Development of a Digital Twin Framework for Predictive Maintenance in Smart Manufacturing Environments

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***Abstract*—Digital Twin (DT) technology is revolutionizing predictive maintenance (PdM) by creating real-time virtual models of physical assets, enabling proactive failure detection, maintenance optimization, and reduced downtime across industries such as manufacturing, aerospace, and energy. This study reviews 98 studies on DT-enabled PdM, examining its applications, key frameworks, and challenges. Frameworks like Smart Factory Digital Twin (SFDT) and Digital Twin-Industrial Internet (DT-II) demonstrate how DTs integrate with IoT and machine learning (ML) to support predictive accuracy and operational resilience. However, challenges such as high computational demands, data security, and interoperability limit widespread adoption. Emerging solutions, including hybrid and cognitive DTs, show promise for flexible, scalable DT systems. This study highlights DTs' potential to enhance PdM within Industry 4.0 and recommends future research to improve ML integration, standardization, and security in DT frameworks.**

***Index Terms*—Digital Twin, Predictive Analytics, Digital supply chain twin, Artificial intelligence.**

I. Digital Twin-Driven Predictive Maintenance Framework for Smart Manufacturing in Industry 4.0

The swift progress in manufacturing technologies is reshaping the industrial sector, driven by Industry 4.0. This concept encompasses not only the merging of information technology with industrial production but also incorporates innovative technologies and new data management strategies. The objective is to empower manufacturers and supply chains to enhance productivity, minimize waste, cut costs, and quickly and effectively address consumer needs. Industry 4.0 advances digitalization by developing smart factories, enhancing manufacturing components and processes through digital integration. A pivotal technology supporting Industry 4.0 is the implementation of the Digital Twin (DT). However, many DT solutions from leading providers are digital models or shadows rather than true digital twins. This is largely due to the lack of a standardized DT definition among these providers, who present slightly varied uses under the broad term DT. This paper proposes a DT framework that simulates a real production line's product assembly processes using the Festo Cyber Physical Factory for Industry 4.0 at Middlesex University. Additionally, it presents a comprehensive approach to linking the physical system with its digital counterpart, enabling advanced predictive maintenance services and creating a fully integrated digital twin solution. The swift progress in manufacturing technologies is reshaping the industrial sector, driven by Industry 4.0. This concept encompasses not only the merging of information technology with industrial production but also incorporates innovative technologies and new data management strategies. The objective is to empower manufacturers and supply chains to enhance productivity, minimize waste, cut costs, and quickly and effectively address consumer needs. Industry 4.0 advances digitalization by developing smart factories, enhancing manufacturing components and processes through digital integration. A pivotal technology

supporting Industry 4.0 is the implementation of the Digital Twin (DT). However, many DT solutions from leading providers are digital models or shadows rather than true digital twins. This is largely due to the lack of a standardized DT definition among these providers, who present slightly varied uses under the broad term DT. This paper proposes a DT framework that simulates a real production line's product assembly processes using the Festo Cyber Physical Factory for Industry 4.0 at Middlesex University. Additionally, it presents a comprehensive approach to linking the physical system with its digital counterpart, enabling advanced predictive maintenance services and creating a fully integrated digital twin solution.

A digital twin serves as a virtual model of a physical process or product, enabling enhanced efficiency and cost reductions within manufacturing. By employing digital twins, production teams gain the capability to analyze diverse data sources, minimize defective products, improve operational efficiency, and decrease downtime in industrial settings. Digital twins facilitate visualization of assets, tracking of changes, and optimization of asset performance, particularly through analysis across a product's lifecycle. The data collected can comprehensively depict the lifecycle of products and processes, supporting optimized production workflows, supply chain management, and quality control.

In smart manufacturing, digital twins offer the potential to shorten time-to-market by allowing manufacturers to design and evaluate processes in virtual environments prior to actual production. These virtual simulations enable thorough analysis and modification of part performance and contribute to decreased factory commissioning times by refining factory layouts. Additionally, the productivity of component manufacturing benefits from predictive maintenance capabilities and data-informed root-cause analyses. This paper examines digital twin applications in smart manufacturing systems, discussing the advantages and obstacles of adjusting part production through this technology. By studying past research, the field can explore new ideas and develop innovative approaches to leveraging digital twins in advanced manufacturing systems.

With advancement in manufacturing, predictive maintenance turns into the need of the hour, but traditional methods of predictive maintenance cannot meet the emerging demands with the improvement in the manufacturing industry. Digital twin technology-based predictive maintenance has recently risen as an area of emphasis in manufacturing in very recent times. In the paper, first, basic methods of digital twin and predictive maintenance technologies will be identified; their gaps pointed out and, more importantly, the value of digital twin technology will be underlined in improving predictive maintenance. Next, a discussion will be provided on the characteristics of the predictive method based on digital twins distinguished from traditional approaches of predictive maintenance. It, furthermore, explores the applications of PdMDT through intelligent manufacturing, power engineering, construction, aerospace, and shipbuilding industries and provides a brief overview of recently achieved results in each discipline. Lastly, the reference framework of PdMDT in manufacturing is presented with an example referring to equipment maintenance, which shall be presented as a specified process illustrated with an industrial robot. The approach still has its limitations and challenges towards the realization of its advantages that it holds; hence, opportunity for further developments in the future are called out for it.

Digital twin technology may simply be described as heuristic technology, through which predictive maintenance is sure to be achieved efficiently. Through the use of digital twin technology, one can design a twin system between real-time machinery and the virtual world. In this direction, it is highly apt for the technique of predictive maintenance. Induction motors represent the pulse of industrial machinery. Their representation in the digital twin domain is very sparse. Motivation for this study comes from the development of the data-driven model developed with squirrel cage induction motors utilizing multiple physics-driven models integrated into a custom predictive maintenance system. End. This framework may extrapolate running parameters to predict motor RUL in addition to erratic fault diagnosis. For introducing the experimental setup of the 2.2 kW squirrel cage induction motor into the digital workspace for frequent calibration and setting the reference signal, a dSPACE MicroLabBox controller has been used. The digital framework has thus been implemented on MATLAB Simulink. This method thus enhances the high accuracy required without having an excessive computational load imposed on the processor. The commercial implementation of this model may provide an opportunity for induction motors to be opened up to computationally intelligent usage in Industry 4.0.

This diagram shows the parts and purposes of a digital twin system for predictive maintenance. Definition brings together the physical and virtual systems into a whole model, including real-time monitoring and optimization for the improvement of machineries surveillance. The Objective improves the efficiency of the maintenance process while saving on costs by avoiding equipment downtime. As a whole, all these parts enable proactive maintenance equipment which includes minimum sudden failures and optimal operation.

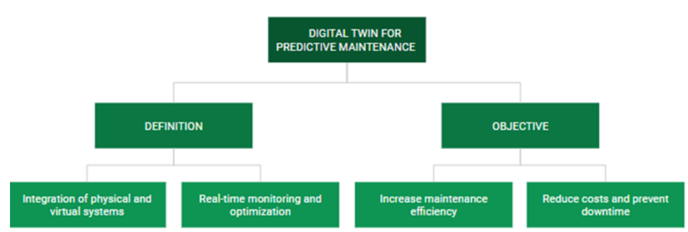

Fig. 1. Framework of Digital Twin for Predictive Maintenance.

II. Digital Twin-Enabled Predictive Maintenance in Industry 4.0: A Systematic Review

Predictive maintenance is the technology applied to make the industry sustainable, safe, and profitable. Developing a predictive maintenance system will involve overcoming the problem of failure data deficiency because the machine usually gets repaired before failure. Digital Twins offers a real-time physics-based model of the machine and information like asset degradation, which might be accessible to the algorithm. Since 2018, the rate at which the scientific literature was composed and released regarding the application of Digital Twins to predictive maintenance has reached a point at which it becomes necessary to review. This paper presents an attempt to bring together studies on predictive maintenance using Digital Twins as an entry point for future studies. A systematic review of published primary studies on predictive maintenance using Digital Twins as an active learning tool, where 42 primary studies have been reviewed up to this stage. This SLR distinguishes different aspects relative to the use of Digital Twins for predictive maintenance, concerning objectives, application domains, platforms of the digital twin, forms of digital twin representation, approaches, abstraction levels, design patterns, communication protocols, twinning parameters, challenges, and solution directions. Such results advance a Software Engineering approach to develop predictive maintenance with Digital Twins in academia and industry. This is the first SLR reporting about predictive maintenance using Digital Twins. We provide answers to key questions for designing a successful predictive maintenance model based on Digital Twins. To date, we found that the biggest obstacles in designing these models include computational burden, data variety, and complexity of models, components, or assests. [1]
A digital twin is a virtual replica of a physical procedure or product that could bring efficiency and cost-cutting to the production process. Using the digital twin, production teams can analyze various sources of data, thereby minimizing defective items to enhance the production process and reduce industrial downtime. A digital twin could be applied to the visualization of an asset and tracking changes, whereas understanding and optimization of asset performance can be achieved during the whole analysis of the product lifecycle. Besides that, data obtained from the digital twin will also give a complete life cycle of products and processes to optimize workflows about the production of parts and manage the supply chain, as well as manage product quality. The digital twins of smart manufacturing can save the time-to-market because design and the simulation of the process of manufacture in a virtual environment take place before physical manufacture. Digital twins can be utilized to represent simulation platforms in detail toward simulating and valuing the performances of products, which may include analysis and modification of the parts produced. The amount can be brought down to a very significant degree if digital twin development and optimization of layouts can be used. Predictive maintenance during part production and data-driven root cause analysis enhances the productivity of part manufacturing. Based on this, this paper examines the application of a digital twin within smart manufacturing systems, analyzes, and discusses the advantages and challenges of modifying part production by a digital twin. The reading and assessment of the previous work would also ensure the continuity of the research field, as new ideas and approaches can be proposed for utilization within the context of smart manufacturing systems. [2]
As the manufacturing industry is improved and developed, predictive maintenance is even more critical. However, in many cases, traditional predictive maintenance cannot meet the development needs. In recent years, digital twin-based predictive maintenance has been the hottest area of research in the field of the manufacturing industry. Generally, digital twin technology and predictive maintenance technology are introduced, and by contrast analysis, the importance of applying the former to achieve the latter is indicated. The next step is an introduction to the predictive maintenance method based on digital twin, its characteristics and features compared with traditional predictive maintenance. This paper introduces the application of this method in intelligent manufacturing, power industry, construction industry, aerospace industry, shipbuilding industry, and sums up the latest development of these fields. Finally, this paper concluded with an overview of the PdMDT as a framework of the production industry that mainly described the concrete execution of device maintenance and, through an example about the use of industrial robots, provided an overview about the limitations, challenges, and opportunities of the PdMDT. [3]
Most industrial firms are unable to identify when machines should be maintained. Most companies today react to occurring breakdowns (reactive maintenance) or maintenance is done at pre-set, fixed time intervals (preventive maintenance). Either way, either unexpected production stoppage is caused or machine operating hours are wasted due to premature changes of components. Thus, big potential is available through predictive maintenance strategies. Predictive maintenance refers to an estimate of the remaining useful life of a machine asset. Estimation techniques of RUL depend on statistical methods as well as algorithms. This calls for an appreciable deal of data. Simulations can also be used to create additional data for enhancement in the estimation of RUL. Companies have barely a view on what data is available and respective modules required to realize an entire strategy for predictive maintenance. The present paper discusses how the problem of data acquisition, data processing and analytical approaches and the creation of corresponding simulation data could be dealt with regarding a holistic approach in a strategy for predictive maintenance. A derived systematic strategy for injecting process maps into current company processes will outline exactly how companies can integrate predictive maintenance into their procedures. The insertion of a digital twin for a production machine will visualize the interaction of measured data, estimated data, and generated data interacting with one another through simulation. The digital twin would be able to provide output in a manner to retrofit the data-driven prediction

model for enhanced RUL estimation. [4]

Intelligent systems applied in the management and monitoring of production system components have ensured that the quality of output is of high quality while productivity within the shop floor in manufacturing has been increased. This paper conducts a systematic review on the digital twin alongside other intelligent systems for predicting the maintenance of equipment on the shop floor. The sources for the data collection include multiple databases, such as IEEE Xplore, Scopus, Google Scholar, ScienceDirect, and Research Gate. The research demonstrated the feasibility of intelligent systems like a digital twin for predictive equipment maintenance in production systems and was found to improve production and reduce time lost through downtimes in production systems. It has drawn attention to current trends, advantages and disadvantages of intelligent systems like Digital Twin, which can be implemented for predictive equipment maintenance in smart factories. [5]

This timeline of the development and relevant technologies in predictive maintenance describes its historical background. The evolution of the strategies of maintenance from being reactive to predictive shifted toward being proactive in terms of upkeep. Digital twins improved maintenance even further by offering detailed virtual models of physical systems. Key technologies that support the evolution include AI, IoT, and Big Data, all of which are capable of collecting and analyzing comprehensive data. It also guarantees that the processed and analyzed data is real time, allowing one to make decisions in the most timely manner based on the insights.

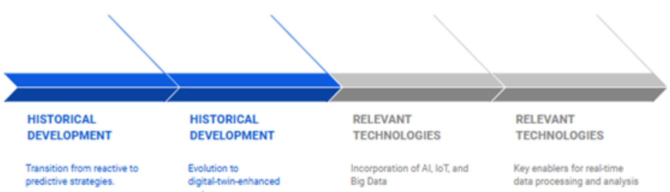

Fig. 2. Evolution and Technologies in Predictive Maintenance.

III. Frameworks and Challenges of Digital Twin Integration in Smart Manufacturing Systems for Industry 4.0

SMS is an enormously complicated, multi-field physical system with complex couplings between different components. Generally, designers of other fields are only allowed to design the subsystems of the SMS with limited cognition of dynamics. Meanwhile, it is difficult to design an SMS synchronously, and it is arduous to create a unified model that could effectively imitate all of the interactions and behaviors of manufacturing processes. It is a novel technology that enables semi physical simulations to bypass the high cost and time requirements of physical commissioning/reconfiguration with the early detection of design errors/flaws of the SMS. Development of this concept of digital twin in SMS design is vague. The new framework for FSBCIP is introduced by reviewing how DSIB has been integrated into and advanced the design of SMS. The current survey is an extension that prov Their definitions, frameworks, the most significant design steps, new blueprint models, key enabling technologies, and design cases as well as research directions on SMS by digital twins. It is believed that the survey is going to give light to some of the pressing industrial concerns regarding developing new SMSs for the Industry 4.0 era. [6]

As Industry 4.0 continues to be implemented and the manufacturing process continues its journey towards digitization, it will be very important to the DT for testing and simulating new parameters and design variants. Solutions via DT involve creating a replica of the physical item in three dimensions such that the manager can make better products and find problems more early with the physical idea and predict results more accurately. DTs have significantly reduced the development cost of new manufacturing approaches over the past few years, enhanced efficiency, minimized waste, and reduced batch-to-batch variability. This paper aims to describe the development of DTs, review enabling technologies, identify challenges and opportunities for the implementation of DT in Industry 4.0, and consider various applications of DT in manufacturing smart logistics and supply chain management. It also discusses some real-life industrial applications of DT. [7]

Because the name is Industry 4.0, the fourth industrial revolution promotes the idea of a smart factory. Highly flexible and efficient manufacturing must be characterized by high-quality products with minimal waste: -A Digital Twin combines the 3-D design model of a physical object, such as a machine, with real-time data from that machine. However, in the case of those products for which the customers utilize them during most of the period, Digital Twins are used for monitoring those products more. In this chapter, we will discuss the usage of digital twin technology in manufacturing a product. This technology can be implemented with performance management for all categories of manufacturing processes, continuous, discrete, batch, additive, and job shop. Traditionally, MES starts production and measures the performance of the manufacturing process. By natural reason, the Digital Twin supervises manufacturing performance. On a global basis, manufacturing performance is conveyed through OEE. An increase in OEE allows for more finished products to be produced from existing resources. In Measurement, Optimization, and Prediction- these three elements of Measurement-the needs of SFDT solution architecture in respect to performance management are delineated. Measurement will involve OEE solution architecture, measurement, and visualization. The leadership in the factory will be made to understand how large losses come about because of availability, performance, speed, and yield through visualization. Following this comes the performance optimization followed by covering the SFDT solution architecture which would include the application of the SPC and AR applications. The paper will be focused on the use of SFDT for performance prediction, especially in regards to determining the Remaining Useful Life (RUL) of the physical objects such as machines, and doing a ”What-If” analysis by simulation. Summary The application of SFDT in manufacturing performance measurement, optimization, and prediction is feasible in a smart factory. This chapter has no kind of relationship with a commercial product or framework. [8]

This is the age of big data brought into this world by the evolvement of information and communication technologies such as Generative AI, IoT, big data analytics, Blockchain technology, and AI. Among the active components of the new smart manufacturing model, digital twin has garnered much interest from enterprises and academia in recent times. With digital twins, it is possible to model many different scenarios and check various configurations without influencing the running process. Testing and optimization of processes increase the efficiency in production process, quality control, and predictive maintenance. Generally, digital twins form a very crucial aspect of smart production that is beneficial to manufacturers as it offers scope for improvement in the outlook of efficiency while low-cost production with good output. This paper presents a digital twin in smart manufacturing using the framework that composes Optimization, Predictive Maintenance, Quality Control, Design, and Simulation of literature on the subject matter within this article could be a good guide for future studies. [9]

The Industry 4.0 networks are evolving and developing so rapidly that they are becoming increasingly complicated and distributed. The complexity of the networks arises from the fact that integrating various technologies could be the foundation of smart manufacturing systems: their need for adaptability, security, and resilience is a particularly challenging task. Serious challenges are mainly represented in the area of complexity, especially with regard to security and integration of different technologies into an operating infrastructure that is productive. New standards of emerging digital twins overcome such challenges by connecting a large number of systems into the system of systems using individual digital twins. The idea of the concept is to work on a ”universal translator” so that the inputs from the real world or the digital world can be merged together as one cohesive cyber-physical reality. It takes the approach of explaining how different technologies and systems of Industry 4.0 networks can be integrated as a ”system of systems.” That indeed enhances interoperability, resilience, and security within smart manufacturing systems. It outlines possible benefits and limitations of the digital twin concept in countering the challenges of Industry 4.0 networks. [10]

This diagram represents some of the fundamental components of a digital twin system. On the inside, the Core Components form the base at the center, connecting the virtual model and the physical asset-these two represent the counterparts, digital and physical respectively. Then, on the outside, the Analytical Engine and Real-Time Data Exchange allow for the data analysis and constant information exchange from the virtual to the physical and vice versa. All these elements, together, present data in a predictive maintenance approach, detailing asset performance in real time.

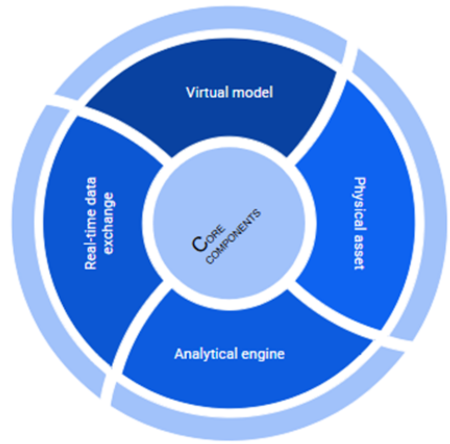

Fig. 3. Core Components of a Digital Twin System.

IV. Applications and Challenges of Digital Twin Technology in Predictive Maintenance for Industrial Operations

The last years have been remarkable, observing applications of DT in different sectors across the industrial world at various levels: design, production, manufacturing, and maintenance. On the contrary, it is one of the most researched applications since the execution of the maintenance task may crucially impact on the business of involved companies. For example, in an energy industry or manufacturing, a maintenance worker may lay on the output of an entire line down out of commission, or, while inspecting a wind turbine, open the safety of an operator to measure one of the simplest indicators. Accordingly, this kind of much more intelligent maintenance strategies seem to offer huge benefits. That means this work should consider only the review of applications in DT for maintenance. Actually, there is no former work having the same objective. For example, a literature review about the concept and the strategies of digital twin and related to maintenance will clearly explain them. Besides illustrating the way DTs are already being applied in maintenance activities, this paper addresses future lines of research and open issues. [11]

Reliability of a machine tool considerably depends on the availability of its functional parts. A prediction of failure of functional parts is useful because it serves as a method of preparation, in good time, for the maintenance scheme needed for stable operation and required quality of production. It is a paper, describing characteristics of DT in virtual reality

interaction and real-time mapping. It proposed the scheme of preventive maintenance and the method of DT-based real-time RUL prediction. The aforementioned method would choose the manufacturing workshop based on the real-time perceptual information the acquisition method the current work has established for the proposed DT model. Apart from the above model, a model of RUL prediction on nonlinear-drifted Brownian motion was established in this study to take into account working conditions and measurement errors in order to predict the real-time RUL of the functional part. After that, the optimal scheme of preventive maintenance can be determined and fed back to the manufacturing workshop for reference purposes in the relevant maintenance. Near the end, the example case study is carried forward to make it clear that how feasible and effective the approach proposed is. [12]
A prerequisite for reliability, a manufacturing unit with high availability must predict maintenance requirements in advance and on schedule. Planned maintenance activities are performed on time and ahead of schedule; hence, the service lifetimes as well as the utilization rates for parts increase, and so does the sustainability of the production. The benefits of predictive maintenance are clear, although its implementation in a plant is not without problems. This paper makes use of digital twins of well-behaving machines to support the concept of predictive maintenance. By comparing each physical unit against its digital twin, the detection of maintenance needs can then be made based on their differences. One promising comparison can be made based on an 18-month evaluation of the detection results produced by the digital twin versus the log data collected from maintenance and control system. The method is efficient in discrepancy detection and the paper is informative in outlining the techniques implemented. Not all discrepancies, however related to maintenance need as most common sources of error according to the evaluations explained and discussed. These generally arise from human interaction through parameter changes, maintenance activities, and replacement of a component. [13]
New data would give the company knowledge in industrial engineering. The concept of a digital twin is basically to capture data from industrial machines, analyze it, and use this knowledge to make better decisions concerning the machine. Sensor technology, Internet of Things platforms, information and communication technology, and smart analytics transform a physical asset into a connected smart item now part of a cyber-physical system and worth considerably more than when it stood alone. Maintenance engineering can actually create enterprise value by leveraging the digital twin to predict the problems well before they arise. In the presented paper, for the first time, authors introduce the maintenance digital twin into an industrial-scale manufacturing shop floor. An issue that makes such efforts hard to be discovered and presented in order to indicate how challenging in practice such a concept can be in real life. A framework has been designed for a digital twin to break the development of a digital twin into activities that can be done in isolation to support the installation process. With a framework, authors begin doing these activities. [14]
Digital twins promise enormous potential use in predictive maintenance applications that may avoid critical failures of components. For standardized defined functionalities of digital twins and the related software tools, which have not existed as yet, the generation of digital twins is closely related to a high investment of resources. This is due to static component connections within the IT-architecture and these are not reusable for other Digital Twins as these IT-architectures are a type of single-case solution. Though some approaches are developed for the construction of flexible IT-architectures, they have not been fully researched yet whether they could be reused in practice for the development of Digital Twins under differing implementation conditions. This would make the purpose of the case study consider investigating reusability and effort reduction associated with building Digital Twins. This can be achieved through the combination of two approaches: building an IoT-platform coupled together with a service-oriented architecture for building reusable and flexible IT-architecture for Digital Twins. Initially, it has been applied to a first use case of the Digital Twin for a compressor and then adapted to a second use case of the Digital Twin for a wind turbine. The implementation conditions are different, but the application area lies within the predictive maintenance. Then reusability is verified and, to the extent that this is the case, to what extent, using a flexible IT-architecture can support resource minimization when creating Digital Twins. [15]
This diagram highlights some of the key aspects of digital twin technology in an industrial setting. Under Trends in Industry, there is an increasingly popular use of AI-based predictive maintenance. The concerns are lack of data, overcomplication of the model, and security-related issues. Key Innovations focus on advanced simulation, virtual commissioning, and lifecycle analysis. Finally, Notable Applications highlight the benefits in root cause analysis, workflow optimization, and downtime reduction. Together, these aspects highlight the current state and future prospects of digital twins in revolutionizing industrial maintenance and operations.

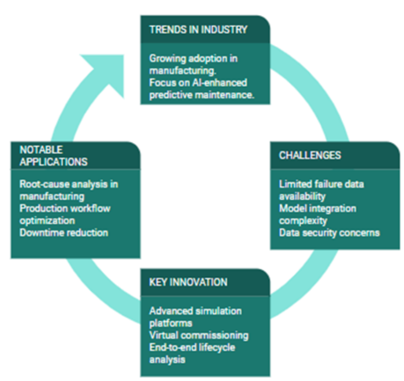

Fig. 4. Digital Twin Trends, Challenges, Innovations, and Applications in Industry.

V. Digital Twin Pipelines for Predictive Maintenance in Smart Manufacturing

This chapter presents a Digital Twin Pipeline Framework of the COGNITWIN project supporting Hybrid and Cognitive Digital Twins through four pipeline steps adapted for Big Data and AI. The pipeline steps have been adapted accordingly to Data Acquisition, Data Representation, AI/ Machine learning and Visualization and Control. Big Data and AI selections of the Digital Twin system are linked with various technologies in the BDV Reference Model. Hybrid digital twin is a kind of hybrid data-driven digital twin and first-order physical models. This chapter will discuss the application example in the maintenance of spiral welded steel industrial machinery based on the approach of a Hybrid Digital Twin and which underlines support for predictive maintenance through a digital twin. There is still one Further extension in the pipe is intended to support cognitive digital twins, which encompasses support for learning, understanding and planning. The inclusion is such that it makes use of both the domain and human knowledge. In this project, through the usage of digital, hybrid, and cognitive twins, its pilot aims at reduction in energy consumption along with the mean duration of downtimes in a machine. Data-driven It explains artificial intelligence techniques and predictive analytics models that can be utilized in the Digital Twin pipeline to mitigate equipment unplanned downtime. Conclusion The pipeline above can be adopted in scenarios as similar to those observed in the process industry. [16]

Digital twin is one of the latest concepts to have dramatically made predictive development manageable and simple. DT for PdM will enable accurate computation of the equipment condition, predictive faults, thereby raising reliability altogether for the whole system. This shift from reactive services to proactive might work better with schedules of maintenance that cut down idle time spent by the equipment and boost profitability and competitiveness for enterprises. However, research into the application of DT to PdM is at a very nascent stage because probably the role and function of ML in DT for PdM have not been investigated or analyzed by industry and academia. This paper carries out a systematic review of the role of ML in DT for PdM. It identifies, evaluates, and analyses a clear, systematic approach to published literature relevant to DT and PdM. Thereafter, the state-of-the-art applications of ML in different application areas of DT for PdM are presented. Finally, the challenges and opportunities of ML for DT-PdM are revealed and discussed. It may possibly provide the outcome with a practical application towards enhancing research and implementation of ML in DT-PdM. [17]

This session addresses the state of the art in digital twin for manufacturing research and practice from the point of view of the simulation community. The paper is a mix of a short introduction to the nature of the digital twin and plus a statement by each panelist - preliminary thoughts on concepts, definitions, challenges, implementations, relevant standard activities, and future directions. Two speakers will share some learned lessons from their digital twin projects. It's not an attempt to make the thinking of the researchers converge but just a list of research questions, initiate deeper discussion, and try to help researchers in the simulation community with future topics for study on digital twins for manufacturing. [18]

Founded on profound coordination, deep virtual and real fusion will enable industrial Internet-based digital twin to become the high-efficiency carrier for smart factory development. Deep real/virtual big data learning and analysis will be the basis for interaction in virtual space and optimized loop control, under the support of digital twins in a smart factory. The condition of industrial Internet, this paper will propose big data virtual and real reference fusion for the application in smart manufacturing. There are three perspectives on synthetically designing the reference framework. It covers: in-depth framework of Industrial Internet, mode and process of BDLA model building of digital twin, and then the DT-BDVRL digital thread of virtual and real fusion analysis process, iteration and closed-loop feedback all through the whole life cycle processes of products. Formulation of the iterative optimization and verification method and process of the BDLA models happens due to different virtual scenes in a virtual space. In addition, the result of application of the outcome of BDLA is a catalyst for driving running inside virtual space. This way, the virtual space can iterate on the BDLA results several times before validation. Meanwhile, this Industrial Internet platform impacts the execution effect of running BDLA models in a virtual space and synchronously realizing it; that is to say, improvement in the physical space. Conclusion Besides, the above-mentioned contents have been used and proved in actual production with practical cases. [19]

Based on the play and interaction between digital twin and the Industrial Internet, it starts with the information. Of the protagonists of the Industrial Internet, sensing/transmission network capability 44 1can be used as a carrier of data acquisition and transmission means for digital twin. On the contrary, with the capability of high-fidelity virtual modeling and simulation computing/analysis, digital twin evolving from lifecycle management for one product towards application production/manufacturing on the shop floor/enterprise, can be further extended to significantly enhance the simulation computing and analysis of Industrial Internet. A DT-II reference framework based on a digital twin enhanced Industrial Internet is proposed toward smart manufacturing in this paper. To explain the reference framework, the implementation and running mechanism of DT-II is illustrated from three aspects, which are at the product lifecycle level, intra enterprise level and inter-enterprise level. Finally, steam turbine is taken to demonstrate how the application scenarios may be presented from the above three perspectives based on the scenario of DT-II. Differences in Design and Development with and without DT-II for Steam Turbine. [20]

Four related domains were described in this chart of developments required for digital twin technology. Advancements Needed focused on standard frameworks to build upon, simulations improved on, and better handling data. Research Opportunities pushed out applications of digital twin further in predictive maintenance in new advanced models. The Impact Goals included higher prediction accuracies, smart factories as a whole, and improving diagnostics through AI. The potentials that were looked towards as potential futures included smart factory frameworks, sustainable manufacture through supply chains, and other possible advancements. Together, these underline the primary routes toward development and deployment.

Fig. 5. Key Areas for Development and Opportunities in Digital Twin Technology.

VI. Future Directions for Digital Twin Integration in Sustainable Manufacturing and Predictive Maintenance

A digital twin integrates virtual and physical systems using disruptive technologies. More precisely, it is a technique to build resilient, smart manufacturing systems toward achieving quality, reduced time, and customized products in real time along the lifecycle of the product. In this paper, the researcher conducts a systematic literature review of 98 research articles that describe digital supply chain twins and its dimensions toward sustainable performance objectives that he reduces into three categories namely the component of the digital twin, applications of the digital twin in manufacturing supply chains, and sustainability. Having examined the study based on the review and future prospects, we hence move our suggestion that technology progresses through these technologies, for example, IoT, cloud computing, and blockchain, increases digital twin application potentials in supply chains. Findings: The scope of things and humans included in the digital supply chain twin should not be limited to the local manufacturing system but include the whole supply chain. From the aforementioned review, we derive a sustainable framework for the digital twin to be implemented in supply chains. [21]

At its foundation, it was envisioned over a decade ago to be the future single, integrated technology that would make dreams like real-time monitoring, simulation, optimization, and high accuracy in prediction come true. So far though, the conceptual framework of digital twin and its concrete implementations still fails to attain this dream on significant scale. Although most work on research and industry has had some successful implementation, not too much information about enough implementations is publicly available in order to adequately judge their constituents and efficiency to make valid comparisons, identify a successful solution, and hence share lessons and move forward and profit from the DT methodology under common consensus. This work begins with relevant DT research and industrial works on main DT features, current approaches in different domains, and successful implementations of DTs for inferring the key DT components and properties and to trace out the present limitations and reasons behind delay in the widespread implementation and adoption of the digital twin. This study determines that the main cause for this delay is, inter alia: it is still a fast-moving concept; there is still no universal DT reference framework, e.g. the DT standards are scarce and still evolving; problem and domain dependence; security issue related to shared data; absence of DT performance metric; and reliance of the digital twin on other technologies which are also fast-changing technologies. All these advancements in machine learning, the Internet of Things, and big data have made dramatic improvements in feature development on DT, like real-time monitoring and fairly accurate forecasting. Even though each company is making a one-off effort, though important, the field itself also undertakes some research and implementation areas that, up to now, have prevented the mass take-up of the concept of DT and its related technologies; it is discussed later in this work. The conceptualization of DT is defined and therefore includes the components and properties. This also validates the distinctiveness of DT as a concept against other similar concepts such as simulation, autonomous systems, and optimisation. The application of conceptualisation will then be presented through real case studies. The main problem is that this work will focus on discussing the state of the art in DT, relevant and timely questions that can be addressed in DT, and novel research questions; therefore, it will contribute toward a better understanding of the paradigm DT, advancement in theory and practice of DT, and allied technologies. [22]

A digital twin is a set of computer-generated models mapping a physical object into a virtual space. The elements from both the physical and virtual sides are interchanging information allowing for monitoring, simulation, prediction, diagnosis, and control of the state and behavior of the physical object in the virtual space. DTs provide information and the operating status of a system that supplies capabilities for creating new business models. We shall concentrate on the construction of DTs. To be more precise, methodologically speaking we are interested in how we should design and build, and interlink the physical object with its virtual counterpart. So we can divide the problem into several phases: the selection of functional requirements and architecture planning, integration and verification of the final (digital) models. We outline how the physical components can convey this real-time information to the DTs and experimental platforms for the

formation of DTs using protocols and standards. Finally, we close by elaborating on issues and open challenges. [23]
Digital Twins is the novelty of solutions that provide permanent digital monitoring and active functional improvements of interlinked products, devices, and machines. With their implementation, Digital Twins will also provide the benefits of horizontal and vertical integration in manufacturing. This paper will be designed to perform methodological, technological, operative, and business aspects related to the development and functioning of Digital Twins based on the test environment of smart factory cells. Other dimensions used to study it scientifically and practically include integration breadth, modes of connectivity, update frequency, CPS intelligence, simulation capabilities, digital model richness, human interaction, and product lifecycle. The design elements in the development of the Digital Twins taken from this are discussed in the succeeding text. [24]
The focus of State-of-the-Art PM of EMs will be to develop new combinations of AI methods with traditional measurement and processing techniques in order to give further consolidation to be a profitable business venture in the industrial field. DT is perhaps the latest trend that has been applied to industrial manufacturing and monitoring with only recent definitions and explorations showing promising results for facilitating the realization of the concept of Industry 4.0. Further, although PM efforts are very similar to the proposed DT methodologies and quite improved by increasing the managing of data and availability, there is no combination of these two concepts in literature. Also, the concept of nexDT seems vague. The reviews of DT continued discussing the broader definition, whereby most of the citations were irrelevant to PM. This work attempts to restated the concept of nexDT from the point of view of new descriptions in general literature, define a precise notation for EM manufacturing, PM, and control as it embraces most of the relevant work done in this process and introduces a new definition especially for PM as the basis of further work. The paper makes up core concepts of both DT research and PM state-of-the-art over the last five years, then mixes those concepts into a defining description. Finally, some surmised benefits and future work prospects are reported with special focus on enabling PM state-of-the-art in AI techniques. [25]

CONCLUSION

Digital Twin technology has proven transformative for predictive maintenance by enabling accurate monitoring, control, and simulation of physical systems in virtual environments. The synthesis of real-time data, machine learning, and IIoT integration allows DTs to optimize equipment performance, predict failures, and extend the useful life of industrial assets. Although challenges remain, including computational demands, interoperability issues, and security concerns, the development of adaptable frameworks and emerging standards holds promise for wider DT adoption. As Industry 4.0 continues to evolve, DT technology will play a pivotal role in shaping predictive maintenance strategies, enhancing operational resilience, and advancing smart manufacturing goals. Future research should focus on refining machine learning applications within DTs, addressing security and standardization needs, and expanding sustainable, scalable frameworks for digital twin technology in complex industrial ecosystems.

REFERENCES

[1] Raymon van Dinter, "Predictive maintenance using digital twins: A systematic literature review," 2022.
[2] Mohsen Soori, "Digital twin for smart manufacturing, A review," in Sustainable Manufacturing and Service Economics, 2023.
[3] Dong Zhong, "Overview of predictive maintenance based on digital twin technology," 2023.
[4] Andreas Werner, "Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin," in Procedia Manufacturing, 2019.
[5] Mgbemena, "A SYSTEMATIC REVIEW OF DIGITAL TWIN SYSTEMS FOR IMPROVED PREDICTIVE MAINTENANCE OF EQUIPMENT IN SMART," in INTERNATIONAL JOURNAL OF INDUSTRIAL AND PRODUCTION ENGINEERING, 2022.
[6] Jiewu Leng, "Digital twins-based smart manufacturing system design in Industry 4.0: A review," in Journal of Manufacturing Systems, 2021.
[7] Mohsen Attaran, "The impact of digital twins on the evolution of intelligent manufacturing and Industry 4.0," in Advances in Computational Intelligence, 2023.
[8] Joshi, "Smart Factory Digital Twin for Performance Measurement, Optimization, and Prediction," in Springer Nature Switzerland, 2024.
[9] Mohsen Ebni, "Digital Twin based Smart Manufacturing; From Design to Simulation and Optimization Schema," in Procedia Computer Science, 2023.
[10] Nahian Ibn Hasan, "Deep Learning Approach to Cardiovascular Disease Classification Employing Modified ECG Signal from Empirical Mode Decomposition," Biomedical Signal Processing and Control, vol. 52, pp. 128-140, 2019.
[11] Itxaro Errandonea, "Digital Twin for maintenance: A literature review," in Computers in Industry, 2020.
[12] Jinyan Guo, "Real-Time Prediction of Remaining Useful Life and Preventive Maintenance Strategy Based on Digital Twin," 2021.
[13] Muhammad Hassan, "Experience from implementing digital twins for maintenance in industrial processes," Journal of Intelligent Manufacturing, vol. Volume 35, pp. 875 - 884, 2023.
[14] Jamie O'Sullivan, "A case-study in the introduction of a digital twin in a large-scale smart manufacturing facility," Procedia Manufacturing, vol. 51, pp. 1523 - 1530, 2020.
[15] Pascal Mrzyk, "Digital Twins for predictive maintenance: A case study for a flexible IT-architecture," Procedia CIRP, vol. 119, pp. 152 - 157, 2023.
[16] Perin Unal, "Data-Driven Artificial Intelligence and Predictive Analytics for the Maintenance of Industrial Machinery with Hybrid and Cognitive Digital Twins," Springer International Publishing, pp. 299-319, 2022.
[17] Chong Chen a b 1, "The advance of digital twin for predictive maintenance: The role and function of machine learning," Journal of Manufacturing Systems, vol. Volume 71, pp. 581 - 594, 2023.
[18] Shao, S. Jain, C. Laroque, L. H. Lee, P. Lendermann and O. Rose, "Digital Twin for Smart Manufacturing: The Simulation Aspect," 2019 Winter Simulation Conference (WSC), 2019.
[19] M. L. Pei Wang, "A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing," Journal of Manufacturing Systems, Vols. 16 -32, p. Volume 58, 2021.
[20] Jiangfeng Cheng, "DT-II:Digital twin enhanced Industrial Internet reference framework towards smart manufacturing," Robotics and Computer-Integrated Manufacturing, vol. Volume 62, p. 101881, 2020.
[21] Sachin S Kamble, "Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework," Technological Forecasting and Social Change, vol. Volume 176, p. 121448, 2022.
[22] Angira Sharma, "Digital Twins: State of the art theory and practice, challenges, and open research questions," Journal of Industrial Information Integration, vol. Volume 30, p. 100383, 2022.

[23] Garcia-Alfaro, ”Design, Modeling and Implementation of Digital Twins,” Design, Modeling and Implementation of Digital Twins, vol. Volume 22, 2022.
[24] Rainer Stark, ”Development and operation of Digital Twins for technical systems and services,” CIRP Annals, vol. Volume 68, no. Issue 1, pp. 129-132, 2019.
[25] Karlis, ”Digital Twin in Electrical Machine Control and Predictive Maintenance: State-of-the-Art and Future Prospects,” vol. Volume 14, no. Issue 18, 2021.