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"SURVEY OF DIGITAL TWIN APPLICATIONS IN PREDICTIVE MAINTENANCE FOR INDUSTRIAL MATERIAL HANDLING EQUIPMENT"

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ABSTRACT

By enabling real-time synchronization between virtual and physical systems, Digital Twin (DT) technology is helping to define Industry 4.0. By combining data analytics, sensor technology, and the Internet of Things (IoT), DT provides improved visibility, diagnosis, and control in intricate industrial settings. The research delves into the basics, technologies that make it possible, and uses of digital twin systems, focusing on predictive maintenance. Predictive maintenance (PM) makes use of DTs, DLs, ML, and real-time monitoring to maximize asset utilization, minimize downtime, and avoid breakdowns. Additionally, the study examines the significance of DT in important industries including manufacturing, healthcare, and smart cities, highlighting its effects on process optimization, problem detection, and cost effectiveness. A detailed discussion on the layered architecture of DT systems from sensor-level data acquisition to middleware integration and application-level decision-making is provided to highlight technological synergies. In addition, issues with scalability, model integrity, and data integration are discussed, along with prospects for further study. In the Age of Industry 4.0, this research emphasizes the critical role that digital twins play in achieving operational excellence and making data-driven choices.

Key Words: Digital Twin, Predictive Maintenance, Industry 4.0, Condition-Based Maintenance, Internet of Things, Fault Detection, Industrial Automation, Data Analytics.

I. INTRODUCTION

The IoT and improved data analytics are driving the DT is leading the Industry 4.0 transformation [1]. The IoT has expanded the amount of data that can be used in smart city, healthcare, and industrial contexts. The rich environment of the Internet of Things, when combined with data analytics, offers a vital resource for fault diagnosis and predictive maintenance, to mention just two. It also makes it easier to detect defects, manage traffic in smart cities, and identify anomalies in inpatient treatment. Additionally, it supports the long-term viability of industrial activities and the growth of smart cities [2][3]. IoT and data analytics may benefit from the development of the issue of a digital twin's seamless integration a linked virtual and physical twin. In a digital twin setting, quick analysis and precise analytics-based decisions may be made instantly. Digital twin applications in healthcare, industrial, and smart city contexts is thoroughly examined in this paper, along with the enabling technologies, difficulties, and unresolved research questions. Since the focus of the literature is on manufacturing applications, the evaluation has made an effort to include relevant papers starting in 2015 in three sectors: smart cities, healthcare, and manufacturing. Using a variety of scholarly sources discovered using IoT and data analytics-related keywords, the paper's ultimate goal is to find publications about digital twins.

The smooth integration of digital analytics platforms with physical systems is a major problem in this new paradigm in industry. Digital twin technology bridges this gap by creating a synchronized virtual copy of a tangible technology or object that allows for real-time monitoring, diagnostics, and decision-making. Predictive maintenance may be

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maximized in this networked setting, decreasing equipment downtime and boosting operational effectiveness.

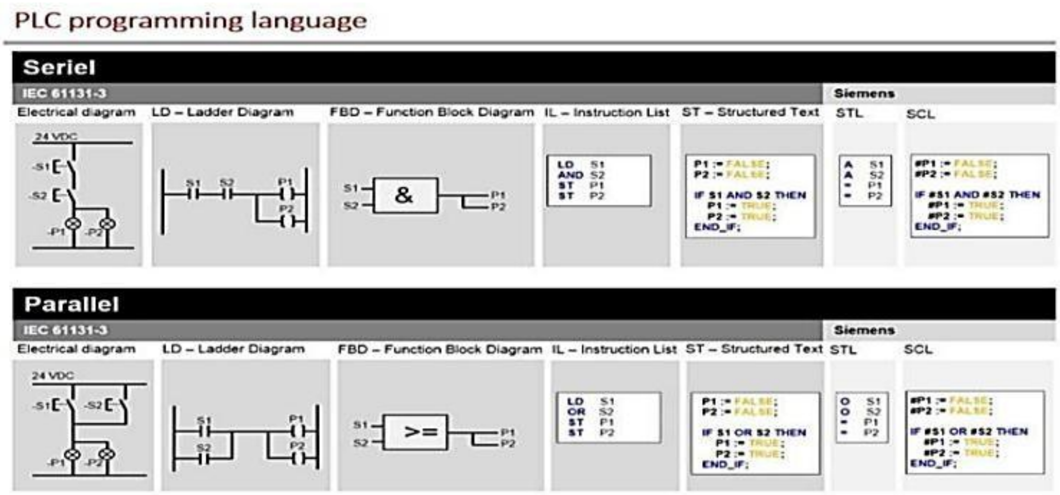
Regarding smart factories, achieving operational goals and strategies requires maintenance in general [4]. According to Mobley, operational expenses account for a sizable portion of a manufacturing or processing facility's maintenance. Maintenance expenses may vary from 15% to 60% of the cost of manufactured items, depending on the industry [5]. An effective maintenance system lowers downtime for machinery and equipment, boosts production, and increases efficiency. Selecting an appropriate maintenance strategy is essential, particularly for accomplishing sustainability objectives within the Industry 4.0 framework, due to the dynamic and complex nature of maintenance management and the difficulty of measuring and evaluating maintenance performance. But according to Moore and Starr, poor maintenance causes more unscheduled plant and equipment failures, which cost the business money in labor, replacement components, scrap, rework, late order fees, and lost orders as a result of unhappy customers.
The fourth industrial revolution that is now underway presents a problem in integrating digital and physical systems [6][7]. The industrial system generates a vast quantity of data through this connection, including maintenance records, real- time events, and IoT data that happens throughout the manufacturing line. Two essential components of Industry 4.0 are data availability and customization. Industry improvements have made machinery more complex, which leads to malfunctions [8]. To prevent stoppages and increase the production line's efficiency, machine failures must be located and fixed. Data science is the most sought-after profession in the twenty-first century, according to Harvard Business Review [9]. To find significant patterns, a data scientist uses statistics, computing power, and subject expertise to modify the raw data.

A. Structure of the Paper

The paper is organized as follows: The foundations and underlying technologies of Digital Twin (DT) systems are explained in Section II. Section III covers predictive maintenance techniques for managing industrial materials. The use of DT in predictive maintenance across important sectors is examined in Section IV. Section V provides a review of recent studies. The end of Section VI offers insights on integrating DT with predictive maintenance in Industry 4.0.

II. FUNDAMENTALS OF DIGITAL TWIN TECHNOLOGY

A DT is a fanciful, animated real-time mapping of a system of physical entities. Real-time data gathering, transmission, and updating are crucial in DTs. Many scattered high-precision sensors of various types, each of which



has a vital sensory function, are the leaders of the whole twin system. Fast speed, safety, and accuracy are the foundations of sensor distribution and sensor network architecture, wherein dispersed sensors gather different kinds of physical quantity data about the system to describe its condition [10]. The simulation of the DT system improves with the accuracy of the data supplied by the sensors, leading to more realistic simulation states and consequences [11]. The ultimate objective of DT interaction, a coupling mechanism that is multi-dimensional and multi-timescale, is to govern reality via the virtual environment However, because multiple-source sensors have different coding formats, data discrepancies during the mutual fusion process are hard to avoid.

A. Definition of Digital Twins

As DT-enabling technologies have been created during the 2000s, DT definitions have been evolving continuously.

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Michael Grieves was initially introduced in 2003, when it was first proposed as the "virtual digital representation on par with tangible goods. Nevertheless, in 2012, NASA defined DT as a comprehensive multi-physics, multi-scale, probabilistic simulation of an as-built system or spacecraft that replicates its equivalent flying twin's life, fleet past, etc., using the finest physical models and sensor updates Later on, the aircraft industry emerged as a significant area of DT research. changed "vehicle" to "product" in 2015, expanding the meaning of DT to include broader applications [12]. In several industrial domains, the DT has been precisely defined. The definition of DT in product design engineering, for instance, is "a true mapping of all product lifecycle components utilizing interaction data, virtual data, and physical data." DT is a dynamic digital profile that shows how a physical thing or process has behaved both historically and currently, which is used in IoT engineering to optimize business performance.

B. Leverage of the Digital Twin in Industry 4.0

Digital twins, which span an asset or process's entire lifecycle and serve as the basis for linked goods and services, to prevent problems before they happen, reduce downtime, and create cloud-based systems, enable data analysis and system monitoring. They are quickly becoming a business necessity [13], with new possibilities and even using simulations to prepare for the future. As an intermediary between the virtual and physical worlds, the 11th International Conference on Knowledge Management and Information Systems (KMIS 2019) suggests that a digital twin be used. Prioritizing simulation aids in comprehending not just the primary procedures but also their connections and effects in order to optimize design and reduce environmental impact. But since Industry 4.0 is a complex issue, it is doubtful that every component of it will apply to every company. Although the field of intelligent manufacturing is a complex one in and of itself, the gathering, use, and comprehension of data also known as "Informatics" is the recurrent component that supports a large portion of this revolution, practically every field associated with the field of intelligent manufacturing research depends in some manner on the collection and analysis of data [14].

At the technological and managerial levels, the DT permits higher levels. Particularly, as discussed in the next sections, the DT permits a high degree of operational efficiency: fewer malfunctions, less machine downtime, fewer defects, and improved logistics and raw material procurement, as seen in Figure 1.

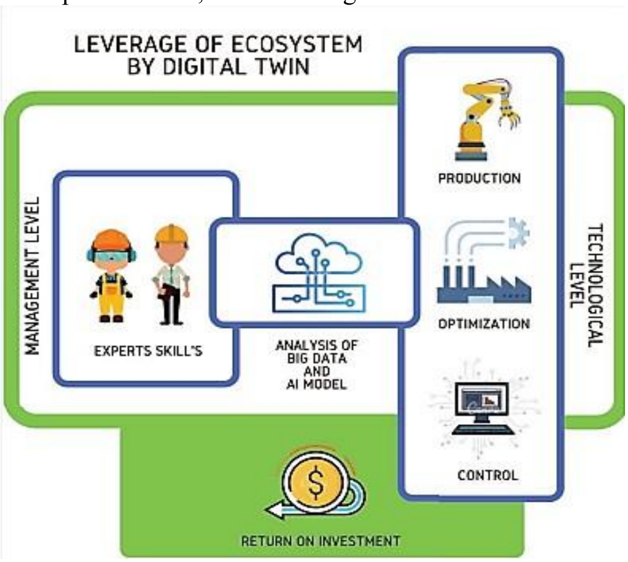

Fig. 1. Leverage of Digital Twin at Management and Technological Level.

C. Digital Twin and Twin Data

The purpose of a DT is to generate digital data that encompasses almost the whole experiment. This is among the best methods for putting dual-purpose engineering into practice. The accuracy of the DT's diagnosis, evaluation, and prediction is increased by real-time evaluation of the system's conditioning and the numerical model [15]. Maintenance and administration of online management systems might guarantee system safety, avoid frequent repairs, or lessen structural design variability. The model is improved or expanded to incorporate all network information using real-time observation data. All the elements are combined in the DT for complex processes, which serves as the foundation for high-accuracy modelling [16]. The DT's primary engine offers accurate and thorough data resources for combining virtual and physical components. Data categorization variation and data set inconsistencies led to complexity, incompatibility, and a lack of coordination in information merging. To enhance the diagnostic, prediction, and decision-making tools that are utilized to find the underlying connection between diverse data collected from different sources.

D. Enabling Technologies for Digital Twin

Additional concepts for a digital twin's functional domains and ancillary technologies are compiled in Table I. First is the

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application domain (D9), then the networking domain (D11), middleware domain (D10), and object domain (D12).

TABLE I. ENABLING TECHNOLOGIES AND FUNCTIONAL BLOCKS: DIGITAL TWIN.

Domain	Enabling Technology
D9 Application Domain	Model Structure and Display
	Software and APIs
	Gathering and Preparing Data
	Storage Technology
D10 Middleware Domain	Data Processing
D11 Networking Domain	Technology of Communication
D12 Object Domain	Wireless Communication
	Hardware Platform
	Sensor Technology

The model architecture and visualization layer, the first of three crucial layers that comprise the application domain, or D9, is crucial for producing high-fidelity representations of the actual object. The layer makes it possible to model architecture and visualize digital twins. This guarantees that more than only physical entity behaviors are used to mimic digital twins. It is made feasible by programs like Simulink and Twin Builder. The second tier's software and API are specifically designed to aid in the creation of a digital twin design, which facilitates the preprocessing and collection of the third tier [17]. This last application domain layer is necessary to guarantee proper data collection; some examples of data collecting applications include Predix, Mind Sphere, and Storm. As it connects domains D9 and D10, this layer makes sure the data is collected accurately to enable Analytics and the IoT for a Digital Twin.

There are two enabling levels in the middleware domain, or D10. First, there is storage technology, which facilitates data storage with MySQL services. Digital twin implementation requires the use of MongoDB and on-demand databases. The data processing-related second layer is required to move the stored data from D10 to D11.

The first enabling layer in D11 is the communication technology layer, which is crucial for making sure the data gathered is shared between domains. D11 is made up of the Network Domain. The wireless communication layer, the second tier of the Digital Twins network domain functional block, is necessary to convey data to the following domain, D12, and to guarantee that wireless data transmission adheres to the proper protocol inside a Digital Twin design.

There are two enabling layers that comprise the object domain (D12). the sensor technology comes in second, followed by the hardware platform. Both are necessary to make sure the right hardware is available for Digital Twin analysis and to make it easier for sensor technology to gather data

III. PREDICTIVE MAINTENANCE IN INDUSTRIAL MATERIAL HANDLING EQUIPMENT

Industrial machinery and equipment, including the MHS, can be subjected to condition monitoring at the system or component level. Several data sources, including production and throughput statistics and sensory data, are used to track an MHS's system-level performance and/or output. If sensory data is gathered, the MHS's health status must be determined using the proper data processing methods. According to the component-level viewpoint, any element in the system that is considered crucial or significant has to be watched. Implementing suitable sensors and data gathering systems for the chosen components is necessary to do that, as is using pertinent data analysis techniques to determine the targeted component's health state, which can lead to an acceptable maintenance plan. High numbers of assets or goods are moved, sorted, and arranged using MHS in large-scale production and storage operations [18]. Effective asset management, operational control, and supervisory systems may optimize MHS's expenses and production for such a fleet of equipment. Material handling might account for as much as 70% of the expenses incurred throughout the production process. MHS that is well-planned and efficient may therefore significantly lower manufacturing costs and boost industry profitability.

A. Common Techniques Used in Predictive Maintenance

In the following section, techniques used for predictive maintenance are discussed, including statistical analysis, machine learning algorithms, signal processing methods, and hybrid approaches that use digital twin models to provide precise failure forecasting and fault identification.

1) Deep Learning for Predictive Maintenance

The reference DL approaches for PdM are gathered, compiled, categorized, and contrasted in this part, which also analyses the most pertinent publications and implementations. On reviewed publications, polls, and field reviews, it includes precise DL models that provide Sot outcomes. While most publications conduct many PdM stages in the same architecture and use multiple approaches [19][20], this part divides the works into five subsections based on the main DL approach used to complete each step, including feature engineering for the previous stage and ignoring preprocessing because the latter's description in the preceding section also applies to DL. Analysis and stage-by-stage comparison of DL approaches are made possible by this categorization. To provide examples of how to combine approaches that can be limitless, the sixth part showcases work that successfully combines the previously described

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strategies to produce more comprehensive structures that fill one or more PdM phases. The last paragraph discusses analogous evaluations and surveys and compiles the most pertinent data from publications that are comparable to this one.

2) Machine Learning for Predictive Maintenance

ML techniques are extensively utilized in computer science and other fields, including PdM of industrial machinery, tools, and systems. Data-driven techniques that might transform several sectors include ANN, RL, SVM, LR, and DT [21][22]. There has been a recent explosion in the use of ML approaches across several disciplines. Choosing the best one that fits the bill while also being simple and effective might be a big concern. Large amounts of data detailing possible failure states and health issues are frequently required for ML algorithms to train their models. Algorithms like LR, DT, RF, and VSM typically need massive datasets. Developing ML algorithms includes picking relevant historical data, preprocessing it, choosing a model, training it, confirming its accuracy, and then keeping it up to date.

B. Industry 4.0 and Predictive Maintenance

It is interesting to note that the first three industrial revolutions occurred before they were given names. This is not the case with the Fourth Industrial Revolution. they have already come to terms with the fact that the revolution is ongoing [23]. The globe is becoming more interconnected, which is accelerating the pace of change. The rise of the Internet marks the next stage of industrialization. The term "Web" wasn't coined until 1987, even though the Internet has been there since 1962. It wasn't until 1994 that it was commercialized. From that point on, it's safe to say that the Internet permeates every aspect of human life. The number of people using the Internet has increased exponentially since the late 90s and is now in the billions.

IV. DIGITAL TWIN APPLICATIONS IN PREDICTIVE MAINTENANCE

Applications domain insights show which domains have made progress and which are still in the early stages of development when it comes to using digital twins for predictive maintenance. Most of the studies that were included used their framework or algorithm in a particular application area. Figure 2 displays the application fields of the research that were included. The graphic shows that the primary application domains are manufacturing and energy [24]. With 25 research studies, the application domain that was covered the most frequently was manufacturing. Five of these studies concentrate on industrial robots, two on semiconductor manufacturing, and eight on computer numerical control (CNC) equipment. In the realm of energy [25], A total of four studies focused on renewable energy sources, the most common of which being wind turbines. The ongoing research are to energy networks (n = 2), nuclear power (n = 1), and fossil fuels (n = 3). Possibly nine researchers focus in this field because NASA provides several datasets related to the aerospace industry, such as the datasets for the Bearing Intelligent Maintenance Systems and the Degradation Simulation of Turbofan Oil. Utilizing these datasets speeds up and standardizes the research process by removing the requirement to create a specific Virtual Twin since the data has previously been modelled.

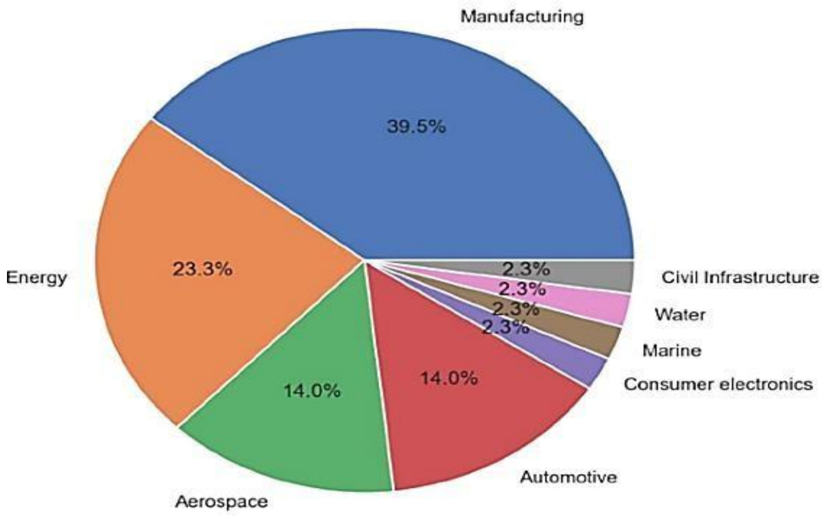

Fig. 2. Application Domain.

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A. Predictive Maintenance Method

A common component of predictive maintenance is condition-based maintenance. Determine the equipment's existing state, project its future development trend, and create predictive maintenance plans beforehand based on regular (or continuous) condition monitoring of system components to identify possible reasons of equipment failure and trends in status development. Predictive maintenance covers particular topics including residual life estimation, equipment status monitoring, problem diagnostics, and maintenance decision- making [26]. The predictive maintenance system function model was introduced by Wang in the industrial sector. According to the model, predictive maintenance includes data gathering and processing, health forecasting, administration and execution of maintenance, and the detection and localization of status and defects. Gathering and analyzing information. Data collectors and sensors make up the essential hardware for data processing and collecting. On the production site, the sensor is mostly used to gather environmental and equipment status and process data, while the data collector is primarily used to transmit process data. Recognizing your position, state identification ascertains the present status of the equipment by combining state characterization data with threshold judgment utilizing feature analysis. To serve as the foundation for defect detection or health prediction, the recognized equipment state is fed into the state prediction process. Prior to state identification, the collected data must undergo preprocessing and feature analysis.

B. Fault Prediction and Diagnosis Using Digital Twins

In recent years, according to keyword analysis, one of the most popular phrases right now is predictive maintenance. An increasingly important part of predictive maintenance in facility management is early failure detection and diagnosis (EFDD). EFDD entails utilizing algorithms and data analysis techniques to find performance irregularities in building systems and components before they cause serious problems [27]. Facility managers can save expensive repairs or replacements by proactively addressing issues as soon as they are discovered. Investigating more EFDD techniques employed in recent articles, categorizing them, and determining the best ways to apply them in smart building systems are becoming increasingly important. To fully utilize EFDD in smart facility management, it is also crucial to identify the technique that integrates with DT the best. The three groups that FDD techniques may be categorized into are shown in Figure 3: data-driven, knowledge-based, and analytical approaches. Analytical-based techniques use physical rules and mathematical models to find flaws and irregularities in building systems. Conversely, knowledge- based methods use guidelines and subject-matter expertise to make decisions and spot mistakes. Last but not least, data- driven approaches identify mistakes by utilizing Techniques for ML and statistical analysis to find patterns and anomalies in data. they can effectively compare these three categorized approaches since they may comprise various fault detection and diagnostic methodologies.

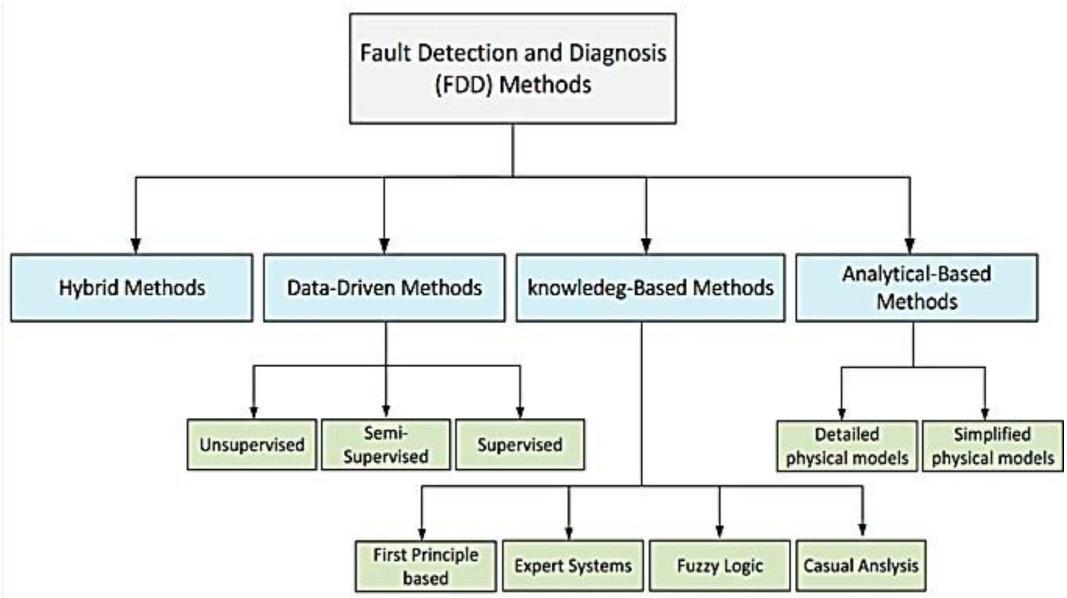

Fig. 3. Classification of FDD Methods

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C. Data-Driven Decision Making in Organizations

The significance of organizational decision-making has been emphasized by several academics [28]. The quality of an organization's decisions has a direct impact on its productivity, competitiveness, efficiency, and profitability. However, a number of authors, such as Daft, Lengel & Trevino (1987), Choo (1991), and Snowden and Boone (2007), have highlighted the considerable challenges that organizational decision-making encounters, including ambiguity, complexity, and uncertainty [29]. It is anticipated that these difficulties have grown in recent years as a result of growing organization size, competitive pressure, the availability of enormous volumes of data, and, in certain cases, the requirement to make choices in real time. Scholars have investigated a number of strategies for adapting the organizational decision-making process to the constantly shifting demands and circumstances

V. LITERATURE REVIEW

Recent studies on Digital Twin in predictive maintenance highlight its role in problem detection, improved decision-making and real-time monitoring that lead to reduced downtime and increased efficiency.

Singh et al. (2023) used several physics and data-driven modelling to produce a customized predictive maintenance. system featuring a digital replica of an induction motor in a squirrel cage. This study's objective is to employ Induction motor digital twin technology to perform predictive maintenance and diagnose problems. This framework is capable of extrapolating operating characteristics to diagnose erratic faults and predict a motor's remaining usable life [30].

Mendonca et al. (2022) explain the necessary framework for implementing Industry 4.0 techniques and briefly recap related ideas before identifying research possibilities and obstacles to the implementation of so-called digital twins. Their focus is on modernizing older systems with the goal of bringing Industry 4.0's well-known advantages for older systems include enhanced equipment robustness, better productivity, reduced production costs, and increased process connection [31].

Karlsson, Bekar and Skoogh (2021) provide a logical framework for multi-machine analysis that may be applied to predictive maintenance (PdM) by employing a group clustering model. The framework allows for machine comparison, deterioration modelling, and health state evaluation, and it benefits from the repeating structure that several machines provide. It is based on the Gaussian topic model (GTM), a hierarchical probabilistic model that enables one to directly acquire proportions of patterns throughout the machines by sharing cluster patterns between them. This serves as the foundation for machine-to-machine cross- comparison, where similarities and discrepancies can provide crucial information regarding the devices' deterioration patterns [32].

Li, Zhang and Huang (2021) the elements of the present status numerous studies on the latter employing integrated energy systems and digital twin technologies. The fundamental technological underpinnings of the integrated energy system's digital twin technology are examined, along with the associated technical components. Thus, a more thorough analysis of the use of digital twin technology in the integrated energy system is conducted [33].

Masani, Oza and Agrawal (2019) Explain how to predict the accuracy of manufacturing machine operations using ML techniques. To solve these issues, they have used supervised machine learning for power reporting and binary decision trees utilizing the CART technique. The data is retrieved via the Modbus communication protocol using an RS232 to RS485 converter. By using certain energy meter data as its input characteristics, they were able to estimate the machine accuracy at a particular moment using CART. In order to estimate the accuracy of a manufacturing machine in operation, this study addresses the issue definition, data analysis of energy meter data and its collecting, and, finally, machine learning approaches. It ultimately provides a graphical warning of the machine's declining performance at a certain moment in time, as well as separate power reports for the various machines based on the values that were retrieved [34].

Table II reviews the research on predictive maintenance using digital twins, broken down by study, methodology, main conclusions, problems found, and suggested future research topics

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TABLE II. SUMMARY OF LITERATURE REVIEW BASED ON DIGITAL TWIN APPLICATIONS IN PREDICTIVE MAINTENANCE

References	Study On	Approach	Key Findings	Challenges	Future Work
Singh et al. (2023)	Induction Motor Digital Twin for Squirrel Cage	Multiphysics and data-driven modelling combined with a personalised predictive maintenance program	Enables the detection of issues and the calculation of induction motors' RUL, or Remaining Useful Life	Integration complexity and model validation	Expansion to other types of motors and real-time performance validation
Mendonca et al. (2022)	Adopting Industry 4.0 via Digital Twins for Legacy Systems	Structural and conceptual review to assess readiness for Digital Twin adoption	Highlights benefits of DT for older systems cost reduction, efficiency, and process connectivity	Upgrading legacy systems and lack of interoperability	Designing transition frameworks for legacy system modernization
Karlsson, Bekar and Skoogh (2021)	Multi-machine Predictive Maintenance Framework	Hierarchical probabilistic clustering model (Gaussian Topic Model)	Framework allows machine comparison and degradation pattern detection using shared clustering over multiple machines	Complexity of clustering across heterogeneous machine types	Expand clustering techniques for wider machine types and improve cross-comparison accuracy
Li, Zhang and Huang (2021)	Digital Twin in Integrated Energy Systems	Technical framework review and analysis of DT in energy systems	Describes the architecture and applicability of DT in managing integrated energy systems	Technical integration and system complexity	Further analysis of DT implementation in smart grid or renewable energy systems
Masani, Oza and Agrawal (2019)	Machine Accuracy Prediction via ML	Supervised ML (CART Decision Tree) with RS232/RS485 and Modbus data acquisition.	Predicts machine accuracy and generates performance warnings using energy meter data.	Data collection from legacy protocols and model generalization	Expansion of ML models and automation of alerts through IoT and dashboard integration.

VI. CONCLUSION & FUTURE WORK

The predictive maintenance framework of one essential element of Industry 4.0 refers to digital twin technology, which connects digital and physical systems using sophisticated analytics and real-time Internet of Things data. Proactive decision-making, defect detection, and optimization are supported by this integration in sectors including smart cities, manufacturing, and healthcare. While challenges in data integration, sensor compatibility, and system complexity persist, ongoing advancements in sensor technology and ML are enhancing the accuracy and dependability of Digital Twin applications, promoting cost savings and efficiency in linked businesses. However, ensuring real-time data accuracy and seamless communication remains a critical hurdle.

Future studies should concentrate on creating more scalable and resilient Manufacturing legacy systems are among the many industrial designs that may be readily connected with digital twin frameworks. The growth of IoT, edge computing, and AI can enhance predictive maintenance decision support systems, anomaly prediction, and real-time defect identification. Standardized procedures are also required for data collecting, security, and interoperability across different industries to ensure efficient DT deployment. Exploring hybrid AI models, improving cybersecurity measures, and integrating blockchain for secure data management are promising directions for future research in Digital Twin-based predictive maintenance.

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