

Intelligent Digital Triplets for Autonomous Machine Optimizations

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September 2021

*Submitted in partial fulfilment of the requirements for the degree of Doctor of
Philosophy*



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Faculty of ICT

DECLARATION

I, the undersigned, declare that the dissertation entitled: Intelligent Digital Triplets for Autonomous Machine Optimizations submitted is my work, except were acknowledged and referenced.

Foad Haddod.

September 2021

Acknowledgements

I would like to express my deepest appreciation to my supervisor Prof Alexiei Dingli for all his help and advice with this PhD. Also, special thanks to the University of Malta PhD committee for their valuable feedback.

I would like to extend my sincere thanks to the STMicroelectronics company for giving me the opportunity to conduct this applied research. I am also grateful to the two external examiners for the time they took to review my PhD thesis.

I'm deeply indebted to my wife Maymana and my daughter Rufan. Without their tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study. Finally, I would like to extend my sincere thanks to my family, especially my father, mother, and brother Dr Abubaker Haddud for their encouragement and support all through my studies.

Abstract

This project presents a novel technology named Intelligent Digital Triplet (IDTR) to overcome the traditional Intelligent Digital Twin (IDT) issues. These issues are: reconfigurability, mission critical services, portability, and automation of time critical processes. IDTR targets complex manufacturing processes, and it improves their overall productivity. Also, this project aimed to design a new Digital Triplet system within a semiconductor manufacturing facility. While an Intelligent Digital Twin (IDT) is a virtual replica of a process, product, or service with an Artificial Intelligence (AI) module, the Intelligent Digital Triplet (IDTR) builds upon an IDT and goes beyond its capabilities. The novelty of this project is in providing a fully autonomous virtual environment to act as a triplet replica to improve the performance of traditional IDT systems. More specifically, adding a feature to this new Digital Triplet system so that it becomes a self-trained virtual environment that learns from the errors it identifies and takes actions to rectify them. Consider a manufacturing process that is not producing the desired yield. It receives the same inputs which the system obtains and displays the same output as the live system. Traditional IDT systems would analyse the data and highlight the problem. With some more data crunching, it might also propose some changes to the system.

The Intelligent Digital Triplet (IDTR) builds upon an IDT and goes beyond its capabilities. It loads a virtual replica of the live process inside a sandbox that is referred to as a triplet in the developed system.

By using AI techniques, it starts optimising the virtual system and then analyses the effects of the changes. It only proposes changes once the AI model has tried the new parameters, and it is confident of their effectiveness. The AI algorithms used by the IDTR are intelligent agents that virtually roam the IDTR environment, in a manner similar to Hummingbirds, and we named them Intelligent Digital Humming Tools (IDHT) in this project. They are AI agents that are capable of taking autonomous decisions, reacting to the environment's stimuli, acting proactively, and communicating with each other. IDHT tools roam in the virtual environment to observe pre-determined conditions and parameters about the different elements of the virtual production environment. While the IDT visualizes real-time insights about the process to explain what happens in the physical production lines, the developed IDTR system tackles any predicted behaviours and takes more effective autonomous decisions.

This project uses a case study of an international semiconductor manufacturing company

(STMicroelectronics) to digitize and automate their physical production processes. The developed IDTR facilitates product design, improves the planning and incorporates more effective predictive maintenance practices. The developed IDTR system showed great potential in root-cause analyses and predictive maintenance applications.

IDTR improved the overall prediction accuracy of the IDT from 78% to 93.8%. It has also improved the accuracy of Root Cause Analyses capabilities from 88% to 94.2%. Also, the developed IDTR system reduced unplanned equipment's downtime by 40%. Overall, such improvements could potentially lead to saving the adopters millions of Euros.

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1 Introduction

This part provides an overview of the research project that includes four subsections: Research Motivation, Research Questions, Objectives, and Thesis Structure.

1.1 Research Motivation

The digitalisation of the manufacturing industry fuelled the creation of sophisticated virtual models, which are referred to as Digital Twins (DTs) and this applies throughout all the stages of product realisation (Schleich et al., 2017). Since its inception, DTs have been used in many fields and have demonstrated outstanding potential. With the characteristics of ultra-high synchronisation and fidelity, convergence between the physical and virtual products is exhibiting high potential in product design, product manufacturing, and product service (Qi and Tao, 2018). ISO/FDIS 23247-1 (2020) standard has four parts:

1. Overview and general principles:

ISO 23247 standard explains the general idea of modelling physical assets and how it differs from one process to another depending on the available technologies for each use case. Each use case needs to consider the scope and the output context when modelling different physical entities. The standard also highlights the importance of synchronising between the Physical and Digital twins to visualise the physical edge's current context. In addition, it highlights the need for communication protocols between the two twins to apply constant optimisation processes.

2. Reference architecture:

Several developed DT systems have been mentioned in previous studies, and they were structured differently based on the use case. However, ISO 23247 standard introduces four domains that need to be used as an architecture reference when developing DT systems. The four domains are as follows:

- a) Observable manufacturing domain. This domain is about the collected data from the physical side to be used in DT platforms.
- b) Data collection and device control domain. This domain is also about the data collection side, and it handles the needed synchronising of any collected information.
- c) Core domain. ISO 23247 standard included this domain to provide standard management approaches about the DT and its operations. This domain hosts all

the DT services, including analytics results, simulation processes, and control on the modelling process and verifies any needed synchronisation.

- d) User domain. DT technology introduced several interaction methods and provided more friendly user experiences. ISO 23247 standard introduces this domain to define the best interaction method between the DT systems and other end-users. The end-users could be humans, smart devices, virtual agents, and other integrated applications that are not part of the DT platform. Furthermore, the standard includes clear guidance on how the domains mentioned above are functioned and implemented.

3. Digital representation:

DT is mainly used to visualise the different types of data, static or dynamic. ISO 23247 standard recommends some standards such as IEC 62264-2 when DT is used as a visualisation tool. It defines which data needs to be used by the core domain and which data needs to be visualised on the virtual models. This part considers the uniqueness of the data and makes decisions to classify them based on some domain standards.

4. Information exchange:

This part is responsible for the inner communication protocols between the DT different entities. It identifies multiple communication levels, including users, provided services by the different entities, and the communication between the physical and the virtual twins.

An Intelligent DT (IDT) for a production process enables the coupling of the production system with its digital equivalent, ensuring the minimum delay between data acquisition and creating the DT (Uhlemann et al., 2017). From our perspective, we define IDT as a Digital Twin that can be developed by merging the advances of AI, ML, and traditional DT in one system. We also define IDT as an innovative virtual environment that includes three main elements: virtual, intelligence, and automation. As a result, IDT can provide almost a full solution for several daily manufacturing challenges. In the coming years, it is expected that an enriched big data environment incorporating smart manufacturing concepts such as DT will further enable advanced analytics. However, it is expected that the need to incorporate subject matter expertise in solution design will remain (Moyné and Iskandar, 2017). Furthermore, the integration of data collection, planning algorithms and performance prediction of guaranteed cycle times with a high probability is still an open task (Furmans et al., 2017). Zhong et al.

(2017) stated that to implement intelligent manufacturing fully; it is essential to focus on; platform technologies such as networks, IoT, virtualisation, service technologies and smart objects. Finally, Posada et al. (2015) also stated that the scientific community, especially those in visual computing, will face new exciting research fields linked to the upcoming Industrial Revolution's challenges.

Nowadays, smarter technologies are being developed and tested by different manufacturers which will revolutionise the manufacturing industry. What is known as the fourth industrial revolution (Industry 4.0)¹ has provided a platform to develop smart technologies that attracted the interest of academics, researchers, and industry professionals alike (Hermann et al., 2016). Digitising and transforming manufacturing is becoming of interest to most manufacturing companies (Qi and Tao, 2018). Driven by emerging technologies such as the Internet of Things (IoT), industrial big-data, DTs and Industry 4.0, the concept of smart manufacturing will continue to grow (Tao et al., 2019), and it is expected that new technologies and methods will emerge in this domain. Figure 1 shows the most relevant Industry 4.0 technologies used in this PhD research project.

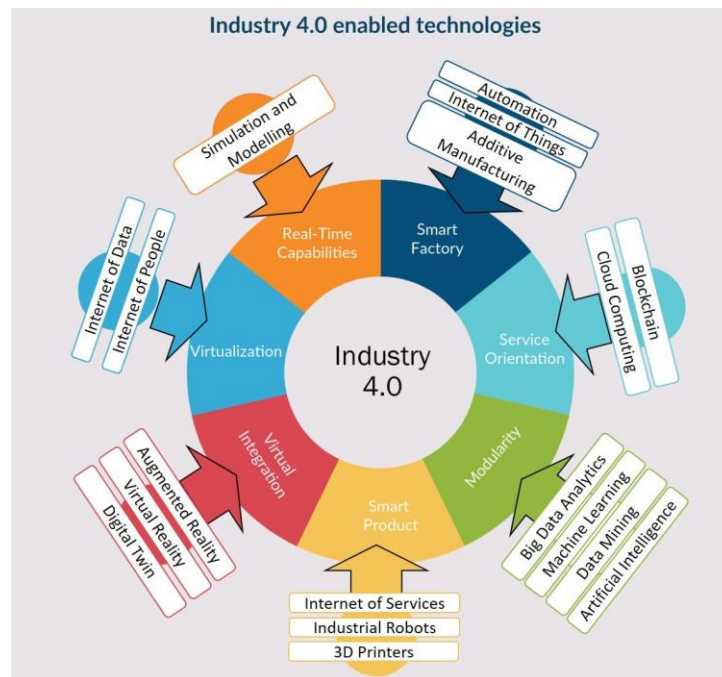


Figure 1: Most relevant Industry 4.0 enabled technologies used in this project (Source: Self).

As it can be seen from Figure 1, several technologies can be used to design a system that can collect, record, accumulate, and comprehensively process all data from product design until retirement (Qi and Tao, 2018). Those systems have been mostly used for

¹ "a paradigm that includes a new approach to production and changes in traditional, centralised control structures in favour of decentralised structures" (Szyman'ska et al., 2017, p.305)

fault diagnosis, cause-and-effect identification, predictive maintenance and improving performance analysis. In the area of product design and development (Tao et al., 2019), those technologies have been used to determine how to create effective real-time interaction between the virtual system and its physical twin. The next section highlights some benefits of implementing Industry 4.0 enabled technologies in multiple factories and how it has improved manufacturing processes towards better, cheaper, and innovative new products.

Several previous related publications to IDT technologies focused on the user perspective. Many previous studies highlighted the benefits of integrating AI models' output and visualising their predictions within the DT environments (Zhao et al., 2020; Danilczyk et al., 2019). Thus, DT is used as a visualisation tool to present multiple AI algorithms predictions that use the same streamed data. However, despite the valuable information added to the DT and the provided insights to help users make better decisions about their physical systems' live behaviours, this research focused on the intelligent aspect of the IDT technology and introduced a new concept that concentrates on the AI systems perspective. The idea is to create a new virtual sandbox when optimising a new IDTR and analysing possible changes. In such a way, the original IDT environment stays protected and available for users.

To conclude, traditional IDT systems would analyse data and highlight the potential problems. As a result, it can be used to propose some changes to the system. However, there is no way of testing the system apart from reconfiguring the physical machines involved in that process. Also, that makes the testing and validating processes time-consuming. All the predicted events require the IDT waiting for the changes to occur on the physical side. There are possible risks resulting from this approach that may include:

1. The training processes take a long time to collect enough data from the physical systems.
2. Assuming the training processes ended up with acceptable accuracy levels, the testing and validation processes would be time-consuming.
3. Any machines' downtime would be expensive, and it is not guaranteed to be solved due to any wrong predictions and changes.

IDTR avoids such risks by travelling to the future and simulating all the possible changes by optimising the predictions and analysing the effects of such changes. If the changes propose improvement to the IDT, the IDTR would make those changes; otherwise, the IDT system would keep the original configuration before the change.

1.2 Research Questions

This research aims to answer the following two main questions:

1. What are the limitations of Intelligent Digital Twins in general?
2. How to develop a triplet system including intelligent digital humming tools and use them to overcome traditional limitations of IDT systems?

1.3 Objectives

There are two main research objectives for this project, and they are as follows:

1. To develop an Intelligent Digital Triplet system which overcomes the limitations of the IDT that involves the design, development, testing, and validation of the developed system. Details about how this objective has been met can be found under sections 4.1.1, 4.2 and 5.2.
2. To develop virtual intelligent agents named Intelligent Digital Humming Tools and add them to the created IDTR system to make it more efficient to overcome common IDT challenges. Sections 4.1.1, 4.2.2 and 5.2 provide information about how this objective has been achieved.

1.4 Document Structure

This thesis consists of the following parts: the next section presents insights about key aspects contributing to the concept of the manufacturing of the future. Section 3 discusses Digital Twin technology and highlights its adoption within semiconductor manufacturing. Section 4 presents the methodology and methods used to execute this research, including details about the platform used and the adopted Big Data methodologies. Section 5 provides results and discussions. Section 6 presents the evaluation methods and results of the developed IDTR system. Section 7 presents the main research conclusion and information about the future work.

2 Manufacturing of the Future

This part reviews a number of trends impacting current manufacturing practices that will impact the future of the manufacturing sector. This part reviews the following topics: Industry 4.0 in manufacturing highlighting its benefits and challenges, Artificial Intelligent in manufacturing, Intelligent Automation in manufacturing, and Smart Manufacturing. It is essential to highlight that Industry 4.0 is an overarching concept that makes use of Artificial Intelligent to become intelligent. Artificial Intelligence is a crucial technology of the Industry 4.0. Whereas Intelligent Automation is the automation

of company processes using Artificial Intelligent. While Smart Manufacturing is the process of transforming all the physical manufacturing parts and processes into a digital format, ideally, each physical asset will have an identical virtual Digital Twin. The digital environment allows collecting data during production and inspection processes, assembly, and test processes. Figure 2 shows the difference between the concept of Industry 4.0, Artificial Intelligence, Smart Manufacturing, and Intelligent Automation. The adoption of these Industry 4.0 technologies will enable machines to detect fluctuations by themselves in the manufacturing process. This provides the manufacturing environments with smart manufacturing capabilities to respond in real-time and will require less human interference.

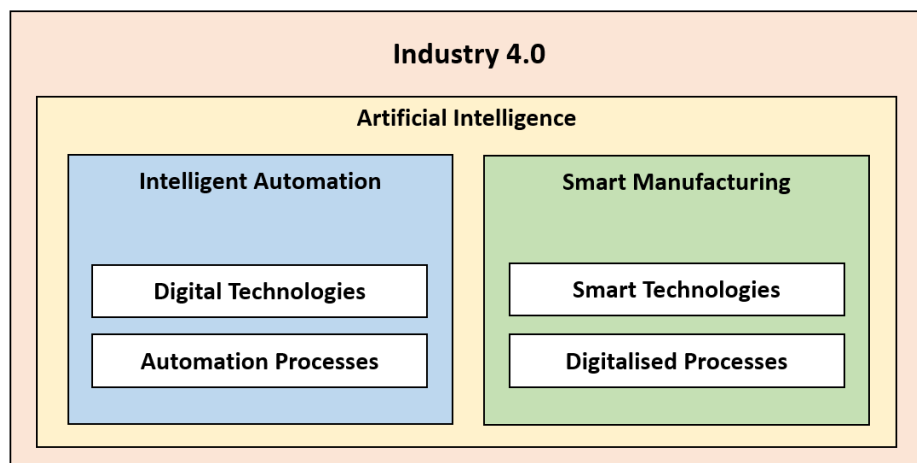


Figure 2: The difference between Industry 4.0, AI, Intelligent Automation and Smart Manufacturing (Source: Self).

As shown in Figure 2, Artificial Intelligence is one of the key technologies that come under Industry 4.0. The concepts of Intelligent Automation and Smart Manufacturing have overlapping similarities and differences. For example, Intelligent Automation deals with Digital technologies and Automation processes. At the same time, Smart Manufacturing deals with achieving a level of digitalisation and developing more smart manufacturing processes. Details about each of the mentioned content on figure 2 will be described in sections 2.1, 2.2, 2.3, and 2.4.

2.1 Industry 4.0

Industry 4.0 is a concept that refers to the fourth industrial revolution enabled by the use of the Internet of Things (IoT) technologies to create smart products, a smart production, and smart services. The use of Industry 4.0 applications holds an excellent opportunity to realize sustainable industrial value creation on three dimensions: economic, social and environmental (Stock and Seliger, 2016). Industry 4.0 has emerged as one of the most

discussed concepts and has gained significant popularity in both academia and the industrial sector (Buer et al., 2018). In manufacturing, Industry 4.0 significantly influences the production environment with radical changes in the execution of operations (Sanders et al., 2016). In order to successfully implement Industry 4.0 technologies, it is essential to secure and effectively handle data and protect cross company communication against attacks (Wallis et al., 2017). In manufacturing and production, the purpose of the Industry 4.0 initiatives is to bring together IT technologies and production processes to enable the emergence of smart, connected manufacturing (Lalanda et al., 2017). In general, Industry 4.0 consists of several technologies and methods connected to the Internet of Data (IoD) (Peng et al., 2019), Internet of Services (AL-Salman and Salih, 2019), and Internet of Things (Askar, 2019) leading to improved overall quality, productivity and its integration can be categorized as; horizontal integration, vertical integrations and end-to-end engineering integration (Manogaran et al., 2017).

2.1.1 Benefits of Industry 4.0

It does not take much effort to understand the magnitude of Industry 4.0 influence on many industries, including its impact on supply chain and the customer. More specifically, and from the manufacturers perspective, Industry 4.0 technologies implementation improved product quality, manufacturing productivity, and the overall performance of different manufacturing industries (Rüßmann et al., 2015; Horvat et al., 2019). However, industry 4.0 implementation has been more capitalised by the developed countries (Roland Berger, 2016). Furthermore, Industry 4.0 technologies have introduced new production technologies to enhance production flexibility and time leading to reduced costs (Dachs et al., 2019). Noticeably, the impact of all the mentioned technologies in section 2.1 has touched the different levels of manufacturing processes from the shop floor to project management, and product designing levels (Cebeci, 2019). Also, all the technologies mentioned above and many more can influence ‘Product Safety and Quality’, ‘organisational agility’, and production flow in a positive way. As a result, this makes any possible investment in more use of Industry 4.0 technologies more accessible, organised, and beneficial as well (Sony and Naik, 2019). In my opinion, I believe that it can be difficult to accurately measure the significant benefits from Industry 4.0 because of:

1. The vast number of developed applications and systems,
2. The provided broad solutions for a wide range of different technical and management issues, and
3. More technologies are developed and considered as part of Industry 4.0.

However, all the enabling technologies can transfer current and near-future industries towards developing better, accurate, and safer manufacturing environments (Majstorovic et al., 2019). Despite all the promising benefits, the adoption of Industry 4.0 technology still faces some challenges. The next section highlights some of the significant challenges that usually face the implementation of Industry 4.0 in manufacturing in general.

2.1.2 Challenges of Industry 4.0

In its early implementation stage, Industry 4.0 faced a significant challenge related to the existent centrality of many systems in most industries. Implementing Industry 4.0 requires restructuring of such centrality, and this becomes a very complex challenge. Also, it has been clear from the beginning that Industry 4.0 will impact manufacturing processes infrastructure, employees, and some existent used technologies (Sony and Naik, 2019). On the other hand, most of Industry 4.0 technologies aim to change the way work is done nowadays by providing more decentralised solutions for several challenges (Lasi et al., 2014).

Even though many industrial environments have substantially improved on the adoption of some Industry 4.0 technologies, most of Industry 4.0 paradigms in manufacturing have also faced several challenges. That includes ingesting data from multiple sources, handling different sources, and different data formats. Another challenge is the convergence of the physical system and the gathered data (Tao et al., 2019). The industry settings generally include a large number of operations and process. These have been enhanced through the installation of data sensors located in various machines which measure and log a multitude of readings. Predicting the future is not something easy, but it is a very desirable feature, especially when one considers issues such as machine downtime is one of the largest sources of production loss (Luo et al., 2018). With the DT system, such challenges changes. Because the IDT performs these calculations without the need to prompt it by anyone and it will continuously analyse

different supply chain performance and quickly simulate the ideal and most efficient scenario for any particular job (Zheng et al., 2018). IDT system does so by looking at the current production, predicts potential downtime, slots in new tasks in the pipeline and makes suggestions based upon deadlines such as delivery targets, the material available. All of this was done at the click of a button. It is the ultimate aim of the IDT to ensure that the production plant is optimised at all times, and it is continuously readjusting those optimisation parameters in a real-time based upon changes which occur on the factory floor. This will allow the factory to organise predictive maintenance, thus shifting the managements strict dependency on planned events, thus allowing for real-time actions from actual events (Fernandes et al., 2018). Furthermore, the proposed IDT system will not only predict a potential failure, but it will also help the management identify the root cause of the issue. Because of this approach, a few of the failures might be eliminated from the production cycle, while others will be handled promptly. In doing so, unplanned downtime can be massively reduced or even eliminated in some cases, thus maximising profitability and equipment reliability.

2.2 Artificial Intelligence in Manufacturing

Artificial Intelligence, as part of Industry 4.0, has been investigated and implemented to make manufacturing more efficient and intelligent. Thus, the idea of improving system performance in a different manufacturing environment has become essential to enhance productivity. AI has been used in several manufacturing environments to invest the advanced computing power to develop more adaptive and intelligent machines. This resulted in extensive dependence on AI to create intelligent manufacturing processes (Heiden et al., 2021). Several AI-enabled technologies are used individually or merged within platforms to extend intelligent features to the manufacturing industry in general. Thus, AI has seen multiple generations that are used differently. Moving from centralised applications to decentralised AI systems, AI was used to control multiple manufacturing processes and make them more intelligent (Yao et al., 2017). In general, AI acts as a driving force that powers the manufacturing industry nowadays. According to Ransbotham et al. (2017), 85% of executives believe in the concept of AI and its impact on their companies. Also, AI has been described in several recent studies as a key that plays a significant role in the modern manufacturing industry (Zeba et al., 2021; Bag et al., 2021).

Overall, AI impact differs from one application to another as it depends on the level of incorporation. However, several previous studies sought to design a road map that explains AI's possible general impact in the manufacturing industry. For example, Sharp et al. (2018) highlighted the impact of AI on manufacturing automation, and they concluded the difficulty of accurately measuring the interest level in such technologies. Applications such as "Decision support", "Digital knowledge management: data management", and "Lifecycle management" were reported as areas already impacted by the AI technologies. Another study focused on the importance of AI technology in the digital transformation processes (Brock and Von et al., 2019). The study summaries different areas impacted by AI technology, such as data and intelligence. Also, the study stated that the main focus is on self-learning AI projects. The manufacturing industry adopted many AI applications categorised based on the scope of the services and their context. For example, Supply Chain, Decision Making, Product and Services, and Smart production are areas where AI have been already implemented (Cioffi et al., 2020; Cunningham, 2021). This research focuses on the self-learning type of AI systems and targeted two main manufacturing applications categories: decision-making and Smart Production and automation. One of the proven successful technologies is Deep Learning (DL) (Wang et al., 2018). On this basis, researchers continue to investigate new technologies to design smarter manufacturing environments. The fact that manufacturing processes generate large amounts of data with a high dimensionality makes it necessary to use cutting-edge technologies such as AI, ML, and deep learning (Wang et al., 2018). Using these technologies has great potential in enhancing existing statistical tools due to their reputation. Specifically, these technologies are reliable when working with all the data challenges and are able to explore new insights from large, collected data (Essien and Giannetti, 2020). The importance of DL technology has been seen in different areas and different use cases, and this resulted in promising outcomes improving multiple manufacturing industries. Examples of improved processes are predictive maintenance (Nguyen and Medjaher, 2019; Namuduri et al., 2020), product development (Lai et al., 2021; Krahe et al., 2020), and supply chain management (Kilimci et al., 2019; Husna et al., 2021). DL uses data sets as input and measures correlations between the input and the targeted output values. Such data-driven approaches have been improved using DL technology, allowing the creation of non-linear correlations between the input features.

Another important technology that can be used is Big-Data technologies where Big-Data can comprehensively promote the future of smart manufacturing processes (Qi and Tao, 2018). “Big-data is high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization” (Özköse et al., 2015, p.1043). As a result, the use of Big-Data can be implemented to support smart manufacturing to provide more efficient production plans and propose more intelligent shop floor schedules (Tao, Qi, Liu and Kusiak, 2018). A new generation of Machine Learning (ML) that has recently received more considerable attention is called Generative Adversarial Networks (GANs). GANs are recent models that are made of two main concepts: DL and Generative Learning. It was another attempt to simulate how humans’ brain works and, correctly, how the humans’ memory works (Hanke, 2012). This type of learning was introduced in the past, where some research defined Generative Learning as a ‘brain process’ (Witrock, 1992). With the idea of merging two or more different types of ML; GANs was introduced in 2014, and it has received many attention (Goodfellow et al., 2014). GANs are made of two models to compete against each other. Goodfellow et al. (2014, p.1) stated that “a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G”. Since then, GANs has shown an enormous contribution in multiple fields of image processing. GANs were initially used to generate images from random noise that can be described as real images in some applications (Jiang et al., 2019). Nevertheless, in a short time, GANs has been implemented in multiple tasks and applications (Bau et al., 2019). To sum up, GANs has successfully provided promising results, and it was described as “one of the most exciting recent breakthroughs in machine learning as a subfield of artificial intelligence” (Ling et al., 2019, p.1). This PhD research focused on using three of the leading developed GANs models as follows: 1) Semi-supervised GANs, 2) Image synthesis and manipulation using GANs, and 3) conditional GANs. GANs have been used in several manufacturing applications, including the semiconductor manufacturing industry. Several classification challenges were handled by using this type of ML and yielded promising results. Decision Support Systems, Defect Detection, and Predictive and Proactive Maintenance are good examples where GANs have been efficient (Singh et al., 2002; Xu and Yan, 2020). Another implementation using GANs was in the visual defect segmentation applications. GANs models were used to process signal images that had been created using limited

collected real data from an industrial environment (Seo et al., 2020). In summary, although several promising positive results have been reported from the use of some smart manufacturing technologies within several manufacturing environments, “there are still some limitations and significant challenges for further exploration” (Wang et al., 2018, p.154). Thus, there is a room for development and a need to investigate more technological advances to implement smarter manufacturing industries. Overall, more attention has been given to the approach that has been used in this research using GANs to generate synthetic data that can be used over a wide range of applications. Manufacturing environments that have challenges to collect enough data to train ML models can use such an approach to generate more data that is similar to any missed data from the real systems (Jain et al., 2020; Singh et al., 2020; Kaloskampis et al., 2020; Chen et al., 2021).

2.3 Intelligent Automation

The concept of automation can be defined as the use of advanced technologies to replace traditional systems that were built by merging human and equipment by more automated platforms. Thus, developing more efficient systems to enhance productivity and the provided quality (Shekhar, 2019). Nowadays, there is an interchangeable use for both Artificial Intelligence (AI) and automation terminologies. While they are different, they can be combined to enhance manufacturing productivity. One of the main differences can be understood from the definitions of both technologies. Whilst automation means developing either software or hardware capability of automating processes without the need to have a human intervention, AI is defined as an engineering technology that aims to develop more intelligent machines (Shekhar, 2019). Furthermore, to develop an autonomous production control system, several factors should be considered. Besides, there is a need to understand the correlation between the manufacturing process elements and try to establish a link between the different mentioned factors. For example, “machine and process flexibility, plant availability, and process stability” (Glawar et al., 2019, p.482). Several kinds of research have concluded that Artificial Intelligence technologies can be used to automate a wide range of tasks including those that need human intervention to execute (Ali and Frimpong, 2020; Shekhar, 2019; Donepudi, 2018; Bolton et al., 2018). While some studies showed a high level of optimism to provide accurate results that can overcome some outstanding challenges, those approaches could easily create a tension between the developed AI systems and the

experts Heer (2019). The manufacturing industry is no exception. In many cases, the productivity effect was used as a golden parameter to evaluate the outcomes of both human and automated AI systems. Despite the fast-growing concerns about designing and implementing fully automated systems for the future of some industrial environments, automation implications still lack a clear conceptual framework (Acemoglu and Restrepo, 2018).

Different and more beneficial intelligence work frames have been proposed towards more automated manufacturing processes. For example, Wen-Chin et al. (2018, p.9) proposed an AI manufacturing system 'IMS' for 'plastic injection moulding (PIM)' manufacturing process and develop "a multiple response optimization systems of PIM". The proposed work merged three subsystems: "intelligent parameter optimization system of 'PIM' process, database management system, and real-time monitoring and control system" (Wen-Chin et al., 2018, p.13). The researchers concluded very positive results to enhance the investigated 'PIM' manufacturing processes. Also, Wen-Chin et al. (2018) concluded an interesting compression summary about 'manufacturing automation modelling' and control through four industrial revolutions and mainly highlighted the influence of digitization on individual and isolated equipment. Besides, the study focused on the possible impact of digitization on large-scale manufacturing production processes to discuss all possible challenges when there is a need to enhance used technologies to become more automated. The study resulted in an exciting conclusion that researches in data and system modelling community have developed creative and innovative solutions that can be used to resolve much automation challenges (Morel et al., 2019).

Another promising approach was proposed at the beginning of 2019 aimed to design a novel platform that can automate a very complex semiconductor manufacturing process. The project proposed a novel approach to enhance the overall effectiveness of equipment by implementing semi-automated assembly and testing processes. Thus, decreasing any possible drop-down time while the equipment is not producing any products due to unforeseen failure events. The used approach recommended combining both AI and different automation techniques to predict the possibility of when a machine can stop and interact accordingly and in advance to ensure keeping machines producing products. The research project concluded a higher possibility to overcome automation challenges due to the use of multiple technologies such as Digital Twin, Big Data, Deep Learning, and AI (Dingli and Haddod, 2019).

2.4 Smart Manufacturing

Smart Manufacturing (SM) refers to the use of smart technologies within the manufacturing industry. It is considered as an improved version of Intelligent Manufacturing (IM), reflecting the magnitude and impact of smart technologies such as the Internet of Things, Cloud Computing, Cyber-Physical Systems and Big Data (Yao et al., 2017). “Cyber-physical production systems (CPPS) consist of autonomous and cooperative elements (e.g., Smart Machines) and sub-systems (e.g., Smart Factories)” (Francalanza, Mercieca and Fenech, 2018, p.486). SM refers to the use of advanced data analytics to improve system performance and decision-making (Wang et al., 2018). Technically, Smart Manufacturing can be defined as the process of an “emerging form of production integrating manufacturing assets of today and tomorrow with sensors, computing platforms, communication technology, control, simulation, data-intensive modelling and predictive engineering” (Kusiak, 2018, p.518).

Smart manufacturing systems include two main elements that are data management and analysis. These provide real-time actionable information that can be used to optimize and build system intelligence into manufacturing operations (Kuhn and Ahrens, 2017). Smart manufacturing is becoming the focus of global manufacturing transformation and upgrading. This was mainly because of the advances in new-generation information technologies, especially Big Data and DT, (Qi and Tao, 2018). With the aid of the enabled industry 4.0 technologies, “the concept of smart manufacturing will continue to grow, and new technologies and methods will emerge in the manufacturing intelligent systems domain” (Dingli and Haddod, 2019, p.3). Smart manufacturing initiatives led to factories becoming more digitalized, and the concept of Digital Factory was introduced. “The aim of the digital factory is the holistic planning, evaluation and ongoing improvement of all the main structures, processes and resources of the real factory in conjunction with the product” (Francalanza, Borg and Constantinescu, 2018, p.136).

2.5 Chapter Summary

Overall, this research utilised Artificial Intelligence to develop Intelligent technology that improves the performance of manufacturing processes. Smart manufacturing was chosen to introduce a novel approach to help develop Intelligent manufacturing environments. On the other hand, the use of the Intelligent Automation in our work well-suited to the nature of the manufacturing facility and processes of the company that this

research is based on. Thus, to facilitate implementing a novel smart semiconductor manufacturing process, it is vital to design an intelligent digital twin system that manages Big Data and leverages the interconnectivity of machines in order to reach the goal of intelligent, resilient and self-adaptable machines. “Digital twin technology is capable of integrating various technologies in one robust system” (Dingli and Haddod, 2019, p.14). Figure 3 shows a number of cutting-edge technologies that can be used within the DT.

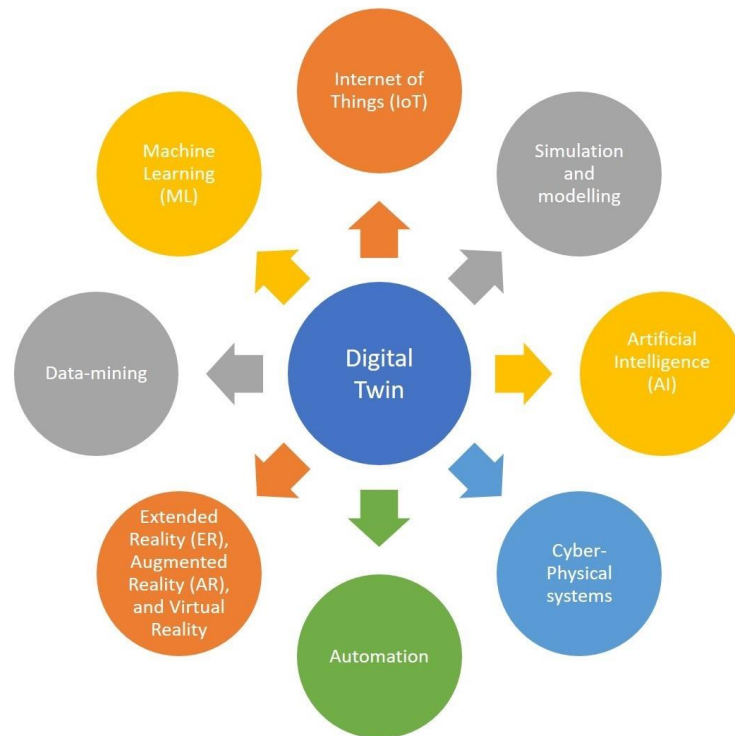


Figure 3: Cutting-edge technologies that can be integrated with Digital Twin environments (Source: Self).

In summary, the manufacturing sector has been heavily influenced by the adoption of several technologies that made its processes and operations smarter. The concept of Industry 4.0 continues to reshape the manufacturing sector and more Artificial Intelligence applications have been embedded. This allowed manufacturing companies to achieve more automation levels which I expect to see more of in the future.

3 Digital Twin Technology

This part provides information about DT technology. This includes an overview of its concept, and its use within the semiconductor industry, some key implementation challenges, its use as a base for Machine Learning, human-computer interaction, and Extended Reality in DT systems.

3.1 The Concepts of Digital Shadow, Digital Twins, and Digital Triplet

Digital Shadow (DS) technology aims to digitalise any production system, assuming it can generate and share data with other systems (Ehrhardt and Hoffmann, 2020). The data flow in DS is always one way from the physical edge to any other virtual systems that can apply analyses and present multiple new insights. “The Digital Shadow can be the virtual representation of an industrial asset or the product as well as an aggregated structure like a working station” (Brecher et al., 2019, p. 9327).

The DT term is not new, and it was first introduced by Dr Michael Grieves, in 2003, in his Executive Course on Product Management Lifecycle (PML) at the University of Michigan in the United States (Grieves, 2014). What is new; however, is the recent interest in the digital twin concept and the applications that are fuelled by the emergence of a digitalized manufacturing, cyber-physical systems, and the need to gather large amounts of data and process such a vast collection of data sets (Schleich et al., 2017). DT allows two-way connections between the physical twin and the virtual representation. However, the traditional definition of the DT is about reflecting the geometric dimensions, shapes, and other attributes of physical objects (Wang and Luo, 2021). Also, DT needs to map all the logic of the processes and behaviours of the physical entities (Chen et al., 2020).

Moreover, the concept of Industry 4.0 has also further impacted the visibility of DT applications within different sectors. “The digital twins describe the current state of a product, process or resource. Each digital twin is a multi-dimensional model that empowers applications to create better products, more quickly and efficiently” (ISO/FDIS 23247-1, 2020, p.1). A DT system consists of three main parts; the physical product to be “virtually twinned”, the virtual product mimicking the physical product/twin and the connected data that ties the physical and virtual products (twins) together (Tao et al., 2019). Thus, the main objective of a DT system is to design, test, manufacture and use the virtual version of the physical product, process, operation, or

system (Grieves and Vickers, 2017). Since its introduction, the DT concept has been presented in several ways. For example, Boschert and Rosen (2016, p.59) state that “the vision of the DT itself refers to a comprehensive physical and functional description of a component, product or system, which includes more or less all the information which could be useful in all the current and subsequent lifecycle phases”. It is also defined as the creation of virtual models for physical objects in the digital world to simulate their behaviours (Qi and Tao, 2018).

The DT system is a hierarchical system of mathematical models, computational methods, and software services, which provides near real-time synchronization between the state of the real-world process or system and its virtual copy (Borodulin et al., 2017). Furthermore, the system can consistently provide all subsystems with the latest state of all the required information, methods, and algorithms (Brenner and Hummel, 2017). In a factory setting, a DT system is about creating and maintaining a digital representation of the real world of the factory and supporting its management and reconfiguration through optimization and simulation tools, which are fed with real and updated factory data (Kuts et al., 2017). Based on these definitions, Tao et al. (2019) identify three main characteristics of a DT system; real-time reflection; interaction and convergence; and self-evolution. Realtime reflection is a crucial feature of any DT system. The included communication middleware within the DT system should offer real-time interworking environments that provide an accurate reflection of a virtual model concerning physical asset and time synchronization between each simulator (Yun et al., 2017). DT systems allow real-time monitoring of the status and progress of the physical ‘twins’ through real-time data collection, data integrations, and analysis (Qi and Tao, 2018). On the other hand, the digital twin characteristic of interaction and convergence includes three main aspects; interaction and convergence in the physical space, interaction and convergence between historical data and real-time data; and interaction and convergence physical space and virtual space (the twins) (Tao et al., 2019). Finally, the ‘self-evolution’ characteristic of digital twin refers to the ability to update, in a real-time continuously, the acquired data so that the virtual models of the digital twin system can be continuously improved by comparing the physical and virtual twin design and configurations (Tao et al., 2019; Tuegel et al., 2011).

The concept of Digital Triplet (DTR) has emerged recently, and it was introduced in different ways. Unlike Digital Shadow systems, the developed system in this project introduces multiple ways to flow data between different domains. While a

two-way data flow system was used to connect the physical and the virtual representations, another two-way connection was implemented between the DT and the developed system. The architecture of the developed system uses the IDT system as a core domain to automate the entire manufacturing process. For example, Gichane et al. (2020) introduced the concept as an extra layer to the DT architecture to enhance its intelligent capabilities. The introduced extra layer was used by integrating the ML pre-trained model to detect objects from authentic captured images and the DT system. Also, multiple control systems were used to simulate the general operations of the related physical entities. However, the used DTR concept was similar to the concept of the IDT system that has already been used in previous studies. The core domain of the implemented DTR was connected directly to the physical side, and the used ML model classified the captured images. In addition, another approach was introduced to provide more intelligent automation capabilities to the DT systems (Talkhestani et al., 2019). The study compared different methodologies of developing IDT systems from previous studies, and it introduced a new IDT system architecture using multiple ML models to control multiple physical assets and different data sets. However, this paper's introduced methodology mimicked the traditional IDT concept in adding an extra layer to contain the used ML models and feed their output into the digital replicas to implement "what-if-scenarios". The above two studies rely on the availability and quality of collected data from the physical side.

In this thesis, the developed system handles such a challenge, and it generates synthetic data to measure the impact of any automated recommended actions. Also, a standard modelling approach was used to handle multiple events. An auto feature selection function was added to the developed system to avoid any manual changes when training a new model using a different set of features is needed. A significant difference between this research and the previous studies is the ability of the developed system to validate the ML models' predictions before the IDT makes actions. In the two above-mentioned examples, all the used ML models are pre-trained and directly integrated with DT, and these settings are risky when any data issues occur. Any incorrect or missed data will be results in inaccurate optimisation or incorrect classification outputs. In other scenarios, it may result in issues in the entire IDT system architecture, particularly the synchronous type. Furthermore, none of the similar previous studies to this research introduced any approach of testing the impact of any made decisions, and they relied on

pre-identified statements (Umeda, et al., 2019; Gichane, et al., 2020; Talkhestani et al., 2019). Perhaps the used implemented methodologies limited measuring such an impact. The next section explains the concept of Digital Twin within Semiconductor manufacturing industry.

3.2 Digital Twin and the Semiconductor Industry

The digitalisation of manufacturing fuels the application of sophisticated virtual product models, which are referred to as DTs, and this applies throughout all stages of product realisation (Schleich et al., 2017). Since the concept of DT was proposed, it has been applied in many industrial fields and has demonstrated its great potential (Dingli and Haddod, 2019). DT, with the characteristics of ultra-high synchronisation and fidelity, convergence between physical and virtual product, has high potential application in product design, product manufacturing, and product service (Tao et al., 2019). “Industry 4.0 is one of the most prevalent subjects in production engineering, and intelligent DT technology acts as an essential element of this fourth industrial revolution” (Dingli and Haddod, 2019, p.6). An intelligent DT for a production process enables coupling of the production system with its digital equivalent as a base for optimisation with a minimised delay between the time of data acquisition and the creation of the DT (Uhlemann et al., 2017).

Semiconductor manufacturing processes are considered as “the most capital-intensive and fully automated manufacturing systems”, and usually there are a massive number of similar equipment and tools employed in one processing line (Khakifirooz et al., 2018, p.990). This research was based a collaborative work between STMicroelectronics and the University of Malta. The company has sophisticated manufacturing processes that have been utilised to conduct multiple research projects that I executed. The amount of gained knowledge and collected results positively contributed to the decision of implementing the IDT research on semiconductor manufacturing processes. Thus, it is crucial to design an intelligent DT system that manages the ingested Big Data of those manufacturing processes and leverages the interconnectivity of the machines in order to reach the goal of intelligent, resilient and self-adaptable machines (Lee et al., 2015). Based on that, DT interacts with these physical entities in the semiconductor factory together with their functions (Balta et al., 2018). In the last three years, the increased intention has been giving to digital

manufacturing to open new opportunities to invest collected digital data and improve decision making (Cavalcante et al., 2019). “Microelectronics manufacturing industry is characterised by increased complexity, analysis, integration, distribution, data sharing and collaboration, all of which is enabled by the big data explosion” (Moyne et al., 2018, p.291). Thus, that makes it challenging to design a perfect virtual environment for such complex assets. However, some previous studies used digital technology to visualise innovative intelligent manufacturing systems’ results. For example, Moyne et al. (2018) highlighted the possibility to invest the Digital Twin advances to overcome the primary challenges of microelectronics industry smart manufacturing. Besides, the proposed work focused on the security of microelectronics manufacturing process and concluded optimistic initial results. While Bao et al. (2019, p.534) proposed an interesting “approach of modelling and operations for the digital twin in the context of manufacturing”. The research concluded positive findings to reduce manufacturing processes effectiveness, “improve logistics accuracy rate and reduce machine downtimes” (Bao et al., 2019, p.552). Another use of the Digital Twin technology in semiconductor production was at the end of 2018. Waschneck et al. (2018) proposed a novel approach of using Digital Twin to adopt deep learning techniques in the semiconductor industry. The developed system aimed to “automatically develops global optimal scheduling solutions without human intervention” and shown a significant improvement in the delay of scheduling processes from 17% to 1.3% (Waschneck et al., 2018, p.306). Another novel approach was proposed to improve processes optimisation and used a semiconductor industrial case study. However, the suggested system focused mainly on data-driven modelling use to perform Big Data analytics using historical data (Stojanovic and Milenovic, 2018). Supply chain nowadays provides massive data about the manufacturing environment that include machines, production lines, activities, processes, and systems. For example, the use of RFID and tags during supplier, manufacturing and transportation generates massive supply chain data (Dai et al., 2020).

Thus, companies are developing new analytic tools to extract better meaning to help them to improve their performance and decision-making processes. With the benefits of multiple technologies like Machine Learning, Big-data, and Artificial Intelligence, maintenance processes can be improved (Susto et al., 2014). With the amount of collected data, the traditional descriptive maintenance tools had to be changed. Descriptive maintenance techniques provide historical information about equipment maintenance operations. As a result, we can know what happened to the equipment

before facing the current failure event (Nemeth et al., 2018). On the other hand, Predictive Maintenance focuses on when failures might occur using data analytics such as Big Data, Data Mining, and Machine Learning. The idea here is to develop a model that can detect future failures by analysing historical data about previous fails events (Curran and King, 2019). In contrary, Prescriptive Maintenance techniques aim to answer the question of what is going to happen and what the best reactions will be? Moreover, try to suggest the best maintenance strategies. Having such features can improve the life-cycle costs, safety, and maximising operator's availability (Kuhlenkötter, 2019).

Recently, several published articles proposed accurate solutions and systems to improve the capabilities of predicting failures before they occur in manufacturing production lines. For example, Whitaker et al. (2018) proposed a data analysis tool that measures predictive maintenance. The project aimed to reduce the amount of product waste, and it summarised an accuracy of 100%. Also, it showed the ability to predict a condition of grinding tool performance. However, achieving accuracy of 100% is rare because industrial processes are typically very noisy so that such a high level of accuracy is hard to achieve. In addition, King and Curran (2019) summarized the possibility of using machine learning technologies to automate predictive maintenance strategies. The article proposed a summary of using different machine learning algorithms and developed a new model that demonstrated collected data from some equipment. Most of the semiconductor manufacturing processes contain different types of equipment that contain different quality control sensors that can be used to explain and monitor the status of the equipment (King and Curran, 2019) Overall, there are limited previous studies that have proposed a final design for a Digital Twin system that tackles an entire microelectronics manufacturing production line. Thus, the developed approach would enhance the performance of such manufacturing processes and would improve the overall productivity and achieve better levels of equipment automation. Some previous studies highlight some of the DT benefits in semiconductor manufacturing as following:

- DT can solve various business problems in different industries, and semiconductor manufacturing is no exception. Semiconductor manufacturing industry has a vast number of challenges about yields, productivity, and management. DT handles most of these challenges and provides unexplored insights about the entire manufacturing processes (Tao and Qi, 2019).

- Improving the accuracy and precision of several critical decisions. DT can continually provide analytics and give a more comprehensive view of multiple manufacturing processes (Tao et al. 2018).
- Semiconductor manufacturing is such a complicated process, and it generates a massive amount of data. DT can easily handle this challenge and visualise all the collected data (Patel et al., 2018). However, visualisation of numeric data is easier than visualising complex processes and complex data. The next section talks about DT key technologies and some implementation challenges.

3.3 Digital Twin Implementation Challenges

There has been a surge in DT research and application in different industries, and some industrial leaders begin to introduce DTs into their product offerings (Tao et al., 2018). Similar to many technologies, DT requires many elements and integrated technologies. However, and as it has been mentioned so far, there is no clear approach that can be implemented to design a DT system for various purposes various purposes, and it has always depended on many factors. For example, the complexity of the physical twins; the amount of the gathered real-time data; and the accessibility to the physical assets data. On the other hand, many published articles introduced and proposed a set of concentrations for developing DT systems. For instance, Tao, Cheng, Qi, Zhang, Zhang and Sui (2018) summarize essential aspects that should be considered when designing a DT system that include the intelligent perception, data-driven construction and management, and the perception of the service. Although the paper suggested five aspects seem to summarise the key requirement to develop DT systems, the paper mention several challenges such as 'synchronisation and fidelity', the required processing capabilities, and most importantly, the possibility of deploying ML technologies in DT systems. Modoni et al. (2019) highlighted a real challenge that should be overcome; that is the difficulty of designing a comprehensive Digital Twin system that can handle massive data about an extended period's activities. Furthermore, Wang and Wang (2019, p.3894) concluded that the DT main challenges are related to two main aspects: "data utilisation and connectivity". According to Kaur et al. (2020) the implementation of DT faced several challenges that can be summarised in three main categories:

1. Connection between physical and virtual systems

2. Data management
3. The capability of addressing the collected data through simulations

However, if we look into these challenges separately, we could see a huge possibility to use several cutting-edge technologies such as Big Data, Cyber-Physical Systems, AI, and ML that can overcome many challenges. In addition to that, from our perspective, it is important to mention another real challenge about DT implementation. That challenge is to develop a DT system that handles various data and information about different systems and to create consistent decisions (Zhang et al., 2017).

Overall, although the DT technology has shown great potential in various manufacturing environments, several technological challenges still need to be overcome. Thus, a great opportunity arises to investigate novel solutions to improve the DT significant challenges and the capabilities' limitations.

To conclude, DT technology has brought several economic and technical benefits to the existing manufacturing environments. This PhD research focuses on the following benefits:

- Economic benefits: the fact that DT can generate new knowledge about production lines that will make it an economically beneficial tool to improve the overall productivity of several industries (Min et al., 2019). These benefits are in particular useful to companies like STMicroelectronics where production yield improvement is a continuous endeavour.
- Automation benefits: DT can be used to optimise production lines and improve the control process through a perfect level of automation (Min et al., 2019). As mentioned earlier, the semiconductor manufacturing industry is a fully automated manufacturing system. However, there is always room for more enhancements in achieving higher levels of automation, specifically those related to automating time-critical actions.
- Efficiency and accuracy of real-time analysis: DT technology can analyse the properties of all the production lines in real-time, and it can quickly deal with statistical and dynamical processes with a high efficiency and accuracy (Martinez Hernandez et al., 2019). Usually, there are challenges with capturing, integrating, analysing, and reporting the data in real-time, and this has been observed in the manufacturing facility this research is based on. With the introduction of DT technology, the aim is to improve the efficiency and accuracy

of the real-time analyses to create real-time insights to help identify, intercept, mitigate, and resolve errors immediately.

- Digitisation and its benefits: DT has also proven its capabilities to transform data from physical format to total digital insights in various situations. Thus, this makes it easier to leverage all the digital information to improve the business of any manufacturing process (Joppen et al., 2019). These benefits are important for manufacturing companies with a limited level of digitisation. For example, STMicroelectronics would benefit greatly from the adoption of the DT technology in a cost-effective manner.

3.4 Intelligent Digital Twin

An Intelligent Digital Twin (IDT) is a Digital Twin (DT) with an Artificial Intelligence (AI) module. The AI's role is to process the generated data by the live system, analyse it, and then make predictions of its future state. It helps with understanding the root-cause behind errors; it analyses why a process has a lower yield than others or predicts if a machine will stop working at a certain time.

So far, I have seen a good number of DT projects and publications that have shown a dramatic improvement in terms of the design and implementation of this technology. With more data from physical assets, DT systems have become more accurate about the real-time behaviour of multiple physical systems. As a result, more design advances have been investigated, and in many cases, more advanced designed IDT systems have been developed. The idea of using Digital Twin as a training environment has been given more attention recently (Koch et al., 2019; Kulkarni et al., 2019; Leal et al., 2019). IDT is an excellent example of 'Extended Reality (XR)' where very enhanced environments can be developed, and interaction between users and the IDT system can be created (Leal et al., 2019). Traditionally, to train agents in virtual environments, Big Data is required, which is usually provided from users or physical assets. Such an approach has faced several challenges such as consuming time, computational power requirements, and more. On the other hand, different methods have been applied such as 'Data Augmentation' where agents can deal with various problems by adding augmented data rather than using real-time data (Leal et al., 2019).

3.5 Intelligent Digital Twin Challenges and Issues

This section addresses the main challenges and limitations of using Digital Twin as a base for machine learning. It is essential to highlight that this research focuses on the AI perspective and proposes a solution for the IDT system' capabilities. On the other hand, it introduces extra features beyond the traditional IDT capabilities (Rasheed et al., 2020; Kaur et al., 2020; Kharchenko et al., 2020). However, although IDT technology started to have a strong foothold in several application areas, there were still several significant challenges and issues. While some of those challenges focused on the implementation aspects, other studies focused on the technological aspect. According to Rasheed et al. (2020), the common challenges would be summaries in three main challenges as follows: 1) Time critical 2) Safety critical, and 3) Mission critical services. Also, issues such as: a) System integrity, b) System and data availability, and c) System reconfigurability were also highlighted in other studies (Lou et al., 2019; Eckhart and Ekelhart, 2018; Park et al., 2018).

The benefits from integrating AI and ML were always related to the physical entities. All the explored published papers shared a common interest in DT technology and added AI and machine learning models to improve the prediction capabilities. Although ML and AI provide more intelligence to any industrial process, integrating them with DT systems faced several challenges. Alexopoulos et al. (2020, p.430) summarize some of those issues into two main problems: the availability of high-quality data and" labelling the dataset for training an ML model". The study also highlighted another critical issue related to training AI and ML models for new applications. To sum up, the IDT concept was proposed in several recent studies highlighting several challenges that need to be addressed. This research focused on the 'reconfigurability', 'mission-critical services', portability, and automation time-critical challenges of IDT.

IDT technology faced a validation challenge that requires attention. We need a way to validate the changes proposed before they happen in the physical system. The only way to validate such important prediction is to wait until those events happen and are confirmed from the physical side. However, with the limited number of published articles about the IDT technology, this issue seems to have not been addressed so far (Zhao et al., 2020). As a result, there is no way of testing the system apart from reconfiguring the physical machines involved in that process and this may lead to the following risks:

- Machine downtime (due to the reconfiguring process) is expensive (Liu et al., 2018; Redelinguys et al., 2019).
- Human interaction will always be needed to implement the changes (Liu et al., 2021).
- There is no guarantee that the changes will produce the expected results. If they do, then the IDT has to look for the next improvement; otherwise, the system has to reset to the original configuration before the change. Such changes take a lot of time, are risky and expensive (Leng et al., 2020).

3.6 Human Computer Interaction and Extended Reality in Intelligent Digital Twin Systems

Interaction in virtual environments is different from the interaction with traditional computer-generated virtual interfaces. In the DT system, several technologies can be used to design accurate and nearly realistic environments such as Virtual Reality, Augmented Reality, and 3D CAD simulations. In some cases, users of such designed environments need to rotate, roll, twist and turn. Thus, this requires them to have access to 6D elements (up, down, front, back, left, and right) in the developed systems Dix (2009) Human's emotion and personality factors impact how people interact with technology (Szalma, 2014). Since computers have been invented, they have become a key element in our lives and the way users interact with computers have been improved and it became such an important matter.

Most of the current interaction techniques are built on some PC standard interactions tools and methods. For example, VR technology enables some new interaction technologies that use PC's tools such as a mouse to provide some physical and natural interactions (V´elaz et al., 2014). Also, VR technology has enabled some other recent interactions including gesturing, gazing, and voice interactions. Using such interactions will enhance the user's experience when they try a DT experience. Industry 4.0 introduced multiple technologies that can be used as interaction tools when using DL systems. An example of these technologies is the Intelligent Virtual Agents (IVA). The IVA system is an advanced chatbot system that uses AI to improve interaction capabilities and help users gain clear information about any questions they may ask. As a result, the IVAs systems continue long discussions with the users and go beyond the traditional chatbot systems ability to provide answers. With the advances of AI

technologies, new IVA generations have been developed to move from answering any questions following a set of statements to understand multiple aspects of the users' questions. For example, an IVA agent can detect users' emotions and react to them (Grover et al., 2002). Grover et al., (2002) introduced different approaches to developing virtual agents and measuring their impact on productivity. The developed system used a text processing technique to classify the users' input to determine their emotions, whether sad, happy, or other emotional messages. This type of virtual agent has been widely used in different sectors such as education (Li et al., 2020), gaming (Caci and DHou, 2020), driving assistance (Urrea wt al., 2021), and robotics (Lee et al., 2020). Another type of these IVAs is the "Swarm Intelligence", which is multi-virtual agents' systems that act similar to natural systems such as animals (Daylamani-Zad et al., 2017). The idea here is to develop a swarm of IVAs that can be decentralised using AI technologies. In addition, this type of IVA needs to have these main characteristics; Decentralised, self-organised, and virtualised (Nayyar et al., 2018). This research introduced IVAs tools that are motivated by a hummingbird's natural system and improved by ML, VR, and AR technologies. The goal was to simulate a natural system that allows to include all the IVA characteristics and allows them to act separately when there is a need to automate particular processes. The developed IVAs use the VR technology advances and visualised information to collect some observations to understand how the physical entities behave in real-time. Using a natural language processing ML algorithm, these IVAs are able to classify the given voice commands to decide on which action needs to be taken. All these processes are done automatically and individually. However, there is a need to communicate with the other IVA swarm members to gather input information or to produce further instructions. As a result, the developed IVAs are multi-autonomous tasks tools that can handle multiple processes and automate manufacturing processes. Using the fast reaction of IVAs and their capability of integrating multiple ML algorithms through multiple APIs, the productivity of the manufacturing processes will become more efficient.

The ability to design a high level of visualization and allowing users to use their hands and move freely to interact with the 6D environment can provide "attractive and natural alternative to these cumbersome interface devices for human-computer interaction" (Rautaray and Agrawal, 2015, p.2). Furthermore, using eye-gazing can provide more effective interaction. In VR, the technique of eye-tracking and movement has been used to calculate the user's intention. Such interaction can be implemented to "focus depth

implementation on a standard VR headset” (Pai et al., 2016, p.171). In another recent project, it has been used to record users voice orders in real-time to interact with VR environments (Kefi et al., 2018). Voice-recognition ordering can be used to interact with some objects in computer-generated 6D environments where users speak some keywords representing instructions for different functions such as: pick, drop, next, and play. In our designed IDT system, voice interaction plays a crucial role, and it has provided a very positive influence on the users’ experience and interaction. (Dingli and Haddod, 2019) proposed promising results in the implemented interaction technologies in DT environment. The proposed technique was adopted in a DT system of a very complex semiconductor manufacturing process and improved the whole platform experience towards designing more user-friendly DT systems. Figure 4 shows how users interact with both the physical and the digital twins.

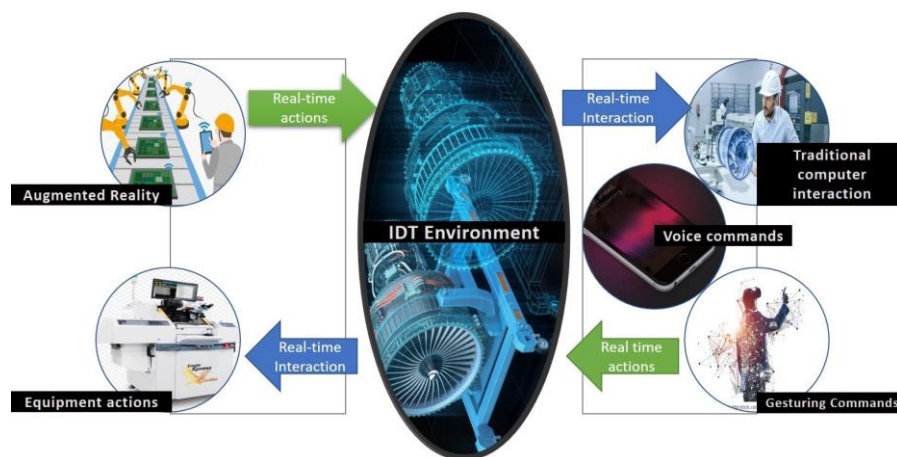


Figure 4: User interaction with physical and the designed Digital Twin system (Source: Self).

It is essential to mention that even though several technologies were used in the proposed system, there will be some interaction with the system. Therefore, Extended Reality (ER) is considered to facilitate such interaction between users and the designed system.

ER refers to the fields where users can interact with advanced digital environments and serve different purposes. Industry 4.0 and Digital Twin technology have both enabled several technologies that have been used to transform various manufacturing environments to virtual environments. For instance, with the advances of multiple technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), DT systems have become more capable of handling several visualization challenges (Leal et al., 2019). Extended Reality (ER) is defined as a technology that

consists of different immersive technologies like VR and AR (Kailas et al., 2021). Such technology was needed to develop this research project to develop a unique architecture that meets the nature of the developed system requirements. With the advances of immersive technologies such as VR, AR, and Mixed Reality, many developed systems became smarter (Zheng et al., 2018). As a result, a large amount of knowledge can be visualised easily into computer-generated experiences and immerse users into them (Deac et al., 2017).

VR technology showed great potential when simulating real-life entities into complete computer-generated virtual environments (Havard et al., 2019). As a result, adding digital elements can enhance how digital transformed knowledge will be presented to users. Also, introducing cutting-edge interaction technologies to improve the interaction between users and the VR environment added more benefits to the VR technology itself. AR technology has shown great potential when merging a real-life scene with a computer-generated element to create an excellent matching between the two worlds and enhance the user experience (Zhu et al., 2019). Both VR and AR technologies include virtual elements that can potentially transfer knowledge between real-life and imaginary worlds. Thus, by immersing users in the VR and AR experience, a knowledge visualisation occurs efficiently and smoothly to achieve the best information transformation for users. The use of VR and AR technologies provided promising results in multiple areas. Therefore, the ER concept was introduced to create a contained grouping of all those immersive technologies in one place (Palmas et al., 2020). The central concept of ER technology is to include all elements of the knowledge transformation cycle within one terminology integrating real-world elements, a virtual world, and user interactions within one process. Also, it adds robustness to the communication, interaction, and digital information domains (Chuah et al., 2018). This cutting-edge technology was used at an early stage of this research to improve the developed user interaction domain of the developed system. Also, ER technology was used to manage the communication between the main domains of the developed system. This includes the physical manufacturing process entities, the digital replicas for those entities, and the interacted users.

However, due to some hardware limitation and difficulty with streaming using a wireless connection, only VR and AR technologies have been investigated at this phase of the research project. This limitation was mainly due to the physical configurations of the investigated manufacturing environment where a wireless network was not available.

However, such technical limitations may not be present in other manufacturing environments. The potential negative impact of using any wireless signals on some products made testing the developed IDTR system on processes that include wireless networks challenging. For example, it was challenging to install cameras to real-time stream videos and apply more image processing techniques within the IDTR environments. Therefore, the wired communication networks for the investigated machines should be made wireless.

It is important to highlight that this research focused on the idea of creating a level of interaction between end-users and the physical environments through virtual representations. Thus, the Augmented Virtuality concept was implemented. The Augmented Virtuality “is defined as a synthetic or virtual world in which the user can interact with both virtual and/or real objects in the same environment” (Ghazwani and Smith, 2020, p.39). Alternative resources have been sought to investigate the possibility of using more advanced MR systems. In this project, the investigated production processes require human intervention, and this required the adoption of this approach. Figure 5 shows where the ER part of the system is used.

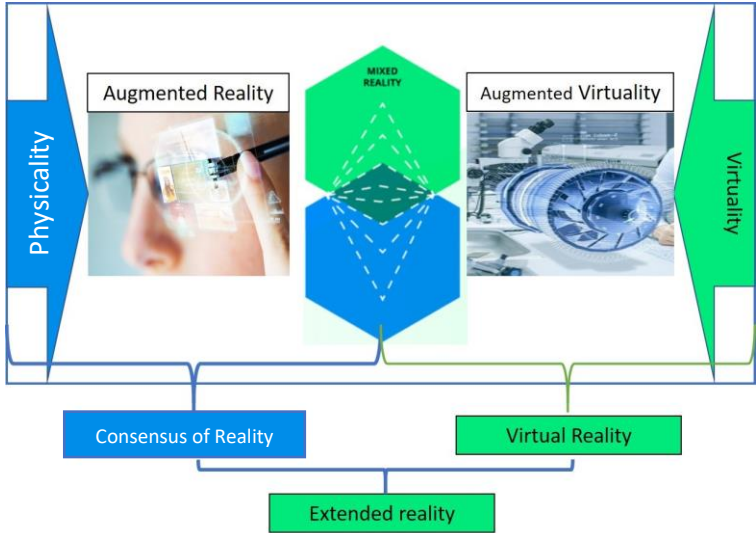


Figure 5: How the Extended Reality used within the designed system (Source: Self).

This part highlights the importance and effectiveness of using AR technology in DT technologies. Augmented Reality technology can be defined as the function of an overlaying real-world scene with augmented reality information when the area of physical objects is captured in a view in a camera of any smart devices. Where a smart device needs to have “AR mode view and AR target objects can be presented on a graphical

display screen” (Swaminathan and Ramachandran, 2018, p.1). Uva et al. (2018) stated that AR technology is playing a key technology in the evolution of smart manufacturing. Thus, it provides several advances that can be used to help manufacturers tackle several tasks. However, the authors also stated their concern about fulfilling the benefits of AR technology in some industrial scenarios. It is essential to mention that AR technology is one of the enabling technologies of Industry 4.0. The majority of the enabling technologies have shown great success in manufacturing, but some challenges face their combination (Urbas et al., 2019). Besides, there will be an excellent opportunity to merge several technologies and provide more robust designs. AR technology has been used over different manufacturing tasks such as in maintenance (Palmarini et al., 2018). An excellent example of using AR in maintenance was proposed in the aviation sector. The research aimed to demonstrate an AR experience to improve aviation maintenance. Although the proposed AR experience achieved some insights, the research stated that there is an excellent possibility to integrate more of the industry 4.0 enabled technologies to improve maintenance in Aeronautics (Ceruti et al., 2019). Moreover, a developed AR platform was designed, and some real-time streamed data were integrated to label equipment parts in real-time. As a result, the maintenance processes time was reduced and the total cost of maintenance operations was dropped (Sabarinathan et al., 2018). However, the proposed work targeted a simple laptop machine and did not mention any complexity in the used physical assets. Overall, there is a noticeable attention to the use of AR technology in the industry in general and more attention has recently been given to investigate its advances (e.g., Google Glasses) over different industrial aspects.

3.7 Chapter Summary

Digital Twin technology emerged in 2003 and it became an instrumental technology that different sectors and industries can use. The idea of adding AI and ML to the DT showed a remarkable improvement in the intelligence level and the overall simulation capabilities. With the IDT technologies, many manufacturing processes become more understandable and explorable. As a result, unseen patterns and insights were explored and used to improve many industries’ overall productivity. One of the most suitable industries are semiconductor manufacturing. Although this technology provides several benefits to its adopters, there are always certain implementations challenges that need to be overcome to gain many benefits. Some of the commonly used IDT applications make

use of Machine Learning and Human-computer interaction. Digital Twin technology has been on the top list of the Hype Cycle of emerging technologies for many years, and I expect it to remain as such in the coming years. Figure 6 shows where DT technology was placed on the Hype Cycle published by Gartner in 2019 (Hype cycle with digital twin at the top of the peak of expectations (Memon et al., n.d.). Also, Figure 7 shows that in 2020 the DT technology is growing rapidly towards the plateau of productivity. Thus, more attention has been given to the technology and there are more plans to implement it (Lima et al., 2020).

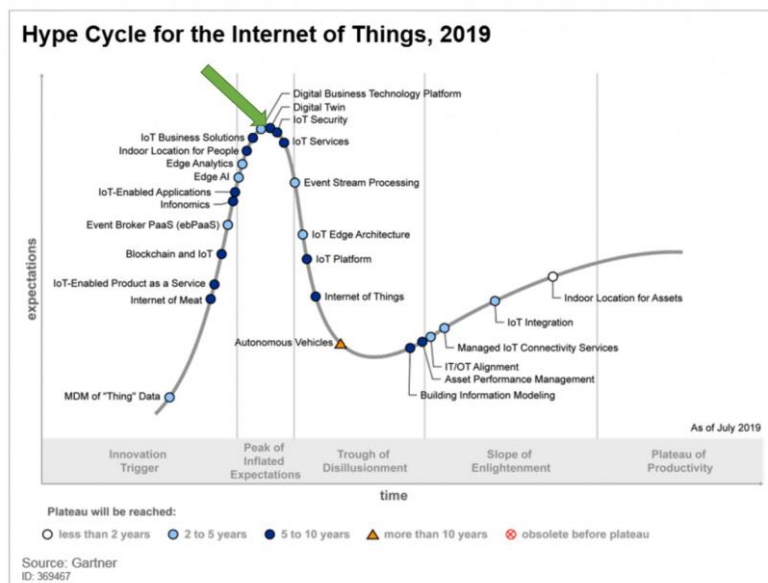


Figure 6: Hype cycle with Digital Twin at the top of the peak of expectations. (Source: Gartner, 2019).

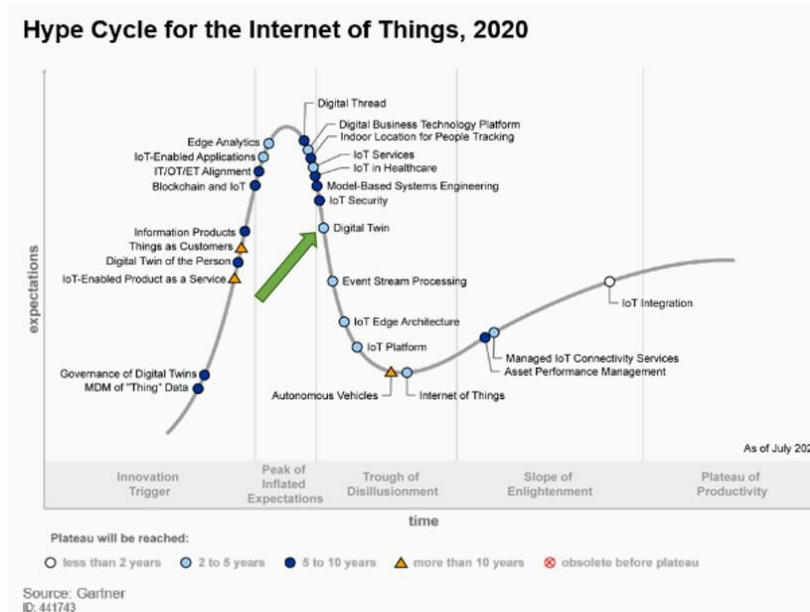


Figure 7: Hype cycle expectations for the Digital Twin technology. (Source: Gartner, 2020).

However, similar to many technologies, IDT faced several significant challenges when it moved from the development level to the deployment stage. Some implementation challenges from the used technologies, software and hardware were highlighted in previous studies. In comparison, some other inherited issues from the ML and AI limitations were faced with the IDT technology, especially at the deployment level. This research introduced a state-of-art technological solution that addressed many IDT issues and exceeded its traditional capabilities.

4 Methodology

This section talks about the used approach to design the developed Intelligent Digital Triplet system. This includes an overview of the proposed IDTR system; its design and progress; the design of the IDTR system platform using Extended Reality; and details about the use case study for this project.

4.1 Overview

Intelligent Digital Twin is a digitalization technology that merges simulations with AI. Such a mix provides more benefits to any real-world production entities. It is essential to mention that none of those benefits can be achieved without a live data stream from the physical entities which then be fed into the IDT edge. Data collected from different parts of the production lines are usually extensive and requires a lot of work to make it ready for analyses and processing. Some of the key-reported issues with such collected raw data are missing entries, incomplete entries, and corrupt entries (data noise) (Khan et al., 2019; Al-Sai et al., 2019). A digital twin shows the status of the physical assets by the transferred context to the virtual twins, and such transferring needs to be streamed in a real-time manner. The IDTR system allows the observable manufacturing domain to pre-process the collected data from the physical twin and feeds it to the core domain to operate all modelling processes. Processing the streamed data is not smooth and faces many challenges, including missing values, noisy data, isolated points, and data inconsistency (Cheng et al., 2018). Previous studies highlighted other challenges when capturing and streaming data about manufacturing processes such as volume, velocity, variety, veracity, and value (Tao et al., 2018). Data cleansing is always needed when capturing data from complex manufacturing processes because of using different types of machines and data collection methods. At STMicroelectronics, by default, machines

collect different data formats using multiple sensors and the collected data is then processed by different analytics systems. In this research, data cleansing did not occur during one stage; instead, it was done at different stages in the data collection process. However, the streamed data was transferred into one format to apply constant optimisation processes at the IDTR system edge.

Such critical issues are usually observed when making the collected data-sets ready for conducting data analyses. It is unclear what the real causes of such issues; however, I suspect the reasons are:

1. The way data is collected
2. Inconsistent manual data entry by users
3. After data is collected, it is stored and later treated as historical data
4. No real-time data streaming, analyses, and visualisation.

Therefore, it is important to develop an intelligent system that will be able to:

1. Capture accurate data.
2. Conduct real-time and correct data analyses.
3. Visualize the analysed data.
4. Help with the decision-making processes by providing indications of what may happen depending on past systems' behaviours.
5. Provide users with control capabilities that can rectify any abnormalities in the manufacturing processes.
6. Fully-automate certain manufacturing tasks and processes to get rid of human interactions (see Figure 8 for more details).

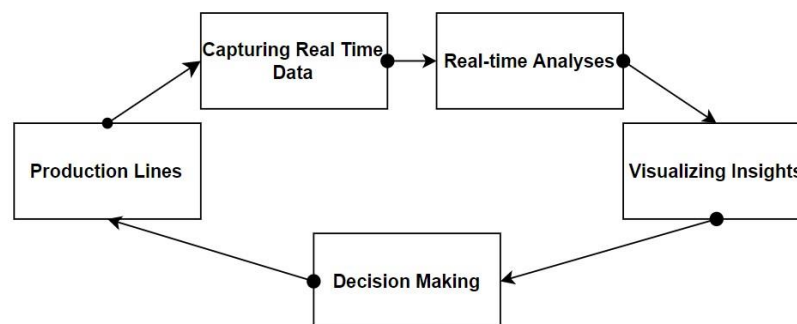


Figure 8: Autonomous decision-making process (Source: Self).

However, developing such intelligent systems faced several issues from various perspectives such as: implementation, connectivity, availability, and accessibility of data. This project introduces a new methodology to improve the overall efficiency of a

microelectronics manufacturing production facility driven by a state-of-the-art IDT system. The developed IDTR system aims to merge various technologies and determine the best one among them that can be designed, developed, tested, and implemented. Our developed IDTR system is based on the operations of a manufacturing facility in one of the plants of a semiconductor manufacturing company. The developed technology is a new generation of Intelligent Digital Twin systems that overcome the challenges mentioned in section 3.5.

4.1.1 Intelligent Digital Triplet technology

The Intelligent Digital Triplet (IDTR) builds upon an IDT system, and it goes beyond its capabilities, and it can be used for a process that is not producing the desired yield. The main concept of IDTR technology is, instead of using historical knowledge to predict what might happen, the IDTR system works ahead of time to test and validate any predicted behaviours before they occur in the real world. Also, it simulates any possible future changes and validates only one realisable solution and applies it. It is essential to highlight that the maintenance teams and equipment suppliers collected and validated a list of possible maintenance procedures for each targeted failure event. Then, these procedures were used to automate the predicted recommendations of the IDTR system and give them different priorities based on the validated list of the maintenance procedures. When a failure event occurs, the IDTR uses these validated recommendations as a reference to automate or semiautomated the entire manufacturing process. The process of simulating any possible future changes was supported by a historical dataset that included manual entries by the maintenance teams and machine operators reporting past failure events and the decisions made to fix them. However, some of the reported failure events were fixed by the machine operators, and they were excluded because of the high amount of dummy data. Thus, this research focused on three main critical failure events that require the maintenance teams to fix them. However, the maintenance teams used a trial-and-error approach to fix several failures, and this required developing an automated solution to fix such failures. The developed IDTR system solved this issue by optimising those recommended maintenance solutions.

As a result, the IDTR system mapped the validated predicted events with the best set of automated maintenance procedures and recommended them to the end-user. The IDTR

system uses these maintenance recommendations procedures to measure the impact of any predicted suggestions on the performance of the machines. The impact is measured by considering the prediction accuracy of the failure prediction and the recommended reactions about the failure to highlight any possible impact on the behaviour of the machine. The length of equipment downtime (the shorter, the better) was used as a critical factor to prove the concept of this process. The IDTR system tests the future impact of the suggested changes by calculating possible correlations between the models' accuracy and the made decisions. This results in either accepting or cancelling the made recommendations. The results from this impact test were documented as predicted downtime values, and they were used as threshold values to accept any future recommended changes. For example, when the IDTR system validates a particular failure event, it recommends the best action to fix it. The recommended solution is then correlated to a fixed downtime value. The future impact will be measured by subtracting the downtime of the predicted automated recommendations from the past downtime values. If the subtraction result is positive, the IDTR system will accept the new-made recommendations because they will decrease the machine downtime and vice versa. As a result, the only maintenance recommended solutions that showed possible improvements were validated and accepted and then forwarded to the end-user.

Traditional IDT systems would analyse data and highlight problems. With some more data crunching, it might also propose some changes to the system. However, it is impossible to test the system without reconfiguring the physical machines that are involved in that process and there are several risks that may arise here. First, machine downtime (due to the reconfiguring process) is time-consuming and costly. Second, to fix any issues that caused a machine to go down, human interactions (technicians and/or engineers) will be needed to implement any necessary changes. Furthermore, there is no guarantee that the changes that technicians or engineers make will yield the expected results. An IDTR reduces these risks drastically. It loads a virtual replica of the live process inside a sandbox. By using AI techniques, it starts optimising the virtual system and analysing the effects of the changes. The benefit of using this approach is that if the sandbox breaks (because of wrong parameters), the IDTR discards it, and it generates a new sandbox. Thus, the live system is not affected at all, instead, it only changes once the AI has tried the new parameters and it is confident of their effectiveness. Figure 9 explains the how IDTR system works.

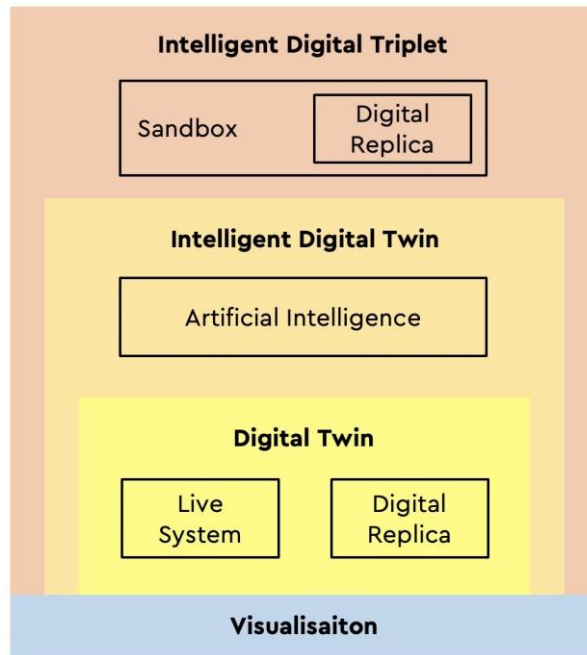


Figure 9: IDTR system's structure (Source: Self).

As shown in Figure 9, the IDTR works on its own to test and evaluate any possible changes.

Such a level of protection stores the provided data to the end-users as well as the DT environment. Also, there is literally no associated costs with using this approach and the system does all the optimisation processes virtually. As a result, only the accurate and validated changes take place in the DT system. To sum up, IDTR declines/rejects all the wrong predictions by the traditional AI algorithms and tests decisions in nearly real-life scenarios. Also, it applies all its decisions autonomously.

I believe that the novelty and the unique contributions of our work lie in the following aspects:

1. Developing autonomous Intelligent Digital Triplet (IDTR) system that generates training synthetic data sets, self-tests them, and then makes appropriate autonomous decisions. As a result, with IDTR, IDT overcomes the reconfigurability and automation time-critical issues.
2. A novel ML algorithm was used that adds human iteration and machines as a primary input to classify training datasets. By using such an approach, the IDTR introduces higher portability capabilities than the traditional IDT.
3. Developing and adding intelligent tools as a triplet addition to the physical and intelligent digital twins to add more intelligent features to any

manufacturing processes. Those features introduce more intelligent processes and highlight new insights to make better improvement decisions.

4. Use of Extended Reality to build IDTR systems instead of traditional techniques. In such a way, IDTR improves the automation of the critical services of the IDT systems.

Under those circumstances, an autonomous IDTR system is going to adopt complex procedures to enhance the performance of the IDT framework predictive capabilities. The designed Intelligent Digital Triplet (IDTR) system will represent the physical assets that include equipment, communications protocols, data acquisition systems, and any other information related to the physical manufacturing environment.

A combination of AI and automation techniques have been used to transfer the complex processes of the semiconductor company to an intelligent virtual environment. Processes like data capturing, data processing, and Predictive Maintenance are going to be digitalized. Also, Predictive Maintenance processes will be automated to help the maintenance teams predicting some failures before they occur in the physical production lines. On the other hand, I propose a fully automated approach to failure prediction, maintenance decision making, and system training actions. Figure 10 shows how the IDTR system works.

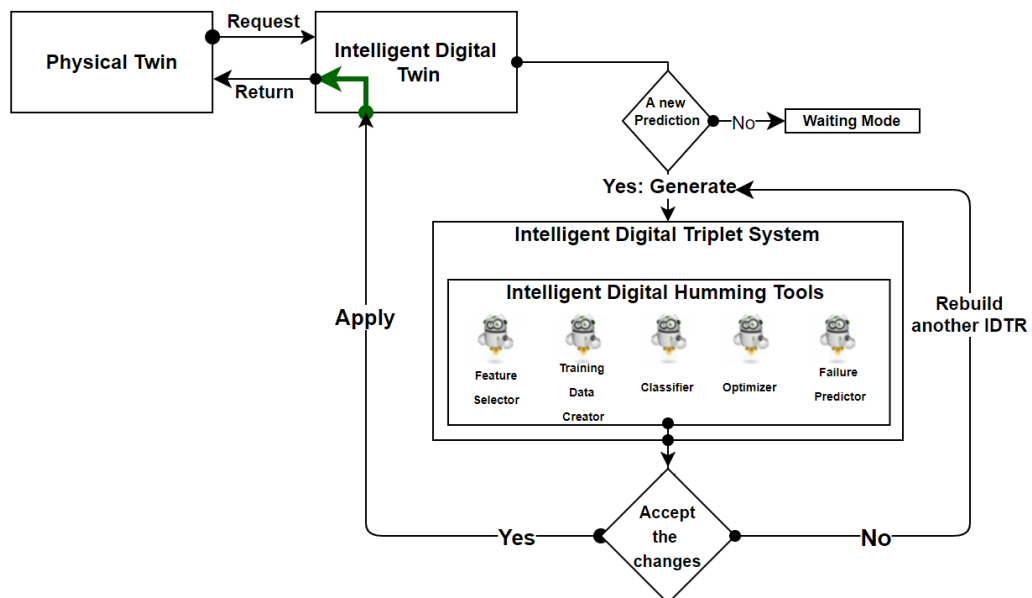


Figure 10: A high level structure of the developed IDTR system (Source: Self).

As shown in Figure 10, different fully automated actions can be implemented in a virtual and digital triplet replica of a physical equipment. With high protection level, the

IDT stays live and leaves the IDTR working for the optimization and automation processes. As a result, IDTR makes confident decisions of when and what configurations need to be changed, when and what processes need to be automated, and when and what new improvement needs to be embedded in the used processes. The next section highlights how the IDTR system was used by swarm of AI agents to add further autonomous features and optimization. As it has already been mentioned earlier, this research aims to develop an IDTR system that can be scaled up upon multiple manufacturing processes with this approach. The idea here was to design multi-purposes agents that can be modified to target multiple manufacturing actions.

IDTR SYSTEM Functionality

```

Function start
  If IDT makes a new prediction:
    Call IDTR_Generating function ()
  Else
    Return
End function

IDTR_Generating function ()
  Function start
    Activate IDHT-1 function
    Call rewarding array
    Call the IDHT-2 function ()
    Call the IDHT-4 function()
    If the prediction accuracy is accepted:
      Call the IDHT-5 function ()
      Call the IDHT-4 function()
      If the downtime improvement verified:
        Call ARupdate function()
      else
        Continue till finishing all the
        verification process
    Else:
      Return
  End function
Call crashingIDTR function ()
Call waitingModeFunction ()

```

4.2 Intelligent Digital Triplet System Design

4.2.1 Two-way Connection Between the Physical Twin and the Digital Twin

In order to design effective connectivity between the physical system and its intelligent digital twin, several different platforms were used. Since the data used was extensive, it was essential to design a high level of interconnectivity that provides smooth and real-time data flow between the physical system and its digital twin which provides smooth and real-time interaction with the user. The uniqueness of the designed system is its ability to process all the ingested data at the IDT edge. Two different data distribution systems were used to tackle challenges associated with streamed data and to provide real-time data that is visualized into the IDT edge. The KAFKA platform <https://kafka.apache.org> was used as a distributed storage system to structure all the acquired streamed data from the different production stages. “Kafka is defined as a real-time data Streaming publish/subscribe message broker redesigned as a distributed commit log” (Penas Fernandez, 2019, p.25). Also, KAFKA was also used to build a stream base process with fault tolerance features to provide high-quality streaming data to the IDT edge. Figure 11 shows a diagram of the designed data management system. It includes, from left to right, an IoT sensor tile system, an Equipment Integration Controller, a TIBCO Rendezvous (TRV) bus system ², and a KAFKA system ³ to transfer data from the physical twin to the digital twin.

TIBCO technology was chosen to be used because the manufacturing environment that this research is based on already utilises it. TIBCO acts as a one-way combination medium between the equipment and multiple systems used to present insights about the equipment performance. The IDTR technology requires a distribution system and storage that handles a large amount of collected data with a high-efficiency level. This includes the ability to request and sending data between the IDTR edge and the physical assets. Thus, KAFKA technology was chosen to provide distribution and distribution streaming capabilities to the communication medium between the IDTR edge and the physical assets. Also, there was an available open-source API to connect KAFKA with TIBCO. Furthermore, IDTR technology needs a wide range of knowledge about physical assets, requiring extensive data collection. In most cases, the collected data is sensitive and needs a high level of protection at different system stages. If such

² TIBCO RV system allows distributed applications to exchange data across an expanded network (Alperin et al., 2019)

³ KAFKA system is an open-source stream-processing software platform (Hiraman et al., 2018)

information is hacked, it could lead to substantial financial damage. As a result, this research project developed all the systems, including data collection, data streaming, and data usage in the company's premises. Thus, the use of any cloud technologies to deploy the design system was not an option. Figure 11 shows the designed data management system infrastructure.

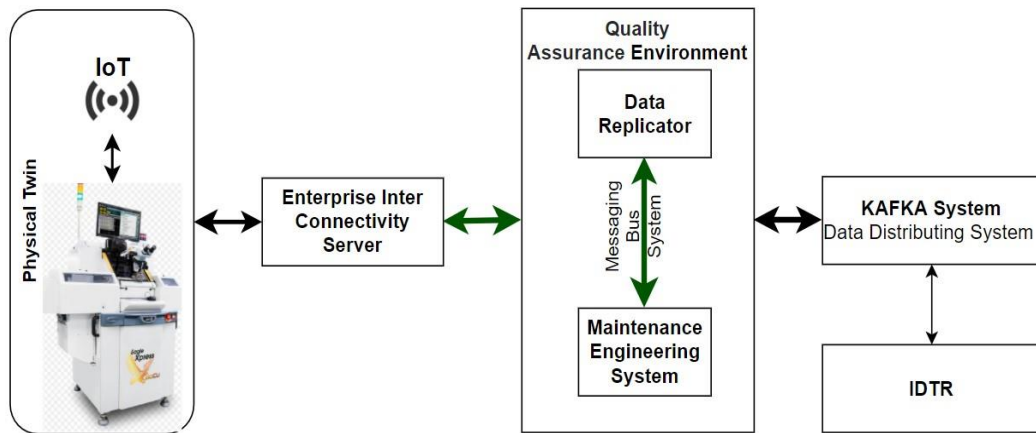


Figure 11: Data management system infrastructure (Source: Self).

As it can be seen from the diagram, the physical edge is connected to the IDT edge through messaging bus systems and a streaming API. Such a connection is a two-way connection to maintain a 24/7 accessibility to the physical production lines. The following subsections explain how the final IoT infrastructure was developed.

At this stage, all the developed IoT system is deployed on a Quality Assurance (QA) environment. QA is an environment that is used to ensure the quality of the collected data and test any changes. It is essential to mention that the designed IoT system was added to the physical production lines to collect extra information. The developed SensorTile captures data from Magnetometer, Accelerometer, Gyroscope, Microphone, Temperature, Pressure sensor onboard. The captured data was needed to provide extra insights about the equipment behaviour because the equipment cannot provide such data directly. Streaming this data was required while the equipment is operational. However, the used IoT SensorTile generated large amount of data and grouping, and patching techniques were implemented to only stream the average of captured readings within a fixed time window. For example, every 30 seconds, the IoT platform sends the average of the collected pressure readings during this time window and streams it to the IDTR edge.

Such a process required a high level of protection to avoid crashing the current data management system. As a result, a QA environment was designed to test and validate such an upgrade process (Martínez Bevia, 2017). The QA was also used by the data processing team to test the quality of any collected data before using it. The designed QA is used to test all the suggested data processes from the Intelligent Digital Humming (IDH) tools and the intelligent Digital Twin edge before being applied to the physical twin assets. Although the QA can simulate the physical production environment and it allows developing and testing different scenarios before actually deploying them, it is highly recommended to test the final system directly on the actual physical twin to validate all of the developed techniques. To better help understand how QA environment was utilized in this research project, Figure 12 shows the designed QA environment structure.

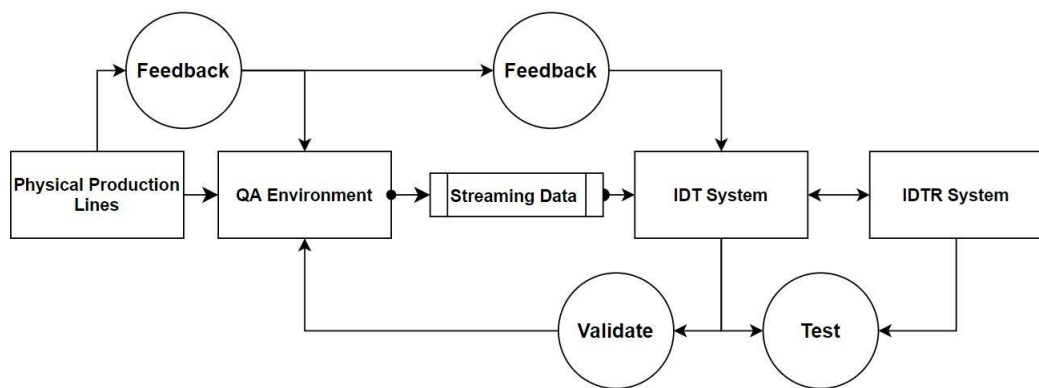


Figure 12: QA environment structure (Source: Self).

The developed structure took into consideration many factors and real-life cases to allow to upgrade the system during future developments. Examples of some challenges include the scalability, maintenance, and upgrading the systems in case of adding more equipment. Because of the number of collected parameters from the physical twin side, it was important to use a distribution platform. Thus, adding such a distribution system was helpful to tackle issues such as multi-format, size, and any possible latency in the collected data during streaming it to the IDTR edge. Kafka supports many traditional data structuring techniques with a high-level of usability.

The primary data used during this research have been collected directly from the machines. Different data management systems are responsible for data collection, filtering, and streaming into a data bus system. Different synchronous and asynchronous processes are involved in this domain, and they provide real-time and offline data. This

research implemented a specific observable manufacturing domain structure to capture data from the physical side and stream it into the virtual representations. Because of some used technologies by the physical edge, it was necessary to build a new architecture to handle the collected data from the physical assets. This research focused on the streamed real-time data to be used on the virtual side. It is essential to highlight that this research targeted all the available information streamed in a real-time manner. The implemented data collection logic was to request any information about the selected physical assets whenever they are available. The retrieved data is then streamed to the virtual side through a distribution system, and data selection logic is applied to the streamed data. These logics were needed to ensure that the developed system can target different features and explore new insights. Thus, two streaming APIs were developed to listen and capture the streamed data from the bus system and to stream it to the virtual representation side. However, the captured data from the physical entities using different data management systems resulted in different data structures. Thus, a standard streaming protocol was used to provide one data structure, and it was applied when streaming data from the data bus system to the distributing system.

4.2.2 Intelligent Digital Humming Tools

In addition to the IDTR concept, this research developed a number of intelligent agents to improve the overall IDT performance and to add a higher level of automation. The idea is to develop intelligent tools that can use IDTR systems as a training base to make accurate predictions about what might happen over different stages of complex manufacturing processes. Furthermore, allowing those tools to automatically decide when they can retrain themselves on new events. Additionally, they can implement an automation feature selection to decide on which data can be used to make a better decision about future control actions.

Those tools have been named as Intelligent Digital Humming tools and they got the name from the hummingbirds because of the following:

- Hummingbirds are territorial and in the same way intelligent digital humming tools have specialization on specific items.
- Hummingbirds swarm feeders in a coordinated way, IDH tools swarm data in a coordinated way.

- Hummingbirds move with absolute freedom (the only bird that can fly backwards), IDH tools have absolute freedom of movement inside the sandbox.
- Hummingbirds make a humming sound so that it can be easily detected, IDH tools expose what they are doing using VR, AR, and voice commands in a transparent way. (Duque et al., 2018; Haddod and Dingli, 2021).

Figure 13 shows a high-level scenario of how Digital Humming tools work and how they communicate with each other to identify different manufacturing processes.

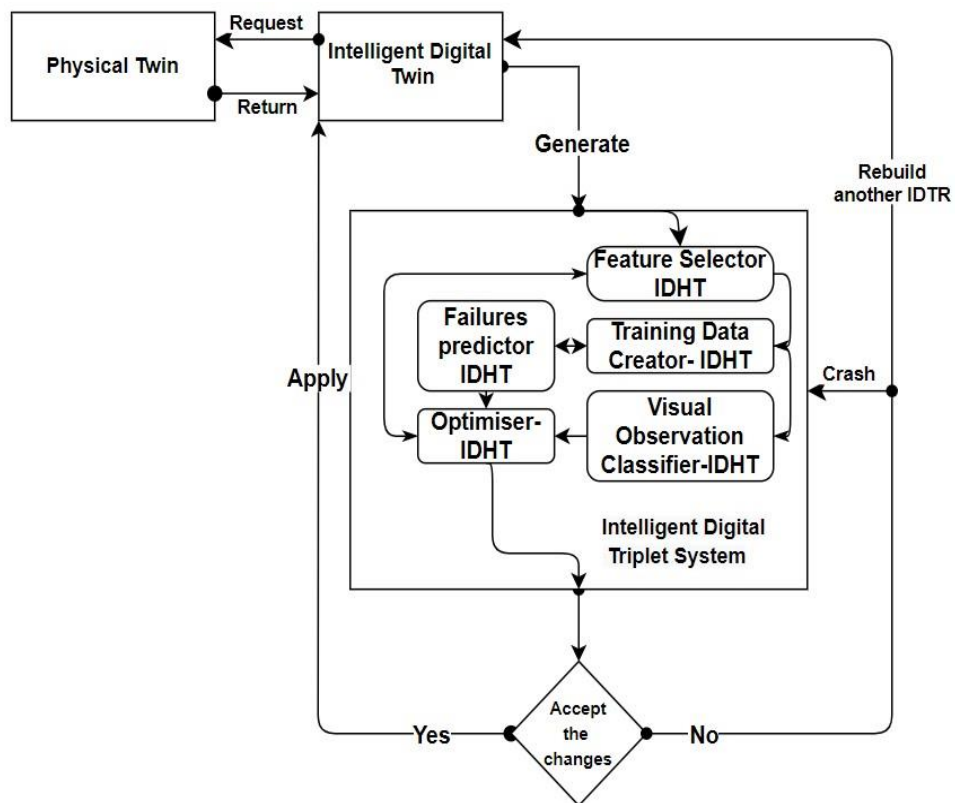


Figure 13: The use of the designed Digital Humming tools in the IDTR system (Source: Self).

AI agents can be categorized into two main types: data-driven and symbolic. The data-driven type requires samples of a set of behaviours, then the agent learns autonomously from them. The symbolic type requires some structured representations (Rossi and Loreggia, 2019). AI agents can also be categorized based on their behaviour into; “hostile agents, non-hostile agents, leader following agents, goal following agents, selfish agents, and fuzzy agents” (Sharma et al., 2019, p.167-1). “An agent does not need user intervention to work, but it could collaborate with humans and other agents” (Mallia-Milanes and Montebello, 2017, p.2). Traditionally, AI agents are automated

entities that require data from sensors and actuators to perform any decided actions and operations (Baughman et al., 2019). Such a concept can be invested and developed in environments such as IDTR.

It is essential to highlight that this research focused on the following AI Agent characteristics:

- **Situatedness:** the agent receives some form of sensory input from its environment, and it performs some action that changes its environment in some way—examples of environments: the physical world and the Internet (Yildirim and Stene, 2010).
- **Autonomy:** the agent can act without direct intervention by humans or other agents and controls its own actions and internal state (Di and Shi, 2021).
- **Adaptivity:** the agent is capable of (1) reacting flexibly to changes in its environment; (2) taking goal-directed initiative (i.e., is pro-active), when appropriate; and (3) learning from its own experience, its environment, and interactions with others (Holstein et al., 2020; Schilling et al., 2019).
- **Sociability:** the agent is capable of interacting in a peer-to-peer manner with other agents or humans (Bowman and Banks, 2019).

The AI algorithms used by the IDTR are called Intelligent Digital Humming Tools (IDHT). They have the same characteristics of AI agents but in a similar way to hummingbirds and they are goal-oriented agents (Shen et al., 2004). To monitor, interact and solve issues, they have the freedom to roam in 3D virtual space just like hummingbirds do in the real world. To add such hummingbirds' mechanism to the designed DH tools, they were integrated with virtual cameras to collect visual observations while roaming inside the IDTR environment. By using AI algorithms, a non-controlled movement mechanism was applied to help those agents move from one element to another and collect different knowledge when needed. As a result, the designed IDH tools were flexible to any required positioning and knowledge collection changes. It is essential to highlight that IDTR technology has a great potential in the training and in the deployment stages. In this research, the IDTR system was used as a virtual environment to train the Humming tools and make sure the IDHT tools are accurate enough when making autonomous decisions about different scenarios. Such a flexibility in the mechanism of the IDTR allows to achieve continuous training when a new training is needed. Many previous studies, including several related projects to this

research, reported lower levels of accuracy when the designed models were embedded into the live production lines. Real-time data captured directly from multiple sensors installed on different physical assets. During the production processes, the sensors generate information about various parts of the equipment and their status in a real-time manner. The collected data then processed and arranged in a helpful and meaningful format e.g., Tabular format. Machine learning models are usually trained by using a collection of observations and parameters structured in rows and columns and this type of data is known as tabular data. The creation of tabular data faces many issues such as missing data, incorrect readings, and dummy data. At an early stage of this research, the use of tabular data made it inefficient to collect a total new dataset to retrain the same models to improve the output accuracy. Perhaps the use of tabular data has resulted in the reported lower level of accuracy.

The IDTR system keeps the trained Digital Humming tools to perform normally unless a new level of accuracy is achieved. This process is done separately within the generated IDTR environment, and it overrides the newly trained models to allow users to use the updated versions without interrupting the live system process. IDHT tools are AI agents that use the IDTR environment to learn how to cooperate and perform multiple tasks to handle several manufacturing processes and actions. They integrate multiple AI agents' characteristics and act fast towards any testing and validation processes the IDTR makes. Figure 14 shows the overall mechanism of the IDH tools and how they communicate and work inside the IDTR systems.

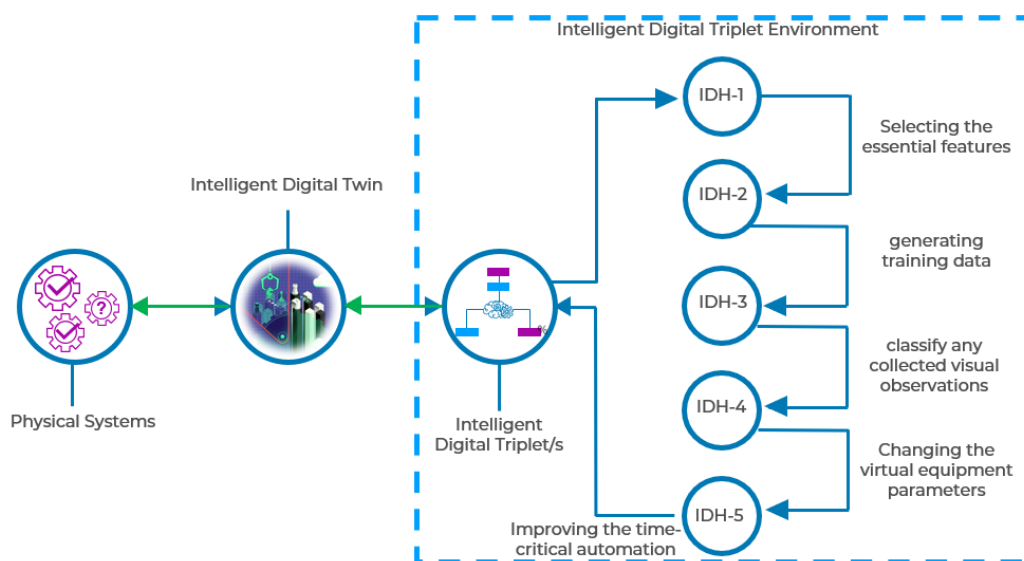


Figure 14: The mechanism of the IDH tools (Source: Self).

The IDTR system was mainly developed using the Unity engine and several CAD APIs to create the virtual assets. There was a need to create a virtual environment using VR and AR technologies and develop the IDH tools to use the VR environment to optimise and control the physical assets. The developed IDTR system visualises all the collected data from the physical side and presents it in multiple ways to allow the IDH tools to observe, understand, and use it. Those IDH tools are made using virtual cameras and modelling APIs. The virtual cameras collect insights about the virtual assets, and the APIs are used to run some GANs models. IDH tools are synchronous tools that follow a constant communication method and work automatically without human control. Several APIs were developed to link the IDTR edge with the data and processing distribution systems to stream information from and to the virtual side. 'Request' and 'reply' approaches were implemented to run all these IDH tools to control the entire training, testing, and validation processes. The mentioned above APIs are two-way connection channels that allow the IDH tools to gather information about the physical edge and send feedback from the IDH tools to the physical side. Also, these APIs were used to run the different GANs models used by the IDH tools when there is a need to predict, classify, and recommend a solution to fix a failure. A Hadoop environment was built to handle those GANs models processes in a streaming manner, and a Spark-Kafka API was used to manage the streaming between the distributed processing environment and the data distribution environment. Also, a Tibco-Kafka streaming API was developed to stream data from the physical side to the data distribution system.

To sum up, similar to the traditional AI agents, IDH tools are used to support manufactures in multiple decision-making scenarios (Rossi and Loreggia, 2019). IDH tools target both expected and unexpected scenarios and try to be very responsive to any sudden changes in a near real-time manner (Rossi and Mattei, 2019). Also, they make autonomous decisions based on the predictions they make and suggest specific actions that had been either difficult or slow with human intervention. In doing so, IDHT tools can make multiple tests before taking any final actions and all this will be done in the Intelligent Digital Triplet system. Section 4.2.2 provides more details about the developed IDTR system and the IDHT tools.

IDH tools are virtual assistants that gather visual observations about specific conditions of equipment and use the Intelligent Digital Triple to allow it to become a self-training environment. A swarm of Digital Humming tools freely move in the IDTR environment to monitor the performance of its different elements, detect any change in their

conditions, report these errors, and make self-actions to rectify such errors. They continue to visually observe what happens in real-time and make predictions of what might happen in the future. Six wire-bonding equipment were chosen to demonstrate the developed IDTR system. The reasons for choosing the wire-bonding processes were: 1) more streamed data was collected from these machines than any other equipment in the rest of the stages. 2) these machines usually yield more defects. 3) these machines are physically configured in an accessible manner to experiment adding new sensors to capture more data. Figure 15 shows the screenshot of the developed IDTR system for a number of wire-bonding equipment.



Figure 15: A screenshot of the developed IDTR system (Source: Self).

This new generation of IDT system will provide a large number of observations that can be captured by the IDH tools. Various techniques to provide the best automated results were used.

The following sections explain how each of the five developed IDH works and other insights and details.

4.2.2.1 Feature Selector (IDHT-1)

IDHT-1 is the Feature Selector which gathers data from the live system and selects the essential features for the task at hand using Machine Learning. The reason why this tool was needed is to automate the feature selection processes within the IDTR system and to only use features that improve the output classifications. Naturally, IDT systems can handle many streamed readings in nearly real-time manner from the physical entities. In many cases, the gathered and visualised data in the IDT systems would be about various elements within a manufacturing process. The reason behind such a situation is the need

to copy the physical system's behaviour and to present it in a virtual replica at the same time. The size of the collected data would undoubtedly improve the IDT system's capabilities from a knowledge representation perspective. Thus, users would have all the knowledge they might need to understand what performance their physical systems will have in real-time. Although most of the visualised data lack any correlation, having them together would help any decision-maker better understand the root cause behind the normal and the abnormal behaviour of any manufacturing processes. However, this process might be the most challenging stage to develop in traditionally supervised ML systems.

IDTR technology uses the available data on the IDT environment and creates a copy inside a self-designed sandbox to simulate multiple scenarios to make accurate predictions. Thus, it is essential to have a statistically significant correlation proportion between the used features by the IDTR to guarantee better output accuracies. Also, because the IDTR allows different AI agents to roam and make their visualised information, it is crucial to only use the feature that leads to better prediction accuracy. As mentioned in section 4.1.1, IDTR technology mainly targets complex manufacturing actions and automates several critical manufacturing processes including straightforward linear, noisy, and automated with human intervention processes. Thus, the IDTR system needs an effective agent to handle the feature selection process and make flexible decisions to target different features whenever the output accuracy is below the expectations. It is essential to mention that IDTR systems support multiple AI agents, and this allows various machine learning algorithms to collect training data. This research focused on one of the most promising and exciting Machine Learning technologies: Generative Adversarial Networks (GANs) (Goodfellow et al., 2014). The concept of AI agents and the Machine Learning Agent (ML-Agents) using Convolutional Neural Networks (Nandy et al., 2018) and Reinforcement Learning (Lample et al., 2017) also was tested. Because GANs work efficiently on images, there was a need to target the most critical features correlated to any output predictions to decrease training time. Image data was used so the IDTR acts as a virtual training environment where IDH tools capture virtual observations that are translated to images. The created images include insights about the physical assets through the virtual representations. This research aimed to have the ability to control the amount of the represented information and automatically add more perspectives when needed. Also, this approach provided the ability to utilise the best training data quality to achieve the

best GANs models performances. Furthermore, the nature of the developed IDH tools required the ability to capture observations from the environment through virtual cameras, and this process can become expensive due to using numerical readings. The ultimate goal of this research is to replicate physical assets and allow the IDH tools to automate and manage their entire processes. Thus, this research aimed to use one of the most important ML types to allow for future development to add more features to the IDTR system. GANs has been implemented widely in media in general and particularly in image processing and showed a good potential to meet the nature of the IDTR concept. Applications such as text-to-image translation, image-to-text translation, and synthetic data generation are good examples of such potential (Huang et al., 2018). It is important to highlight that some of the captured information from the investigated manufacturing process was in a visual inspection format. Thus, the IDTR can handle different data types in the future by using more image processing techniques and by using technologies such as AR and Mixed Reality.

IDTR works in parallel with the IDT systems and interacts directly with the live system and the physical entities within the manufacturing lines. To achieve such a high level of automation, DHT-1 was developed, and it was added to the IDTR concept to change the selected features when that process is needed. As highlighted in sections 4.1.1 and 4.1.2, IDTR technology targets various automation levels, starting from when the IDTR environment is created until a decision is made. It begins when a new prediction is needed to estimate what might happen, the impact(s) caused by the change, and what should be done as a preventive action(s). All those processes would be time-consuming when dealing with complex manufacturing events. IDTR applied different approaches to compare and validate the best autonomous feature selection technique and use it in the training phase to move towards to better automation levels. At an early stage of this research, a manual feature selection was applied to the IDTR system's collected readings. At a later stage, a digital humming tool named IDHT-1, was integrated within the IDTR environment to automatically tackle the feature regeneration process. The performance of this tool was also compared to and evaluated by multiple perspectives, such as the number of generated features, time of regenerating features, and the impact on the IDTR system prediction accuracy.

IDHT-1 uses a modified automated feature selection approach to measure and discover the best applied features within the IDTR system. The use of the entire approach was motivated by an automatic Feature Engineering that introduced by Cerqueira et al.

(2020). IDHT-1 applies an autonomous feature selection in three main steps. Firstly, randomly select several visual observations and represent a statistical summary that shows the correlation between the considered features. Secondly, record all the selected features and measure their correlation to the output accuracy levels. Finally, apply a reward algorithm to filter out the best feature selections records. The developed rewarding algorithm was integrated with IDHT-1 and motivated by the "temporal difference Learning Algorithm". While the IDT system uses historical data to make predictions, the IDTR then uses the made predictions by the IDT as a reference to compare them with its future prediction results. This algorithm has full access to a KAFKA topic to store the IDT predictions results, the IDTR new prediction results, and the rewards of all the correct new predictions when they occur in the physical edge. The algorithm gives an initial zero reward value when a new task begins and amends it after each successful classification and prediction done by the IDTR system. The output of this algorithm is a table that includes 1) many chains of features sets that refer to the selected features, and 2) the given rewards to be used as a weight for those tested and validated selected features sets. The title of the head of each chain was named based on the predicted failures, e.g., machine failure 1. The rewarding algorithm output was visualised using different tree graphs to represent all the successful selected features' chains that won at least one reward point during the validation process. Figure 16 shows how the Rewarding algorithm works.

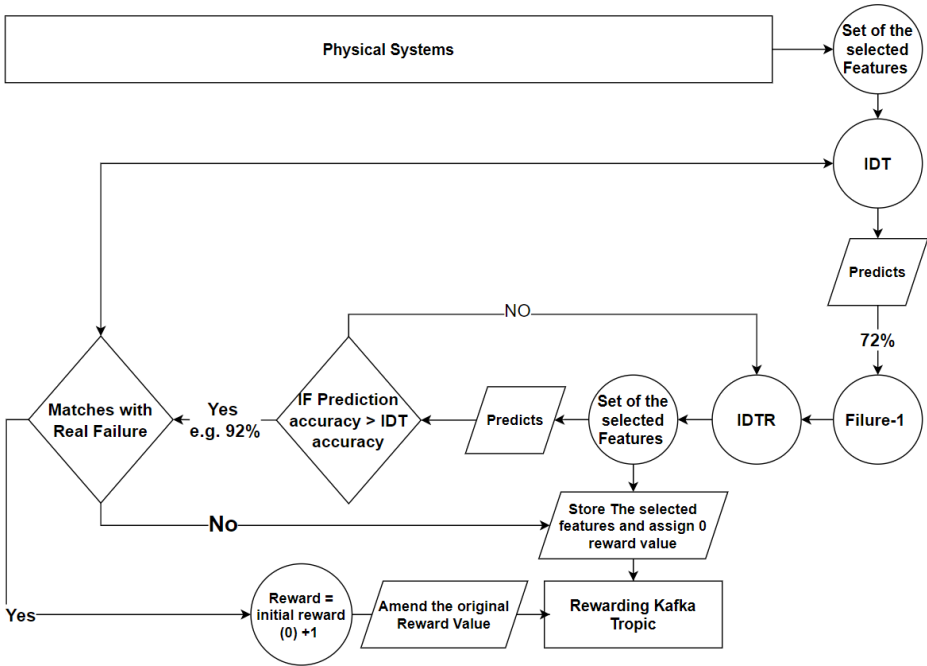


Figure 16: How the Rewarding algorithm works (Source: Self).

As shown in Figure 16, IDHT-1 uses all the positive rewarded features collected in the previous rewarding processes to predict future actions. The IDTR uses the results from the rewarding system to select the validated features in the past and give them a higher priority when it starts evaluating new predicted actions. Also, when the IDTR has a longer prediction time window, new sets of selected features will be added to the rewarding topic. Figure 17 shows an example of a tree graph that was created using the rewarding algorithm results about one of the selected failures.

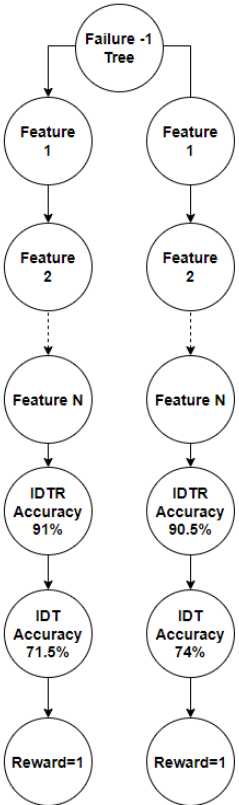


Figure 17: A sample of rewarding tree graph for one failure event (Source: Self).

It is essential to highlight that adding IDHT-1 improved the IDTR overall performance and explored interesting correlations that had not been explored using traditional feature selections within IDT systems. Figure 18 illustrates how the IDHT select engineering features autonomously.

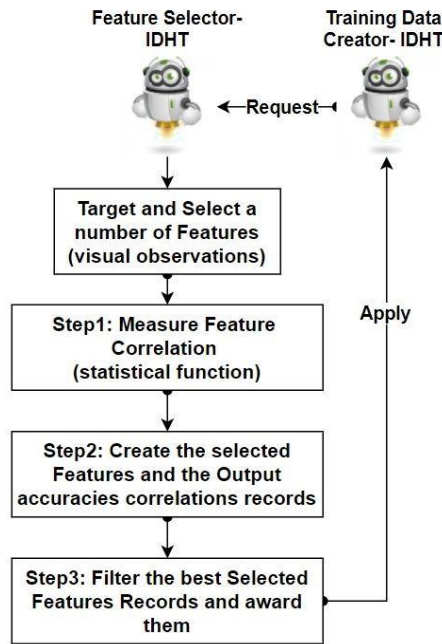


Figure 18: The IDTR autonomous feature selection process (Source: Self).

The feature selector-IDHT is located at the beginning of the IDTR system, and it acts as an essential tool. Figure 19 shows how this tool works and where its order position on the IDTR system infrastructure.

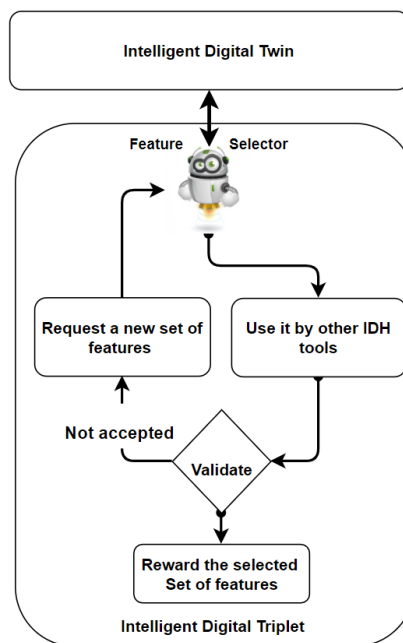


Figure 19: How the IDHT-1 works (Source: Self).

An algorithm was developed to automate the feature selection process and to identify the best features that lead to accurate classifications. A recursive approach has been

implemented to randomise the considered features every time the IDHT-1 needs to train and test a new set of features. This tool then communicates with the training data creator-IDHT2 to generate new training data sets. Like RL's concept, this algorithm would reward any selected features that improved the classification accuracy. It is essential to highlight that this tool was upgraded by integrating with a Bayesian Inference algorithm to reduce the selected features' dimensionality (Izmailov et al., 2020). As a result, the Training Data Collector-IDHT2 was able to convert the original selected features of the reconstructed images that represent the original images with much less dimensionality.

It is essential to highlight that automating the Feature Engineering selection showed a promising potential improvement compared to the manual selection process. It also showed a more remarkable improvement in the main targeted areas, accuracy, speed, and selected features size. There was a need to have a faster and more robust autonomous feature selection technique to handle some short-term predictions and to decrease the training process time when possible. Figure 20 shows the structure of IDHT-1 and how it works.

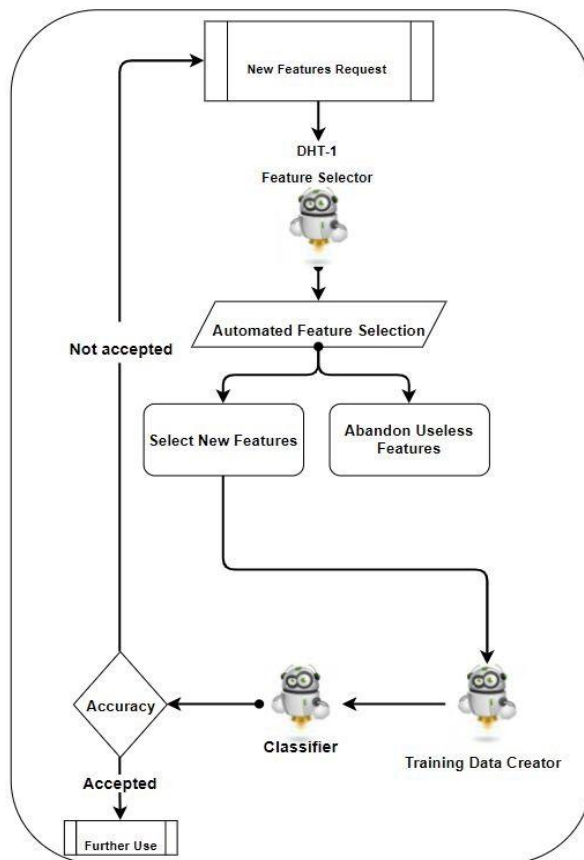


Figure 20: How the IDHT-1 implements the autonomous feature selection process (Source: Self).

To conclude, the research focused on criteria such as: development time, number of selected features versus better accuracy, and improvement percentage relative to the humming tools' prediction accuracy. To sum up, IDHT-1 automates the decision-making process of whether a new feature selection technique is needed or not. A set of thresholds were assigned to evaluate the outputs from the other humming tools and to request a new set of features to reset any training and prediction processes. So far, this tool proved to be capable of improving the overall training time within the IDTR. This includes the idea of creating new features to find new patterns from the original data and the process of extracting a new representation of the generated training data by the IDTR and its IDH tools.

4.2.2.2 Training Data Creator (IDHT-2)

IDTR uses another IDH tool named as IDHT-2 to generate training data and to use it to train other IDH tools within the designed system. IDTR applies a continuous training process to improve multiple manufacturing processes. IDHT-2 was designed to improve the quality of training data process and to help the IDTR system overcome any critical services issues. Besides, IDHT-2 provides training data to help the IDTR reconfiguring the IDT systems based on any possible changes.

The IDHT-2 generates images by collecting several visual observations that are captured in real-time from the developed IDTR environment. The generated images can be in a different format for examples, heat-maps, diagrams, histograms, and 3D meshes. Also, a set of descriptions will be generated to describe each generated image. The IDHT-2 tool creates a description of a failure event and it describes the equipment status using multiple parameters that are captured in real-time from the different physical twins. It also trains intelligent agents using real-time data and scales the visualized machines yielded benefits. As a result, IDHT-2 generates more accurate training data and description captions for the newly created images. Figure 21 illustrates the mechanism of the IDHT-2.

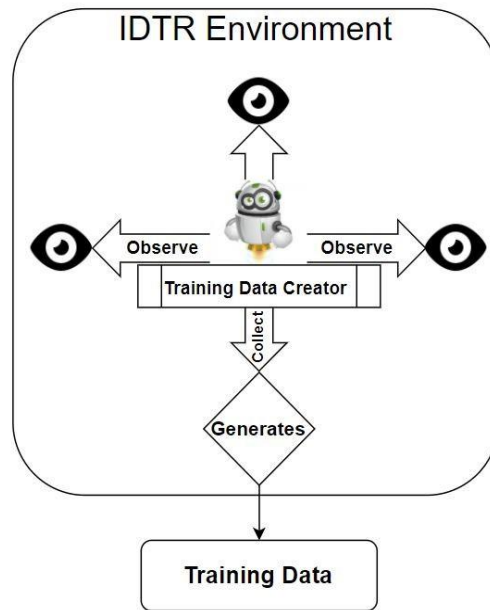


Figure 21: How the IDHT-2 generates training data (Source: Self).

As shown in Figure 21, IDHT-2 captures any changes in the IDTR environment and translates them into training data. Thus, it consumes the generated data to the classifier to predict the behaviour of the physical twins. However, because IDTR captures all the available data in the IDT, some data availability issues occurred during the training stage of this tool. To overcome such a challenge, a decision was made to generate an endless stream of synthetic data that is statistically similar to the real-data selected by the IDHT-1. The idea was to generate high-quality images that include virtual configurations to simulate multiple manufacturing processes and machine configurations. These images need to be accurately classified to help the IDTR system better understand the simulated scenarios and make better recommendations. Thus, the IDTR system generates synthetic images with mean and standard deviation values that are similar to the statistics of a collection of actually created images from the target manufacturing processes events.

To do so, the IDHT-2 used a Generative Adversarial Network that learns the nature of the underlying structure of the data. GANs is capable of generating images from random noise in a contentious manner (Richardson and Weiss, 2018). As a result, IDTR addressed the possibility to lose data from the IDT system. Also, when the IDT system crashes due to losing the streamed data from the physical systems, IDTR generates synthetic data using a concept of virtual data generation technology. The idea behind having such a virtual data source is to make sure IDTR stays on and to explore new synthetic data that can improve the overall performance. It is essential to highlight that IDHT-2 works together with the IDHT-1 to transfer all the collected features into

training data. This technique helps IDTR guarantee data availability similar to the real streamed data and generates a new set of synthetic data to explore different solutions towards any suggested change.

IDTR has introduced an innovative aspect to use the IDT environment to generate synthetic data at a high frequency rate. Because IDT takes a long time to collect enough data to train AI and ML models. IDHT-2 makes use of a GANs model to generate synthetic data with high level of accuracy to sustain appropriate level of performance and to simulate multiple scenarios even when there is a risk of losing input from the IDT and the physical system. As a result, IDTR will continue to generate the needed data even if the IDT and the physical twin were off-line. Figure 22 shows the functionality of this tool and its location in the IDTR system.

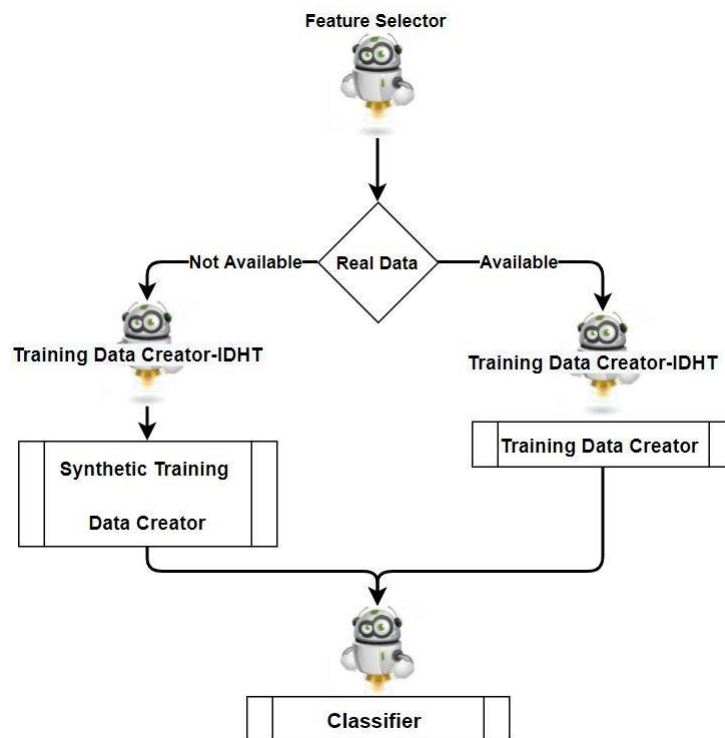


Figure 22: How the IDHT-2 works (Source: Self).

IDHT-2 generates synthetic data as images as well as text format. The generated images are then used to generate captions that describe a particular event. Then the synthetic text is used to generate synthetic images that simulate multiple scenarios about an investigated manufacturing event. Figure 23 shows the process of synthetic data generation and how the IDHT-2 handles various manufacturing events autonomously.

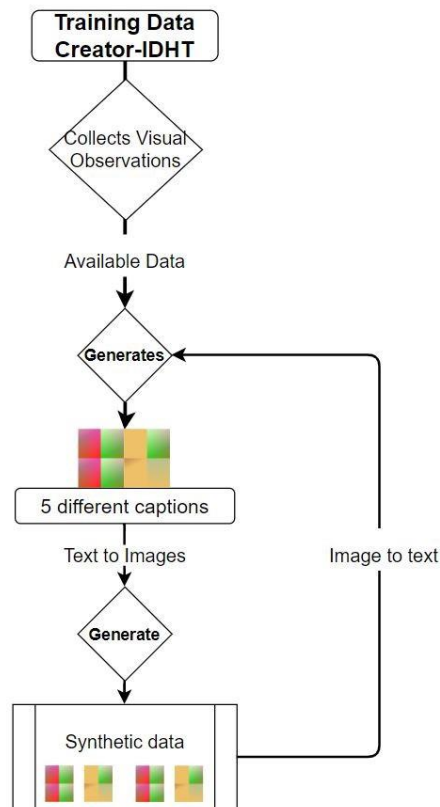


Figure 23: Synthetic data generating process (Source: Self).

The captured data from the physical edge included all the known different data types, Quantitative data, Nominal data, Qualitative data, and Ordinal data. Also, the streamed data was as Discrete data and Continuous data. Using multiple data types required multiple models to address multiple challenges and handle different issues. The ability to deploy multiple models within one system and work with high parallelism needs robust hardware infrastructures such as Cloud systems. However, in this research, using Cloud systems was not possible because of the high level of confidentiality of the streamed data from the manufacturing processes. Therefore, it was essential to introduce a new approach to processes and transfer different data types in one data type that can be used to train GANs models to handle multiple issues and challenges. A hashing algorithm was developed to transfer the readings of all the different parameters to hash codes and then transform them to colour distributions. The generated colour distributions were visualised on their virtual components inside the IDTR system. The hashing algorithm is used whenever a new IDTR system is generated.

During the generating stage of the IDTR environments, all the streamed data, real or synthetic, will be fed into this function and be hashed. Then, the IDTR system uses these hash values to visualise the different statuses of the virtual assets. Also, there was a

security reason to hash the captured data into colours distribution because, in reality, data will be collected from multiple plants and distributed through the internet. In doing so, the captured data will be encrypted at the physical edge and rehashed at the IDTR edge with a high level of protection. After that, IDHT-2 tool collects the generated distributions and merges them to generate images used as datasets to train, test, and validate the developed IDH tools. Figure 24 shows how the hashing process works.

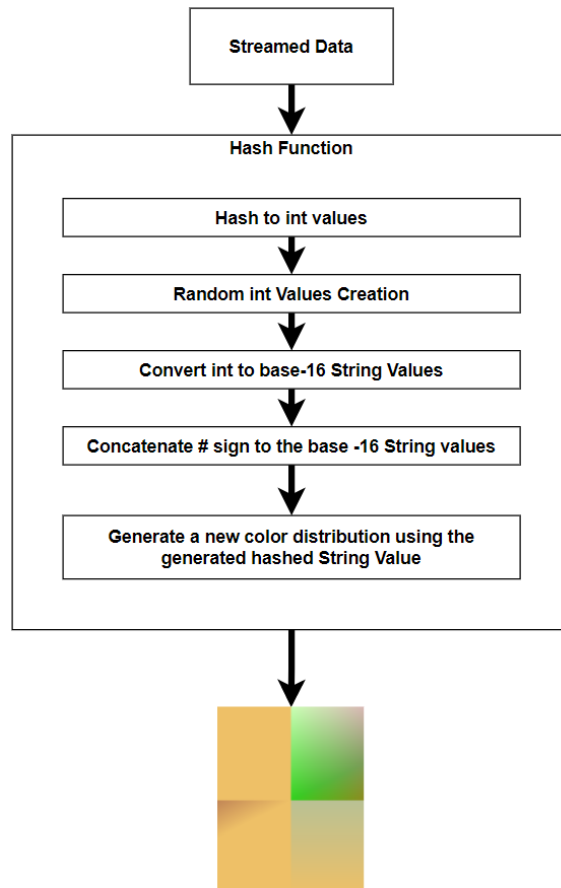


Figure 24: Numerical-to-colour hashing process (Source: Self).

Function to convert data from raw string format to unity colour

Start function

Get data in string format from data streams

Convert string data to Hash Code using the GetHashCode function

Generate a unique number by supplying the generated hash code to the following algorithm

where un is the unique number and hc is the hash code of the raw data

4.2.2.3 Visual Observations Classifier (IDHT-3)

IDTR simulates several possible changes when the IDT predicts any issues in manufacturing processes. There was a need to design another IDH tool that accurately predicts and classifies multiple events such as equipment status, failure events, and warning alarms. An IDH tool named as IDHT-3 was developed to tackle such critical processes.

IDHT-3 uses the information obtained by IDHT-2 to classify any collected visual observations from the IDTR environment. As highlighted in section 4.2.2.2, all the collected observations are transferred into canvas images representing a knowledge about different manufacturing processes. Additionally, IDHT-2 assigns five different descriptions collected from multiple visualised parameters about the physical twins. As a result, all the generated images will have five different labels to explain multiple aspects about various manufacturing events. IDHT-3 reads those generated labelled images and accurately classifies them. In reality, the semiconductors industry includes multiple complex manufacturing processes that face several challenges. Thus, it requires hundreds, or more, of different events and actions to overcome particular challenges and make one manufacturing production line works with its best efficiency. Such a matter always results in minimal prediction capabilities when designing multiple classifiers using AI technology. Figure 25 highlights where the IDHT-3 tool is located within the IDTR system and explains how it works.

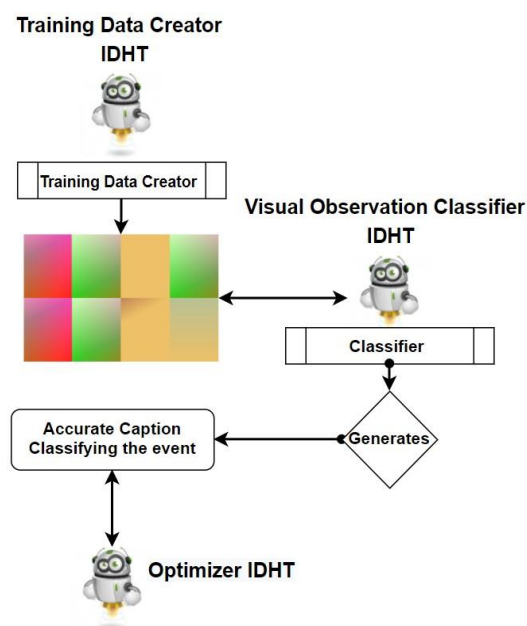


Figure 25: How the IDHT-3 classifies the collected visual observations (Source: Self).

IDHT-3 tool introduced a robust technique that advances the prediction capabilities of the traditional IDT systems. Using the generated data from the IDHT-2, IDHT-3 was developed using a modified GANs model (refer to section 2.3 for details) that generates images and classifications. IDHT-3 uses the Discriminator of a GANs model to serve as a classifier to understand all the collected visual observations better. Thus, making more accurate predictions about multiple events such as failures, decision making, and reconfiguring. A promising GANs model was recently introduced by (Gao et al., 2019) that has shown better results in a classification called Auxiliary GANs. It is a state-of-the-art of the conditional GANs algorithms. Similar to traditional GANs models, Auxiliary-GANs generates images from random input noise. The main difference is that Auxiliary-GANs generates real images and classify them as well. First, it classifies if the generated images from random noise (Z) using the generator (G) are real or fake. Also, it classifies the real images into different classifications using the real data from the discriminator (D). Figure 26 shows the original structure of the Auxiliary-GANs algorithm.

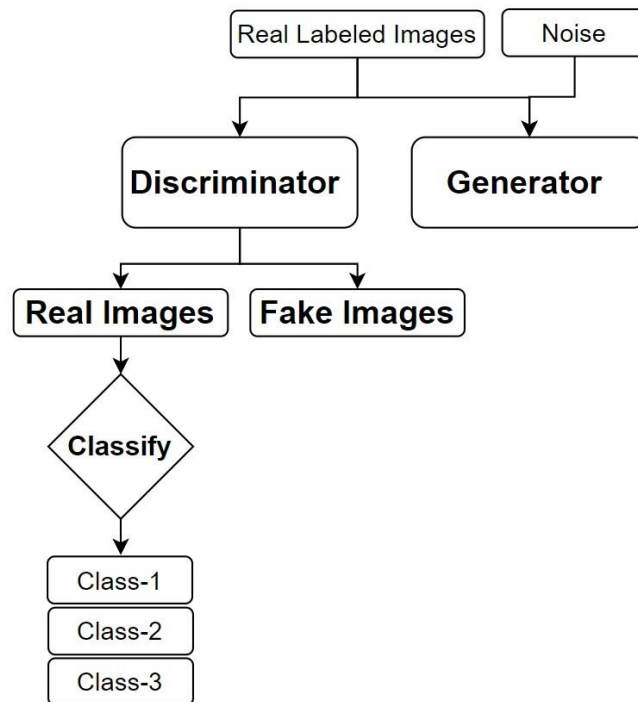


Figure 26: Auxiliary-GANs algorithm structure (Source: Self).

As shown in Figure 26, this type of GANs firstly generates samples of realistic events and secondly implements multiple classification techniques that helps to accurately classify various events. IDHT-3 introduced a new modified Auxiliary-GANs model by

adding another input layer to the original Class C input. A new interface was added to allow classifying the generated canvas images from two different sources; 1) labels generated from real events using IDHT-2 and 2) users (experts) labels to improve the labelling process of the original data. However, human labelling was done by three wire-bonding experienced users, and it was only needed to validate the labelled generated training data by the IDHT-2. Also, this feature was added to increase the level of trust between the system and the experienced users. As a result, human labelling was needed during the first training phase of the IDHT-3, and it was needed only if the IDHT-2 provided wrong labels. Also, the same steps of human labelling were required when there was a change in the bonded products. Figure 27 shows the modified Auxiliary-GANs model structure and how it works.

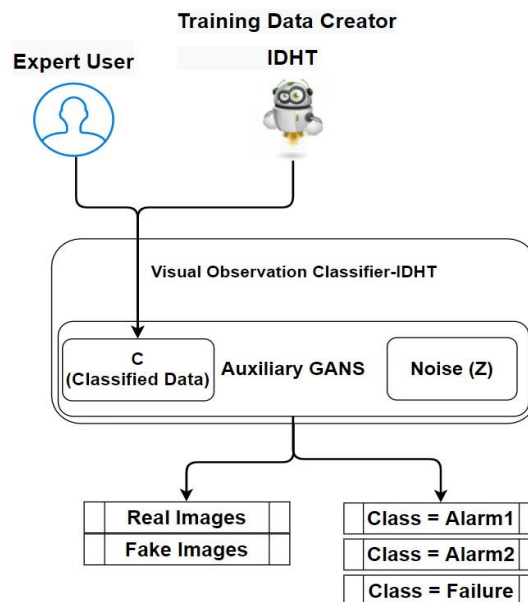


Figure 27: The structure of the developed Auxiliary-GANs model (Source: Self).

It is essential to mention that there is a real challenge in complex manufacturing processes such as the semiconductor manufacturing sector when automating various processes due to the high level of human intervention and the different specifications of the used equipment. As a result, there was a need to include the human element in the training processes to validate some semi-automated procedures. For example, most of the maintenance procedures rely on humans and require physical reactions. Thus, the IDHT-3 was designed to interact with experts to learn how the systems normally work and how their different status is handled. An example of using the IDHT-3 in the IDTR

system is the alarm detection events process. In several situations, equipment provides extended downtime due to regular alarms. Because of the automation limitations, those equipment always need human physical input to clear those alarms and force the equipment to change their status.

The IDHT-3 serves as a classifier to predict whether an alarm event is a technical failure with the machine or other non-machine failures such as defective materials or required cleaning. If the prediction was a machine technical failure event, the IDHT-3 would request maintenance actions accordingly. Whereas if the predicted failure was a non-machine technical failure, IDHT-3 helps the IDHT-4 (optimiser) to take the right action and then it clears the warning and keeps the machine running. Figure 28 shows how the IDHT-3 predicts the two types of the mentioned failure events.

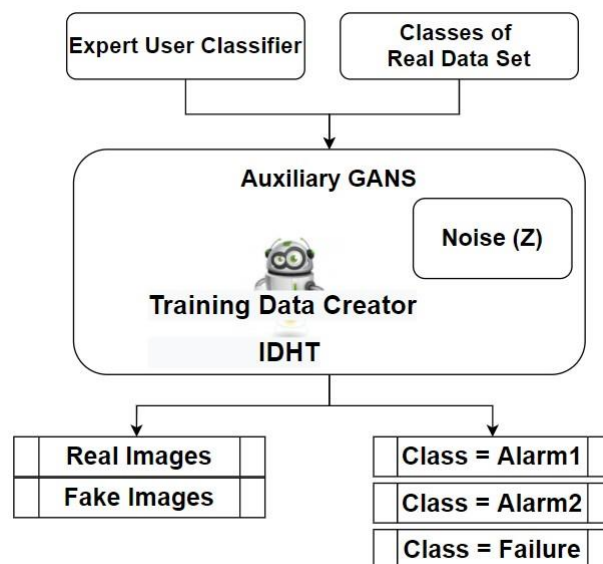


Figure 28: Failure or warning classification process using the Visual Observation Classifier (Source: Self).

To conclude, this tool is responsible for any prediction capabilities of the IDTR system. The main task of this tool is to accurately classify multiple events to help the IDTR system make better autonomous decisions to improve the overall effectiveness of the system. Also, it handles all the classifications of the subscribed data to the IDTR system. The IDTR system uses this tool to predict all the collected visual observations and autonomously makes a decision/s accordingly. The next section explains another IDH tool name as IDHT-4 and acts as an autonomous optimizer within the IDTR system.

4.2.2.4 Optimiser (IDHT-4)

IDHT-4 acts as an autonomous reconfiguring tool and it reacts to any needed changes when the IDTR system simulates any predictions for the IDT system. DHT-4 role is to change the virtual equipment parameters and it generates different outputs by using the data generated by the IDHT-2 and classified by IDHT-3. The need to train the humming tools to classify multiple events requires multiple scenarios in the IDTR. Thus, to train those tools to understand and predict a particular output of a process of an equipment, there is a need to have different output scenarios to create a useful training data set. IDTR generates multiple scenarios to simulate any possible changes and their potential impact. This process happens in advance to validating any predicted events by the IDT that are correct and valid to be applied.

The number of possible changes/scenarios in the virtual assets configurations was identified by using two main techniques. 1) continue to generate different configurations during the predicted time of any predicted failure event and it stops right before the event occurs in the physical assets. This technique was used for the critical-time scenarios. A threshold was set to stop the optimisation process using a simple function that measures the failure prediction time P_t and subtracts it from the creation time C_t of the IDTR environment. Thus, the optimisation time = prediction time window (P_t) - IDTR creation time (C_t). 2) another logic was implemented mainly for scenarios with a long prediction time window. Thus, IDHT-4 continues to create synthetic virtual configurations using the original accepted equipment's configurations values. In the physical environment, the equipment accepts certain values and measurements and dismisses all the values outside the determined ranges. For example, X, Y, and Z positions of the capillary of a wire-bonding machine accepts limited error values to continue bonding a wire and stops the entire process if one of those coordinating values goes outside the accepted reading. The IDHT-4 uses all those values to continue to generate different configurations and to combine them with the other selected features by the IDHT-1. As a result, IDHT-4 uses these combined features to simulate different virtual stati of the virtual equipment while testing the impact of any changes or recommended solutions. For example, when the accepted measurements of a temperature feature range from 299 to 302 C, and using increments of 0.02, this will result in 151 possible configurations. Thus, the IDTR keeps generating different configurations based on all those 151 possible values to measure any possible changes to allow the IDTR to make better decisions. However, in case

longer prediction time is used, the IDTR continues to test more scenarios using values outside the accepted ranges and to explore new correlations that might lead to new insights. Figure 29 shows how the IDHT-4 is used to generate virtual scenarios within the IDTR system.

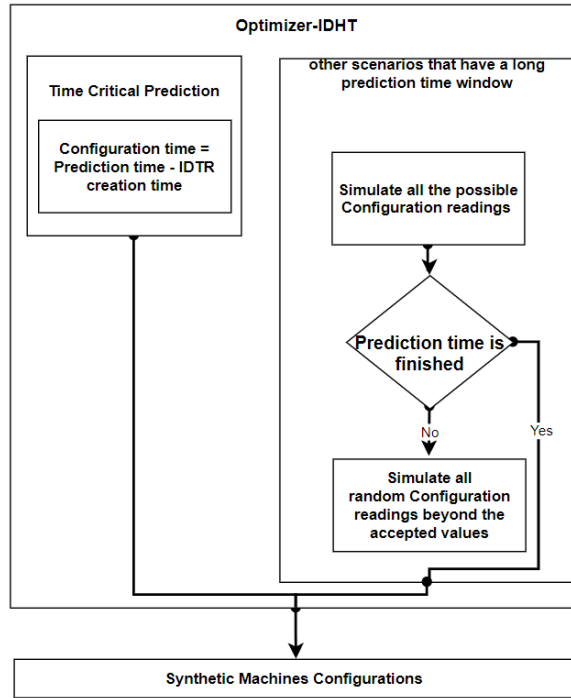


Figure 29: How IDHT-4 generates virtual machine configurations within the IDTR system (Source: Self).

An algorithm was developed to change the parameters of equipment on the IDTR environment only. IDHT-4 was used to generate synthetic tabular data that is similar to the real equipment's configurations. The generated data is used when the IDTR system requests it to simulate several scenarios and, as a result, it is expected to make better decisions. It is essential to mention that the IDHT-4 uses a GAN model called 'Wasserstein GAN' (WGAN) and it was developed earlier in 2017 (Gulrajani et al., 2017). There was a need to have a stable and accurate model that can create reliable parameters similar to the real readings in the physical system. WGAN is an upgraded version of GANs, and it addresses the training convergence and consistently stabilizes the training of the traditional GANs models. WGAN uses different discriminator that uses different weighting technique (Petzka et al., 2017; Song and Ermon, 2020). Also, a threshold was used to disable this tool when a change in the status of a real equipment is occurred. In such a way, the possibility of missing information from a real equipment is declared to zero per cent. In reality, it is a bit challenging to collect data set that include

enough information about different events. It requires a long time to collect enough data about an event, and it depends on whether that even happens regularly.

The IDHT-4 acts as an autonomous optimiser to generate different outputs about the status of different equipment and to make them available when training the IDHT-3. This tool speeds up all the training processes by creating various synthetic outputs and train the humming tools on their behaviour. IDHT-4, together with IDHT-2 and IDHT-3, can generate a full synthetic scenario where synthetic data can be generated based on synthetic equipment status, and it classifies the output accordingly. Figure 30 shows the mechanism of the optimiser-IDHT-4 and where it is located in the IDTR system.

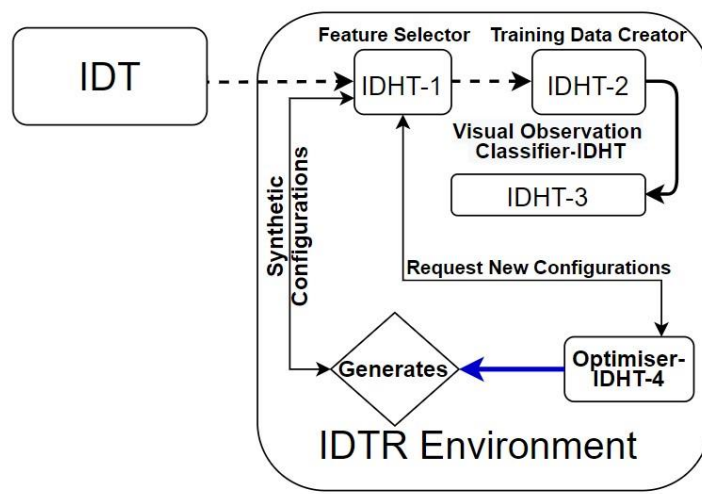


Figure 30: How the optimiser-IDHT-4 works (Source: Self).

As it can be seen from Figure 30, IDHT-4 generates equipment configurations that are very similar to the real-world ones. It is essential to mention that GANs models depend on their generators to improve their ability to extract synthetic data. Such improvement is measured by using an actual dataset as a reference to define the level of similarity of any generated new images. In general, the number of developed GANs applications continues to grow, attracting different interested stakeholders. As a result, more evaluation metrics are introduced to develop more accurate predictors. However, among the GANs evaluation metrics, the overall generator accuracy remains a key metric about the performance of the GANs models. Also, different quantitative techniques were used to measure factors such as image quality and similarity. This research focused on a well-known validation technique called Frechet Inception Distance (FID) to ensure that the IDTR system would use only accurate images similar to the generated images using

captured actual data. Accurate synthetic images were used to avoid making wrong classifications when simulating virtual scenarios using any generated synthetic data.

Frechet Inception Distance evaluation matrix evaluates the quality of the synthetic data and captures the similarity level compared with the actual images. It does that by comparing the statistics of a synthetic dataset with the statistics of real images from the target failure event. The IDTR system focused on the Feature Distance measurements between the real images and the generated synthetic data to set up a similarity threshold. This step was done after training the model and used two different datasets: real and synthetic. Figure 31 shows the achieved FID results.

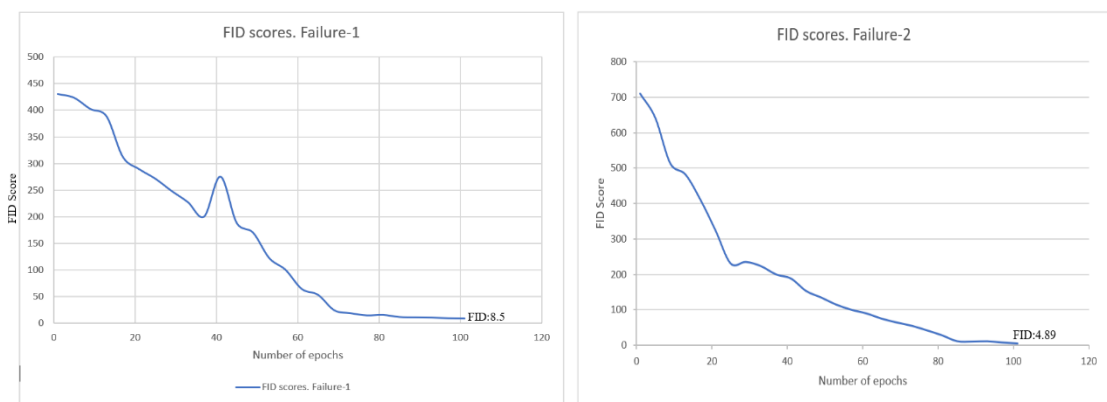


Figure 31: Sample results from the FID Algorithm (Source: Self).

Figure 31 shows the FID scores for two classes of images for three different failure events. The measured feature distance values for the three tests were relatively small. Thus, the generated synthetic data was accepted to be used to simulate virtual processes that are similar to the actual manufacturing processes. Overall, the achieved FID scores were expected because the used images did not include many objects. However, using larger datasets is likely to improve the measured scores and achieve smaller FID scores.

Also, it generates such configurations when they are not available to improve the quality of training process and to reduce any needed training time. The impact of adding and using this tool was noticeable and it improved the overall quality of the training process.

4.2.2.5 Failures Predictor (IDHT-5)

IDHT-5 main role is to improve the time-critical automation challenges of IDT and to provide more accurate predictions. The IDHT-5 works on information generated by IDHT-3 to predict future failures of the system. The ultimate goal of IDTR technology is to become an adaptive virtual triplet system that can visualise physical systems, fully control them, predict regular and irregular failures and events, and automate all procedures to run complex manufacturing processes. As a result, IDTR becomes an essential element of any manufacturing process. Many manufacturing industries seek to use tools to improve various complex manufacturing processes such as: Predictive Maintenance, Root Cause Analysis, and Risk Assessments. One of the promising developed humming tools was to achieve such a high-quality predictive and proactive maintenance capability. However, with the concept of Machine Learning, this tool can be easily upgraded to meet different application requirements. IDHT-5 works in parallel with the IDHT-2 to create different training data to make future predictions. It flags and highlights, in advance, particular critical failures events that cause high losses proportion. Such prediction time window helps IDTR to simulate various proactive actions to prevent equipment down time. Even though equipment failures need direct human intervention, IDTR with the advanced of the IDHT-5 managed to decrease that equipment's downtime by informing maintenance teams in advance. In such a situation, IDTR predicts an event, makes the right action that should be taken, and involves the relevant teams needed to repair failures. As a result, the required time for maintenance has remarkably reduced due to the right preparation time before a failure occurs. It is essential to highlight that IDTR involves autonomous decisions related to several elements of the manufacturing processes. This includes material request actions, replacement tools requests and more.

The IDHT-5 used the IDTR as a training environment to read useful insights to improve its prediction capabilities. The IDHT-5 tested the concept of IDTR and proved the capability to transfer traditional IDT environment and make it to act as a training environment. This research produces a new generation of IDT system that is autonomous. It is essential to highlight that the IDTR and particularly the IDHT-5 were tested in a production facility of a semiconductor manufacturing company. The whole process began with one failure event and targeted the possibility of predicting when this failure event might reoccur. Such a prediction helps maintenance teams be alerted in

advance and it gives them enough time for any needed preparation. Although, the concept is subjective to the type of failure event and whether it can be fixed straight forward, the benefit of using the IDHT-5 is to automate warning processes to the IDTR system and users simultaneously. Similarly, to other developed tools, this tool was designed using Deep Learning algorithms. A modified GANs model was developed to tackle multiple failure events classifications concurrently. An extra layer to a traditional GAN model was added to add two discriminators instead of one. Considering the need to predict when a set of events might occur in the process, three different classification types were tested. Supervised, semi-supervised, and regression using GANs techniques were implemented to predict when such events might happen and to predict the remaining time for certain parts in equipment before they need to be replaced. The idea here is to collect visual observations typically using the IDHT-2 tool but within fixed time cycles based on different assumptions. For instance, visual observations can be collected every half-hour, one hour, six hours, and keep using similar chosen pattern. Finally, the fifth IDH tool makes predictions based on these time cycles to classify any possible failures. Figure 32 shows the preliminary proposed design.

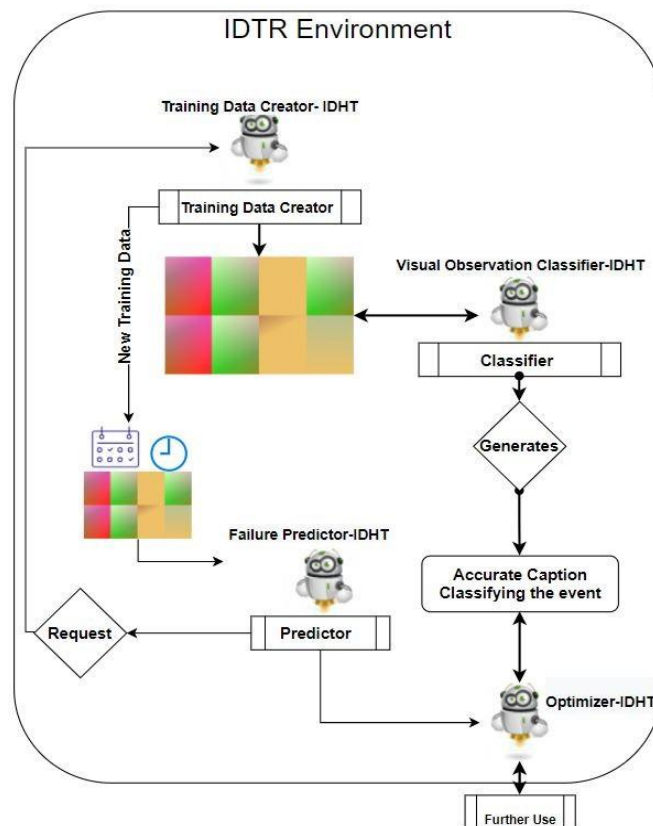


Figure 32: How the failure predictor-IDHT-5 works (Source: Self).

As shown in Figure 32, all the classified events from the IDHT-3 tool will be re-classified based on different time cycles. As a result, the IDTR system will request all the possible events within a specified time sequence. As such, the IDTR system can make autonomous decisions to deal with all the predicted events.

It is crucial to highlight that the role of the IDHT-5 does not stop at the failure prediction process, but it recommends the best reactions. Because IDTR aims to virtually achieve the adaptive machine concept, this research added a new feature to the IDHT-5 to make decisions in nearly real-time to automate several optimization processes of equipment. As it can be seen from Figure 2832 the prescriptive feature requires very accurate classification for an event to suggest the right action(s) to take and to handle the predicted events accordingly. As a result, the IDTR system becomes more efficient in decision-making processes. IDHT-5 was developed to consider the prediction time frame and the needed period to fix such failure events. The upgraded IDHT-5 uses the time cycles to give time priorities to all made autonomous decisions. Another GANs algorithm was used, and it is called “Text-to-Image Synthesis Stack GANs” (Zhang et al., 2018) to create a correlation between all the events predictions and the right procedures that should be taken to overcome any detected issues.

There was a need to make the IDTR system predict failure events in advance and recommend the best maintenance plans. Such an approach required a set of conditions such as the expected failure's type, the prediction time window, the recommended maintenance procedures, and their possible impact on the downtime efficiency factor. IDHT-5 identifies the failure type and related time factors, including the remaining time before the failure happens and how long it takes to be fixed. It also uses the predicted failure event as keywords to search for the best maintenance plan. IDHT-5 also changes the state of any targeted wire-bonding to 'investigate mode' to validate the best maintenance plan in terms of downtime, efficiency, and the needed preparation time. Figure 33 shows how the IDHT-5 works.

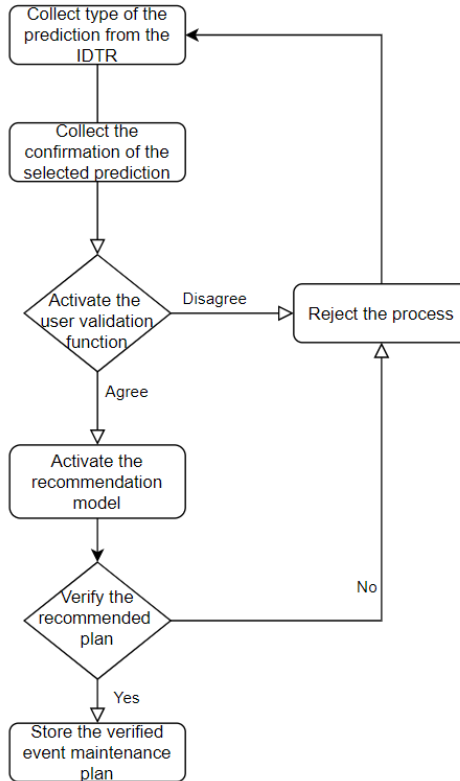


Figure 33: How IDHT-5 works (Source: Self).

As shown in Figure 33, IDHT-5 starts working after the predictor tool (IDHT-3) validates the predicted failure state of any of the wire-bonders. Then, it automates the entire maintenance plan after verifying any improvement in the machine downtime. The algorithm that IDHT-5 tool uses works as follows. Step 1. Request the classified failure event from the IDT system. Step 2. Receive the confirmed and validated prediction failure events from IDHT-3. Step 3. Activate the user validation layer based on the user's request. This process is done by the wire-bonding maintenance engineers when they suspect any wrong classification by IDHT-3. Step 4. Activate the recommendation model to suggest the best maintenance plans. This step is done by verifying only the recommendations that provide shorter downtime than the original measured machine's downtime on the physical side. Step 5. Store all the confirmed maintenance plans in a Kafka topic to be used as a reference for future predictions and to evaluate the overall IDTR system predictive maintenance capabilities.

4.2.2.6 Section Summary

To conclude, this research seeks to develop an intelligent system that overcomes the IDT systems challenges, and it goes beyond of it is technical capabilities. Instead of building

a new environment to overcome the portability issues of the IDT system, the IDTR system will take a virtual copy of any IDT system. In such a way, the IDTR acts as an autonomous training environment, and which will then be used by the Intelligent Humming Tools. The role of these IDH tools is to collect visual observations and to improve the overall performance of the IDT system. With making small changes, the functionality of the IDH tools can be modified to suit the nature of any new IDT system and be adopted. How the feature selection algorithm works needs to be changed so that it can collect different virtual assets observations. Such change is needed in order create new training datasets that can explain any possible new targeted manufacturing processes.

Also, the concept of IDTR does not impact the IDT systems and it works in parallel to avoid any wrong predictions and classifications of results. The IDTR system will be generated when the IDT system predicts a manufacturing event, and it will work in advance to simulate any expected results out of that prediction. Using the prediction time to simulate all the benefits and circumstances of such predictions would protect all manufacturing processes. Wrong predictions, low levels of predictions' accuracy, challenges from implementing changes, and new root causes issues are all avoided with the IDTR technology. Figure 34 shows a high-level scenario of how the Intelligent Digital Triplet system works.

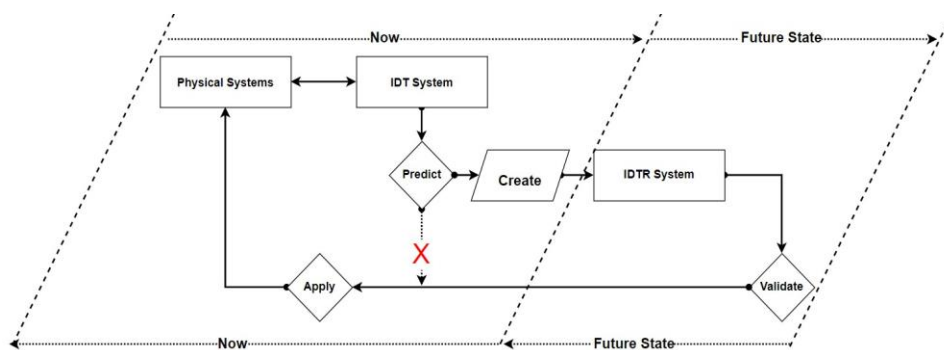


Figure 34: How the Intelligent Digital Triplet system works (Source: Self).

The idea is to develop intelligent tools that can use IDTR systems as a training base to make accurate predictions about what might happen over different stages of complex manufacturing processes. Besides, improving the intelligence and capabilities of the developed IDHTs can be done in real-time with 24/7 accessibility to speed up training processes. Furthermore, allowing the humming tools to automatically decide on when they can re-train themselves on new events. Additionally, they can implement an

automation feature selection to decide which data can be used to make a better decision about future control actions. The next section highlights the used technologies to visualize the developed IDTR system.

4.3 Extended Reality Use in the Developed IDTR System

Digital Twin refers to designing an identical replication of physical assets where both the physical and the virtual twins are dynamically connected. As a result, users can gather more insights and take better actions accordingly. In domains such as semiconductor manufacturing factories, there is a desperate need to meet business goals and to achieve more advanced product designs. Furthermore, achieving higher revenues with a minimum cost function. Achieving these benefits has become more accessible by using immersion technologies like Augmented Reality and Virtual Reality. With the aid of IoT technology, VR and AR can utilize better results and achieve more challenging business goals.

This research aims to implement a recently developed term called ‘Extended Reality’ to enhance the traditional IDT environments and to add more engagement capabilities to immerse users in the IDTR environments. ‘Extended Reality’ refers to the field of developing enhanced environments that allow users to interact with some virtual elements using various techniques (Leal et al., 2019). The need to use technologies such as VR and AR was to meet the nature of the IDH tools and how they work. IDH tools use virtual cameras to capture some observations that are selected automatically to build an overall perception about the performance of the manufacturing processes. There was a need to allow the developed IDH tools to act rationally and implement multiple tasks autonomously. Such functionality requires the ability to move freely inside a virtual environment and communicate to implement multiple actions. On the other hand, IDTR used AR technology to allow different users, mainly operators and maintenance engineers, to use the made recommendation by the IDTR and merge them with the physical parts that need to be fixed or controlled. IDTR invested the ability to interface with the physical machines and their virtual assets to visualise all the decisions and pass all the validated recommendations to the end-users. Such advantages would be missed using traditional 2-d visualisations technologies. As a result, the end-users demonstrated all recommendations in real-time while still seeing the targeted physical parts and better understanding all the required changes.

The following subsections highlight two different visualization stages that the IDTR system uses. The aim of using those cutting-edge technologies is to create enhanced digital environment that allows users to interact and validate some specific autonomous actions. Thus, this will improve the decision-making capabilities of the developed IDH tools.

4.3.1 VR Cave Experience

Virtual Reality (VR) technology has been used widely over different manufacturing sectors and it has shown a great success in different aspects. The idea of using VR as a tool for visualizing manufacturing lines status and behaviour can help manufacturers to better understand what is happening and help them to react appropriately to different situations. The potential and the capabilities of the VR technology can help integrate various elements of manufacturing processes within one VR environment. This helps decision-makers better plan activities and following simpler action-making processes for solving multiple factory issues. As it is mentioned in section 5.4, VR can quickly improve user experience by designing user-friendly experience that allows users to interact with 3D assets and understand more about the different complex manufacturing processes. With the capabilities of adding real-time streaming data to visualize real-time reading, this can also be more beneficial to all manufacturing processes. For this project, a recently developed VR technique is used, which will allow users to freely move in a VR environment and interact through different techniques such as sound commands, gazing, and gesturing. Figures 35 and 36 illustrate an interactive approach for the developed IDTR in the semiconductor factory system.

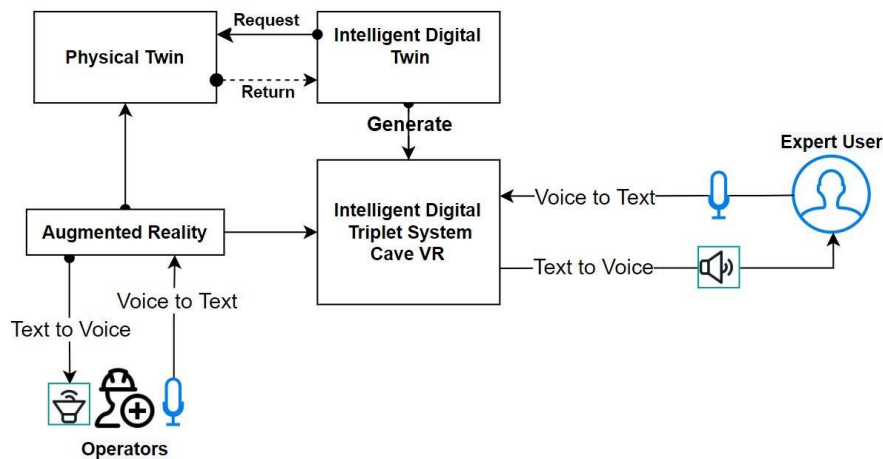


Figure 35: Voice recognition interaction technique (Source: Self).

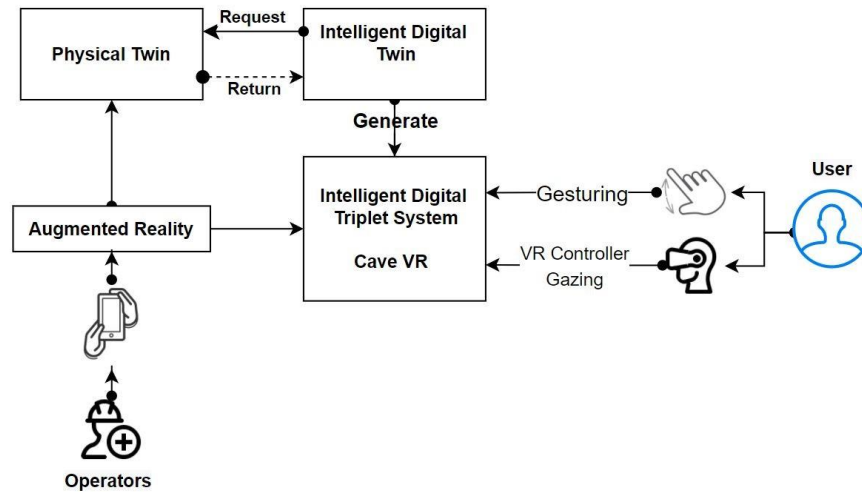


Figure 36: Leap Motion and VR controller’s interaction technique (Source: Self).

Cave VR experience, including 3D assets of all the wire bonding manufacturing process will be embedded. Thus, modelling what happens in the physical twin assets in virtual reality assets and creating an advanced simulation that can be used for several purposes. The developed Cave VR experience will help to adopt more technologies to improve user experience and to bring manufacturers closer to their manufacturing lines. The novelty of this research is to use the developed VR environment as a training base to simulate different scenarios. The VR environment will be used to train some of the Intelligent Digital Humming tools to automate various complex manufacturing production processes such as maintaining, stopping, restarting, and configuring machines.

In summary, the advantages of using VR technology to simulate the real-time behaviour of a physical manufacturing process can be flexible and beneficial to train AI and machine learning systems. Doing so will help develop Intelligent Digital Humming tools to semi-automate or fully automate different manufacturing processes. Thus, decreasing any possible equipment downtime and ensuring machines keep operational in an efficient manner.

4.3.2 AR Experience

Augmented Reality is the technology of merging computer-generated 3D assets into live captured scenes for real-life environments. In such ways, users can easily use those 3D computer-generated assets to analyse real-world manufacturing processes in more depth. In the semiconductor manufacturing company that this research was based on, various processes require manual human intervention to control, set up, and validate different

processes. Applying some changes and being physically present at manufacturing productions limited the possibilities of using VR and other PC platforms. Maintenance teams need access to real-time information about the equipment and failure events while they are at the location. Thus, an AR application was developed to help them use light smart devices to visualise real-time predictions and insights about how to deal with any failure events that might occur. The developed AR application is dynamically connected to the IDT system, and it was used to explain any automatically taken actions by the Intelligent Digital Humming. Besides, the AR experience is used to explain all the maintenance actions and it provided a real-time guidance to engineers to ensure achieving high-level of efficiency in following maintenance procedures.

On the other hand, the developed AR experience was used as a feedback forum to help the Intelligent Digital Humming tools validating their automated actions and improving their future decision-making actions. Figure 37 illustrates the use of AR in the IDTR system.

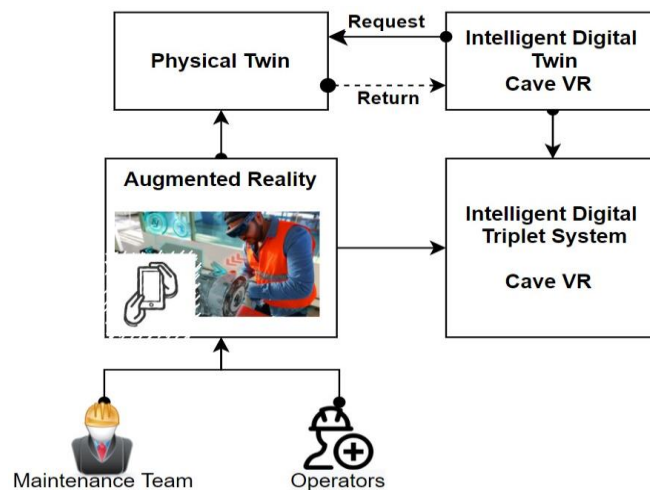


Figure 37: The use of AR technology in the IDTR system (Source: Self).

Traditionally, there are different maintenance procedures and those are performed on different parts of the used equipment such as Preventive and Predictive Maintenance. In this research project, there is a need to know more than what has happened whenever a failure occurs. Furthermore, there is a need to know what might happen and what to do as a result. The developed AR experience allows engineers to see which component needs repairing as well as any potential insights that might help them to improve the overall efficiency of maintenance processes. Moreover, engineers can interact with the internal parts of equipment through the AR 3D assets. As a result, this will provide more capabilities to detect more root causes of failures that had not been explored using

traditional statistical tools. Figure 38 shows screenshots of the developed VR. Also, Figure 39 shows the developed AR application.

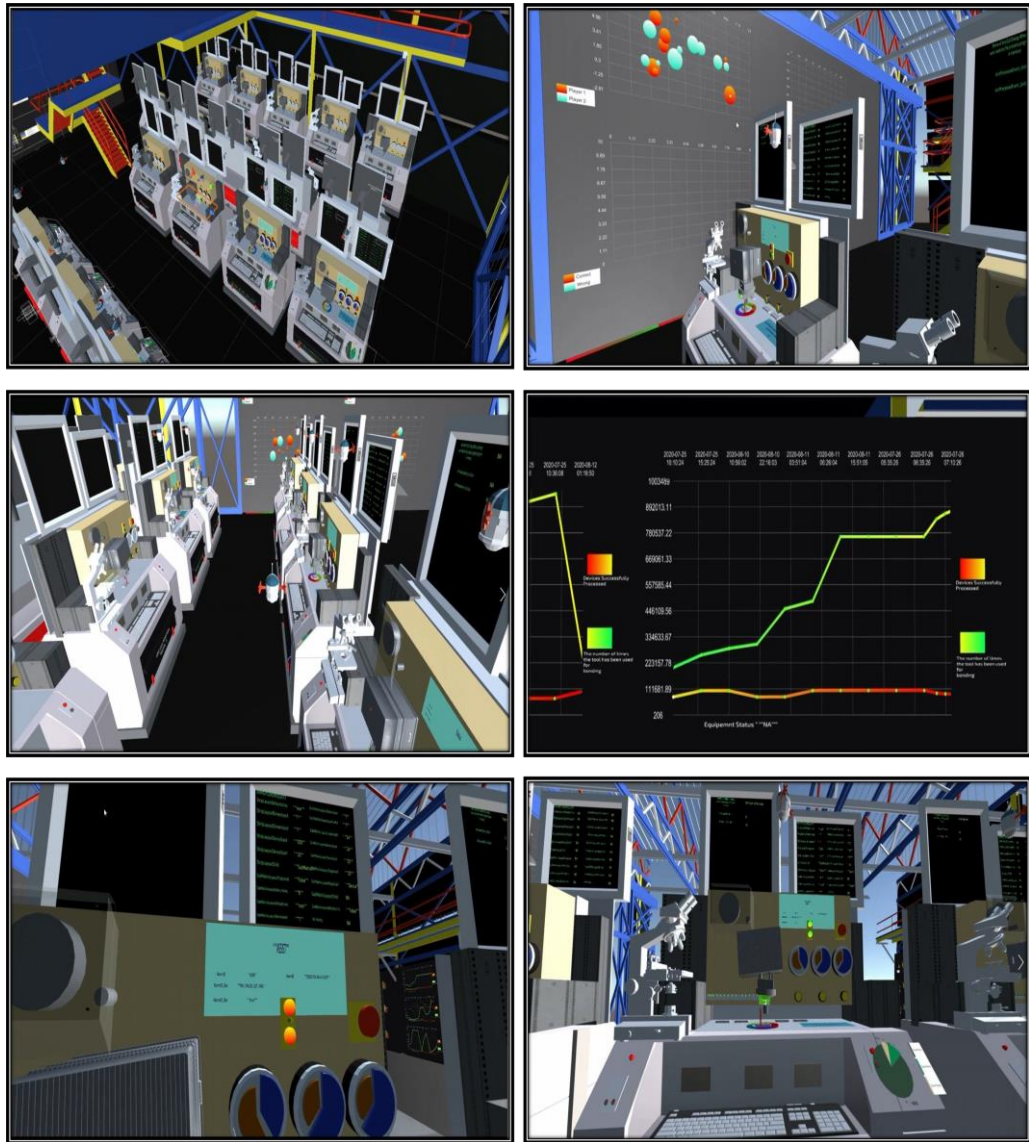


Figure 38: Screenshot of the developed VR tool (Source: Self).

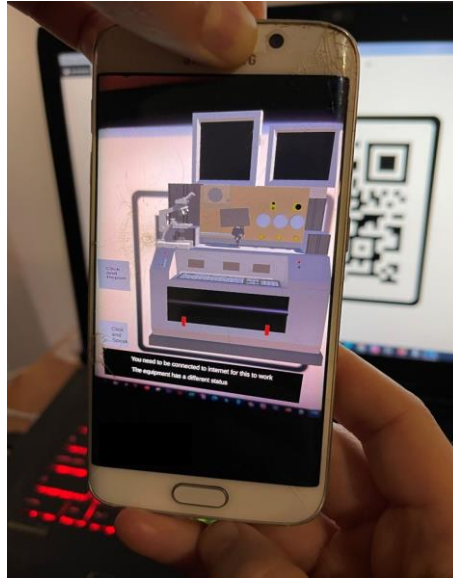


Figure 39: A screenshots of the developed AR tool (Source: Self).

It is essential to highlight that the developed AR experience was used in two different manufacturing stages: operations and maintenance. While the IDTR automates some processes, there was a need to design such a tool to provide real-time insights about the IDTR actions and changes. Considering the safety of operators and maintenance engineers, the AR application was used to receive the suggested changes from the IDTR. Some of those changes need human intervention and the designed AR system tackles the communication between the operators and the IDTR in real-time. Maintenance engineers also use the same tool to understand any autonomous changes and react to any suggested instructions by the IDTR system. An example of using the designed AR system was when the IDT predicted a failure event and then the IDTR confirmed the same failure event. Furthermore, the IDTR updates a list of instructions on the AR applications. Also, a set of notifications was sent to the maintenance team to prepare for some physical rearing procedures. Figure 40 illustrates a scenario of using the AR applications.

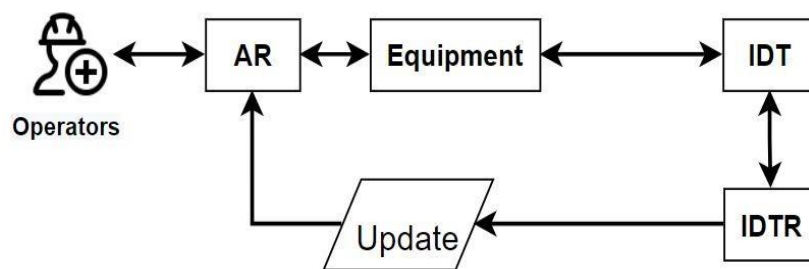


Figure 40: The use of AR technology in the IDTR system (Source: Self).

To conclude, AR technology provided a quick access to the different physical assets in real-time. Also, it allows faster feedback to the IDH tools to learn and train more algorithm that will improve the overall predictive maintenance procedures. Section 4.4 provides more details about how the AR experience was used in a semiconductor manufacturing process and it shows how it improved the overall system accuracy.

4.4 Case Study

4.4.1 Microelectronics Manufacturing Plant Description

This research project had full access to a semiconductor manufacturing plant, and the developed system was tested in a real-life manufacturing environment. Such an environment allowed more use of assets to scale the capabilities of the developed system. Also, the developed IDTR system was tested in a real-time manner in a physical manufacturing environment. Thus, the IDTR concept was proven in an actual semiconductor manufacturing environment rather than developing in a research laboratory environment. Also, it was not possible to complete this research outside the chosen manufacturing company due to a lack of similarly needed capabilities.

STMicroelectronics manufacturing company uses hi-tech machines and smart equipment in its production processes. Production and assembly lines are equipped with smart devices that monitor the behaviours of the entire production processes to understand how each action is executed. With the emerging field of Big Data, STMicroelectronics collects large datasets about almost every part of the different manufacturing processes. Within the company, a Big-Data team continuously seek better ways to:

1. Capture data from different manufacturing processes.
2. Analyse captured data to form meaningful indications.
3. Make decisions based on the analysed data.
4. Develop a way to execute the made decisions back into the manufacturing processes to rectify any abnormalities (see Figure 41 for more details).

Figure 41 shows the current used infrastructure to collect data from the different manufacturing lines. Also, it illustrates how the collected data is used to present insights to their teams to use it for further decisions.

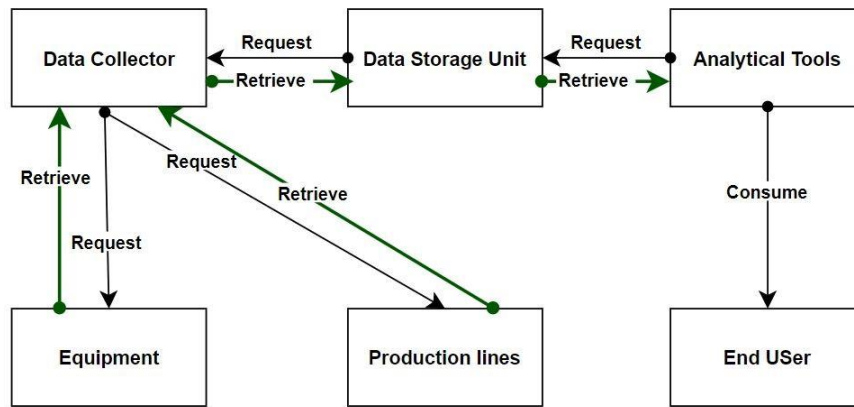


Figure 41: The current data collection approach (Source: Self).

This project is based on the STMicroelectronics manufacturing settings, where there was a need to combine many manufacturing stages that are involved in the manufacturing process. This was needed to group these stages in a logical method based on time sequence and typical sequence of the production process. For this project, the entire production line was divided into three main stages namely: Back-end, Assembly and Final testing process. Multiple processes were grouped under each of these three categorized production stages. Figure 42 shows the architecture of the three main manufacturing stages.

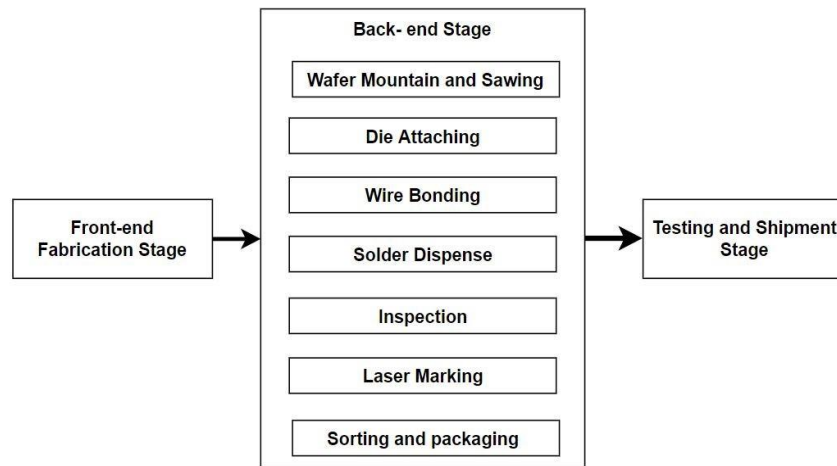


Figure 42: The different processes and stages of the used case study (Source: Self).

It is essential to highlight that due to data accessibility limitations, this research focused only on the wire bonding stage and targeted all the available parameters. As mentioned under section LLL, the wire-bonding process provided an excellent environment to test the concepts of the developed IDTR system and the IDH tools. By default, the wire-bonding machines generate limited real-time data, but more parameters and information about them were streamed during this research. Also, the nature of those

machines helped to install extra sensors and capture more previously unexplored data. However, the focus on this process did not limit the overall performance of the developed IDTR system. The concept of the IDTR system and IDH tools can handle the changes in the IDT system side and reshape itself. When a different process rather than wire-bonding is targeted, the IDTR system will generate new training data leading to new insights related to new automated actions. Table 1 presents the number of sub-stages grouped under the three main stages and the number of the parameters each one has.

Event	Number of messages	No. of used parameters
Equipment Status	8	362
Equipment Failures	6	119
Equipment Warnings	5	82
Maintenance Actions	18	122

Table 1: Total of the used messages and parameters

An excellent example of those fully automated processes is a failure related to labelling process. The current equipment failure classification process depends on human intervention and entries. So far, operators and maintenance teams can report machine failure events manually and that has caused lots of noisy data together with dummy data. Such noisy data could quickly impact the acquired statistics and will provide inaccurate information and lead to inaccurate decisions. This research aims to automate such operations to make sure that only the accurate and the right warnings are captured and classified correctly. The IDTR system corrects the individual entries, suggests accurate procedures, and automates actions.

As shown in Table 1, for every considered main stage, several data messages were selected based on some pre-defined priorities. Each selected data message included several parameters that were collected from production lines in real-time. Some of the used parameters were considered as more important the others. For example, parameters about the used materials were grouped in one message, while parameters about the materials error messages were grouped in another message. Engineers working on the wire-bonding machines did all the grouping processes to cluster multiple parameters within multiple groups, including the abovementioned examples. Also, an association mining technique was implemented to create several probable association rules that led to better grouping results. FB-Growth method was selected to handle this step and tackle all the categorical data attributes (Shabtay et al.,2021). A historical dataset was used to provide all the considered associations and helped to assign different priorities to all the

used parameters in the final stage. However, the collected historical data included limited parameters, and there was a need to gather more insights from the engineers working on the wire-bonding about all the used parameters.

In contrast, more parameters were discussed and selected by the company to be used by the IDTR system. Adding these new parameters provided an accurate indication of what could be the cause of some of the failures in specialised equipment. Also, all the analysed data messages included both; request events to ingest data from the machines and reply to messages which included real-time data from equipment status. Also, the tested equipment had a small amount of real-time data due to the limited number of installed sensors. Because IDT systems should be identical, more parameters were modelled into the virtual twin which are naturally not generated by the machines. For instance, parameters such as vibration, temperature change, and air pressure that are generated by the surrounding environment could quickly become root cause for failures. I assumed that these parameters could strongly impact the performance and behaviour of such smart machines. However, because the machines were installed in different periods, it was essential to capture more data and take in consideration the possible impact of such parameters. The added IoT system was installed on multiple parts of the machines, and it was re-used to measure the mentioned parameters about the different mechanical parts. Thus, an IoT platform was installed to provide more data and to measure more mechanical movements directly from the machines in the base stream. Such information was visualised on the IDT edge. The next section highlights the main considered technical issues that the investigated semiconductor manufacturing process was encountering. In summary, the developed IDTR system aims to improve the overall equipment efficiency and to decrease required maintenance time and machine downtimes.

4.4.2 Developed IDTR Platform

An IDT platform has been developed to create a high-level simulation to the entire the wire bonding production line. The designed IDT system is built on a live stream of data that was gathered in a real-time manner from a wire bonding manufacturing line. Semiconductor manufacturing provides a massive amount of data about all the different manufacturing processes, materials, and operators. I realised that it is challenging to control the fast flow of data through interactive dashboards. It has always been a challenge to determine which parameters should be given priority to make fast and

accurate decisions. Also, using traditional interaction techniques such as: mouse and keyboard can cause potential delays and damages when dealing with emergencies that require instant attention. The IDT was integrated with a number of AI systems that aimed to improve the root cause analyses and the predictive maintenance predictions. Multiple classifiers using different Machine Learning algorithms were developed to predict the leading root causes of production losses. The output of those ML models then is fed into the IDT to present nearly real-time insights to users. Another system was also developed to enhance the maintenance processes and to help the company's engineers predict when some failures might occur.

It is essential to highlight the overall performance of the developed models was accepted during the testing phase, but they behaved inaccurately in the live stage. Accepting the IDTR system performance was based on the IDH tools overall accuracy, and several validation metrics were used to validate their predictions. Validation metrics such as F1, Precision, Recall, and FID Scores were used to validate the performance of the IDH tools models during the training and testing stages. All the development and implementation took place in a lab using collected historical datasets to train and test the GANs models' accuracy and ability to predict and classify multiple failure events. The accuracy levels of predictions and the amount of the fake predictions dramatically increased when the ML models were deployed in the real manufacturing lines. Intelligent Digital Triplet technology was introduced to overcome such a challenge and to add extra level of validity where any incorrect and unexpected classifications can be improved or replaced autonomously. However, the developed system improved more than the two mentioned tasks: root cause analyses and the predictive maintenance. IDTR was tested to improve a Risk assessment and a Die-to-Die correlation systems that aimed to detect any correlations between initial stages and the final losses in the entire semiconductor manufacturing process. The Die-to-Die correlation task was to detect any correlation between the dies used to make product X positions and the defective products. The idea here was to find a selection algorithm that guarantees to select the right dies to produce the best products. The main idea was to use the developed IDTR as an environment to help the Intelligent Digital Humming tools to make visual observations in real-time. After that, the IDH tools use those visual observations to understand the actual behaviour of manufacturing processes. The designed IDTR environment and the IDH tools create accurate, real-time, and reliable training data to train virtual IDH agents that control and automate various processes of multiple production lines.

The designed environment allows the IDH tools to create different image datasets used as training sets for further intelligent actions. The developed IDTR platform contains several elements: IDH tools, virtual assets, and real-time visualised statistics. A priority was given to the user experience to design light and smooth interaction methods between users and the IDTR system. With the use of AI technology and Natural Language Processing Machine Learning, an IDH tool was added to take care of all the users required information. That allows users to interact directly via speech orders to ingest information about the manufacturing processes through the virtual IDT system. The integrated model was responsible for deducting users voice commands and identify what has been said. This feature was needed mainly with the Augmented Reality application because it was tested in a relatively noisy environment. Wire-bonding equipment generates a relatively high noise, and this impacted the used feature. An extra text layout was added to the AR application to present two different messages to the end-user when using the application in the production line; 1) the predicted commands by the model to validate the users' commands and avoid any miscommunications. 2) A percentage scale to highlight how much is the model accurate about the predicted commands. Figure 43 shows the high-level structure of the developed IDTR for the mentioned use case, and it highlights the main tasks that IDTR was used to prove its concept.

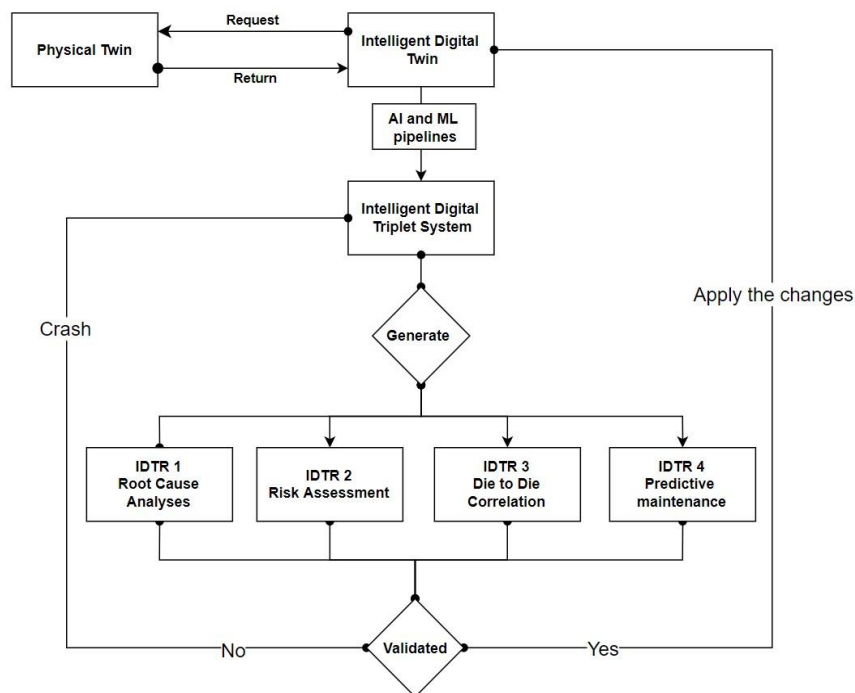


Figure 43: Autonomous failure type detection process (Source: Self).

As shown in Figure 43, and as explained in section 4.4.1, the developed IDTR was designed based on a wire-bonding manufacturing process. Where IDT developed, system was used to visualise the entire production line in nearly real-time, the IDTR was developed to automate and improve the productivity of manufacturing processes. Thus, digitizing several manual actions and reacting to them autonomously. To prove the Intelligent Digital Triplet technology concept, two main critical processes were targeted including, the Root Cause analyses and the Predictive Maintenance. The technology showed a great potential and achieved auspicious results.

To sum up, in a real semiconductor manufacturing setting, similar to the one used in this research, IDT concept was not enough to improve the performance of the AI and ML models. Issues such as data quality and availability were causing low levels of prediction accuracies. The developed IDT provided a considerable number of wrong failure predictions that resulted in more extended machine downtimes. Also, the retraining processes were time-consuming and costly. On the other hand, there was a real challenge when any portability was needed. Therefore, it was necessary to design and to train different ML models to introduce new prediction capabilities. Finally, a critical issue was measured: the need to wait for any predicted event to happen in the physical systems to validate the developed model's prediction capabilities. This challenge faced with a huge number of wrong predictions and caused more downtime challenges.

Besides, the IDTR improves the IDT's overall performance and develops more accurate platform. An improvement of 15% in the prediction accuracy of multiple manufacturing failure events was achieved by the IDTR system. Thus, accurate recommendations were applied to automate various actions related to the maintenance procedures. Such progress also improved the wire-bonding machines' downtime by 40% less than the IDT improvement. With a focus on the AI and ML models performance, IDTR provides the right environment that allows any virtual AI agents to collect any needed knowledge to achieve higher level of automation. As a result, the developed Intelligent Digital Humming tools can be used for automating the communications between the physical and the intelligent digital twins' systems tackling the data processing problems, automating interactions between users and the different edges of the IDT system, automating training data creating, and finally, automating predictive and descriptive maintenance of wire-bonding production stage.

4.5 Chapter Summary

To conclude, the aim of designing the IDTR environments is to develop an interactive environment that tackles various issues within processes and allows users to intervene when there are critical decisions that need to be taken. IDTR is a user-friendly environment that uses various creative technologies to allow users to smoothly interact in a real-time manner to help to validate some of the IDH tools autonomous actions. The idea of adding a triplet system to the IDT and the physical systems adds a new level of evaluation. It simulates any possible solutions as well as problems that might result from the IDT predictors. The research showed the great potential of such a concept and an exciting level of improvement in the overall performance of the IDT systems. All the completed stages of this project have been executed in a smooth manner and interesting results and findings have been achieved. The next section highlights the collected results, and it discusses all the interesting findings from this project.

5 Results and Discussion

This section explains all the conducted experiments to test the concept and performance of the IDTR and the IDH. It also summarizes the results and findings related to the IDTR systems implementation, the IDH tools, how the developed IDTR system makes machines adaptive, and how the IDTR system becomes portable.

Digital Twin technology has shown dramatic growth in various fields in recent years. It appeared in the 2017, 2018, 2019 and 2020 Gartner's hype cycle for emerging technologies and it moved from being a rising star in 2017 to the top of the curve in 2018. Also, there is still a need to increase the level of required analyses and to provide more unexplored insights to design more intelligent systems. As a result, it has become more challenging to improve the traditional IDT systems (Tygesen et al., 2018).

In the semiconductor manufacturing sector, manufacturers seek reliable information that can lead to more controlled and improved manufacturing processes (Fielden, 2018). Such insights can be used to handle existing problems as well as to detect any hidden issues that had never been explored. IDT systems can explain what is happening in the physical assets in a near real-time manner. It also successfully proved the beneficial results that can be achieved by integrating DT and AI technologies. An example of such benefits is predicting different events and using IDT to visualize them in a high explainability and transparency levels. However, the concept needs more investigations, and it has faced several critical challenges. As a result of mixing several technologies to develop the IDT systems, different problems were encountered, and they impacted the overall quality of the predictions made by the IDT systems. All the main encountered issues took place during the course of this research, and they were behind the development of the concept of IDTR technology. To prove the concept of IDTR, the developed system was tested on a semiconductor manufacturing complex processes known as wire bonding. An IDT system was designed and the IDTR concept was built upon it. The main idea was to test the performance of the developed IDTR system and to measure the performance of its different elements. IDTR targeted critical failure events, warning events, and normal behaviour of 12 wire bonders installed in different times and were different models included in the testing stage. The reason behind that decision was to measure the portability capabilities and reconfigurability of the designed IDTR. Also, the testing stage intensively focused on variables such as the IDTR creation time, IDTR process time, and the reconfiguration of IDT time. There was a need to

consider the short time prediction events and to define several thresholds when IDTR should stop all its processes. A straightforward testing technique was implemented to measure all of these variables and visualise them as part of a performance report that is presented on a dashboard inside the IDT system. Figure 44 shows the used testing processes.

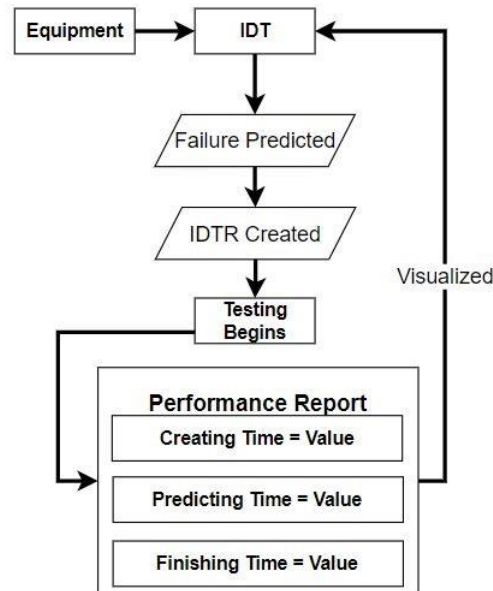


Figure 44: Autonomous IDTR performance testing method (Source: Self).

It is important to mention that the designed system was tested following independent and integration testing methods. Each component of the system was tested separately to measure all the added desired capability. The IDTR system was tested as a whole within the used manufacturing facility's environment to measure the gained benefits and improvements' levels. As a result, the designed system was deployed, and it used an autonomous testing method to collect different variables. The developed IDTR system included an interactive dashboard that is used to visualise all the collected insights during the testing process. Variables such as counting how many times the IDTR predicted different manufacture events versus how many wrong predictions, IDTR versus the IDT prediction accuracy, IDTR downtime improvement and level of similarity of the generated synthetic versus the real data were all calculated and visualised in real-time. Also, from a model validation perspective, the performance of all the developed humming tools was measured during the testing processes, and all the calculated accuracy and confusion matrices were visualised. Figure 45 illustrates the testing

methodology of the IDTR system and its components in the wire bonding manufacturing process.

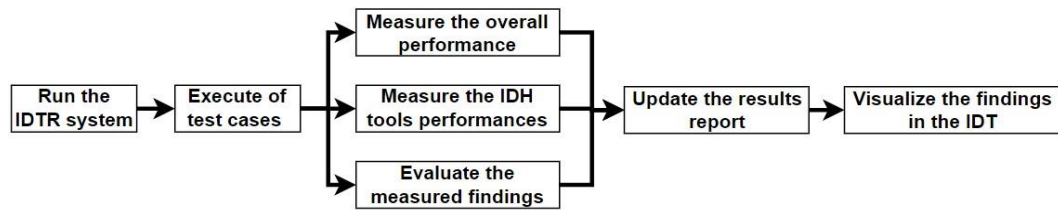


Figure 45: Autonomous IDTR system performance testing method (Source: Self).

This research also focused on the performance of the five developed IDH tools and measured several confusion matrixes to ensure the accuracy of their actions. Although the overall performance of the developed IDTR system indicates the accuracy level of the developed IDH tools, there was a need to consider the performance of each IDH tool on its own. Measuring accuracies such as Precision, Recall, F1, and the overall accuracy of the developed ML models for the IDH tools helped define the best models' structure and implemented techniques. The testing of these accuracies was conducted in a lab using historical data and generated synthesis data. In addition, another method was used to measure the level of similarity and quality of the generated synthetic data. This was done to ensure that the generators of the used GANs models' are capable of creating images similar to raw images used for training stages.

All the designed IDH tools that used GANs models (IDHT-3, 4, and 5) were tested starting from the precision accuracy matrix to make sure that higher precision percentages are collected. These high precision values indicated that the generated synthetic images are similar to those generated using real information from the physical domain. The developed IDH tools were tested on different failure and warning events, and multiple precision values were collected to validate the structure of the used GANs models. It is essential to mention that for IDHT-3, the Precision matrix played a crucial test. In addition to quality and similarity, the classifier needs to predict these images classification accurately. IDH-4 was mainly tested using the FID scores to ensure all the generated synthetic data represents similar real-life scenarios to measure the impact of the IDTR system recommendations. The Recall matrix was also used to measure the capability of the GANs models' generators to generate all the distributions of the real training data correctly. This measurement is essential to ensure that the used GANs model makes minimum wrong classifications using the real data, and these incorrect classifications do not impact predictions when using the synthetic data. After that, the

F1 score matrix was measured to calculate the harmonic average of both Precision and Recall accuracies. All the accuracy matrixes have been measured using the following equations:

1. Precision = all the generated images (Pg) that overlap the Pr distribution divided by the generated images (Pgf) located out of the Pr. Where Pr is the distribution of all the real used images, Pg is the distribution of all the generated images by the generator that overlap the real images, and Pgf are those fake images that look different from the real ones. It measures the proportion of how many images that look like the real ones were generated and the fake ones that are not similar to the real ones.
2. Recall = all the generated images (Pg) that overlap the Pr distribution divided by the Pr real images.
3. F1 = Precision divided by Recall.
4. Frechet Inception Distance (FID) is another considered accuracy measurement matrix to measure the similarity of the generated synthetic data used for classification and optimisation processes. The used function for this test measures the similarity between real and synthetic distributions by calculating the Fréchet Inception Distance between the location and ordering of the points along with the two distributions (Heusel et al., 2017). This test was done after training the developed GANs models using the following logic:

```
Frechet Inception Distance (FID) algorithm
|
| Start function
| | Load the trained model
| | compute embeddings for real images
| | compute embeddings for generated images
| | Start function
| | | calculate_FID (real_image_embeddings,
| | | generated_image_embeddings)
| | | | calculate mean and covariance statistics
| | | | calculate sum squared difference between
| | | | means
| | | | calculate sqrt of product between covariance
| | | | check and correct imaginary numbers from sqrt
| | | | calculate FIDscore
| | | | return FID
```

```
|           |           | End function
|           | End function
```

The following section discusses the Intelligent Digital Triplet project, and it provides more details about all the collected results. Also, it highlights all the encountered challenges together with all the implemented solutions.

5.1 IDTR Components Testing

As it was mentioned earlier, the developed IDTR system was tested using two main approaches. All the components of the IDTR were tested individually to measure whether they achieved their goals successfully. On the other hand, the IDTR system was tested as an additional component to the traditional manufacturing processes to measure its impact. This section discusses the testing processes of the developed IDH tools and the measurement of their behaviours towards the IDTR concept. It was essential to test them individually to detect any possible flaws in the design of the system and its functionality. As a result, variables such as reliability, performance, and functionality were calculated. It is important to mention that all those variables were tested when the IDTR system was deployed in the manufacturing of the chosen company for this research and the findings were autonomously visualised in the IDTR and IDT environments. Real-time testing insights were visualised in the IDTR environment to provide a full picture of the overall performance of the developed IDH tools. Each developed IDH tool was tested and evaluated differently, and all the measured results were visualised and used by the IDTR system. It is important to mention that some of the testing results were used as thresholds to automate some decisions the IDH and IDTR system make. The following sections explain how the five developed intelligent digital humming tools were tested and present the collected findings.

5.1.1 Feature Selector (IDHT-1) Testing and Evaluation

IDHT-1 acted as a central component in the developed IDTR system and there was a need to make sure it is tested in a real manufacturing environment to validate its functionality. Also, there was a need to have a high level of flexibility and reliability when selecting which features provide better prediction accuracy levels. The idea was to test the performance of this tool using different extracted images that represent the original selected visual observations. Real-time calculations were conducted to calculate

the overall improvement levels in the final training process versus the generated reconstructed images. An intensive testing approach was applied to measure the impact of all the selected features on the final classifications. The rewarding algorithm was developed to measure the impact of the selected features on the final made classifications and to decide the best set of selected features. Table 2 shows an example of two failure actions and the results from the rewarding algorithm of IDHT-1.

	Accuracy	Real or Fake	Prediction time window after mins	Actual failure event occurs after mins	Before the real event occurs	After the real event occurs	Reward
IDTR	91%	Real	31	41	-10	NA	1.11
IDT	72%	Real	45	35	10	NA	0.92

Table 2: Sample results from the Rewarding algorithm

The final calculated rewards are measured in percentage values that only reflect the scenarios when the IDTR makes better predictions than the IDT. A timing threshold was added as a condition to IDHT-1 to check if the prediction actually occurred in the physical edge during that time. The following equation measures the final given rewards values. $\text{Rewarding} = \text{IDTR prediction value} + (D/100)$, where D is the difference in the time errors in minutes between the IDTR and the original IDT prediction times divided by 100. The idea behind this logic was to add more weight values to the IDTR prediction accuracy and use it as a reward value. Also, the rewarding algorithm uses a threshold of accepting only values between 0.8 and 1.0 to give a value of 1 rewarding to the selected features. On the other hand, any rewarding values above one was excluded because that means the IDT system prediction was more accurate than the IDTR. Therefore, the IDTR used the final rewards values to utilise different selected features.

The used rewarding system was tested in real-time when the IDTR system was deployed in the production line. The aim of the test was to measure the correlation between the selected features and the made predictions by the IDHT-3 and IDHT-5 autonomously and to visualize the results on the IDTR environment. It does that by calculating how many correct predictions were measured out of each of the selected sets of features. In contrast, the rewarding algorithm highlights how many wrong predictions were captured. Table 3 shows a sample of the used rewarding algorithm testing results.

	IDT Accuracy	IDTR Accuracy	Selected features chains	Rewards
FeatureSet-005-Failure1	60%	91%	[parameter-11, Parameter13, Parameter14, Parameter25, Parameter26....., Parameter N]	1
FeatureSet-005-Failure2	74%	92.30%	[parameter-1, Parameter3, Parameter4, Parameter5, Parameter6....., Parameter N]	1
FeatureSet-005-Failure3	71%	88.70%	[parameter-2, Parameter3, Parameter4, Parameter5, Parameter19....., Parameter N]	0

Table 3 The used Rewarding algorithm testing results

All the comparatives were done with the real failure events that occurred in the physical equipment. Many critical failure events occur in the investigated manufacturing plant. While some of them are predicted and regular, others are challenging and unpredicted. This research focused on those failures that cause a higher level of defects and have been challenging to avoid, and they were selected based on three main criteria:

1. The prolonged downtime they usually cause.
2. The failures were identified as crucial by the experienced maintenance team.
3. The failures with the most available and accessible information from the targeted machines.

These selected failures were related to the Capillary part of the wire-bonding machines, which is one of the most critical parts. These failures include No-Stick-On-Pad, No-stick-on-Lead, and bad-tail-exceptions failures. Figure 46 highlights the collected results from testing the IDHT-1 on two different failure events.

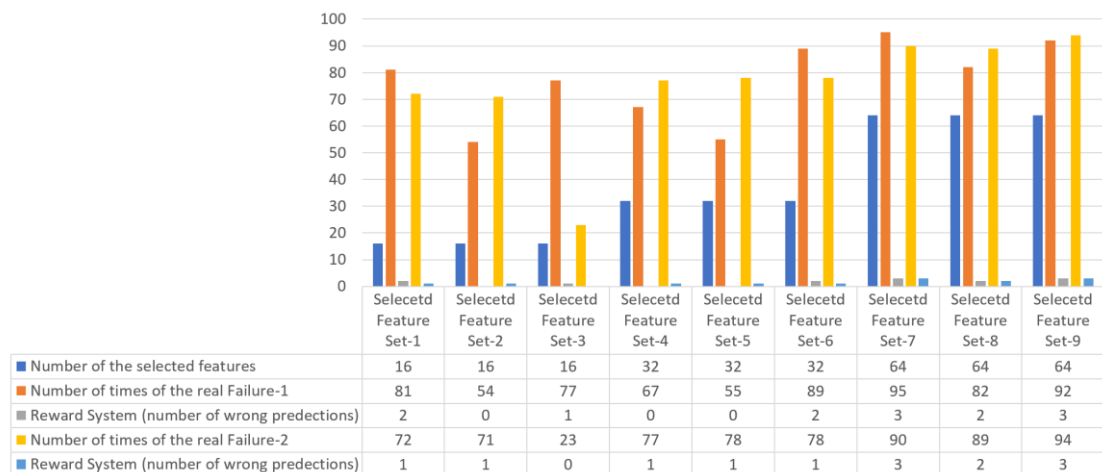


Figure 46: The testing results from the IDHT-1 (Source: Self).

As it can be seen from Figure 46, the selected features impacted classification level of accuracy. The idea of building multiple systems over past years that served differently ended up with significant challenges in terms of format, accuracy, accessibility and many

more. That created different blocks of parameters' readings (messages) about the status of machines and other manually entered data as reports and actions. Many of these messages are available in real-time and were used to provide real-time statistics about multiple aspects of manufacturing processes. However, since this project aimed to provide AI solutions, there was a need to process many of those data blocks and extract only the correlated parameters to the out functionalities. The extraction process was done using extracted historical data sets from the manufacturing processes. Thus, several statistical correlation methods and feature selection techniques, such as a wrapper, filter, and intrinsic, were applied to identify the best possible parameters that can be used for any further development. The selected best parameters were used as features to train several ML and AI algorithms.

During the IDTR training, testing, and validation processes, the IDTR system saves any chosen features. This provides complete traceability of the selected features to be used in the final validation stage. Then the IDTR system compares the made predictions using those saved features with the actual events that occur on the physical side. Also, IDTR groups and indexes those sets of features to allow the rewarding system to track and gather them for future processes. For example, selected feature set-1 included 32 different parameters about the status of the wire-bonding machines when facing a particular failure event. These 32 features are temperatures measurements, materials parameters, information about the surrounding environment of the Capillary device, and the occurred failure to be used as an observation label when classifying this failure event. While feature set-2 includes the different features collection about other observations; but keeps the same failure event as a labelling parameter.

As a result, the results from the awarding system were used to decide which features will be selected when IDT predicted similar failures in the future. The designed IDHT-1 was evaluated by counting how many times the IDTR predicted failures have later occurred on the wire-bonders. The level of impact was measured to prove any impact on the predictions made by the IDT system. It is important to highlight that a supervised machine learning approach using tabular data was integrated with the IDT system and was used to validate the functionality of IDHT-1. Also, the same selected features were applied on the two systems and the level of prediction accuracy of the IDT and IDTR were compared. Figure 47 highlights some of the IDHT-1 evaluation results.

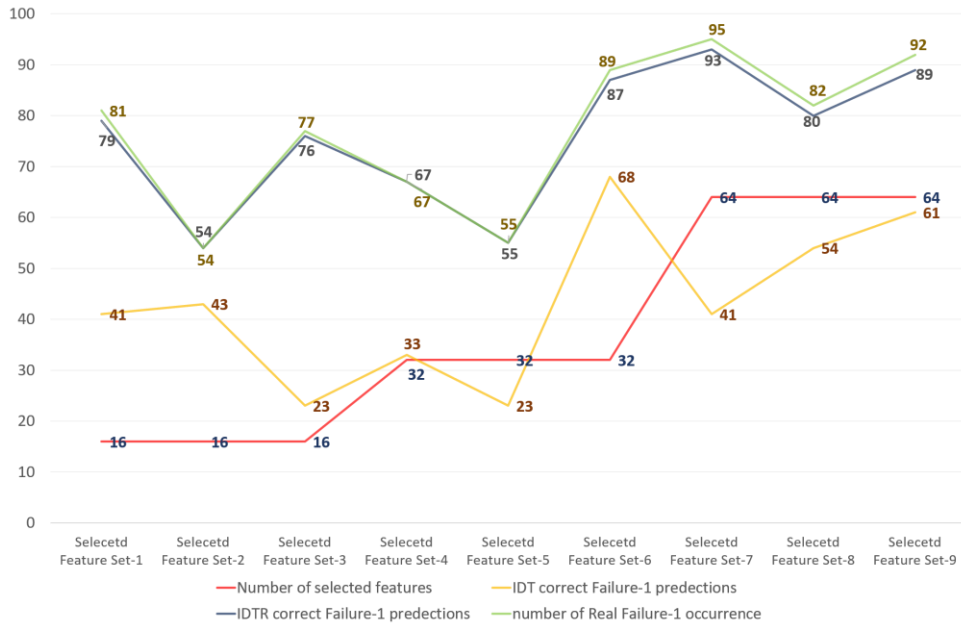


Figure 47: The evaluation results from the IDHT-1 (Source: Self).

As shown in Figure 47, different feature sets were selected during the validation stage to automate such a critical process within the IDTR system. Only the actual streamed data from the physical edge was used during this stage to help the IDTR system choose different features to improve its rewarding algorithm to identify the best features that improve the overall accuracy of the IDTR system. While the IDT system applied linear and supervised feature selection methods, the IDTR system applied different feature selection approaches, such as supervised, unsupervised, and intrinsic methods. Also, the IDTR system used all the historical information of the rewarding algorithm to achieve higher levels of accuracy. As seen from Figure 47, the same number of the selected features was used during this validation process to test the IDT and IDTR systems. The IDTR and IDT predictions were compared with the actual failure events in the physical wire-bonding machines to validate and keep the correct predictions. Overall, the accuracy of the IDTR system and the number of correctly predicted failures events were higher than the correct predictions of the IDT system. The automation of the feature selection processes and the added rewarding function to the IDTR system were behind such an improvement. For example, the IDT system predicted only 41 correct failures and could not correctly predict the other 40 failures in the physical machines. The selected features to train the IDT model were not the best and overall led to a low number of correct predictions and low levels of accuracy. In the IDTR system, using the same feature set led to better prediction accuracy and a higher number of correct predictions.

The IDTR system used all the rewarding algorithm results to simulate multiple scenarios and automatically used the already validated feature sets. As a result, the IDTR system predicted 79 failures out of 81 that occurred in the physical machines. Therefore, the IDTR system. was very efficient by predicting 97.5% of the failures in the physical edge. The results showed a great potential for improvement by applying such an autonomous feature selecting approach. IDHT-1 managed to select different features continuously and improved its applicability to handle any future changes. A noticeable improvement in the prediction level of accuracy using IDTR was measured.

5.1.2 Training Data Creator (IDHT-2) Testing and Evaluation

It is essential to mention that evaluating this tool was a bit challenging. There was a contrast between the performance of this tool, from a modelling perspective, and its performance towards generating higher quality training data. The performance of this tool was tested when the IDTR system deployed, and all the findings were used to improve the system's overall performance.

The idea was to test if the IDHT-2 can generate training data that can be used to train another IDH tools to improve their quality. Variables such as the impact of the generated data on the predictions' capabilities of IDH tool 3 and 5. One of the used testing methods of this tool was to measure the accuracy of generated synthetic data. Thus, this testing measured the similarity between the generated data and the real captured data from the physical system. The testing of this tool was done using Utility Metrics Classification Accuracy method (Lu et al., 2019). The idea was to train and test accuracy levels of IDHT 3 and 5 using real data. After that, the same tools were trained using real datasets and tested using synthetic data. Finally, the same tools were trained and then were tested using the synthetic datasets only. Figure 48 shows the implemented testing experiment for this tool.

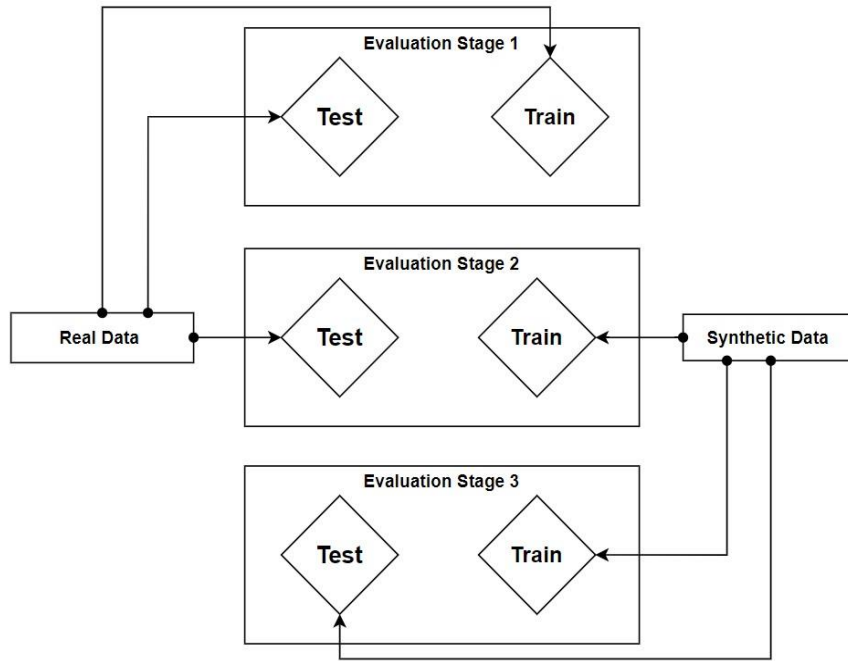


Figure 48: Modified Utility Metrics testing implemented method (Source: Self).

All the calculated variables that resulted from testing IDHT-2 were then visualised on the IDTR system in a real-time manner. Figure 49 shows the used measurements to test this tool, and it shows some statistics that explains the levels of accuracy of the autonomous feature selection process.

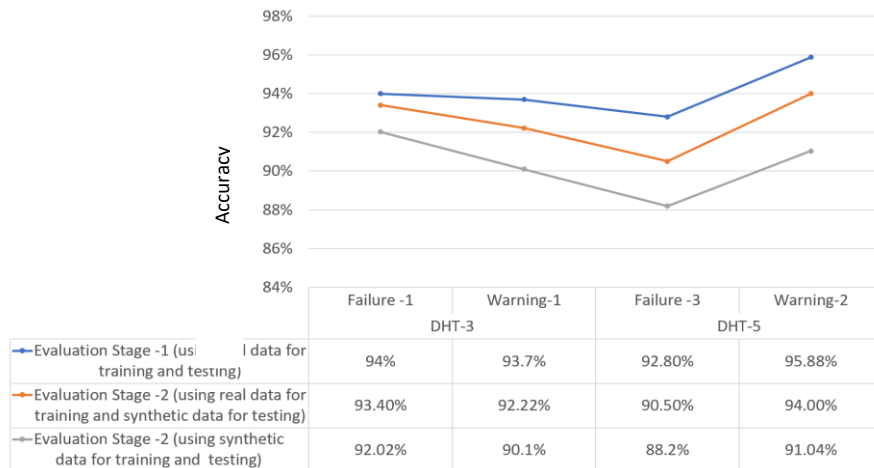


Figure 49: IDHT-2 Utility Metrics Classification Accuracy Results (Source: Self).

As shown in Figure 49, IDHT-2 was tested on different types of manufacturing events, failures and warning. Both events were tested using real data and synthetic data as well. The test showed that the accuracy level of this tool dropped when using synthetic data, but the overall predictive capabilities were still at a promising level despite some

issues in synthetic data. Because of some similarity error in the generated synthetic data, the synthetic data had a small number of misclassified images, leading to inaccurate predictions. Also, the quality of some used synthetic images was another contributor to such a drop in the overall accuracy of IDHT-2. To avoid such impact when dealing with real events, this research aimed to use a combination of real and synthetic data. Also, using synthetic data was needed to simulate virtual manufacturing processes that are similar to existing manufacturing processes. Such virtual simulations were used to measure the impact of the IDTR recommendations and to overcome any limitations and availability of the real data collected from the physical side. Thus, those synthetic images with similarity errors were used to simulate fictional scenarios assuming that they had never been captured in the real collected data in the past. However, the results in Figure 49 showed that the overall accuracy of IDHT-2 using a dataset that included authentic and synthetic images was nearly the same compared to when a real data set was used.

Several evaluation matrices were targeted to prove the quality of the generated synthetic data. The evaluation focuses mainly on the generated ‘data utility’ and the ‘information’ disclosure. The used data utility metrics measured the similarity between the generated data and the real captured data from the physical systems from the statistical properties perspective. On the other hand, the information disclosure measures how reliable generated synthetic data is and how the IDTR system uses them (Goncalves et al., 2020). Figure 50 shows how the used data utility evaluation approach works.

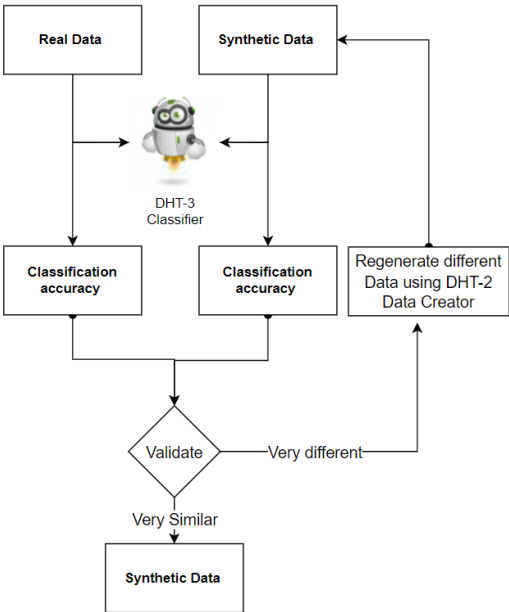


Figure 50: Data Utility testing and evaluation approach for the IDHT-2 (Source: Self).

As shown in Figure 50, an extra validation level was implemented to make sure that IDHT-2 extracted synthetic data that is similar to real collected data. This validation method was done by using the same real and synthetic data used by IDHT-3 and IDHT-5 and measured their behaviour on the two datasets (Lu et al., 2019). Figure 51 shows some statistical accuracy levels highlighting the comparison between the performance of the same models using both real and synthetic data inputs.

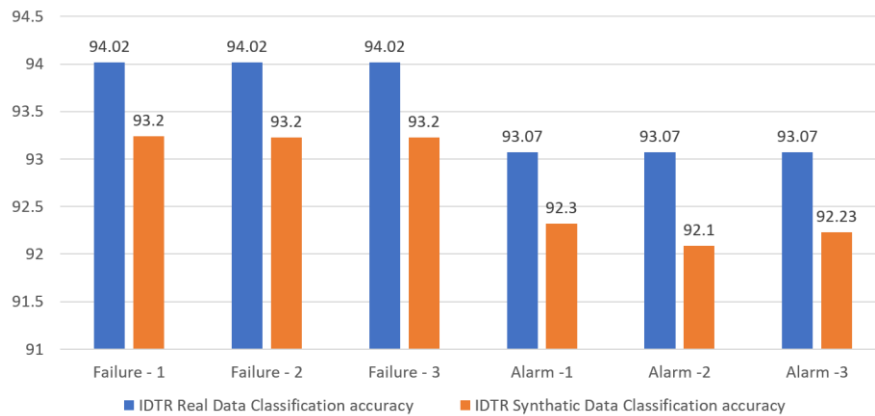


Figure 51: IDHT-2 Data Utility evaluation results (Source: Self).

As shown in Figure 51, this evaluation method mainly used two metrics; support coverage and cross-classification where the former matrix calculates the convergence between the supported variables between the real and the generated synthetic data [1]. While the latter matrix focuses on how far the synthetic data have similar statistical structure to the real data (Porcu et al., 2020). IDHT-2 achieved a high level of similarity between the real and the synthetic data. The differences between the calculated level of accuracies were minimal and did not register a huge impact on the overall prediction capabilities of the IDTR system.

5.1.3 Visual Observation Classifier (IDHT-3) Testing and Evaluation

IDHT-3 produces a flexible technique to use multiple AI technologies to achieve a high level of classification accuracy. Because the collected information about physical entities contains correlated and uncorrelated readings about elements of different manufacturing processes, it is not guaranteed to use one category of algorithms to tackle different events. Thus, to achieve a standardisation level that fits all deep learning, reinforcement, and General Adversarial Networks algorithms to use all the collected

visual observations and classify them accordingly. However, this research tested only a deep neural network and a GANs model to classify multiple events. See Appendix C for the DL and GANs pseudocodes that include details about how the two models were developed. Similar to IDHT-1 and IDHT-2, this tool was tested during the deployment stage of the IDTR in the used company’s manufacturing processes. Thus, the performance of this tool was tested using a modal validation technique. It is important to mention that IDHT-3 was tested and evaluated using two different approaches; 1) when using real images generated using real collected data from the physical twins, 2) when using the synthetic data generated by IDHT-2. In both cases, the evaluation focused on two main criteria; the Inspection Score of the GANs model and the Precision, Recall and F1 scores. This research concentrated on the quality of the generated synthetic data, the model’s diversity, and the classification accuracy aspects. The status of different equipment has been targeted including; when a machine is processing normally (On Status), when a machine is facing failures events (e.g., Failure-1, Failure-2...etc), and when a machine is having warning events. Table 4 and Figure 52 show the collected results about those measurement criteria.

Equipment Status	Similarity of the Syntactic data vs real data	DHT-4 Accuracy
On status	99.02%	96.1%
Failure-1	98.1%	95.9%
Warning events	97.6%	96.6%

Table 4: IDHT-3 testing results

It is essential to highlight that the similarity percentage values from Table 4 were calculated using the FID scores to make it easier to understand the similarity between the generated images and the real ones from the training dataset. The overall similarity percentage was calculated using the following equation: Similarity of Synthetic Images = $100 - ((\text{The best FID score} * 100) / \text{the initial FID Score from the first epoch})$. For example, the similarity value of the Failure-1 synthetic data was measured as follows: Similarity of Synthetic Images = $100 - ((9.6 * 100) / 980) = 99.02\%$. This means that the generated synthetic data is similar to the actual images used for the training stage.

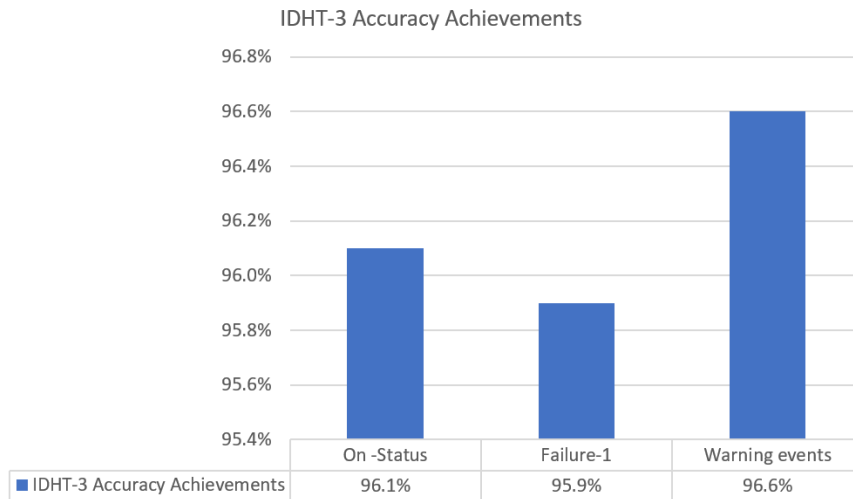


Figure 52: IDHT-3 accuracy results (Source: Self).

As shown in Figure 52, IDHT-3 testing results showed that overall prediction accuracy was accepted using the synthetic data. There are slight differences between the prediction accuracy of the different events due to the amount of collected actual data about each one of them. While data about 'On-status' and 'Warning' events were available from the physical wire-bonding machines, data about different failure events was limited because these failures occur less frequently than the other events. Also, the overall IDHT-3 accuracy was impacted by some of its wrong predictions. This was because of issues in some of the used synthetic data images. Despite the impact of the used synthetic data issues on IDHT-3, the overall performance of the IDTR system was not impacted. Evidence about improvement in machine downtime and prediction accuracy are discussed in the following sections. In addition to calculating the IDTR system overall accuracy, evaluation confusion matrixes have been used to measure the performance of IDHT-3. The matrixes included measuring Precision, Recall, and F1 Score over multiple processes by using different data sets. The goal was to test the level of similarity of all the generated images that had been accurately classified. Also, to check if IDHT-3 can correctly create any distribution from the real used images. After that, the F1 matrix was measured to calculate the harmonic average of precision and recall results. Table 5 shows an example of the measured confusion matrixes for two different failure events.

	Accuracy	Precision	Recall	F1-score
Failure-1	97%	92.80%	69.90%	94.7
Failure-2	95.20%	90.85%	95.60%	93.2

Table 5: Confusion matrixes for two different failure events

This tool proved its concept and reconfigurability capabilities when switching between real and synthetic data due to the high level of achieved similarity between the two types of data. Also, the collected accuracy levels showed a great potential in classifying different manufacturing events. Furthermore, the measured accepted level of accuracy using synthetic data make it easier to use the same tool to classify different manufacturing processes. Collecting different visual observations and generating new synthetic data about different manufacture processes can be classified using IDHT-3. The next section highlights the testing method that was used to test IDHT-4 and the captured results from this process.

5.1.4 Optimizer (IDHT-4) Testing and Evaluation

This tool played a key role, and it remarkably improved the speed of the training process. The idea behind adding this tool was to guarantee continuous learning for the humming tools and to generate non exist equipment with different status while training them. The testing and evaluation of this tool was challenging because of the nature of its performance. However, a decision was made to measure the similarity between the generated data and the real collected ones from the physical systems.

Also, other criteria such as the generating time and the proportion of caused conflict with the real status changes were considered. IDHT-4 was deployed in the IDTR system, and all the measurements were visualised in real-time. Also, this tool was tested mainly when the IDTR system started evaluating any possible changes. The IDTR depended on this tool to reconfigure the equipment configurations and simulates real life different status. Figure 53 shows results from the testing process of IDHT-4. It highlights the achieved levels of accuracy over different manufacturing events, and it also shows the level of similarity of the generated synthetic configurations.

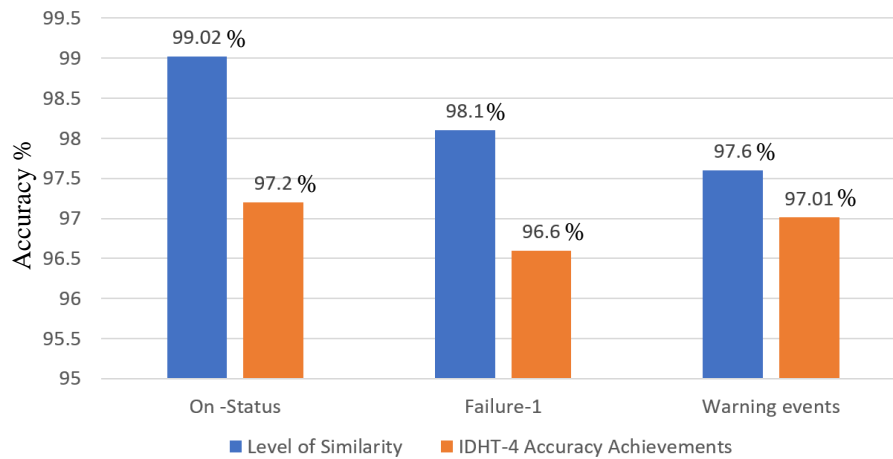


Figure 53: Results of testing the performance of IDHT-4 (Source: Self).

As shown in Figure 53, this tool generates similar data that simulate real equipment configurations. Because the testing of this tool aimed to measure how similar those generated parameters are compared to the real captured ones from the physical system, there was a need to validate the accuracy of the model first. Also, because all the generated synthetic data by IDHT-2 was validated, IDHT-4 managed to generate new sets of parameters smoothly, and it managed to simulate multiple events successfully. Thus, those accurately generated parameters can be easily fed into IDHT-1 and are used as real features. Furthermore, the generated parameters were used to reconfigure the physical equipment and change their processes autonomously. It is important to mention that it was possible to test it a couple of times in a real production environment.

This PhD research targets regular and irregular complex manufacturing processes to optimize a number of them and improve the overall productivity. By using the optimizer IDHT-4, the IDTR system achieved a high level of parallelism when predicting equipment's failures and to automate maintenance procedures. IDHT-4 works in advance to help the IDTR system to better classify and predict failures and to generate better machine's configurations to react to particular failures. Thus, IDHT-4 was tested on maintenance scenarios to troubleshoot some predicted failures before they occur. In addition to testing the performance of this tool by using a model validation, a testing algorithm was embedded in the IDTR system to count how many times IDTR-4 managed to optimize the equipment during the testing and validation periods. As a result, the speed of the maintenance process improved, and it was rapidly increased in several scenarios. It is important to highlight that the testing stage of the optimization impact took eight days to ensure that the collected data includes as many failure events as possible.

Different failure events that require different maintenance times were used to test the performance of IDH-4 optimisation improvement. Figure 54 shows the results of testing the optimisation impact of the IDHT-4 on maintenance and equipment failures.

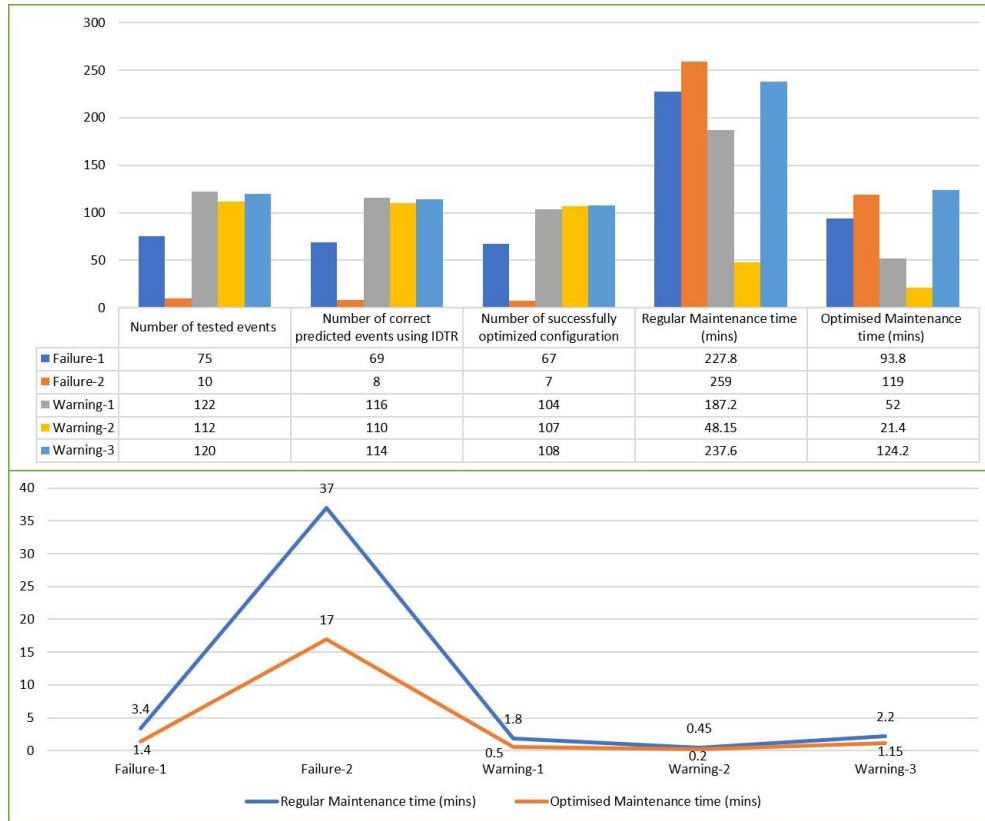


Figure 54: IDHT-4 testing and evaluation results (Source: Self).

As shown in Figure 54, the maintenance optimization process began prior to the failure happened. Such a time window gives the IDTR system more room to simulate, test, and validate the best new configurations that are required to handle any upcoming predicted failure events. Five events from one wire-bonding equipment were tested, and the results show the improved downtime after using the IDTR compared to when the IDT system was used. The selected machine was out of service for 37 hours due to a wrong diagnosis about a particular failure event on the equipment. Also, this downtime indicated the needed time to fix the failure and switch on the machine again. During this downtime, the maintenance team tried to resolve the issue by following a trial-and-error approach to identify the error's root causes. However, after using the IDTR system, the same failure was classified more accurately, resulting in a noticeable shorter downtime from 37 to 17 hours. While the 17 hours may seem long, it is important to highlight that in order to fix the classified failure, some materials need to be ordered to make physical

repairs on the equipment. However, the overall improvement in downtime was directly impacted by the accuracy of IDTR classification and the automated recommendations regarding different actions such as material ordering and notifying the maintenance team. All that resulted in a substantial enhancement in the entire maintenance process and automated multiple clearing processes of warning events. Thus, reducing equipment downtimes.

5.1.5 Failure Predictor (IDHT-5) Testing and Evaluation

To provide better prediction capabilities to the IDTR systems, this tool was designed to achieve better accuracy failure predictions. IDHT-5 was tested in a similar way as IDHT-3. However, because of the extra importance of this tool, more attention was given to the evaluation method to ensure that the IDTR system makes autonomous decisions based only on reliable predictions. This tool was tested using the IDTR system utilizing criteria such as model validation, prediction accuracy levels, and prediction validity. A model evaluation technique was applied too, and all the measurements were visualised in the IDTR environment. Thus, the humming tools can understand the accuracy level and they make confident decisions about any further actions. It is important to mention that an extra evaluation feature was added to compare all the predictions made by IDHT-3 with the real equipment status. The results then indicate whether IDHT5 could predict different events such as equipment’s failures accurately. A timing indication was also added to the testing method to measure the predicted failures times’ errors values. It measures how earlier or later the predicted failure occurs compared to the real failure action. Such information was used as a threshold to make any other decisions related to IDHT-5 prediction accuracy. Figure 55 shows the best IDHT-5 accuracy achievements.

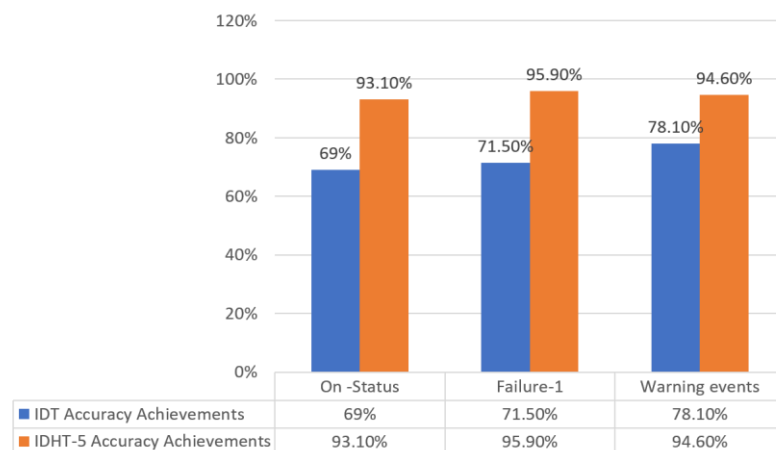


Figure 55: Failure Predictor-IDHT-5 accuracy results (Source: Self).

As shown in Figure 55, this tool was tested using the model validation technique to measure the overall accuracy of the tool. Also, it was validated using two different keys; 1) counting how many times this tool successfully predicted actual failure events. 2) measuring those predictions' time windows to identify any latency or earlier occurrence of actual failure events. The performance of IDHT-5 when used in the IDTR system showed significant improvement compared to another predictive maintenance model that was developed using numerical data and it was integrated with the IDT system. Accuracy improvement of 16% was measured in some failure prediction events. IDTR system prediction accuracy did not exceed 78%, while the IDHT-5 achieved 94% of the overall model accuracy. The IDTR system prediction accuracy was improved when using IDHT-5 and was because of the generated synthetic data. I also believe that the accuracy of this tool can even become more accurate with future improvements.

5.2 IDTR performance in production lines

From a production point of view, the IDTR system aimed to provide accurate and useful insights to improve the manufacturing processes. The main idea here is to verify the performance of different tasks as expected and even predicted. It is clear to notice the challenging aspect of this step. The IDTR system makes decisions in two different methods; one responds to any possible changes, while the second method predicts some events in advance. It is important to highlight that testing processes were developed in such a way to be autonomous. The idea here is to verify the IDTR system's performance and decisions and make sure they are expected. Intensive tests were conducted by deploying the developed IDTR system within a wire bonding manufacturing process. The system targeted the predictive maintenance IDT capabilities of several critical failure events. Also, the designed IDTR system was tested on many warning and standard processes. The idea here is to verify the IDTR system's performance and decisions and make sure they are expected.

The IDTR system's generating time was also tested and measured to identify any differences when targeting different events of manufacturing processes. Another parameter was added to the IDTR dashboard to measure the different generating times. Thus, findings were used to identify any remaining time for the IDTR processes before any failure predictions were to happen. A set of thresholds applied to decide when a new IDTR environment is created and when it needs to be crashed and regenerated again.

Through interaction techniques such as voice commands, the IDTR environment was created using all the IDT environment elements and applying further testing and validation processes. Table 6 shows measurements about the timing of IDTR creation process. It is important to mention that the overall IDTR creating time is impacted by hardware capability, the amount of the visualised assets, streaming processes latency, and the amount of the streamed data.

No. of Virtual Assets	IDTR Creating Time	Latency
Wire bonders_Virtual_Assets (4)	41 Sec	30 Sec
Wire bonders_Virtual_Assets (8)	79 Sec	30.12 Sec
Wire bonders_Virtual_Assets (12)	145 Sec	30.38 Sec
Wire bonders_Virtual_Assets (18)	281 Sec	31.0 Sec

Table 6: IDTR creating process time calculations

As shown in Table 6, IDTR creation takes a few seconds from the moment the creating order is applied till the moment the IDTR environment starts running. All the testing results showed an accepted creating time range and did not impact the overall IDTR process time. Also, intensive analyses were conducted to highlight some causes behind the encountered latency and to help the company make better decisions when developing the project's hardware infrastructure. The creation time of the IDTR system is dependent on many factors, and its range can vary. However, the upper limit of the creation time is set by a threshold value based on the IDT prediction time. It is essential to mention that the IDTR system's creation time can be shortened by creating an IDTR environment using the virtual equipment where the failure event will occur. This approach was particularly needed for the time-critical failures requiring quick actions to avoid the IDTR system creation time exceeding the IDT prediction time.

The number of the created Humming tools directly impacts the generating time of the IDTR environment. For example, when the IDTR system targets two different predictions simultaneously, the final generated IDTR environment takes longer to develop. Thus, the IDTR creation time directly correlates to the used hardware technologies and specifically to the rendering capabilities of the used hardware. Also, the size of the selected features played a crucial impact in the creation time. Furthermore, the hashing function was developed asynchronously, and this requires different processing times to convert various data formats. It is essential to highlight that the IDTR creation process needs to start with the best features that can be transformed and used within the prediction time window when dealing with time-critical predictions.

The IDTR system was also tested to measure any improvement in the downtime of the physical system. Two variables were tested to measure and compare the regular calculated downtime from the physical system and the improvement level using the IDT and IDTR systems. Figure 56 shows some insights and collected results about the overall performance of the IDTR system and the equipment downtime improvements.

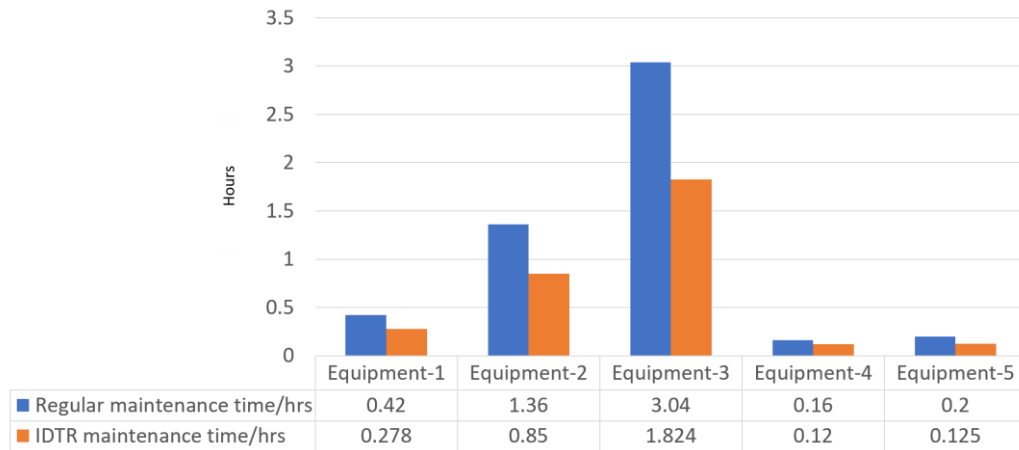


Figure 56: A sample results of equipment downtime improvement before and after using the IDTR system (Source: Self).

As shown in Figure 56, the same equipment's overall downtime and multiple failure events decreased by approximately 40%. The used approach to verify the downtime improvement is as follows.

Step 1. Collected historical data about the operation of the selected wire-binding machines, and this data was used setup several threshold values about multiple parameters. Threshold constants such as machine downtime, maintenance procedures, reports from the maintenance teams were used to develop multiple breakpoints for future predictions. The collected data was divided into periods of 12 hours each. Step 2. The IDT system was used to predict possible failure events that may occur on a particular wire-bonding machine. Step 3. If the IDT system predicted the machine's status as On-state (no expected issues), the IDTR system would not be generated. Step 4. If the IDT system predicted one of the targeted failure events, the IDTR system would be generated. Step 5. IDHT-5 compares the accuracy of the IDTR system predictions and their possible impact on the length of the machine downtime with the original setup threshold values. Then, IDTR system decides whether to accept recommended maintenance plans or reject them and start a new process. The overall cost of machine downtime resulting from a failure event was calculated using historical data considering multiple factors.

Factors include the total maintenance cost (Tm), reporting time (Rt), and latency in the reported failures (LRt) and this can be represented in the following equation:

$$\text{Overall downtime cost} = Tm + Rt + LRt$$

The constant threshold values of Tm, Rt, and LRt of the targeted failure events were measured by calculating the average needed maintenance time to fix each of these events in the past. The IDTR system efficiency in improving machine downtime was measured by considering the IDTR system prediction time window (Pt) and the needed time to complete the recommended maintenance procedures (RMPt) in the traditional manner using the following equation:

$$\text{IDTR downtime prediction efficiency} = Pt - \left(\sum \text{RMPts} \right).$$

The IDTR system total calculated downtime prediction efficiency was then compared with the calculated original downtime average values as mentioned above in Step 1 to decide whether the IDTR system achieved improvement or not. Table 7 shows the IDTR system verification process for improving machine downtime results of one wire-bonding machine and four different failure events.

Predicted Failure State	Original Downtime Cost/minutes	IDT Prediction time window (accuracy 87.8%)	IDTR Downtime Cost/minutes						Best Case Improvement percentage
			Prediction time (93.8% accuracy)	Downtime Check point-1= IDTR prediction time (worst case)- original downtime	Recommended Maintenance Procedure -1	Recommended Maintenance Procedure -2	Downtime Check point-2= IDTR prediction time (worst case)- original downtime	IDTR Decision (Original Downtime-IDTR downtime > 15 minutes)	
Failure-1	160	240 ± 33	240 ± 15	95	42 ± 1.5	24 ± 1.5	67	Verified	41%
Failure-2	230	360 ± 50	360 ± 24	154	72 ± 4.7	10 ± 0.6	87.3	Verified	36%
Warning-1	8	30 ± 4	30 ± 2	24	2 ± 0.26	1 ± 0.06	3.32	Verified	39.80 %
Warning-2	11	8 ± 1.1	8 ± 0.52	-2.48				Rejected	

Table 7: Sample of the downtime improvement results

As shown in Table 7, the overall measured machines downtime improved efficiency impacted by the accuracy of the IDTR system predictions. The IDTR system uses a set of thresholds prepared in advance to define when the IDTR system accepts or rejects any improvements in the machines downtime efficiency. As a result, the IDTR system rejects all the predictions that recommend downtime improvements exceeding the original needed maintenance time. Predictions that provided machine downtime improvement taking less than the original needed maintenance time were accepted. The average improvements in the machine downtime for each failure event were calculated. These averages were used to identify the improvement the IDTR system added to the machine downtime, resulting in 40% less required maintenance time than the original downtime.

However, the measured downtime using the IDTR system was impacted by some latency that was caused by a communication delay between the physical and the digital twin system. It is important to highlight that the measured improvement in the downtime is due to the prediction accuracy improvement using the IDTR system. All the predictions made by IDT were validated and tested by the IDTR system before they were confirmed. The idea was to allow the IDTR system to further test and validate any made predictions by IDT and make a better decision whether to accept those predictions by IDT or not. IDTR has three types of decisions that are relevant to this property.

1. It identifies whether a failure prediction is true or fake. It uses the Visual ObservationClassifier-IDH3 and the Failures Predictor-IDH5 tools to do that. As a result, IDTR decides to scrap any wrong predictions.
2. When IDTR makes equal or better prediction accuracy for a failure event, IDTR then confirms the predicted event with a higher level of confidence.
3. The third probability is when the IDTR predicts the same event with the same or better accuracy level, but it does not pass the validation process within the IDTR. IDTR then decides to recreate another IDTR environment and restarts the whole processes from the beginning.

During the final testing stage, attention was given to the scenarios when the IDTR needed to be stopped and regenerated. Six wire-bonding machines were used to test the IDTR self-rejection functionality. These machines were selected because they had the most available data and were used to process multiple products. However, during this testing process, there was a need to keep the IDTR running to train, test, and validate any predictions and scrap any selected set of features that led to low accuracy, wrong predictions, and lower inaccurate recommendations.

This functionality was tested in two intervals to avoid any issues when dealing with time-critical events. Two validation checkpoints were applied to check two thresholds as follows:

1. A timing threshold was assigned as a first checkpoint to define the accepted predictions failure time. This verification process was developed to take into consideration the prediction time and decide what training data should be used to classify the predicted events. Thus, the failure events were divided into two main categories; critical and regular failure events and they were targeted differently. When the prediction is critical, the IDTR should use the past recommended features to proceed directly to the classification process. Based on the output accuracy of IDHT-3, the IDTR decides to either continue testing the impact of the made prediction or to crash itself and wait for the next prediction from the IDT side. On the other hand, IDTR uses the prediction time as a threshold to keep training and testing new data sets using different features and explore new findings. However, this stage needs further attention to design better thresholds values that can improve the overall performance of the IDTR system. Thus, using the testing results from this research would help overcome any inaccurate thresholds used at this stage. Table 8 shows how many times the developed IDTR system was rejecting its classifications and recommendations.

IDTR						
	Number of successful times				Number of failed processes	
	Classification stage		All the stages		Classification stage	
	Critical	Regular	Critical	Regular	Critical	Regular
Failure-event 1	19 out of 22	26 out of 28	14 out of 19	22 out of 26	3 out of 22	2 out of 28
Failure-event 2	16 out of 22	24 out of 28	13 out of 16	17 out of 26	8 out of 22	4 out of 28
Warning event-1	14 out of 22	18 out of 28	10 out of 14	11 out of 18	8 out of 22	10 out of 28
Warning event-2	12 out of 22	15 out of 28	7 out of 12	13 out of 15	10 out of 22	13 out of 28

Table 8: A sample of how many times the IDTR system rejected predicted failure events.

As it can be seen from Table 8, the developed IDTR system was tested on four different events: two failures and two warnings. The system showed that the number of times the IDTR rejected itself was relatively lower than those times the IDTR successfully passed the final validation stage.

2. The output accuracy of IDHT-3 was used as a second checkpoint to check if the achieved accuracy was equal to or higher than the original prediction accuracy made by the IDT. Thus, if the threshold verification result was true, the IDTR continues to measure the impact of the made prediction. However, if the threshold verification result was false, the IDTR stops and crashes itself and return to the waiting mode to wait for any new predictions from the IDT side.

It is essential to highlight that the IDTR system validates all the predicted events virtually and uses synthetic data to achieve such a process quickly. Using the Training Data Creator-IDHT2, the IDTR system simulates all the related events that are impacted by the made predictions. As a result, the IDTR system also measures any improvements in the accuracy of the made predictions by the IDT system. Figure 57 shows a comparison between the predictions accuracies before and after validating them using IDTR technology.

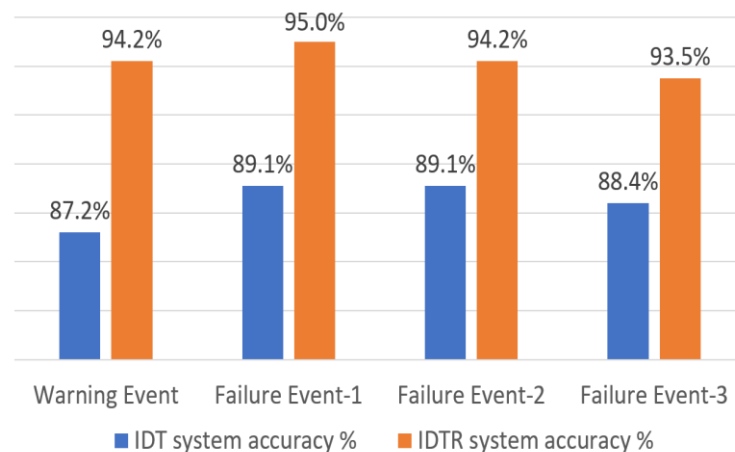


Figure 57: A sample results of the measured improvement in the predictions accuracies of the IDT using the IDTR (Source: Self).

As shown in Figure 57, the IDTR applied extra training, testing, and validation processes to improve the accuracy of predictions and to increase user’s trust in autonomous decisions. Because of the extra generated synthetic data and the interaction between expert users and IDTR, the overall system classification accuracy increased by 7% in some scenarios. To sum up, IDTR showed a great potential to improve the predictions made by IDT in a high-level of explainability.

It is important to mention that several previous studies addressed multiple interesting methods to evaluate the performance of IDT system from a user’s perceptive. They

mainly focused on IDT systems and infrastructure, privacy and security, and user’s trust. Some other research studies focused on the modelling challenges and how it is challenging to standardise them seeking for a standard approach to develop a full IDT system from the first stage of the physical entities to the end-user. Unluckily, most previous studies concluded that there is no standardised approach to modelling different IDT systems and modelling the multiple stages to develop one IDT system (Ma et al., 2019). This research applied a model validation to measure all the correct and wrong predictions. The IDTR system was tested in a real manufacturing production line over three months to measure its reliability. It is essential to highlight that the shown insights are about the overall performance of the IDTR system, including the five developed IDH tools. The evaluation was done by deploying the IDTR with two wire-bonders and it was tested on 7 different events including normal on status, different critical failure events, and different alarm and warning events. Figure 58 shows some statistics about the overall performance improvements of the IDTR and how accurate they were.

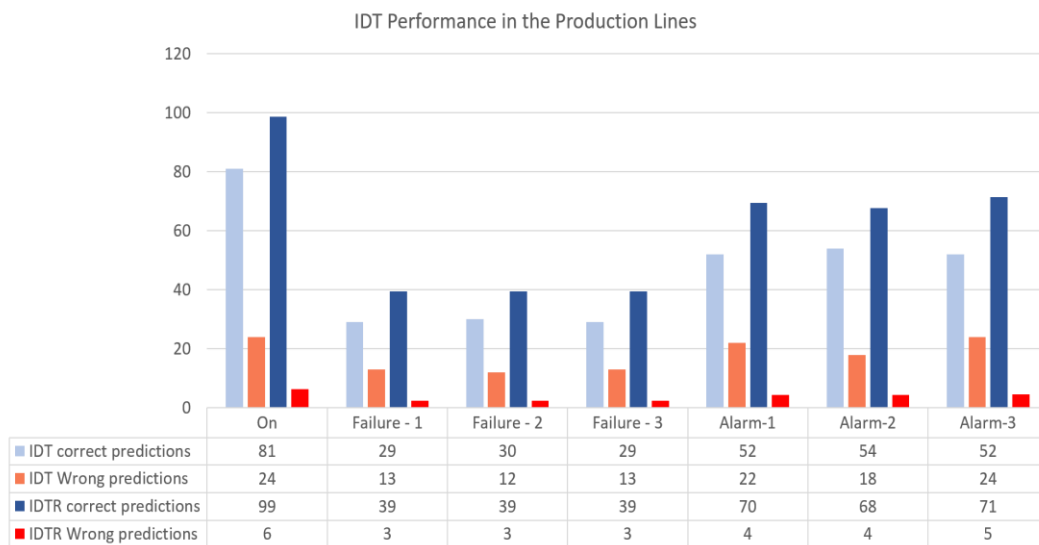


Figure 58: Statistics about the overall performance improvement of the IDTR system (Source: Self).

As shown in Figure 58, the overall performance of the IDTR system was compared to the IDT performance in terms of predictions and classification capabilities. Both IDT and IDTR systems were tested using the same number and type of manufacturing events. The evaluation approach managed to compare the real events with the correct predicted events using IDT and IDTR. Figure 58 shows how many times the IDTR correctly predicted real failure and alarm events and implemented the same approach with the IDT system. The overall IDTR’s performance was noticeable in understanding and predicting

different equipment status events. As a result, such improvement reflected on the IDT system overall performance and improved its prediction accuracy. Such achieved accuracy reduced the overall equipment downtime and automated and semi-automated the reactions of all the tested seven events. I believe that the Extended Reality's role in this evaluation method was behind such improvement and played a crucial key. All in all, IDTR has managed to predict much higher number of correct predictions and fewer wrong predictions compared to the IDT system. To sum up, different complex and unforeseen failures are now explored and simulated on high dimensionality virtual platforms. As a result, manufacturers are now becoming closer to their manufacturing processes rather than any time before, especially in global companies where there is a complicated layer of communication between the physical assets. IDTR can serve as a digital replica to simulate various real-time behaviours. Also, IDTR systems will be expected to efficiently handle multiple tasks and process them virtually before making any physical implementation.

5.3 User experience

Human-IDTR interaction (HIDTRI) is a key in this research. Thus, implementing an efficient method to capture any flaws in the design and performance of the IDTR system was essential. While IDT technology was introduced to handle several cyber-physical main issues such as safety, efficiency, and the limited capabilities of integrating some cutting-edge technologies, The IDTR technology introduces a novel approach to address such issues together with the capability of emerging many technologies such as AI, Big Data, and immersion technologies. Using the IDTR system helps to provide a high level of flexible interactivity between users and machines using AI agents. Considering the extended reality concept, users can request and retrieve, information from the machines and explain possible suggestions (Ma et al., 2019). This evaluation is vital in the overall visual tests of the IDTR system as it measures the immersion and the interaction levels with the designed IDTR system and the IDH tools. We live in the era of immersion technologies and the IDTR system has been designed using multiple virtual technologies such as VR and AR. As a result, this research gave attention to the visual representation and how far they mirror the physical assets. Factors like sensory visual and user experience were measured to indicate any flows in the entire experience. Several vital

interactive methods were measured to collect some observations that can be used in the future to predict and visualize improvement.

Many previous studies tested the impact of Extended Reality from the effectiveness perspective of used case studies. Factors such as the correlation between the technology and its impact on the user interaction activities were measured. Several studies highlighted the benefits of using this technology to simulate complicated environments that are difficult to be handled using other traditional technologies (Kaplan et al., 2020). This technology was used in this research to implement various interaction techniques to suit the needs of different users. The developed IDTR system end-users are different, and some of the used traditional interactive methods do not suit the nature of the physical environment where they work. On the other hand, different devices needed to be integrated to meet manufacturing safety requirements. While using VR wearable devices at the management offices was possible, doing the same in the production lines was challenging. Alternatively, AR technology was used to make it easier to carry smart devices while implementing any recommended maintenance plans by the IDTR system. Maintenance engineers used the developed AR system to interact with the primary IDTR system. This allowed them to seek more information and explanations by using voice commands and traditional touch interaction methods to select parts and change the presented information. As a result, the end-users have different interaction methods used in different environments and different challenging situations. For example, users completed the work and interacted with the IDTR system in the production lines despite the noise that made it challenging to interact using voice commands. Figure 59 compares the improvement in finalising one maintenance task using the AR and the VR IDTR system with traditional methods.

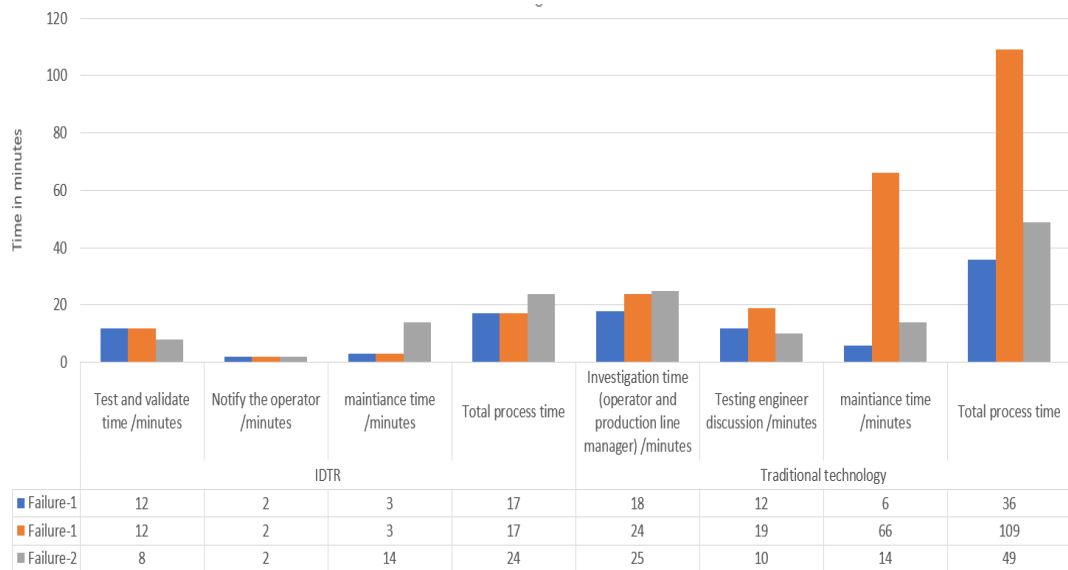


Figure 59: The measured impact of the used VR and AR technologies results (Source: Self).

The presented results in Figure 59 were tested in a lab using historical data about actual maintenance processes for one targeted failure event. As shown in Figure 59, the impact of the ER technology was measured by comparing the implementation times of many maintenance plans using the ER with the traditional maintenance method. The impact of the developed ER interaction in the IDTR system was promising and decreased the machine downtime in several processes. However, measuring the exact maintenance time in the physical manufacturing environment was a challenge due to changing maintenance teams shifts and scheduled break times.

Also, Extended Reality is used to measure the level of explainability of the different developed IDH tools. The developed IDTR system was tested in a complex manufacturing environment where human interaction exists in multiple stages and always impacts decisions. For example, maintenance teams and operators keep wondering about the IDTR system's automated actions in the predictive maintenance processes and seek more details about any made predictions. Using the concept of VR and AR technologies, this research visualised multiple aspects related to any predicted failure events, and the recommended maintenance plans to provide a whole picture of any automated processes. With the easiness of interacting with the virtual assets and merging them with real images of the physical wire-bonding machines, the IDTR system allows the end-users to request any needed information about the performance of the IDH tools. Such information includes model accuracies, testing and validation results, and historically validated recommendations for the same failure events. The use of ER

in this research led to benefits observed on the AR application when implementing Pose estimation, image recognition, and audio recognition techniques. Such benefits include scanning QR codes to identify a particular machine to avoid entering more details about the investigated failure event. Also, using voice commands in some situations helped the IDTR system detect the user required information and trigger some visual presentation effects to visualise different insights. Furthermore, the AR system detected the positions of users' fingers to interact with virtual buttons inside the IDTR system to trigger different views when using any voice interaction was problematic. On the other hand, the use of ER in this research led to benefits observed on the VR developed application by allowing the different developed IDH tools to move inside the IDTR virtual environment and use it as a training and validating environment. This allowed the developed IDH tools to act autonomously and roam around the 3D assets to detect abnormal behaviours. 24 face-to-face interviews were conducted with different candidates to collect their perspective about the developed IDTR system. Several questions were discussed to measure the user experience in multiple aspects. The designed user experience survey focused on measuring users' immersion level in the developed VR and AR technologies in the IDTR system. Questions about the immersion level, benefits, and the designed system's future were asked and discussed with experts from multiple departments. Figure 60 shows some statistics about the users' experience after using the IDTR system.

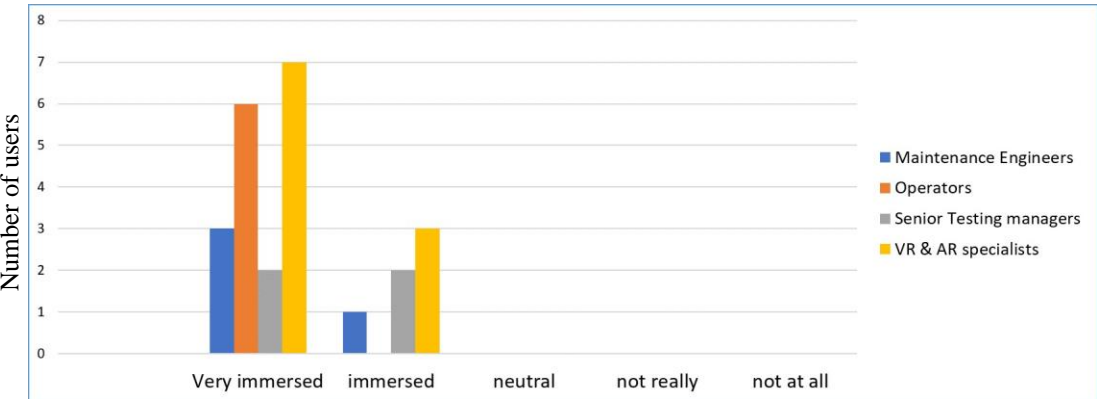


Figure 60: Level of immersion and user experience after trying the IDTR system (Source: Self).

The developed applications using the VR and AR immersive technologies were tested by gathering qualitative data about end-users' views about the level of immersion and virtuality in the developed VR and AR environments. Figure 60 shows the results from the analysed qualitative data. This test was conducted during the development stage with

all features implemented. Data was collected from four main groups including VR and AR specialists, operators, maintenance teams, and managements. The test gathered users' views about the quality of the visualised text, voice commands, and the overall given instructions by the IDTR system. The management ad VR and AR specialists tested the developed VR application. While the operators and the maintenance teams tested the developed AR application. The nature of used instructions in the tested applications differ from one group to another based on their duties. Key elements such as the reliability of the visualised information, quality of the used images, and communication efficiency were also collected. Then all this feedback was used to validate the level of interaction between the users and the IDTR system. From the results, it can be seen that most of the users from the included groups reported as being fully immersed. The rest reported as being immersed and the lower levels have not been reported. For example, 7 out of 10 VR and AR specialists indicated being fully immersed after using the developed VR and AR systems. Although the involved four groups had different knowledge, interest, and experience about the Extended Reality, the developed VR and AR systems appealed to them, and they reported a positive level of acceptance.

5.4 IDTR user trust

To ensure an adequate level of trust, a self-evaluation feature was added to the IDTR system to add a trusted level of exploitability and transparency. With IDTR, real-time statistics are available to be gathered by an end-user whenever they are needed. Thus, there is a desperate need to provide a high level of trust in the system's autonomous decisions. To consider all these challenges and to overcome such challenges, this research introduces a modified evaluation approach to measure the performance of the IDTR system and the end-user's levels of trust. While the IDTR system interacts directly with the end-users through IDH tools, intensive statistics are collected to build up a clear idea about the user experience. Indications about the system expectations are measured and visualised within the IDTR environment to reflect any flaws when using the system. The IDTR system measures the impact of the IDH tools accuracy and their autonomous decisions on users' trust. Also, it measures the influence of explainability and fidelity of all the provided information on the end-users. Overall, the used survey to measure the users' level of trust focused on the following two aspects:

1. The accuracy of the developed IDTR system and Humming tools.

- The explainability level of the results from the Humming tools and the different processes of the IDTR system.

It was not easy to measure and understand the users' level of trust in the developed IDTR system. Two main observations were noticed during the interviews 1) users were too excited about AR and VR technologies, which may have impacted their evaluations by providing inflated scores. 2) some users had limited knowledge about AI technologies and how they work, which may impact their interpretation of the predictions of the IDTR system. The survey included three main questions about the level of interaction, users verification about the predicted failure events and if they happen on the physical side, and the accepted level of all the made predictions correlated to the models' accuracies. The collected insights from answers to these questions collectively indicated the overall users' level of trust in the developed IDTR system.

In addition, the survey measured the level of explainability of the predictions of the IDTR system and the presented context on the representation domain. This part of the survey included two main questions, 1) which interaction method users liked most and 2) did users find the shared information helpful and easy to understand the relation between the processes of the IDTR system and the final automated decisions. Figure 61 shows results about users' evaluation of the level of explicability.

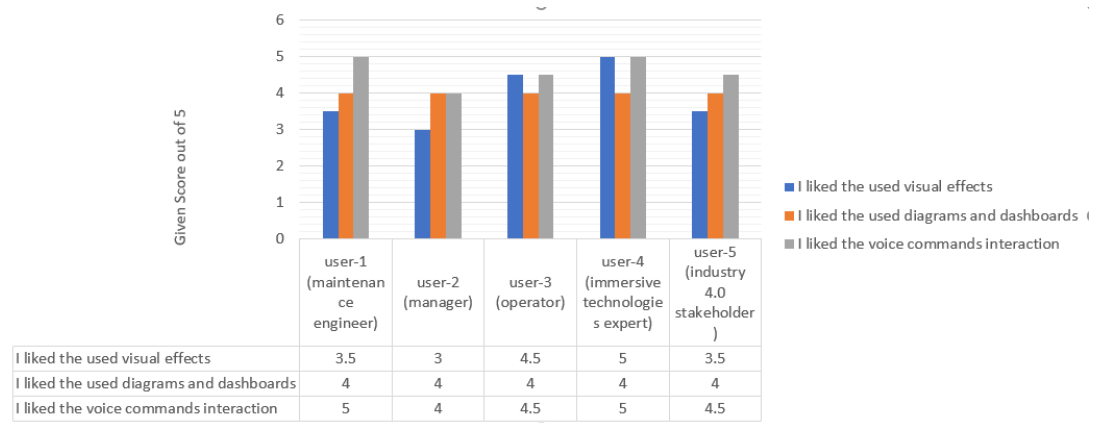


Figure 61: Sample results of the end-users' evaluation about the level of the IDTR system explicability (Source: Self).

Measuring all those factors depended mainly on the overall classifications accuracy and the explainability of any autonomous decisions the system makes. They collect data directly from the users using self-reporting methods. Users were asked to complete a survey after trying the system and to reflect their opinions from different aspects. All the used instructions were subjective to measure the user experience only. A 5-point Likert

scale was used to gather different users' opinion after trying the IDTR system. 22 expert users tried the developed IDTR system, and the overall average was promising and showed a great level of user's trust in the IDTR performance. Table 9 shows a survey sample of 22 users who tried the developed IDTR system and tested all its functionality.

users	No. of Participants	Level of trust
Maintenance Engineers	8	4.1
Operators	9	4.4
Managers	5	4.3

Table 9: A sample results from a user trust survey about how far expert engineers trust in the IDTR decisions (Source: Self)

The post-survey aimed to collect various observations from different types of users. The report includes three main sections; general overview about the system, level of immersion from a user point of view, and how far users feel that IDTR decisions are trusted.

Also, users were asked to self-report directly to the IDTR system and interact with a few objective questions measuring the overall level of trust from an expert point-of-view (Papenmeier et al., 2019). In such a way, IDTR collects all the given answers and transforms them into scores that can be used to measure the overall levels of trust. This integrated self-reporting feature in the IDTR system contains two main sections: 1) user's criticism about the system design and realism. 2) user's opinion about the level of automation, including the made decisions and prediction accuracy.

The concept of this evaluation method is efficient and does not require multiple statistical tools to be built. It adds more automation to the IDTR system and makes the interaction with the end-users flexible and more trusted. The main goal of this trusted method was to compare the performance of the two main elements, IDTR, including the IDH tools, and the users. In such a way, IDTR calculates different parameters such as time, accuracy, and level of trust automatically. IDTR uses an integrated dashboard to visualise all the findings and provide them in an explainable way to the end-users. Afterwards, further improvements can be suggested as a result of these findings, and it helps to upgrade the IDTR system mechanism. Table 9 shows the resulted level of trust after the selected groups have tested the developed VR ad AR applications as follows: maintenance teams (4.1), operators (4.4), and managers (4.3). Although the three levels of trust were close to each other, some reasons of such variations can be attributed to; 1)

maintenance team felt more comfortable with following traditional means of fixing failures. 2) operators appreciated the instant automated failure reporting processes, and 3) the developed IDTR system provided unique visualisation and access to the management.

5.5 How the IDTR technology Makes Machines Adaptive

For many decades, manufacturers have tried various technologies to make their production lines more efficient and agile. They have been developing smarter machines to produce better quality products and thus to decrease losses. One of the old/new targets is to achieve automation capabilities and to improve the future of any manufacturing processes. In many cases, this was done by using, for example, robotics systems and simulations that show how equipment possibly behave. However, there are many types of equipment in the complex manufacturing processes that still need more improvement and investigations to process automated tasks. We are living in the era of the fourth industrial revolution and eyes are on the fifth revolution to explore cutting edge technologies that seek to achieve more automated processes. As a result, several advances can easily be implemented and tested to handle some technical challenges of equipment. This research proposes a novel approach that will revolutionize the semiconductors manufacturing industry. I have developed an autonomous IDTR system that achieved promising results in Adaptive Machines. With this approach, equipment can produce, test, validate, and re-configure themselves automatically. In doing it in a such way, there is no need to stop machines for an extended period of times to make small changes in their performance or to spend more time on maintenance procedures. In addition to that, equipment will be protected from multiple failure events. For instance, in the developed IDTR system, wire-bonder equipment can predict and automate various operations. Figure 62 illustrates an example of adaptive wire bonding equipment through the IDTR system.

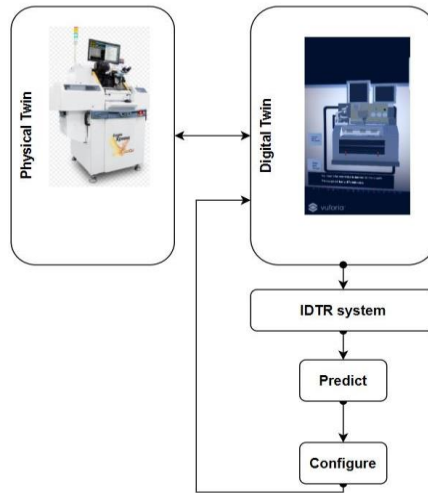


Figure 62: An adaptive wire bonder structure using the IDTR system (Source: Self).

As shown in Figure 62, wire bonding equipment is autonomously controlled by the IDTR system. IDTR predicts different events in processes and suggests the right changes. Since the IDTR system uses the equipment’s IDT replica, it can validate any suggested changes without interrupting the physical twin. As a result, the machine manages to reconfigure its parameters to handle the required changes quickly. Such a useful feature contributed to minimizing machine downtimes.

While working on the live system, it was noticed that some machines remain off for days because of a straightforward technical failure. Figure 63 shows a snapshot that was taken from a historical data collected from a randomly selected wire-bonder. The IDTR project aims to avoid such unnecessary scenario from happening and to keep the machines running as long as they provide the required high-quality products. I have discussed this proposed design intensively with the company’s engineers and they have shown a higher interest in the concept.

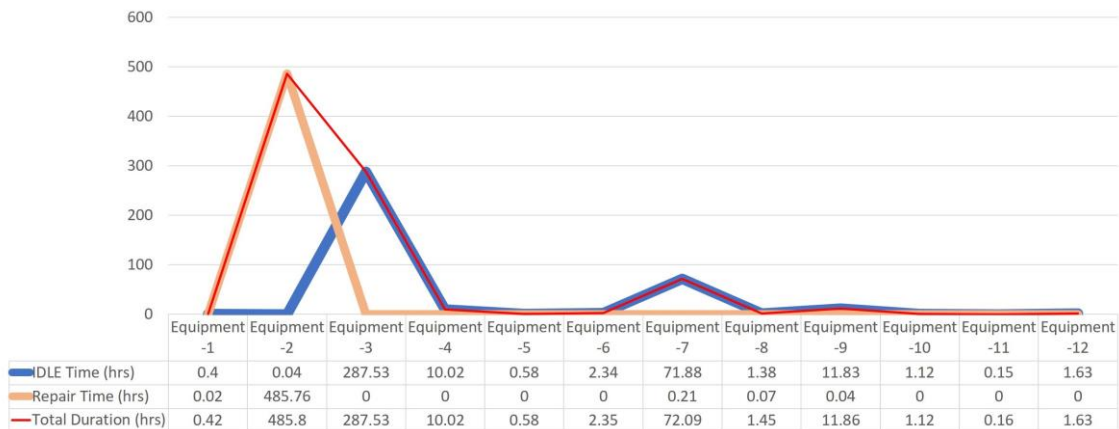


Figure 63: A sample from the used raw dataset (Source: Self).

At the Testing Department, several testing engineers will make much less effort to investigate some reported failure events. With an IDTR system, they will be very close (virtually) to the physical equipment and will be updated in real-time about any possible and predicted failure events before they occur. To conclude, I firmly believe that IDTR technology will provide autonomous descriptive feedback to users to take the right actions and to solve many current technical problems. Thus, users spend less time on error troubleshooting multiples failures, ending with more producing times.

5.6 How the Designed IDTR System Became Portable

IDTR technology aims to solve a wide range of challenges that IDT systems face. Since IDT can be applied to various systems and applications, IDTR needed to address portability limitations and provide a straightforward approach to help user switch between different use cases. The IDTR system is generated upon IDT systems, and it makes a copy of all their content. However, within the same manufacturing processes, there is a possibility to handle different type of equipment. Such a challenge was handled by only changing a few configurations when using the IDTR on those different systems. Data sources APIs need to be reconfigured to help the IDTR identifying any new change in the targeted processes. It is important to highlight that how the humming tools work remain the same over different processes. The change will be seen in the creation stage of the training data. Different parameters, together with different captions, will be generated to train all the IDHTs on the new targeted changes. Such portability feature makes it easier to implement IDTR for multiple manufacturing processes.

IDTR concept handled the portability challenge and showed promising results. IDTR has real-time access to different parameters of different manufacturing processes. This make IDTR system more flexible when targeting new equipment and manufacturing processes. Also, IDTR uses a database that includes multiple 3D equipment models from different manufacturing processes. This database is upgraded, and it can be expanded using cutting-edge plug-ins. Using Unity engine to develop the IDTR environments allows real-time changes on the 3D CAD equipment models when needed. Plug-ins such as PiXYZ and CAD Exchanger SDK were used and tested to prove the portability concept (Chambers, 2020; Arnedo Blanco, 2016). Figure 64 shows the high-level portability process to use IDTR over two different equipment.

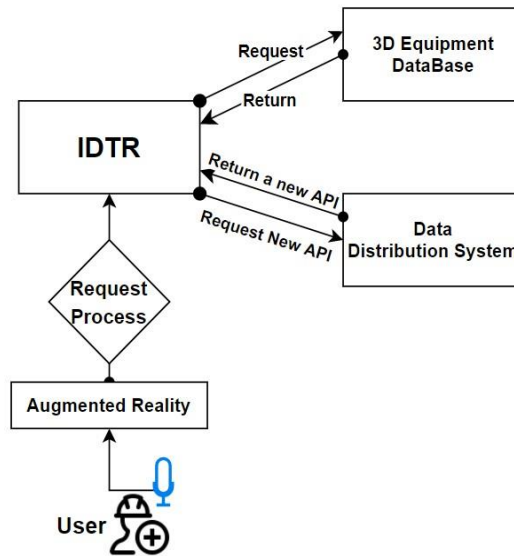


Figure 64: How a portable IDTR system works (Source: Self).

As shown in Figure 64, using advances such as voice commands and VR, IDTR managed to switch between 2 different production lines and created virtual sandboxes of them.

From the beginning stage of this research, a decision was made to investigate the possibility of developing a generic, intelligent, and portable IDTR platform that can be used over different semiconductor manufacturing processes. Also, there were some concerns about the scalability of the developed system in the sense of using a high number of equipment that have been used for different periods of times. However, I have faced more challenges such as using the same equipment to produce different types of products including size, design, and mechanism differences. I have found many insights that indicate some severe failures when equipment needed new configurations changes. I have taken into consideration such impact and how it might be the case when a new product is needed and what type of automatic changes can be made to avoid having some downtime. The IDH tools were developed to make a prompt investigation and to automate some set-up configurations to decrease any possible downtime. After the system was developed, an intensive investigation has been done to confirm the possibility of using the same training data creation technique over different collected parameters from different models of the same type of equipment. The developed IDTR was tested and validated during the design stage, and it will be generalised over the stages and processes that will be added in the future. It is also important to mention that the used approach will allow extracting an IDTR platforms that support various

operating systems. For example, Windows, Android, and more. Also, because the developed IDTR system has multiple visualisation levels, some of the features were displayed on smart devices that support Android.

The use case had already used architecture to capture physical assets' data and pass it through a data message system. Software technologies were used for many years to provide some streamed data fed into several statistical tools to provide real-time insights about the status of different manufacturing lines. This limited the possibility of integrating new technologies in this research and required designing several APIs that act as bridges between the observable domain and the core domain of the developed IDTR system. For example, a streaming API was developed to capture streamed data from the machines to a distribution system. This API was designed in an asynchronous way to stream any available information only if they are available. Then the streamed data was distributed using a Kafka distribution system that was developed to handle any parallelism challenges when dealing with multiple machines. On the other hand, other asynchronous APIs were developed to feed the streamed data into the IDTR edge. Those APIs are two-way connection processes to establish communication between the IDTR core and the distribution system and vice versa. Furthermore, another API was developed to allow the distribution system to communicate with a Hadoop system to process the IDH tools' models and create a communication protocol between the IDTR and the distribution system. All the mentioned technologies were developed from scratch to meet the system requirements and handle the size of the used data and process it in a distributed way. There was no possibility of accessing the production systems remotely, which limited the possible technologies that can be used. For example, it was not possible to use any Cloud services to test the developed IDTR system.

The Unity engine was used to develop the virtual representation and design the IDTR system VR and AR environments. The Unity engine was chosen because of its capabilities to use all the different ER elements and technologies. Also, the Unity engine supports several APIs that can be integrated into more virtual entities on the digital representation domain. Furthermore, the Unity engine supports multi-processing services and creates robust communication protocols that meet the nature of the developed IDTR system. It is important to mention that all the used hardware infrastructures for the proof of concept of the IDTR system were developed during this research. A distribution system was developed using a powerful server with high graphics capabilities to handle any rendering challenges. Also, the server contains a good

storage capacity to handle the large size of the exchanged data between the physical entities and the virtual twins. All the used technologies were open-source, and they improved the overall performance of the IDTR system.

To conclude, the fact that the IDTR system is created upon IDT systems makes the portability and interoperability of IDTR systems possible. A copy of the IDT is automatically created and processed in nearly real-time. However, how the IDH tools work needs to be tweaked to make minor changes to collect different visual observation whenever manufacturing processes are changed.

6 Conclusion and Future Work

This section explains the overall findings and achievements of this PhD research. Also, it explains the top achieved benefits in complex semiconductor manufacturing processes—details about the future stages of this research from the implementation and research perspectives.

6.1 Future Work

IDTR showed a great potential towards developing autonomous virtual environments that can train, test, and validate themselves. Such a concept is required in several manufacturing applications. The idea of developing an intelligent system that can control the entire manufacturing process, including several complex processes, is challenging. The need to handle regular and irregular manufacturing events leaves a room for development to design more beneficial and reliable solutions. This project work was done in collaboration with a global manufacturing company. Thus, the concept of IDTR will be tested over multiple manufacturing lines individually to provide more results. Processes such as die attaching, moulding, and sawing will be targeted next, and they will be used to test the concept of IDTR and IDH tools. The IDTR concept will be designed upon the entire semiconductor manufacturing process, and it will evaluate all the captured improvements at a later stage. Applications such as root cause analyses, risk assessment, proactive and predictive maintenance will be investigated using different processes and equipment. I strongly believe that potential benefits from using the IDTR technology can be investigated on challenging and critical manufacturing issues. Adaptive Equipment concept and Overall Equipment Effectiveness can be tested using the IDTR technology and, it is expected that great improvements can be achieved.

It is essential to highlight that this research is ongoing, and more enhancement will be targeted. One the key future improvements is in the area of system portability. IDTR concept needs to be able to work on different manufacturing processes with a high level of interoperability. This includes adding more flexibility when using the IDTR by multiple users at the same time. User experience when switching between different equipment is going to be investigated as well. Also, this research seeks two primary manufacturing areas including optimization and automation. More tests will be conducted to ensure the reliability of the IDTR technology and its impact the productivity levels of different manufacturing processes.

Finally, some results from this research have already been published as conference papers and book chapters. Also, several presentations at high profile events have been delivered to introduce the IDTR concept and to seek future collaborations with research groups. I aimed to introduce the concepts of IDTR and IDH tools to allow other researchers to build upon our findings and to develop different perspectives about the possibility of deploying the IDTR technology. One of the areas that could be investigated further is exploring means to better optimize the used hardware to achieve more portability, flexibility, and cheaper resources. Another area that could be examined more is the used technologies to create the IDTR environment. This may include exploring the adoption of different technologies and bench mark the results to the finding of this research. Furthermore, the potential use of the newly developed Intelligent Digital Humming tools in this project can be explored further by using different technologies to create them and/or implement them in different manufacturing settings other than semiconductor manufacturing sector.

6.2 Conclusion

This research sought to answer two main questions. First, “What are the limitations of Intelligent Digital Twins in general?”. Three main categories of limitations were identified as a result of this research. These include:

1. Implementation issues related to aspects as a) time critical services, b) safety critical services, c) mission critical services, d) labelling the dataset for training an ML model, and e) training AI and ML models for new applications.
2. Technological issues related to aspects as a) system integrity, b) system availability, c) system reconfigurability, and d) availability of high-quality data.
3. Validation challenge.

This research focused on the following IDT technology limitations: reconfigurability, mission critical services, portability, and automation time-critical challenges of IDT.

Second, “How to develop a triplet system including intelligent digital humming tools and use them to overcome traditional limitations of IDT systems?”. During this research, a number of technologies, methodologies, and approaches were used to overcome the above mentioned four IDT technology limitations. These include:

1. **Reconfigurability:** This challenge was overcome by developing an intelligent optimizing humming tool. The developed IDTR system uses the tool in its virtual environment to generate a new set of configurations as needed. The tool executes the reconfiguration task by either simulating possible system synthetic configurations during the training stage or recommending a new set of machine configuration based on the classifications and predictions of the IDTR system.
2. **Mission-critical services:** IDTR technology overcomes this challenge by using all developed IDH tools. The IDTR system and the developed IDH tools provide real-time services and recommendations to multiple manufacturing processes. A high level of parallelism was developed to allow the IDTR system to work on multiple tasks simultaneously. The IDTR system treats some critical services with higher priority whenever one of them is predicted.
3. **Portability:** This limitation issue was overcome by developing two IDH tools; autonomous feature selector and autonomous training data creator. They are used by the IDTR system to react to any changes in manufacturing processes. While the feature selector tool collects a new set of features about a new targeted machine or

process, now the training data collector generates data sets and a new set of captions about them. Furthermore, using the Unity engine as a key to create multiple IDTR platforms supported by different operating systems.

4. **Automation time-critical:** this challenge was overcome using the concept of the IDTR technology. The IDTR system prepares itself ahead of time before different manufacturing events happen. This enables the IDTR system to react to any possible failures autonomously. This gives the IDTR plenty of time to automate any needed reconfigurations and reactions. As a result, the IDTR system automates the entire processes including, predicting, classifying, and making recommendations so that operators make better final decisions. It is important to highlight the importance of using Extended Reality to execute this task.

Also, this project aimed to achieve two main objectives. The first objective was to develop an Intelligent Digital Triplet system which overcomes the limitations of the IDT that involves the design, development, testing, and validation of the developed system. Several technologies were used to develop this intelligent virtual environment including Big Data to manage the collected data from the manufacturing facility of the chosen manufacturing company for this research. Also, an IoT system was used to develop a two-way streaming connection between the physical and virtual parts of the developed IDTR system. Furthermore, the Unity game engine was used to design the actual virtual environment itself.

The second objective was to develop virtual intelligent agents named Intelligent Digital Humming Tools and add them to the created IDTR system to make it more efficient to overcome common IDT challenges. This is considered as a third part of the developed system and three leading technologies were used to develop it that included the Unity game engine that designed the IDTR environment where the testing and validation of the performance of the system takes place. These AI agents roam in the virtual environment and observe its performance and take appropriate actions to rectify any errors. Also, GANs Machine Learning models were used to train the IDH tools to be able to better classify reactions. Overall, the developed digital triplet performed autonomously and self-train its AI agents using the captured data and the best possible reactions.

The research project met all the required objectives and tasks. An advanced Intelligent Digital Triplet system was developed and tested using captured streamed data

from various physical wire bonding equipment. The developed IDTR system simulates what is happening in the live wire bonding production line in nearly real-time and provides several practical and visual insights to make an initial of automated processes. This research focused on adding more intelligent elements to the IDT system and to create more innovative IDH tools. Another ultimate goal was to create fully autonomous Intelligent Digital Triplet system that can improve the overall effectiveness of equipment. A number of IDH tools were integrated in the developed IDTR system to engage more Intelligent Automation elements. Furthermore, more attention was given to the Extended

Reality since it is still a new area, and it can further improve the entire user's experience when using the IDTR system. IDTR technology was introduced to overcome all the IDT critical issues and to add more innovative automation capabilities to the area. I believe that the novelty and the unique contributions of our work lie in the following aspects:

1. This research introduced a new concept of IDTR technology and solved main issues associated with the use of IDT systems. A new set of characteristics were developed to design autonomous, intelligent, and innovative system. Issues such as reconfigurability and automation time-critical issues were arranged with a high level of reliability.
2. The IDTR system provided better testing and validation capabilities of any predicted failure events. Instead of waiting for real-life events to occur to validate any made predictions by the IDT system, the IDTR system works ahead of time to simulate all probabilities of impact, change, and results of those made predictions.
3. The IDTR system introduced an upgraded intelligent virtual environment and proved the capability of integrating a wide range of AI enabled technologies.

It is essential to highlight that the IDTR concept showed significant potential results in several aspects. Overall, it showed a great potential to design such intelligent systems only when they are needed. Rather than manually reconfiguring such complex environments, IDTR automatically captures all the IDT elements and runs them inside a virtual sandbox. Some of the highlighted findings showed a great improvement in the IDT overall prediction accuracies. Approximately a 7% of accuracy improvement was measured during testing the IDTR system to predict several manufacturing failures events. Implementing an autonomous feature selection process, using the Feature Selector-IDHT1, helped IDTR improve the accuracy of the predictions it makes. Also,

the concept of collecting visual observations using the Training Data Creator-IDHT2 and create synthetic data were behind the achieved accuracy improvement. Another major improvement was achieved is the reduction of downtimes of the investigated equipment. Wire bonding is classified as a critical stage in semiconductor manufacturing processes, and it uses complex and smart machines. That equipment faces several challenges that result in long downtime periods. IDTR technology managed to solve such a challenge with promising results. Because of the added autonomous capabilities of the IDTR system and the use of the IDH tools, machine downtimes went down to around 40% and these improvements were captured during the system's evaluation stage. Also, using IDTR, I managed to improve the IDT root cause analysis accuracies from 87% to up to 94%. This means that the IDTR system provides more accurate decisions about the possible reasons for multiple failure events. Any highlighted cause(s) behind such failure events is 87% accurate [leaving 13% for uncertainty] in the IDT system. On the other hand, the IDTR system has less than 6% of uncertainty about the predicted root causes. The IDTR system applied an intrinsic root cause analysis's function that measures the importance of the different used features when classifying failure events. The output from this function is presented in percentage values that highlight the different main reasons behind the predicted failures. For example, Failure event-1 occurs because of (5% used materials, 2.6% production time, 1.4% X position coordinator). Therefore using 87% accuracy of the IDT system, the root cause accuracies are 4.35% used materials, 2.26% production time, and 1.21% X position coordinator. On the other hand, using 94% accuracy of the IDTR system, these root cause percentages become 4.7% used materials, 2.34% production time, 1.26% X position coordinator.

Such an improvement will have an impact on predictive maintenance practices, machine downtimes, and the productivity of the entire wire-bonding manufacturing process. Overall, such improvements

could potentially lead to saving the adopters millions of Euros. I believe that the concept of IDTR will change how we look at our manufacturing processes today. Challenges such as reconfigurability and portability became much easier to deal with. This research proved that IDTR technology should be considered a new added element to any manufacturing processes that seek more autonomous capabilities, better and accurate predictions, and better Overall Equipment Effectiveness.

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Appendices

A A Sample from the Used Raw Dataset

Equipment name	Idle time (hrs)	Repair time (hrs)	Solution	Total duration (hrs)
WB-KS-ICONN_PLUS-041	0.4	0.02	NSOP-OK	0.42
WB-KS-ICONN_PLUS-041	0.04	485.76	ALIGNMENT	485.8
WB-KS-ICONN_PLUS-041	287.53	0	CLEAN	287.53
WB-KS-ICONN_PLUS-041	10.02	0	SETUP	10.02
WB-KS-ICONN_PLUS-041	0.58	0	SETUP	0.58
WB-KS-ICONN_PLUS-041	2.34	0	ALIGNMENT	2.35
WB-KS-ICONN_PLUS-041	71.88	0.21	PM	72.09
WB-KS-ICONN_PLUS-041	1.38	0.07	OthersOk	1.45
WB-KS-ICONN_PLUS-041	11.83	0.04	ALIGNMENT	11.86
WB-KS-ICONN_PLUS-041	1.12	0	ALIGNMENT	1.12
WB-KS-ICONN_PLUS-041	0.15	0	SETUP	0.16
WB-KS-ICONN_PLUS-041	1.63	0	SETUP	1.63
WB-KS-ICONN_PLUS-041	3.04	0	ALIGNMENT	3.04
WB-KS-ICONN_PLUS-041	0.06	0.82	ALIGNMENT	0.88
WB-KS-ICONN_PLUS-041	0.8	0.28	OthersOk	1.09
WB-KS-ICONN_PLUS-041	9.07	0	CLEAN	9.07
WB-KS-ICONN_PLUS-041	12.67	0.02	ALIGNMENT	12.68
WB-KS-ICONN_PLUS-041	0.43	0	OCAP	0.43
WB-KS-ICONN_PLUS-041	1.18	0.04	SETUP	1.22
WB-KS-ICONN_PLUS-041	1.51	0	CLEAN	1.51

Figure 65: A sample from the used raw dataset (Source: Self).

B

Samples of Collected Statistics During the Research

Lot ID	Yield percentage	Number of good devices	Total tested devices
22729UX00C	96.40%	30763	31911
22718Q2URF	96.57%	9006	9325
22729UYD1C	18.89%	321	1699
22729V5909	97.40%	16052	16480
22729V5908	96.82%	29854	30834
22730VL301	97.5%	31198	31986
22730VL303	97.90%	31922	32606
22730VL304	97.66%	30635	31366
22730VL308	96.41%	30698	31840
22731VPROB	96.81%	29327	30293
22731VPROC	97.90%	33434	34149
22731VPRO6	91.67%	17873	19497
22731VPRO7	95.40%	29580	31006
22730VJQ0B	96.08%	29639	30846
22730VJQ0C	93.83%	31182	33232
22730VJQ0D	97.58%	30288	31036
22730VJQ0E	94.00%	29126	30982

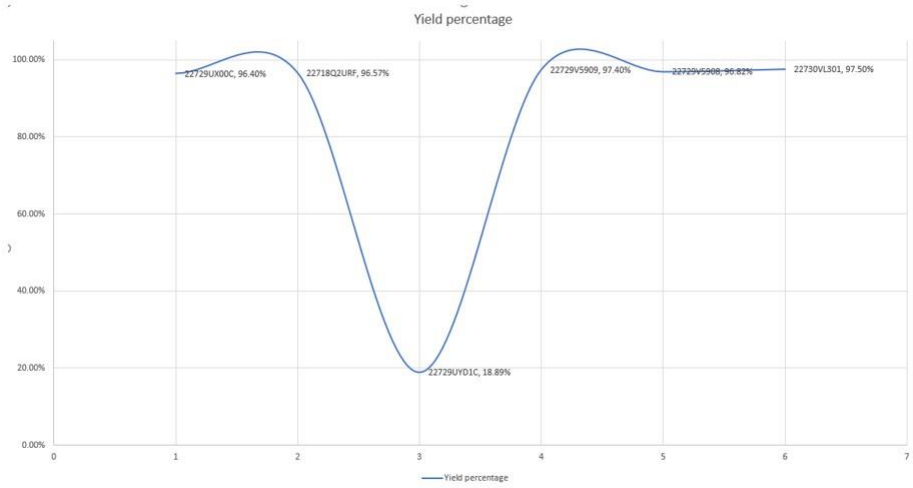


Figure 66: A sample of yield statistics (Source: Self).

LOT_ID	SBIN	SBIN Yield percentages	Number of tested devices per SBIN
22729UYD1C	6	49.55 %	842
	20	19.65 %	334
	19	2.88 %	49
	64	2.35 %	40
	58	1.76 %	30
22729V7C02	82	1.83%	352
22729V5908	71	1.18%	366
22729V540E	54	4.77%	720
22718Q2URF	103	1.06%	99
22730VAQ1T	7	2.33%	777
22730VAQ01	5	1.77%	574
22729V540D	54	2.24%	353
22729V7C0L	71	1.10%	334
22730VAQ1W	7	1.93%	609
22730VFD09	254	1.63%	500

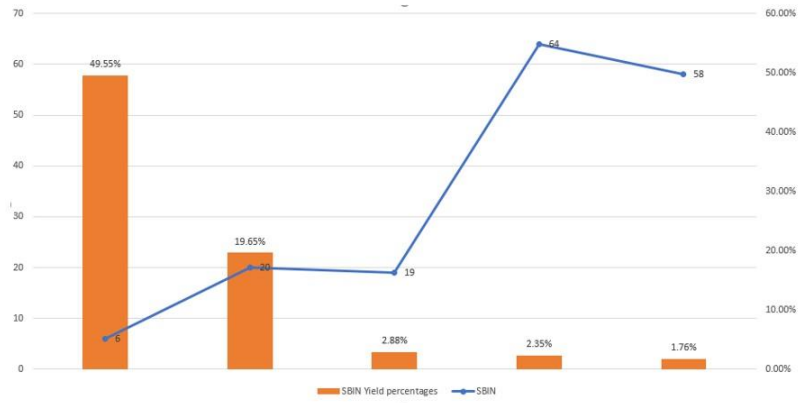


Figure 67: A sample of failure yield percentages per lots (Source: Self).

LOT_ID	SBIN	Site Number	SBIN Yield percentages per site	Number of tested devices per SBIN	LOT_ID	SBIN	Site Number	SBIN Yield percentages per site	Number of tested devices per SBIN
22729UX00C	SBIN	SITE	Yield Percentage	Total Devices	22730VJQ0B	SBIN	SITE	Yield Percentage	Total Devices
	7	1	11.1 %	9		5	7	7.19%	167
	7	5	1.3 %	1042		7	17	1.17%	1026
	7	4	1.3 %	1013		7	33	1.15%	960
	42	31	1.5 %	712		20	7	1.20%	167
	42	1	66.7 %	9		42	11	1.21%	247
	42	24	3.2 %	711		71	28	1.06%	1035
	42	21	4.5 %	751		71	16	1.78%	1011
	42	30	2.7 %	997		71	4	1.78%	1014
	96	14	1.5 %	711		71	32	2.31%	1039
	103	27	1.4 %	1063		71	14	1.17%	1024
	103	20	1.0 %	1062		71	2	1.09%	1010
	103	19	1.2 %	1057		103	22	1.17%	1027
	103	15	1.0 %	1059		103	13	1.27%	1023
	103	11	1.0 %	1052		103	3	1.28%	1014
	103	33	1.1 %	1062		103	15	3.51%	1025
103	14	1.1 %	711	103	9	1.37%	1023		
250	1	22.2 %	9	103	35	1.69%	473		
254	23	100.0 %	5	103	23	2.51%	1034		
22730VAQ1S	5	1	2.04%	49	22730VAQ06	5	11	1.132503%	883
	5	29	3.85%	52		82	20	1.009082%	991
	6	15	1.92%	52		250	13	100%	4
	19	29	3.85%	52		250	35	100%	3
	20	29	1.92%	52		250	8	100%	4
	21	29	5.77%	52		250	30	100%	3
	33	24	1.92%	52		-	-	-	-
	33	29	1.92%	52		-	-	-	-
	39	29	5.77%	52		-	-	-	-
	48	29	1.92%	52		-	-	-	-
	49	27	1.92%	52		-	-	-	-
	49	14	3.92%	51		-	-	-	-
	54	6	2.04%	49		-	-	-	-
	54	17	2.00%	50		-	-	-	-
58	12	2.00%	50	-	-	-	-		
58	16	1.96%	51	-	-	-	-		

Figure 68: More statistics from a device level (Source: Self).

C DL and GANs used pseudocodes

Deep Learning Photo Caption Generator algorithm

Generate Data by IDTR

```
Function to convert data from raw string format to unity  
colour
```

```
    Start function
```

```
        Get data in string format from data  
        streams
```

```
        Return colour object
```

```
    End function
```

```
Function to capture visual observations
```

```
    Start function
```

```
        Get the list of selected features
```

```
        Captured their colure value
```

```
        Merge the collected observations
```

```
        Create 5 captions from the selected  
        features
```

```
            For I in features list:
```

```
                Convert the reading to text
```

```
                Concatenate the text with  
                caption sentences
```

```
                Amend the caption list
```

```
                Assign the generated captions  
                with the generated image
```

```
            Return image canvas and list of captions
```

```
    End function
```

```
Function to store generated data
```

```
Function to Prepare Photo Data
```

```
    Function Extract features from the image
```

```
    Function Prepare text data
```

```
        Start function
```

```
            Converting uppercase to lowercase.
```

```
            Removing all punctuation.
```

```
            Removing all words that include  
            one character or less in length
```

```

    Removing all words that include
    numbers in them.
    End function
Function Deep Learning Model
    Start function
        Loading Data
        Defining the Model
        Fitting the Model
        Evaluate Model
    End function

```

Visual Observations Classifier Auxiliary Classifier GAN (AC-GAN)

```

Function Images uploader
    Start function
        Load canvas images from images topic (Kafka)
        Split it into training and testing datasets
    End Function
Function Discriminator Model
    Start function
        Gaussian weight initialization ()
        LeakyReLU()
        Dropout()
        2x2 stride for downsampling instead of pooling
        layers()
    End Function
Function Generator Model
    Start function
        label input
        embedding for categorical input
        linear multiplication
        reshape to additional channel
        image generator input
        merge image gen and label input
        define the standalone generator model
    End Function

```

```
Function Auxiliary Classifier GAN (AC-GAN)
```

```
    Start function
```

```
        define the combined generator and discriminator model,  
        for updating the generator
```

```
        make weights in the discriminator not trainable
```

```
        connect the outputs of the generator to the inputs of  
        the discriminator
```

```
        define gan model as taking noise and label and  
        outputting real/fake and label output.
```

```
        compile model
```

```
        return model
```

```
    End Function
```

D A sample from real collected data from the physical side

ProcessStartEvent	"NA"	"WB-KS-ICONN-424"	"2020/08/08 21:20:34.361"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"
AlarmEvent	"de2c53ec-7e57-4db1-ba04-95e08caacd3"	"NA"	"20200809-01:05:47:097"	"6099"	"2020/08/09 01:05:47"	"MH_FAILED_GET_MAG_O"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"f7f017eb-99f1-455a-a9b8-e4771d0f3d9"	"NA"	"20200809-02:16:46:689"	"6049"	"2020/08/09 02:16:46"	"POT Error - BITS Error NSOP "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"f4732a6d-940e-4a2f-bf9d-def01c802c8f"	"NA"	"20200809-02:28:45:744"	"6051"	"2020/08/09 02:28:45"	"POT Error - BITS Error SHTL "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"e2511c0a-de31-41a6-b67f-1020111b0be6f"	"NA"	"20200809-02:28:59:909"	"6049"	"2020/08/09 02:28:59"	"POT Error - BITS Error NSOP "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"6bee2c17-03d6-446d-abf2-f9459eb474d"	"NA"	"20200809-02:43:56:759"	"6077"	"2020/08/09 02:43:56"	"empty input magazine slot "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"1d2641a3-67a6-4476-8f42-627426a3f22c"	"NA"	"20200809-05:15:19:340"	"6099"	"2020/08/09 05:15:19"	"MH_FAILED_GET_MAG_O"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
AlarmEvent	"c9f541a-2a9c-4b61-a264-7caaf5f219f5"	"NA"	"20200809-07:14:39:832"	"6100"	"2020/08/09 07:14:39"	"MH_INPUT_TRAY_EMPTY"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QB3R"	
TrackOutLotEvent	"390508e2-41b9-4e74-81cc-24e5af70382e"	"NA"	"20200809-07:19:16:344"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QB3R"
LotTrackInConfirm	"NA"	"WB-KS-ICONN-424"	"2020/08/09 08:26:19"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
TrackInLotEvent	"b125a39e-f66c-4b2b-9cc9-5ab15f996c68"	"NA"	"20200809-08:26:20:250"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
AlarmEvent	"f5f61f39-d265-4276-be9e-ed3ad27e4f6d"	"NA"	"20200809-09:09:33:080"	"6271"	"2020/08/09 09:09:33"	"AUTO-NEARING-TOOL-USAGE-LIMIT"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"febc49c-8343-47c-b213-19306a9507d"	"NA"	"20200809-11:38:21:344"	"6077"	"2020/08/09 11:38:21"	"empty input magazine slot "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"94984035-7d8b-4846-b911-b78eb4f6762d"	"NA"	"20200809-11:38:35:119"	"6271"	"2020/08/09 11:38:35"	"AUTO-NEARING-TOOL-USAGE-LIMIT"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"72e54d5e-f634-4dec-b66e-447e1b7b31e0"	"NA"	"20200809-11:38:43:356"	"6055"	"2020/08/09 11:38:43"	"AUTO-VLL-WIDTH-FAIL"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"7f01104d-65af-486d-95cc-f22929f3c28"	"NA"	"20200809-11:38:50:610"	"6055"	"2020/08/09 11:38:50"	"AUTO-VLL-WIDTH-FAIL"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"8e054c8b-e06f-460c-abab-0ab579d146ac"	"NA"	"20200809-11:42:48:059"	"6051"	"2020/08/09 11:42:48"	"POT Error - BITS Error SHTL "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"2d26432f-5cd0-4e4a-bcb9-26a972464f6d"	"NA"	"20200809-11:42:51:787"	"6049"	"2020/08/09 11:42:51"	"POT Error - BITS Error NSOP "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"120f80dc-3dfa-48fb-a3ce-81e408ec3ba4"	"NA"	"20200809-11:42:52:739"	"6051"	"2020/08/09 11:42:52"	"POT Error - BITS Error SHTL "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"cbe9e0dc-f5e8-4ad2-b6ca-baf9fc9d75d3"	"NA"	"20200809-11:44:49:506"	"6151"	"2020/08/09 11:44:49"	"WHL_HAS_DEVICE_CLAMPED"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"1b02612f-605f-4fde-bb8a-ef21c6374a7e"	"NA"	"20200809-13:18:03:483"	"6051"	"2020/08/09 13:18:03"	"POT Error - BITS Error SHTL "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"3e84166f-0918-4915-b5dc-3fa64c1d1315"	"NA"	"20200809-13:50:02:993"	"6054"	"2020/08/09 13:50:02"	"AUTO-VLL-FIND-FAIL"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"40a81426-9373-40a0-a236-2bc6176dc59b"	"NA"	"20200809-13:53:06:689"	"6054"	"2020/08/09 13:53:06"	"AUTO-VLL-FIND-FAIL"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"9596d95e-63ea-416e-897e-ebb70a90757c"	"NA"	"20200809-13:57:41:999"	"6054"	"2020/08/09 13:57:41"	"AUTO-VLL-FIND-FAIL"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"82ba2291-5939-49cf-94b6-5ff10ec2437d"	"NA"	"20200809-15:30:33:965"	"6005"	"2020/08/09 15:30:33"	"POT-WIREFEED-ERROR"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"3aedcd28-7241-495e-947b-77d7a8c7766a"	"NA"	"20200809-16:44:47:996"	"6077"	"2020/08/09 16:44:47"	"empty input magazine slot "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"17f73e6-8ed2-4040-aacc-cf0e4db4d374"	"NA"	"20200809-19:16:15:389"	"6099"	"2020/08/09 19:16:15"	"MH_FAILED_GET_MAG_O"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"71801898-4b18-40bd-9c5f-8683d674208e"	"NA"	"20200809-21:15:45:444"	"6100"	"2020/08/09 21:15:45"	"MH_INPUT_TRAY_EMPTY"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
TrackOutLotEvent	"19cd25c8-33f2-40a4-ac54-d10c8a95c3cb"	"NA"	"20200809-22:36:47:247"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
LotTrackInConfirm	"NA"	"WB-KS-ICONN-424"	"2020/08/09 22:52:53"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
TrackInLotEvent	"b31c331b-e291-4861-b886-0fa94068fea3"	"NA"	"20200809-22:52:53:689"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
AlarmEvent	"4ac48518-67b9-4b21-855b-9da0b97bde7c"	"NA"	"20200810-03:53:56:561"	"6077"	"2020/08/10 03:53:56"	"empty input magazine slot "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
AlarmEvent	"d5c44634-d9d0-4cd3-b683-dff6f26e1299"	"NA"	"20200810-04:40:39:818"	"6100"	"2020/08/10 04:40:39"	"MH_INPUT_TRAY_EMPTY"	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	
TrackOutLotEvent	"cc5065d5-12a3-4954-870b-cebf3bd994d51"	"NA"	"20200810-04:48:12:434"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
LotTrackInConfirm	"NA"	"WB-KS-ICONN-424"	"2020/08/10 04:43:50"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
TrackInLotEvent	"27c76f75-a5bd-40af-b159-731d449c423d"	"NA"	"20200810-04:43:50:826"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"NA"	"22032QD701"
AlarmEvent	"de065e74-fccf-4e57-9f6c-b73eb5757da2"	"NA"	"20200810-08:29:15:457"	"6077"	"2020/08/10 08:29:15"	"empty input magazine slot "	"Error"	"EICEventAlarm"	"EIC.SC"	"22032QD701"	

E List of Publications

1. Artificial Intelligence in Industry 4.0 Book.
 - (a) Publisher: Springer International Publishing
 - (b) Publication date: 2021
 - (c) Citation: Dingli A, Haddod F, Kluver C 2021. Artificial Intelligence in Industry 4.0: A Collection of Innovative Research Case-studies that are Reworking the Way We Look at Industry 4.0 Thanks to Artificial Intelligence. Springer, Cham.
2. Intelligent Digital Twin System in the Semiconductors Manufacturing Industry.
 - (a) Publisher: Springer International Publishing
 - (b) Publication date: 2021
 - (c) Citation: Haddod F, Dingli A. Intelligent Digital Twin System in the Semiconductors Manufacturing Industry. Artificial Intelligence in Industry 4.0: A Collection of Innovative Research Case-studies that are Reworking the Way We Look at Industry 4.0 Thanks to Artificial Intelligence. 2021:99-113.
3. Interacting with Intelligent Digital Twins.
 - (a) Conference: International Conference on Human-Computer Interaction
 - (b) Publication date: 2019
 - (c) Citation: Dingli A, Haddod F. Interacting with Intelligent Digital Twins. In International Conference on Human-Computer Interaction 2019 Jul 26 (pp. 3-15). Springer, Cham.
4. ACE: Big Data Approach to Scientific Collaboration Patterns Analysis
 - (a) Conference: Scientometrics 2017 – Scientometrics workshop @ ESWC
 - (b) Publication date: 2017
 - (c) Citation: Zammit A, Penza K, Haddod F, Abela C, Azzopardi J. ACE: Big Data Approach to Scientific Collaboration Patterns Analysis.
5. MIRAI: A Modifiable, Interpretable, and Rational AI Decision Support System.
 - (a) Publisher: Springer International Publishing
 - (b) Publication date: 2021
 - (c) Citation: Mallia N, Dingli A, Haddod F. MIRAI: A Modifiable, Interpretable, and Rational AI Decision Support System. Artificial Intelligence in Industry 4.0: A Collection of Innovative Research Case-studies that are Reworking the Way We Look at Industry 4.0 Thanks to Artificial Intelligence. 2021:127-41.
6. Optimizing Root Cause Analyses with Intelligent Digital Triplet System
 - (a) Conference: AIAI 2021, 17th International Conference on Artificial Intelligence Applications and Innovations
 - (b) Publication date: 2021
 - (c) Status: pending
7. An intelligent system to revolutionize the root cause analysis in the semiconductor manufacturing industry.
 - (a) Conference: International Joint Conference on Artificial Intelligence (IJCAI-21)
 - (b) Publication date: 2021
 - (c) Citation: pending