, Introduction to Machine Learning, 2nd Edition ed., Massachusetts Institute of Technology, 2010.

-
- [18] B. Scholkopf and A. Smola, *Learning with Kernels - Support Vector Machines, Regularisation, Optimisation and Beyond*, Cambridge, Massachusetts: The MIT Press, 2002.
 - [19] V. Vapnik, *The Nature of Statistical Learning Theory*, NY: Springer, 1995.
 - [20] V. Vapnik, S. Golowich and A. Smola, "A Support Vector Method for Function Approximation, Regression Estimation and Signal Processing," *Advances in Neural Information Processing Systems*, pp. 281-7, 1998.
 - [21] S. Diaz, J. Carta and J. Matias, "Performance Assessment of Five MCP Models Proposed for the Estimation of Long-term Wind Turbine Power Outputs at a Target Site Using Three Machine Learning Techniques," *Applied Energy*, no. 209, pp. 455-477, 2018.
 - [22] M. Mifsud, T. Sant and R. Farrugia, "A Comparison of Measure-Correlate-Predict Methodologies using LiDAR as a Candidate Measurement Device for the Mediterranean Island of Malta," *Renewable Energy*, no. 127, pp. 947 - 959, 2018.
 - [23] "Clean Choice Energy," [Online]. Available: https://cleanchoiceenergy.com/news/what_is_a_floating_wind_farm. [Accessed 11 07 2021].
 - [24] F. Barnes and J. Levine, "Applications of Energy Storage to Generation and Absorption of Electrical Power," in *Large Energy Systems Handbook*, Boca Raton, Florida: CRC Press, 2011.
 - [25] P. Du and N. Lu, *Energy Storage for Smart Grids - Planning and Optimisation for Renewable and Variable Energy resources (VERs)*, Academic Press, 2015.
 - [26] S. Alvarez, "Tesla's Big Battery in Australia is Starting an Energy Storage Movement," [Online]. Available: <https://www.teslarati.com/tesla-powerpack-farm-australia-energy-storage-movement/>.
 - [27] "New York State, USA Web Site," [Online]. Available: <https://www.nyserda.ny.gov/All%20Programs/Programs/Energy%20Storage>. [Accessed 20 10 2020].
 - [28] S. Xia, K. Chan, X. Lou, S. Bu and B. Zhou, "Optimal Sizing of Energy Storage System and its Cost Benefit Analysis for Power Grid Planning with Intermittent Generation," *Renewable Energy*, vol. 12, pp. 472-486, July 2018.
 - [29] M. Mifsud, T. Sant and R. Farrugia, "Investigating the Influence of MCP Uncertainties on the Energy Storage Capacity Requirements for Offshore Windarms," in *Proceedings of the ASME 2019 2nd International Offshore Wind Technical Conference*, St. Julain's, Malta, 2019.
 - [30] C.-L. Hor, S. Watson and S. Majithia, "Analysing the Impact of Weather Variables on Monthly Electricity Demand," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 2078-85, 2005.
 - [31] S. Tzafestas and E. Tzafestas, "Computational Intelligence Techniques for Short-Term Electric Load Forecasting," *Journal of Intelligent and Robotic Systems*, vol. 31, pp. 7-68, 2001.
-

-
- [32] H. Hahn, M.-N. S. and P. S., “Electric Load Forecasting Methods: Tools for Decision Making,” *European Journal of Operational Research*, vol. 199, pp. 012-7, 2009.
 - [33] G. Box, G. Jenkins and G. Reinsel, *Time Series Analysis - Forecasting and Control*, Third ed., Prentice Hall, 1994.
 - [34] “ZephIR 300 - Onshore Wind Lidar,” ZephIR, [Online]. Available: <https://www.zephirlidar.com/products/zephir-300/>. [Accessed 18 February 2018].
 - [35] <https://www.zxlidars.com/wind-lidars/zx-300/>. [Online]. [Accessed 19 January 2020].
 - [36] “Vaisala Energy Support,” [Online]. Available: <https://www.3tier.com/en/support/wind-online-tools/>. [Accessed 11 July 2021].
 - [37] C. Cordina, R. Farrugia and T. Sant, “Wind Profiling using LiDAR at a Coastal Location on the Mediterranean Island of Malta,” in *9th European Seminar OWEMES*, 2017.
 - [38] M. Mifsud, T. Sant and R. Farrugia, “A Comparison of Measure-Correlate-Predict Methodologies using Lidar as a Candidate Site Measurement Device for the Mediterranean Island of Malta,” *Renewable Energy*, no. 127, pp. 947-959, 2018.
 - [39] M. Mifsud, T. Sant and R. Farrugia, “Analysing Uncertainties in Offshore Wind Farm Power Output using Measure-Correlate-Predict Methodologies,” *Wind Energy Science*, vol. 5, pp. 1-21, 2020.
 - [40] “National Statistics Office, Malta,” [Online]. Available: <https://nso.gov.mt/en/Pages/NSO-Home.aspx>. [Accessed 19 10 2020].
 - [41] A. Myhr, C. Buerkseter, A. Agotnes and T. Nygaard, “Levelised Cost of Energy for Offshore Floating Wind Turbines in a Life Cycle Perspective,” *Renewable Energy*, vol. 66, pp. 714-28, 2014.
 - [42] I. Scott and S.-L. Lee, “Battery Energy Storage,” in *Large Energy Storage Systems Handbook*, F. Barnes and J. Levine, Eds., Boca Raton, Florida: Taylor and Francis Group, 2011, pp. 153-197.
 - [43] “Handbook of Battery Energy Storage System,” Asian Development Bank, 2018.
 - [44] P. Larsson and P. Borjesson, “Cost models for battery energy storage systems,” 2018.
 - [45] I. Pawel, “The Cost of Storage - How to Calculate the Levelised Cost of Stored Energy (LCOS) and Applications to Renewable Energy Generation,” in *Energy Procedia*, 2014.
 - [46] J. Carta, S. Velazquez and P. Cabrera, “A Review of Measure-Correlate-Predict (MCP) Methods used to Estimate Long-Term Wind Characteristics at a Target Site,” *Renewable and Sustainable Energy Reviews*, vol. 27, pp. 362-400, 2013.
 - [47] A. Rogers, J. Rogers and J. Manwell, “Comparison of the Performance of Four Measure-Correlate-Predict Models for Long-Term Prosecution of the Wind Resource,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 93, no. 3, pp. 243-64, 2005.
 - [48] J. Clive, “Non-linearity of MCP with Weibull Distributed Wind Speeds,” *Wind Engineering*, vol. 28, pp. 213-24, 2004.
-

-
- [49] J. Carta and S. Velazquez, "A New Probabilistic Method to Estimate the Long-Term Wind Speed Characteristics at a Potential Wind Energy Conversion Site," *Energy*, vol. 36, pp. 2671-85, 2011.
 - [50] M. Bilgili, B. Sahlin and A. Yasar, "Application of Artificial Neural Networks for the Wind Speed Prediction of Target Station Using Artificial Intelligent Methods," *Renewable Energy*, vol. 32, pp. 2350-60, 2007.
 - [51] M. Monfared, H. Rastegar and H. Kojabadi, "A New Strategy for Wind Speed Forecasting Using Artificial Intelligence Methods," *Renewable Energy*, vol. 34, pp. 845-8, 2009.
 - [52] A. Oztopal, "Artificial Neural Network Approach to Spatial Estimation of Wind Velocity," *Energy Conversion and Management*, vol. 47, pp. 395 - 406, 2006.
 - [53] P. Zhao, J. Xia, Y. Dai and J. He, "Wind Speed Prediction Using Support Vector Regression," in *The 5th IEEE Conference in Industrial Electronics and Applications (ICIEA)*, Taiwan, 2010.
 - [54] J. Carta, S. Velasquez and J. Matias, "Use of Bayesian Network Classifiers for Long-Term Mean Wind-Turbine Energy Output Estimation at a Potential Wind Energy Conversion Site," *Energy Conversion and Management*, vol. 52, pp. 1137-49, 2011.
 - [55] A. Rogers, J. Rogers and J. Manwell, "Uncertainties in Results of Measure-Correlate-Predict Analyses," *American Wind Energy Association*, May 2005b.
 - [56] M. Lackner, R. A.L. and J. Manwell, "Uncertainty Analysis in Wind Resource Assessment and Wind Energy Production Estimation," in *45th AIAA Aerospace Sciences and Exhibition*, Reno, Nevada, 2012.
 - [57] J. Zhang, S. Chowdhury, A. Messac and B.-M. Hodge, "A Hybrid Measure-Correlate-Predict Method for Long-Term Wind Condition Assessment," *Energy Conversion and Management*, vol. 87, pp. 697-710, 2014.
 - [58] A. Perea, J. Amezcua and O. Probst, "Validation of Three New Measure-Correlate Predict Models for the Long-Term Prospection of the Wind Resource," *Journal of Renewable and Sustainable Energy*, vol. 3, pp. 1-20, 2011.
 - [59] S. Velazquez, J. Carta and J. Matias, "Comparision between ANNs and Linear MCP Algorithms in the Long-Term Estimation of the Cost per kWh Produced by a Wind Turbine at a Candidate Site: A Case Study in the Canary Islands," *Applied Energy*, vol. 88, pp. 3869-81, 2011.
 - [60] D. Bechrakis, J. Deane and E. MCKeogh, "Wind Resource Assessment of an Area using Short-Term Data Correlated to a Long-Term Data-Set.," *Solar Energy*, vol. 76, pp. 724-32, 2004.
 - [61] M. Bilgili, B. Sahin and A. Yaser, "Application of Artificial Neural Networks for the Wind Speed Prediction of Target Station using Reference Stations Data," *Renewable Energy*, vol. 34, pp. 845 - 848, 2009.
 - [62] D. Patane, M. Benso, C. Hernandez, F. de la Blanca and C. Lopez, "Long Term Wind Resource Assessment by means of Multivariate Cross-Correlation Analysis," in *Proceedings of the European Wind Energy Conference and Exhibition*, Brussels, Belgium, 2011.
-

-
- [63] S. Diaz, J. Carta and J. Matias, "Comparison of Several Measure-Correlate-Predict Models using Support Vector Regression Techniques to Estimate Wind Power Densities. A Case Study," *Energy Conversion and Management*, vol. 140, pp. 334-354, 2017.
- [64] S. Diaz, J. Carta and J. Matias, "Performance Assessment of Five MCP Models Proposed for the Estimation of Long-term Wind Turbine Power Outputs at a Target Site Using Three Machine Learning Techniques," *Applied Energy*, no. 209, pp. 455-477, 2018.
- [65] O. Probst and D. Cardenas, "State of the Art and Trends in Wind Resource Assessment," *Energies*, vol. 3, pp. 1087 - 1141, 2010.
- [66] L. Bosart and P. Papin, "www.atmos.albany.edu," 16 November 2017. [Online]. Available: www.atmos.albany.edu/.../2017/pptx/ATM305_Statistics_16Nov17.pptx. [Accessed 3 March 2019].
- [67] J. Manwell, J. McGowan and A. Rogers, *Wind Energy Explained - Theory, Design and Applications*, 2nd ed., John Wiley and Sons Ltd., 2009.
- [68] E. Bossanyi, C. Maclean, G. Whittle, G. Dunn, N. Lipman and P. Musgrove, "The Efficiency of Wind Turbine Clusters," in *Proceedings of the Third International Symposium on Wind Energy Systems*, Lyngby, DK, 1980.
- [69] P. Lissaman and E. Bates, "Energy Effectiveness of Arrays of Wind Energy Conversion Systems," Pasadena, CA, 1977.
- [70] P. Vermeulen, "An Experimental Analysis of Wind Turbine Wakes," in *Proceedings of the Third International Symposium on Wind Energy Systems*, Lyngby, DK, 1980.
- [71] J. Ainslie, "Calculating the Flowfield in the Wake of Turbines," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 27, pp. 216 - 224, 1985.
- [72] A. Crespo and J. Hernandez, "A Numerical Model of Wind Turbine Wakes and Wind Farms," in *Proceedings of the 1986 European Wind Energy Conference*, Rome, 1986.
- [73] A. Crespo and J. Hernandez, "Analytical Correlations for Turbulence Characteristics in the Wakes of Wind Turbines," in *Proceedings of the 1993 European Community Wind Energy Conference*, Lubeck, 1993.
- [74] B. Sanderse, "Aerodynamics of Wind Turbine Wakes: Literature Review," Energy Research Centre of the Netherlands.
- [75] F. Gonzalez-Longatt, P. Wall and V. Terzija, "Wake Effect in Wind Farm Performance: Steady State and Dynamic Behaviour," *Renewable Energy*, vol. 39, pp. 329 - 338, 2012.
- [76] M. Churchfield, "A Review of Wind Turbine Wake Models and Future Directions," National Renewable Energy Laboratory, Boulder, Colorado, 2013.
- [77] S. Frandsen, "Turbulence and Turbulence-Generated Structural Loading in Wind Turbine Clusters," Riso National Laboratory, 2005.
- [78] N. Jensen, "A Note on Wind Generator Interaction," Technical University of Denmark, 1983.
-

-
- [79] G. Larsen, H. A. Madsen, T. J. Larsen and N. Trolborg, "Wake Modelling and Simulation," Technical University of Denmark, 2008.
 - [80] T. Larsen, H. Madsen, G. Larsen and K. Hansen, "Validation of the Dynamic Wake Meander Model for Loads and Power Production in the Egmond aan Zee Wind Farm," *Wind Energy*, vol. 16, pp. 605-624, 10 October 2013.
 - [81] R. Barthelmie, G. Folkerts, G. Larsen, K. Rados, S. Pryor, S. Frandsen, B. Lange and G. Schepers, "Comparison of Wake Model Simulations with Offshore Wind Turbine Wake Profiles Measured by SoDAR," *Journal of Atmospheric and Oceanic Technology*, vol. 23, pp. 888-901, 2006.
 - [82] I. Katic, J. Hojstrup and N. Larson, "A Simple Model for Cluster Efficiency," in *EWE'86 Proceedings*, 1987.
 - [83] L. van der Maaten, E. Postma and J. van den Herik, "Dimensionality Reduction: A Comparative Review," *Journal of Machine Learning Research*, vol. 10, pp. 66-71, 26 October 2009.
 - [84] I. Fodor, "A Survey of Dimension Reduction Techniques," Lawrence Livermore National Laboratory, 2002.
 - [85] F. Anowar, S. Sadaoui and B. Selim, "Conceptual and Empirical Comparison of Dimensionality Reduction Algorithms (PCA, KPCA, MDS, SVD, LLE, ISOMAP, LE, ICA, t-SNE)," *Computer Science Review*, vol. 40, 2021.
 - [86] Y. Ma and L. Zhu, "A Review of Dimension Reduction," *International Statistics Review*, vol. 81, no. 1, pp. 134-150, 2013.
 - [87] "MEPS Geoportal," [Online]. Available: <https://meps.eraportal.org.mt/>. [Accessed 17 01 2022].
 - [88] Mott-MacDonald, "Strategy for Renewable Electricity Exploitation in Malta," Malta Resources Authority, 2005.
 - [89] "Malta's National Renewable Energy Action Plan as Required by Article 4(2) of Directive 2009/28/EC," 2010.
 - [90] [Online]. Available: https://era.org.mt/wp-content/uploads/2020/03/20191018_MT0000009-Rdum-Madonna-SAC-scaled.jpg. [Accessed 11 11 2020].
 - [91] "Innovation Outlook Offshore Wind," International Renewable Energy Agency (IREA), 2016.
 - [92] F. Adam, F. Dahlhaus, T. Mylrad and J. Grossmann, "GICON - TLP for Wind Turbines - The Path of Development," in *Renewable Energies Offshore*, London, 2014.
 - [93] "Floating Offshore Wind Comes of Age with Break-Through Pipeline of Projects," Wind Europe, 8 6 2017. [Online]. Available: <https://windeurope.org/newsroom/press-releases/floating-offshore-wind-comes-of-age-with-break-through-pipeline-of-projects/>. [Accessed 16 01 2022].
 - [94] "Industrialising Floating Offshore Wind," Equinor, [Online]. Available: <https://www.equinor.com/en/what-we-do/floating-wind.html>. [Accessed 01 03 2022].
 - [95] "Pelastar," [Online]. Available: <https://pelastar.com/>. [Accessed 1 03 2022].
-

-
- [96] S. Heidari, "Economic Modelling of Floating Offshore Wind Power - Calculation of the Levelised Cost of Energy," 2017.
 - [97] J. Jonkman and M. Buhl Jr., "Development and Verification of a Fully Coupled Simulator for Offshore Wind Turbines," in *45th Aerospace Sciences Meeting and Exhibition*, Reno, Nevada, 2007.
 - [98] "Windfloat," Principle Power, [Online]. Available: <https://www.principlepowerinc.com/en/windfloat>. [Accessed 5 11 2020].
 - [99] "Offshore Wind Market Report: 2021 Edition," US Department of Energy, 2021.
 - [100] W. Musial, P. Beiter and J. Nunemaker, "Cost of Floating Offshore Wind Energy using New England Aqua Ventus Concrete Semisubmersible Technology," National Renewable Energy Laboratory, 2020.
 - [101] L. Castro-Santos, A. Filgueria-Vizoso and I. Lamas-Galdo, "Methoology to calculate the installation costs of offshore windfarms located in deep waters," *Journal of Cleaner Production*, vol. 170, pp. 1124-1135, 2018.
 - [102] A. Ahmed, "Technical and Economic Feasibility of the First Wind Farm on the Coast of Mediterranean Sea," *Ain Shams Engineering Journal*, vol. 12, pp. 2145-2151, 2021.
 - [103] M. Saadat, F. Shirazi and P. Li, "Modelling and Control of an Open Accumulator Compressed Air Energy Storage (CAES) System for Wind Turbines," *Applied Energy*, no. 137, pp. 603-616, 2015.
 - [104] M. Saadat and P. Li, "Modelling and Control of a Novel Compressed Air Energy Storage System for Offshore Wind Turbine," in *American Control Conference*, Montreal, 2012.
 - [105] A. Aghajani, R. Kazemzadeh and A. Ebrahimi, "Optimal Energy Storage Sizing and Offering Strategy for the Presence of Wind Power Plant with Energy Storage in the Electricity Market," *International Transactions Electrical Energy Systems*, vol. 28, 2018.
 - [106] I. N. Moghaddan, B. Chowdhury and M. Doostan, "Optimal Sizing and Operation of Battery Energy Storage Systems Connected to Wind Farms Participating in Energy Markets," *IEEE Transactions on Sustainable Energy*.
 - [107] J. Levine, "Pumped Hydroelectric Energy Storage," in *Large Energy Systems Handbook*, F. Barnes and J. Levine, Eds., Boca Raton, Florida: Taylor Francis Group, 2011, pp. 51-75.
 - [108] M. Beaudin, H. Zareipour, A. Schellenberg and W. Rosehart, "Energy Storage for Mitigating the Variability of Renewable Electricity Sources," in *Energy Storage for Smartgrids: Planning and Optimisation for Renewable and Variable Energy Resources (VERs)*, P. Du and N. Lu, Eds., London, Academic Press, 2015, pp. 1-27.
 - [109] P. Donalek, "Pumped Storage Hydro," *IEEE Power and Energy Magazine*, vol. 18, no. 5, pp. 49-57, 2020.
 - [110] "DOE Global Energy Storage Database," [Online]. Available: <https://sandia.gov/ess-ssl/gesdb/public/index.html>. [Accessed 1 03 2022].
-

-
- [111] R. Farrugia, T. Sant and C. Caruana, “Integrating Deep Offshore Wind with Pumped Hydro Storage in a Central Mediterranean Archipelago’s Electricity Generation System,” London, 2014.
 - [112] P. Brown, J. Pecos Lopes and M. Matos, “Optimisation of Pumped Storage Capacity in an Isolated Power System with Large Renewable Penetration,” *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 523-31, 2008.
 - [113] A. Tuchy and M. O’Malley, “Pumped Storage in Systems with very High Wind Penetration,” *Energy Policy*, vol. 39, pp. 1965-74, 2011.
 - [114] A. Slocum, G. Fennell, G. Dundar, B. Hodder, J. Meredidith and M. Sager, “Ocean Renewable Energy System (ORES). Analysis of an Undersea Energy Storage Concept,” *Proceedings of the IEEE*, vol. 101, no. 4, pp. 906-924, 2013.
 - [115] A. Silver, “New Ways to Store Renewable Energy with Water.,” *IEEE Spectrum*, pp. 11-13, February 2017.
 - [116] G. Martin, “Underground Pumped Hydroelectric Energy Storage,” in *Large Energy Storage Systems Handbook*, F. Barnes and J. Levine, Eds., Boca Raton, Florida: Taylor and Francis Group, 2011, pp. 77-109.
 - [117] J. Olsen, K. Paasch, B. Lassen and C. Veje, “A New Principle of Underground Pumped Hydroelectric Storage,” *Journal of Energy Storage*, vol. 2, pp. 54-63, 2015.
 - [118] S. Succar, “Compressed Air Energy Storage,” in *Large Energy Storage Systems Handbook*, F. Barnes and J. Levine, Eds., Boca Raton, Florida: Taylor and Francis Group, 2011, pp. 111-152.
 - [119] P. Vella, T. Sant and R. Farrugia, “A Review of Offshore-based Compressed Air Energy Storage Options for Renewable Energy Technologies,” in *9th European Seminar, OWEMES*, Bari, Italy, 2017.
 - [120] J. Wang, K. Lu, L. Ma, J. Wang, M. Dommer, S. Miao, L. J. and D. Wang, “Overview of Compressed Air Energy Storage and Technology Development,” *Energies*, vol. 10, no. 7, p. 991, 2017.
 - [121] O. Ramadan, S. Omer, H. Jradi, H. Sabir and R. S., “Analysis of Compressed Air Energy Storage for Large-scale Wind Energy in Suez, Egypt,” *International Journal of Low-Carbon Technologies*, vol. 11, pp. 476-488, 2016.
 - [122] P. Carson, J. McGowan and W. Jasianek, “Evaluating the Underwater Compressed Air Energy Storage Potential in the Gulf of Maine,” *Wind Engineering*, vol. 66, pp. 141-8, 2015.
 - [123] A. Alami, “Experimental Assessment of Compressed Air Energy Storage (CAES) System and Buoyancy Work Energy Storage (BWES) as Cellular Wind Energy Storage Options,” *Journal of Energy Storage*, vol. 1, pp. 38-43, 2015.
 - [124] D. Buhagiar, S. T. and R. Farrugia, “Analysis of a Novel Offshore Platform with Integrated Energy Storage Operating in Central Mediterranean Waters,” in *Sustainable Energy 2016: The ISE Annual Conference*, Valletta, 2016.
 - [125] “FLASC,” FLASCstorage, [Online]. Available: <https://www.offshoreenergystorage.com/>. [Accessed 15 July 2021].
-

-
- [126] X. Hu, C. Zou, C. Zhang and Y. Li, "Technological Developments in Batteries," *IEEE Power and Energy Magazine*, vol. 15, no. 5, pp. 20-31, September/October 2017.
 - [127] H. Akhavan-Hwjazi and H. Mohsenian-Rad, "Operation of Independent Large-Scale Battery-Storage Systems in Energy and Reserve Markets," in *Energy Storage for Smart Grids*, Academic Press, 2015, pp. 295-320.
 - [128] H. Chen, T. Cong, C. Tan, Y. Li and Y. Ding, "Progress in Electrical Energy Storage System: A Critical Review," *Progress in Natural Science*, vol. 19, pp. 291-312, 2009.
 - [129] M. Armand and J. Terascon, "Building Better Batteries," *Nature*, vol. 451, no. 7, pp. 652-657, 2008.
 - [130] "South Australians Turn on Tesla's 100 MW battery: 'History in the making'," *The Guardian*, 1st December 2017. [Online]. Available: <https://www.theguardian.com/australia-news/2017/dec/01/south-australia-turns-on-teslas-100mw-battery-history-in-the-making>. [Accessed 12th March 2018].
 - [131] "Tesla Megapack(R)," Tesla, [Online]. Available: <https://www.tesla.com/megapack>. [Accessed 07 02 2022].
 - [132] "Victorian Big Battery," Neoen, [Online]. Available: <https://victorianbigbattery.com.au/>. [Accessed 07 February 2022].
 - [133] "NS Energy," Vistra Energy Corporation, [Online]. Available: <https://www.nsenergybusiness.com/projects/moss-landing/>. [Accessed 07 February 2020].
 - [134] A. Cunha, J. Martins, N. Rodrigues and B. F.P., "Vanadium Redox Flow Batteries: A Technology Review," *International Journal of Energy Research*, no. 39, pp. 889-918, 2015.
 - [135] J. Waever, "World's Largest Battery: 200MW/800MWh Vanadium Reflow Battery - Site Work Ongoing," 21 December 2017. [Online]. Available: <https://electrek.co/2017/12/21/worlds-largest-battery-200mw-800mwh-vanadium-flow-battery-rongke-power/>. [Accessed 10 February 2022].
 - [136] Z. Yang, "Is this the Ultimate Grid Battery," *IEEE Spectrum*, pp. 36-41, November 2017.
 - [137] F. Lambert, "Tesla Launches its Megapack, a new Massive 3MWh Energy Storage Project," *Electrek*, 29 July 2019. [Online]. Available: <https://electrek.co/2019/07/29/tesla-megapack-massive-energy-storage-product/>. [Accessed 8 February 2022].
 - [138] "Energy Storage Association," [Online]. Available: <https://energystorage.org/why-energy-storage/technologies/solid-electrode-batteries/>. [Accessed 12 February 2022].
 - [139] "Vionx Energy," Vinox Energy Cooperation, [Online]. Available: <https://www.energy-xprt.com/products/vionx-model-vhx1200-8-vanadium-redox-flow-battery-8-mwh-716226>. [Accessed 12 February 2022].
 - [140] S. Sabihuddin, A. Kiprakis and M. Mueller, "A Numerical and Graphical Review of Energy Storage Technologies," *Energies*, vol. 8, pp. 172-216, 2015.
 - [141] F. Klumpp, "Comparison of Large-Scale Energy Storage Technologies," *Proceedings of the Institution of Civil Engineers*, vol. 169, no. EN4, pp. 148-160, 29th March 2016.
-

-
- [142] V. Julch, "Comparison of Electricity Storage Options using Levelised Cost of Storage (LCOS) Method.," *Applied Energy*, vol. 183, pp. 1594-1606, 2016.
 - [143] Z. Topalovic, R. Haas, A. Ajanovic and A. Heisl, "Economics of Electric Energy Storage. The Case of Western Balkans," *Energy*, vol. 238, 2022.
 - [144] "The Paris Agreement," United Nations Climate Change, [Online]. Available: <https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement>. [Accessed 16 01 2022].
 - [145] A. Poullikkas, "A Comparative Overview of Large-Scale Battery Systems for Energy Storage," *Renewable and Sustainable Energy Reviews*, vol. 27, pp. 778-788, 2013.
 - [146] W. Cole and A. Frazier, "Cost Projections for Utility Scale Battery Storage," National Renewable Energy Laboratory, 2020.
 - [147] B. Zakeri and S. Syri, "Electrical Energy Storage Systems: A Comparative Life Cycle Cost Analysis," *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 569-596, 2015.
 - [148] R. Fu, T. Remo and R. Margolis, "2018 U.S. Utility-Scale Photovoltaics-Plus-Energy Storage System Costs Benchmark," National Renewable Energy Laboratory, 2018.
 - [149] "Lazard's Levelised Cost of Storage Analysis - Version 6," Lazard, 2020.
 - [150] J. B. D. Ringwood, "Forecasting Electricity Demand on Short, Medium and Long Time Scales Using Neural Networks," *Journal of Intelligent Robotic Systems*, vol. 31, pp. 129-147, 2001.
 - [151] S. Islam and S. Al-Alawi, "Principles of Electricity Demand Forecasting - Part I Methodologies," *Power Engineering Journal*, vol. 10, no. 3, pp. 139-43, 1996.
 - [152] S. Islam and S. Al-Alawi, "Principles of Electricity Demand Forecasting - Part II Applications," *Power Engineering Journal*, vol. 11, no. 2, pp. 91-5, 1997.
 - [153] D. Swider and C. Weber, "The Costs of Wind's Intermittency in Germany: Application of a Stochastic Electricity Market Model," *European Transactions on Electrical Power*, vol. 17, pp. 151-72, 2007.
 - [154] J. Taylor, L. de Menezes and P. McSharry, "A Comparison of Univariate Methods for Forecasting Demand Up to a Day Ahead," *International Journal of Forecasting*, vol. 22, pp. 1-16, 2006.
 - [155] A. Papalexopoulos and T. Hesterberg, "A Regression Based Approach to Short-Term System Load Forecasting," *IEEE Transactions on Power Systems*, vol. 5, no. 4, pp. 1525-1549, November 1990.
 - [156] A. Ghanbari, S. Naghavi, M. Ghaderi and P. Nielsen, "Artificial Neural Networks and Regression Approaches Comparison for Forecasting Iran's Annual Electricity Load," in *Powereng 2009*, Lisbon, 2009.
 - [157] S. Makridakis, S. Wheelwright and R. Hyndman, *Forecasting: Methods and Applications*, 3rd ed., John Wiley & Sons, Inc, 1998.
 - [158] G. Ogcü, O. Demirel and S. Zaim, "Forecasting Electricity Consumption with Neural Networks and Support Vector Regression," *Procedia Social and Behavioral Sciences*, vol. 58, pp. 1576-1585, 2012.
-

-
- [159] K. Kavaklioglu, "Modeling and Prediction of Turkey's Electricity Consumption using Support Vector Regression," *Applied Energy*, vol. 88, pp. 365-375, 2011.
- [160] N. An, W. Zhao, J. Wang, D. Shang and E. Zhao, "Using Multi-Output Feedforward Neural Network with Empirical Mode Decomposition Based Signal Filtering for Electricity Demand Forecasting," *Energy*, vol. 49, pp. 279-288, 2013.
- [161] J. Wang, D. Chi, J. Wu and H. Lu, "Chaotic Time Series Method Combined with Particle Swarm Optimisation and Trend Adjustment for Electricity Demand Forecasting," *Expert Systems with Applications*, vol. 38, pp. 8441-8429, 2011.
- [162] C. Gellings, *Demand Forecasting in the Electric Utility Industry*, 2nd ed., Penwell Books, 1996.
- [163] C. Chatfield, *The Analysis of Time Series*, CRC Press, 2004.
- [164] J. Stock, "Time Series: Economic Forecasting," in *International Encyclopedia of the Social and Behavioral Sciences*, Elsevier, 2001.
- [165] R. Shumway and D. Stoffer, *Time Series Analysis and its Applications - with R Examples.*, 3rd ed., Springer, 2011.
- [166] P. Brockwell and R. Davis, *Time Series: Theory and Methods*, 2nd ed., Springer, 1991.
- [167] M. Abonazel and A. Abd-Elftah, "Forecasting Egyptain DDP using ARIMA Models," *Reports on Economics and Finance*, vol. 5, pp. 35-47, 2019.
- [168] N. Razak, A. Khamis and M. Abdullah, "ARIMA and VAR Modeling to Forecast Malaysian Economic Growth," *Journal of Science and Technology*, vol. 9, no. 3, pp. 16-24, 2017.
- [169] N. Wei, K. Bian and Y. Z., "Analysis and Forecast of Shaanxi GDP based on the ARIMA Model," *Asian Journal of Agricultural Research*, vol. 2, no. 1, pp. 34-36, 2010.
- [170] J. Barton and D. Infield, "Energy Storage and its use with Intermittent Renewable Energy," *IEEE Transactions on Energy Conversion*, vol. 19, no. 2, pp. 441-8, 2004.
- [171] S. Garvey, "Integrating Energy Storage with Renewable Energy Generation," *Wind Engineering*, vol. 39, no. 2, pp. 129-40, 2015.
- [172] G. Santamaria-Bonfil, A. Reyes-Ballestros and C. Gershenson, "Wind Speed Forecasting for Wind Farms: A Method Based on Support Vector Regression," *Renewable Energy*, vol. 85, pp. 790-809, 2016.
- [173] M. Shcherbakov, A. Brebels, N. Shcherbakova, A. Tyukov and T. Janovsky, "A survey of Forecast Error Measures," *World Applied Sciences Journal*, vol. 24, pp. 171 - 176, 2013.
- [174] H. Madsen, P. Pinson, G. Kariniotakis, H. Nielsen and T. Nielsen, "Standardizing the Performance Evaluation of Short-Term Wind Power Prediction Models," *Wind Engineering*, vol. 29, no. 6, pp. 475 - 489, 1 December 2005.
- [175] J. Hu, J. Wang and G. Zeng, "A Hybrid Forecasting Approach Applied to Wind Speed Time Series," *Renewable Energy*, vol. 60, pp. 185 - 194, 2013.
-

-
- [176] A. Poli and M. Cirillo, "On the use of the Normalised Mean Square Error in Evaluating Dispersion Model Performance," *Atmospheric Environment*, vol. 27A, no. 15, pp. 2427-2434, 1993.
 - [177] N. Draper and H. Smith, *Applied Regression Analysis*, 3rd ed., John Wiley and Sons, Inc, 2015.
 - [178] R. Anderson, "Distribution of the Serial Correlation Coefficient," *Annals of Mathematical Statistics*, vol. 13, pp. 1-13, 1942.
 - [179] M. Bartlett, "On the Theoretical Specification of Sampling Properties of Autocorrelated Time Series," *Journal of the Royal Statistical Society*, vol. 8, no. 27, 1946.
 - [180] M. Quenouille, "The Joint Distribution of Serial Correlation Coefficients," *Annals of Mathematical Statistics*, vol. 20, pp. 561-71, 1949.
 - [181] P. Larsson and B. P., "Cost Models for Battery Energy Storage Systems," KTH School of Industrial Engineering and Management, Stockholm, 2018.
 - [182] M. Mifsud, T. Sant and R. Farrugia, "Combining Wind Speed and Energy Demand Prediction in the Determination of Energy Storage Capacity Requirements of Offshore Wind Farms," in *Offshore Energy and Storage Symposium*, Valletta, 2016.
 - [183] L. Marvin, *Neural Networks with Matlab*, Amazon.
 - [184] C. Gellings, *Demand Forecasting in the Electric Utility Industry*, 2nd ed., Penwell Books, 1996.
 - [185] "math doctors," 4 April 2018. [Online]. Available: <https://www.themathdoctors.org/averaging-angles/>. [Accessed 21 May 2019].
 - [186] "EMD International," [Online]. Available: <https://www.emd-international.com/windpro/>. [Accessed 25 January 2022].
 - [187] wind-turbine-models.com, "wind-turbine-models.com," 2019. [Online]. Available: <https://en.wind-turbine-models.com/turbines/1-repower-5m-offshore>. [Accessed 19 March 2019].
 - [188] "Wind Power - Wind Energy Market Intelligence," [Online]. Available: https://www.thewindpower.net/turbine_en_14_repower_5m.php. [Accessed 24 January 2021].
 - [189] Vestas, "Vestas," Vestas, [Online]. Available: www.vestas.com. [Accessed 24 7 2021].
 - [190] Enemalta Corporation, 10 July 2019. [Online]. Available: <https://www.enemalta.com.mt/news/high-electricity-demand-registered/>. [Accessed 29 November 2021].
 - [191] "Offshore Wind Outlook 2019," International Energy Agency (IEA).
 - [192] R. Caiazza, "Watts up with that?," [Online]. Available: <https://wattsupwiththat.com/2019/07/16/nrel-energy-storage-system-cost-benchmark/>. [Accessed 1 May 2021].
 - [193] W. Cole and A. Frazier, "Cost Projections for Utility-Scale Battery Storage: 2020 update," National Renewable Energy Laboratory, 2020.
-

- [194] M. Moore, R. Counce, J. Watson and T. Zawodzinski, "A Comparison of the Capital Costs of a Vanadium-Redox-Flow Battery and a Regenerative Hydrogen-Vanadium Fuel Cell," *Journal of Advanced Chemical Engineering*, vol. 5, no. 4, 2015.
- [195] K. Kolhe, Wind Energy Forecasting by Using Artificial Neural Network - Genetic Algorithm, Saarbrücken, Germany: Verlag Dr. Müller Aktiengesellschaft & Co. KG, 2008.

A. Filtering the LiDAR data

Sporadic missing data has been averaged out in the transformation of the data into hourly readings. For example, if two readings were available for a single hour, the wind speed and direction for the hour was the average of the two readings. When an entire hour was missing data was extrapolated using the average of the five previous wind speed and direction readings. When an entire day was missing, data was extrapolated using the moving average of the previous 24 hours. Duplicate entries have been verified and removed.

A.1 2015 LiDAR Data

Table A-1: LiDAR missing and duplicate for 2015.

Jun 2015	
25 th – 30 th June	Sporadic missing 10 min average readings.
30 th June	Data entry for 8:00 – missing for 10 m, 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m and 200 m.
July 2015	
1 st – 31 st July	Sporadic missing 10 min average readings.
1 st July	Data entry missing for 2:00 for 200 m height.
9 th July	Repeated entry removed.
August 2015	
1 st – 31 st August	Sporadic missing 10 min average readings.
1 st August	Data entry missing for 20:00 for 10 m, 20 m, 30 m height.
September 2015	
1 st – 30 th September	Sporadic missing 10 min average readings.
October 2015	
1 st – 31 st October	Sporadic missing 10 min average readings.
18 th October	Missing readings for 05:00 for height 200 m Data entry missing for 04:00 for 150 m, 200 m height. Data entry missing for 05:00 for 150 m, 200 m height.
November 2015	
1 st – 30 th November	Sporadic missing 10 min average readings.
6 th November	Date entry missing for 09:00 for 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
11 th November	Data entry missing for 12:00 for 10 m, 20 m, 30 m height. Data entry missing for 13:00 for 10 m height.
December 2015	
1 st – 31 st December	Sporadic missing 10 min average readings.

A.2 2016 LiDAR Data

Table A-2: LiDAR missing and duplicate for 2016 (Part 1).

January 2016	
1 st – 31 st January	Sporadic missing 10 min average readings.
21 st January	Repeated entry removed.
February 2016	
25 th February	Repeated entry removed.
26 th February	Data entry missing for 23:00 for 60 m, 100 m height.
March 2016	
30 th March	Data entry missing for 18:00 for 40 m, 50 m, 60 m height. Data entry missing for 19:00 for 60 m height. Data entry missing for 11:00 for 150 m height.
31 st March	Data entry missing for 01:00 for 100 m height.
April 2016	
1 st – 30 th April	Sporadic missing 10min average readings.
22 nd April	Data entry missing for 11:00 for 20 m, 30 m, 100 m, 150 m height.
22 nd April	Data entry missing for 12:00 for 40 m, 50 m, 60 m, 80 m, 100 m, 150 m height.
May 2016	
1 st – 31 st May	Sporadic missing 10 min average readings.
10 th May	Data entry missing for 23:00 for 150 m height.

Table A-3: LiDAR missing and duplicate for 2016 (Part 2)

June 2016	
1 st – 30 th June	Sporadic missing 10 min average readings.
15 th June	Data entry missing for 23:00 for 150 m height.
18 th June	Data entry missing for 10:00 for 150 m height.
21 st June	Data entry for 16:00 missing for 10 m, 20 m, 30 m, 40 m, 50 m, 100 m height.
July 2016	
1 st – 31 th July	Sporadic missing 10 min average readings.
8 th July	Missing data entry for 02:00 missing for 100 m Missing data entry for 03:00 for 150 m height.
27 th July	Missing data entry for 20:00 missing for 10 m height.
August 2016	
1 st – 31 th August	Sporadic missing 10 min average readings.
6 th August	All data missing for 10 m, 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
September 2016	
1 st – 30 th September	Sporadic missing 10 min average readings.
October 2016	
1 st – 31 th October	Sporadic missing 10 min average readings.
November 2016	
1 st – 30 th November	Sporadic missing 10 min average readings.
18 th November	Missing data entry for 13:00 for 20 m, 30 m height.
20 th November	All data missing for 10 m, 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
December 2016	
1 st – 31 st December	Sporadic missing 10 min average readings.
31 st December	All data missing for 10 m, 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.

A.3 2017 LiDAR Data

Table A-4: LiDAR missing and duplicate for 2017.

January 2017	
1 st – 31 st January	Sporadic missing 10 min average readings.
February 2017	
1 st – 28 th February	Sporadic missing 10 min average readings.
1 st February	Missing data for 21:00 at 100 m height.
March 2017	
1 st – 31 st March	Sporadic missing 10 min average readings.
12 th March	All data missing for 10 m, 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
13 th March	Missing data entry for 03:00 at 100 m, 150 m, 200 m height.
22 nd March	Missing data entry for 17:00 at 20 m, 30 m, 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
April 2017	
1 st –30 th April	Sporadic missing 10 min average readings.
7 th April	Missing data entry for 19:00 at 40 m, 100 m, 150 m, 200 m height. Missing data entry for 20:00 at 20 m, 30 m, 100 m, 150 m, 200 m height. Missing data entry for 21:00 at 40 m, 50 m, 60 m, 80 m, 100 m, 150 m, 200 m height.
26 th April	Missing data entry for 00:00 at 200 m height.
27 th April	Missing data entry for 07:00 at 150 m height.
May 2017	
1 st – 31 st May	Sporadic missing 10 m average readings.
6 th May	Missing data entry for 14:00 at 40 m, 60 m height. Missing data entry for 22:00 at 60 m, 80 m, 100 m, 150 m, 200 m height. Missing data entry for 23:00 at 60 m, 80 m, 100 m, 150 m, 200 m height.
7 th May	Missing data entry for 00:00 at 80 m, 100 m, 150 m height.
June 2017	
1 st – 30 th June	Sporadic missing 10 m average readings.
30 th June	Missing data entry for 09:00 at 150 m, 200 m height.
July 2017	
1 st – 18 th July	Sporadic missing 10 m average readings.

B. Quarterly Economic Data

Table B-1 and

Table B-2 show the quarterly values for econometric data for the Island of Malta for the years 2011-2020. The values are in millions of Euros. Table B-1 shows the Total Gross Domestic Product, data for Agriculture, Forestry and Fishing, Manufacturing, Mining Quarrying and Water Supply, Construction and Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service activities.

Table B-1: Malta's quarterly econometric data for the years 2011-2020 (Part 1) [40]

Year	Quarter	Total GDP (MEuros)	Agriculture , forestry and fishing (MEuros)	Manufacturing (MEuros)	Mining, Quarrying, Water Supply (MEuros)	Construction (MEuros)	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service Activities (MEuros)
2011	2011Q1	1,609	22.44	191.82	31.28	66.34	269.32
	2011Q2	1,658	22.71	191.52	16.40	65.78	311.88
	2011Q3	1,758	22.38	185.90	15.06	65.83	342.26
	2011Q4	1,669	25.33	182.12	16.63	65.27	278.07
2012	2012Q1	1,625	20.87	178.32	6.33	65.27	268.35
	2012Q2	1,709	21.68	192.70	8.10	65.26	324.96
	2012Q3	1,815	23.04	195.04	19.70	65.20	373.76
	2012Q4	1,730	30.62	187.27	11.84	65.20	301.13
2013	2013Q1	1,681	21.79	181.12	22.03	64.16	278.27
	2013Q2	1,797	23.33	178.62	29.99	63.69	336.64
	2013Q3	1,898	22.88	172.26	21.07	64.95	386.32
	2013Q4	1,810	31.47	167.51	31.00	64.64	305.97
2014	2014Q1	1,970	19.85	185.90	33.24	75.90	337.30
	2014Q2	2,096	21.14	191.24	28.98	76.05	426.47
	2014Q3	2,211	21.34	181.65	23.92	75.69	463.15
	2014Q4	2,177	33.68	187.54	31.98	75.81	401.43
2015	2015Q1	2,215	22.09	181.54	34.02	82.27	400.71
	2015Q2	2,364	22.31	190.48	36.61	82.78	507.20
	2015Q3	2,498	25.05	171.07	39.01	82.51	557.68
	2015Q4	2,440	35.33	186.52	28.19	82.60	483.40
2016	2016Q1	2,412	23.20	188.74	44.41	80.17	441.92
	2016Q2	2,516	24.76	191.19	43.61	81.19	521.18
	2016Q3	2,652	24.83	178.30	46.56	83.08	563.73
	2016Q4	2,611	34.83	190.24	25.81	84.47	503.58
2017	2017Q1	2,674	24.39	203.71	39.41	88.20	458.88
	2017Q2	2,812	24.76	211.55	39.00	90.64	571.78
	2017Q3	2,978	24.81	198.54	48.14	91.24	630.15
	2017Q4	2,948	35.25	203.37	49.40	91.62	529.91
2018	2018Q1	2,554	24.45	214.69	45.29	95.85	490.63
	2018Q2	2,749	23.31	237.15	37.83	97.98	603.64
	2018Q3	2,854	24.80	223.89	57.25	97.72	655.50
	2018Q4	2,739	35.26	238.93	46.96	101.56	559.84
2019	2019Q1	2,759	25.75	220.97	45.15	103.13	522.95
	2019Q2	2,933	22.38	237.76	49.03	110.98	624.33
	2019Q3	3,057	23.64	230.97	58.90	114.18	694.58
	2019Q4	2,965	33.90	258.47	50.08	119.54	603.55
2020	2020Q1						
	2020Q2						
	2020Q3						
	2020Q4						

Table B-2 shows Information and Communication, Financial and Insurance Activities, Real Estate Activities, Professional, Scientific and Technical Activities, Public Administration and Defence,

Compulsory Social Security, Education, Human Health and Social Work Activities and Arts, Entertainment and Recreation, Repair of Household Goods, and other Services.

Table B-2: Malta's quarterly econometric data for the years 2011-2020 (Part 2) [40]

Year	Quarter	Information and Communication (MEuros)	Financial and Insurance Activities (MEuros)	Real Estate Activities (MEuros)	Professional, Scientific and Technical Activities (MEuros)	Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities (MEuros)	Arts, Entertainment and Recreation, Repair of Household Goods and other Services (MEuros)
2011	2011Q1	86.19	112.04	88.56	134.03	273.25	140.39
	2011Q2	89.60	110.49	88.42	143.61	277.76	142.47
	2011Q3	92.66	121.11	88.67	167.00	274.38	145.56
	2011Q4	89.60	114.81	89.08	140.76	274.86	141.70
2012	2012Q1	92.49	127.02	88.45	138.88	282.83	145.47
	2012Q2	96.56	124.27	87.43	143.81	292.94	147.64
	2012Q3	98.12	124.03	89.31	178.75	290.80	147.33
	2012Q4	94.46	117.54	89.00	151.51	296.00	148.53
2013	2013Q1	99.26	130.41	89.49	154.85	300.31	147.25
	2013Q2	102.74	131.35	91.05	166.16	306.38	148.04
	2013Q3	107.15	123.30	89.15	197.89	313.71	148.62
	2013Q4	102.61	121.19	92.02	173.52	306.91	149.67
2014	2014Q1	109.95	128.32	94.64	191.85	332.75	233.88
	2014Q2	117.45	126.33	95.50	203.53	340.54	236.12
	2014Q3	119.33	132.38	95.93	238.45	340.94	236.78
	2014Q4	118.85	128.16	96.63	223.69	343.30	241.62
2015	2015Q1	130.14	134.32	107.69	245.52	360.19	295.74
	2015Q2	137.55	134.50	110.47	264.16	367.27	306.64
	2015Q3	142.49	147.19	110.78	300.64	364.85	305.80
	2015Q4	147.04	133.35	113.65	271.55	364.17	301.04
2016	2016Q1	142.80	142.98	116.09	279.12	382.50	330.14
	2016Q2	152.27	148.77	118.37	289.76	392.72	332.76
	2016Q3	159.38	153.36	119.87	334.49	392.01	333.22
	2016Q4	158.34	143.53	122.56	311.68	383.51	337.98
2017	2017Q1	158.26	152.70	119.10	344.62	407.98	362.56
	2017Q2	165.56	153.67	117.22	368.07	419.74	366.48
	2017Q3	168.55	158.36	119.58	390.51	424.69	366.29
	2017Q4	174.75	154.44	121.29	378.54	383.51	367.37
2018	2018Q1	176.30	155.03	127.49	376.38	451.30	396.97
	2018Q2	180.37	166.16	127.79	401.89	450.05	415.47
	2018Q3	189.16	163.50	127.90	444.65	453.18	415.59
	2018Q4	187.52	158.13	131.53	423.18	453.32	403.30
2019	2019Q1	191.60	168.93	134.39	426.27	487.76	432.40
	2019Q2	195.16	165.12	134.85	449.02	488.56	455.05
	2019Q3	198.09	167.45	137.97	484.58	494.53	453.73
	2019Q4	201.81	155.33	144.41	543.75	497.58	446.22
2020	2020Q1						
	2020Q2						
	2020Q3						
	2020Q4						

C. Measure-Correlate-Predict Results – 3Tier Data

This Appendix presents the results obtained for the analysis of suitable regression techniques for the MCP methodology carried out with Data Set A (3Tier) and Data Set B (MIA Weather Station) carried out in Section 7.1. This analysis served to identify adequate regression techniques which could be used for the MCP methodology. The regression techniques identified were Linear Regression, ANN, and DT regression techniques and SVR technique. The results leading to this choice of techniques are summarised below. The results are presented in Section 12.6.

C.1 Regression Techniques for the MCP methodology.

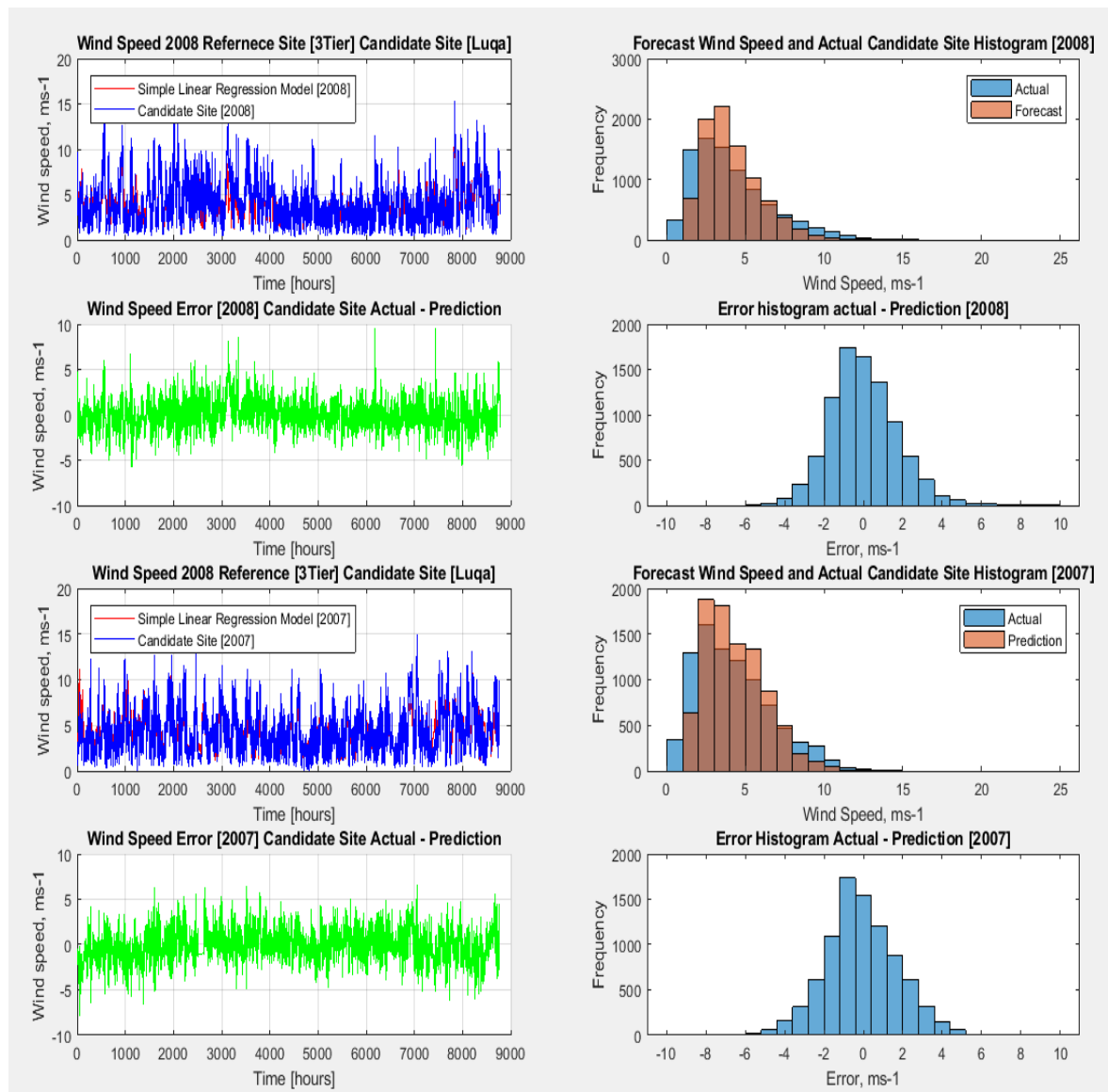


Figure C-1: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the SLR regression model with the 2008 data and then predicting the 2007 wind data.

Figure C-1 represents the results obtained by using the concurrent data for 2008 to create the MCP model and then using the model to predict the wind speed for the years 2008 and 2007, using SLR as described in Section 7.1.1. The top 4 charts in Figure C-1 represent the actual and the predicted wind

distribution, a time-series and a distribution of the residuals (Error Histogram) for the year 2007. The MCP model for 2008 was then used to predict the wind speed for the year 2007. The results are seen in the bottom 4 charts, where the measured wind speed was compared to the actual wind speed in an analysis of the residuals.

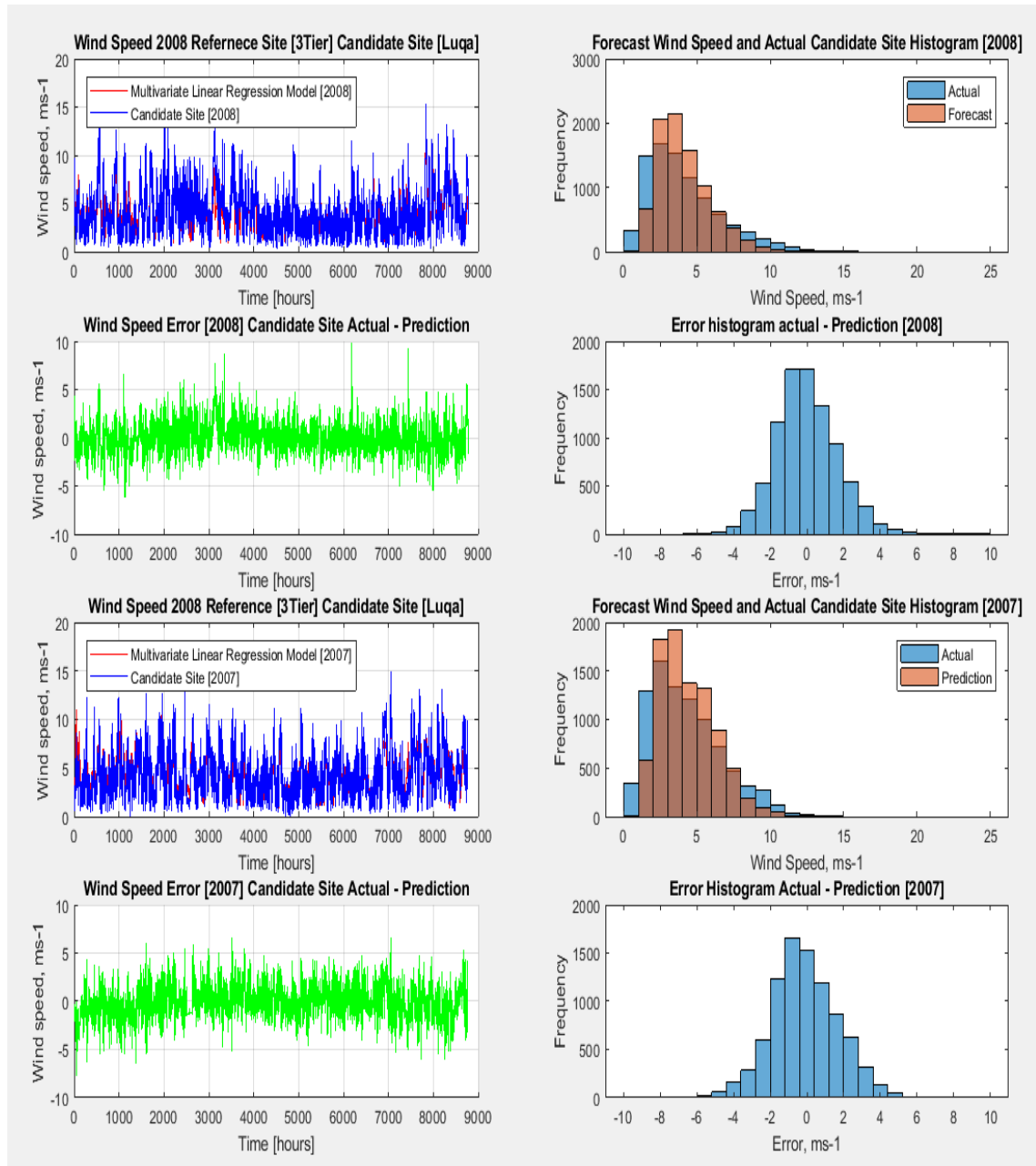


Figure C-2: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the MLR model with the 2008 data and then predicting the 2007 wind data.

Figure C-2 shows similar results which were obtained by using the concurrent data for 2008 to create the MCP model and then using the model to predict the wind speed for 2008, using MLR technique as described in Section 7.1.1. Again, the diagrams show the actual and the predicted wind distribution, a time-series and a distribution of the residuals (Error Histogram) for the years 2008 and 2007.

Similar results are shown for the ANN regression technique in FigureC-3. Figure C-4 represents the results obtained from the DT regression technique, while Figure C-5 represents the results from the SVR technique.

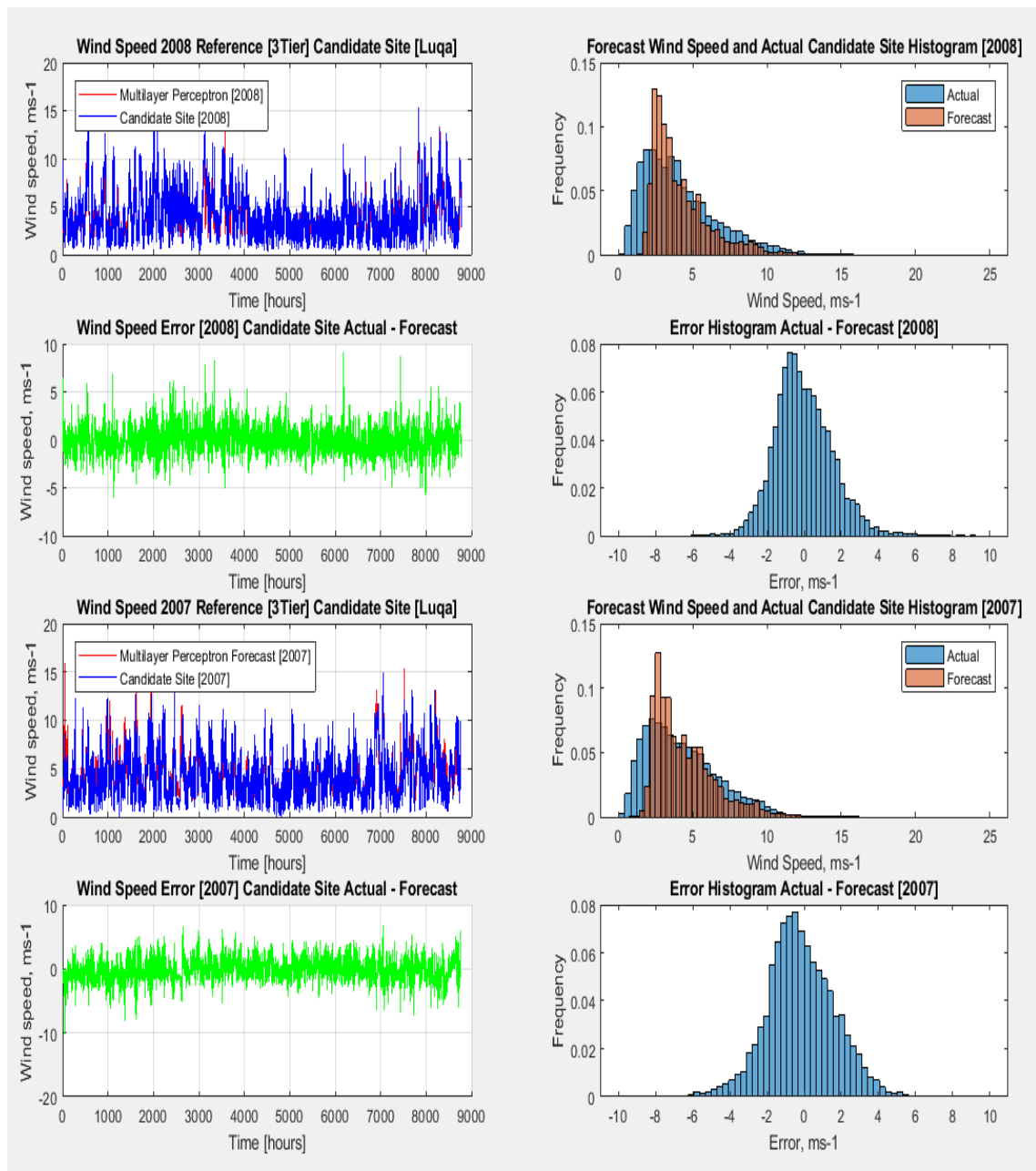


Figure C-3: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the ANN model with the 2008 data and then predicting the 2007 wind data.

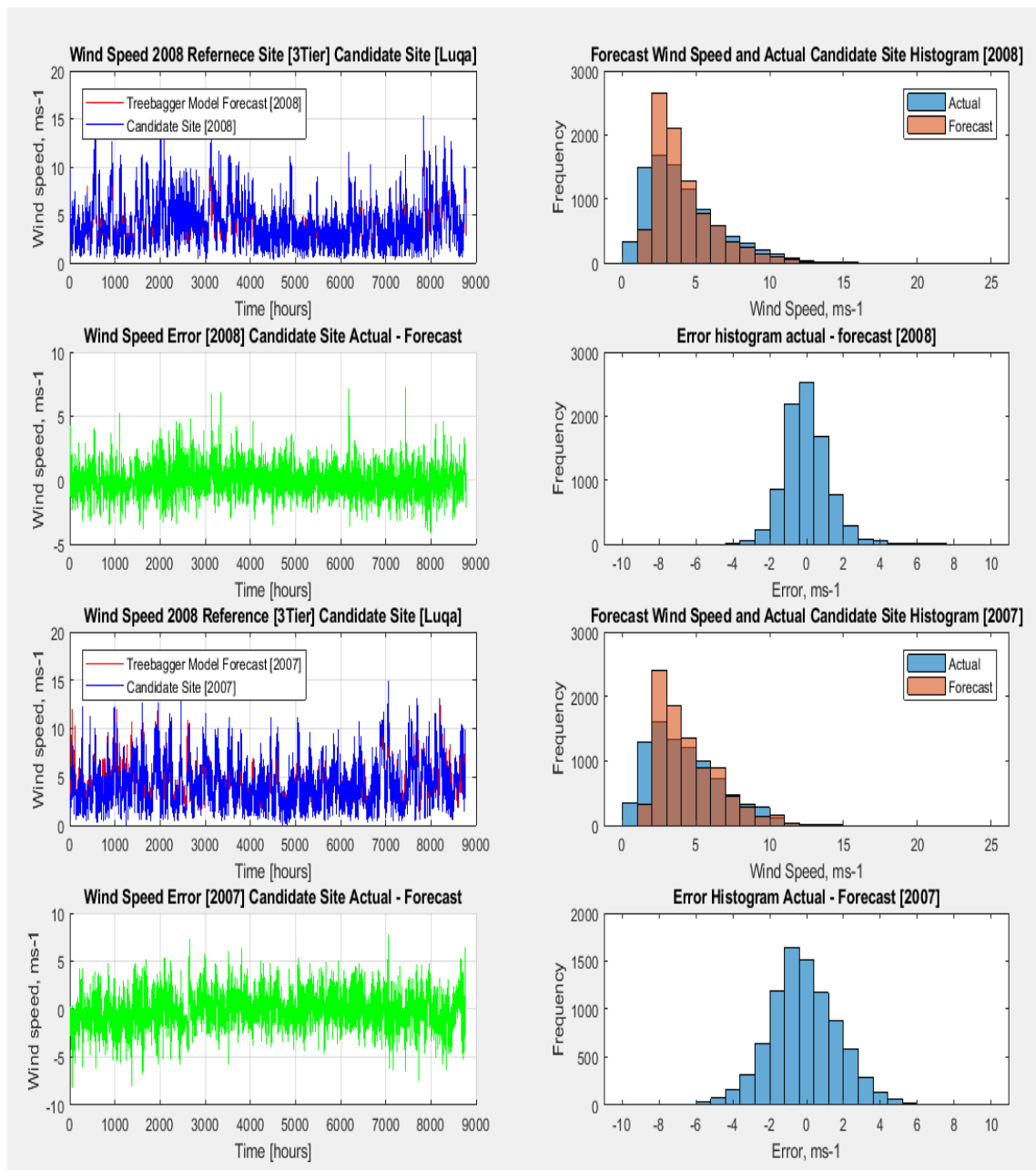


Figure C-4: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the DT regression model with the 2008 data and then predicting the 2007 wind data.

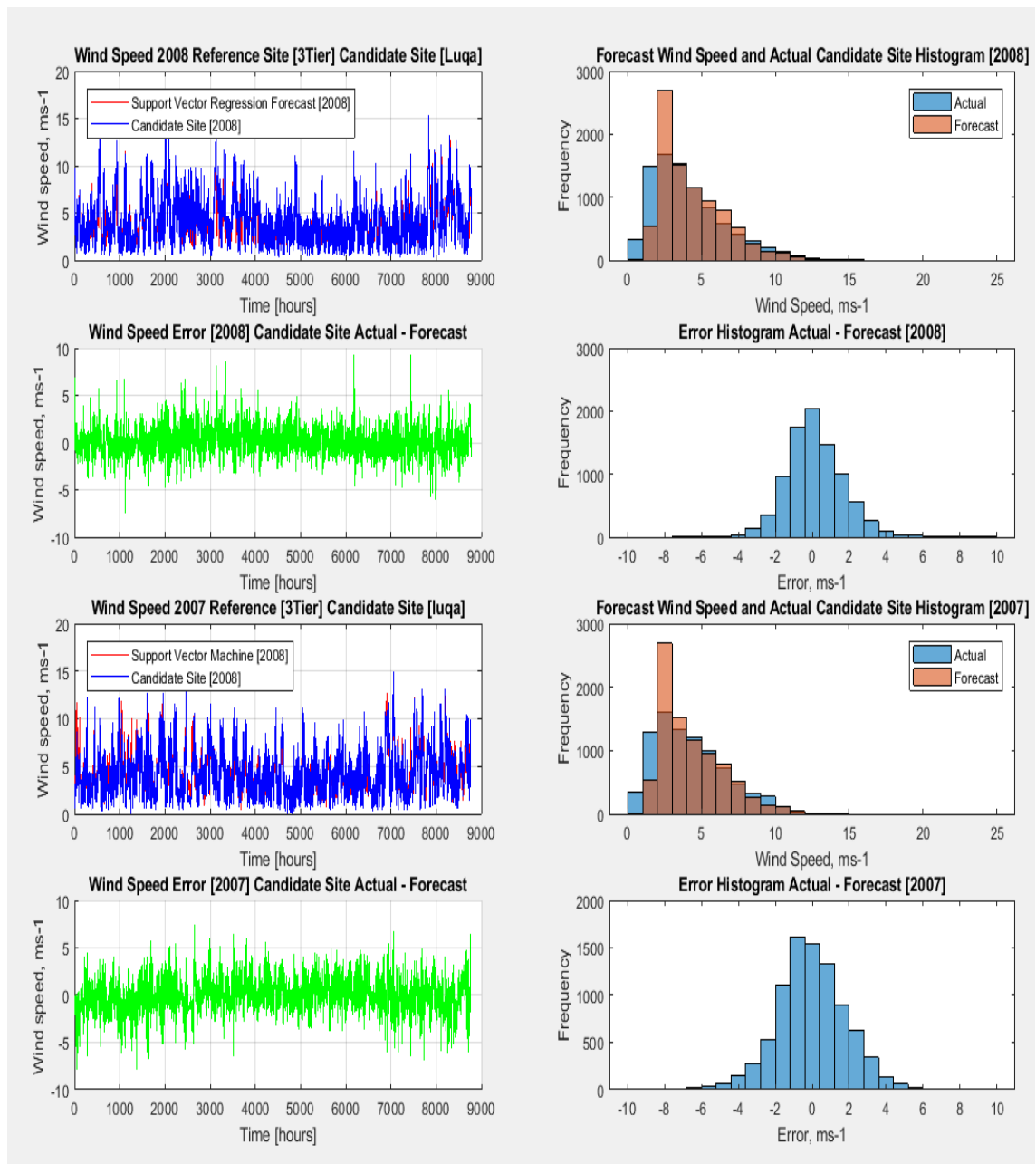
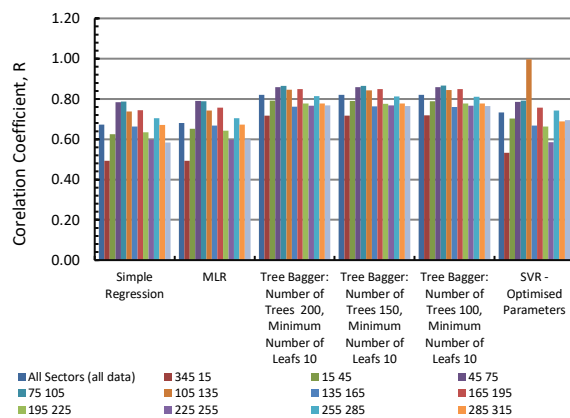


Figure C-5: Actual and predicted data for the years 2008 and 2007 (all sectors), defining the SVR regression model with the 2008 data and then predicting the 2007 wind data.

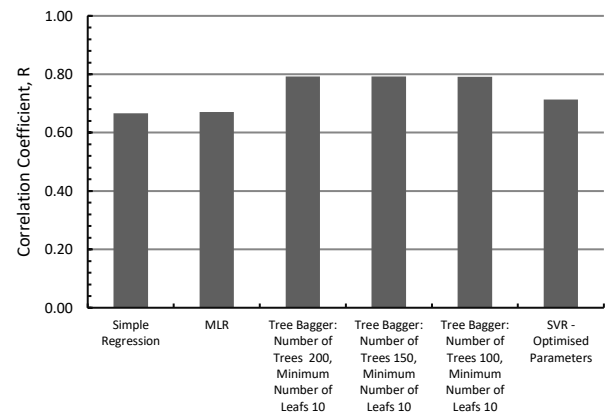
C.2 Results from Decision Trees Regression and Support Vector Regression Techniques

The results achieved by applying different parameters to the DT regression technique and the SVR technique are presented below. The results from both regression techniques were compared with those from the SLR and the MLR techniques, and those from the SVR technique with optimised parameters. The MCP model is based on the concurrent data of 2008, while for the year 2007 wind data is that predicted at the candidate site with the MCP model of the year 2008. The charts show the coefficient of determination, R . The measured wind data of the years 2007 and 2008 is used to analyse the residuals thus deriving the MAE and the MSE. Results for both sectorial analysis and non-sectorial analysis are shown.

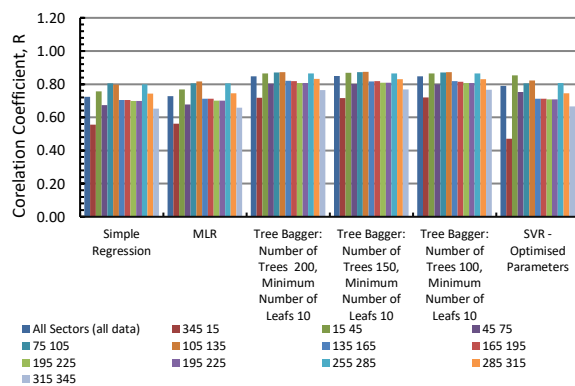
C.1.1 Decision Trees



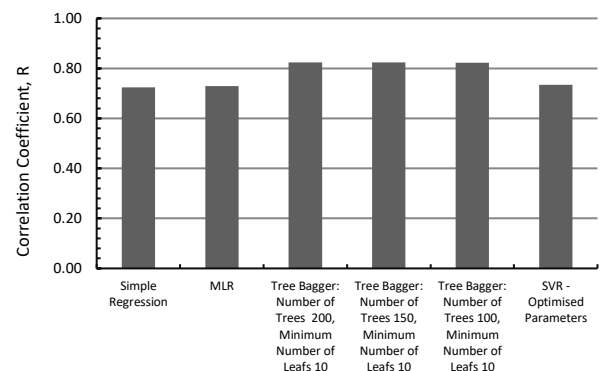
(a) Coefficient of Determination, R , for predicted wind speed at the candidate site for the year 2007 using a sectorial analysis.



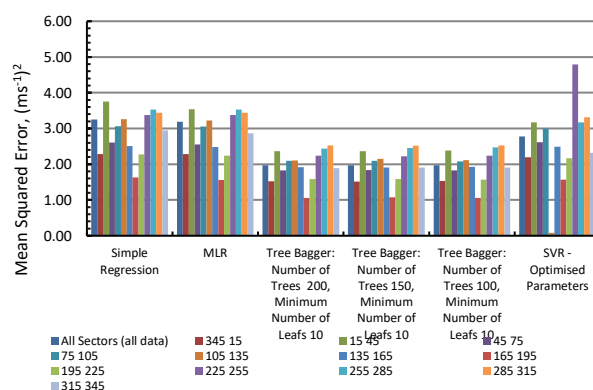
(b) Coefficient of Determination, R , for predicted wind speed at the candidate site for the year 2007, weighted value.



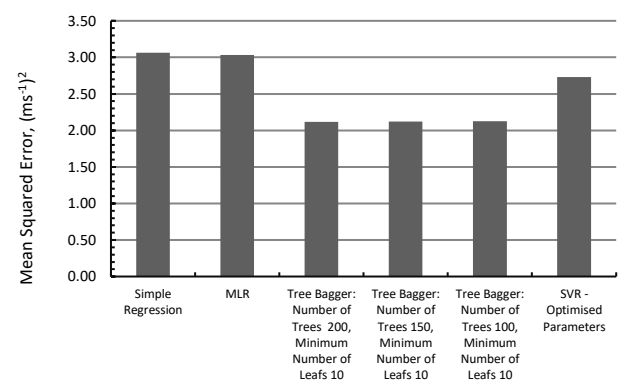
(c) Coefficient of Determination, R , from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



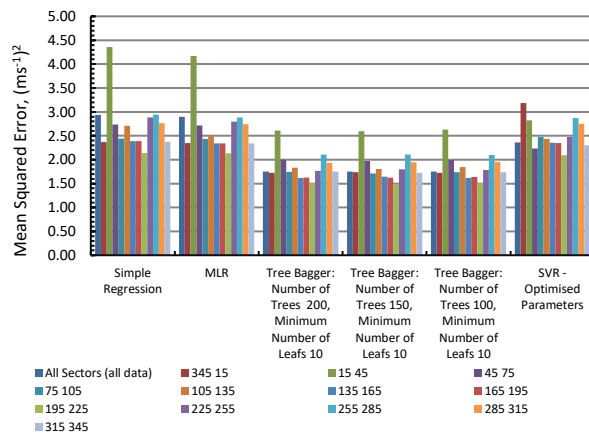
(d) Coefficient of Determination, R , from the MCP model from the wind speed data for the year 2008, weighted value.



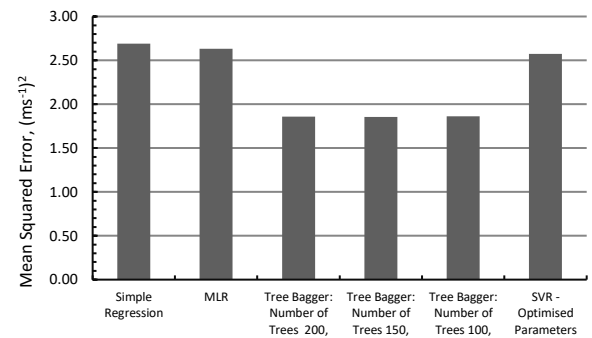
(e) Mean Squared Error, for predicted wind speed for the year 2007, using sectorial data.



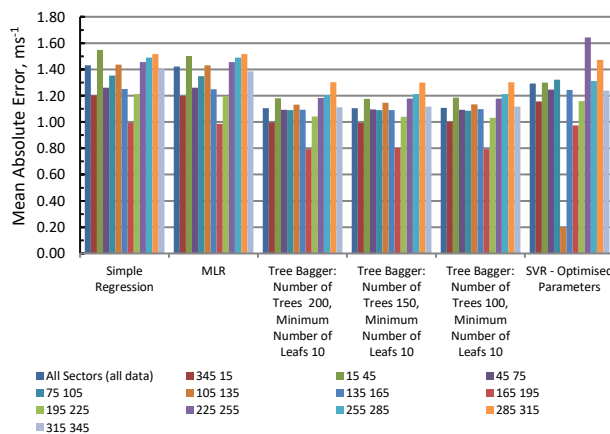
(f) Mean Squared Error, for predicted wind speed at the candidate site for the year 2007, weighted value.



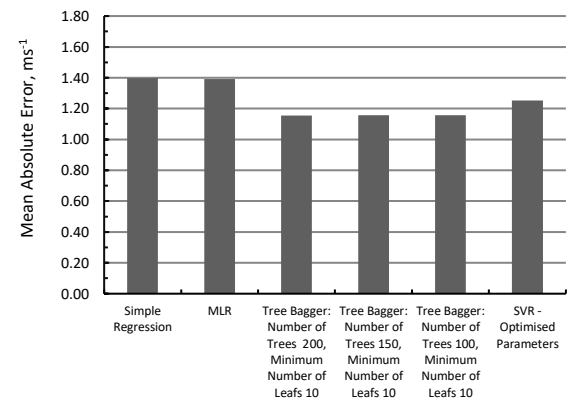
(g) Mean Squared Error, from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



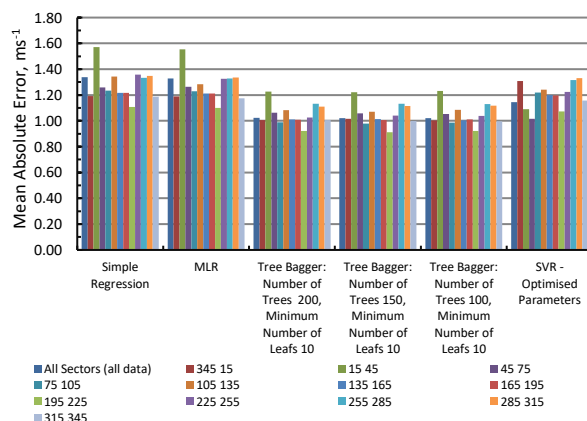
(h) Mean Squared Error, from the MCP model from the wind speed data for the year 2008, weighted value.



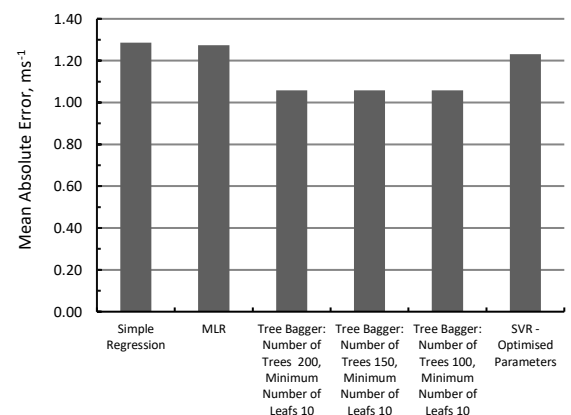
(i) Mean Absolute Error, for predicted wind speed for the year 2007, using sectorial data.



(j) Mean Absolute Error, for predicted wind speed at the candidate site for the year 2007, weighted value.



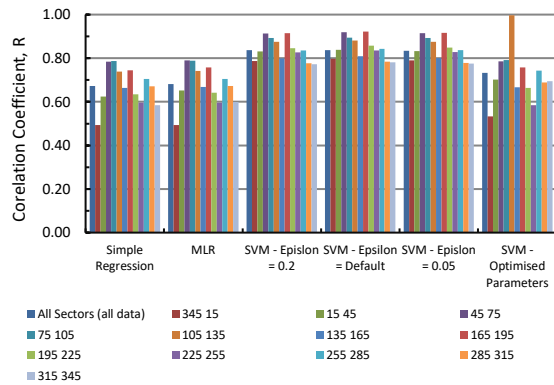
(k) Mean Absolute Error, from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



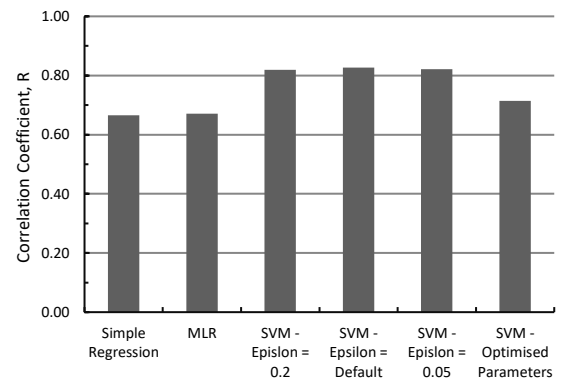
(l) Mean Absolute Error, from the MCP model from the wind speed data for the year 2008, weighted value.

Figure C-6: Results from the DT regression technique, comparing different model parameters, number of Trees and Leafs.

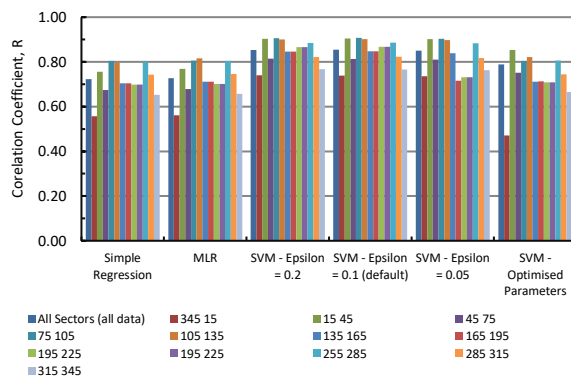
C.1.2 Support Vector Regression



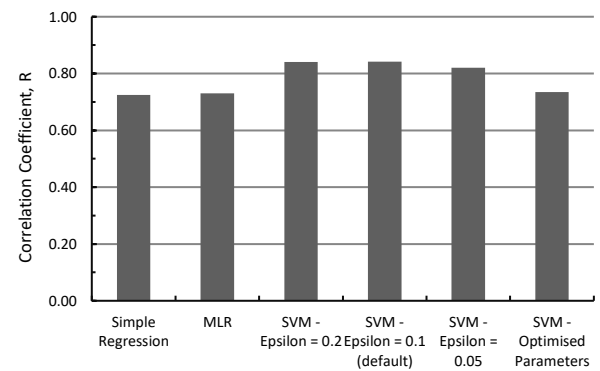
(a) Coefficient of Determination, R , for predicted wind speed at the candidate site for the year 2007 using a sectorial analysis.



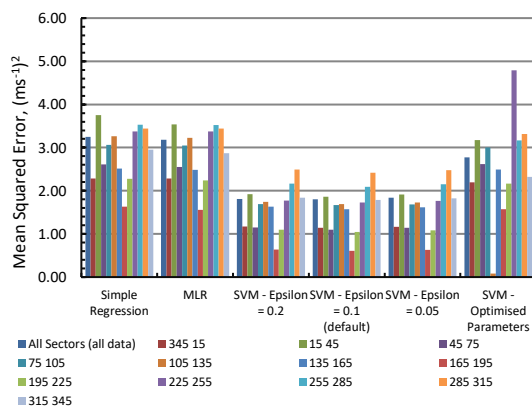
(b) Coefficient of Determination, R , for predicted wind speed at the candidate site for the year 2007, weighted value.



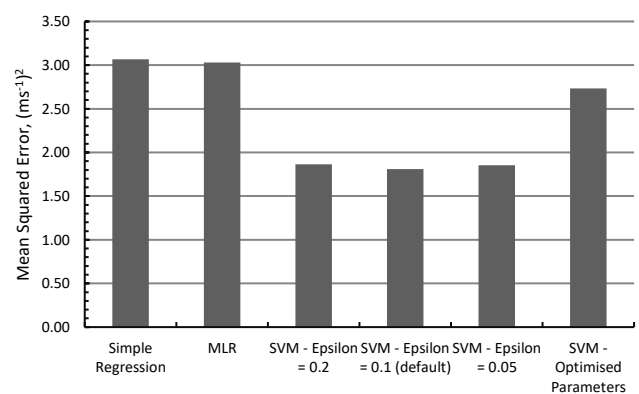
(c) Coefficient of Determination, R , from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



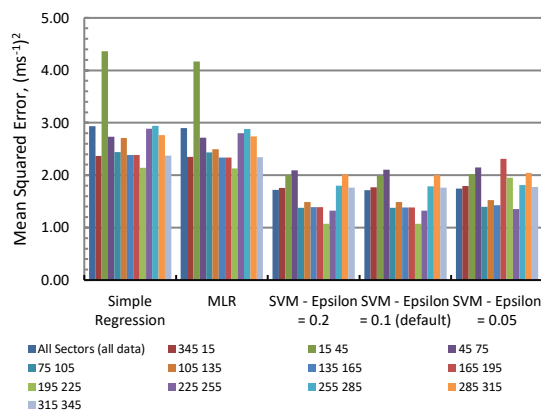
(d) Coefficient of Determination, R , from the MCP model for the wind speed data for the year 2008, weighted value.



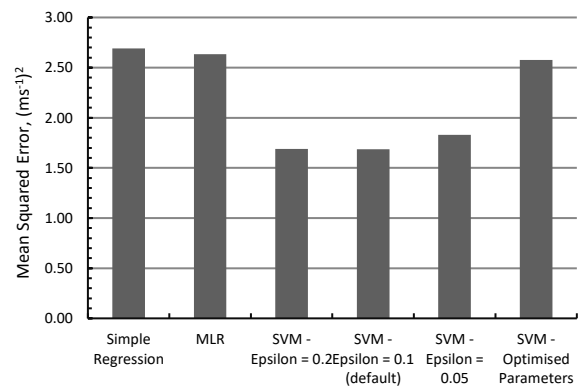
(e) Mean Squared Error, for predicted wind speed for the year 2007, using sectorial data.



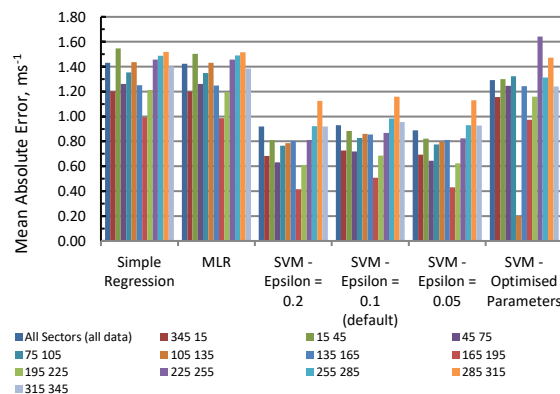
(f) Mean Squared Error, for predicted wind speed at the candidate site for the year 2007, weighted value.



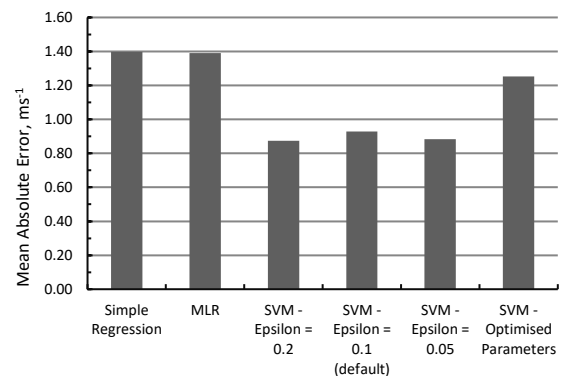
(g) Mean Squared Error, from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



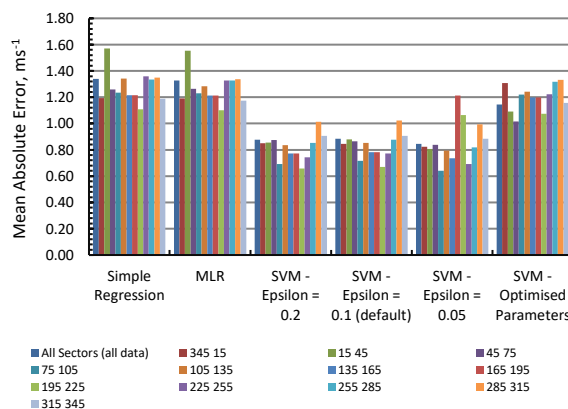
(h) Mean Squared Error, from the MCP model from the wind speed data for the year 2008, weighted value.



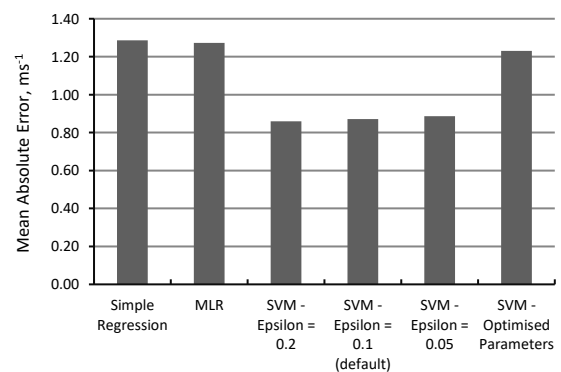
(i) Mean Absolute Error, for predicted wind speed for the year 2007, using sectorial data.



(j) Mean Absolute Error, for predicted wind speed at the candidate site for the year 2007, weighted value.



(k) Mean Absolute Error, from the MCP model for the wind speed data for the year 2008 using a sectorial analysis.



(l) Mean Absolute Error, from the MCP model from the wind speed data for the year 2008, weighted value.

Figure C-7: Results from the SVR technique, comparing different hyperparameter values.

D. Forecasted Quarterly Economic Data using ARIMA and SARIMA Methodology.

Table D-1: Forecast scenario for the years 2016-2020 with ARIMA methodology (Part 1).

Forecast Data							
Year	Quarter	Total GDP (MEuros)	Agriculture, Forestry and Fishing (MEuros)	Manufacturing (MEuros)	Mining and Quarrying, Water Supply (MEuros)	Construction (MEuros)	Wholesale and retail trade; repair of motor vehicles and motorcycles, transportation and storage, accommodation and food service activities (MEuros)
2016	2016Q1	2,518	22.88	184,557	29.28	89.26	139.82
	2016Q2	2,650	20.99	204,137	34.24	90.03	146.98
	2016Q3	2,766	25.01	189,759	36.75	89.97	158.93
	2016Q4	2,716	37.25	203,222	25.71	90.29	143.30
2017	2017Q1	2,778	23.68	190,843	26.79	97.16	148.77
	2017Q2	2,916	22.30	202,002	31.77	98.15	154.26
	2017Q3	3,041	27.42	182,005	34.24	98.31	166.71
	2017Q4	2,987	42.15	197,632	23.24	98.84	151.66
2018	2018Q1	3,056	27.52	195,457	24.33	105.93	157.60
	2018Q2	3,191	26.81	214,937	29.30	107.14	163.94
	2018Q3	3,312	32.93	200,472	31.77	107.53	176.16
	2018Q4	3,259	50.01	213,969	20.78	108.26	160.82
2019	2019Q1	3,326	34.40	201,738	21.86	115.57	166.53
	2019Q2	3,462	34.32	213,017	26.84	116.99	172.45
	2019Q3	3,585	41.36	193,102	29.31	117.59	184.78
	2019Q4	3,531	60.61	208,699	18.32	118.55	169.59
2020	2020Q1	3,600	44.10	206,379	19.40	126.07	175.40
	2020Q2	3,735	44.60	225,741	24.38	127.72	181.53
	2020Q3	3,858	52.49	211,198	26.85	128.52	193.81
	2020Q4	3,805	73.73	224,727	15.86	129.71	178.54

Table D-2: Forecast scenario for the years 2016-2020 with ARIMA methodology (Part 2)

Forecast Data							
Year	Quarter	Information and Communication (MEuros)	Financial and Insurance Activities (MEuros)	Real Estate Activities (MEuros)	Professional, Scientific and Technical Activities (MEuros)	Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities (MEuros).	Forecast Arts, Entertainment and Recreation, Repair of Household Goods and Other Services (MEuros).
2016	2016Q1	153.88	139.82	122.47	301.06	380.87	361.77
	2016Q2	161.39	146.98	124.30	315.94	387.88	369.67
	2016Q3	164.61	158.93	125.36	359.73	385.48	368.98
	2016Q4	168.00	143.30	125.85	341.24	384.81	367.31
2017	2017Q1	177.17	148.77	127.59	373.06	401.32	426.59
	2017Q2	184.17	154.26	128.61	392.49	408.26	435.17
	2017Q3	189.04	166.71	129.08	438.93	405.88	434.53
	2017Q4	193.39	151.66	130.74	411.67	405.22	432.24
2018	2018Q1	200.54	157.60	131.70	450.77	421.55	491.81
	2018Q2	207.98	163.94	132.15	467.06	428.40	500.23
	2018Q3	211.42	176.16	133.74	520.46	426.06	499.57
	2018Q4	214.92	160.82	134.66	502.41	425.41	497.42
2019	2019Q1	223.84	166.53	135.09	544.16	441.55	556.93
	2019Q2	230.90	172.45	136.59	564.46	448.33	565.39
	2019Q3	235.59	184.78	137.47	620.82	446.01	564.73
	2019Q4	239.83	169.56	137.88	595.31	445.36	562.55
2020	2020Q1	247.21	175.40	139.32	644.02	461.33	622.07
	2020Q2	254.60	181.53	140.16	661.67	468.03	630.52
	2020Q3	258.19	193.81	140.55	724.72	465.74	629.86
	2020Q4	261.79	178.51	141.92	707.19	465.10	627.69

E. Econometric and Demographic Forecasts

Figure E-1 to Figure E-11 demonstrate the trends for the end-user data of Table 4-4. Values shown are quarterly data for the years 2011 to 2019 [40]. The years 2016-2020 were forecasted using the ARIMA and SARIMA [33] model described in Section 3.2.

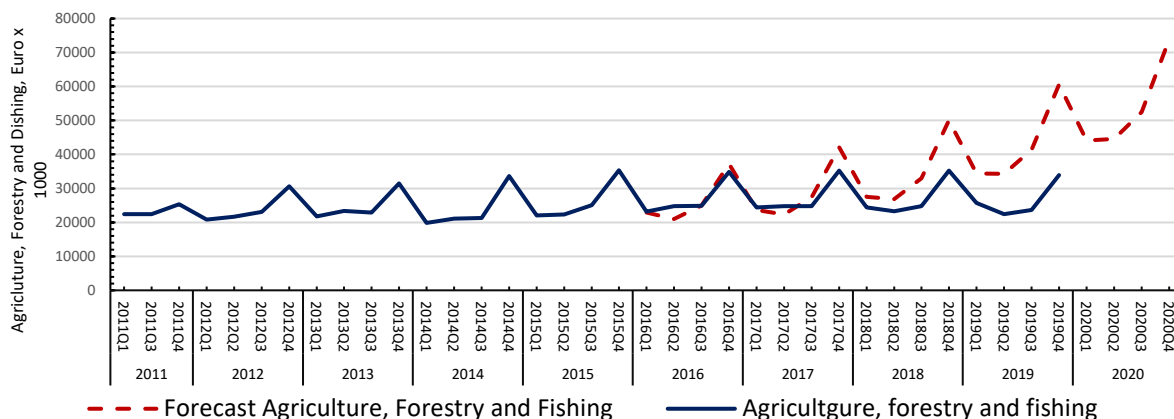


Figure E-1: Actual Agriculture, Forestry and Fishing trends for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

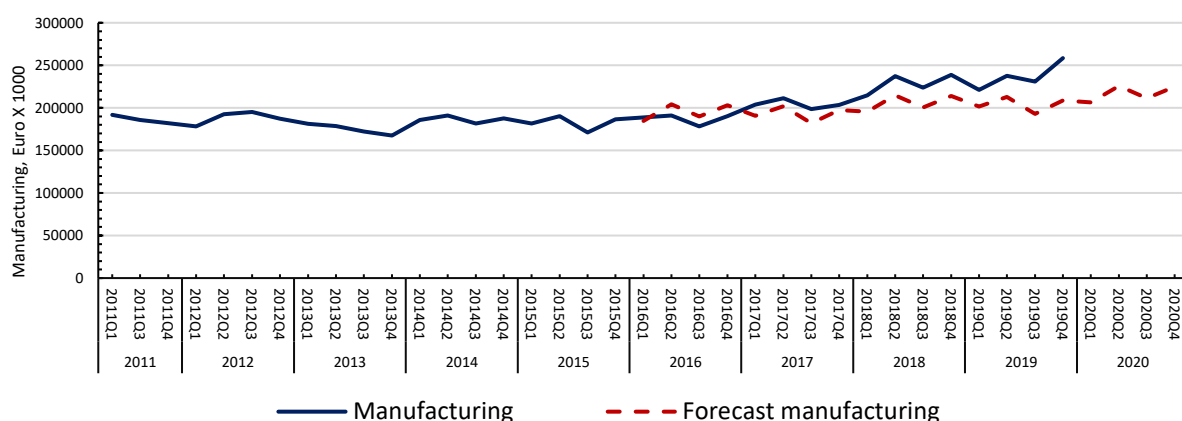


Figure E-2: Actual Manufacturing trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

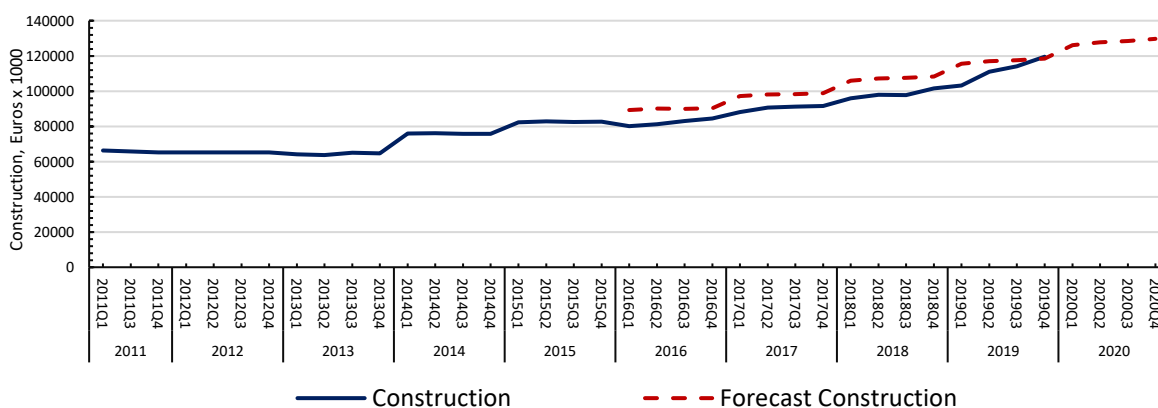


Figure E-3: Actual Construction trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

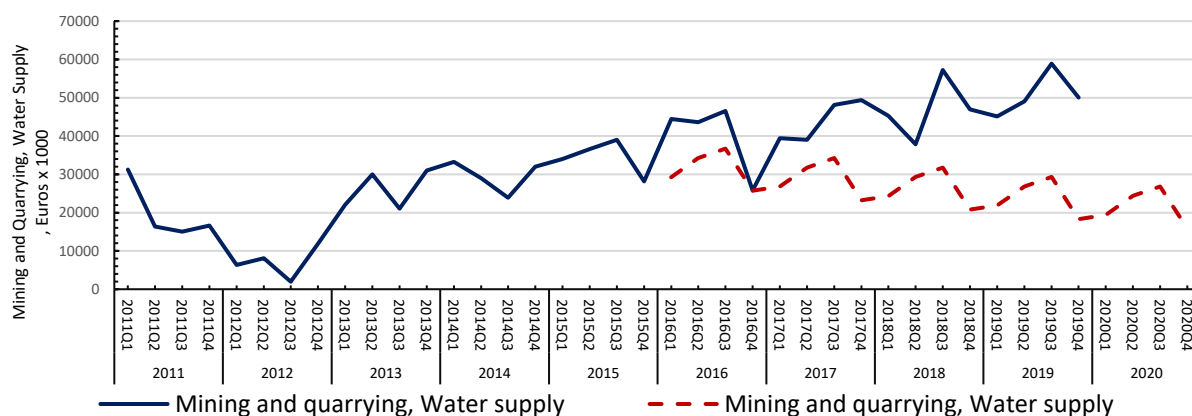


Figure E-4: Actual Mining, Quarrying and Water Supply trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

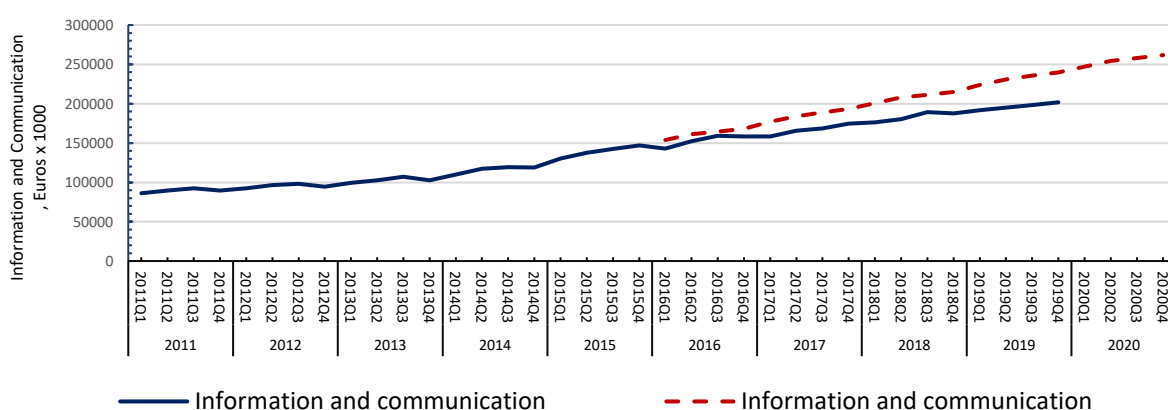


Figure E-5: Actual Information and Communication trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

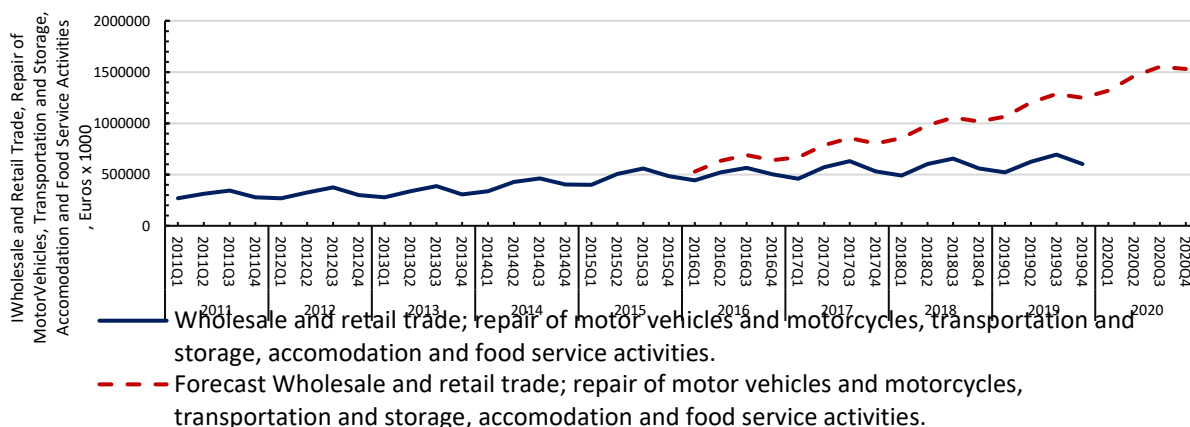


Figure E-6: Actual Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

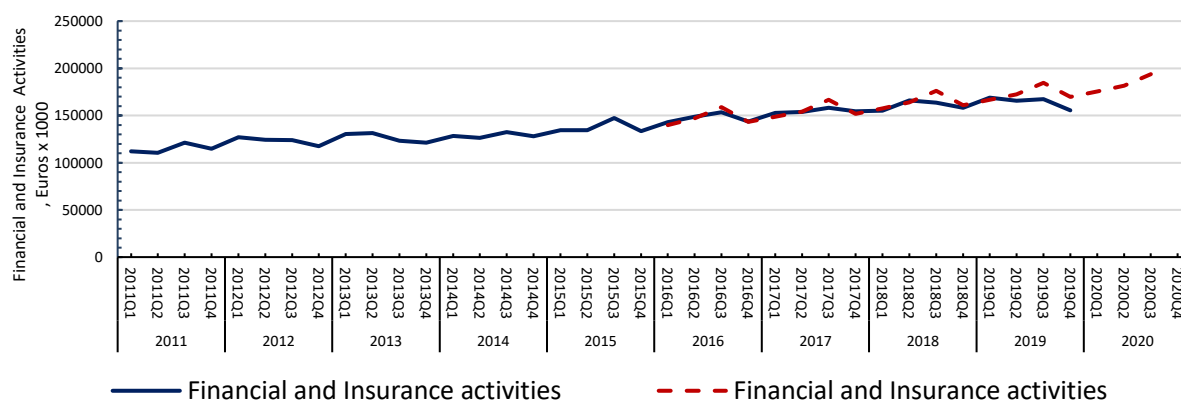


Figure E-7: Actual Financial and Insurance Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

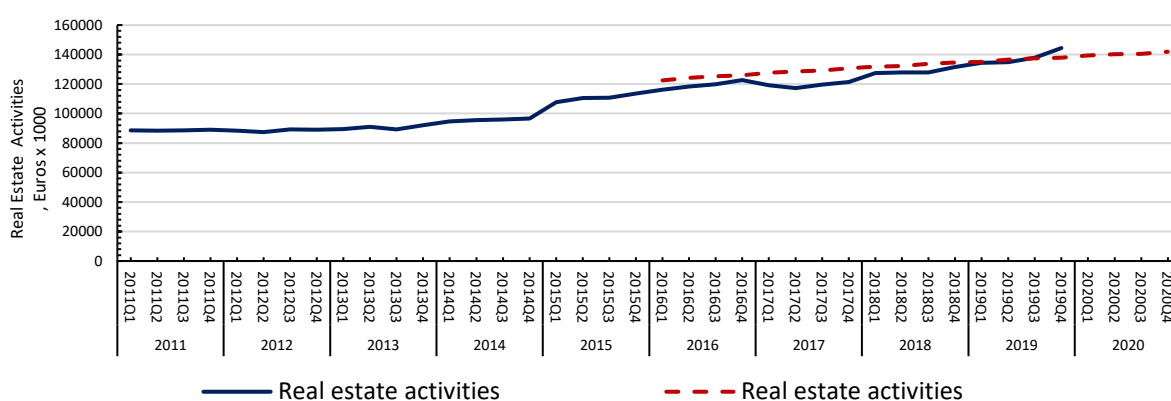


Figure E-8 Actual Real Estate Activity trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

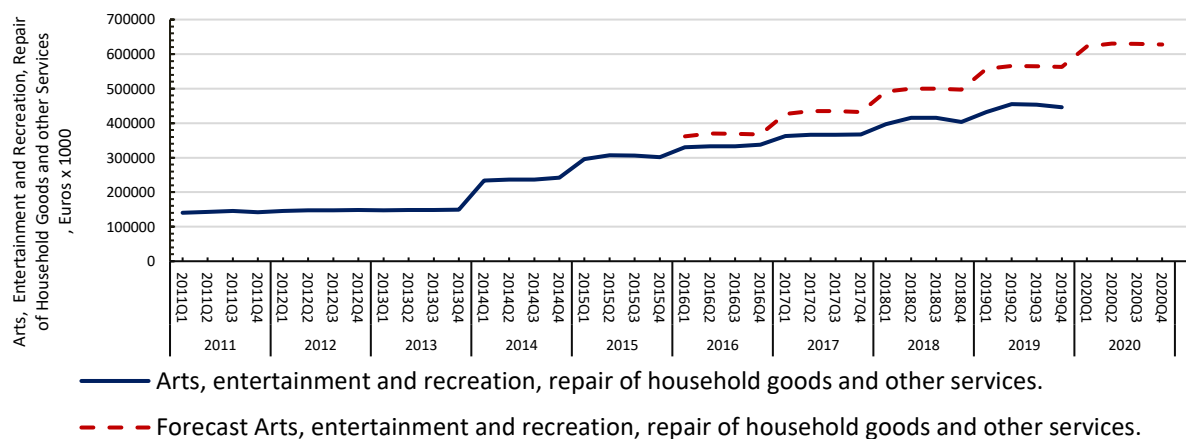


Figure E-9: Actual Arts, Entertainment and Recreation, Repair of Household Goods and other Services trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

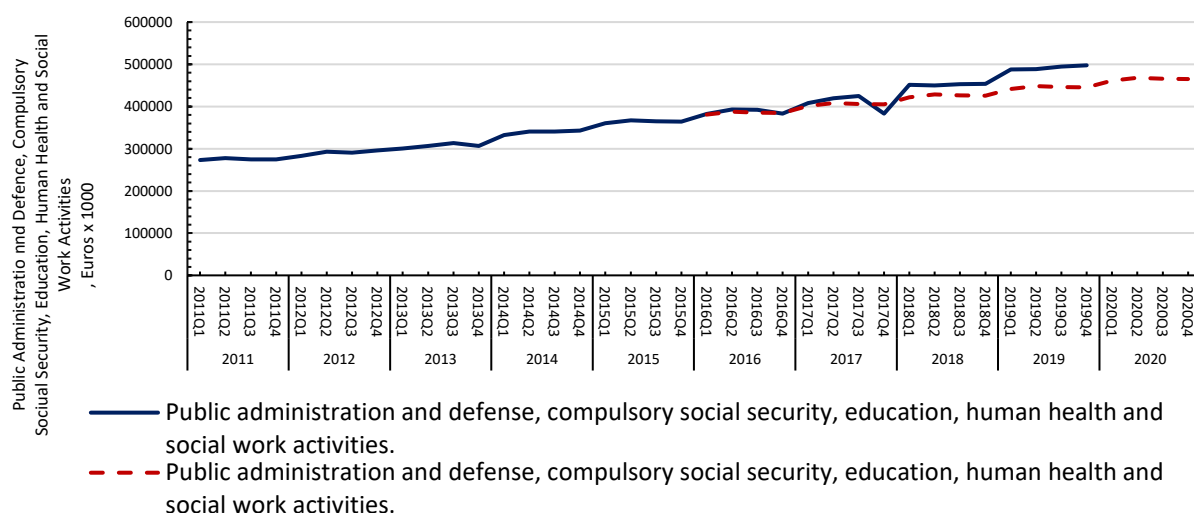


Figure E-10: Public Administration and Defence, Compulsory Social Security, Education, Human Health and Social Work Activities trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

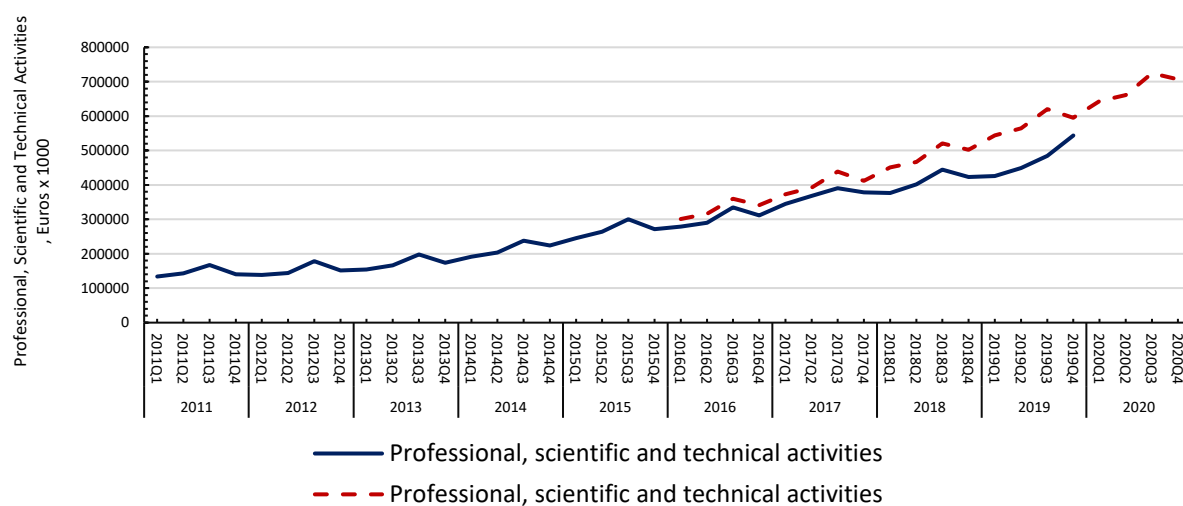


Figure E-11: Professional, Scientific and technical Activities trend for the years 2011-2019 and forecasted values for the years 2016-2020 using ARIMA model.

F. Energy Demand Forecasting

Below figures show more results from the EDF methodology described in Section 4.3 and the results presented in Section 8.2. The energy demand from 2011-2016, GDP, end-user data and demographic data has been used to create the models. Figure F-1 to Figure F-3 show the analysis of residuals, the Q1, Q2, Q3 and Q4 actual and forecasted energy demand and residuals time-series, using the MLR technique for EDF.

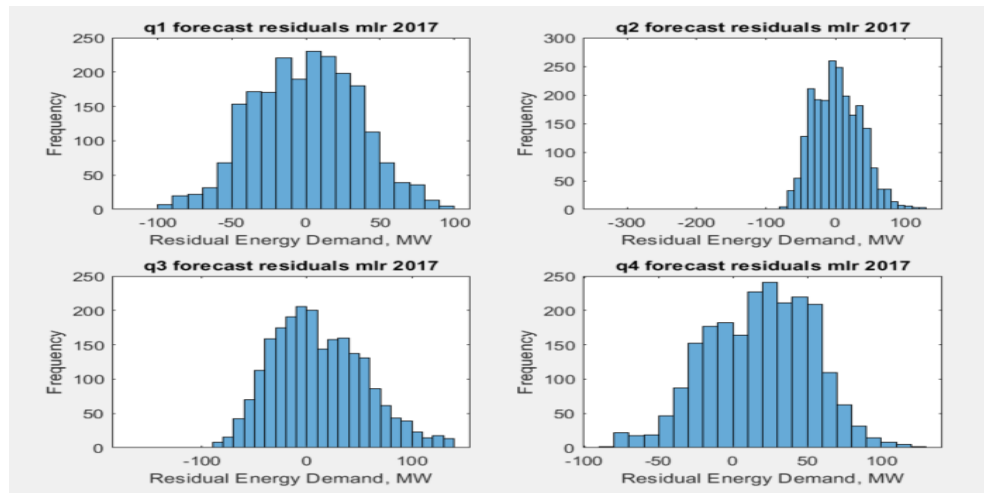


Figure F-1: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.

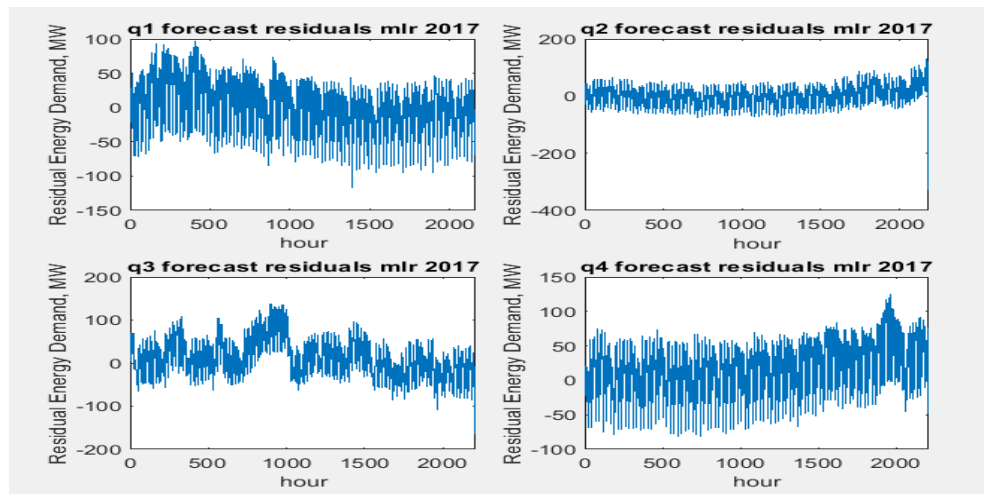


Figure F-2: Residuals' time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.

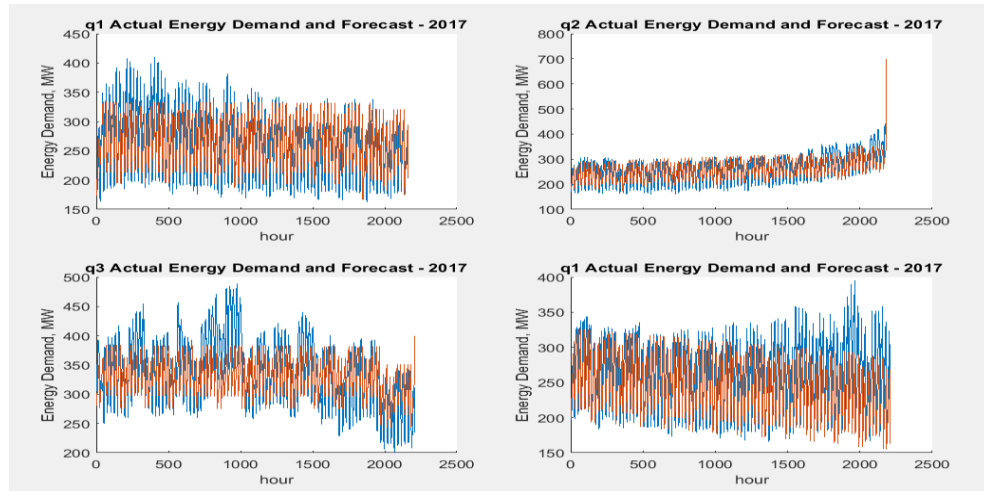


Figure F-3: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using MLR technique for EDF.

Figure F-4 to Figure F-6 show the analysis of residuals, the Q1, Q2, Q3 and Q4 actual and forecasted energy demand and residuals time-series, using the ANN regression technique for EDF.

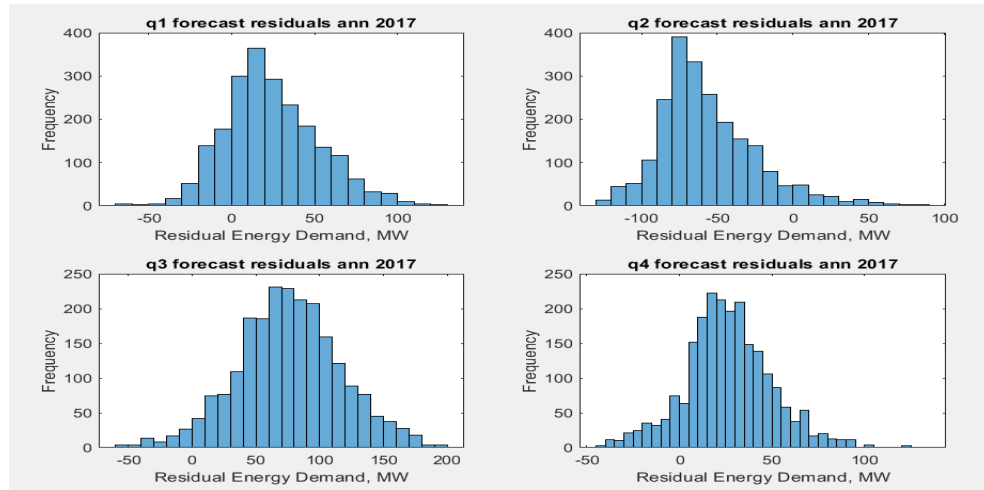


Figure F-4: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.

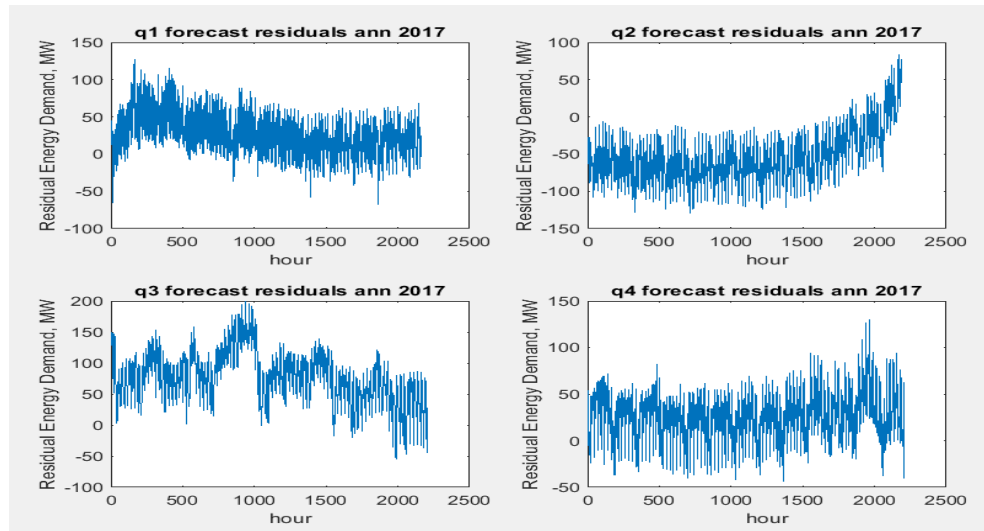


Figure F-5: Residuals' time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.

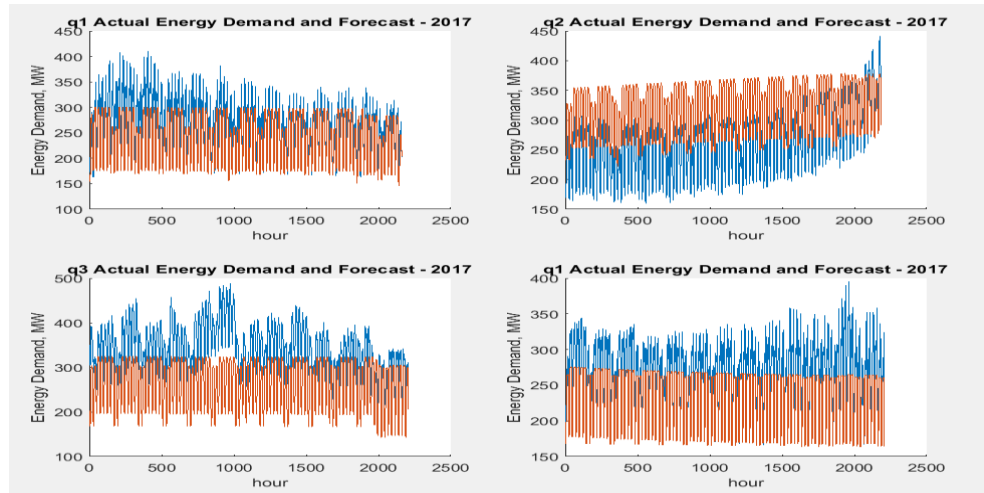


Figure F-6: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using ANN regression technique for EDF.

Figure F-7 to Figure F-9 show the analysis of residuals, the Q1, Q2, Q3 and Q4 actual and forecasted energy demand and residuals time-series, using the DT regression technique for EDF.

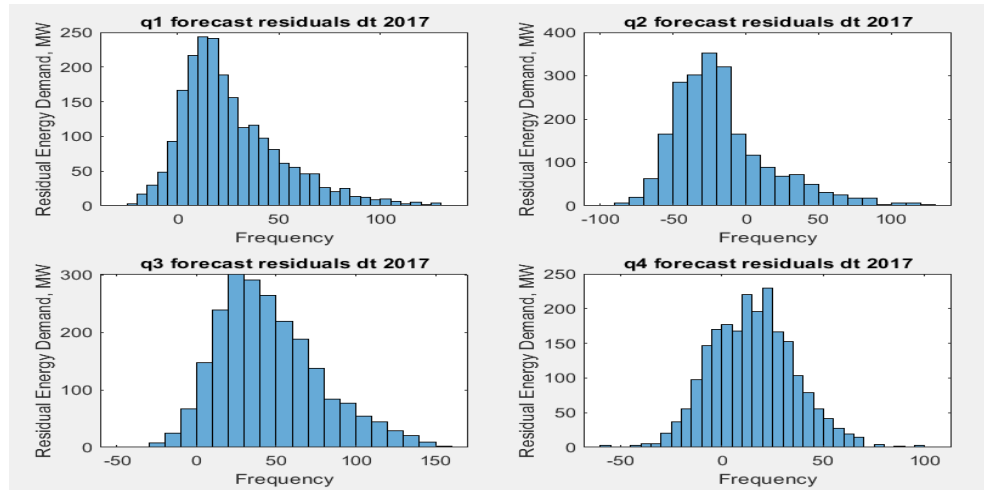


Figure F-7: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.

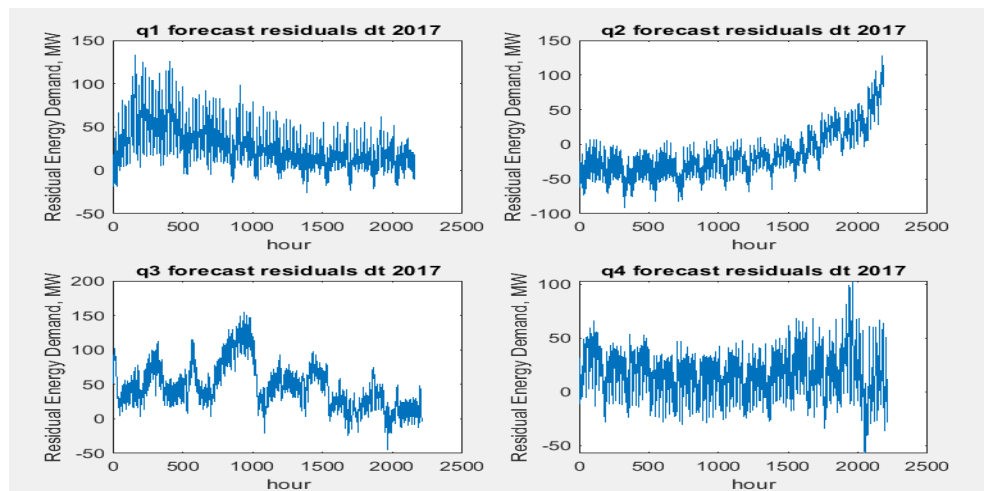


Figure F-8: Residuals' time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.

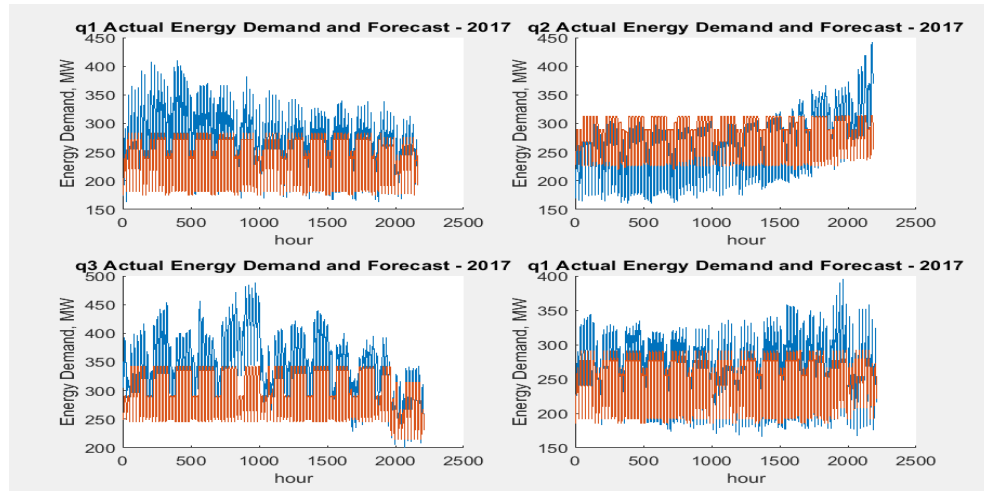


Figure F-9: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using DT regression technique for EDF.

Figure F-10 to Figure F-12 show the analysis of residuals, the Q1, Q2, Q3 and Q4 actual and forecasted energy demand and residuals time-series, using the SVR technique for EDF.

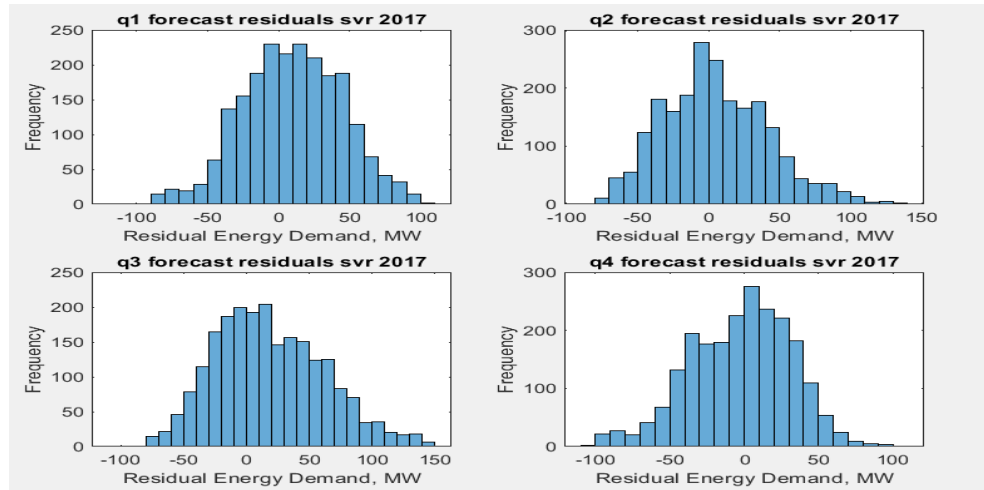


Figure F-10: Analysis of residuals for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.

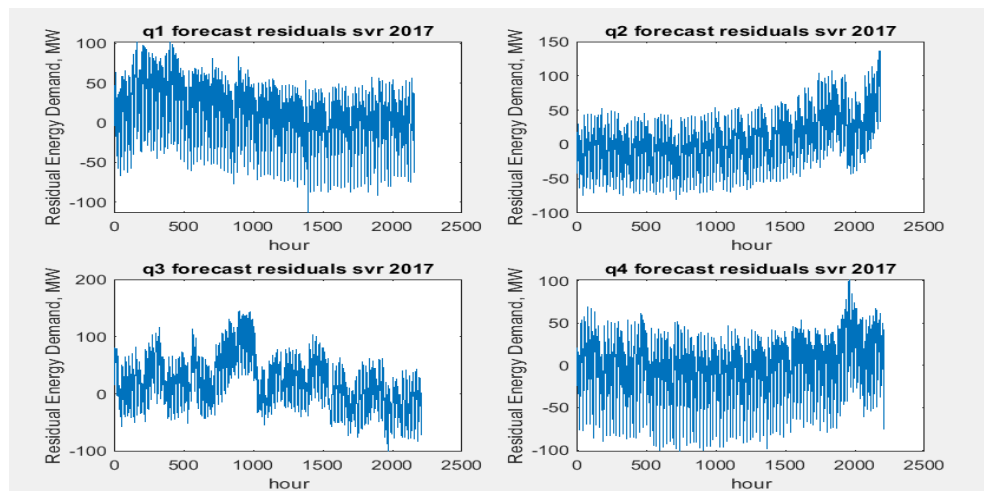


Figure F-11: Residuals' time-series for the energy demand forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.

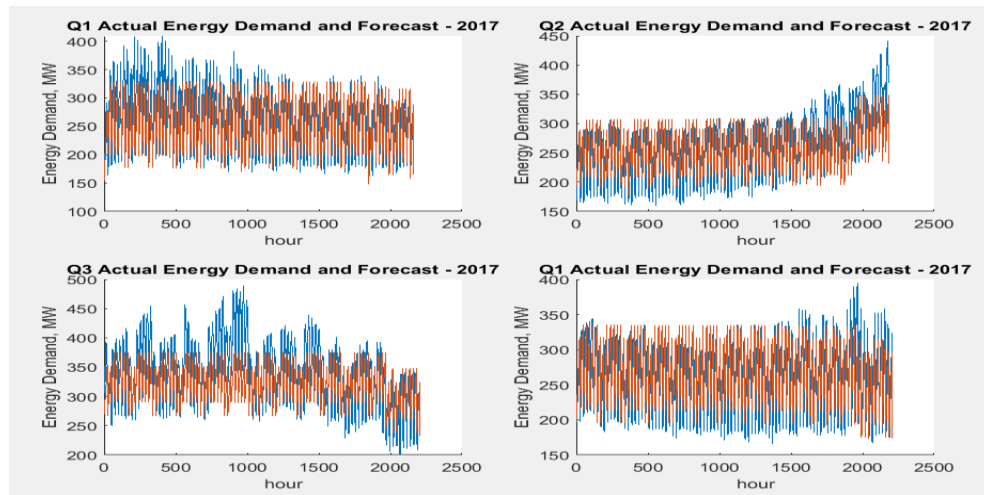


Figure F-12: Time-series for actual energy demand and forecast, carried out for the year 2017, using the years 2011-2016 to create the models using the SVR technique for EDF.

Noting that the best models for energy demand forecasting are ANN and DT, Figure F-13 to Figure F-18 show the analysis of the residuals, the time-series of the residuals and the forecasted and actual energy demand by quarter for 2016 based on the model shown in Figure 4-10.

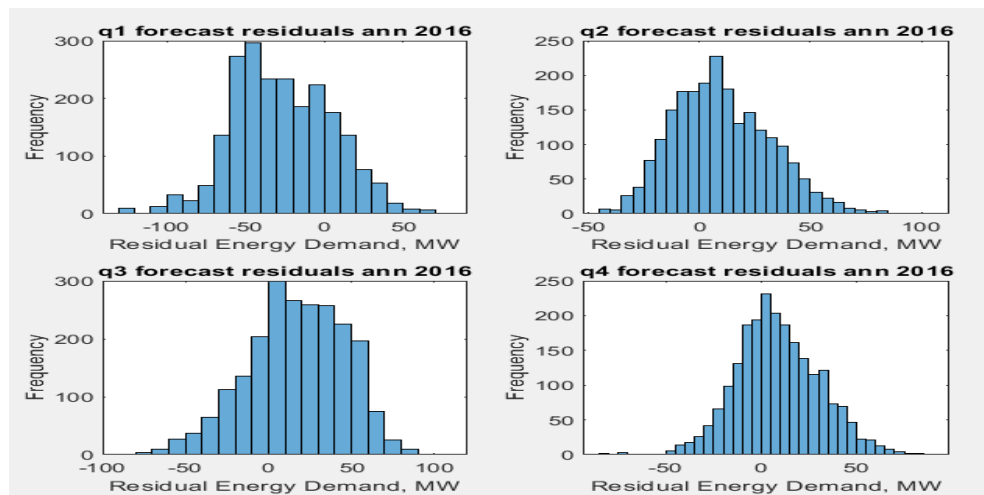


Figure F-13: Analysis of residuals for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using ANN regression technique for EDF.

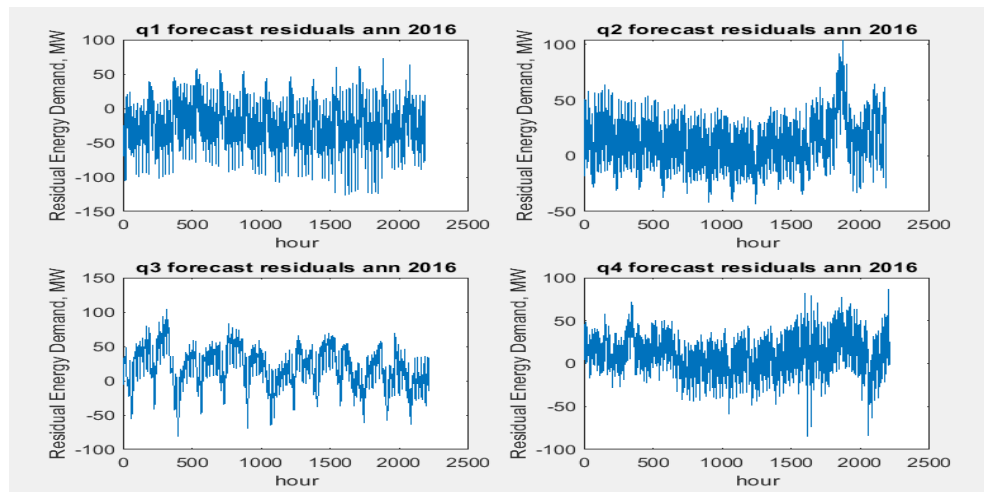


Figure F-14: Residuals' time-series for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using ANN regression technique for EDF.

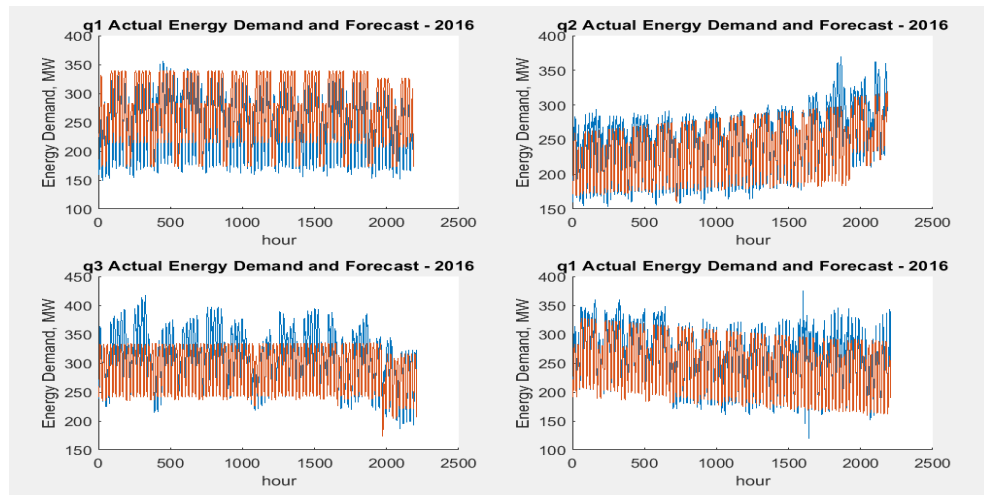


Figure F-15: Time-series for actual energy demand and forecast, carried out for the year 2016, using the years 2011-2015 to create the models using the ANN regression technique for EDF.

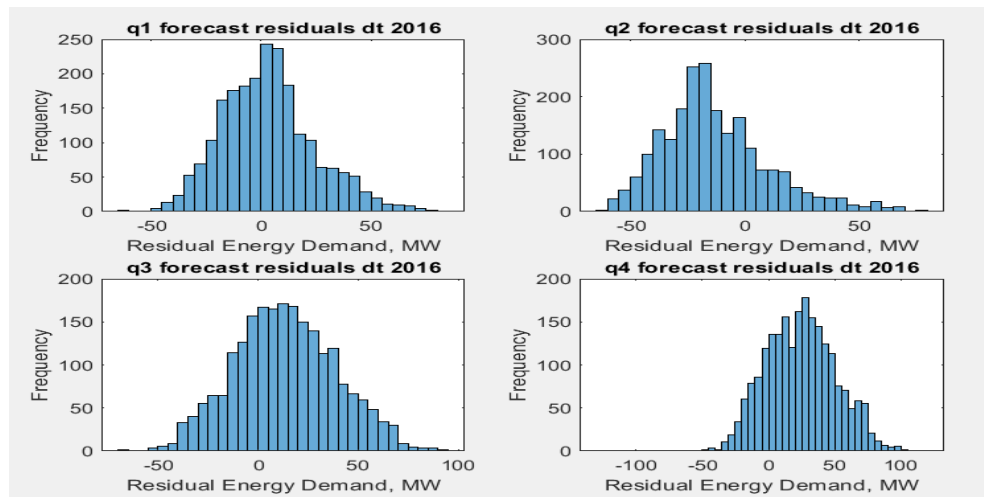


Figure F-16: Analysis of residuals for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using DT regression technique for EDF.

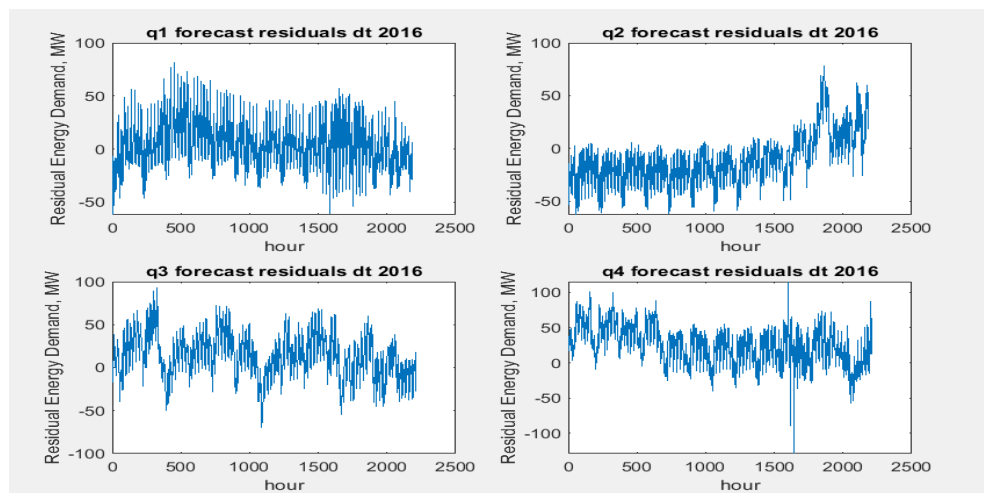


Figure F-17: Residuals' time-series for the energy demand forecast, carried out for the year 2016, using the years 2011-2015 to create the models using DT regression technique for EDF.

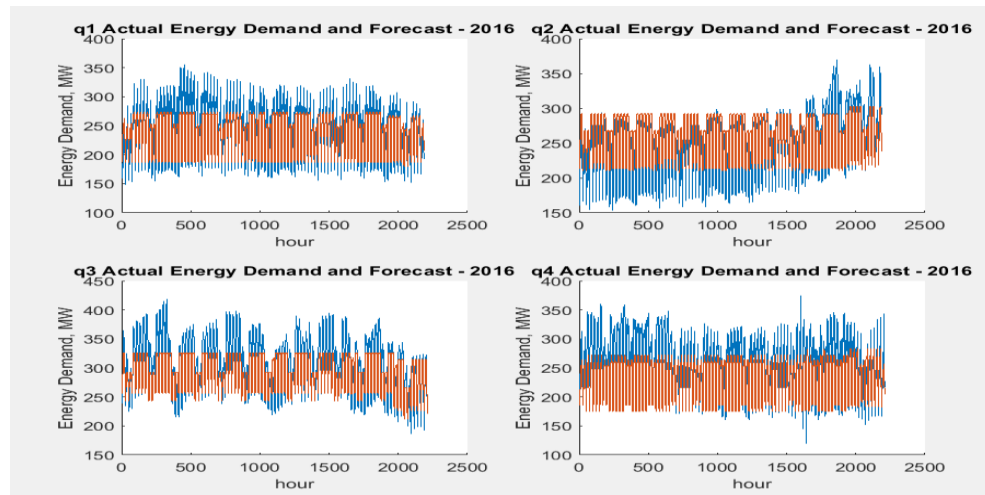


Figure F-18: Time-series for actual energy demand and forecast, carried out for the year 2016, using the years 2011-2015 to create the models using the DT regression technique for EDF.

G. Matrix Results for Windfarms with Installed Capacities of 200 MW and 150 MW

This Appendix shows the detailed results from the matrix of combinations for the various regression techniques which are used for the MCP and EDF methodologies. The results are for windfarms with installed capacities of 200 MW and 150 MW. Detailed results for a windfarm with an installed capacity of 250 MW are shown in Chapter 9.

G.1 Results for a Windfarm with an Installed Capacity of 200 MW

As shown previously the following tables present the results for percentage error of energy discharged from the ESS, curtailed energy from the windfarm and energy transferred from the windfarm to the electricity grid for 100, 125 and 150 MW generation baseload. The percentage error in energy yield is calculated by using Eq. (3-85).

100 MW Generation Baseload

Table G-1: Percentage error in the total energy discharged from the ESS into the electricity grid, for an offshore windfarm with capacity of 200 MW and a generation baseload of 100 MW.

		Percentage error in total energy discharged from the ESS for an MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	2.6	6.6	10.8	6.6	7.6	10.9	14.9	16.6	16.7	16.8
	ANN	23.8	22.9	32.3	31.7	32.6	39.3	44.3	48.4	56.3	157.6
	DT	15.0	21.1	31.4	34.6	38.7	46.1	52.3	58.7	62.2	65.9
	SVR	27.4	25.0	27.3	27.6	29.0	31.1	31.3	31.7	32.0	31.4
Mean Percentage Error		33.0%									
		Percentage Error in Total Energy Discharged from the ESS for an ANN Energy Demand Forecast Model									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	63.1	64.2	63.6	62.8	62.4	62.3	62.4	62.0	61.0	60.5
	ANN	35.7	32.7	37.2	41.0	43.4	47.0	49.4	51.9	53.7	55.1
	DT	41.9	48.2	50.4	53.9	58.3	60.6	62.4	64.3	65.6	66.7
	SVR	46.2	45.5	48.8	50.9	55.7	58.1	60.0	62.0	63.4	64.6
Mean Percentage Error		55.0%									
		Percentage Error in Total Energy Discharged from the ESS for a DT Energy Demand Forecast Model									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	50.7	48.5	46.0	45.1	41.7	39.7	37.7	36.5	34.6	32.6
	ANN	17.6	21.6	20.5	22.9	19.8	17.7	14.6	15.8	15.8	15.2
	DT	35.5	34.4	36.0	37.3	37.6	37.6	36.3	36.4	36.5	35.5
	SVR	35.0	34.1	33.1	35.4	36.8	36.4	37.2	37.1	36.5	37.0
Mean Percentage Error		32.9%									
		Percentage Error in Total Energy Discharged from the ESS for an SVR Energy Demand Forecast Model									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	52.6	52.4	49.7	45.6	41.0	40.3	27.5	22.7	17.2	13.4
	ANN	20.7	16.6	11.2	7.9	4.0	0.5	4.2	5.5	8.5	9.8
	DT	22.6	22.7	22.6	27.4	26.8	22.8	17.9	15.0	11.4	9.9
	SVR	28.6	23.8	18.2	20.0	19.4	15.0	11.7	11.9	12.4	12.7
Mean Percentage Error		20.6%									

Table G-1 presents the percentage error in energy yield for the total energy discharged by the ESS into the electricity grid, for a windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW. Table G-2 presents the percentage error in curtailed energy for the windfarm, for a windfarm capacity of 200 MW and a baseload of 100 MW.

Table G-2: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW.

		Percentage error in curtailed energy from the windfarm for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	82.7	116.9	130.7	199.4	259.6	366.4	389.5	533.9	714.1	837.4
	DT	98.8	136.1	128.6	194.7	251.3	368.7	471.3	665.7	809.5	861.6
	SVR	62.1	89.8	107.1	111.4	150.1	227.4	335.5	480.5	528.8	534.4
Mean Percentage Error		58.2	79.2	73.8	112.2	157.8	223.1	235.6	352.7	431.4	435.2
		310.1%									
		Percentage error in curtailed energy from the windfarm for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	69.9	68.9	75.2	70.0	61.6	48.9	39.1	32.9	54.0	88.3
	DT	75.7	80.3	88.4	91.5	98.7	100.0	100.1	100.0	100.0	100.0
	SVR	66.2	91.6	85.3	134.4	164.7	245.3	299.0	427.6	532.9	575.6
Mean Percentage Error		81.8	90.3	96.6	99.9	100.0	100.0	100.0	100.0	100.0	100.0
		128.5%									
		Percentage error in curtailed energy from the windfarm for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	33.8	20.6	26.0	5.4	0.3	15.0	30.8	90.5	135.7	110.4
	DT	46.6	35.9	40.1	36.9	61.0	82.8	93.2	89.6	82.7	83.7
	SVR	65.6	67.7	66.4	67.8	84.2	92.6	91.4	89.3	85.0	85.4
Mean Percentage Error		62.5	66.8	70.0	66.2	85.7	96.5	97.7	98.1	98.9	100.0
		68.9%									
		Percentage error in curtailed energy from the windfarm for an SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	40.9	26.9	19.5	2.1	11.2	31.4	49.4	103.5	131.4	100.4
	DT	45.2	38.4	40.3	29.7	26.1	30.3	48.1	42.2	69.8	76.2
	SVR	60.6	55.7	53.1	44.3	38.5	37.5	51.5	69.9	80.8	86.3
Mean Percentage Error		56.5	55.2	59.0	56.7	59.1	69.5	82.8	91.1	94.1	100.0
		56.6%									

Table G-3 shows the percentage error in energy from the windfarm transferred to the electricity grid, for a windfarm capacity of 200 MW and a 100 MW generation baseload.

Table G-3: Percentage error in energy from transferred to the electricity grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW.

		Percentage Error for energy from windfarm transferred to the grid for a MLR EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	0.9									
	ANN	1.3									
	DT	8.1									
	SVR	8.4									
Mean Percentage Error		4.7%									
		Percentage Error for energy from windfarm transferred to the grid for an ANN EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	7.9									
	ANN	10.2									
	DT	3.6									
	SVR	0.9									
Mean Percentage Error		5.6%									
		Percentage Error for energy from windfarm transferred to the grid for a DT EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.8									
	ANN	5.3									
	DT	1.6									
	SVR	4.2									
Mean Percentage Error		3.45%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	6.3									
	ANN	8.0									
	DT	1.7									
	SVR	0.9									
Mean Percentage Error		4.2%									

125 MW Generation Baseload

The results for the percentage error in the energy discharged from the ESS to the electricity grid, for a generation baseload of 125 MW are shown in Table G-4.

Table G-4: Percentage error in the total energy discharged from the ESS into the electricity grid, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.

		Percentage Error in energy discharged from the ESS for an MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	6.4	4.0	12.7	10.8	8.5	8.0	7.3	7.4	8.2	8.6
	ANN	21.6	21.3	26.7	28.9	28.3	26.3	25.4	26.4	30.3	28.8
	DT	12.3	11.3	20.1	23.8	20.0	17.9	16.2	20.5	22.5	26.9
	SVR	16.3	9.7	5.9	4.8	3.8	1.8	3.1	4.0	6.2	7.9
Mean Percentage Error		17.9%									
		Percentage error in energy discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	56.8	57.1	55.7	53.7	55.0	55.1	54.7	53.6	52.4	51.4
	ANN	32.7	29.7	28.1	29.2	33.5	35.8	36.1	35.4	34.4	33.8
	DT	34.8	37.3	39.0	40.2	44.6	46.2	45.5	44.1	42.3	41.7
	SVR	31.5	28.9	27.1	24.0	25.2	27.0	26.7	26.0	28.2	36.4
Mean Percentage Error		43.0%									
		Percentage error in energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	47.7	48.6	46.2	44.5	43.5	42.2	41.5	39.3	37.0	35.0
	ANN	25.7	22.5	18.0	14.3	12.3	6.9	10.0	11.1	11.5	7.8
	DT	30.0	27.7	24.9	23.8	24.4	25.0	23.1	21.7	21.9	22.2
	SVR	25.3	22.4	21.0	18.1	16.6	19.1	20.6	21.8	22.4	22.9
Mean Percentage Error		27.0%									
		Percentage error in energy discharged from the ESS for an SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	47.7	49.3	46.9	44.0	41.5	42.8	42.7	39.3	35.7	31.8
	ANN	21.6	19.2	13.4	9.1	7.4	6.0	4.2	2.1	1.8	2.8
	DT	26.5	24.6	16.5	15.5	18.0	18.1	17.8	16.1	16.6	15.9
	SVR	18.4	21.8	21.5	19.6	20.7	20.6	17.6	17.4	18.3	23.9
Mean Percentage Error		23.1%									

Table G-5 shows the percentage error in curtailed energy for the windfarm, for a windfarm capacity of 200 MW and a generation baseload of 125 MW.

Table G-5: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.

		Percentage error in curtailed energy from the windfarm for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	82.7	116.9	130.7	199.4	259.6	366.4	389.5	533.9	714.1	837.4
	DT	94.3	118.2	125.3	128.2	136.4	167.2	202.9	228.0	202.6	208.0
	SVR	62.1	89.8	107.1	111.4	150.1	227.4	335.5	480.5	528.8	534.4
Mean Percentage Error		51.6	55.6	57.4	56.7	58.1	75.3	108.6	127.3	110.8	113.8
		217.1%									
		Percentage error in curtailed energy from the windfarm for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	69.9	68.9	75.2	70.0	61.6	48.9	39.1	32.9	54.0	88.3
	DT	63.6	66.7	70.5	72.2	69.6	69.3	75.6	86.3	94.0	92.2
	SVR	66.2	91.6	85.3	134.4	164.7	245.3	299.0	427.6	532.6	575.6
Mean Percentage Error		73.1	78.4	80.4	81.4	88.6	94.9	98.8	99.6	99.6	99.8
		122.1%									
		Percentage error in curtailed energy from the windfarm for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	33.8	20.6	26.0	5.4	0.3	15.0	30.8	90.5	135.7	110.4
	DT	32.6	28.8	26.8	28.8	27.2	27.5	27.7	28.8	35.9	28.9
	SVR	65.6	67.7	66.4	67.8	84.2	92.6	91.4	89.3	85.0	85.4
Mean Percentage Error		48.2	51.0	54.9	58.4	57.1	58.5	61.5	72.2	71.6	69.3
		54.0%									
		Percentage error in curtailed energy from the windfarm for an SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	40.9	26.9	19.5	2.1	11.2	31.4	49.4	103.5	131.4	100.4
	DT	29.8	23.7	23.3	26.7	26.9	18.7	15.5	15.9	18.4	15.5
	SVR	60.6	55.7	53.1	44.3	38.5	37.5	51.5	69.9	80.8	86.3
Mean Percentage Error		43.1	45.7	44.7	48.4	51.0	51.6	53.5	56.9	60.7	61.8
		45.6%									

Table G-6 shows the percentage error in energy from the windfarm transferred to the electricity grid, for a windfarm capacity of 200 MW and a 125 MW generation baseload.

Table G-6: Percentage error in energy transferred to the electricity grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW.

		Percentage error for energy from windfarm transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	3.8									
	ANN	4.9									
	DT	9.9									
	SVR	11.2									
Mean Percentage Error		7.4%									
		Percentage error for energy from windfarm transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	11.5									
	ANN	13.4									
	DT	6.9									
	SVR	4.3									
Mean Percentage Error		9.0%									
		Percentage error for energy from windfarm transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.8									
	ANN	5.3									
	DT	1.6									
	SVR	4.2									
Mean Percentage Error		3.5%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	8.5									
	ANN	9.2									
	DT	3.2									
	SVR	0.7									
Mean Percentage Error		5.4%									

150 MW Generation Baseload

The results for the percentage error percentage error in energy yield for the energy discharged from the ESS to the electricity grid, for a generation baseload of 150 MW are presented in Table G-7.

Table G-7: Percentage error in the total energy discharged from the ESS into the electricity grid for an offshore windfarm of an installed capacity of 200 MW and a baseload of 150 MW.

		Percentage error in the total energy discharged from the ESS for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	18.8	18.3	20.8	20.3	18.0	20.1	18.2	11.9	11.9	10.0
	ANN	3.7	4.4	6.0	8.2	8.4	12.8	13.3	7.4	7.1	2.0
	DT	7.5	5.9	14.1	13.2	12.8	16.4	17.4	10.5	10.2	7.6
	SVR	13.0	12.2	17.1	18.7	21.3	25.4	25.7	19.6	17.7	14.8
Mean Percentage Error		11.9%									
		Percentage Error in the Total Energy Discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	15.3	14.3	10.7	11.1	9.7	7.1	6.8	10.8	11.4	15.7
	ANN	20.8	28.6	21.4	20.7	18.7	12.3	11.9	22.3	22.0	25.5
	DT	16.7	17.2	14.1	17.6	17.0	10.8	10.8	23.5	24.9	27.2
	SVR	12.8	16.2	8.8	8.3	11.8	8.6	9.0	19.2	19.0	20.4
Mean Percentage Error		16.6%									
		Percentage Error in the total energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	39.6	39.1	44.3	45.6	43.0	46.1	46.4	43.6	42.0	39.7
	ANN	21.0	18.5	16.8	15.8	15.0	17.9	18.0	14.3	15.2	14.9
	DT	32.7	25.4	24.2	23.4	19.5	23.2	23.9	21.8	23.1	22.4
	SVR	34.6	27.1	26.3	27.3	27.5	31.4	31.3	29.2	29.6	28.1
Mean Percentage Error		27.9%									
		Percentage Error in the total energy discharged from the ESS for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.5	33.8	40.7	41.0	40.2	38.0	38.9	29.8	29.4	28.1
	ANN	27.6	41.1	54.4	63.3	67.0	75.0	76.2	83.5	90.6	96.9
	DT	20.4	14.8	14.5	10.2	11.4	16.7	16.5	10.7	10.7	8.6
	SVR	22.4	19.6	19.0	15.3	13.7	21.7	23.6	21.9	23.2	22.5
Mean Percentage Error		46.5%									

Table G-8 shows the percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW.

Table G-8: Percentage error in curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a baseload of 150 MW.

		Percentage Error in curtailed energy from the windfarm for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	67.8	86.4	90.4	91.9	98.2	128.4	142.5	163.4	170.9	163.8
	ANN	24.3	22.1	22.9	19.4	21.9	18.9	25.6	25.8	25.0	21.4
	DT	59.2	63.0	63.6	68.8	74.7	81.1	78.2	71.2	69.4	71.6
	SVR	37.6	40.6	41.5	45.3	47.4	46.4	53.4	64.1	62.5	64.5
Mean Percentage Error		65.9%									
		Percentage Error in Curtailed Energy from the Windfarm for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	54.8	50.5	48.6	48.4	49.0	46.2	49.8	48.6	52.3	52.8
	ANN	86.1	100.1	110.2	117.4	120.6	150.9	171.4	208.3	246.7	252.5
	DT	62.1	89.8	107.1	111.4	150.1	227.4	335.5	480.5	528.8	534.4
	SVR	59.8	68.2	72.9	82.2	81.2	103.9	114.8	129.6	168.7	173.4
Mean Percentage Error		143.7%									
		Percentage Error in Curtailed Energy from the Windfarm for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	28.8	23.4	19.4	15.5	15.3	12.4	15.4	10.0	7.7	4.4
	ANN	54.0	53.7	54.0	54.0	53.9	51.4	54.6	52.7	49.6	49.8
	DT	66.2	91.6	85.3	134.4	164.7	245.3	299.0	427.7	532.9	575.6
	SVR	65.3	68.5	72.7	73.7	74.6	74.1	76.3	79.2	83.3	87.4
Mean Percentage Error		101.4%									
		Percentage Error in Curtailed Energy from the Windfarm for an SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	29.4	24.7	19.8	15.8	14.8	9.2	13.4	12.2	2.9	6.2
	ANN	21.1	18.1	19.4	22.5	20.1	5.6	2.5	4.4	11.7	14.4
	DT	65.6	67.7	66.4	67.8	84.2	92.6	91.4	89.3	85.0	85.4
	SVR	38.9	38.9	42.8	45.2	46.5	42.1	42.6	34.3	30.3	30.5
Mean Percentage Error		42.3%									

Table G-9 shows the percentage error in energy from the windfarm transferred to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW.

Table G-9: Percentage error in energy from the windfarm transferred to the grid from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 150 MW.

		Percentage Error for energy from windfarm transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	9.8									
	ANN	11.5									
	DT	16.2									
	SVR	17.1									
Mean Percentage Error		13.6%									
		Percentage Error for energy from windfarm transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	16.6									
	ANN	17.8									
	DT	11.1									
	SVR	8.9									
Mean Percentage Error		13.6%									
		Percentage Error for energy from windfarm transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.8									
	ANN	5.3									
	DT	1.6									
	SVR	4.2									
Mean Percentage Error		3.4%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	11.9									
	ANN	11.5									
	DT	5.5									
	SVR	3.4									
Mean Percentage Error		8.0%									

G.2 Results with a Windfarm with an Installed Capacity of 150 MW

The results considered for this analysis are those for energy discharged from the ESS and energy transferred from the windfarm to the electricity grid.

100 MW Generation Baseload

Table G-10 shows the percentage error in energy yield for the total energy discharged by the ESS into the electricity grid, for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW.

Table G-10: Percentage error in energy yield for the total energy discharged from the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW.

		Percentage Error in the total energy discharged from the ESS for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	13.7	9.5	2.1	8.4	27.9	40.2	54.0	64.4	75.2	81.0
	ANN	140.7	167.5	214.9	244.7	289.4	326.6	367.2	373.4	420.7	2343.8
	DT	21.2	25.8	26.9	38.0	52.9	72.1	83.6	89.9	91.4	91.4
	SVR	52.9	51.8	53.8	56.6	56.6	56.6	56.6	56.6	56.6	56.6
Mean Percentage Error		160.3%									
		Percentage Error in the total energy discharged from the ESS for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	71.6	65.2	67.4	63.3	63.3	63.3	63.3	63.3	63.3	63.3
	ANN	38.9	66.0	107.1	125.3	155.1	183.4	212.1	233.7	252.3	266.1
	DT	79.5	78.4	80.0	81.2	81.2	81.2	81.2	81.2	81.2	81.2
	SVR	80.6	74.5	76.3	77.8	77.8	77.8	77.8	77.8	77.8	77.8
Mean Percentage Error		96.72%									
		Percentage error in the total energy discharged from the ESS for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	48.2	51.3	46.7	44.9	44.9	44.9	44.9	44.9	44.9	44.9
	ANN	52.9	84.2	119.5	148.6	183.4	211.0	240.8	264.8	275.2	299.4
	DT	50.7	52.1	56.1	58.8	58.8	58.8	58.8	58.8	58.8	58.8
	SVR	54.3	56.4	56.3	59.0	59.0	59.0	59.0	59.0	59.0	59.0
Mean Percentage Error		87.25%									
		Percentage Error in the Total Energy Discharged from the ESS for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	65.1	65.0	57.7	54.6	44.7	36.3	36.3	36.3	36.3	36.3
	ANN	66.9	93.3	123.9	152.7	183.8	218.8	251.8	264.8	284.2	300.2
	DT	69.1	73.5	74.9	76.5	76.5	76.5	76.5	76.5	76.5	76.5
	SVR	72.3	69.3	69.0	70.8	70.8	70.8	70.8	70.8	70.8	70.8
Mean Percentage Error		96.70%									

Table G-11 shows the percentage error in energy from the windfarm transferred to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW and a 100 MW generation baseload.

Table G-11: Percentage error in energy from the windfarm transferred to the grid from an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW.

		Percentage error for energy from windfarm transferred to the grid for a MLR EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	1.2									
	ANN	40.7									
	DT	4.3									
	SVR	6.1									
Average Percentage Error		13.1%									
		Percentage error for energy from windfarm transferred to the grid for an ANN EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	5.3									
	ANN	62.9									
	DT	1.7									
	SVR	1.6									
Mean Percentage Error		17.9%									
		Percentage error for energy from windfarm transferred to the grid for a DT EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.6									
	ANN	67.7									
	DT	1.3									
	SVR	4.3									
Mean Percentage Error		3.5%									
		Percentage error for energy from windfarm transferred to the grid for a SVR EDF									
		Methodology									
		80 m LiDAR Measurement Height - Baseload 100 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	4.9									
	ANN	57.1									
	DT	1.4									
	SVR	1.9									
Mean Percentage Error		16.3%									

125 MW Generation Baseload

Table G-12 shows the results for the percentage error in the energy yield discharged from the ESS for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW.

Table G-12: Percentage error in energy yield for the total energy discharged from the ESS into the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW.

		Percentage error for energy discharged from the ESS to the electricity grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	7.7	13.4	17.9	24.7	43.1	59.2	72.6	76.1	105.8	118.9
	DT	77.6	117.2	146.4	164.1	187.8	212.0	230.0	251.4	271.2	301.5
	SVR	11.3	28.8	45.9	52.3	67.4	78.2	92.7	106.7	120.3	130.5
Mean Percentage Error		3.1	13.2	31.1	35.7	47.1	64.3	79.3	89.5	98.9	108.8
		95.1%									
		Percentage Error for energy discharged from the ESS to the electricity grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	66.3	67.0	65.5	60.9	57.3	57.3	57.3	57.3	57.3	57.3
	DT	22.9	48.1	71.2	89.6	118.8	148.5	182.6	186.0	195.9	224.1
	SVR	62.0	62.8	61.9	65.1	65.7	65.7	65.7	65.7	65.7	65.7
Mean Percentage Error		68.4	67.4	66.0	67.9	68.5	68.5	68.5	68.5	68.5	74.5
		80.6%									
		Percentage Error for energy discharged from the ESS to the electricity grid for a DT Energy Demand Forecast Model									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	48.6	45.6	42.8	42.1	39.8	39.8	39.8	39.8	39.8	39.8
	DT	34.5	67.0	94.6	108.1	127.7	144.8	160.1	176.8	193.5	210.2
	SVR	49.1	46.4	46.5	50.9	51.8	51.8	51.8	51.8	51.8	51.8
Mean Percentage Error		59.9	60.1	58.5	60.3	61.0	61.0	61.0	61.0	61.0	61.0
		70.1%									
		Percentage Error for energy discharged from the ESS to the electricity grid for a SVR Energy Demand Forecast Model									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
MCP Methodology	MLR	500	1000	1500	2000	2500	3000	3500	4000	4500	5000
	ANN	55.3	52.5	52.3	45.0	40.9	38.9	31.3	29.1	27.9	22.4
	DT	54.2	80.0	103.9	115.2	132.8	149.4	166.6	186.6	204.3	223.9
	SVR	40.9	41.2	38.8	34.8	31.4	31.4	31.4	31.4	31.4	31.4
Mean Percentage Error		46.2	39.9	39.1	35.9	32.8	30.0	30.0	30.0	30.0	30.0
		62.6%									

Table G-13 presents the percentage error in energy from the windfarm transferred to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW and a 125 MW generation baseload.

Table G-13: Percentage error in energy from the windfarm transferred to the grid for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 125 MW.

		Percentage error for energy from windfarm transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	1.0									
	ANN	31.8									
	DT	6.2									
	SVR	8.6									
Mean Percentage Error		11.9%									
		Percentage error for energy from windfarm transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	8.0									
	ANN	62.0									
	DT	4.3									
	SVR	1.0									
Mean Percentage Error		18.9%									
		Percentage Error for energy from windfarm transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.6									
	ANN	67.7									
	DT	1.3									
	SVR	4.3									
Mean Percentage Error		18.95%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 125 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	7.0									
	ANN	55.4									
	DT	3.2									
	SVR	0.1									
Mean Percentage Error		16.2%									

150 MW Generation Baseload

The results for the percentage error in the energy yield discharged from the ESS, for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 150 MW are presented in Table G-14.

Table G-14: Percentage error for the energy discharged from the ESS into the electricity grid for an offshore windfarm of an installed capacity of 150 MW and a generation baseload of 150 MW.

		Percentage Error for energy discharged from the ESS to the electricity grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	31.3	33.5	37.4	39.1	38.1	36.7	34.9	31.8	28.6	25.6
	ANN	27.2	40.7	57.8	65.5	75.5	81.7	84.9	99.5	113.0	128.1
	DT	25.0	29.2	31.9	28.7	27.4	27.6	28.1	27.8	26.8	25.4
	SVR	27.2	28.3	30.4	29.3	26.4	25.3	26.0	25.8	23.2	24.5
Mean Percentage Error		46.3%									
		Percentage Error for energy discharged from the ESS to the electricity grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	4.0	8.8	13.4	21.0	24.6	27.6	27.6	29.9	33.5	36.9
	ANN	67.2	85.2	97.5	107.4	126.2	132.1	130.8	136.4	141.0	145.2
	DT	6.4	14.6	23.7	27.6	36.5	43.1	50.8	60.6	65.7	87.6
	SVR	3.7	9.3	17.2	20.3	28.4	39.0	37.7	46.6	50.0	51.7
Mean Percentage Error		60.4%									
		Percentage Error for energy discharged from the ESS to the electricity grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	64.3	63.5	62.0	63.0	62.5	61.9	61.3	59.0	60.2	61.1
	ANN	8.9	26.8	40.5	47.7	56.6	60.1	64.4	72.2	75.7	83.6
	DT	46.0	52.1	53.2	56.9	59.4	61.3	63.1	63.8	64.6	65.3
	SVR	50.7	50.4	51.9	56.3	58.7	60.7	62.5	63.3	64.4	64.8
Mean Percentage Error		50.0%									
		Percentage Error for energy discharged from the ESS to the electricity grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	49.7	48.9	49.0	47.4	42.6	38.8	36.6	33.5	28.6	25.6
	ANN	27.6	41.1	54.4	63.3	67.0	75.0	76.2	83.5	90.6	96.9
	DT	40.4	38.1	38.2	37.4	31.7	29.4	27.8	26.5	25.0	23.9
	SVR	39.4	35.2	36.4	35.7	33.4	30.3	28.0	24.8	26.3	27.8
Mean Percentage Error		46.5%									

Table G-15 shows the percentage error in energy from the windfarm transferred to the electricity grid for an offshore windfarm with an installed capacity of 150 MW and a 150 MW generation baseload.

Table G-15: Percentage error in energy from the windfarm transferred to the grid with an offshore windfarm with and installed capacity of 150 MW and a generation baseload of 150 MW.

		Percentage Error for energy from windfarm transferred to the grid for a MLR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	7.2									
	ANN	18.5									
	DT	12.7									
	SVR	14.3									
Mean Percentage Error		13.2%									
		Percentage Error for energy from windfarm transferred to the grid for an ANN EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	13.0									
	ANN	62.9									
	DT	8.8									
	SVR	5.6									
Mean Percentage Error		22.6%									
		Percentage Error for energy from windfarm transferred to the grid for a DT EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	2.6									
	ANN	67.7									
	DT	1.3									
	SVR	4.3									
Mean Percentage Error		19.0%									
		Percentage Error for energy from windfarm transferred to the grid for a SVR EDF Methodology									
		80 m LiDAR Measurement Height - Baseload 150 MW									
		ESS Capacity in MWh									
		500	1000	1500	2000	2500	3000	3500	4000	4500	5000
MCP Methodology	MLR	10.2									
	ANN	52.8									
	DT	5.5									
	SVR	2.3									
Mean Percentage Error		17.7%									

H. Curtailed Energy as a Criterion for Establishing the Optimal Capacity of the Energy Storage System

H.1 An Offshore Windfarm with an Installed Capacity of 200 MW

Results included those from the optimal combination of regression techniques for MCP and EDF methodologies, which were compared to those for measured wind speed and direction and energy demand.

H.1.1 Using the Optimal Combination of Regression Techniques for MCP and EDF Methodology (DT_DT).

The results for predicted wind speed and direction and forecasted energy demand for the *DT_DT* combination of regression techniques for MCP and Energy Demand Forecasting methodologies are now presented. The results are for an offshore windfarm with an installed capacity of 200 MW and generation baseloads of 100, 125 and 150 MW. The ESS power rating varies from 10 to 50 MW, in steps of 10 MW. These results are for the year 2017 and use curtailed energy from the windfarm as a metric.

100 MW Generation Baseload

The results shown Figure H-1 and Figure H-2 are those for an offshore windfarm with an installed capacity of 200 MW coupled to an electricity grid with a generation baseload of 100 MW. Figure H-1 shows the variation in curtailed energy with ESS capacity. Figure H-2 shows the differentiated 2nd order polynomial for the 3rd order polynomials fitted to the curves shown in Figure H-1, according to Eq. (4-13).

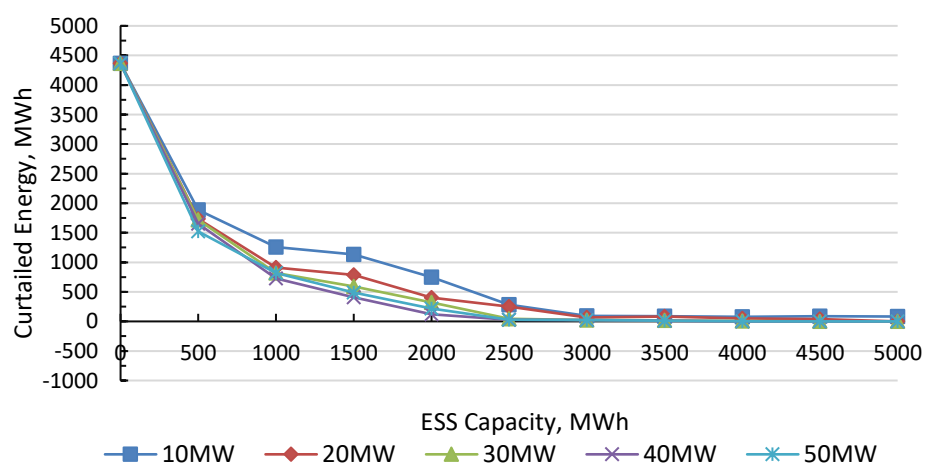


Figure H-1: Curtailed energy from an offshore windfarm with an installed capacity of 250 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

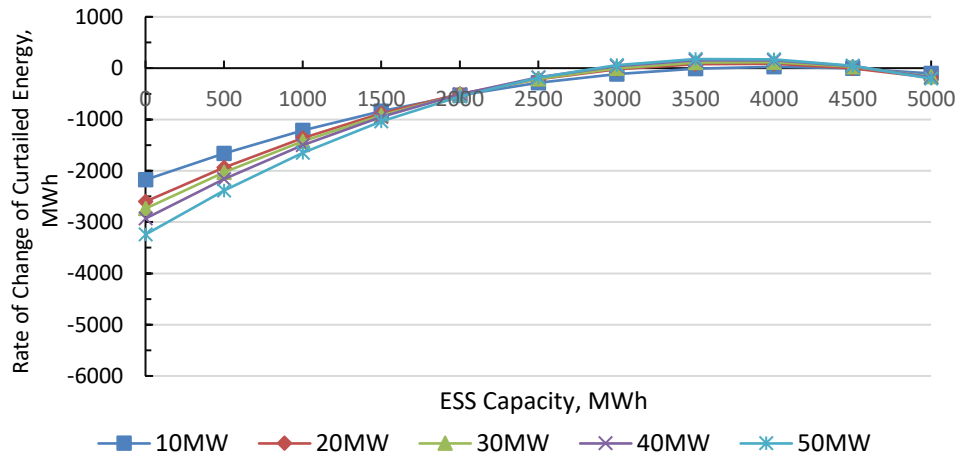


Figure H-2: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

125 MW Generation Baseload

The results shown in Figure H-3 and Figure H-4, are those for an offshore windfarm with an installed capacity of 200 MW coupled to an electricity grid with a generation baseload of 125 MW generation baseload. Figure H-3 shows the variation of curtailed energy with ESS capacity. Figure H-4 shows the differentiated 2nd order polynomials for the 3rd order polynomials fitted to the curves shown in Figure H-3, according to Eq. (4-13).

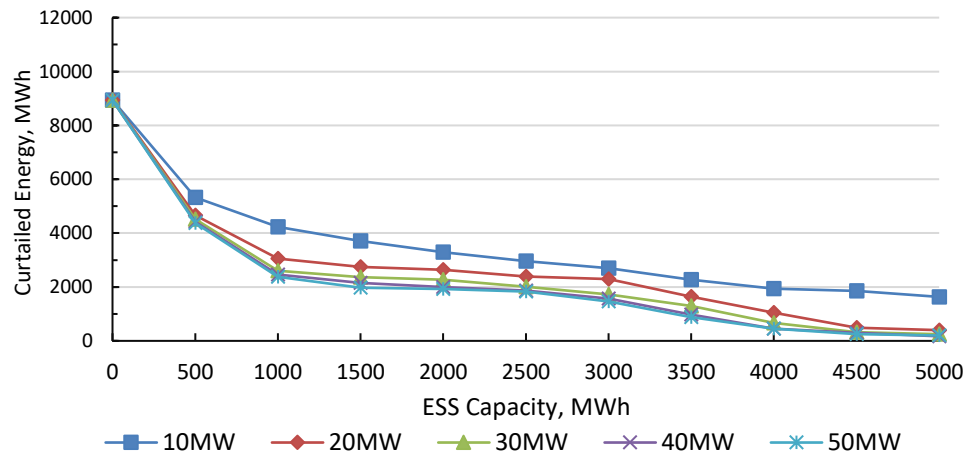


Figure H-3: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW, and a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

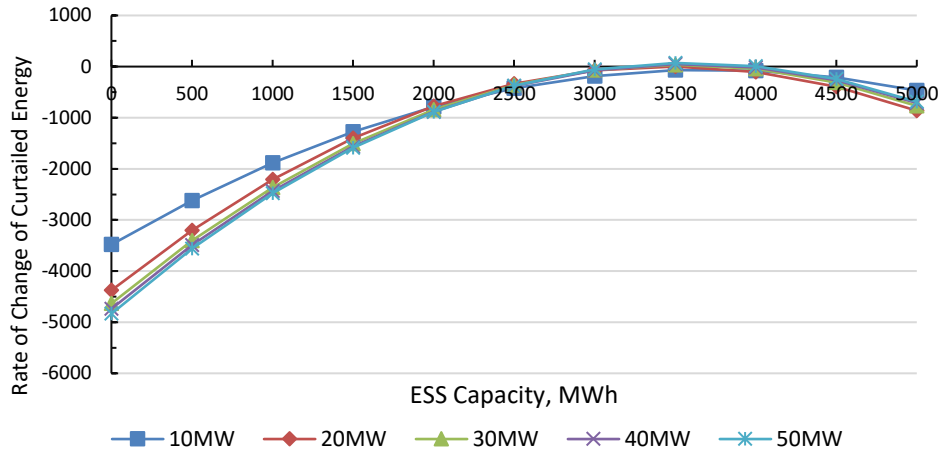


Figure H-4: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

150 MW Generation Baseload

The results shown in Figure H-5 and Figure H-6, are those for an offshore windfarm of 200 MW generation capacity coupled to an ESS and an electricity grid with a generation baseload of 150 MW generation baseload. Figure H-5 shows the variation in curtailed energy with ESS capacity. Figure H-6 shows the differentiated 2nd order polynomials for the fitted 3rd order polynomials fitted to the curves shown in Figure H-5, according to Eq. (4-13).

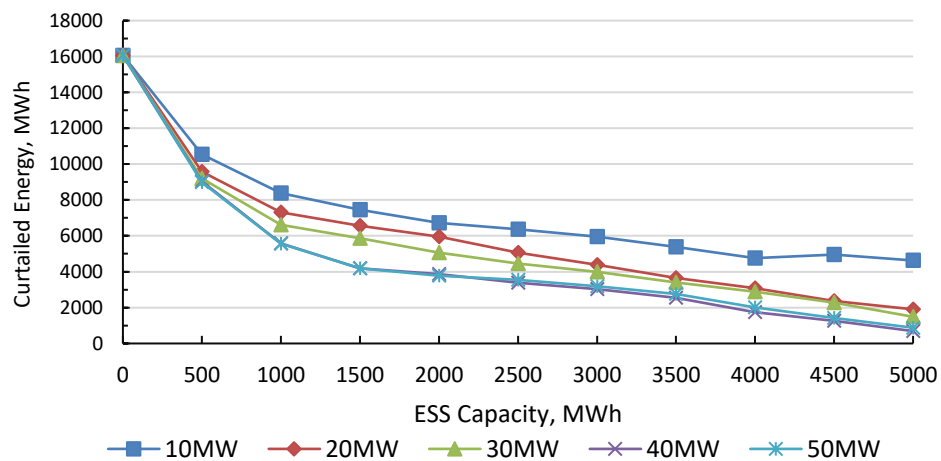


Figure H-5: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction, and forecasted energy demand.

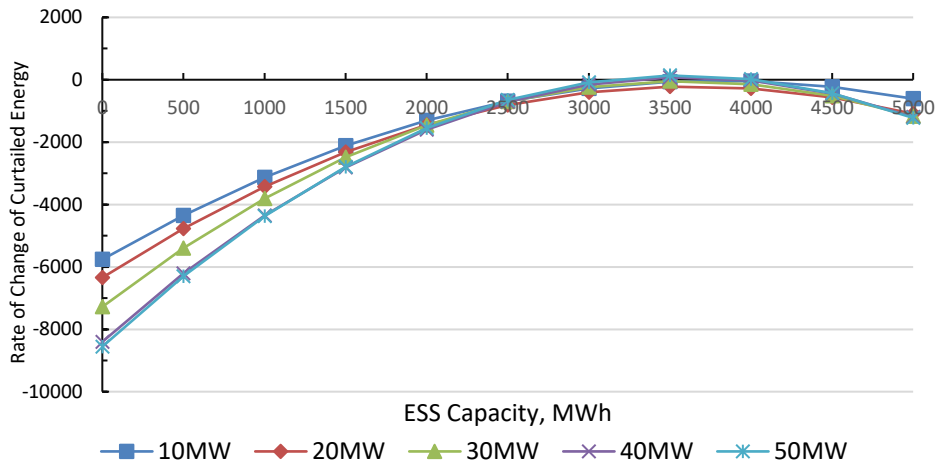


Figure H-6: Rate of change of curtailed energy with ESS capacity, for a 200 MW offshore windfarm with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

H.1.2 Using Measured Wind Speed and Direction and Energy Demand

The results below are those for measured wind speed and direction and energy demand for a 200 MW offshore windfarm. The wind speed and direction were those measured for the year 2017 at the candidate site at a LiDAR measurement height of 80 m, and the measured energy demand for the year 2017. Generation baseloads of 100, 125 and 150 MW were assumed. The ESS power rating varies from 10 to 50 MW, in steps of 10 MW.

100 MW Generation Baseload

The results shown in Figure H-7 and Figure H-8, are those for a 100 MW offshore windfarm coupled to an electricity grid with a generation baseload of 100 MW. Figure H-7 shows the variation of curtailed energy with ESS capacity. Figure shows the differentiated 2nd order polynomials for the fitted 3rd order polynomials of the curves shown in Figure H-8, according to Eq. (4-13).

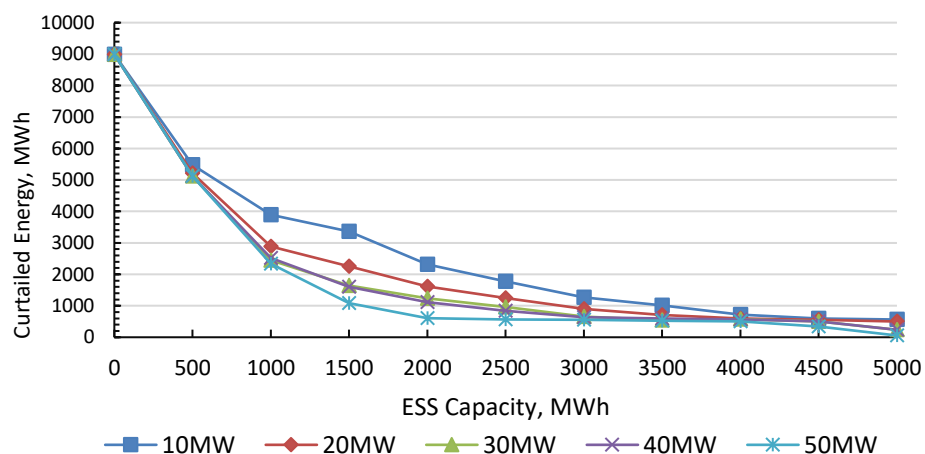


Figure H-7: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

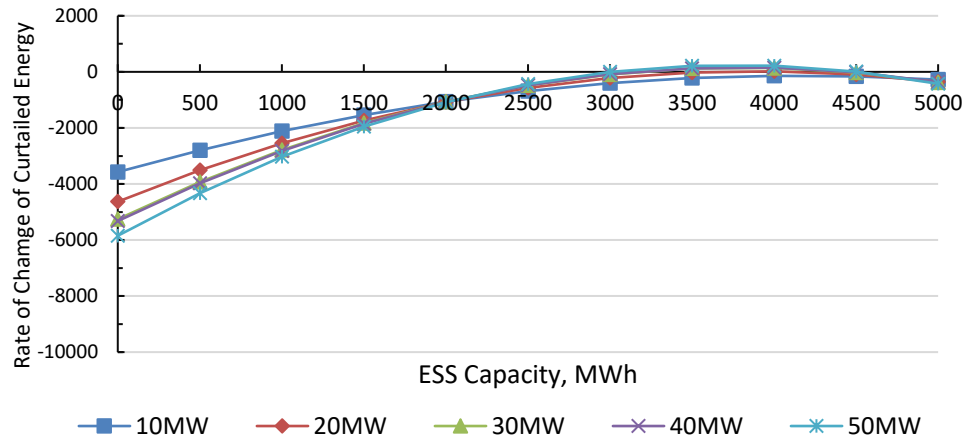


Figure H-8: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 M and a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

125 MW Generation Baseload

The results shown in Figure H-9 and Figure H-10, are those obtained for a 200 MW offshore windfarm coupled to an electricity grid with a generation baseload of 125 MW, using measured wind speed and direction at the candidate site, and energy demand for the year 2017. Figure H-9 shows the variation in curtailed energy with ESS capacity. Figure H-10 shows the differentiated 2nd order polynomial for the fitted 3rd order polynomials, according to Eq. (4-13).

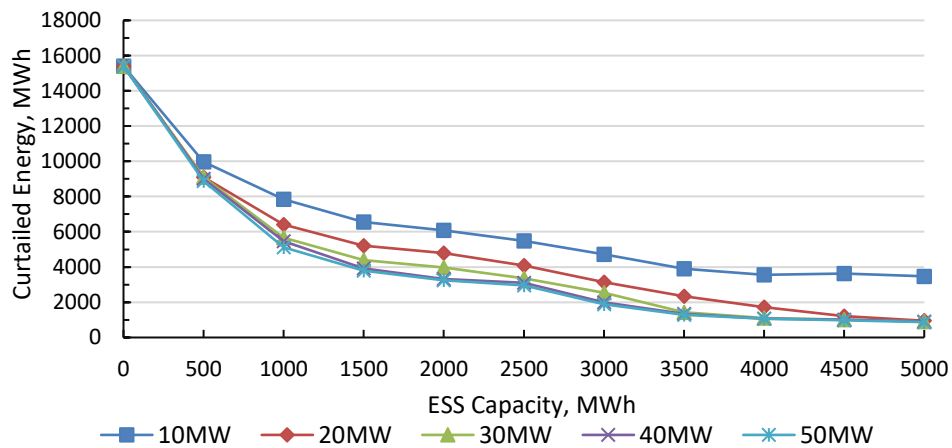


Figure H-9: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW, with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

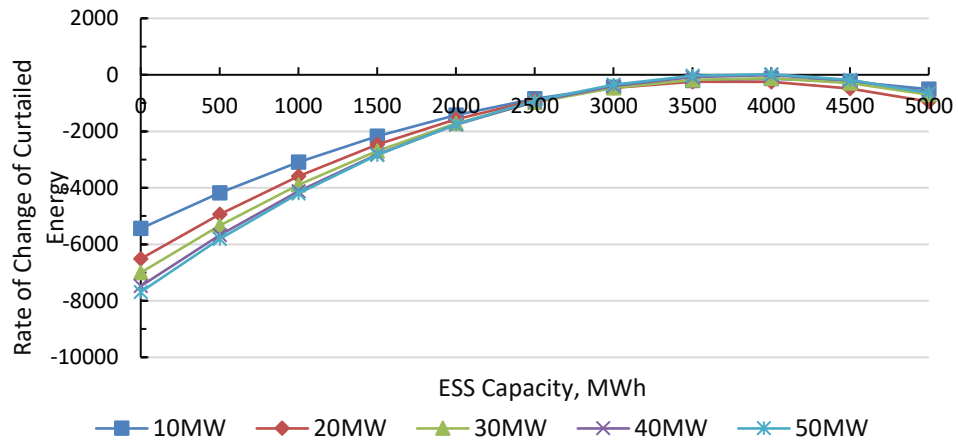


Figure H-10: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

150 MW Generation Baseload

The results shown in Figure H-11 and Figure H-12 are those obtained for an offshore windfarm of 200 MW capacity which is coupled to an electricity grid with a generation baseload of 150 MW. Figure H-11 shows the variation in curtailed energy with ESS capacity. Figure H-12 shows the differentiated 2nd order polynomials for the fitted 3rd order polynomials according to Eq. (4-13).

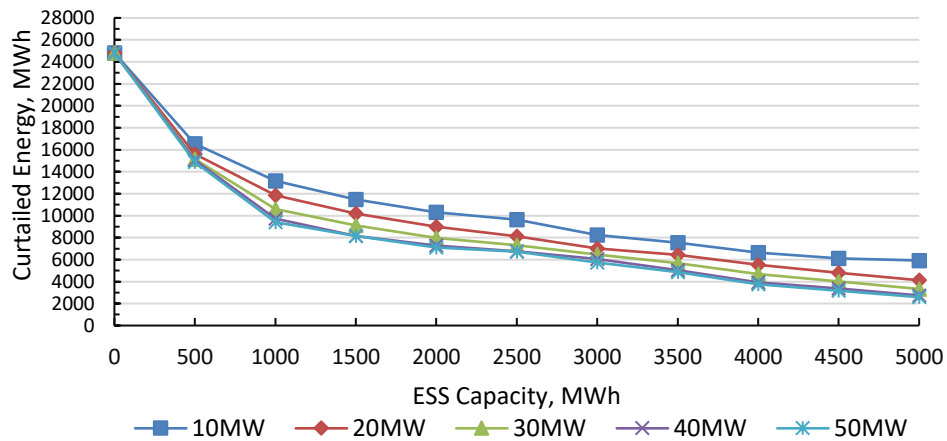


Figure H-11: Curtailed energy from an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction, and energy demand.

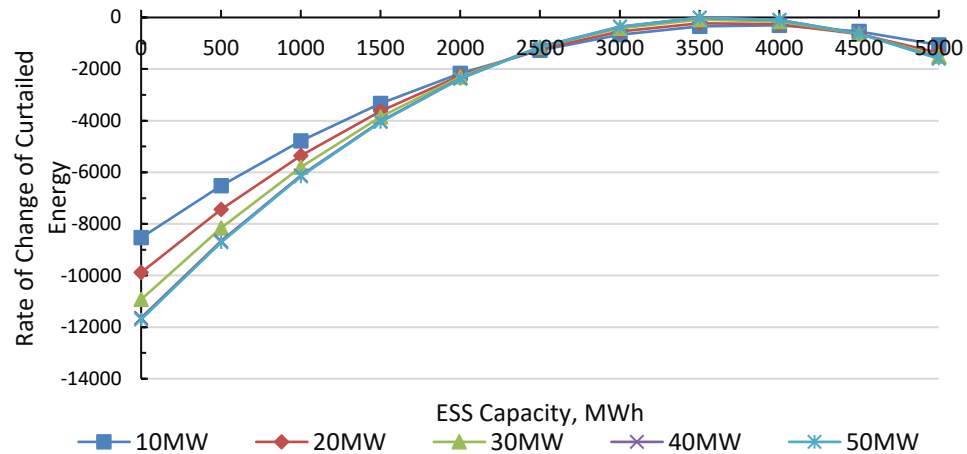


Figure H-12: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

H.2 An Offshore Windfarm with an Installed Capacity of 150 MW

Finally, the behaviour for windfarms with a capacity of 150 MW was analysed. Results included those from the optimal combination of regression techniques for MCP and EDF methodologies which, in a similar fashion to the above, were compared to those for measured wind speed and direction, and energy demand. The results for predicted wind speed and direction and forecasted energy demand for the (DT_DT) combination are presented below. ESS power rating was varied in the range of 10 MW to 50 MW in steps of 10 MW.

H.2.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)

100 MW Generation Baseload

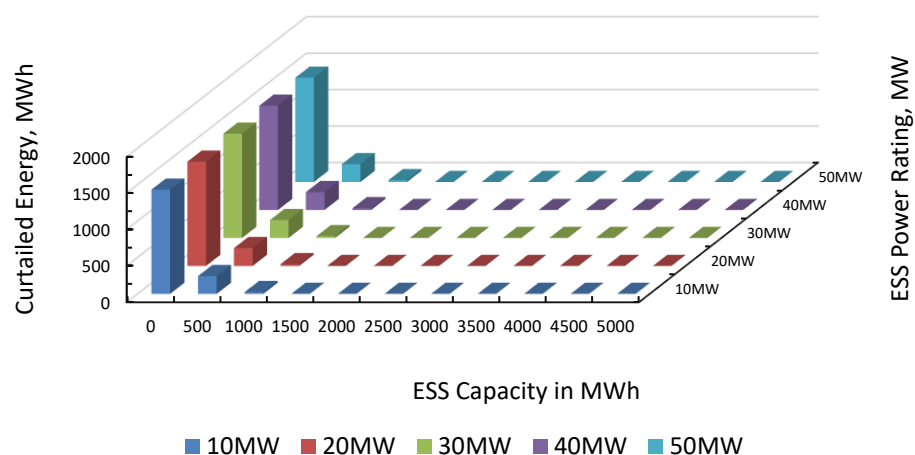


Figure H-13: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 100 MW generation baseload and ESS power ratings of 10 MW to 50 MW.

For the case of an offshore windfarm of 150 MW capacity, with a generation baseload of 100 MW, the amount of curtailed energy was drastically reduced, as can be observed in Figure H-13. At all

values of ESS power rating, the amount of curtailed energy was zero for ESS capacities of 1000 MWh or greater. With these conditions it was not viable to have an ESS with a capacity larger than 1000 MWh.

125 MW Generation Baseload

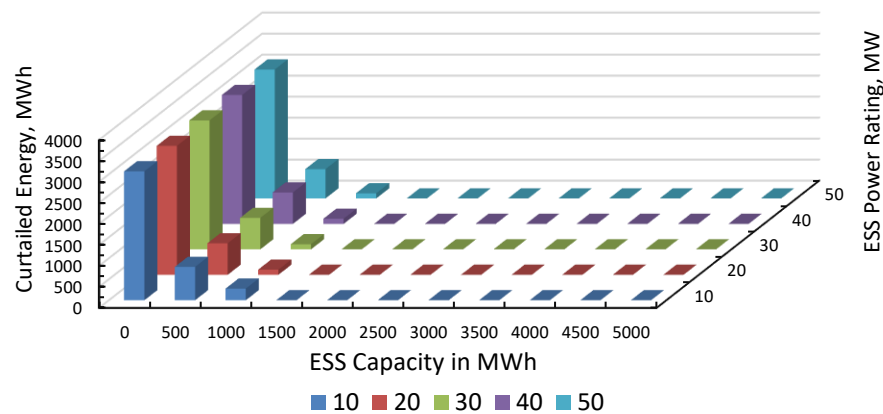


Figure H-14: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.

The results shown in Figure H-14 are those for an offshore windfarm with a capacity of 150 MW coupled to an ESS and an electricity grid which has an assumed generation baseload of 125 MW. The results showed that the amount of curtailed energy is zero for values of ESS capacity which was greater or equal to 1000 MWh. This value of ESS capacity was therefore considered to be the optimal ESS capacity for these conditions.

150 MW Generation Baseload

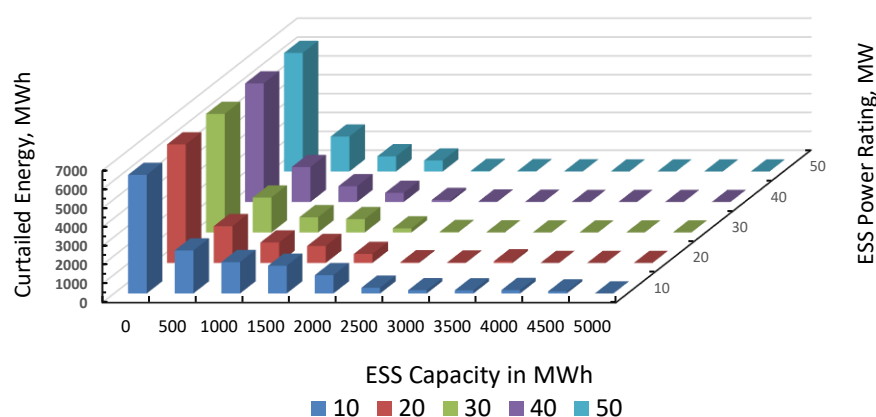


Figure H-15: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW, using predicted wind speed and direction, together with forecasted energy demand for the year 2017, for a 150 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.

The results presented in Figure H-15 are those obtained for a 150 MW offshore windfarm with a 150 MW generation capacity coupled to an ESS and an electricity grid with a generation baseload of

150 MW. Results again showed that the amount of curtailed energy was zero for values of ESS capacity which was greater or equal to 3500 MWh and an ESS power rating which were greater or equal to 20 MW. The curtailed energy was also equal to zero for capacities greater than 3000 MWh for ESS power ratings which were equal or greater than 30 MW.

It was observed that a 3rd order polynomial could be fitted to the curtailed energy from the offshore windfarm which was coupled to an ESS with a power rating of 10 MW, and hence a 2nd order polynomial could be derived by differentiating the 3rd order polynomial, according to Eq. (4-13). The results are shown in Figure H-16 and Figure H-17.

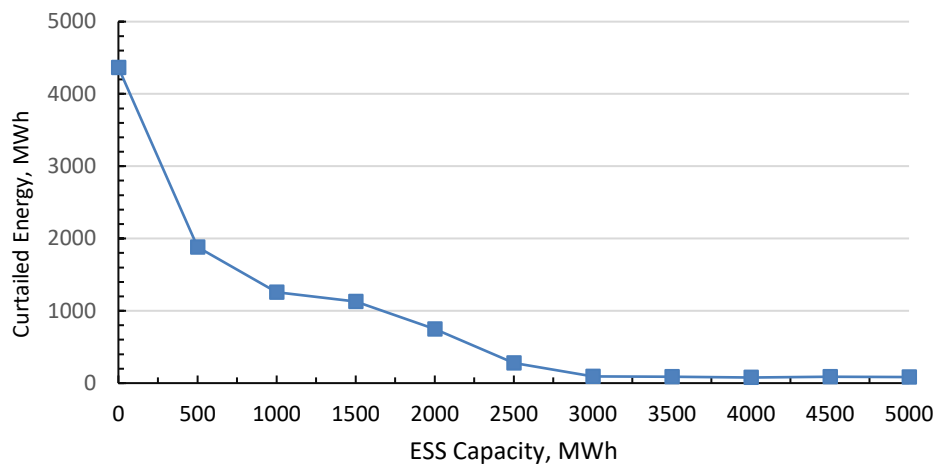


Figure H-16: Curtailed energy from a 150 MW offshore wind farm with a generation baseload of 150 MW, for ESS power rating of 10 MW, for predicted wind speed and direction, and forecasted energy demand.

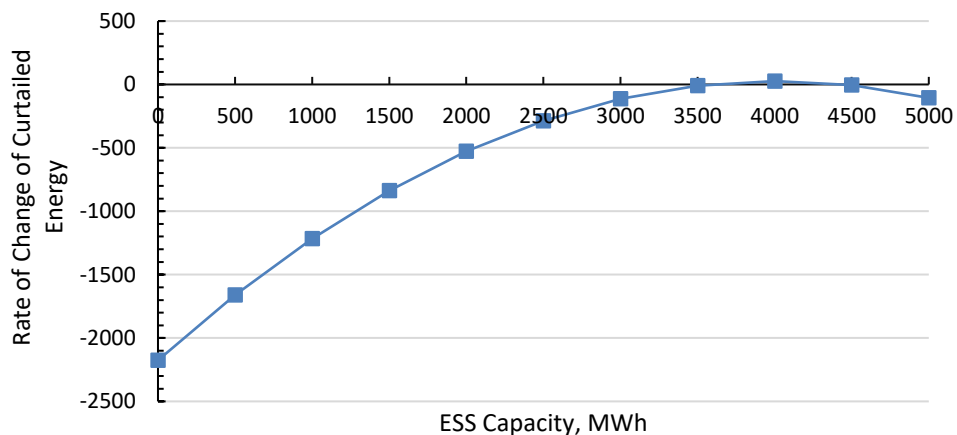


Figure H-17: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for an ESS power rating of 10 MW, for predicted wind speed and direction and forecasted energy demand.

H.2.2 Using Measured Wind Speed and Direction and Energy Demand

The results below are those for measured wind speed and direction and energy demand for an offshore windfarm with a generation capacity of 150 MW. As above, the measured wind speed and direction were those measured at the candidate site at a LiDAR measurement height of 80 m for the year 2017.

The energy demand was that measured for the year 2017. Generation baseloads of 100 MW, 125 MW and 150 MW were assumed. ESS power rating was varied in the range of 10 MW to 50 MW in steps of 10 MW.

The amount of curtailed energy for the offshore windfarm with an installed capacity of 150 MW coupled to an electricity grid with a generation baseload of 100 MW, is shown in Figure H-18. For an ESS power rating of 10 MW the amount of curtailed energy was zero for an ESS capacity of 1500 MWh, hence this was the optimal ESS capacity for these conditions. For ESS power ratings equal to or greater than 20 MW, the amount of curtailed energy was zero for ESS capacities of 1000 MWh or greater, hence this was the optimal ESS capacity for these conditions.

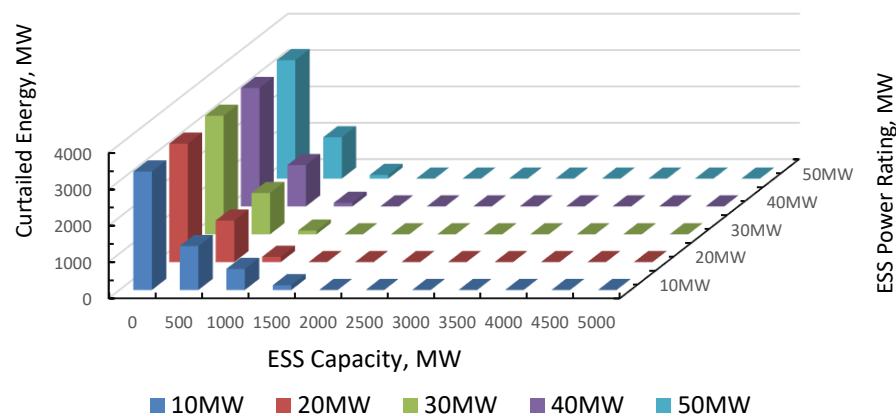


Figure H-18: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW offshore windfarm using measured wind speed and direction, and energy demand for the year 2017, with a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.

The results shown in Figure are for an electricity grid with a generation baseload of 125 MW.

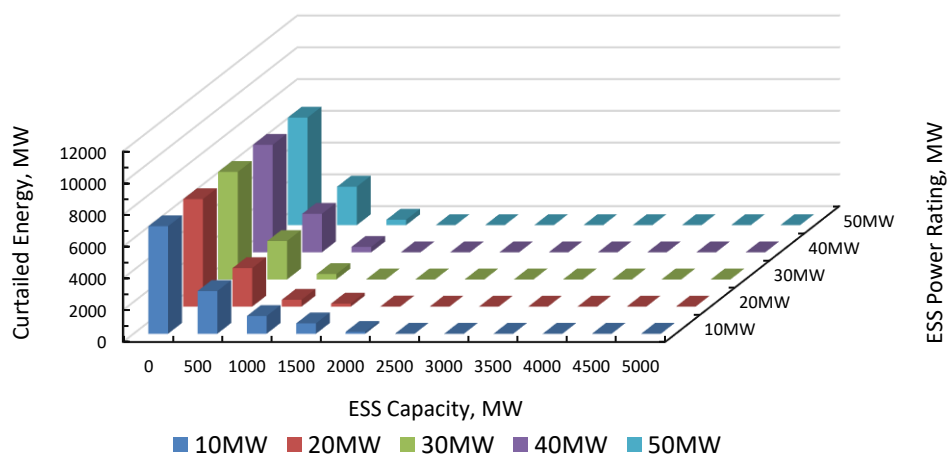


Figure H-19: Curtailed energy from a 125 MW offshore windfarm using measured wind speed and direction, together with energy demand for the year 2017, for a 100 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.

The results showed that the amount of curtailed energy is zero for values of ESS capacity which is greater or equal to 2000 MWh at an ESS rating of 10 MW, 1500 MWh for an ESS rating of 20 MWh, and 1000 MWh for ESS power ratings of 30 MW or more. These ESS capacities were therefore considered to be the optimal ESS capacity for these conditions.

The results presented in Figure H-20 are for an electricity grid with a generation baseload of 150 MW. The results showed that the amount of curtailed energy was zero for values of ESS capacity which was greater or equal to 4000 MWh for an ESS power rating less than 30 MW and equal to 3500 MWh for an ESS power rating of 30 MW or more.

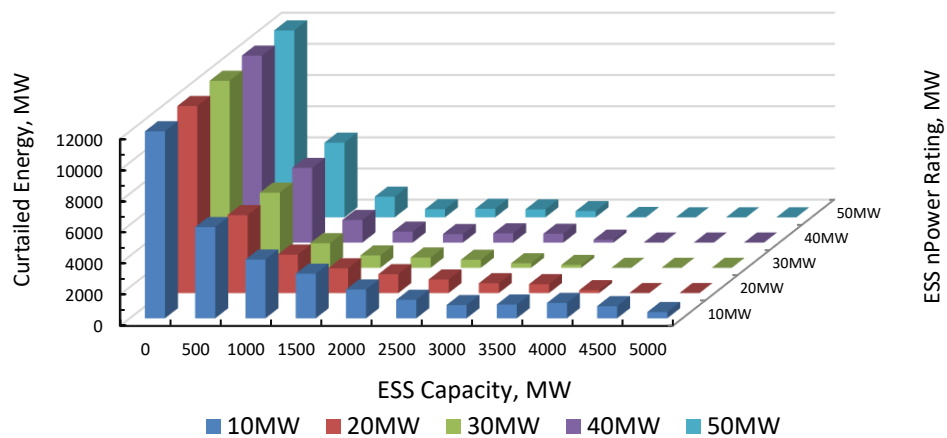


Figure H-20: Curtailed energy from an offshore windfarm with an installed capacity of 150 MW, using measured wind speed and direction, and energy demand for the year 2017, with a 150 MW generation baseload, for ESS power ratings of 10 MW to 50 MW.

It was noted that a 3rd order polynomial could be fitted to the curtailed energy for an ESS power rating of 10 MW and 20 MW, and thus a 2nd order polynomial could be derived according to Eq. (4-13), as shown in Figure H-21 and Figure H-22.

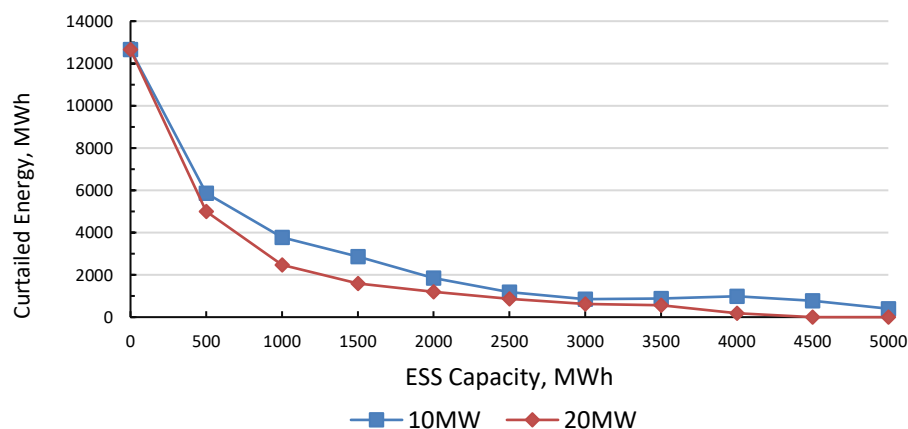


Figure H-21: Curtailed energy for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power rating of 10 MW and 20 MW, for predicted wind speed and direction, and forecasted energy demand.

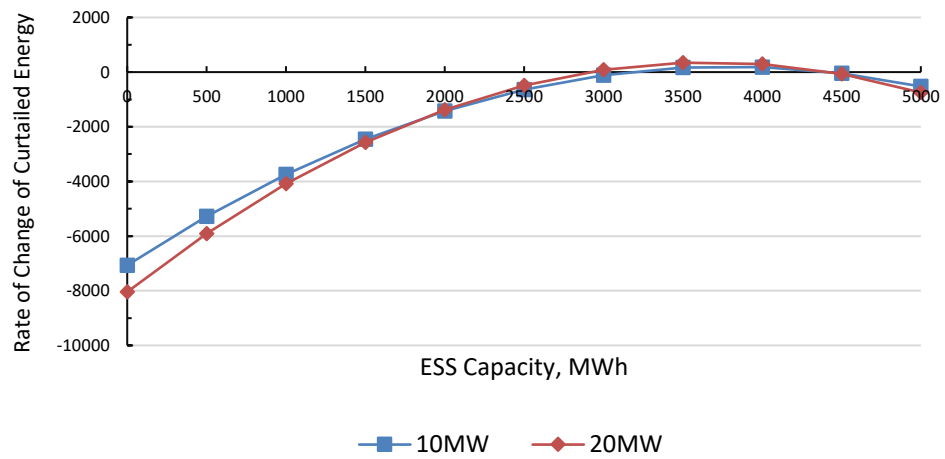


Figure H-22: Rate of change of curtailed energy with ESS capacity, for an offshore windfarm with an installed capacity of 150 MW windfarm with a generation baseload of 150 MW, for an ESS power rating of 10 MW and 20 MW, for predicted wind speed and direction and forecasted energy demand.

I. Discharged Energy as a Criterion for Establishing the Optimal Capacity of the Energy Storage System

I.1 An Offshore Windfarm with an Installed Capacity of 250 MW

I.1.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)

The results for predicted wind speed and direction and forecasted energy demand for the *DT_DT* combination of regression techniques for MCP and EDF methodologies are now presented. The results are for an offshore windfarm with an installed capacity of 250 MW and generation baseloads of 100 MW, 125 MW and 150 MW. The ESS power rating varies from 10 MW to 50 MW, in steps of 10 MW. These results are for the year 2017 and the energy discharged from the ESS to the electricity grid as a metric.

100 MW Generation Baseload

Figure I-1 and Figure I-2 show the results for a windfarm with a generation baseload of 100 MW. Figure I-1 shows the energy discharged from the ESS with ESS capacity. Figure I-24 shows the plots of the 2nd order polynomials of the differentiated 3rd order polynomials, according to Eq. (4-17).

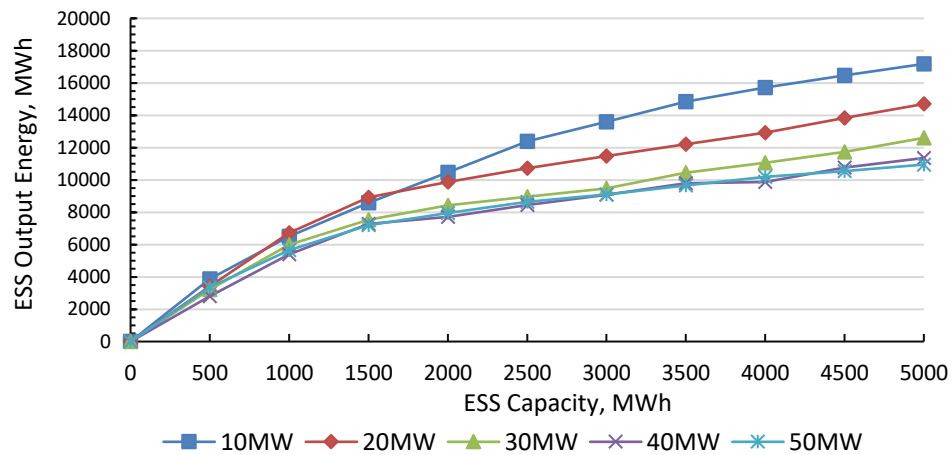


Figure I-1: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, using predicted wind speed and direction and forecasted energy demand.

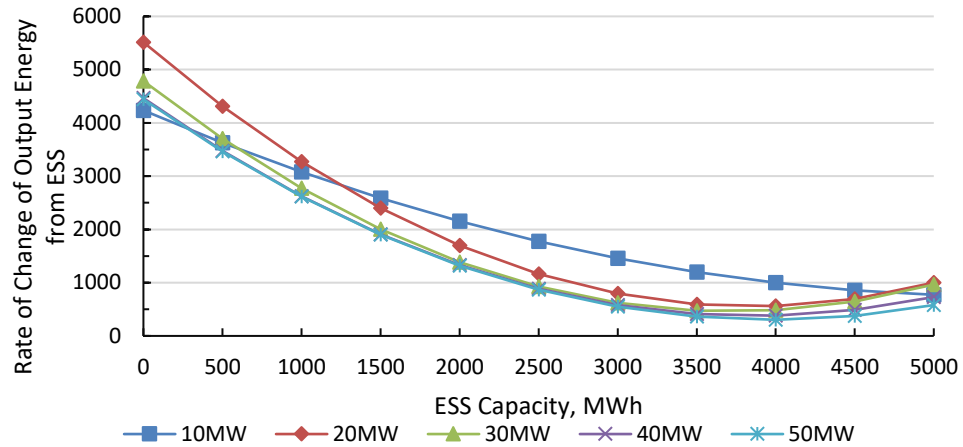


Figure I-2: Rate of change of energy discharged from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW1 with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, using predicted wind speed and direction and forecasted energy demand.

125 MW Generation Baseload

As above Figure I-3 and Figure I-4, show the results for a windfarm with a 125 MW baseload. Figure I-3 shows the relationship obtained between the discharged energy from the ESS to the electricity grid. Figure I-4 shows the rate of change of energy discharged to the electricity, according to Eq. (4-17).

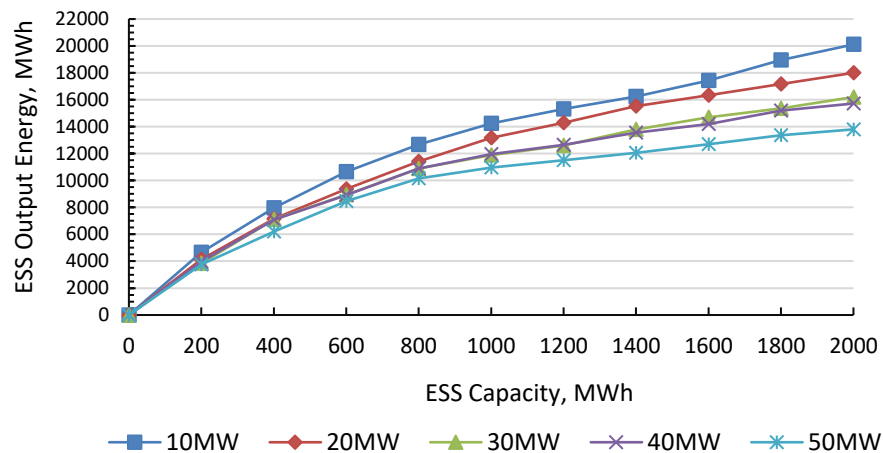


Figure I-3: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

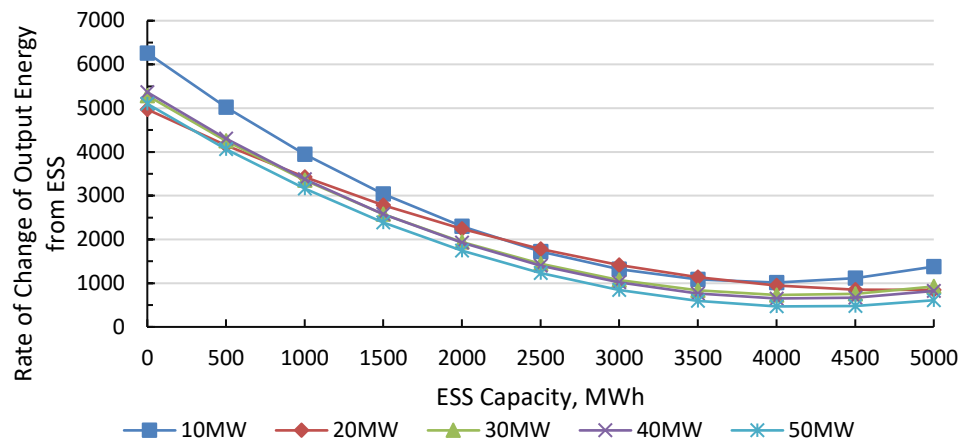


Figure I-4: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

150 MW Generation Baseload

Figure I-5 and Figure I-6 show the results for a windfarm with a 150 MW baseload. Figure I-5 shows the relationship obtained between the energy discharged to the electricity grid from the ESS. Figure I-6 shows the rate of change of energy discharged by the ESS to the electricity grid, according to Eq. (4-17).

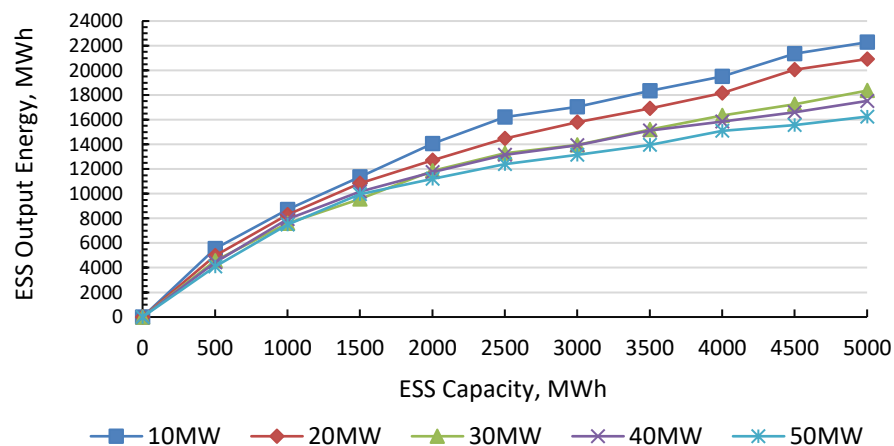


Figure I-5: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW for predicted wind speed and direction and forecasted energy demand.

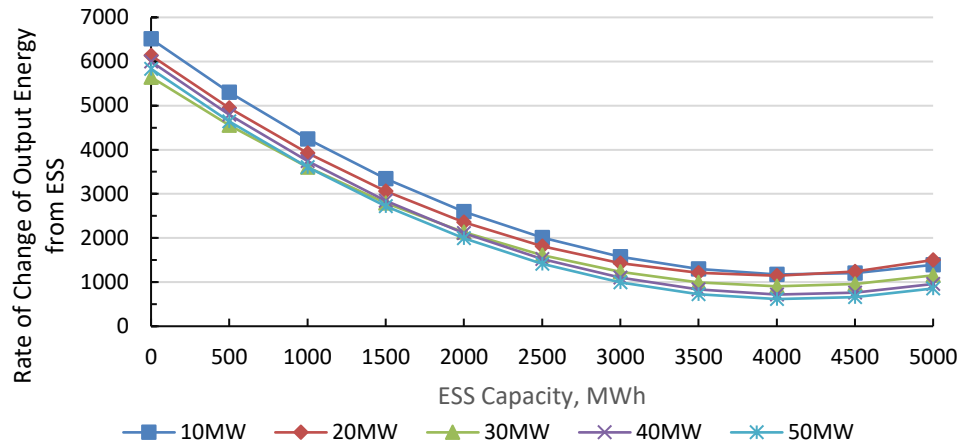


Figure I-6: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW. for predicted wind speed and direction and forecasted energy demand.

I.1.2 Using Measured Wind Speed and Direction, and Energy Demand

The results below are those with measured wind speed and direction, and energy demand for an offshore windfarm with an installed capacity of 250 MW. Generation baseloads are 100 MW, 125 MW and 150 MW and the ESS rated power ranges from 10 MW to 50 MW in steps of 10 MW.

100 MW Generation Baseload

Figure I-7 and Figure I-8 show the results an offshore windfarm with a 100 MW baseload. Figure I-7 show the relationship obtained between the energy discharged from the ESS to the electricity grid. Figure I-8 shows the differentiated equations of the fitted polynomials, according to Eq. (4-17).

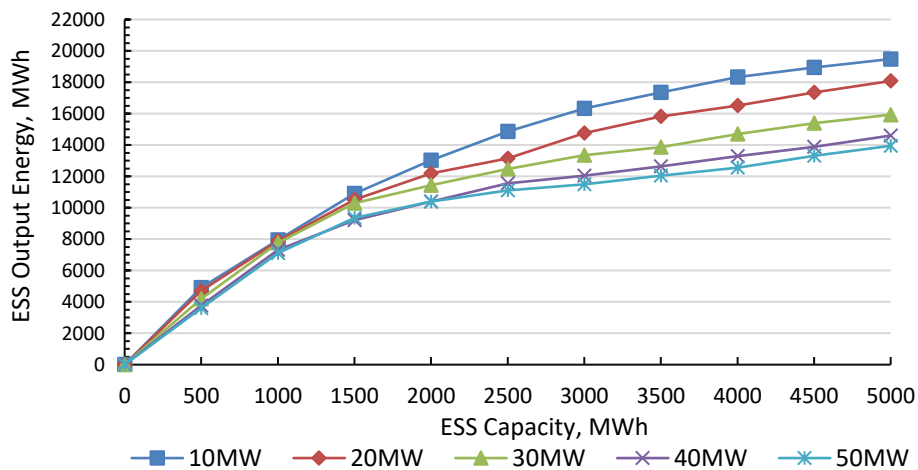


Figure I-7: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW with measured wind speed and direction and energy demand.

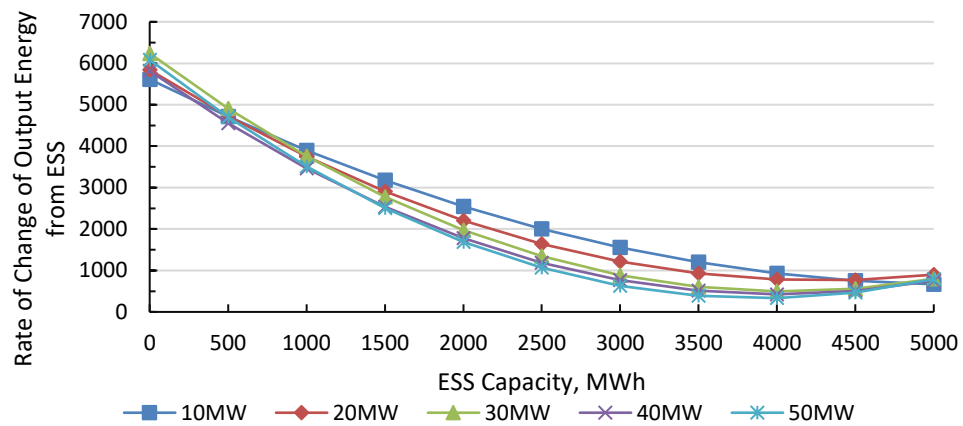


Figure I-8: Rate of change of Energy output from the ESS to the electricity grid, for a 250 MW offshore windfarm with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW.

125 MW Generation Baseload

Figure I-9 and Figure I-10 the results an offshore windfarm with a generation baseload of 125 MW. Figure I-9 shows the relationship obtained between the energy discharged by the ESS to the electricity grid with ESS capacity. Figure I-10 shows the differentiated equations for the fitted polynomials, according to Eq. (4-17).

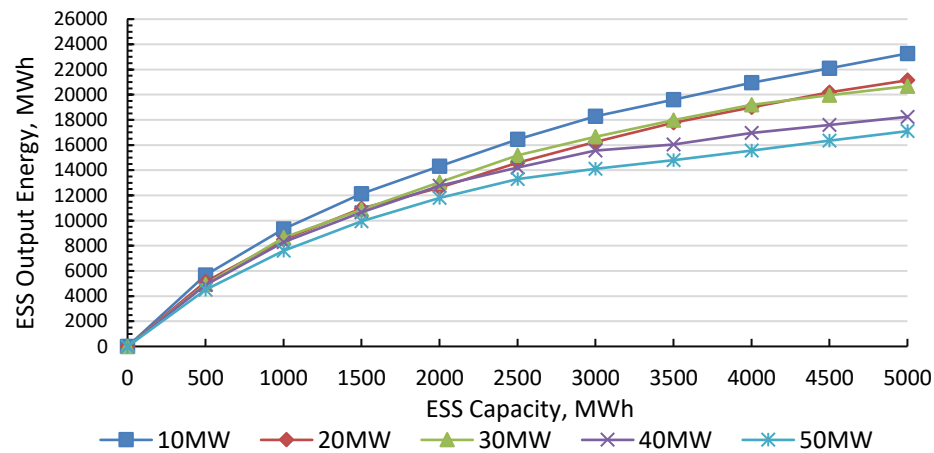


Figure I-9: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW offshore windfarm with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

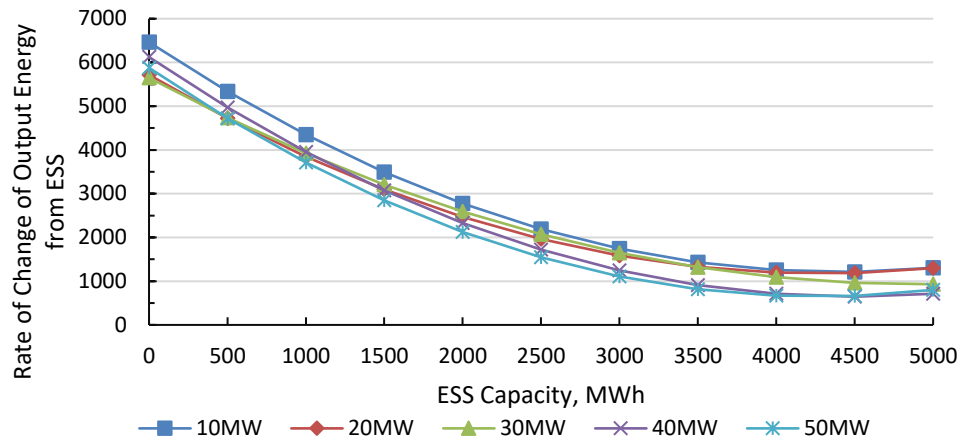


Figure I-10: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 125 MW, for measured wind speed and direction and energy demand.

The results shown in Figure I-11 and Figure I-12 show the results for a windfarm coupled to an ESS and an electricity grid with a generation baseload of 150 MW. Figure I-11 shows the relationship obtained for the energy discharged from the ESS with ESS capacity. Figure I-12 shows the differentiated equations for the polynomials according to Eq. (4-17).

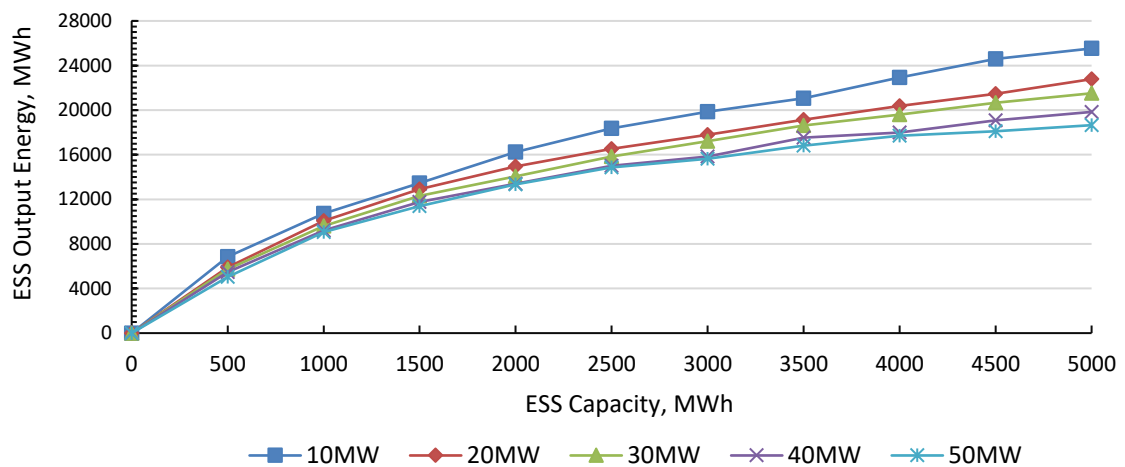


Figure I-11: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW for measured wind speed and direction and energy demand.

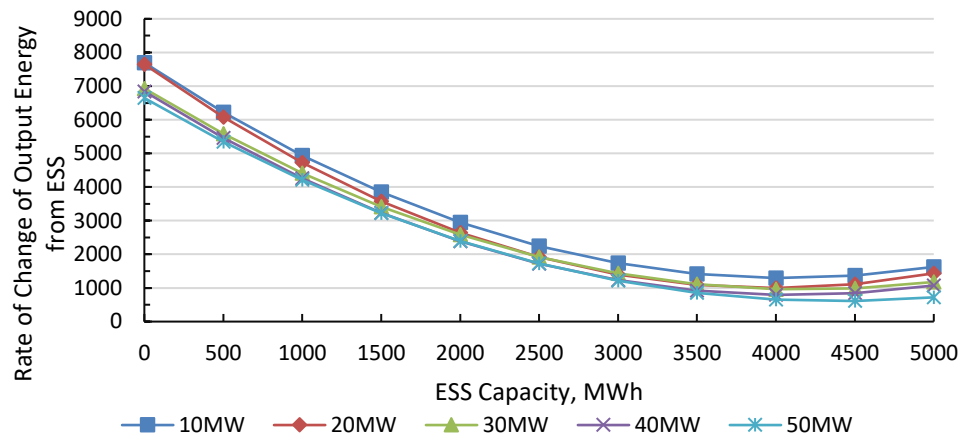


Figure I-12: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 250 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

I.2 Windfarm of 200 MW Capacity

The behaviour for a windfarm with a capacity of 200 MW is now shown. Results include those from the optimal combination of MCP and forecasted energy demand and those from measured wind speed and direction at the candidate site and the actual energy demand. The wind and the energy demand data are those for the year 2017.

I.2.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)

The results below are for predicted wind speed and direction (MCP) and forecasted energy demand. This is for an offshore windfarm with an installed capacity of 200 MW and a generation baseload of 100, 125 and 150 MW. The ESS power rating was varied in the range of 10 to 50 MW in steps of 10 MW.

100 MW Generation Baseload

Figure I-13 and Figure I-14 show the results for a windfarm with a generation baseload of 100 MW. Figure I-14 shows the relationship obtained for the energy discharged from the ESS with ESS capacity. Figure I-14 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

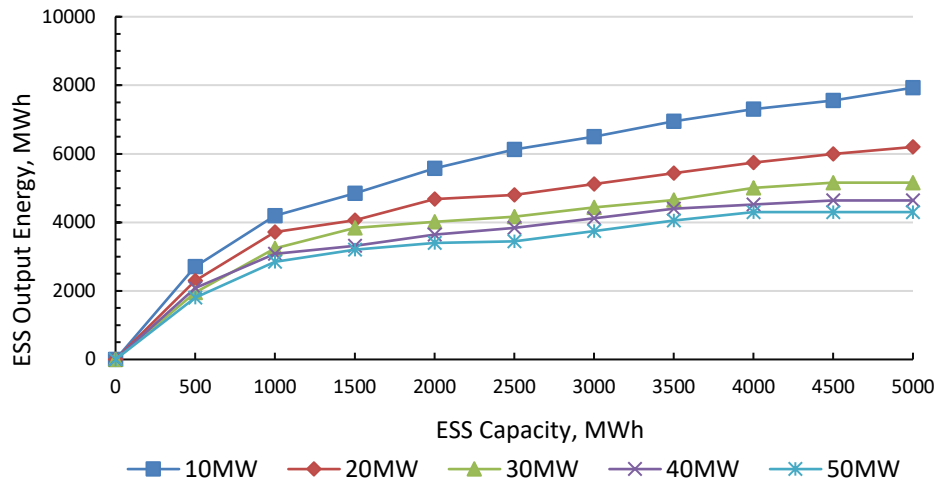


Figure I-13: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW for ESS power ratings from 10 MW to 50 MW for a generation baseload of 100 MW, for predicted wind speed and direction and forecasted energy demand.

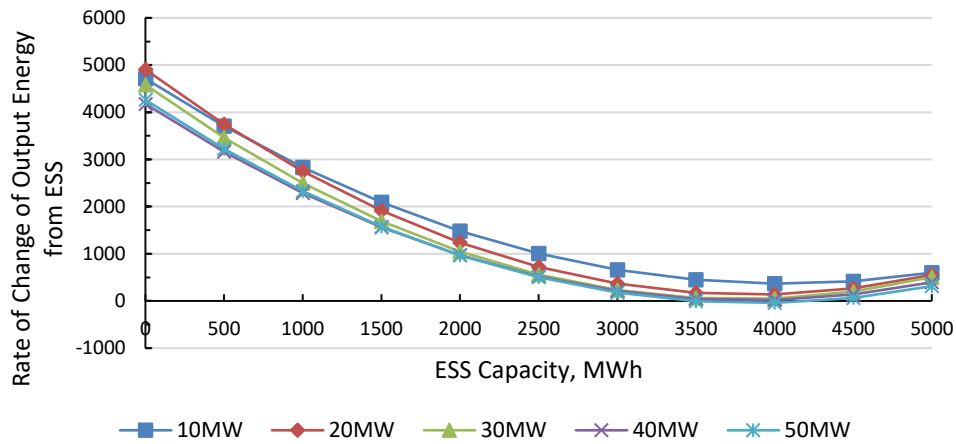


Figure I-14: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity 200 MW with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

125 MW Generation Baseload

The results shown in Figure I-15 and Figure I-16 are those for a windfarm with a generation baseload of 125 MW. baseload. Figure I-15 shows the relationship obtained for the energy discharged from the ESS with ESS capacity. Figure I-16 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

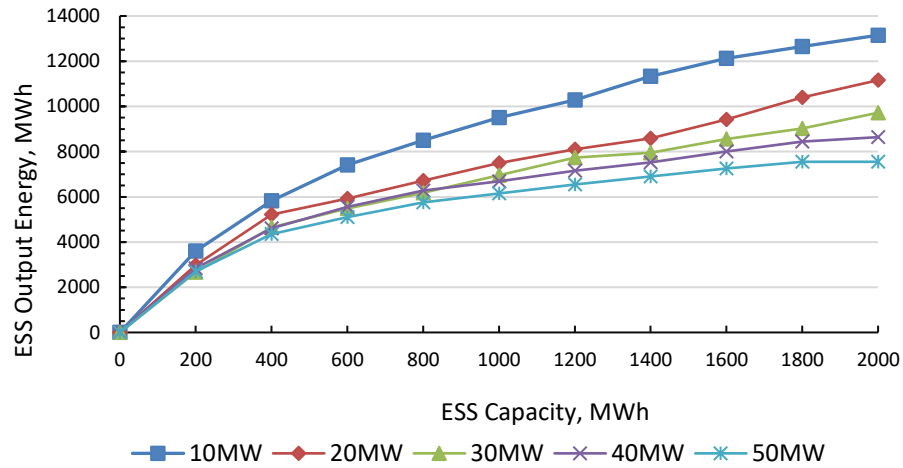


Figure I-15: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

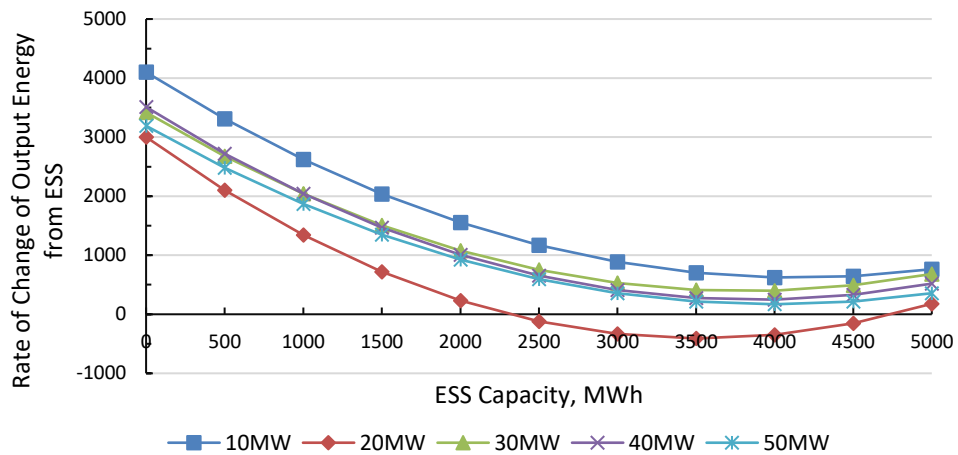


Figure I-16: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

150 MW Generation Baseload

The results shown in Figure I-17 and Figure I-18 are those for a windfarm with a generation baseload of 150 MW. Figure I-17 shows the relationship obtained for the energy discharged from the ESS. Figure I-18 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

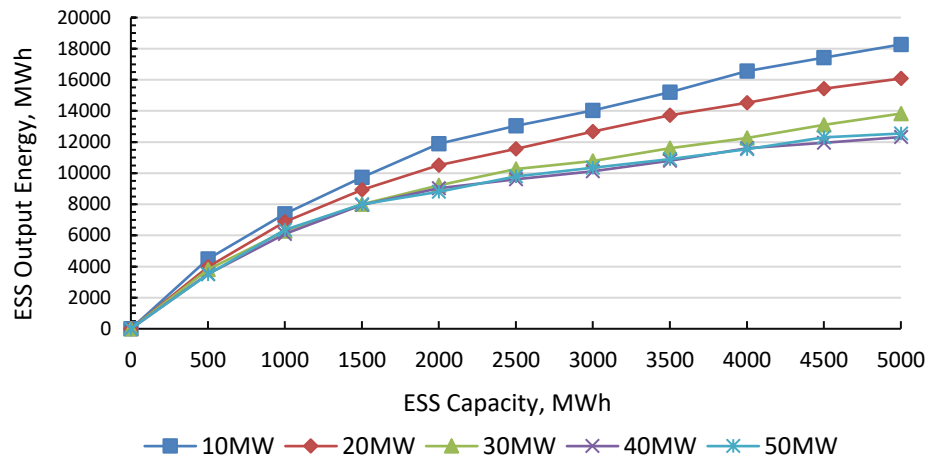


Figure I-17: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

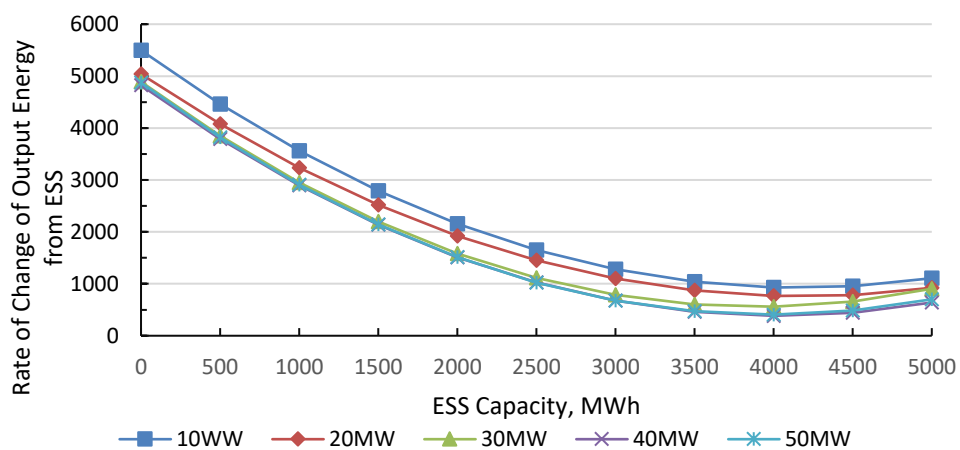


Figure I-18: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

I.2.2 Using Measured Wind Speed and Energy Demand

The results below are those for measured wind speed and direction and energy demand. As above, the measured wind speed and direction are those for 2017 at the candidate site, at a LiDAR measurement height of 80 m, and measured energy demand. Generation baseloads of 100, 125 and 150 MW are used. The ESS power rating is varied from 10 to 50 MW in steps of 10 MW.

Figure I-19 and Figure I-20 show the results for a windfarm with a generation baseload of 100 MW. Figure I-19 shows the relationship between the energy discharged from the ESS to the grid with ESS capacity. Figure I-20 shows rate of change of energy discharged to the electricity grid according to Eq. (4-17).

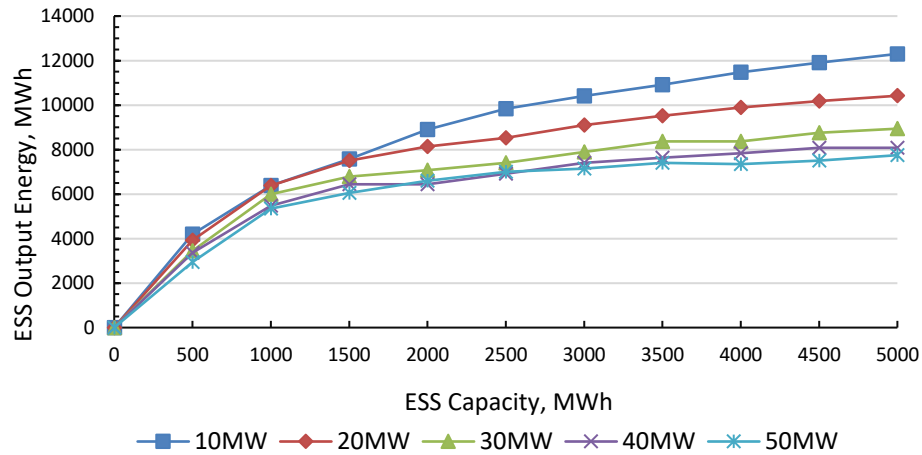


Figure I-19: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

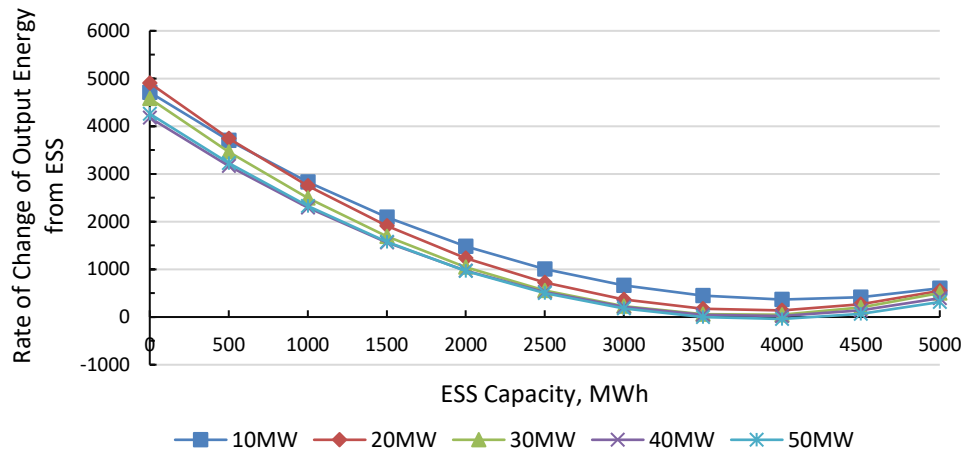


Figure I-20: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 100 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

125 MW Generation Baseload

Figure I-21 and Figure I-22 show the results for a windfarm with a generation baseload of 125 MW. Figure I-21 shows the relationship between the energy discharged to the electricity grid and the ESS capacity. Figure I-22 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

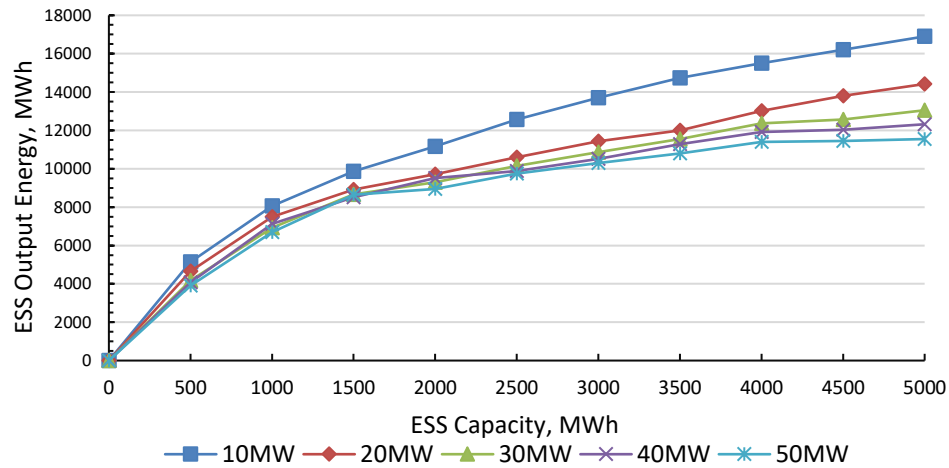


Figure I-21: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

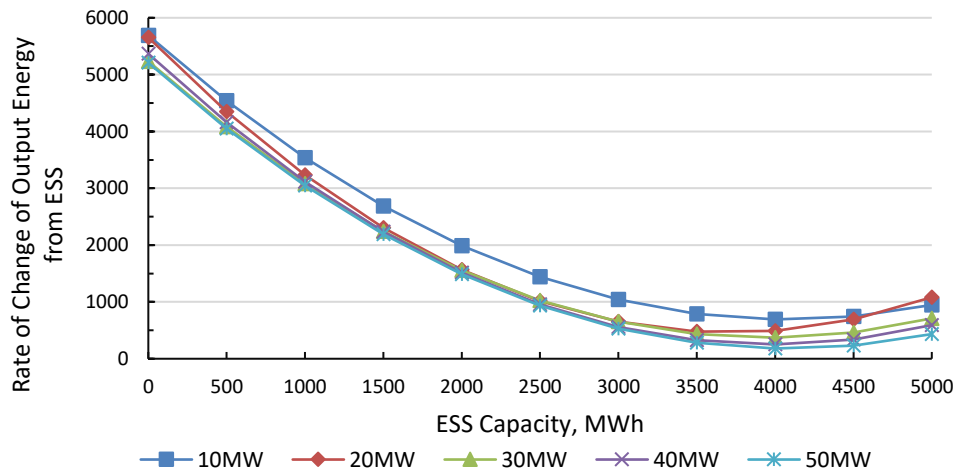


Figure I-22: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 125 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

150 MW Generation Baseload

Figure I-23 and Figure I-24 show the results for a windfarm with a generation baseload of 150 MW. Figure I-23 shows the relationship between the energy discharged from the ESS with ESS capacity. Figure I-24 shows rate of change of energy discharged to the electricity grid according to Eq. (4-17).

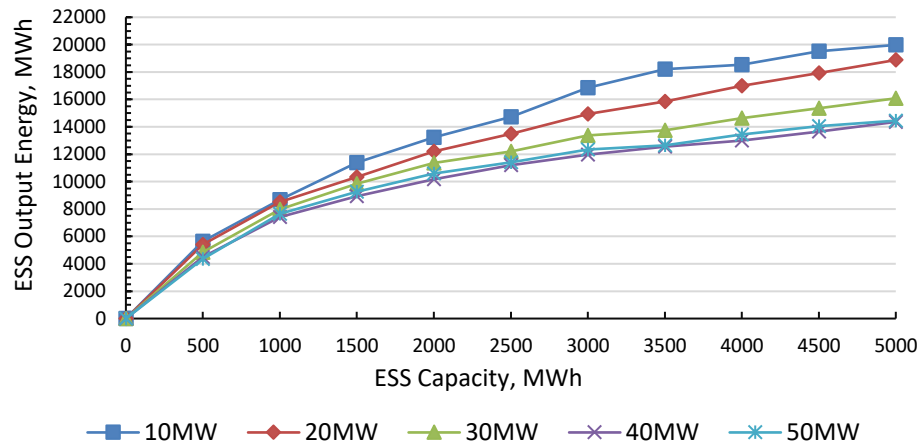


Figure I-23: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

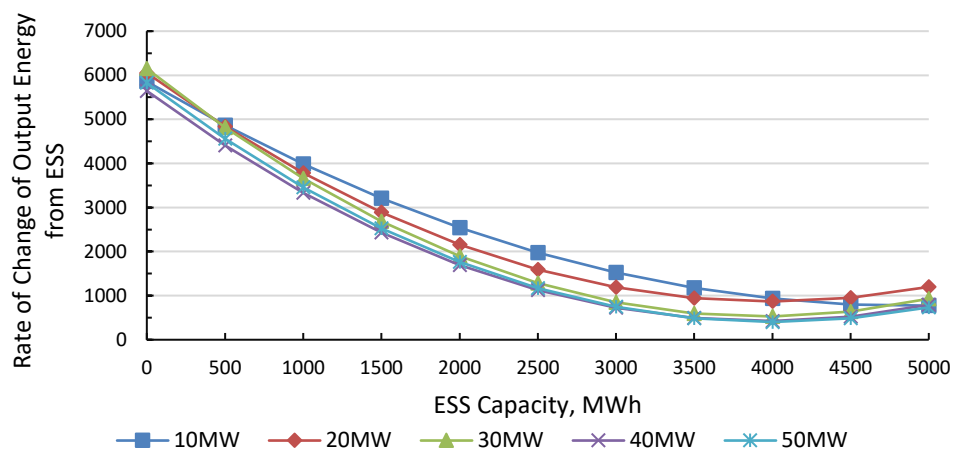


Figure I-24: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 200 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

I.3 An Offshore Windfarm with an Installed Capacity of 150 MW

Finally, the behaviour for offshore windfarms with an installed capacity of 150 MW is shown below. Results include those from the optimal combination of MCP and energy demand forecasting methodologies, which like the above results were compared to those for measured wind speed and direction, and energy demand. The results for predicted wind speed and direction (MCP) and forecasted energy demand for the (DT_DT) combination are shown below.

I.3.1 Using Optimal Combination of Regression Techniques for MCP and Energy Demand Forecasting Methodologies (DT_DT)

The results below are for predicted wind speed and direction for the year 2017 and forecasted energy demand for an offshore windfarm capacity of 150 MW and generation baseloads of 100, 125 and 150 MW. The ESS power rating was varied in the range of 10 to 50 MW in steps of 10 MW.

100 MW Generation Baseload

Figure I-25 presents the results for the windfarm with a 100 MW generation baseload. The figure shows the relationship between the energy discharged from the ESS to the electricity grid with ESS capacity. It was observed that, with these conditions, there was no increase in the amount of energy discharged to the grid for ESS capacities which are equal or greater than 1500 MWh. Therefore, for an offshore windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW, the use of fitted polynomials did not apply, as is clearly demonstrated in Figure I-25.

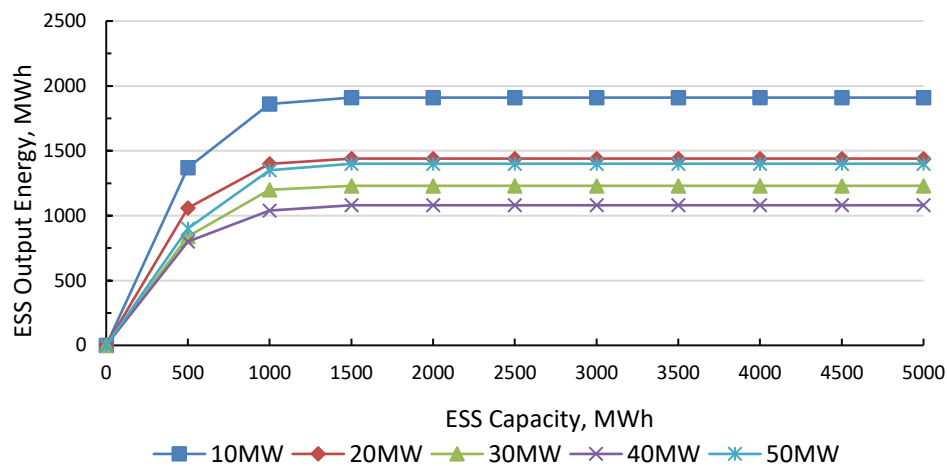


Figure I-25: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

125 MW Generation Baseload

Figure I-26 presents the results for a windfarm with a generation baseload of 125 MW. The figure represents the relationship between the energy discharged by the ESS to the electricity grid. It will again be observed that under these conditions, there was no increase in the amount of energy discharged to the grid for ESS capacities which were equal or greater than 150 MWh. Thus again, for a windfarm of 150 MW capacity and 125 MW generation baseload, the use of fitted polynomials did not apply and the value of 150 MWh was considered to be the optimal ESS capacity at an ESS power rating of 10 MW, while 1000 MWh is considered to be the optimal ESS capacity at ESS power ratings which are greater or equal to 20 MW.

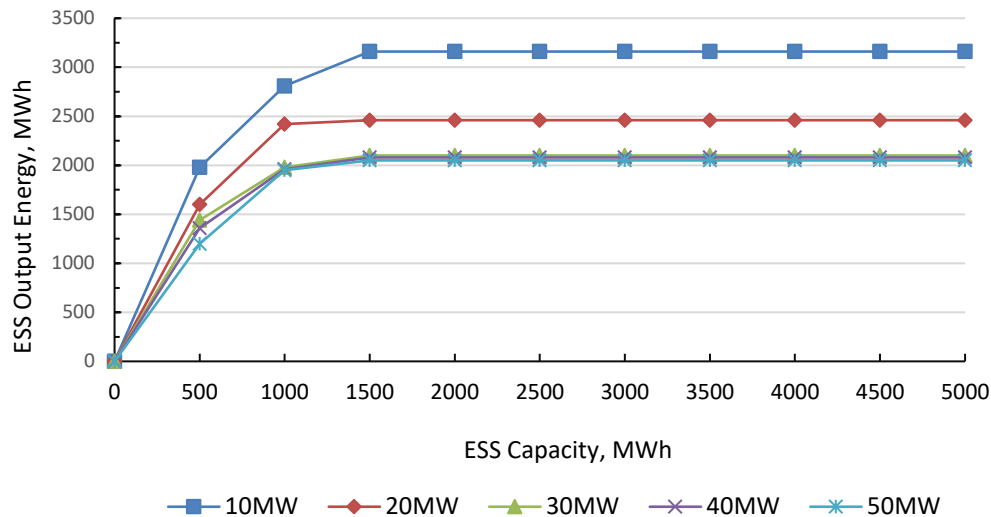


Figure I-26: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW offshore windfarm, with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

150 MW Generation Baseload

Figure I-27 and Figure I-28 represent the results for a windfarm with a generation baseload of 150 MW. Figure I-27 represents the relationship between the energy discharged from the ESS to the electricity grid with ESS capacity. Figure I-28 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

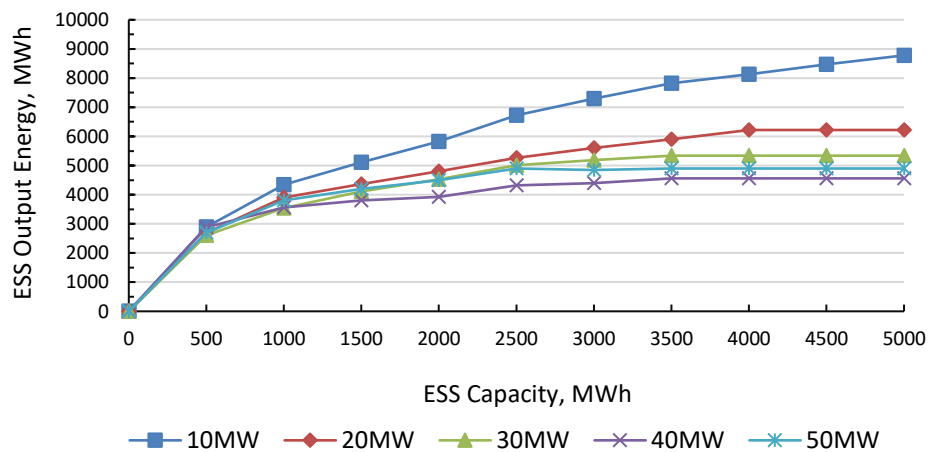


Figure I-27: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

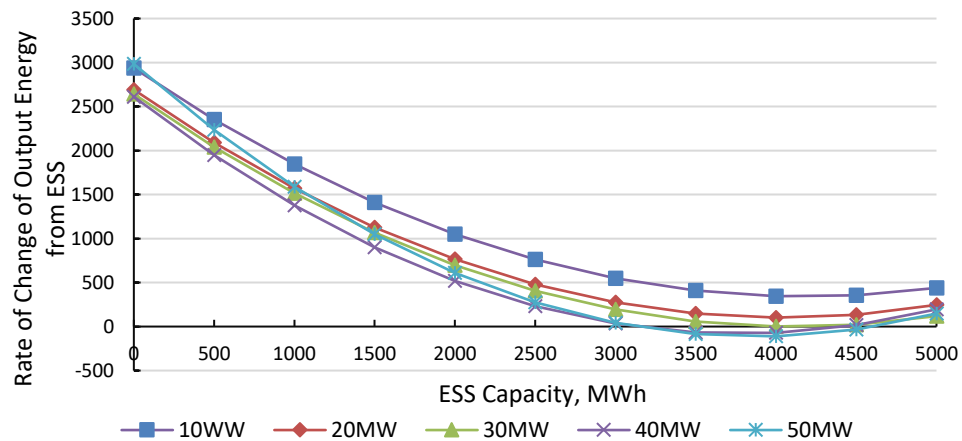


Figure I-28: Rate of change of energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for predicted wind speed and direction and forecasted energy demand.

I.3.2 Using Measured Wind Speed and Direction and Energy Demand.

The results below are those for measured wind speed and direction and energy demand for an offshore windfarm with an installed capacity of 150 MW. As above, the measured wind speed and direction were those for the year 2017 at the candidate site, at a LiDAR measurement height of 80 m and measured energy demand. Generation baseloads of 100, 125 and 150 MW were used. The ESS power rating was varied from 10 to 50 MW in steps of 10 MW.

100 MW generation Baseload.

Figure I-29 presents the results for a windfarm generation baseload of 100 MW. The figure shows the relationship between the energy discharged from the ESS to the grid, with ESS capacity. It was again observed that, with these conditions, there was no increase in the amount of energy discharged to the grid for ESS capacities which are equal or greater than 2000 MWh for an ESS power ratings equal or less than 20 MW. For an ESS power rating which is equal or greater than 30 MW there is no increase in the energy discharged to the electricity grid for an ESS capacity which is greater than 1500 MWh. Therefore, for a windfarm with an installed capacity of 150 MW and a generation baseload of 100 MW baseload, the use of fitted polynomials did not apply.

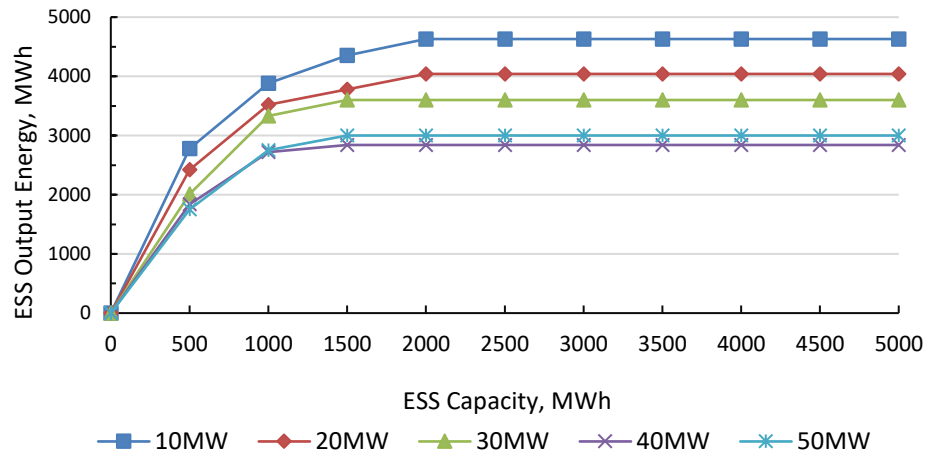


Figure I-29: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 100 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

125 MW Generation Baseload

Figure I-30 represents the results for a 150 MW offshore windfarm with a 125 MW generation baseload. The figure shows the relationship between the energy discharged from the ESS to the electricity grid with ESS capacity. There was no increase in the energy discharged to the electricity grid for an ESS capacity which was greater or equal to 2500 MWh at an ESS power rating of 10 MW, 2500 MWh for an ESS power rating of 20 MW, 2000 MWh for an ESS rating of 30 MW and 1500 MWh for power ratings which were greater than 40 MWh. Therefore, for a windfarm of 150 MW capacity and 125 MW generation baseload, the use of fitted polynomials did not apply.

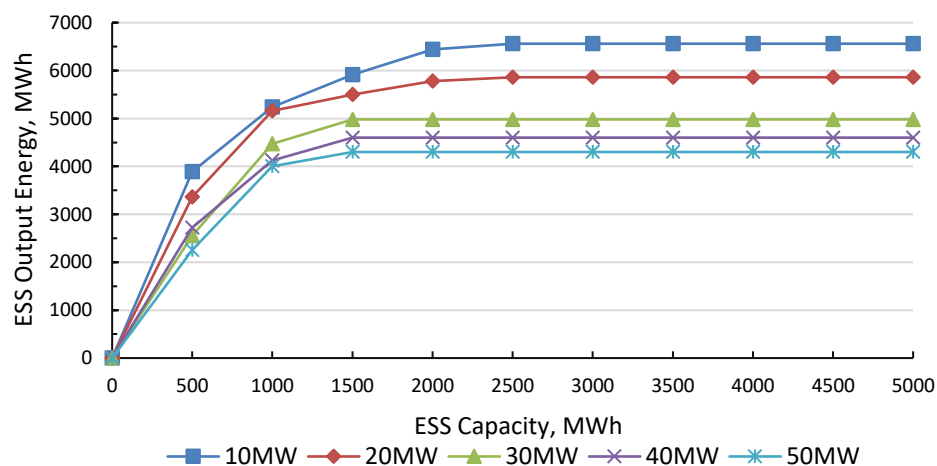


Figure I-30: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 125 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

150 MW Generation Baseload

Figure I-31 and Figure I-32 show the results for a windfarm with a generation baseload of 150 MW. Figure I-31 shows the relationship between the energy from the ESS discharged to the electricity grid

with ESS capacity. Figure I-32 shows the rate of change of energy discharged to the electricity grid according to Eq. (4-17).

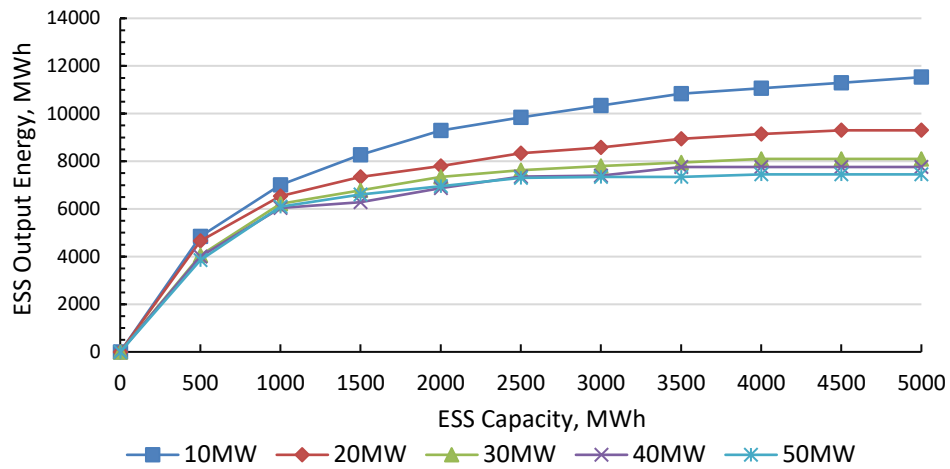


Figure I-31: Energy discharged by the ESS to the electricity grid for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings from 10 MW to 50 MW, for measured wind speed and direction and energy demand.

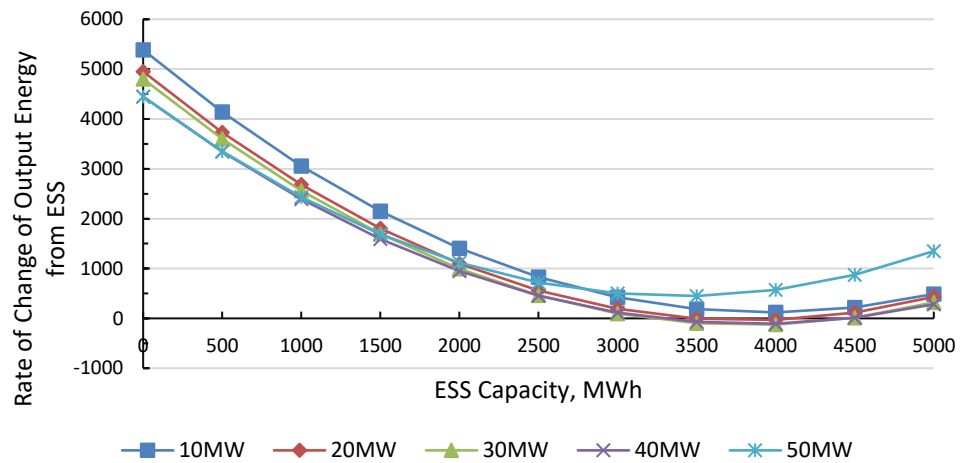


Figure I-32: Rate of change of Energy output from the ESS to the electricity grid, for an offshore windfarm with an installed capacity of 150 MW with a generation baseload of 150 MW, for ESS power ratings of 10 MW to 50 MW, for measured wind speed and direction and energy demand.

J. LCOE and LCOS Calculations

This Appendix shows the calculations for the LCOE of the hypothetical floating offshore windfarm and the ESS. Table J-1 shows the values of $(1 + r)^t$, with r (WACC) having a value of 8%.

Table J-1: Values of $(1 + r)^t$ for a WACC of 8%.

t	$(1+r)^t$
1	1.080
2	1.166
3	1.260
4	1.360
5	1.469
6	1.586
7	1.714
8	1.851
9	1.999
10	2.159
11	2.332
12	2.518
13	2.720
14	2.937
15	3.172
16	3.426
17	3.700
18	3.996
19	4.316
20	4.661

J.1 LCOE Calculations for a Floating Offshore Windfarm

J.1.1 Installed Capacity of 240 MW

LCOE calculations for a floating offshore windfarm with an installed capacity of 240 MW are shown in Table J-2 to Table J-4, for SB, Semi-Submersible and TLP, respectively.

Table J-2: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using Spar Buoy.

Spar Buoy					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	609.341			609.341	564.204
2014-2031		24.429 (p.a.)		24.429 (p.a.)	211.98 ¹³
2032			24.998	24.998	5.361
Total					781.549

Table J-3: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using a Semi-Submersible Platform.

Semi-Submersible					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	582.146			582.146	539.026
2014 to 2031		21.857 (p.a.)		21.857 (p.a.)	170.931 ¹⁴
2032			26.898	29.898	5.771
Total					734.463

¹³ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

¹⁴ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

Table J-4: LCOE calculation for a floating offshore windfarm with an installed capacity of 240 MW using a Tension Leg Platform.

Tension Leg Platform					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	626.951			626.951	580.051
2014 to 2031		22.714 (p.a.)		22.714 (p.a.)	177.633 ¹⁵
2032			51.671	51.671	11.085
Total					777.617

J.1.2 Installed Capacity of 320 MW

LCOE calculations for an offshore floating windfarm with an installed capacity of 320 MW are shown in Table J-5 to Table J-7, for SB, Semi-Submersible and TLP, respectively.

Table J-5: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using Spar Buoy.

Spar Buoy					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	812.454			812.454	752.273
2014-2031		32.571 (p.a.)		32.571 (p.a.)	282.209 ¹⁶
2032			33.318	33.318	7.148
Total					1042.065

Table J-6: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using a Semi-Submersible Platform.

Semi Submersible					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	776.194			776.194	718.698
2014-2031		29.142 (p.a.)		29.142 (p.a.)	252.893 ¹⁷
2032			35.864	35.864	7.694
Total					979.284

Table J-7: LCOE calculation for a floating offshore windfarm with an installed capacity of 320 MW using a Tension Leg Platform.

Tension Leg Platform					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	835.935			835.935	774.013
2014-2031		30.286 (p.a.)		30.286 (p.a.)	355.61 ¹⁸
2032			68.894	68.894	14.781
Total					1036.823

J.1.3 Installed Capacity of 400 MW

LCOE calculations for a 400 MW capacity windfarm are shown in Table J-8 to Table J-10 for SB, Semi-Submersible and TLP, respectively.

¹⁵ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

¹⁶ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

¹⁷ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

¹⁸ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

Table J-8: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using Spar Buoy.

Spar Buoy					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1015.568			1015.568	94.034
2014-2031		40.714 (p.a.)		40.714 (p.a.)	353.304 ¹⁹
2032			41.646	41.646	8.935
Total					1302.581

Table J-9: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using a Semi-Submersible Platform.

Semi-Submersible					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	970.240			970.240	89.372
2014-2031		36.429 (p.a.)		36.429 (p.a.)	316.12 ²⁰
2032			44.830	44.830	7.985
Total					1224.106

Table J-10: LCOE calculation for a floating offshore windfarm with an installed capacity of 400 MW using a Tension Leg Platform.

Tension Leg Platform					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1044.918			1044.918	96.751
2014 - 2031		37.857 (p.a.)		37.857 (p.a.)	328.511 ²¹
2032			81.024	81.024	17.384
Total					1296.029

J.2 Energy Storage System

J.2.1 Lithium-Ion Battery ESS

LCOS calculations for a Li-Ion ESS are shown below. Results are by the capacity range selected in Section 11-5. The results shown in Table J-1 are used in the calculations. In this case the OPEX accounts for two battery changes each after seven years of usage.

600 MWh Capacity

Table J-11: LCOE calculation for a Lithium-Ion ESS with 600 MWh capacity.

Lithium-Ion Battery ESS – 600 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	183.355			183.355	169.773
2014-2019		1.301 (p.a.)		1.301 (p.a.)	5.567 ²²
2020		56.901		56.901	30.742
2021-2026		1.301 (p.a.)		1.301 (p.a.)	3.248 ²³
2027		41.101		41.101	12.957
2028-2031		1.301 (p.a.)		1.301 (p.a.)	1.358 ²⁴
2032			5,740	5,740	1.231
Total					224.877

¹⁹ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

²⁰ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

²¹ Summation carried out according to Eq. (3-87) for the calculation of the LCOE for the years 2014-2031.

²² Summation carried out according to Eq. (3-88) for the calculation of the LCOS for 2014-2019.

²³ Summation carried out according to Eq. (3-88) for the calculation of the LCOS for 2021-2026.

²⁴ Summation carried out according to Eq. (3-88) for the calculation of the LCOS for 2028-2031.

3600 MWh Capacity*Table J-12: LCOE calculation for a Lithium-Ion ESS with 3600 MWh capacity.*

Lithium-Ion Battery ESS – 3600MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1100.128			1100.128	1018.637
2014-2019		7.804 (p.a.)		7.804 (p.a.)	33.404
2020		341.410		341.410	184.453
2021-2026		7.804 (p.a.)		7.804 (p.a.)	19.491
2027		246.607		246.607	77.741
2028-2031		7.804 (p.a.)		7.804 (p.a.)	8.148
2032			34.439	34.439	7.389
Total					1349.265

4200 MWh Capacity*Table J-13: LCOE calculation for a Lithium-Ion ESS with 4200 MWh capacity.*

Lithium-Ion Battery ESS – 4200 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1283.483			1283.483	1188.410
2014-2019		9.105 (p.a.)		9.105 (p.a.)	38.972
2020		398.312		398.312	215.196
2021-2026		9.105 (p.a.)		9.105 (p.a.)	22.739
2027		287.709		287.709	90.698
2028-2031		9.105 (p.a.)		9.105 (p.a.)	9.506
2032			40.179	40.179	8.620
Total					1574.143

4800 MWh Capacity*Table J-14: LCOE calculation for a Lithium-Ion ESS with 4800 MWh capacity.*

Lithium-Ion Battery ESS – 4800 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1466.838			1466.838	1358.183
2014-2019		10.405 (p.a.)		10.405 (p.a.)	44.539
2020		455.214		455.214	245.938
2021-2026		10.405 (p.a.)		10.405 (p.a.)	25.988
2027		328.810		328.810	103.655
2028-2031		10.405 (p.a.)		10.405 (p.a.)	8.453
2032			45.919	45.919	9.852
Total					1799.020

5400 MWh Capacity*Table J-15: LCOE calculation for a Lithium-Ion ESS with 5400 MWh capacity.*

Lithium-Ion Battery ESS – 5400MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1650.193			1650.193	1527.956
2014-2019		11.706 (p.a.)		11.706 (p.a.)	50.106
2020		512.116		512.116	276.680
2021-2026		11.706 (p.a.)		11.706 (p.a.)	29.236
2027		369.912		369.912	116.612
2028-2031		11.706 (p.a.)		11.706 (p.a.)	12.222
2032			51.659	51.659	11.083
Total					2023.898

6000 MWh Capacity

Table J-16: LCOE calculation for a Lithium-Ion ESS with 6000 MWh capacity.

Lithium-Ion Battery ESS– 6000 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1833.547			1833.547	1697.729
2014-2019		13.007 (p.a.)		13.007 (p.a.)	55.674
2020		569.017		569.017	307.422
2021-2026		13.007 (p.a.)		13.007 (p.a.)	32.485
2027		411.013		411.013	129.569
2028-2031		13.007 (p.a.)		13.007 (p.a.)	13.580
2032			57.399	57.399	12.316
Total					2248.775

J.2.2 Vanadium Redox Battery ESS

LCOS calculations for a VRB ESS are shown below. Results are by the capacity range selected in Section 11.5. The results shown in Table J-1 are again used in the calculations. In this case there are no battery changes throughout the projected lifetime of the ESS.

500 MWh Capacity

Table J-17: LCOS calculation for a Vanadium Redox Battery ESS with 500 MWh capacity.

Vanadium Redox Battery ESS – 500 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	172.704			172.704	159.911
2014-2031		2.111 (p.a.)		2.111 (p.a.)	18.321 ²⁵
2032			4.783	4.783	1.026
Total					179.258

3000 MWh Capacity

Table J-18: LCOS calculation for a Vanadium Redox Battery ESS with 3000 MWh capacity.

Vanadium Redox Battery ESS – 3000 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1036.225			1036.225	959.467
2014-2031		12.668 (p.a.)		12.668 (p.a.)	109.929
2032			28.700	28.700	6.157
Total					1075.554

3500 MWh capacity

Table J-19: LCOS calculation for a Vanadium Redox Battery ESS with 3500 MWh capacity.

Vanadium Redox Battery ESS – 3500 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1208.929			1208.929	1119.379
2014-2031		14.779 (p.a.)		14.779 (p.a.)	128.250
2032			33.483	33.483	7.184
Total					1254.813

²⁵ Summation carried out according to Eq. (3-97) for the calculation of the LCOE for the years 2014-2031.

4000 MWh Capacity*Table J-20: LCOS calculation for a Vanadium Redox Battery ESS with 4000 MWh capacity.*

Vanadium Redox Battery ESS – 4000 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1381.633			1381.633	1279.290
2014-2031		16.891 (p.a.)		16.891 (p.a.)	146.572
2032			38.266	38.266	8.210
Total					1434.071

4500 MWh Capacity*Table J-21: LCOS calculation for a Vanadium Redox Battery ESS with 4500 MWh capacity.*

Vanadium Redox Battery ESS – 4500 MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1554.337			1554.337	1439.201
2014-2031		19.002 (p.a.)		19.002 (p.a.)	164.893
2032			43.049	43.049	9.236
Total					1613.331

5000 MWh Capacity*Table J-22: LCOE calculation for a Vanadium Redox Battery ESS with 5000 MWh capacity.*

Vanadium Redox Battery ESS – 5000MWh					
Year	CAPEX (MEuros)	OPEX (MEuros)	DECEX (MEuros)	CAPEX+OPEX+DECEX (MEuros)	$\frac{(\text{CAPEX}+\text{OPEX}+\text{DECEX})}{(1+r)^t}$ (MEuros)
2013	1727.041			1727.041	1599.112
2014-2031		21.113 (p.a.)		21.113 (p.a.)	183.215
2032			47.833	47.833	10.262
Total					1792.590