Combining Wind Speed and Energy Demand Prediction Techniques in the Determination of Energy Storage Capacity Requirements of Offshore Wind Farms

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Abstract

The intermittency of the wind resource may not necessarily match the consumers' demand for electrical energy. Hence, the use of energy storage facilities will increase the efficacy and usefulness of wind energy, thus making wind farms a more viable investment. This paper develops a methodology to couple Measure-Correlate-Predict (MCP) techniques and electric load forecasting methods with the scope of optimising the energy storage facility sizing and costs. A review of current MCP techniques and electrical load prediction methods is carried out, followed by a review of energy storage technologies. The final objective is to formulate a methodology which brings together all of the above into one tool which may be used to optimise the integration of energy storage with wind farms depending on the availability of long-term wind resources, energy demand trends and the chosen storage technology.

1. Introduction

There is today increased interest to integrate offshore wind farms with energy storage facilities. Different energy storage technologies exist. Amongst these are pumped hydro, underground hydro, compressed air and battery storage systems [1], [2]. Some technologies are offshore-based and include the installation of compressed air or pumped hydro storage through the deployment of underwater structures [3], [4]. Minimising the costs of energy storage is crucial, especially in the case of offshore wind farms where costs of energy generation are still comparatively higher than for other renewable energy generation technologies [5].

The design of energy storage facilities coupled with wind farms relies on accurate prediction of wind resources and on the energy demand over the entire project lifetime. The Measure-Correlate-Predict (MCP) methodology is used to generate longer-term wind conditions at a given candidate site. Short-term readings from a target site are correlated to concurrent short-term readings from a single or multiple reference sites, such as a nearby airport, that also possess historical wind databanks. Based on these correlations, the wind resource at the target site in the long-term can therefore be generated. One fundamental assumption is that the historical wind conditions generated for the target site will reflect wind conditions in the future. Various types of MCP techniques exist, such as Linear Regression (LR), Variance Ratio (VR), Artificial Neural Networks (ANNs) and Support Vector Regression (SVR) methods, amongst others [6], [7].

Energy demand 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 changes in people's habits [8]. Various techniques such as Artificial Neural Networks [9] and regression based techniques [10], [11] can be applied according to the required time span. Energy demand forecasting techniques involves the analysis of trends, end-use of energy and econometric analysis, with each technique having its advantages and disadvantages.

When using the above methodologies in isolation, one can independently project wind behaviour and predict energy demand. The study of the behaviour of energy storage systems to changing wind patterns and energy demand in the short- and the longer-term requires integrating the above two projections. With the current need to integrate energy storage from wind generation technologies to the existing electricity grid, these tools become limited in scope. This is also especially true in calculating the feasibility of any proposed project which involves energy storage. The relationship between MCP and energy load prediction methodologies is shown in Figure 1.

The challenges of integrating energy storage with the electricity grid are mentioned below. A very short description of available energy storage technologies and the technical challenges for integrating this with the grid is also included. A literature review of existing works dealing with MCP techniques and electricity demand prediction is also conducted. The available methods are also compared.

The literature review identifies a knowledge gap that exists because there is no single model which integrates the projection and forecasting techniques into one which is capable of predicting the behaviour of a large scale energy storage system. Such a methodology is therefore being proposed. This model will be tested for reliability and uncertainty using the same mathematical techniques which are used to test MCP and energy load prediction models for reliability and uncertainty.

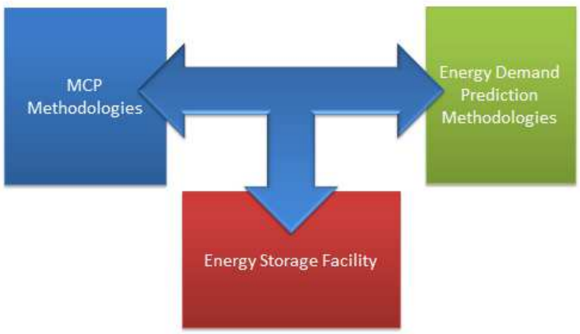

Figure 1: Establishing a relationship between MCP methodologies, energy demand prediction and energy storage facilities.

The coupling of MCP and energy demand prediction models will facilitate the design optimisation of large-scale energy storage systems to be integrated with offshore wind farms. The methodology will enable the development of various scenarios for energy storage management, resulting in an optimised wind-farm energy storage system.

2. Energy storage technologies

If renewable energy is to be a viable alternative to conventional generation, it must result in a reduction of the baseload generation. With the penetration of renewable energy, the ability to manage an increased level of variable generation will become critical. To manage this increased variability, electric grids require flexibility in load and generation management [2].

When renewable generation comes online coincident with low demand, it presents a further challenges because it may not be possible to ramp down the baseload of thermal generation systems. With the introduction of more offshore wind energy to the grid, the addition of energy storage systems becomes an option that utilities should consider in order to increase reliability and to reduce the costs of providing power when needed. Energy storage systems such as Pumped Hydroelectric Energy Storage (PHES) [12], Underground Pumped Hydroelectric Energy Storage (UPHES) [13], Compressed Air Energy Storage (CAES) [14] and Battery Storage [15] can be considered. However, the energy storage system must be managed carefully. Different management scenarios can be analysed to find out which strategy would result in an economical rate of return. Various operating scenarios are possible with offshore wind farms and energy storage [16] and several possibilities for the integration of energy storage and renewable energy generation exist [17]. One can therefore see the importance of analysing the different possible scenarios which will need to be analysed and integrated into the model. The optimal size and cost of the energy storage system will also depend on the chosen scenarios.

Figure 2 shows the interaction between the energy demand, thermal generation, wind energy and energy storage over a 36-hour period for a hypothetical island. The island has an average energy demand of 350MW with a base load capacity of 250MW. The island also has an offshore wind farm consisting of 20, 5-MW wind turbines. The demand load is reduced during the night-time and this coincides with the wind farm increasing output. In order not to curtail the wind farm, 70% of the energy generated from the wind farm is used to charge the energy store. Therefore, there is some thermal generation above the base load. During periods of high demand, with the wind energy reduced, the energy store is used to generate energy together with what is available from the wind farm. During this period, there is no need for thermal generation to go above the base load.

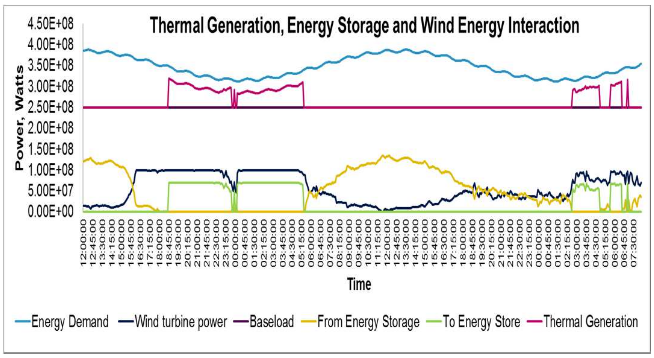

Figure 2: Interaction between energy demand, thermal generation, energy storage and wind energy for an island scenario.

Energy storage could therefore be a key component to ensure flexibility and reliability with a large penetration of offshore wind energy and facilitates the alignment of renewable generation with loads.

Studies involving the use of pumped hydroelectric energy integrated with wind energy resources have considered the use of old quarries on the Island of Malta as a store for hydroelectric energy [18], with a study investigating their integration with deep offshore wind [19]. Another study analysed different scenarios to optimise reservoir capacities in isolated systems which have a large renewable energy penetration [20], while yet another study considered different scenarios for hydro storage in the Republic of Ireland [1]. A type of hydroelectric storage has been suggested as an undersea storage concept known as Ocean Renewable Energy Storage (ORES) [3]. This is especially suited for floating wind farms as the storage spheres can serve as anchorage points.

To date, no UPHES system, commercial or otherwise, has been installed and used. However, an interesting variation is proposed in the form of an Energy Membrane Underground Pumped Hydroelectric Storage (EM-UPHS) system [21].

The two existing CAES plants, Huntorf in Germany and McIntosh in the USA, have both demonstrated very high reliability and economic feasibility. CAES can use a broad range of reservoirs for air storage and has a modest footprint, giving it greater siting flexibility relative to PHES. CAES is considered especially important for wind balancing [14]. Recent research into CAES has also resulted in the evaluation of the possibility of Underwater CAES in the Gulf of Maine [4]. A further study shows the possibility of integrating CAES with Buoyancy Work Energy Storage (BWES) [22], which is a fairly novel concept that is also applicable for direct coupling with wind farms, especially if appropriate anchoring provision is integrated in the foundations of the wind turbines while they are being built.

Sodium Sulphur (NA-S) Batteries are also a very attractive emerging technology [15]. In this case, a 34-MW (204-MWh) Na-S battery facility has been in operation at Rokkasho, Japan, since 2008, together with several other installations in the USA. Other classes of batteries include flow batteries such as Zinc Bromine (ZBR) Batteries and Vanadium Redox Batteries (VRBs) [15], where commercial applications of such batteries are already in existence with the largest installation being a 4-MW (6MWh) installation in Tomamae Wind Villa, Japan. Other commercial applications for Vanadium Redox Batteries have been developed by Cellstrom, a German company [23].

3. MCP techniques for the long-term projections of wind energy

An accurate estimation of the mean values of the wind performance of a candidate site for a wind farm is difficult with less than 10 years of data. Since wind characteristics vary over time (diurnal, seasonal, inter-annual) [24], [25], [26], historical series of wind data measurements for a candidate site are required for an evaluation of that variability. When it comes to estimating the economic feasibility of installing a wind farm at a candidate site, this element of uncertainty needs to be somewhat reduced. Some authors maintain that at least 5 years' worth of wind data for a candidate site is required [26]. Other authors also argue that 20 or even 30 years of data is indispensable for the long-term characterisation of a wind resource. In the majority of cases, there are no historical wind measurements available at a candidate site. The standard way to resolve this issue is to carry out sufficiently long measurement campaigns at the candidate sites, but this involves an often unacceptable postponement of the decision as to whether to install the wind farm or not.

In one particular case on the Canary Islands [27], the time between publication of the tender documents and the deadline of proposals by an investor was very limited. Consequently, there was little time available to carry out wind measurement campaigns, as investors normally have about one year to analyse the wind resource at a candidate site. While it may be possible to acquire information about the seasonal wind variations at a candidate site in such a short period of time, knowledge of the inter-annual variability of the wind characteristic is impossible with such a short period of data. The statistical method, known as the Measure-Correlate-Predict (MCP) technique, is proposed as a way of getting round this lack of long-term data [28]. This makes use of historical wind data series made available from nearby weather stations, for example an airport. These are known as reference stations. A requirement with these method is that the short-term measuring period for the wind data of the reference station must also coincide in length and date with a measuring period at the candidate site. The concept is based on the assumption of the existence of a correlation between the wind performance at the candidate and reference sites.

At first, MCP methods [29] only estimated the mean long-term annual wind speed. Later, the most commonly used MCP methods made use of linear regression (LR) algorithms [30] to establish the relationship between hourly wind characteristics of the candidate and the reference site. More recently other models have been proposed which establish non-linear type relationships [31], [32]. Likewise, automatic learning techniques have also been proposed, of which particular mention can be given to techniques which employ statistical learning algorithms such as Bayesian networks (BNs) [33], techniques such as Artificial Neural Networks (ANNs) [34], [35] and the use of Support Vector Regression (SVR) [36].

A very comprehensive review of MCP techniques is carried out by Carta et al., [6] in which a very wide variety of MCP techniques is examined. In addition, the research also describes various wind energy software applications for long-term wind energy forecasts. Such applications are WindPro® [37], Windfarmer [38], Mint [39] and WindLogics® [40], which all include the MCP techniques mentioned above. Amongst others, the MCP methodologies which were reviewed by the authors include those for a single reference station which include techniques such as the method of ratios, those based on first-order linear regression, higher than first-order linear methods, non-linear methods and probabilistic methods. Methodologies with multiple reference stations include the use of Bayesian Network classifiers to estimate the long-term wind speed frequency distribution at a site with few wind resource measurements and the use of Artificial Neural Networks [27], [41].

Rogers et al [30] compared four linear MCP algorithms, which included the standard Linear Regression, a model which uses distributions of ratios of wind speeds at the two sites, a Variance Ratio method and another method, which is based on the ratio of the standard deviations of the two data sets. In this case the authors concluded that the Variance Ratio method gave the best results. Other authors [7], evaluated three MCP methodologies which are based on a concurrent wind speed time series for two sites. One method included Linear Regression, which was derived from the bivariate normal joint distribution and Weibull Regression. The other method was based on conditional probability density functions applied to the joint distributions of the reference and the candidate sites. These included a Linear Regression approach and a Weibull Regression approach. The results from these two methodologies were in turn compared to the Variance Ratio method [30]. Although concluding that the Variance Ratio method predicted all the parameters very accurately, the probability density function which was based on the Weibull distribution stood out as far as prediction accuracy was concerned.

Zhang et al., [42] proposed a hybrid MCP methodology to assess long-term wind data. The hybrid methodology was used to compare results from four MCP methods. They concluded that the accuracy of the method was very sensitive to the combination of the individual MCP algorithms. In another study, Velazquez et. al., [27] came to the conclusion that ANN methods were superior to other methods in forecasting long-term wind data. The authors came to this conclusion after running and comparing the errors on nineteen scenarios for the data from six reference stations and a candidate site on the Canary Islands. In this case, the data sets were divided into different subsets for training, validation and test data. The training subset was used to estimate the parameters of the ANN, while the validation subset was used to check the ANN training. The test data subset was then used to compute the percentage error. This was an independent measure of how well the model was performing. The models used to perform the long-term data were built using 100% of the available short-term data.

Another more recent method which is gaining popularity is the Support Vector Regression methodology (SVR). This is based on statistical learning [43]. The input to the SVR is the wind speed at one reference site and output of the SVR is the wind speed at the target site. The SVR is trained using the concurrent short-term wind speed at both the reference site and the target site. The long-term wind speed at the target site is then predicted based on the long-term wind speed at the reference site [42].

To assess the best MCP technique, however, it is also necessary to quantify and model the uncertainty and the level of error in the MCP method. It is necessary to compare the various MCP methodologies and then use established metrics [41], [42] such as, the Mean Absolute Percentage Error (MAPE) [44], the Mean Squared Percentage Error (MSPE) [45] and the Mean Absolute Error (MAE) [46] to better establish the credibility of the resource assessment. Table 1 below is shows a comparison of the different MCP methodologies.

In this research the MCP methodology is being used in conjunction with Energy Storage and Electric Load Forecasting; one of the aims being to establish the relationship between MCP methodologies, energy storage and load prediction and to determine the optimum energy storage capacity for a wind energy source, while taking the forecasted electric load into consideration. Load prediction is now discussed.

MCP Methodology	**Type**	**Advantages**	**Disadvantages (Limitations)**
Methods of Ratios	Variance Ratio (VR) Method	Proposed as an alternative for the limitations of the Linear Regression method. Found to be relatively accurate in many occasions.	Is based on an assumption of a linear relationship between the reference and the candidate site. Shows a higher level of errors for when compared to ANNs.
Methods based on regressions	Linear Regression (LR) method	Most commonly used methods used with a single reference station.	Can result in biased predictions of wind speed distributions. Has a limited capability and requires a significantly high level of correlation between the reference and the candidate site. Does not hold well when between sites whose distributions are Weibull distributed.
Probabilistic methods	Weibull Distribution	Based on widely accepted distribution models. Improved prediction accuracy when compared to methods based on linear regression.	Still requires a significant correlation between concurrent measurements of candidate and reference sites.
Computational Intelligence Techniques	Artificial Neural Networks (ANN)	Can compute data from multiple reference stations. Able to recognise patterns in a noisy or otherwise complex data environment. Generate lower errors and produce a higher level of certainty than VRM methods.	Requires considerable computational power and may be time consuming. Will behave differently when subjected to different learning algorithms.
	Support Vector Regression (SVR).	Becoming very popular within the renewable energy community due to statistical learning capability.	Requires considerable computational power and may be time consuming.

Table 1: A comparison between various MCP methodologies [6], [42], [27], [47].

4. Energy demand prediction modelling

With increasing drives towards efficiency in the supply of electrical energy, both for economic and environmental reasons, accurate prediction of electricity demand is vital if generating capacity is to be closely matched to the demand. In 1984, an improvement in forecasting accuracy of 1% was estimated to yield savings of approximately GBP 10 million per annum in operating costs [48]. The deregulation of the electricity markets and the increasing utilisation of renewable energy sources has changed the electricity market from a static one-day ahead market to a flexible real-time market that allows interaction between the participants [10]. Energy demand profiles may be defined as daily, medium-term and long-term. Long-term, predictions are used for strategic planning of generating plant [49]. Methodologies for long-term prediction will therefore be analysed.

Long-term demand predictions are dependent on several factors. The long-term energy demand pattern will depend on changing climatic patterns [8]. Hor et al., established a correlation between the demand and climatic variables such as temperature, degree days and enthalpy latent days to produce a long-term forecast. Another study [49] shows that demand values display a strong cyclic pattern, reflecting the change in temperature throughout the year. The demand curve also changes depending on the prevailing weather conditions. A further study by the same authors [50], shows that in addition to climate, weather, holiday patterns and economic parameters can alter the demand curves, e.g., during an economic boom, the demand may increase. Swider et al., [51], showed the dependency of the demand on season, working days and weekends, holidays, etc., when deriving a model to calculate the cost of integrating wind energy into a stochastic electricity market model.

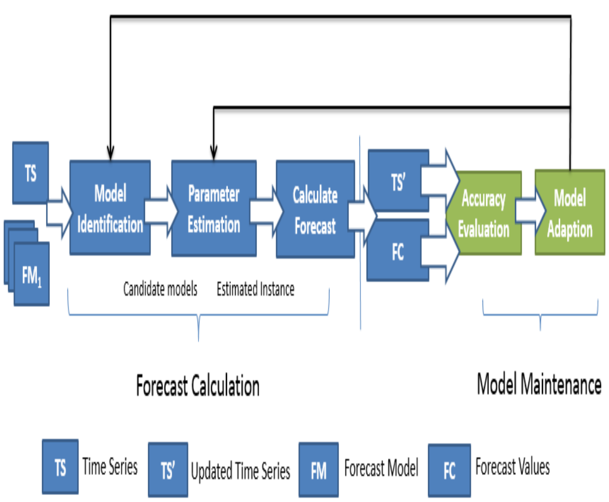

Figure 3: Energy demand forecasting methodology [10]

Energy demand prediction can be done using a variety of modelling techniques [48]. Mathematical techniques include Structural State-Space techniques [48], Bayesian methods [52], the Box-Jenkins methodology [45], [10] and computational intelligence techniques [9], which include Fuzzy Logic and Artificial Neural Networks [53], [48].

Dannecker [10] describes the current state of energy management and forecasting. In his work, he describes a methodology which is based on an iterative approach [45] and proposes that the forecasting method be divided into two phases, which are the actual forecasting and the maintenance of the model. This is shown in Figure 3. As in the case of MCP techniques, the decision on the adequacy of the model depends on the metrics chosen to determine the uncertainty or the prediction error. Again, in this case, these are classified as Mean Squared Percentage Error (MSPE), Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE).

Table 2 compares the various energy demand prediction techniques and shortlists their advantages and limitations. The table shows that the technique chosen will depend on the timescale under consideration. It is therefore very likely that the methodology used will include econometric methods, but it is too early at this stage of the research to discount any methodology. The chosen methodology will need to be analysed by establishing its level of uncertainty. As shown in Table 2, not all methodologies can be used for long-term prediction [54].

5. Methodology

5.1 Research Questions

The above review serves to prompt further research in the use of prediction methods to analyse the operation of energy storage systems coupled to offshore wind farms. It also highlights the need for the following questions in the field of MCP techniques, energy storage, and energy demand prediction:

- Which MCP technique best suits integration of offshore wind energy and energy storage? Will the technique change when energy storage is involved?
- Which demand prediction technique is best suited for use with energy storage modelling?
- How can MCP techniques be integrated numerically with energy demand and energy storage models?
- How can MCPs and energy prediction models be combined to predict the long-term overall efficiency of offshore wind farms with integrated energy storage?
- What is the role of such models in optimising the sizing and utilisation of energy storage?

The literature review for both MCP and demand prediction methodologies shows that both methods have their own uncertainty and reliability issues. The combination of the two models will increase the uncertainty, and it is not known how this effects the predicted storage capacity requirements.

Method	Description	Advantages	Limitations
Trend	Done in terms of one day to a week and plays a very important role in a power system's basic operating functions.	Easy data availability and fast processing of information. Tools are commercially available.	This is only suitable for short-term forecasting.
Similar Day	Analyses the natural pattern of the power load and the forecasting day's weather features to define specific parameters which can be compared to previous days with similar characteristics.	High, short term forecasting accuracy. Several computational tools (ANNs, Fuzzy logic, etc.) can be used.	Prediction accuracy decreases with increased time-span. Pre-processing of the data (training sets) has a strong impact on the model's performance.
End-use	The method uses the impact of energy usage patterns of different devices/systems in the overall energy consumption in a disaggregated approach.	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.
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 and 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 lowers the model's accuracy.

Table 2: A comparison of the different methodologies for prediction of energy demand [54].

Therefore, the following research questions will also need to be addressed:

- Which are the most reliable MCP and energy demand prediction methods?
- What is the level of uncertainty resulting from the different coupled MCP and energy demand prediction methods? How does this impact the design optimisation and operation modelling of energy storage systems integrated with offshore wind farms?

5.2 Research Needs

Several studies on energy demand modelling and energy storage have been conducted, but no connection between MCP methodologies, energy demand and storage has yet been made. A methodology for interconnecting MCP techniques and energy demand prediction modelling needs to be developed to optimise the integration of large-scale offshore wind farms with energy storage. This methodology should serve to determine the behaviour of an energy storage system vis-à-vis wind behaviour, energy demand and storage availability. It should also provide an accurate model for the feasibility analysis of offshore wind farms supplying dispatchable energy through the use of energy storage facilities. The different aspects on which the required methodology is based is shown in Figure 4, which is also a high-level depiction of the intended research approach.

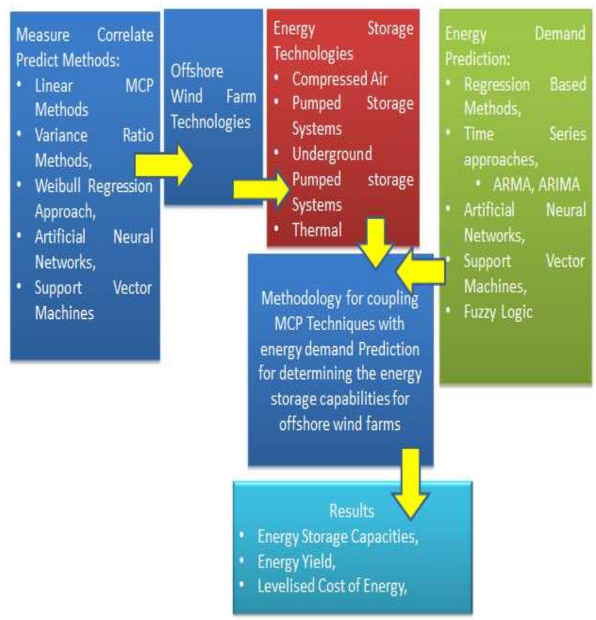

Figure 4: Integrating MCP techniques with energy demand prediction models.

Different methodologies for combining MCP techniques with energy demand prediction models in order to determine the energy storage capacity of offshore wind farms need to be explored. Figure 5 shows possible combinations between the several MCP and demand prediction methods. Every combination will need to be analysed and tested for its reliability and uncertainty. This will determine the best combination of MCP and demand prediction methods, which will provide the least uncertainty and error.

Figure 6 presents a flowchart for a generalised methodology being proposed and which will be applied in further work. This will be based on the minimisation of the errors and uncertainties in the wind prediction, in the energy demand prediction and those in the merged model.

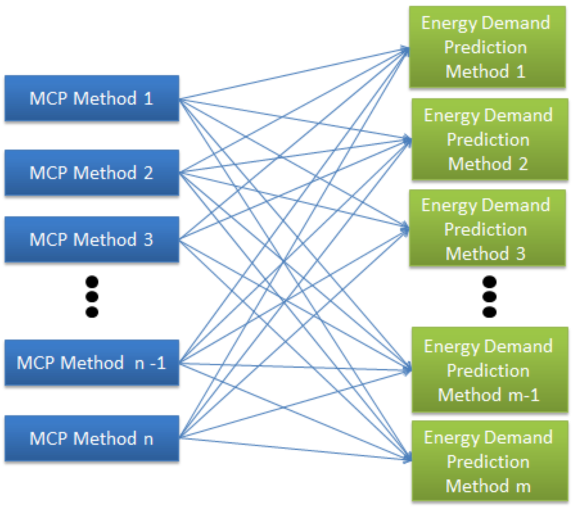

Figure 5: The possible combinations resulting from coupling different MCP methods and energy demand prediction methods.

The final outcome is to derive a value for an optimised energy storage capacity, energy yield and a minimum Levelised Cost of Energy taking into consideration the lifetime of the wind farm and energy storage infrastructures.

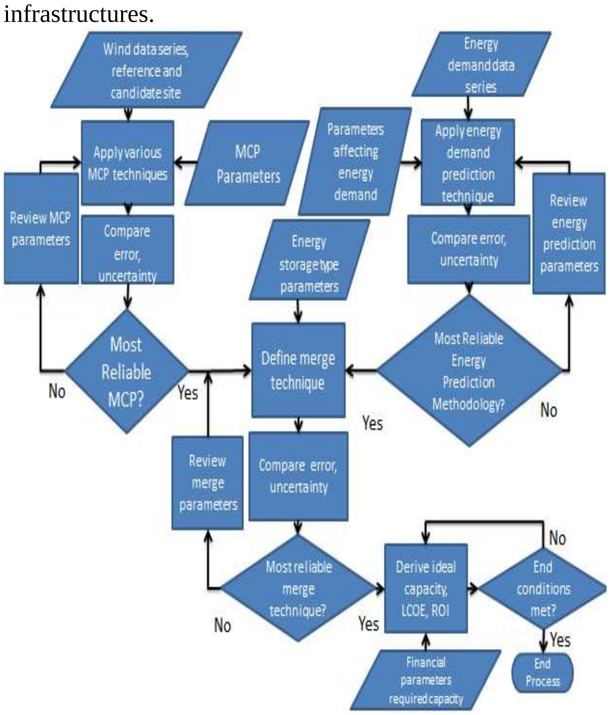

Figure 6: The proposed generalised iterative methodology in the form of a flow chart.

Figure 7 shows in detail how the available data will be utilised. In the case of the MCP technique, the long-and short-term data will be used to project the wind data at the target site. The energy demand data will be used to build the prediction model with some of the data being used to test the model. The comparison of actual data to the predicted data will be used to estimate the error and uncertainty of the model. Once the optimal MCP and energy demand prediction models are established, the available data will be used to establish the actual behaviour of the energy storage system according to the established strategy for its management. A model for its behaviour will be established, using part of the data available as test data. The comparison of the actual behaviour and the test data will establish the uncertainty of the model coupling MCP with energy demand prediction.

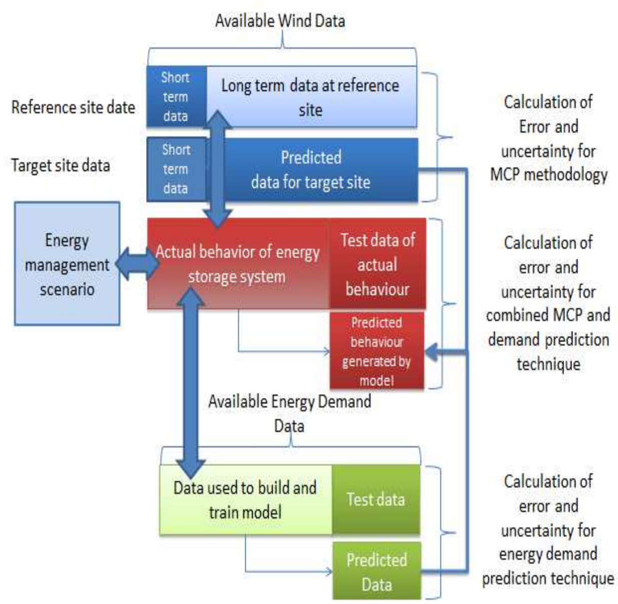

Figure 7: Utilisation of the available data to establish the model for the behaviour of the energy storage system.

6. Conclusion

The penetration of renewable energy can only be taken a step further if it is used in conjunction with energy storage. Despite the fact that accurate wind speed prediction is considered to be of fundamental importance for the evaluation of the wind resource at a candidate site, there is still no connection with energy storage and energy demand by end consumers. This paper highlights the research needs for addressing this matter, presenting a methodology for integrating MCP techniques with energy demand prediction models. The methodology depends on the capability of the various techniques to be merged together, giving a forecast for the storage and dispatch of energy from offshore wind resources. The accuracy of the model is defined according to its capability to provide a prediction with the least error and uncertainty. In the end, the model should be subjected to different scenarios in order to obtain an optimised energy storage capacity and an optimised wind farm size. The outcome is to use the model to calculate the Levelised

Cost of Energy and to make an economic feasibility study of the optimised system.

The application of the proposed methodology will address the several questions which have arisen as a result of the above analysis, namely as to how MCP techniques, energy storage and energy prediction techniques will behave when merged together as a single model. The outcome should be the optimised setup for the energy storage facility integrated in offshore wind generation plants.

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