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Review article

# Paradigm shift for predictive maintenance and condition monitoring from Industry 4.0 to Industry 5.0: A systematic review, challenges and case study

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ABSTRACT

This paper examines the integration of Industry 5.0 principles with advanced predictive maintenance (PdM) and condition monitoring (CM) practices, based on Industry 4.0's enabling technologies. It provides a comprehensive review of the roles of Machine Learning (ML), Digital Twins (DT), the Internet of Things (IoT), and Big Data (BD) in transforming PdM and CM. The study proposes a six-layered framework designed to enhance sustainability, human-centricity, and resilience in industrial systems. This framework includes layers for data acquisition, processing, human-machine interfaces, maintenance execution, feedback, and resilience. A case study on a boiler feed-water pump is also presented which demonstrates the framework's potential benefits, such as reduced downtime, extended lifespan, real-time equipment monitoring and improved efficiency. The findings of this study emphasises the importance of integrating human intelligence with advanced technologies for a collaborative and adaptive industrial environment, and suggest areas for future research.

## 1. Introduction

The industrial landscape has undergone a profound transformation over the past decades, with the latest advancements in automation technologies driving the so-called Fourth Industrial Revolution or Industry 4.0 [1]. The advent of Industry 4.0, characterised by digitisation, automation, and data-driven decision-making, promised a new era of efficiency and productivity. Through the integration of Industry 4.0's enabling technologies, manufacturing systems have become more interconnected and intelligent, facilitating the adoption of improved predictive and proactive maintenance tools. With the introduction of Industry 5.0, the fusion of cutting-edge technologies with the core principles of human-centricity, resilience, and sustainability is setting a new paradigm for predictive maintenance and condition monitoring in industrial operations, promising a transformative era in maintenance practices. Predictive Maintenance (PdM), a smart maintenance technique, utilises data analysis and monitoring techniques to predict equipment failure, enabling maintenance activities to be performed just in time to prevent failure. Condition Monitoring (CM), also sometimes referred to as condition-based maintenance (CBM), involves the continuous or periodic measurement of equipment parameters to assess its health and detect early signs of failure. The primary distinction between PdM and CM is that PdM anticipates future failures and schedules maintenance accordingly, whereas CM focuses on real-time monitoring to identify current equipment conditions and immediate maintenance requirements. Traditionally, the industries have employed various maintenance techniques, such as corrective and preventive maintenance, to address faults and minimise equipment downtime. Corrective maintenance, also known as breakdown maintenance, run-to-failure, or reactive maintenance is a technique in which maintenance activities are carried out once the equipment experiences a failure. Preventive maintenance, also referred to as routine or planned maintenance, is a more cautious approach which involves the execution of maintenance activities in advance to proactively prevent potential faults or breakdowns.

This review paper delves into the evolving landscape of PdM and CM. It begins with a review of PdM and CM practices within the context of Industry 4.0, followed by an exploration of the definitions and principles of Industry 5.0. The study then maps the PdM and CM based on enabling technologies of Industry 4.0, such as the Internet of Things

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(IoT), Big Data (BD), Machine Learning (ML), and Digital Twin (DT), to the core principles of Industry 5.0. Based on this mapping, a layered framework for implementing PdM and CM in Industry 5.0 is developed. The framework is further supported by a case study, which demonstrates its practical application in a real-world scenario, specifically focusing on a boiler feed-water pump in a steam power plant.

The significance of maintenance has become paramount for industries, primarily driven by the rising complexity of interactions among diverse production activities within ever-expanding manufacturing ecosystems [2,3]. The emergence of IoT has infused intelligence and connectivity into industrial processes and equipment, enabling real-time monitoring, data collection, and analysis. This has revolutionised maintenance practices with PdM and CBM leading this transformation. These tools rely on advanced sensors, big data analytics, and machine learning techniques to shift from conventional reactive maintenance practices to proactive and data-driven approaches, resulting in lower costs, reduced downtime, improved efficiency, availability, and resilience.

PdM and CM concepts have attracted significant interest from the research community in recent years. Considerable work has been conducted to explore the potential of these methods. Thus our research process for selecting relevant papers included examining existing review articles on PdM and CM implementation. While these reviews comprehensively explored various enabling technologies, a critical gap remains. Specifically, these reviews focused on individual enabling technologies such as IoT, BD, ML, and DT for PdM and CM, but did not map these technologies to the core principles of Industry 5.0. Furthermore, none of these reviews presented or discussed any framework for implementing PdM and CM within the context of Industry 5.0. In the following section, we will provide a summary of the key findings from these existing review papers, highlighting the enabling technologies they discussed for PdM and/or CM implementation.

In PdM, the data handling is a vital task and to give detailed insights about the research work in BD the authors of [4] comprehensively review the techniques being employed in the work related to the manufacturing industry. The authors of [4] reported that 74% of the selected publications in BD belonged to the area of industrial maintenance and diagnostics. The study [5] developed a review for the existing open source BD streaming technologies being used in PdM. Two use cases of open-source BD technologies for the predictive maintenance in railway transportation and wind turbines were also presented in the study. A set of guidelines for using BD techniques in PdM applications was developed to establish a reference point for decision-makers. In [6] an overview of evolution of BD analytics from detection, and diagnosis to prognosis in industrial process monitoring (IPM) was presented with a description of various BD analytic techniques employed to detect and diagnose abnormal behaviour in industrial processes. With the advancement in ML and BD analytics, industrial processes are becoming more smart, self-aware, intelligent, and capable of prognostics. The research work [7] presents the review of literature on various ML and deep learning (DL) models being employed for the condition monitoring (CM) of wind turbines. The study converges that the most widely used ML and DL models for the CM of critical components of wind turbines are Support Vector Machines, Neural Networks and Decision Trees.

Innovation in data acquisition and data handling techniques is a key factor in enabling CM and PdM in industrial sector. Industrial intelligence is enhanced by the use of modern technologies such as Internet of Things (IoT). With IoT enabled systems, industries are able to monitor the real-time condition of the machines by collecting the streaming data and communicating to the processing units using internet. The integration of IoT into the industrial sector has given rise to what is known as the Industrial Internet of Things (IIoT), as discussed in a study [8]. This study conducted a review of previous research, centring on the techniques that make IIoT possible and the latest advancements in the field. Specifically, the research delves into three key domains: IIoT architectures and frameworks, communication protocols, and data management techniques, examining each comprehensively. The study [9] focused on reviewing the PdM in smart factories by using intelligent sensors. The intelligent sensors are capable of connecting to higher levels of communication and to the internet which is a key factor in enabling IoT devices in industries.

Advancements in digital technologies, cyber-physical systems (CPS) and IoT have led to the connected virtual and physical world. Digital Twin (DT), a virtual model of a physically existing system, which depicts every process from design to disposal, is created based on physics and is connected to the real-time physical system through IoT devices. The study [10] presents a benchmark for defining the DT in scientific literature by reviewing the existing literature in this context. The application of DT technology in industrial maintenance has a potential to shape the future of maintenance in industrial sector, as discussed in a review study [11]. This study gives the concept of DT and maintenance in detail and provides a literature review where these two concepts are interlinked. It also highlights the future prospects regarding DT and maintenance. Another study [12] focuses on the literature review of application of DT systems in industrial operations, and presents a review of 41 papers selected in between the years 2016 and 2020. Similarly, a narrower study [13] focuses on reviewing the available literature on the predictive maintenance using DT systems. It highlights the implementation of DT systems in the PdM of electrical systems. Future challenges regarding the use of DT in after sales services were also discussed. As the industrial sector advances, the benefits of deploying DT systems are on the rise. In a recent investigation [14], DT systems were analysed in the context of 13 diverse industries, shedding light on their expanding application possibilities throughout the industrial sector.

Table 1 provides an organised presentation of additional information from other review papers, highlighting a variety of techniques and tools utilised for conducting PdM and CM within the industrial sector.

*Rationale for the Study*

While existing research covers a broad range of industrial applications for PdM and CM, a significant gap remains in addressing these practices within the specific framework of Industry 5.0. Moreover, the existing work lacks reviewing all the key enabling technologies of Industry 4.0 in context of PdM and CM essential for mapping Industry 4.0's enabling technologies to the core principles of Industry 5.0 such as human-centricity, sustainability and resilience. The challenges here involve integrating human-centric approaches, ensuring operational resilience, and promoting sustainability in industrial systems. Our study aims to fill this gap by examining how PdM and CM practices, empowered by Industry 4.0 technologies, can be effectively aligned with the core principles of Industry 5.0. The key novelty of our work lies in developing a framework that bridges these practices with Industry 5.0 goals. This framework is based on a thorough analysis of enabling technologies like the Internet of Things (IoT), Big Data (BD), Machine Learning (ML), and Digital Twins (DT) being used for PdM and CM. By mapping these technologies to the principles of human-centricity, resilience, and sustainability, our framework illustrates how PdM and CM can evolve to meet the demands of modern industry. The proposed framework not only supports PdM and CM practices but also helps achieve the goals of sustainability, resilience, and human-centricity, which are central to Industry 5.0. Additionally, the case study shows how these technologies can be put into practice to develop a more resilient, sustainable, and human-centric industrial system. Fig. 1 highlights the structure of this paper.

We approached this study with the following steps:

- In Section 2, we reviewed over 100 research papers published between 2015 and 2023 to identify trends and patterns in how enabling technologies are being used to enhance PdM and CM practices. Whereas, Section 3 introduces Industry 5.0 by providing its definitions, core principles and key enabling technologies.

**Table 1**
An analogous assessment of previous studies on Predictive Maintenance (PdM) using novel techniques.

| Reference | Year | CM | RUL | IoT | DT | ML/DL | Big Data | Fault Prediction | Industry 5.0 |
|---|---|---|---|---|---|---|---|---|---|
| [4] | 2015 | X | X | ✓ | X | ✓ | ✓ | X | X |
| [15] | 2016 | X | ✓ | ✓ | X | ✓ | X | ✓ | X |
| [6] | 2017 | X | ✓ | ✓ | X | ✓ | ✓ | ✓ | X |
| [10] | 2017 | ✓ | X | ✓ | ✓ | X | X | X | X |
| [16] | 2017 | ✓ | ✓ | X | ✓ | X | X | ✓ | X |
| [7] | 2019 | ✓ | X | X | X | ✓ | ✓ | ✓ | X |
| [17] | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | X |
| [5] | 2020 | ✓ | X | ✓ | X | ✓ | ✓ | X | X |
| [11] | 2020 | ✓ | X | ✓ | ✓ | X | ✓ | ✓ | X |
| [8] | 2020 | ✓ | X | ✓ | X | ✓ | ✓ | X | X |
| [18] | 2020 | ✓ | X | X | X | X | X | X | X |
| [13] | 2021 | ✓ | ✓ | ✓ | ✓ | X | ✓ | X | X |
| [12] | 2021 | X | X | ✓ | ✓ | ✓ | X | X | X |
| [9] | 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | X |
| [14] | 2022 | ✓ | X | ✓ | ✓ | ✓ | ✓ | X | X |
| **Our Paper** | 2023 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

- Section 4 analyses these trends to understand how technologies like IoT, BD, ML, and DT can be mapped to the core principles of Industry 5.0.
- In Section 5, based on this analysis, we developed a six-layered framework for PdM and CM that integrates these technologies with the goals of Industry 5.0, emphasising human-centricity, resilience, and sustainability.
- A case study is presented in Section 6 in which we applied this framework for the PdM and CM of boiler feed-water pump in a steam power plant, demonstrating its practical benefits.

The remaining sections of this paper are organised as follows: Section 7 provides a comprehensive discussion, analysing the implications of our findings in the context of existing literature and identifying the gaps and limitations of the current research. Section 8 delves into future challenges and presents a detailed roadmap for the way forward. Finally, Section 9 concludes the paper by summarising the key contributions, emphasising the significance of our findings, and underlining the potential benefit of the proposed framework on enhancing sustainability, resilience, and human-centricity in industrial maintenance practices.

## 2. Detailed review of PdM and CM in Industry 4.0

It is evident from history that the technological innovations lead to industrial revolutions [19]. With the invention of steam engines, the industrial sector witnessed its 1$^{st}$ industrial revolution. The transition from an economy dominated by handicrafts to one dominated by machinery, significantly influenced various sectors. In the late 19$^{th}$ and early 20$^{th}$ centuries, the industrial sector experienced a series of notable shifts. The invention of electric power and assembly line production lead to the 2$^{nd}$ industrial revolution which resulted in substantial increase in productivity. The advancements in communication technologies and embedded systems played a pivotal role in automating the production processes which resulted in the 3$^{rd}$ industrial revolution, often referred to as Industry 3.0. This particular phase centered on the adoption of integrated circuit chips, digital logic, mass production, and related technologies. Notable examples include digital cellular phones, computers, and the internet. Innovation in digital technologies led to the conversion of physical technology to digital format. The 4$^{th}$ industrial revolution utilises various enabling technologies like AI, 3D printing, IoT, robots, and cloud computing with the physical assets to increase the productivity and production flexibility [20]. This concept is later referred to as Cyber-Physical Systems (CPS) [21]. Industry 4.0 is resulting in mass production and increased productivity through the utilisation of its enabling technologies.

Currently, there is a substantial amount of research dedicated to implementing predictive maintenance (PdM) and condition monitoring (CM) using the enabling technologies of Industry 4.0. The aim of this paper is to manoeuvre towards a framework that facilitates the implementation of PdM and CM based on the core principles of Industry 5.0, leveraging these advanced technologies. A thorough review of PdM and CM within the context of Industry 4.0 is essential to understand the current state and future directions of research in this field. By examining the existing literature, we identified significant advancements and ongoing trends which is crucial for transitioning from the current Indus-

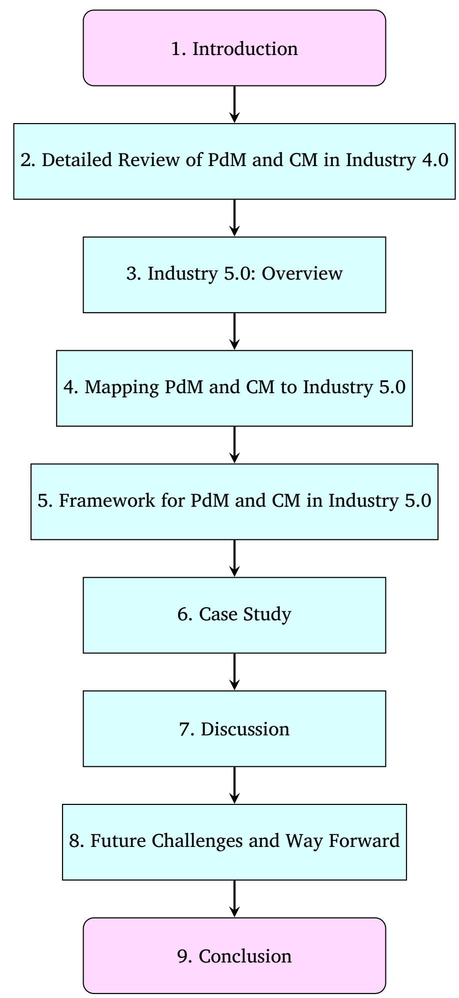


**Fig. 1.** Structure of the paper.

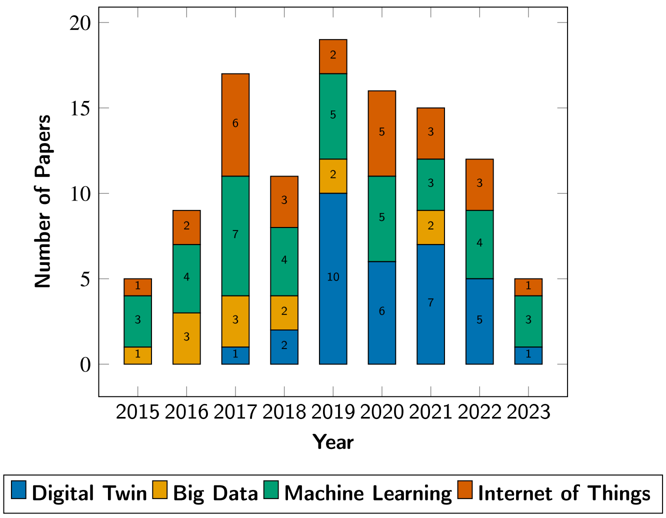


**Fig. 2.** Trend of enabling technologies in Predictive Maintenance (2015-2023).

try 4.0 paradigm to the more advanced, human-centric, and sustainable framework envisioned in Industry 5.0.

In this section, we present a comprehensive review of research papers from reputable sources such as Springer, Elsevier, and IEEE. We have selected over 100 papers published between 2015 and 2023 based on their focus on enabling technologies for PdM and CM in industrial settings. These technologies include digital twins, the Internet of Things (IoT), machine learning, and big data analytics, which are central to the evolution of PdM and CM. This review aims to provide a detailed overview of how these technologies are currently being applied, their impact on maintenance strategies, and their potential for future enhancements. Fig. 2 represents the overall trend of research work regarding PdM using enabling technologies in the years 2015 to 2023. By understanding the role of these technologies in advancing PdM and CM, we lay the groundwork for developing a robust framework for Industry 5.0.

### *2.1. PdM and CM based on Digital Twin*

The Digital Twin technology, with its ability to create digital models of physical assets, has emerged as a foundation for reshaping the PdM and CM strategies. Digital twins which are virtual replicas of machines, are continuously updated with real-time sensor data from the physical machines, enabling the real-time condition monitoring of the machines. This data is processed and analysed in data centres to optimise machine performance, predict maintenance needs, and ultimately extend their operational life. Fig. 3 demonstrates the PdM and CM enabling using DT technology. Digital Twins play an important role by providing dynamic virtual models of physical systems that enable real-time simulations and analysis. These virtual models are continuously updated with data from their physical counterparts. This not only allows for precise condition monitoring and predictive maintenance, but also helps in simulating the failures beforehand based on real-time data and trends. The Digital Twins fed with the real-time data also help in analysing the situations for increasing operational efficiency and extending the machine life by changing the operating parameters in real-time. With the help of Digital Twins, industries can simulate various scenarios, predict potential failures, and optimise maintenance strategies without shutting down the equipment or process. This capability is helpful in enhancing operational efficiency and it also contributes to sustainability by minimising resource consumption and reducing downtime. Digital Twins are in fact helping to bridge the gap between physical and digital worlds. This section comprehensively reviews the research papers that utilise Digital Twin technology in implementing PdM and CM across a diverse set of industrial domain.

A model-based approach for monitoring heat and implementing predictive maintenance in an automotive braking system is used in [22]. The method involved establishing a simulation-based digital twin to enable monitoring, prognostics, and diagnosis of automotive braking system. The study [23] investigates a predictive maintenance framework for aero-engines utilising a DT. It focuses on developing an implicit digital twin (IDT) model. The method's validity is demonstrated through the consistency of results for virtual and real datasets. Furthermore, the dataset is applied to a Deep Learning technique called Long Short-Term Memory (LSTM), showing effective and efficient RUL prediction results. Introduction to an advanced physics-based modelling approach for enabling DT in PdM was presented in [24]. It outlines two key steps: the creation of a digital model and the implementation of DT. The work focused on developing a digital model specifically for an industrial robot, with the goal of enhancing its application in Predictive Maintenance. The study [25] explores the application of a Digital Twin in supporting both predictive and dynamic maintenance within the Facility Management and Maintenance process. The proposed framework involved the integration of data and processes among Building Information Models, IoT sensors, and facility management systems. The predictive maintenance implementation comprised of three modules which are fault detection, condition prediction and maintenance planning. A DT based PdM of an automotive brake pad was presented in [26]. Real-time pressure data was gathered from the physical brake pad through the ThingWorx IoT platform. The brake pad was replicated in CREO, and the collected pressure data was incorporated into the CREO Simulate model. This integration allowed for the assessment of brake pad wear based on the actual pressure data. The study [27] focused on estimating the RUL through a physics-based model within a DT framework, aimed to enable PdM with PHM techniques. The case study centered on an industrial robot. Real-time machine data was fed into the virtual model for predicting the remaining useful life. Implementation of PdM based on DT in flexible production systems are discussed in details in the study [28]. A framework that establishes connections between physical and real processes to facilitate efficient PdM is presented in this work [29]. Using this framework, the RUL of a tunnel furnace system was determined. The research study [30] introduces a multi-degree-of-freedom (DOF) torsional model for a drive-train of offshore wind turbines, serving as a DT model. The proposed algorithm takes in torsional response, estimated generator and rotor torques, and computes drive-train dynamic properties. The study explores the application of this model in predicting the RUL of a gear-train. In this study [31] a Reference Architecture for DT-based predictive maintenance systems is developed and evaluated, using domain analysis and Unified Modelling Language (UML) diagrams to design the architecture, and demonstrates its application in three case studies, showing its potential for reducing time-to-market and ensuring consistency in design. This research work [32] implements DT for condition monitoring of knuckle boom crane. The crane was modelled using non-linear finite element (FE) approach and estimated weight was used as input. The DT model gives a number of readings of load, stresses and strain at various points on the crane. Hence providing a way for predictive maintenance and life cycle assessment. The study [33] focuses on the implementation of PdM using historical data and simulation data for industrial equipment (combining data-driven and physics based models). It provides a framework for implementing PdM based on DT on the existing industrial approaches. It also formulates the methods for interacting the historical data with simulation data, which can result in better RUL prediction. Conceptual design of DT for subsea pipelines is presented [34], where the asset was modelled in Finite Element (FE) software and supplied with the actual data from the field sensors. The computational model based on machine learning predicted any behaviour due to sudden changes in loading regarding pressure changes, slags, leakages etc and helped in implementing effective PdM along with reducing operational costs and downtime. This study [35] presents a data-driven model for digital twin. A DT is constructed for machine tool and a deep learn-

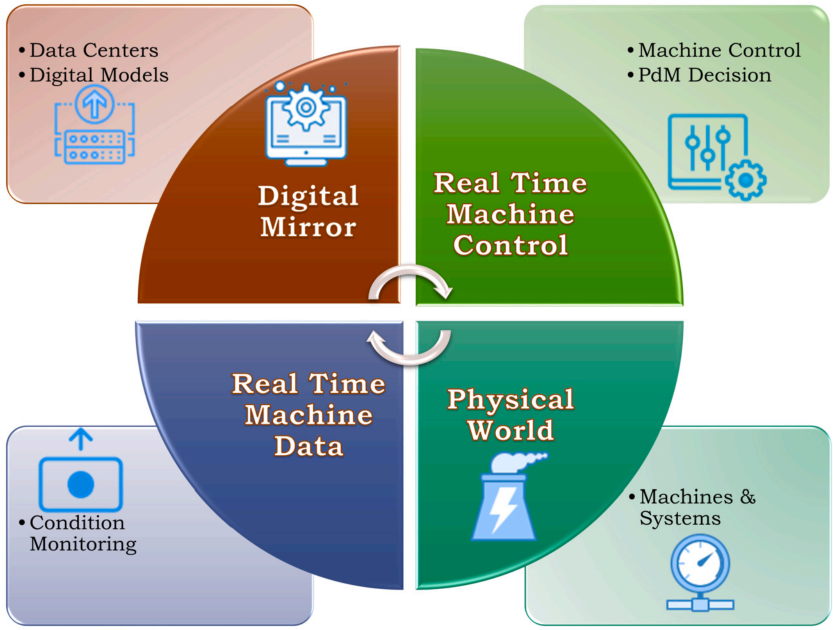


**Fig. 3.** DT technology in enabling of PdM & CM.

**Table 2**
An overview of reviewed papers on DT technology in PdM.

| References | Application Area | Key Findings |
|---|---|---|
| [39] | General Industry | An overview of PdM based on DT technology and its application in various industries. |
| [40] | Manufacturing | DT driven hybrid approach for PdM of a CNC machine cutting tool |
| [41] | Fault Detection | DT adopted fault detection based on simulations on high fidelity models and transferring these models from virtual to real world using deep transfer learning techniques. |
| [42] | Mechanical Transmission Systems | A framework based on DT which analyzes sensor data for mechanical transmission systems to devise maintenance strategy. |
| [43] | Aerospace | Identification of role of data fusion in DT technology for PdM of an aircraft is presented. |
| [44] | Wind Turbines | DT based on physical model for condition monitoring of drivetrains of test rig. |
| [45] | Manufacturing | DT technology is implemented with an integration framework for various industries for dynamic maintenance decision making. |
| [46] | Wind Turbines | A methodology to predict the remaining useful life of an offshore wind turbine power converter in digital twin frame work as a means of predictive maintenance strategy is presented. |
| [47] | Manufacturing | DT and AR application in manufacturing industry for PdM framework. |
| [48] | Manufacturing | A DT based framework for RUL prediction based on nonlinear-drifted Brownian motion for smart manufacturing. |

ing technique Deep Stacked Gated Recurrent Unit (DS-GRU) is used for tool wear prediction. The work [36] explores the current status of research and technology in the automation of maintenance. It proposes the use of DT for automating decision-making in PdM by leveraging operational data and the machine's DT. A DT approach for drive-train condition monitoring in floating offshore wind turbines, incorporating a torsional dynamic model, online measurements, and fatigue damage estimation for remaining useful life prediction in the study [37]. DT is based on edge computing, where the data is sorted and processed at the edges and then it is transmitted to DT model where it is used for condition monitoring and anomaly detection. Proof of concept is given for LiBr chillers and showed early detection of anomalies in the study [38].

In the preceding discussion, review of several papers that delve into the application of DT in PdM is provided. The Table 2 provides a summarised overview of the papers, including key findings and application areas. The table highlights the papers which provide an application of DT technology in PdM in different industrial settings.

### *2.2. Big data analytics for PdM and CM*

The vastly generated data in the industries has fuelled the innovations in Big Data. These innovations are proven to be a transformative force in predictive maintenance. In this section, the review of the papers that leverage on Big Data analytics as predictive maintenance optimisation tool is presented. Each selected paper is examined for its role in processing either the static or streaming data, performing more accurate RUL predictions and fault detection for minimising downtime and improving operational efficiency.

The study carried out in [49] addresses the challenges of predicting RUL and maintenance decisions in condition based maintenance using Big Data analytics. The technique used in this study for Big Data analytics is based on fuzzy logic and it performed better as compared to other techniques. The study [50] uses data analytics techniques on real-time sensor data from rail-mounted sensors to predict and improve the RUL of train axle bearings. Online Support Vector Regression is employed for CM through Streaming Data Analysis of big data collected from the sensors. The research work [51] employs envelope analysis and fusion method for processing Industrial Big Data. It proposes a framework for structuring heterogeneous data, considering spatio-temporal properties and extracting intricate features. The goal is to enhance the transparency of production systems and enable effective predictive maintenance implementation. The study carried out in [52] introduces the Opportunistic-Condition-Condition-Based Maintenance (OCBM) technique, integrating condition-based maintenance and opportunistic maintenance thresholds for maintenance optimisation for offshore wind farm. It employed predictive analytics technique

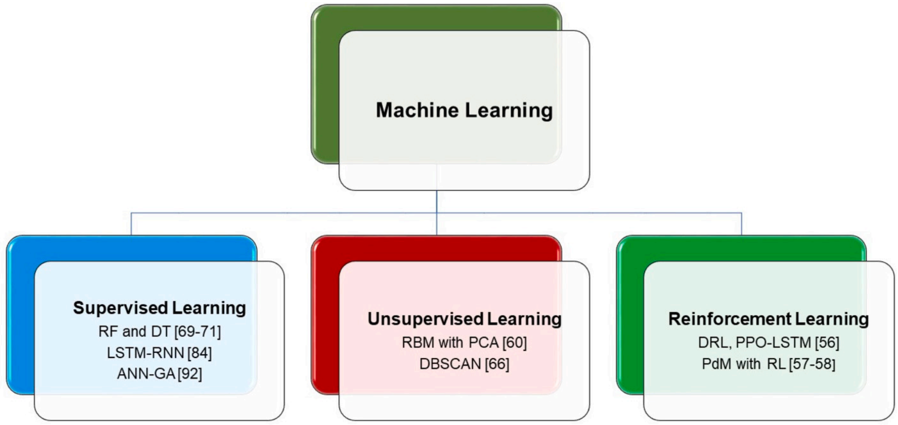


**Fig. 4.** Various techniques adapted for PdM and CM under Machine Learning Paradigm.

which demonstrated a significant annual maintenance cost reduction. The study carried out in [53] proposes a precise and efficient algorithm for feature extraction in time series data for industrial applications such as PdM and production line optimisation. A maintenance alert system based on data mining and IoT sensors for solar panels is presented in this study [54]. The data is collected in the form of current and voltage of solar panels which is then compared to the calibrated values of current and voltage. This system alerts when the actual values are out of range, hence detecting the fault and alerting the maintenance team. Fault diagnosis and prediction for machine centers, with the help of data mining techniques within the context of Industry 4.0 for PdM of equipment and tools is presented in [55]. The framework encompasses data acquisition, preprocessing, data mining, decision support, and the implementation of maintenance strategies.

### *2.3. Machine learning solutions for PdM and CM*

In the realm of predictive maintenance at a wide industrial domain, ML is transforming the PdM landscape because of its adaptive and self-learning capabilities. In the context of PdM, ML employs three key techniques. Supervised Learning utilises historical labelled data to train models for tasks like predicting equipment failures or estimating remaining useful life. This technique enables the model to learn patterns associated with normal and faulty system states. Unsupervised Learning comes into play when labelled data is scarce. It involves detecting anomalies or patterns in unlabelled data, aiding in identifying subtle deviations indicative of potential faults. Lastly, Reinforcement Learning is applied for adaptive maintenance strategies. Agents learn optimal decision policies over time through interactions with the dynamic system, making it suitable for scenarios where the impact of maintenance actions evolves. The Fig. 4 represents the various types of Machine Learning, adopted by the researchers for PdM illustration.

In this sub-section we focused on the review of the papers which focused on utilising the various ML techniques for fault prediction, residual life estimation and other critical aspects of maintenance optimisation. The key findings of various research papers are presented to highlight the diverse ways in which ML is being used to augment the landscape of PdM.

**Reinforcement Learning** The article [56] explores using a model-free deep reinforcement learning (DRL)-based PdM framework to solve the complex resource management problem. Unlike existing frameworks, it considers PdM sensor data and integrates both physical equipment and human resources into the optimisation problem. The Proximal Policy Optimisation Long Short-Term Memory (PPO-LSTM) model outperforms conventional DRL models in determining an optimal decision policy. The research work [57] proposes an RL driven maintenance strategy for optimising long-term aircraft maintenance decisions. It integrates future mission requirements, repair costs, spare component storage, and Prognostics and Health Management (PHM) outputs, outperforming other strategies in simulated scenarios. The study carried out in [58] introduces a novel multi-agent approach employing reinforcement learning for learning maintenance policies employed by maintenance technicians, under the uncertainty from multiple machine failures. RL agents with partial machine state observations coordinate maintenance scheduling, dynamically assigning tasks to technicians with diverse skills. Experimental results demonstrate a 75% improvement in overall performance compared to traditional maintenance policies, including corrective and preventive strategies.

The research carried out in [59] proposes a multi-channel convolutional neural networks (CNNs) and Monte Carlo dropout for probabilistic RUL prognostics. The data for turbofan engines' degradation is taken from NASA which consist of four subsets. Each of this data subset considers a specific set of operating conditions and failure modes. This study employs 14 sensor measurements per flight cycle. For data preprocessing, the clustering is performed on operating conditions to select 6 operating conditions. The study also considers operating conditions' history. After that, the normalisation of sensor measurements is performed with respect to the operating conditions. A set of features for a specific time window of operating cycle is selected as an input to CNN model. The architecture of CNN model for probabilistic RUL prognosis consists of multi-channel convolutional layers, linear layers, and Monte Carlo dropout layer. A total of 5 Conv1D layers and 3 linear layers are employed in this framework. Out of 3 linear layers, 2 layers act as intermediate linear layers and 1 as output linear layer. The output linear layer has a single neuron and no activation. The kernels and biases of convolutional layers and weights and biases of linear layers are optimised by using Adam optimiser. Monte Carlo dropout is applied after each layer both during testing and training the model. The application of Monte Carlo dropout during training prevents the overfitting of the model and during testing to obtain the probability distribution of RUL. This approach reduces total maintenance costs by 29.3%, prevents 95.6% of unscheduled maintenance, and limits wasted engine life to 12.81 cycles.

**Unsupervised Learning** The research work [60] implemented an ML technique for extracting the best features to predict the machine health. Specifically an enhanced Restricted Boltzmann Machine (RBM) with a novel regularisation term for feature extraction was implemented. This technique showed promising results as compared to regular RBM and Principal Component Analysis (PCA). The technique's effectiveness was further validated for run-to-failure datasets from two rotating equipment systems. The research study [61] addresses the absence of a unified definition for anomalies in PdM. The authors propose a flexible evaluation framework for assessing unsupervised anomaly detection algorithms in time series scenarios. The proposal is validated through a case study with Big Data algorithms using real-world time series data. The study [62] introduces an innovative method for early fault detection of machine tools under time-varying conditions. A deep learning model is developed to extract impulse responses from vibration signals collected over 288 days of long-term data. By identifying dynamic properties from these impulse responses, the technique enables early fault detection under time-varying conditions. A hybrid intelligent predictive maintenance model is utilised to address challenges in non-linear, non-stationary, high-dimensional industrial data in this study [63]. This method efficiently reduces the redundant data dimensions, improving convergence speed and classification accuracy. The model proposed in [64] develops an intelligent Health Indicator (HI) model which extracts multi-scale coded features from vibration signals and uses an ensemble health indicator to fuse healthy and damaged feature metrics, improving RUL prediction reliability. The study [65] employs the AutoRegressive Integrated Moving Average (ARIMA) technique to analyse time series data sourced from sensors on a Slitting Machine. The primary objective is to use ARIMA technique for the prediction of both potential failures and quality defects within the context of the Slitting Machine operations. The study [66] introduces a real-time condition monitoring system which utilises IoT-based sensors, data preprocessing, and a hybrid ML prediction model. The system deals with large volumes of unstructured real-time data. Outlier detection is performed using Density-Based Spatial Clustering of Applications with Noise (DBSCAN), while the prediction is carried out using the Random Forest algorithm.

**Supervised Learning** The research work [67] exhibits the transformation of maintenance planning with the help of ML, which analyses data for individual machine performance and environment variables. It effectively identifies failure patterns, providing actionable predictions for specific machine parts, thus enhancing overall maintenance strategies. The research work [68] proposes MCA-BGRU, a novel framework for predicting remaining useful life in mechanical systems. Combining multi-scale CNN, BGRU, MHSA, and fully-connected layers, it captures high-level representations and temporal tendencies in input data. Using particle swarm optimisation for hyper-parameter tuning, it outperforms existing studies by 0.32% in RMSE and 5.6% in Score values on the C-MAPSS dataset. The research study [69] explores the application of the Random Forest (RF) algorithm for predictive maintenance on a real industry machine. It involves the development of data collection, analysis, and the application of machine learning techniques. Comparative analysis with a simulation tool demonstrates the high accuracy of predicting various machine states using ML. The work [70] compares the performance of RF, Decision Trees (DT), and Recurrent Neural Network (RNN) on both experimental and real datasets for PdM. RF and DT exhibit similar performance, whereas RNN demonstrated superiority for large datasets and RF showed better results for smaller datasets. The study suggests a hybrid approach combining RNN and RF for more precise and reliable predictions. In this study [71] novel Decision Support System (DSS) utilising DTs is proposed for an effective decision-making in implementing PdM in the industry. The DSS helped in determining economically feasible conditions for PdM implementation. PdM with DTs is found to be economically suitable when compared to corrective maintenance costs. In this study [72] an ANN based condition monitoring is proposed for gearbox bearings of an off-shore wind turbine. This approach helped in early detection of faults and breakdown. The study carried out in [73] presents a hybrid approach for Prognosis and Diagnosis using a combination of features identified by an expert from big data and Local Feature-based Gated Recurrent Unit (LFGRU) networks. Experimental results, including tool wear prediction, gearbox failure prediction, and bearing failure prediction demonstrate the effectiveness and generalisation ability of this approach. This study [74] conducts a comprehensive survey on the applications of data-driven methods in PdM. Various ML algorithms were applied to a specific dataset related to automatic washing equipment, and the results were compared.

Another study [75] provides an in-depth review of integration of ML into additive manufacturing and highlights how ML models can analyse complex datasets to optimise various AM processes. From the vast data generated during the AM process, ML can find out complex relationships among parameters, leading to more informed decision-making for predictive maintenance of AM system and improved 3D printing outcomes. The study also discusses the potential of emerging ML techniques, such as reinforcement learning and generative models, to further enhance the condition monitoring of AM processes. These techniques can extend the useful life of equipment and reduce disruptions in the manufacturing process.

The remaining useful life (RUL) prediction an machine sate prediction is a crucial requirement for the condition monitoring and PdM of a machine. In the following, the review of the research papers which utilise ML algorithms for carrying out machine state prediction and RUL prediction is presented. The research study [76] discusses a model-based approach for estimating RUL through ML algorithms. A model is constructed using various parameters, and the features are initialised using the Maximum Likelihood algorithm. A Particle Filtering-based algorithm utilises these features for predicting the RUL. In this article [77] explores using Temporal Convolutional Networks (TCNs) for predicting the RUL of Turbofan engines in cyber-physical systems. It compares TCNs with hybrid architectures and achieves high accuracy and precision, demonstrating the effectiveness of TCNs for prognostics. The study [78] presents a novel method for predicting RUL based on stochastic process models. The stochastic degradation process of the machine based on multiple variables is modelled using a stochastic process model. Kalman Particle Filtering-based algorithm is employed to predict both the machine state and RUL. Residual life prediction is a helpful tool in implementing predictive maintenance. Effective and efficient life prediction can help in the reduction of machine downtime by taking necessary measures beforehand. Similarly, for condition monitoring and the condition-based maintenance, the machine state prediction is a vital tool. In Table 3, a brief summary and the key findings of the selected papers based on ML is presented.

### 2.4. Internet of things technology for PdM and CM

With the permeation of IoT in industrial settings, its impact on CM and PdM practices is prominent. In this section, the key findings of the selected papers based on IoT enabled PdM are highlighted. It was aimed to explore how IoT is contributing to real-time monitoring, faults detection and implementing CM and PdM across various industries by carefully examining the applications, methods and overall trends.

The study carried out in the research paper [94] integrates the Building Information Model (BIM) and IoT in Facility Maintenance Management (FMM) which enables efficient PdM. The proposed framework involves Information and Application Layers, utilising Support Vector Machine(SVM) and ANNs for accurate predictions, especially for MEP components. The study [95] introduces NGS-PlantOne, an Industrial IoT(IIoT) device deployed in a power plant for efficient data monitoring. It also highlights the effectiveness of such devices in real-time condition monitoring and implementing efficient PdM in power plants. The research work [96] explores the opportunities and challenges associated with IoT-based Prognostics and Health Management (PHM) in industrial applications. It emphasizes the necessity for collaboration among the engineering, statistics, and machine learning communities to effectively implement these models. Successful PHM implementation entails linking anomalous data patterns to specific failure modes and establishing connections to the fundamental physics of failure. In this study [97] an incremental DNN model for predicting maintenance notifications in IoT systems is proposed, addressing challenges of data availability and non-stationary data distribution. The research work [98] utilises IoT technology aiming to gather specific information for predicting motor bearing failure and real-time CM by analysing the vibration and temperature of an induction motor. The vibration signals are examined to detect faulty operation of motors. The study [99] suggests an approach for online process monitoring and predictive maintenance of equipment through the integration of IoT. The approach comprises of two intercon-

**Table 3**
Key findings, techniques used, and results reported for papers on ML for PdM.

| Year | Reference | Key Findings | Technique Used | Results |
|---|---|---|---|---|
| 2015 | [79] | Bearing RUL prediction based on Simplified Fuzzy Adaptive Resonance Theory Map neural network. | Neural Network | Accuracy 74% |
| 2016 | [80] | Data-driven models are utilised for RUL prediction. The model is constructed in two phases: an offline phase finds variables important for health degradation, and an online phase predicts RUL based on k-nearest neighbour. | k-Nearest Neighbour (KNN) | MAPE 8.7691% |
| 2017 | [81] | An approach based on degradation pattern learning is utilised to predict RUL of an aircraft engine. | Neural Network | Mean Score 2.61 |
| 2017 | [82] | Mobile agent-based approach for PdM, effective in employing signal processing algorithms on distributed servers. | Support Vector Machine (SVM) | Accuracy 99.8% |
| 2018 | [83] | A framework for enabling the production machines for PdM based on IoT architecture and ML. | Random Forest | F1 Score 98.1% |
| 2020 | [84] | ML techniques such as LSTM RNN and Vanilla-RNN are employed for fault prediction and RUL prediction of equipment. | LSTM RNN | Prediction Error 0.79% |
| 2020 | [85] | Early prediction of machine failure using IoT devices with ML algorithms. | Gradient Boosting | Accuracy 98.9% |
| 2020 | [86] | Failure prediction of medical equipment via vibration signals collected and sent to ML models using IoT. | Linear-SVM | Accuracy 96% |
| 2021 | [87] | A condition monitoring application using ML approaches for machine condition prediction. | Decision Tree (DT) | Accuracy 99.84% |
| 2021 | [88] | A PdM model with CNN to classify faults in rotating equipment and recommend maintenance actions. | Convolutional Neural Network (CNN) | Accuracy 99.58% |
| 2022 | [89] | Real-time data from a 280 kW industrial motor is gathered and analysed in an ML model to detect maintenance needs. | SVM | Accuracy 99.8% |
| 2022 | [90] | A PdM framework where data is collected by IoT system, features are selected by CNN, and faults are predicted using LSTM. | CNN and LSTM | MAE 0.4257%, RMSE 0.4505% |
| 2022 | [91] | PdM model for material handling equipment incorporating novel data sources and KNN, RF Classifier. | Statistical Learning Methods (SLMs) | Highest accuracy 99% |
| 2023 | [92] | Resource management framework for predictive maintenance based on Genetic Algorithm. | Genetic Algorithm | Accuracy 94.5% |
| 2023 | [93] | A machine learning method for predictive maintenance using pre-shipment inspection data from equipment manufacturers. | Light Gradient Boosting | Accuracy 94.66% |

nected features: Process Monitoring for quality assurance and Condition Monitoring to prevent unplanned outages.

IoT integration in power generation has shown promising results for condition monitoring and predictive maintenance of business critical and safety critical equipment. The study [100] focuses on CM and PdM of generators through the implementation of an IoT framework. The research involves gathering diverse data related to overloading and vibrations in generators. The study proposes an IoT-based system designed to predict failures in generators. Another research work [101] presents a self-powered IoT solution for monitoring a high-voltage substation connector. It takes power from the substation and monitors temperature, current, and voltage drop to calculate electrical contact resistance. The data is transmitted via Bluetooth to gateways and then sent to servers for storage, analysis, and visualisation. The study [102] proposes predictive maintenance for coal mining equipment using IoT technology. The approach enables the prediction of equipment failure or defects which can help in the prevention of accidents in the coal mines. A framework for remotely monitoring refrigerant cold storage systems through a wireless sensor network and data acquisition is introduced in this study [103]. The focus of the study is on predictive maintenance, employing intelligent algorithms to enhance system reliability. The research study [104] introduces a novel analytical framework based on IoT, specifically designed for vibrational analysis of equipment. The results demonstrate effective results for PdM and estimating RUL of machinery. A novel IoT architecture for a semi-supervised learning technique is proposed to enhance sensor feature selection in the Consensus Self-organised Model Approach (COSMO) in the research work [105]. COSMO serves as a tool for PdM technique in public transport buses, identifying faulty buses from a fleet. In [106] IoT-based PdM is implemented on a welding machine to forecast manufacturing defects. Data from various sensors on the welding machine is collected through an IoT architecture. An ML model is used to predict abnormal welds, which help in carrying out the PdM of the welding machine.

## 3. Industry 5.0: a brief overview

With the adoption of Industry 4.0 by companies, it became evident that it placed a greater emphasis on digitisation and AI-enabled technologies to enhance production flexibility and efficiency, rather than giving top priority to fundamental principles like sustainability and a human-centric approach. The 5$^{th}$ industrial revolution, often referred to as Industry 5.0, is built on the synergy of human intelligence with intelligent systems and smart machines [107]. It focuses on creating more inclusive, human-centric, resilient, and sustainable industrial processes that not only aim for technological advancements but also prioritise the well-being of people and the planet. An illustration depicting the core principles and achieved outcomes of implementing Industry 5.0 is given in Fig. 5.

### 3.1. Definition and key features of Industry 5.0

Industry 5.0 marks a significant industrial transformation driven by human innovation. It represents the next evolutionary phase in the industrial revolution, building upon the foundations of Industry 4.0, which focused on automation, digitisation, and interconnectivity through various enabling technologies. Unlike its predecessor, Industry 5.0 places a strong emphasis on the integration of human intelligence with smart systems, bringing human creativity, decision-making, and complex problem-solving back into the manufacturing process. It aims to create more personalised, efficient, and sustainable production processes by leveraging the collaborative power of humans and machines. A clear definition of Industry 5.0, as highlighted by the European Commission [108], views it as a movement towards a more sustainable, resilient, and human-centric industry. This approach advocates for the balance between productivity and societal goals, ensuring that technological advancements contribute positively to both economic growth and the well-being of society at large. The core principles of Industry 5.0 include:

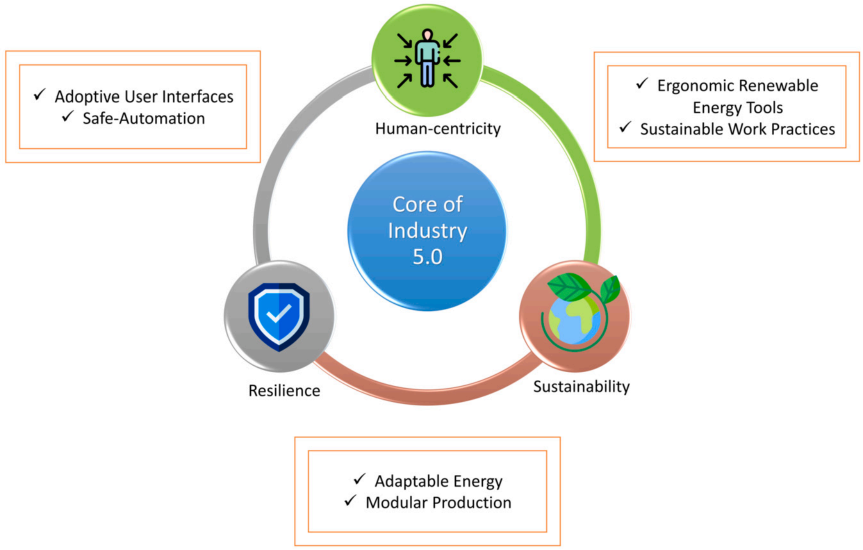


**Fig. 5.** Key principles and achieved outcomes of Industry 5.0.

#### 3.1.1. *Human-centricity:*

Human centricity in Industry 5.0 underscores the importance of putting human workers at the forefront of the industrial processes, not merely as operators or supervisors but as integral components of the creative and decision-making process. This approach values the unique cognitive and emotional capabilities of humans, such as creativity, empathy, and ethical judgment, ensuring that technological advancements contribute positively to societal needs, worker satisfaction, and well-being. Human-centric initiatives in Industry 5.0 aim to leverage technology to augment human abilities, enabling personalised production, enhancing safety, and ensuring that technology serves to improve the quality of life. This paradigm shift advocates for sustainable development, ethical considerations in automation, and ensuring that technological progress does not come at the expense of human employment or well-being.

#### 3.1.2. *Resilience*

Developing flexible and adaptable manufacturing systems that can quickly respond to changes and disruptions. Resilience in the context of Industry 5.0 refers to the capacity of industrial systems to anticipate, prepare for, respond to, and recover from disruptions. This includes adapting to changes in market demand, supply chain interruptions, and other unforeseen challenges in a way that maintains operational continuity, protects the workforce, and minimises environmental impact.

#### 3.1.3. *Sustainability*

While prioritising environmental sustainability through efficient use of resources, reduction of waste, and minimisation of the carbon footprint, sustainability in Industry 5.0 focuses on integrating environmental considerations into the core of industrial processes, aiming to achieve economic growth without depleting natural resources or harming the ecosystem.

The ultimate aim is to elevate living standards, foster innovative solutions, and produce high-quality customised products according to Michael Rada, the founder and leader of Industry 5.0 [109]. According to Friedman and Hendry [110], Industry 5.0 necessitates that professionals from various sectors such as industry, information technology and philosophy collaborate to achieve integration of human elements with technologies within industrial systems.

In the upcoming section, we delve into the enabling technologies that serve as the driving force behind the implementation of key principles of Industry 5.0.

### 3.2. *Enabling technologies*

Industry 5.0's focus on human centricity, resilience, and sustainability is supported by a suite of enabling technologies of Industry 4.0 that drive its implementation and achievement. These technologies facilitate the seamless integration of human intelligence with machine efficiency, ensuring industrial systems are more adaptive, environmentally friendly, and capable of enhancing human well-being. Fig. 6 illustrates how the enabling technologies are shaping the modern industrial landscape. Following section contains the brief overview of these enabling technologies.

**Edge Computing (EC):** Data processing at the network edge. Edge Computing (EC) uses IoT devices and perform necessary data processing at edges. EC has the capability to fulfil expectations concerning latency costs, battery life constraints, response time requirements, data protection, and privacy [111]. EC reduces communication overhead, enables efficient remote computing, and addresses data security concerns, which are significant in Industry 5.0, through local data handling. The study carried out in [112] detects anomalies at the edges. The study employs edge computing devices in order to enhance the real-time condition monitoring of the machinery. The device is powered by an autoencoder, which is a deep learning model, enabling it to analyse the data locally to detect anomalies such as unexpected vibrations and temperature spikes. This system identifies the potential issues instantaneously by processing the data at edges without relying on constant communication with the central servers hence reducing the computational requirements of the central servers. The study also highlights how the employed system reduced latency and bandwidth usage.

**Digital Twins (DTs):** The term "DT" stands for Digital Twin, which refers to the digital replication of physical systems, equipment, or machinery. This concept encompasses the digital modelling of various equipment, machinery, and systems. The scope of DTs is vast, enabling the digital representation of factories, wind farms, jet engines, and even entire cities [113]. The advent of IoT devices has further enhanced the potential of DTs by connecting them to the real world. This connectivity enables the collection of real-time data from physical systems, which can then be processed within the digital model. This not only allows for real-time condition monitoring but also supports early fault prediction, making DTs a valuable tool in various industries [114]. A case study presented in [40] employs digital twin (DT) technology for predicting tool wear of a CNC cutting tool. A digital counterpart of the cutting tool was built both with the physics-based and data-driven approaches. DT model had an ability of mapping the actual physical machine tool's operating

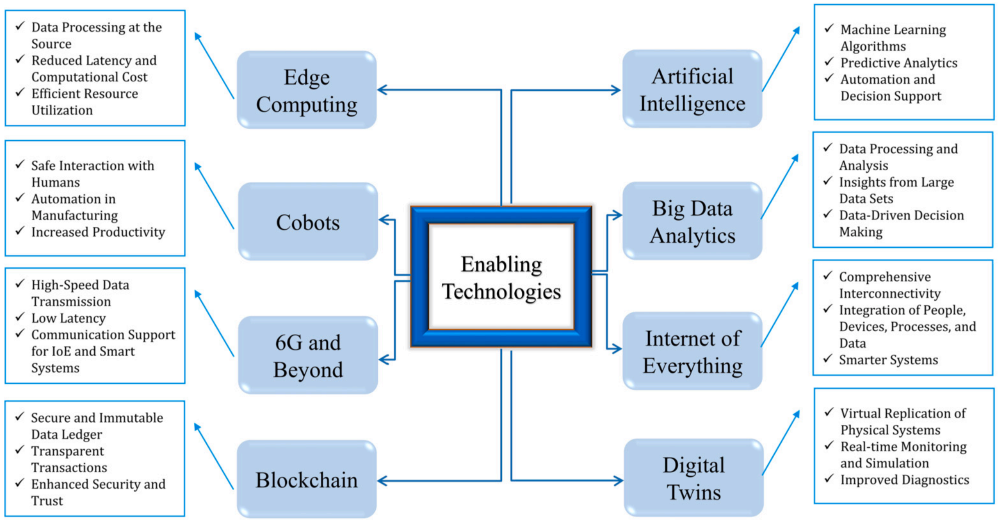


**Fig. 6.** An overview of how the enabling technologies are shaping the landscape of Industry 5.0.

conditions. Sensors such as accelerometer, dynamometer and acoustic emission sensor provided the model with the real-time data. The model utilised a hybrid technique based on both the physics-based model simulation and data-driven approaches to predict tool wear. It was found that the DT model predicts a better result with this hybrid approach instead of using model-based simulation or data-driven approach alone. This study shows how DT technology is helpful in predicting the tool wear and to carry out necessary maintenance activities. Early tool-wear prediction helps not only in utilising the maximum useful life of cutting tool but also minimise the chance of using worn out tool, thereby reducing excessive maintenance and improving product quality side-by-side.

**Big Data Analytics:** The continuous advancement of digital technologies is generating vast volumes of data, collectively referred to as big data, sourced from diverse origins. In response, various analysis techniques and tools, including AI, ML, data mining, and data fusion, have been employed for preprocessing and analysing this substantial dataset [115]. Big data analytics assumes a vital role within Industry 5.0, aiding in the comprehension of consumer behaviour and the optimisation of production facilities. Moreover, it facilitates real-time data analysis, PdM, and equipment condition monitoring in smart factories, empowering experts to make informed and improved decisions. An example of how the big data-analytics is implemented in real life scenarios is also presented to further enhance the depth of this section. A study carried out in [50] showcases the implementation of big-data analytics and machine learning for condition-based maintenance of train axle bearings. This study employed an online-support vector regressor (OL-SVR), an ML model, to predict the remaining useful (RUL) life of a train axle bearing by using the big streams of data. The strategy adopted in the framework also incorporated a trade-off between the accuracy of the model and computational requirements. The framework receives the streams of big data, uses a trained OL-SVR to analyse and predict the RUL of train axle bearing. Hence, providing a vital information about RUL to avoid accidents linked to breakdown of axle bearings.

**Internet of Everything (IoE):** The concept of the IoE integrates people, processes, and systems into a more extensive and interconnected ecosystem [116]. It builds upon the foundation of the Internet of Things (IoT), facilitating seamless integration with diverse systems. Within the context of Industry 5.0, IoE contributes to the establishment of innovative facilities, the development of intelligent systems capable of harnessing human intelligence for enhanced performance, the facilitation of effective maintenance procedures, and the optimisation of informed production systems. This concept holds the potential to drive advancements and improvements across various industrial domains.

**Cobots (Collaborative Robots):** The rapid progress in automation and AI has necessitated close collaboration between humans and robots, giving rise to collaborative robots, or cobots. The concept of cobots traces back to their initial development in 1996 by Professor Edward Colgate and Michael Peshkin of Northwestern University [117]. In the present day, modern cobots have become indispensable in tasks demanding high precision, posing safety concerns for human workers, repetitive operations, and labour-intensive functions. These robots are equipped with highly efficient sensors that make them exceptionally responsive, ensuring reliability in collaborative work settings with humans. This collaboration enhances productivity and safety across a wide range of industrial applications. Moreover, cobots contribute to PdM by providing real-time data, continuous monitoring, efficiency, and safety, all of which enhance the ability to predict equipment failures and perform timely maintenance, ultimately reducing downtime and operational costs improving sustainability and resilience of the industrial settings.

**Blockchain Technology:** Blockchain technology is a pivotal enabler of Industry 5.0, providing a foundation for secure peer-to-peer communication and an immutable ledger for digital record-keeping [118]. It embodies the principles of decentralised record management, accommodating a diverse array of interconnected devices. The immutability inherent to this technology significantly enhances data security and transparency, addressing core concerns in the digitally interconnected world.

**6G and Beyond:** 6G and beyond represent the future development in the wireless communication technology and is based upon the foundation laid by 5G. These technologies are expected to deliver higher data rates, lower latency, and extremely reliable communication network [119]. They will empower augmented and virtual reality experiences, enhance the efficiency of production processes, aid in remote equipment monitoring, and facilitate PdM implementation. Additionally, they will also support high-definition video streaming, and meet the extensive connectivity requirements of IoT.

The progression of enabling technologies has paved the way for their widespread application across a diverse industrial landscape. These technologies, spanning sectors from healthcare [120,121] to energy generation [122,123], are driving the evolution of conventional processes into intelligent and efficient manufacturing systems. Table 4 highlights the diverse applications of enabling technologies that are helping transform traditional industrial systems.

**Table 4**
Application areas of enabling technologies.

| Area | Enabling Technology | Application | References |
|---|---|---|---|
| Energy Generation | ML, DT, IoT | PdM, PHM, Fault Prediction, RUL prediction | [95], [39], [54], [124] |
| Production/ Manufacturing | Cobots, IoE | Cobots-based manufacturing, Smart Manufacturing | [125], [126], [127] |
| Healthcare Industry | IoT, Cobots, ML, AI | Remote health monitoring, cobots-based surgeries | [128], [129], [130] |
| Building and Architecture | DT, IoE, ML | Building Information Modelling (BIM), smart cities | [131], [132], [133] |
| Automotive | DT, IoT, AI | Autonomous vehicles, RUL prediction | [66], [134], [22], [135] |
| Process Industries | Edge computing, IoT, Big Data, DT | Real-time process monitoring, diagnostics and prognostics | [136], [137], [138] |
| Supplychain | Blockchain, IoT, DT | Asset tracking, smart contracts, demand forecasting | [139], [140], [141] |

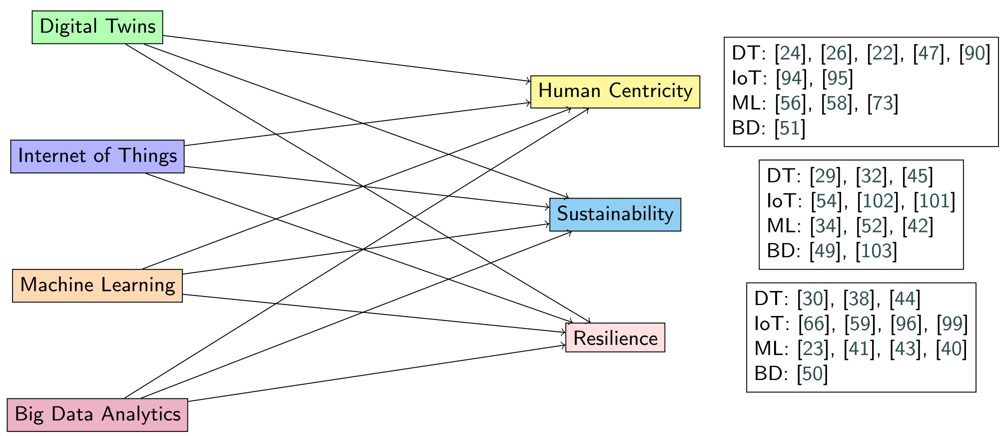


**Fig. 7.** Mapping enabling technologies to Industry 5.0 principles.

## 4. Mapping PdM and CM in Industry 4.0 to Industry 5.0

In the progression towards a more human-centric, sustainable, and resilient industrial future, Industry 5.0 principles significantly enhance the approach to Predictive Maintenance (PdM) and Condition Monitoring (CM). This transformation is facilitated by leveraging advanced technologies such as Digital Twins (DT), Big Data Analytics, Machine Learning (ML), and the Internet of Things (IoT). By analysing selected research papers, this section aims to map how these enabling technologies have evolved from Industry 4.0 to Industry 5.0, focusing on their role in fostering human-machine collaboration, optimising resource utilisation, and building robust PdM and CM systems. A mapping diagram is provided in the Fig. 7 which highlights how the various research work on PdM and CM based on enabling technologies maps with the key principles of Industry 5.0.

### *4.1. Human-centric PdM and CM practices:*

The foundation of human-centric Industry 5.0 principles lies in promoting a collaborative environment between humans and intelligent machines. This section explores how the selected papers leverage enabling technologies to promote this synergy within PdM and CM practices. These innovations not only enhance the efficiency and reliability of maintenance strategies but also foster a more interactive and intuitive interface between humans and machines. This section aims to investigate how these technologies empower human decision-making and equip technicians with advanced tools. The development of a digital model for an industrial robot, as discussed in [24], exemplifies the progression towards technologically enhanced PdM through the lens of human-machine collaboration. This approach not only facilitates maintenance but also bridges the gap between the physical and digital realms, enabling more precise and proactive maintenance decisions. Similarly, the study [26] and [22] demonstrates how real-time data from an automotive braking system can be integrated into a Digital Twin model, offering a tangible example of technology's role in streamlining maintenance processes and increasing the safety of the concerned personnel by enabling monitoring, prognostics, and diagnosis of automotive braking systems. This integration not only aids in the accuracy of maintenance predictions but also enhances the maintenance experience by making it more interactive. The utilisation of Digital Twin (DT) and Augmented Reality (AR) technologies in the manufacturing sector, as explored in [47] and reiterated in another study [90], enriches the predictive maintenance framework. By providing an immersive and intuitive platform for technicians, these technologies significantly improve the way maintenance needs are understood and predicted, marking a significant step towards technology-driven, human-centered maintenance practices.

Explorations into model-free deep reinforcement learning for optimising resource management in PdM [56], along with studies employing reinforcement learning for crafting maintenance strategies [58], underscore the potential of machine learning in enhancing human-machine collaboration. These approaches not only streamline the decision-making process but also ensure that human resources are optimally utilised, reflecting a nuanced application of technology in maintenance practices. The study [59] presents an AI-powered framework for PdM that assists maintenance teams in optimising maintenance plans, potentially reducing costs and workload by predicting engine life and scheduling repairs efficiently. The study [71] proposes a Decision Support System (DSS) that aids human decision-making for implementing PdM in industry. The system analyses costs and helps determine if PdM with Decision Trees is economically beneficial compared to traditional corrective maintenance. The research [73] combines human expertise with machine learning (LFGRU networks) to improve PdM tasks like tool wear and gearbox failure prediction. This collaboration between human and machine learning can potentially lead to more accurate and reliable fault detection.

The employment of data mining and IoT in developing a maintenance alert system for solar panels [54] underscores the shift towards a proactive maintenance culture. This system allows maintenance teams to anticipate potential issues, ensuring the reliability and safety of operations. Furthermore, the integration of Building Information Modelling (BIM) and IoT for Facility Maintenance Management [94], along with the deployment of Industrial Internet of Things (IIoT) devices for data monitoring [95], highlight the growing reliance on technology to support human decision-making in the maintenance domain. Innovations in IoT for predictive maintenance, as seen in studies focusing on welding machines [106], coal mining equipment [102], and motor bearing failure prediction [98], offer promising avenues for enhancing maintenance efficiency and safety not only for maintenance teams but also for the machines, significantly contributing to the operational reliability and safety of industrial systems. The proposal of an IoT architecture for predictive maintenance in public transport buses [105] emphasises the role of sensor data in improving maintenance outcomes. By focusing on feature selection and fault identification, this approach exemplifies how technological advancements can be leveraged to enhance maintenance efficiency and safety, reflecting a commitment to both operational excellence and human welfare. Through these examples, it is evident that the integration of enabling technologies into PdM and CM practices not only enhances operational capabilities but also fosters a more engaged and informed maintenance process. By bridging the gap between humans and machines, these technologies lay the groundwork for a future where maintenance practices are not only more efficient but also more attuned to the needs and safety of human operators.

### 4.2. Sustainability in industrial maintenance

The adoption of advanced technologies in predictive maintenance and condition monitoring is paving the way for more sustainable industrial maintenance practices. By leveraging digital twins, machine learning, big data analytics, and IoT, industries are moving towards maintenance strategies that not only ensure operational efficiency but also prioritise resource conservation and environmental sustainability. The study [29] demonstrates how bridging physical and digital processes in tunnel furnace systems can lead to significant reductions in operational costs and downtime. This study [32] highlights the application of DT technology for monitoring knuckle boom cranes, facilitating life cycle assessments to optimise PdM schedules and efficiently utilise resources. This study [45] focuses on the use of DT technology across various industries to facilitate dynamic and efficient PdM decision-making, ensuring optimal resource utilisation. The research work [49] focuses on employing Big Data analytics in PdM and CM to streamline maintenance schedules and curtail superfluous resource usage. A methodology for increasing production system transparency via Big Data is proposed in [51], leading to more effective PdM strategies. The study [34] showcases modelling subsea pipelines using machine learning to predict maintenance needs, contributing to both operational efficiency and resource conservation. This research [52] introduces and demonstrates a maintenance strategy that merges condition-based and opportunistic maintenance for offshore wind farms, showcasing a method for significant cost reduction and efficient resource management.

The implementation of an IoT-based maintenance alert system for solar panels is presented in this study [54], aiming to detect early faults and extend the operational life of the panels, reflecting a commitment to reduce resource consumption and electronic waste. By focusing on analysing sensor data from mechanical transmission systems, this study [42] creates maintenance strategies that enhance efficiency while minimising unnecessary resource expenditure. The study [50] utilises real-time sensor data to improve the reliability and longevity of train axle bearings, embodying efficient use of resources and enhancing component lifespan. The study [103] emphasises remote monitoring of refrigerant systems to preemptively address maintenance needs, thereby enhancing system reliability and averting energy waste. This study [101] introduces a self-powered IoT solution for monitoring high-voltage substations, emphasising proactive maintenance to prevent failures and ensure efficient energy use. These initiatives underscore a transformative shift in industrial maintenance practices, where the deployment of innovative technologies is not solely focused on enhancing operational efficiencies but also embodies a profound commitment to sustainable development and responsible resource management. This alignment of technology with sustainability goals marks a pivotal step towards a more environmentally conscious and resource-efficient future in industrial maintenance.

### 4.3. PdM and CM for a resilient industrial system

The evolving landscape of PdM and CM in industrial systems through the use of enabling technologies has led to an extended lifespan of machines. These maintenance practices are resulting in systems that can adapt to and robustly withstand operational stresses. These innovations encapsulate a proactive shift towards ensuring operational continuity and efficiency, central to the resilience of critical infrastructures. The development of predictive frameworks for complex systems, such as aero-engines utilising deep learning algorithms like Long Short-Term Memory (LSTM) as seen in studies like [23], exemplifies the strategic foresight in preempting potential system failures. Similarly, the introduction of multi-degree-of-freedom (DOF) torsional models for offshore wind turbine drivetrains, facilitated by DT technology in [30], and the use of edge computing for real-time monitoring and anomaly detection in chillers as discussed in [38], underline the critical measures undertaken to safeguard essential infrastructure. The automation of maintenance decision-making processes through ML and DT, leveraging operational data for improved responses, represents a dynamic approach to maintenance planning. This dynamic is further enriched by integrating data fusion techniques to enhance predictive accuracy, as shown in the aerospace maintenance operations explored in [43]. The DT-driven hybrid approaches based on ML for PdM, such as those applied to CNC machine tools in [40], and innovative fault detection mechanisms that facilitate rapid adaptation to faults, exemplified in [41]. Ensuring continuous monitoring by employing DT for the condition monitoring of wind turbine drivetrains, as noted in [44], underscores the strategic advancements towards ensuring equipment longevity and system robustness.

The essence of industrial resilience is captured in strategies enabling early detection and maintenance of crucial components. For instance, utilising IoT frameworks for predictive health management in various industrial applications, such as those discussed in [96] and [99], highlights a commitment to predictive maintenance. This commitment is evident in the integration of real-time monitoring systems with IoT, enhancing the accuracy of predictive maintenance and the responsiveness of maintenance operations, as seen in studies like [66] and [59]. Moreover, the integration of IoT with advanced data analytics, as demonstrated in [55] and [104], exemplifies a paradigm shift towards maintaining uninterrupted operational resilience. Whether through vibrational analysis for early fault detection or the application of IoT for predictive maintenance to prevent unplanned outages, these strategies underscore the critical integration of technological advancements with maintenance practices. Through these diverse applications of DT, ML, and IoT technologies, the industrial maintenance landscape is undergoing a transformative shift towards inherently resilient practices. This paradigm not only signals a move towards more dependable and efficient industrial operations but also highlights the indispensable role of advanced technologies in crafting the future of industrial maintenance practices.

This transformative shift sets the stage for a comprehensive, multi-layered framework for PdM and CM in Industry 5.0. The proposed framework aims to integrate these technological advancements into a cohesive structure, enhancing the resilience and efficiency of industrial systems. The next section outlines this proposed layered framework, detailing the strategic implementation of PdM and CM within the Industry 5.0 paradigm.

## 5. Framework for PdM and CM in Industry 5.0

The industrial landscape has witnessed profound transformations through the successive waves of industrial revolutions, each marked by significant technological innovations. The advent of Industry 4.0 revolutionised traditional maintenance practices by integrating industrial systems and the Internet of Things (IoT), leading to unprecedented levels of data-driven decision-making in industry [142]. As Industry 4.0 matures, the emergence of Industry 5.0 brings forward a paradigm that not only emphasises efficiency and digitisation but also re-introduces the human element into the automation loop, fostering a collaboration that aims to combine the strengths of both human creativity and technological precision [107]. Predictive Maintenance (PdM) and Condition Monitoring (CM) have been at the core of this technological advancement, providing substantial reductions in unplanned downtime and maintenance costs. These practices have evolved from reactive strategies to highly sophisticated systems powered by data analytics and real-time monitoring technologies. In Industry 4.0, PdM and CM relied heavily on the capabilities of IoT and Big Data to predict machinery failures before they occur, thereby optimising maintenance schedules and extending equipment life [9]. However, despite these advancements, the integration of human-centric approaches was often secondary.

Industry 5.0 seeks to balance automation with human expertise, aiming to create more sustainable, resilient, and customised production processes. This new industrial phase emphasises not only the continuation of technological innovation but also the enhancement of worker satisfaction and environmental sustainability. Thus, the framework for PdM and CM in Industry 5.0 must adapt to these shifts by incorporating advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Digital Twins, while also enhancing the interaction between humans and machines through interfaces like Augmented Reality (AR) and Virtual Reality (VR) [143]. The transition to Industry 5.0 offers an opportunity to redesign PdM and CM systems to be more resilient and adaptable to changes, ensuring that maintenance processes are not only predictive but also responsive to unexpected conditions and capable of learning from new data. This integration promises to enhance operational efficiencies and foster environments where technology amplifies human potential, leading to maintenance strategies that are not only effective but also align with broader societal and environmental goals.

This section will explore a framework as illustrated in 8 that embodies these principles, ensuring that PdM and CM not only prevent failures but also contribute to the sustainability and resilience of industrial operations.

### 5.1. Data acquisition layer

The initial step in any predictive maintenance and condition monitoring system is the acquisition of high-quality data. In Industry 5.0, the data acquisition layer extends beyond traditional sensors, incorporating a sophisticated array of IoT devices capable of capturing a wide range of operational data in real-time. This layer is foundational, as it sets the groundwork for all subsequent analysis and predictive actions.

- The integration of advanced sensors and IoT technology forms the backbone of modern PdM and CM systems. These sensors collect critical data points such as temperature, pressure, vibration, and acoustics, which are essential for monitoring the health and performance of machinery. In Industry 5.0, the role of IoT devices expands to include not only data collection but also the proactive interaction with machine operators and maintenance systems. According to [98], IoT devices enable real-time data streaming that supports instant diagnostics and predictive analytics, enhancing the responsiveness of maintenance systems.
- With the advent of smart sensors equipped with onboard processing capabilities, data acquisition in Industry 5.0 includes preliminary data analysis at the source. These smart sensors can filter and preprocess data, transmitting only relevant information to central systems, thereby reducing bandwidth usage and enhancing data quality [144]. Enhanced connectivity solutions such as 5G technology further enable seamless and efficient data transmission, supporting a robust data infrastructure critical for real-time monitoring and analysis.
- One of the challenges faced in the integration of new IoT technologies is interoperability between different devices and existing enterprise systems. To address this, Industry 5.0 emphasises the development of standards and protocols that ensure seamless integration of heterogeneous devices with ERP and MES systems. This integration enables a holistic view of operational data, facilitating cross-functional data analysis and decision-making [145]. Ensuring that data flows smoothly between sensors, machines, and decision platforms is crucial for the effective implementation of predictive maintenance strategies.
- As the reliance on IoT devices and interconnected systems grows, so does the vulnerability to cyber threats. Protecting the integrity and confidentiality of data in transit and at rest becomes paramount. Implementing robust cybersecurity measures, including encryption and secure data transmission protocols [146], is essential to safeguard maintenance data from unauthorised access and cyberattacks.

In the context of Industry 5.0, the data acquisition layer not only supports predictive maintenance but also contributes to sustainability by optimising machine use and reducing wasteful practices. By enabling more precise monitoring and data-driven decisions, this layer supports the overarching goals of Industry 5.0 to enhance efficiency, reduce environmental impact, and improve overall productivity in a human-centric manner.

### 5.2. Data processing and analytics layer

The Data Processing and Analytics Layer is where the raw data collected by sensors and IoT devices is transformed into actionable insights. In the context of Industry 5.0, this layer not only leverages traditional data processing techniques but also incorporates advanced technologies such as edge computing, machine learning, and artificial intelligence to enable real-time, predictive, and adaptive maintenance strategies.

- **Edge Computing:** To manage the vast amounts of data generated by modern industrial systems and minimize latency in critical operations, edge computing has emerged as a pivotal technology. By processing data near the source rather than relying on distant cloud servers, edge computing ensures rapid response times and reduces bandwidth demands on central systems [147]. This is crucial for maintenance tasks that require immediate action to prevent equipment failure or to mitigate potential hazards.
- **Machine Learning and Artificial Intelligence:** Machine learning algorithms and AI are integral to analysing the complex datasets gathered from various sensors and IoT devices. These technologies can identify patterns and predict potential failures before they occur, significantly enhancing the effectiveness of maintenance schedules. For instance, predictive models can forecast equipment wear and tear based on operational data, allowing maintenance to be performed only when necessary, rather than at fixed intervals [67]. This not only extends the life of the equipment but also reduces unnecessary maintenance costs.

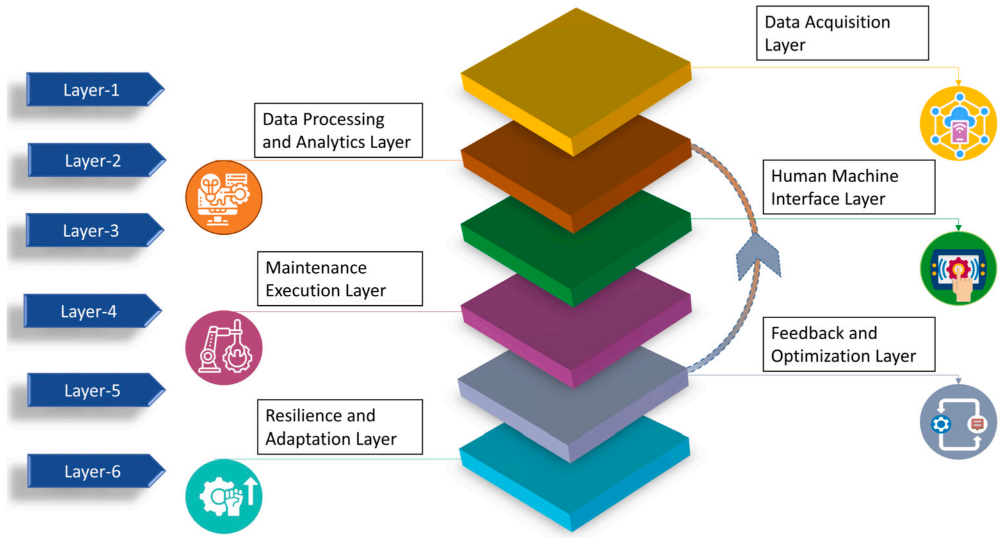


**Fig. 8.** Industry 5.0 framework for Predictive Maintenance and Condition Monitoring.

- **Digital Twins:** Digital Twins represent a technological leap in Industry 5.0, providing dynamic virtual models of physical systems that can be used for simulations and analysis. By integrating real-time data from IoT devices, digital twins allow for the continuous monitoring of systems and the simulation of potential changes to predict their effects on operations. This helps in fine-tuning processes and predicting future failures with high accuracy. Digital twins enable a deep understanding of machinery conditions and can significantly improve decision-making processes in maintenance management [39].
- Implementing comprehensive data analytics platforms that can integrate and analyse data from diverse sources is crucial. These platforms utilise advanced analytics techniques, including statistical analysis, trend analysis, and machine learning, to extract valuable insights from big data. The integration of these platforms with enterprise systems facilitates the dissemination of insights across various departments, ensuring that all relevant stakeholders have access to the information needed for informed decision-making [148].

In Industry 5.0, the Data Processing and Analytics Layer is not just about optimising maintenance; it's also about integrating human insights and enhancing operational transparency. This integration supports the human-centric goals of Industry 5.0, enabling workers to interact with systems more intuitively and make better-informed decisions based on reliable data insights. Moreover, the adaptive capabilities fostered by AI and machine learning contribute to the resilience and sustainability of industrial operations, aligning with the broader goals of efficiency and environmental stewardship.

### 5.3. Human-Machine Interface (HMI) layer

The Human-Machine Interface (HMI) Layer in Industry 5.0 serves as the critical junction where human operators interact directly with the advanced maintenance systems. This layer is designed to enhance the usability and effectiveness of predictive maintenance and condition monitoring by making complex data understandable and actionable for human users, thereby supporting more informed decision-making and efficient maintenance operations.

- Augmented Reality (AR) and Virtual Reality (VR) technologies play pivotal roles in modern HMIs by providing interactive and immersive experiences that bridge the gap between digital information and the physical world. AR can overlay critical information, such as machine performance data or maintenance instructions, directly onto a technician's field of view, enhancing understanding and reducing errors during maintenance tasks [90]. Similarly, VR can be used for training purposes, allowing maintenance personnel to simulate and practice complex procedures in a safe, controlled environment before applying them in real-world scenarios.
- Dashboards are essential tools in the HMI Layer, designed to aggregate and display data from various sources in an intuitive and accessible format. These dashboards provide real-time insights into system performance, alerts, and predictive maintenance recommendations, all tailored to be easily digestible by human operators. Advanced dashboards also incorporate user-friendly interfaces that allow workers to interact with the system, adjust parameters, and make informed decisions quickly based on real-time data.
- Incorporating a user-centric design philosophy in the development of HMIs ensures that the systems are accessible and useful to all workers, regardless of their technical expertise. This involves employing principles of ergonomic design, clear visualisations, and intuitive controls. Such designs help in reducing the learning curve and enhancing the overall user engagement with the technology [149].
- Effective HMIs in Industry 5.0 are equipped with feedback mechanisms that allow operators to provide inputs back to the system, which can be used to refine and optimise the maintenance processes. These mechanisms not only support continuous improvement but also empower workers by giving them a voice in how the systems operate, thereby fostering a more collaborative and responsive maintenance environment.
- To maximise effectiveness, HMIs need to be seamlessly integrated with broader enterprise systems such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) platforms [150]. This integration allows for a holistic view of the operational data and facilitates the coordination of maintenance activities across different departments and functions within the organisation [151].

The HMI Layer is critical in Industry 5.0 as it directly supports the human-centric approach that this new industrial era champions. By enhancing the interaction between human operators and the sophisticated maintenance systems, HMIs help in reducing complexity and making technology more accessible and beneficial to all users. Moreover, by improving the clarity and usability of information, HMIs contribute to quicker, more accurate maintenance decisions, which can significantly reduce downtime and enhance operational efficiency. This layer, therefore, not only supports the technical goals of predictive maintenance but also aligns with the broader objectives of Industry 5.0 to create more sustainable, efficient, and human-friendly industrial operations.

### 5.4. Maintenance execution layer

The Maintenance Execution Layer is where the strategies developed through data insights and human-machine interfaces are implemented. This layer focuses on the actual performance of maintenance tasks, optimising both the efficiency and effectiveness of these operations within the framework of Industry 5.0.

- In Industry 5.0, automated maintenance scheduling leverages AI-driven insights to optimise the timing and scope of maintenance activities. By predicting when maintenance should occur, rather than adhering to a rigid schedule, organisations can minimise downtime and extend the lifespan of their equipment. This approach uses data analytics to determine the optimal maintenance windows, balancing operational demands with maintenance needs, thereby ensuring that maintenance activities are conducted without disrupting production processes [152].
- The integration of robotics and automation technologies plays a pivotal role in enhancing maintenance tasks. Robots can perform dangerous or complex tasks with precision and without fatigue, increasing safety and efficiency. For instance, drones can be used for inspecting infrastructure in hard-to-reach areas, while robotic arms can handle high-precision tasks under hazardous conditions [153]. This not only improves safety by reducing human exposure to dangerous environments but also enhances the quality and speed of maintenance operations.
- While automation and robotics significantly enhance maintenance capabilities, human oversight remains crucial, especially in complex decision-making scenarios where human judgement is invaluable. Technicians and engineers oversee and intervene in the maintenance process, especially in situations where automated systems might not fully comprehend the nuances of a problem. This human-in-the-loop approach ensures that maintenance decisions are not only data-driven but also contextually informed, safeguarding against potential oversights by automated systems [154].
- Advancements in predictive maintenance enable a shift towards more proactive maintenance strategies. By not only predicting potential failures but also actively preventing them through timely interventions, Industry 5.0 maintenance practices move beyond mere prediction to prevention. This proactive approach minimises the risk of unexpected failures and maximises equipment availability and reliability [145].
- To effectively manage the sophisticated technologies used in Industry 5.0, ongoing training and skills development for maintenance personnel are essential. This ensures that the workforce is capable of operating advanced maintenance systems and can adapt to new technologies as they are integrated into the maintenance processes. Training programs often include simulations and VR-based modules to provide hands-on experience in a controlled environment, preparing maintenance staff for real-world scenarios [155].

The Maintenance Execution Layer is critical for translating the insights gained from predictive analytics into tangible actions that directly impact the efficiency and longevity of industrial operations. In Industry 5.0, this layer not only ensures the effective implementation of maintenance tasks but also upholds the human-centric principles of the era by enhancing worker safety and skill development. Furthermore, by integrating proactive maintenance strategies, this layer contributes to the sustainability and resilience of industrial operations, aligning with Industry 5.0's emphasis on sustainable practices and operational excellence.

### 5.5. Feedback and optimisation layer

The Feedback and Optimisation Layer in Industry 5.0 is vital for maintaining a cycle of continuous improvement in predictive maintenance and condition monitoring systems. This layer captures feedback from all previous layers, using it to refine processes, enhance system accuracy, and adapt to evolving operational conditions.

- Incorporating continuous learning mechanisms is essential for updating and improving the predictive models based on real-time operational data and feedback. As new data are collected and analysed, machine learning algorithms adjust to better predict failures and optimise maintenance schedules. This dynamic adaptation ensures that the models remain effective even as equipment conditions change or new types of faults emerge. Regular updates to the models can also account for changes in operational environments or production demands, thereby maintaining high accuracy and relevance [156].
- Continuous performance monitoring is critical to assess the effectiveness of maintenance interventions. By analysing outcomes, such as the frequency and nature of equipment failures post-maintenance, organisations can gauge the efficacy of their predictive maintenance strategies [157]. This monitoring helps in identifying areas where predictions may not align with actual outcomes, highlighting opportunities for improvement in both data handling and maintenance execution.
- This layer also incorporates metrics that evaluate the environmental impact of maintenance activities. These metrics include energy consumption, resource utilisation, waste production, and overall carbon footprint associated with maintenance processes. By tracking these metrics, companies can strive to reduce their environmental impact, optimising maintenance practices not only for operational efficiency but also for sustainability.
- Establishing robust feedback loops that integrate insights from the shop floor up to the management level is crucial for fostering a responsive and adaptive maintenance environment. These loops allow for the continuous flow of information between operators, technicians, and decision-makers, ensuring that insights gained from data analytics and field experiences are utilised to inform broader maintenance strategies.
- Active engagement with all stakeholders, including maintenance personnel, operators, and management, is essential for effective optimisation. By involving stakeholders in the review and refinement process, organisations can ensure that the maintenance strategies are practical, meet the users' needs, and are aligned with organisational goals. This inclusive approach improves the effectiveness of the maintenance procedures and builds a feasible set of maintenance performance indicators [158].

The Feedback and Optimisation Layer is instrumental in realising the full potential of a human-centric approach to predictive maintenance in Industry 5.0. It ensures that the systems are not static but are continually evolving based on actual performance data and user feedback. This layer supports the resilience of maintenance operations by enabling systems to adapt to changes and challenges swiftly. Moreover, by incorporating sustainability metrics, it ensures that maintenance processes contribute to the broader goals of environmental stewardship and sustainability, which are central to the ethos of Industry 5.0.

### 5.6. Resilience and adaptation layer

In Industry 5.0, the Resilience and Adaptation Layer is crucial for ensuring that PdM and CM systems are not only robust but also capable of adapting to unexpected changes and challenges. This layer focuses on building resilience into the systems and enabling them to dynamically adjust their operations in response to new data or external changes.

- Continuously analysing the robustness of the PdM and CM systems against potential disruptions, whether they are physical (such as equipment failure or environmental changes) or digital (such as cyber threats or data integrity issues). By identifying vulnerabilities and potential failure points within the systems, organisations can implement targeted strategies to mitigate risks and enhance system resilience. Regular resilience assessments help ensure that maintenance systems can sustain operations under a variety of stress conditions, thereby minimising downtime and preventing catastrophic failures [159].
- Adaptive predictive models are designed to adjust their parameters based on real-time data and changing conditions [160]. These models use machine learning algorithms that evolve as they are exposed to new operational data, allowing them to continually refine their predictions and recommendations. This adaptability is essential in industries where operational conditions can vary significantly, ensuring that the maintenance strategies remain effective and relevant under diverse scenarios.
- Utilising digital twins and advanced simulation tools, this layer allows for comprehensive scenario planning. Organisations can simulate various operational and failure scenarios to assess how their systems would respond. This proactive approach helps in identifying potential issues before they occur in the real world and allows for the refinement of maintenance strategies to handle those situations effectively [47]. It also aids in training personnel to respond effectively to emergencies, further enhancing operational resilience.
- Incorporating dynamic response systems within the maintenance framework enables rapid adjustments to maintenance schedules and procedures based on sudden changes or emergent issues. These systems can automatically reallocate resources, adjust priorities, and even initiate emergency protocols if needed, ensuring that the organisation can maintain operational continuity under various circumstances [161].
- Ensuring that feedback from all previous layers is integrated effectively into the resilience planning process is key. Learning loops that incorporate insights from the execution and feedback layers help in continuously updating the resilience strategies. This integration ensures that the lessons learned from past incidents and routine operations are used to strengthen the resilience of the maintenance systems.

The Resilience and Adaptation Layer is integral to achieving the goals of Industry 5.0, which emphasises not only efficiency and productivity but also the sustainability and adaptability of industrial operations. By building resilient and adaptive maintenance systems, organisations can ensure that they are prepared to handle both predictable wear and tear and unexpected disruptions. Furthermore, this layer fosters a culture of continuous improvement and learning, which is essential for maintaining the long-term viability and competitiveness of industrial enterprises.

## 6. Case study: implementing a layered framework for predictive maintenance and condition monitoring of a boiler feed-water pump in Industry 5.0

In the complex operational environment of steam power plants, the reliability of boiler feed-water pumps is important to maintaining continuous and efficient plant operation [162]. These pumps serve a critical function by supplying water to the boiler under high pressure, which is essential for steam generation. Historically, the maintenance strategies employed to ensure the operational integrity of these pumps have relied on reactive approaches. However, as the demands on power plants increase in terms of efficiency, sustainability, and reliability, these traditional methods are becoming increasingly inadequate. This case study explores the implementation of a layered framework for Predictive Maintenance (PdM) and Condition Monitoring (CM) in Industry 5.0 for a critical component—the Boiler Feed-Water Pump in a power plant. It addresses challenges traditionally associated with the maintenance of this specialised equipment and aims to provide a preliminary approach for the implementation of Industry 5.0 framework in PdM and CM.

### *6.1. Traditional maintenance challenges*

In steam power plants, the maintenance of boiler feed-water pumps is critical due to their direct impact on the operational efficiency and reliability of the entire facility. The traditional maintenance approaches face several challenges that, if not addressed, could significantly undermine the goals of Industry 5.0, which aims for resilience, sustainability, and human-centric industrial operations.

- **Frequent Unplanned Downtime:** One of the most pressing challenges is frequent unplanned downtime due to pump failures, causing partial or complete plant shutdowns. These shutdowns are disruptive and costly, leading to lost productivity and increased operational expenses [163]. The unpredictability of these failures complicates resource planning and allocation, contradicting Industry 5.0's goal of seamless and sustainable operational workflows.
- **Reactive Maintenance Practices:** Traditionally, the maintenance approach for these pumps is reactive. This approach often results in higher maintenance costs due to more severe damage that occurs when issues are not addressed promptly [164]. Reactive maintenance contradicts Industry 5.0's emphasis on predictive and proactive strategies, which leverage advanced technologies to forecast and solve problems before they lead to failure.
- **Lack of Real-Time Insights:** The absence of real-time insights into the operational health of the pump significantly hampers the ability to perform timely maintenance. Without accurate and real-time data, it is nearly impossible to implement predictive maintenance strategies effectively [165]. Industry 5.0 revolves around the integration of digital technologies that provide real-time data to optimise operations. The inability to access real-time insights is a barrier to achieving the high levels of operational efficiency and agility that Industry 5.0 aims for.

To address these challenges, the implementation of the developed framework as illustrated in Fig. 9 for PdM and CM is necessary. The approach for employing the layered framework for enabling the predictive maintenance of boiler feed-water pump is elaborated in the following section.

### *6.2. Industry 5.0 framework implementation*

*1. Data Acquisition Layer*

The deployment of Data Acquisition Layer forms the foundation of predictive maintenance for boiler feed-water pumps in an Industry 5.0 environment. This layer incorporates advanced IoT sensors strategically installed on the pump to continuously monitor vital parameters such as temperature, pressure, vibrations, and flow rates [166]. These sensors collect real-time data, providing a comprehensive view of the pump's operational health. This data is essential not only for identifying current issues but also for predicting future malfunctions. The integration of these sensors ensures seamless data capture, which is crucial for the subsequent layers of processing and analysis [167]. This layer enables the advanced predictive analytics that drive predictive maintenance decisions by collecting real-time data. Thereby laying the groundwork for a proactive maintenance strategy that significantly enhances operational efficiency and reliability.

*2. Data Processing and Analytics Layer*

Data collected by the sensors is processed locally using edge computing solutions, ensuring rapid response capabilities necessary for predictive maintenance. The local processing includes filtering and preliminary analysis, reducing the volume of data that needs to be sent

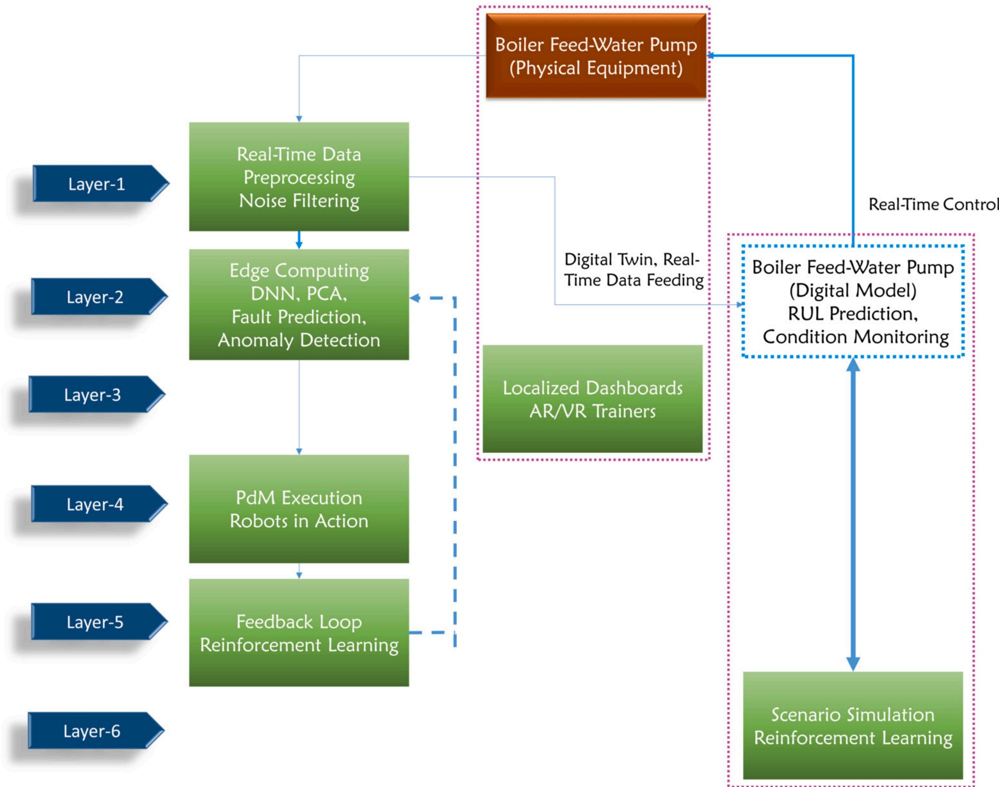


**Fig. 9.** Industry 5.0 implementation - a layered approach for enabling PdM and CM in a boiler feed-water pump.

to central servers, thus enhancing efficiency and reducing latency. The central feature of this layer involves the application of Deep Neural Networks (DNNs). These DNNs are trained on historical performance data alongside the real-time data collected by IoT sensors. By understanding both the historical and current operational signatures of the pump, DNNs can predict potential failure points with high accuracy [168].This capability allows maintenance teams to shift from a reactive maintenance model to a predictive one, addressing issues before failure. To accommodate changes in pump behaviour over the time due to wear and other operational influences, adaptive predictive models are employed. These models are capable of updating their parameters automatically in response to new data, ensuring that the predictive insights remain accurate and relevant. This adaptation is supported by machine learning techniques like online learning, where the model continuously updates itself without requiring a complete retraining process.

*3. Human-Machine Interface (HMI) Layer*

In the next layer, advanced HMI solutions are used to effectively translate the complex data and model outputs into actionable insights [169]. Customised local dashboards are used which provide real-time data visualisations designed for quick decision-making by maintenance staff [170]. These dashboards highlight critical metrics that predict maintenance needs, such as increased vibration levels or unusual temperature readings. AR tools are employed to overlay digital information, such as predictive insights and maintenance instructions, directly onto the technician's view of the physical equipment. This integration helps in reducing errors during maintenance tasks and speeds up the repair process by providing contextual information in real-time. This layer not only improves the efficacy of maintenance team but also helps in the execution of maintenance tasks with more accuracy and reduced time.

*4. Maintenance Execution Layer*

The next layer involves the execution of maintenance. The Maintenance Execution Layer is where the predictive insights generated from data analytics are put into action. In this layer, the integration of automated systems plays a pivotal role. By utilising the forecasts provided by predictive layer, this layer schedules maintenance tasks dynamically, ensuring they are conducted at the most opportune times without disrupting the plant's operations. Supported by the customised dashboards and AR tools to enhance the efficiency of maintenance team, this layer ensures the error free execution of maintenance tasks. The use of robotics and automated tools is crucial here, as they perform high-precision tasks such as shaft balancing and alignment and replacements which not only enhances safety by reducing human involvement in potentially hazardous activities but also increases the accuracy of maintenance procedures. This layer is critical as it translates predictive data into tangible maintenance actions that directly contribute to the durability and reliability of the boiler feed-water pump.

*5. Feedback and Optimisation Layer*

The Feedback and Optimisation Layer is deployed which is essential for refining the predictive maintenance process. It continuously collects data from all executed maintenance activities and analyses the outcomes to assess the effectiveness of the predictive models and the efficiency of the executed maintenance tasks [171]. This layer utilises tools like performance monitoring dashboards that provide insights into maintenance effectiveness, equipment reliability, and areas for improvement. Feedback from this layer is used to adjust the predictive algorithms, enhancing their accuracy and reliability. By creating a loop of continuous improvement, this layer ensures that the maintenance system adapts to changing conditions and remains optimal over time. It also promotes sustainability by optimising resource utilisation and waste reduction. Thus, aligning maintenance practices with the eco-friendly goals of Industry 5.0.

*6. Resilience and Adaptation Layer*

The Resilience and Adaptation Layer focuses on ensuring that the maintenance system can withstand and quickly recover from operational disruptions. It incorporates resilience analysis to identify and mitigate potential risks to the maintenance system, enhancing its ability to operate under a variety of stress conditions [172].Adaptive predictive models are employed which play a key role in this layer. These models are designed to adjust their strategies based on new data or changes in operational conditions. Reinforcement learning techniques are utilised which continuously learn and improve from each scenario. These techniques help in the evolution of boiler feed-water pump's predictive maintenance model along with its operating environment. This layer utilised a physics-based Digital Twin model of boiler feed-water pump, incorporating the real-time data from the Data Acquisition Layer which helps in scenario planning and simulations to forecast and prepare for potential future challenges. The simulations involved creating imaginary scenarios and evaluating the behaviour of the equipment and the predictive maintenance model. This proactive approach not only mitigates risks but also ensures that the maintenance strategies are robust, flexible, and capable of adapting to new challenges as they arise.

### 6.3. Projected outcomes

The design of layered framework for enabling Predictive Maintenance (PdM) and Condition Monitoring (CM) of the boiler feedwater pump would resolve the issues currently encountered with the reactive maintenance approach. By shifting to this advanced framework, the system will proactively identify and address potential failures, thereby improving reliability and efficiency. The associated benefits of utilising this framework are detailed below.

- The integration of advanced IoT sensors and real-time data processing through data processing and analytics layer would reduce the frequency of unplanned shutdowns by giving insights about the machine condition. Predictive analytics, powered by machine learning models such as Deep Neural Networks (DNNs), will enable the early detection of potential failures before they escalate into costly breakdowns. This proactive approach will minimise disruptions, ensuring continuous operation of the power plant.
- By shifting from a reactive to a predictive maintenance strategy, the framework would allow for maintenance activities to be scheduled and performed based on the actual condition of the equipment rather than on a fixed schedule or after the occurrence of failure. Not only would this approach reduce maintenance costs but also extend the lifespan of the equipment by preventing breakdowns and excessive wear and tear.
- Moreover, the deployment of digital twins and augmented reality tools within the maintenance framework would provide maintenance personnel with real-time insights into the operational health of the pump. These technologies offer a dynamic visualisation of performance and potential issues, empowering operators with immediate data to make informed decisions.

The achievements in tackling traditional maintenance challenges through this framework align closely with the key principles of Industry 5.0. This framework helps in achieving the Industry 5.0's goals of operational efficiency and sustainability by reducing unplanned downtime and enhancing the efficiency of maintenance processes. Additionally, the shift towards predictive maintenance and the empowerment of personnel with real-time data and sophisticated tools reflect Industry 5.0's human-centric approach. These technologies not only improve the safety and efficiency of maintenance tasks but also provide a more knowledgeable and proactive workforce, thereby enhancing both human and operational aspects of industrial practices. This alignment demonstrates that integrating advanced, intelligent technologies with a focus on human factors leads to a more resilient, efficient, and sustainable industrial environment.

## 7. Discussion

In an effort to explore the effective implementation and framework development for Predictive Maintenance (PdM) and Condition Monitoring (CM), an exhaustive review of the literature covering the enabling technologies of Industry 4.0 for PdM and CM implementation as presented in Section-2 has uncovered multi-dimensional insights. This literature underscores not only the inherent adaptability and flexibility of systems empowered by the integration of key technologies but also the pivotal role they play in steering maintenance practices towards a predictive and proactive future.The transition from traditional maintenance methods to advanced strategies rely on the enabling technologies such as Digital Twins (DT), Machine Learning (ML) and Internet of Things (IoT). DT enabled systems supported by Big Data analytics, offer insights crucial for condition monitoring and early fault detection. Similarly, the application of ML in predicting Remaining Useful Life (RUL) and anticipating faults demonstrates its potential in making industrial systems more self-aware and adaptable. The integration of ML into systems not only enhances decision-making processes for maintenance strategies but also showcases exceptional accuracy in fault prediction. Central to the integration of all these enabling technologies is IoT, which is facilitating communication between systems, processes, and human beings.

The mapping of PdM and CM based on these enabling technologies with the core principles of Industry 5.0 revealed several key insights. DT-enabled PdM and CM systems align closely with the human-centric approach of Industry 5.0 goals, followed by ML, which aids in decision-making processes. Moreover, DT, IoT, and ML-based predictive maintenance practices align with the sustainability goals of Industry 5.0, ensuring that industrial maintenance practices are more sustainable. Similarly, ML and IoT techniques for PdM and CM contribute to building resilient industrial systems, with DT providing useful insights for RUL prediction of machines. Through the implementation of these techniques, it is evident that the goals of Industry 5.0 in PdM and CM implementation are achievable. Additionally, with the advent of Augmented Reality (AR) and Virtual Reality (VR) techniques and customised interactive dashboards, the goal of human-centricity is further achieved. The six-layered approach based on this mapping helps develop a framework, as elaborated in Section-5, to ensure maintenance practices in the industry powered by the enabling technologies are in accordance with the key principles of Industry 5.0.

From the developed framework the data acquisition layer can provide interoperability and seamless integration with existing ERP and MES systems. This layer can prove instrumental in fusing the existing practices with this novel framework. In data processing and analytics layer the data, after being processed at the edges by edge computing, is utilised for identifying patterns and useful highlights to predict faults and potential failures beforehand. This layer integrates human insights by enabling workers to interact with systems and make informed decisions. The Human-Machine Interface (HMI) layer helps in making a collaborative approach for humans and machines. The maintenance execution layer executes the maintenance processes by AI-driven insights from the previous layer. Trained workers carry out specific tasks along with robots for high precision, risky, and hazardous tasks. The last two layers of this framework focus on incorporating adaptive learning to adapt to any changing scenarios such as wear and tear of machinery. Ensuring the PdM and CM framework can adapt to unexpected changes and disruptions, these layers help in building a resilient industrial system and contribute to sustainable maintenance practices. Dynamic response systems help in enabling rapid adjustments to maintenance schedules and procedures based on sudden changes or emergent issues.

The case study on the boiler feed-water pump in a steam power plant further illustrates the practical implications of the developed framework. Implementing the developed six-layer framework for this boiler feed-water pump's maintenance would result in reducing the unplanned downtime, provide PdM practices instead of reactive measures, and enable continuous condition monitoring of the equipment. Early fault detection using Deep Neural Networks (DNNs) architecture would help identify issues before they cause costly breakdowns. Incorporation of automated shaft balancing and alignment techniques would help in reducing risky work for humans, focusing on a safer work environment. Overall, this sustainable, resilient, and human-centric PdM and CM approach not only achieves better maintenance outcomes but also aligns with Industry 5.0 guidelines. While the research reviewed in this study significantly contributes to understanding and adapting Industry 5.0 principles and enabling technologies for PdM and CM applications, it also reveals notable gaps in the current literature. The upcoming section will delve into a detailed discussion of these gaps, providing insights into areas where further research and development could prove instrumental. Addressing these gaps is crucial for advancing the theoretical foundation of Industry 5.0-driven PdM and CM based on the core concepts of human-centricity, resilience, and sustainability, and for practical implementation in real-world industrial scenarios.

### *7.1. Current challenges, gaps and limitations*

The integration of Predictive Maintenance (PdM) and Condition Monitoring (CM) practices, based on key enabling technologies of Industry 4.0, in accordance with the principles of Industry 5.0 faces several challenges. These challenges also highlight the gaps and limitations in the existing research and implementation strategies.

One of the primary challenges is the integration of diverse and often incompatible data sources from various IoT devices and smart sensors. This issue leads to data fragmentation, creating large data silos that hinder the smooth and continuous data flow. Therefore reducing the effectiveness of PdM and CM practices. Moreover, the vast amounts of data generated from the industrial processes present a challenge in the form of data processing and storage. Industries struggle to implement scalable solutions that can handle big data efficiently. This represents a critical challenge where more advanced and cost-effective data management solutions are required. Another challenge is related to the processing of data that is, the accuracy and reliability of predictive models. Machine Learning (ML) algorithms require high-quality and well-curated datasets for their optimal performance. However, the presence of noisy, incomplete or biased data can lead to flawed predictions which may result in costly maintenance errors. This points to a limitation in current research where more robust methods for data validation and model training are necessary.

Existing research in PdM and CM reveals some noteworthy gaps. Firstly, the literature lacks a comprehensive view of Industry 5.0, with little to no emphasis on cross-industry collaboration, limiting the development of predictive maintenance strategies that are helpful across different industrial domains. Additionally, there is a lack of in-depth exploration into the application of edge computing for PdM and CM, hindering insights into its potential in optimising real-time data processing and reducing the required computational power at central servers. Human-centric considerations, such as user acceptance and behavioural aspects in the adoption of PdM and CM in the context of Industry 5.0 technologies, remain overlooked. Moreover, the intersection of predictive maintenance and collaborative robots (cobots) is under-explored, necessitating further research into the potential contribution of cobots for PdM and CM. There is also limited exploration of blockchain technology for industrial data, raising concerns about data integrity and security. The role of wireless communication-based sensors in PdM lacks thorough investigation, creating gaps in understanding their deployment and implications for a PdM-enabled industry.

The exploration and examination of the literature also highlighted some limitations associated with implementing PdM in the context of Industry 5.0. The heterogeneous nature of industries constitutes a significant challenge in developing a universally applicable PdM framework. The demand for customisation to accommodate industry-specific needs is a limiting factor in implementing PdM in Industry 5.0 settings. Furthermore, the adaptability of PdM and CM may be constrained by the expense-to-profit ratio, as industries with low-profit margins require a delicate balance between implementation costs and potential benefits. Addressing these gaps and limitations in future research can improve our understanding of PdM in the Industry 5.0 landscape. This effort aims to provide a more complete and detailed insight into how predictive maintenance strategies can be enhanced and adapted to meet the evolving needs of Industry 5.0.

## 8. Future challenges and way forward

### *8.1. Security of sensitive data*

Security of sensitive data is a critical aspect in the implementation of PdM and CM framework in Industry 5.0. The increasing connectivity and data exchange in Industry 5.0 can potentially expose systems to various cyber threats, raising questions about the integrity of the data being processed and exchanged. Blockchain technology acts as a robust solution within the principles of Industry 5.0 to address these security concerns. By employing blockchain for data storage and transactions, a decentralised and tamper-resistant system is established. This not only serves to enhance data security but also guarantees transparency and traceability throughout the system.

In the context of PdM and CM applications, blockchain technology can play a pivotal role in securing the integrity of maintenance records and sensor data. For instance, maintenance records stored on a blockchain become resistant to tampering, providing an immutable and auditable history of equipment health and maintenance activities. This aligns with Industry 5.0's emphasis on building a secure and transparent digital ecosystem. One of the key advantages of utilising blockchain in the context of PdM and CM is its ability to mitigate concerns related to data breaches and unauthorised access. With its decentralised nature, blockchain minimises the risk of a single point of failure, making it significantly more challenging for malicious actors to compromise the entire system. The cryptographic principles based on blockchain ensure that once data is added to the chain, it becomes virtually impossible to alter, ensuring the integrity of the information exchanged. Moreover, blockchain's distributed ledger technology promotes a collaborative and trustful environment. In Industry 5.0, where multiple stakeholders across the supply chain and ecosystem interact, blockchain provides a secure foundation for data sharing and collaboration. This is particularly beneficial in PdM and CM applications, where real-time information exchange among different entities, such as equipment manufacturers, service providers, and end-users, is crucial for effective decision-making.

While blockchain technology offers a promising solution by establishing a decentralised and tamper-resistant system, its application in industrial settings is still in its beginning. Future research should explore the scalability of blockchain solutions in large-scale industrial environments and address potential latency issues that could affect real-time data processing. Additionally, the combination of blockchain with other emerging technologies like quantum encryption could offer new avenues for enhancing data security. Moreover, industries must consider the legal and regulatory implications of adopting blockchain technology, specifically related to data privacy laws such as General Data Protection Regulation (GDPR). The establishment of industrial standards for blockchain implementation in PdM and CM would help not only in achieving broader transformation but also ensuring compliance with regulatory requirements. Collaborative efforts among industry stakeholders, cybersecurity experts, and policymakers will be essential in creating a secure and transparent digital ecosystem that aligns with the principles of Industry 5.0.

As the technology landscape evolves, new challenges and vulnerabilities may emerge. Therefore, staying vigilant and proactive in adapting security measures to the evolving threat landscape is crucial for ensuring the long-term efficacy of blockchain solutions in the context of PdM and CM within Industry 5.0. In conclusion, the adoption of blockchain technology for data security in Industry 5.0's PdM and CM applications not only aligns with the principles of a secure and transparent digital ecosystem but also presents a practical and effective solution to address existing and emerging challenges related to data integrity, breaches, and unauthorised access.

### 8.2. Excessive investments

For industries which are looking forward to implement advanced PdM and CM frameworks, the hurdle of excessive investment remains a significant challenge. The costs associated with the implementation of the layered framework for PdM and CM in Industry 5.0, such as data acquisition and data processing layer, can be substantial particularly for small and medium-sized enterprises (SMEs). Future strategies should focus on developing scalable and modular PdM systems that allow companies to implement these technologies in stages, spreading out the costs over time. Research into cost-benefit analysis models, specific to Industry 5.0 technologies, could provide industries with clearer insights into the long-term financial benefits of these investments. This will not only justify the initial expenditure but also encourage the decision-makers to take step for implementing these strategies.

A strategic and cost-effective approach to overcoming these challenges is embedded in adhering to Industry 5.0 principles. The collaborative nature of Industry 5.0 provides a framework for shared investments and resources among interconnected industries. By promoting cross-industry collaboration, the burden of investment can be distributed across multiple stakeholders, making advanced PdM and CM technologies more accessible and affordable for individual organisations. This collaborative approach aligns with the principles of Industry 5.0, emphasising a collective effort towards creating a connected and interdependent industrial ecosystem. As the industries work together the financial burden is reduced. Moreover, the implementation of PdM and CM strategies can be accelerated with the help of shared knowledge, expertise, and resources.

In addition, public-private partnerships and government-funded initiatives could play a critical role in reducing the financial burden on individual companies. An environment of shared resources across the industries could help SMEs to get access to PdM and CM framework implementation and take advantage of the advancements of Industry 5.0. Exploring alternative financing models, such as leasing or subscription-based services for PdM technologies, could also provide more flexible options for industries facing budget constraints.

Moreover, the collaborative and resource-sharing principles of Industry 5.0 can extend beyond financial considerations. Industries can share best practices, standardised protocols, and research findings, creating a collective intelligence that benefits all participants. This collaborative environment not only reduces costs but also fosters innovation and accelerates the maturity of PdM frameworks. Government initiatives and industry associations can play a pivotal role in facilitating this collaborative approach. By establishing frameworks for cooperation, providing incentives, and promoting the exchange of information and resources, these entities can contribute to the creation of a supportive ecosystem for the adoption of advanced PdM technologies. In summary, while the implementation costs associated with PdM and CM framework for Industry 5.0 may initially pose a challenge for the industries, the collaborative and resource-sharing nature of Industry 5.0 offers a strategic solution. By emphasising cross-industry collaboration, the financial burden can be distributed, making advanced PdM technologies more accessible, affordable, and ultimately promoting a collective environment conducive to innovation and progress in the realm of predictive maintenance.

### 8.3. Highly skilled manpower

The demand for highly skilled manpower is a pressing challenge in the implementation of Industry 5.0-centric predictive maintenance. As the industry transitions towards advanced technologies such as data analytics, AI, and ML, there is a growing need for professionals with expertise in these domains. The shortage of such skilled manpower is hindering the full realisation of the benefits associated with advanced PdM implementation. To address this challenge, industries must invest in comprehensive training and development programs that equip their existing workforce with the necessary skills. Research into the effectiveness of various training methodologies, such as on-the-job training, certifications, and continuous learning platforms, will be vital in ensuring that these programs are successful.

The integration of cobots and other automation technologies into maintenance processes can alleviate some of the pressure caused by the shortage of skilled workers, allowing human operators to focus on more complex, value-added tasks. By automating routine maintenance tasks through the use of cobots, organisations can optimise the utilisation of skilled personnel. This automation allows skilled professionals to redirect their focus towards higher-level decision-making and creative tasks which aligns with the human-centric approach promoted by Industry 5.0 principles. The integration of cobots not only addresses the shortage of skilled manpower but also enhances overall efficiency in PdM and CM processes by making a collaborative working environment with the help of human-machine integration.However, it is crucial to ensure that the collaboration between human workers and cobots is flawless and that the technology adjuncts rather than replaces human expertise. Future research should focus on optimising human-cobot interaction, exploring how augmented reality (AR) and virtual reality (VR) can be used to enhance training and ensure that workers are comfortable and effective in this new collaborative environment.

Industry 5.0 emphasises the importance of continuous learning. By utilising AR and VR techniques, workers can be trained to meet the skill requirements for implementing this PdM and CM framework. Organisations can invest in training programs to equip their workforce with the necessary skills to operate and manage advanced technologies.Additionally, the development of educational curricula that incorporate Industry 5.0 principles and technologies could help bridge the skills gap over the long term. By partnering with educational institutions, industries can help shape the next generation of workers who are well-prepared to navigate and excel in a rapidly evolving industrial landscape. These proactive approaches not only help in overcoming the current shortage of skilled manpower but also ensure that the workforce remains adaptable and proficient in the evolving technological landscape.

In summary, while the shortage of highly skilled manpower poses a challenge in implementing Industry 5.0-driven PdM and CM practices. The integration of cobots, promoting human-machine collaboration, using advanced techniques such as AR and VR and collaborating with educational institutions to train the manpower, can be effective solutions. These approaches allow skilled professionals to focus on higher-level tasks, optimising their expertise while addressing the shortage of skilled personnel for routine maintenance activities. Embracing the principles of Industry 5.0 provides a harmonious relationship between human capabilities and technological advancements, ultimately driving innovation and efficiency in predictive maintenance processes.

### 8.4. Interoperability and standardisation

Lack of interoperability and standardisation across different systems and platforms is another key challenge in advancing Predictive Maintenance (PdM) and Condition Monitoring (CM) within the Industry 5.0 framework. As industries increasingly adopt diverse technologies and solutions from various vendors, the ability for these systems to work together becomes vital. Without standardised protocols and interfaces, integrating data from different sources can be cumbersome which can lead to inefficiencies and potential errors in PdM and CM processes. Future research should focus on developing and promoting the standards that facilitate interoperability among different systems and devices. This includes communication protocols, data formats and exchange standards to ensure consistency and compatibility across diverse platforms. The development of open-source frameworks and tools could also play a significant role in promoting interoperability, allowing industries to customise and integrate different solutions more easily.

However, for standardisation to be effectively adopted, it is essential that industry leaders, technology providers, and regulatory bodies collaborate closely. These groups need to work together to develop and implement common standards that can be universally applied across the industry. Such collaboration is important for overcoming the challenges posed by proprietary systems, which often create barriers to interoperability and integration. By establishing these shared standards, the industry can create a more cohesive and efficient ecosystem where different technologies and systems can work together in an effective way. This is especially important as Industry 5.0 progresses, with an increasing focus on integrating advanced technologies like IoT, AI, and ML into a wide range of industrial applications. A standardised approach will ensure that these technologies can be effectively implemented and used to their full potential across the industry.

## 9. Conclusions

The integration of Industry 5.0 principles with advanced Predictive Maintenance (PdM) and Condition Monitoring (CM) technologies represents a major shift towards a more human-focused, resilient, and sustainable industrial approach. This study has thoroughly reviewed and synthesised existing literature to understand how technologies like Machine Learning (ML), Digital Twins (DT), the Internet of Things (IoT), and Big Data (BD) are laying the groundwork for moving PdM and CM practices from Industry 4.0 to Industry 5.0. Digital Twins have proven essential in creating human-centric maintenance environments by providing virtual replicas of physical systems that predict maintenance needs and facilitate intuitive decision-making processes. Big Data Analytics plays a crucial role in generating actionable insights, enabling industries to process vast amounts of data for optimized maintenance strategies and operational efficiency. Machine Learning, with its adaptive algorithms, enhances system resilience by predicting and mitigating potential failures. The IoT underpins these advancements by enabling seamless communication across diverse industrial settings and enhancing the efficacy of predictive maintenance through real-time data collection and analysis.

Our proposed six-layered framework for implementing PdM and CM in Industry 5.0 is a significant contribution to the field. It includes a data acquisition layer for real-time data collection, a data processing and analytics layer powered by edge computing and advanced ML algorithms, a Human-Machine Interface (HMI) layer for enhanced human-machine collaboration, a maintenance execution layer incorporating automation and robotics, a feedback and optimisation layer for continuous improvement, and a resilience and adaptation layer to help systems adapt to unexpected disruptions. The practical application of this framework is demonstrated through a case study on a boiler feed-water pump in a steam power plant. The implementation of this approach would result in reducing unplanned downtime, a shift from reactive to predictive maintenance, and continuous condition monitoring. The framework's early fault detection capabilities, AR tools for worker training, and automated maintenance processes, along with the integration of real-time data analytics and adaptive learning, would enhance system's resilience and safety. This approach aligns with Industry 5.0's goals of sustainability by reducing resource consumption and waste, human-centricity by improving worker training and collaboration, and resilience by ensuring systems can quickly adapt to changes and disruptions.

However, the journey towards fully realising Industry 5.0-driven PdM and CM is not without challenges. The study highlights several gaps in current literature, including the need for a comprehensive view of Industry 5.0, deeper exploration of edge computing, consideration of human-centric aspects, and the integration of collaborative robots (cobots). Addressing these gaps is essential for advancing both theoretical and practical aspects of Industry 5.0-driven PdM strategies. Looking forward, it is crucial to tackle challenges related to data security, investment costs, demand for skilled manpower, and interoperability and standardisation requirements. Blockchain technology offers promising solutions for ensuring data integrity and transparency. The collaborative nature of Industry 5.0 can help manage costs and standardise PdM practices, making advanced PdM technologies more accessible. Additionally, integrating cobots and enhancing human-machine collaboration can address the shortage of skilled labour.

## CRediT authorship contribution statement

**Aitzaz Ahmed Murtaza:** Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Amina Saher:** Writing – review & editing, Writing – original draft, Visualization, Software, Data curation. **Muhammad Hamza Zafar:** Writing – review & editing, Writing – original draft, Visualization, Resources. **Syed Kumayl Raza Moosavi:** Validation, Software, Writing – review & editing, Writing – original draft. **Muhammad Faisal Aftab:** Writing – review & editing, Writing – original draft, Validation, Supervision, Investigation. **Filippo Sanfilippo:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition.

## Declaration of competing interest

None.

## Data availability

No data was used for the research described in the article.


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## References


[1] J. Lee, B. Bagheri, H.-A. Kao, Recent advances and trends of cyber-physical systems and big data analytics in industrial informatics, in: International Proceedings of Int Conference on Industrial Informatics (INDIN), Citeseer, 2014, pp. 1–6.
[2] E. Sezer, D. Romero, F. Guedea, M. Macchi, C. Emmanouilidis, An industry 4.0-enabled low cost predictive maintenance approach for smes, in: 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), IEEE, 2018, pp. 1–8.
[3] M.-L. Tseng, M.I. Aslam, E.A. Ismail, F.A. Awwad, N.E. Gorji, Ct scan, ebsd and nanoindentation analysis of 3d-printed parts with post-process heat-treatment, Metall. Res. Technol. 121 (2024) 101.
[4] P. O'donovan, K. Leahy, K. Bruton, D.T. O'Sullivan, Big data in manufacturing: a systematic mapping study, J. Big Data 2 (2015) 1–22.
[5] R. Sahal, J.G. Breslin, M.I. Ali, Big data and stream processing platforms for industry 4.0 requirements mapping for a predictive maintenance use case, J. Manuf. Syst. 54 (2020) 138–151.
[6] M.S. Reis, G. Gins, Industrial process monitoring in the big data/industry 4.0 era: from detection, to diagnosis, to prognosis, Processes 5 (2017) 35.
[7] A. Stetco, F. Dinmohammadi, X. Zhao, V. Robu, D. Flynn, M. Barnes, J. Keane, G. Nenadic, Machine learning methods for wind turbine condition monitoring: a review, Renew. Energy 133 (2019) 620–635.
[8] W.Z. Khan, M. Rehman, H.M. Zangoti, M.K. Afzal, N. Armi, K. Salah, Industrial Internet of things: recent advances, enabling technologies and open challenges, Comput. Electr. Eng. 81 (2020) 106522.
[9] M. Pech, J. Vrchota, J. Bednář, Predictive maintenance and intelligent sensors in smart factory, Sensors 21 (2021) 1470.
[10] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of digital twin in cps-based production systems, Proc. Manuf. 11 (2017) 939–948.
[11] I. Errandonea, S. Beltrán, S. Arrizabalaga, Digital twin for maintenance: a literature review, Comput. Ind. 123 (2020) 103316.
[12] T.Y. Melesse, V. Di Pasquale, S. Riemma, Digital twin models in industrial operations: state-of-the-art and future research directions, IET Collab. Intell. Manuf. 3 (2021) 37–47.
[13] G. Falekas, A. Karlis, Digital twin in electrical machine control and predictive maintenance: state-of-the-art and future prospects, Energies 14 (2021) 5933.
[14] M. Singh, R. Srivastava, E. Fuenmayor, V. Kuts, Y. Qiao, N. Murray, D. Devine, Applications of digital twin across industries: a review, Appl. Sci. 12 (2022) 5727.

[15] S. Selcuk, Predictive maintenance, its implementation and latest trends, Proc. Inst. Mech. Eng., B J. Eng. Manuf. 231 (2017) 1670–1679.

[16] M. Tahan, E. Tsoutsanis, M. Muhammad, Z.A. Karim, Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: a review, Appl. Energy 198 (2017) 122–144.

[17] T. Zonta, C.A. Da Costa, R. da Rosa Righi, M.J. de Lima, E.S. da Trindade, G.P. Li, Predictive maintenance in the industry 4.0: a systematic literature review, Comput. Ind. Eng. 150 (2020) 106889.

[18] B. De Jonge, P.A. Scarf, A review on maintenance optimization, Eur. J. Oper. Res. 285 (2020) 805–824.

[19] A.K. Mallik, The future of the technology-based manufacturing in the European Union, Results Eng. 19 (2023) 101356.

[20] S. Vaidya, P. Ambad, S. Bhosle, Industry 4.0–a glimpse, Proc. Manuf. 20 (2018) 233–238.

[21] E.R. Griffor, C. Greer, D.A. Wollman, M.J. Burns, Framework for cyber-physical systems: volume 2, Working group reports, 2017.

[22] R. Magargle, L. Johnson, P. Mandloi, P. Davoudabadi, O. Kesarkar, S. Krishnaswamy, J. Batteh, A. Pitchaikani, A simulation-based digital twin for model-driven health monitoring and predictive maintenance of an automotive braking system, in: Modelica, 2017, pp. 132–133.

[23] M. Xiong, H. Wang, Q. Fu, Y. Xu, Digital twin–driven aero-engine intelligent predictive maintenance, Int. J. Adv. Manuf. Technol. 114 (2021) 3751–3761.

[24] P. Aivaliotis, K. Georgoulias, Z. Arkouli, S. Makris, Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance, Proc. CIRP 81 (2019) 417–422.

[25] H.H. Hosamo, P.R. Svennevig, K. Svidt, D. Han, H.K. Nielsen, A digital twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics, Energy Build. 261 (2022) 111988.

[26] P. Rajesh, N. Manikandan, C. Ramshankar, T. Vishwanathan, C. Sathishkumar, Digital twin of an automotive brake pad for predictive maintenance, Proc. Comput. Sci. 165 (2019) 18–24.

[27] P. Aivaliotis, K. Georgoulias, G. Chryssolouris, The use of digital twin for predictive maintenance in manufacturing, Int. J. Comput. Integr. Manuf. 32 (2019) 1067–1080.

[28] A. Barthelmey, E. Lee, R. Hana, J. Deuse, Dynamic digital twin for predictive maintenance in flexible production systems, in: IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society, vol. 1, IEEE, 2019, pp. 4209–4214.

[29] S. Mihai, W. Davis, D.V. Hung, R. Trestian, M. Karamanoglu, B. Barn, R.V. Prasad, H. Venkataraman, H.X. Nguyen, A Digital Twin Framework for Predictive Maintenance in Industry 4.0, 2021.

[30] F.K. Moghadam, G.F. d, S. Rebouças, A.R. Nejad, Digital twin modeling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains, Forsch. Ingenieurwes. 85 (2021) 273–286.

[31] R. van Dinter, B. Tekinerdogan, C. Catal, Reference architecture for digital twin-based predictive maintenance systems, Comput. Ind. Eng. 177 (2023) 109099.

[32] T. Moi, A. Cibicik, T. Rølvåg, Digital twin based condition monitoring of a knuckle boom crane: an experimental study, Eng. Fail. Anal. 112 (2020) 104517.

[33] A. Werner, N. Zimmermann, J. Lentes, Approach for a holistic predictive maintenance strategy by incorporating a digital twin, Proc. Manuf. 39 (2019) 1743–1751.

[34] S. Bhowmik, Digital twin of subsea pipelines: conceptual design integrating iot, machine learning and data analytics, in: Offshore Technology Conference, OTC, 2019, D011S010R004.

[35] Q. Qiao, J. Wang, L. Ye, R.X. Gao, Digital twin for machining tool condition prediction, Proc. CIRP 81 (2019) 1388–1393.

[36] S. Khan, M. Farnsworth, R. McWilliam, J. Erkoyuncu, On the requirements of digital twin-driven autonomous maintenance, Annu. Rev. Control 50 (2020) 13–28.

[37] F.K. Moghadam, A.R. Nejad, Online condition monitoring of floating wind turbines drivetrain by means of digital twin, Mech. Syst. Signal Process. 162 (2022) 108087.

[38] H. Huang, L. Yang, Y. Wang, X. Xu, Y. Lu, Digital twin-driven online anomaly detection for an automation system based on edge intelligence, J. Manuf. Syst. 59 (2021) 138–150.

[39] D. Zhong, Z. Xia, Y. Zhu, J. Duan, Overview of predictive maintenance based on digital twin technology, Heliyon (2023).

[40] W. Luo, T. Hu, Y. Ye, C. Zhang, Y. Wei, A hybrid predictive maintenance approach for cnc machine tool driven by digital twin, Robot. Comput.-Integr. Manuf. 65 (2020) 101974.

[41] Y. Xu, Y. Sun, X. Liu, Y. Zheng, A digital-twin-assisted fault diagnosis using deep transfer learning, IEEE Access 7 (2019) 19990–19999.

[42] S. Centomo, N. Dall'Ora, F. Fummi, The design of a digital-twin for predictive maintenance, in: 2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), vol. 1, IEEE, 2020, pp. 1781–1788.

[43] Z. Liu, N. Meyendorf, N. Mrad, The role of data fusion in predictive maintenance using digital twin, in: AIP Conference Proceedings, vol. 1949, AIP Publishing, 2018.

[44] S.S. Johansen, A.R. Nejad, On digital twin condition monitoring approach for drivetrains in marine applications, in: International Conference on Offshore Mechanics and Arctic Engineering, vol. 58899, American Society of Mechanical Engineers, 2019, V010T09A013.

[45] S. Mi, Y. Feng, H. Zheng, Y. Wang, Y. Gao, J. Tan, Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework, J. Manuf. Syst. 58 (2021) 329–345.

[46] K. Sivalingam, M. Sepulveda, M. Spring, P. Davies, A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective, in: 2018 2nd International Conference on Green Energy and Applications (ICGEA), IEEE, 2018, pp. 197–204.

[47] S. Rabah, A. Assila, E. Khouri, F. Maier, F. Ababsa, P. Maier, F. Mérienne, et al., Towards improving the future of manufacturing through digital twin and augmented reality technologies, Proc. Manuf. 17 (2018) 460–467.

[48] J. Lee, M. Azamfar, J. Singh, S. Siahpour, Integration of digital twin and deep learning in cyber-physical systems: towards smart manufacturing, IET Collab. Intell. Manuf. 2 (2020) 34–36.

[49] A. Kumar, R. Shankar, L.S. Thakur, A big data driven sustainable manufacturing framework for condition-based maintenance prediction, J. Comput. Sci. 27 (2018) 428–439.

[50] E. Fumeo, L. Oneto, D. Anguita, Condition based maintenance in railway transportation systems based on big data streaming analysis, Proc. Comput. Sci. 53 (2015) 437–446.

[51] J. Yan, Y. Meng, L. Lu, L. Li, Industrial big data in an industry 4.0 environment: challenges, schemes, and applications for predictive maintenance, IEEE Access 5 (2017) 23484–23491.

[52] P. Zhou, P. Yin, An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics, Renew. Sustain. Energy Rev. 109 (2019) 1–9.

[53] M. Christ, A.W. Kempa-Liehr, M. Feindt, Distributed and parallel time series feature extraction for industrial big data applications, arXiv preprint, arXiv:1610.07717, 2016.

[54] S. Shakya, A self monitoring and analyzing system for solar power station using iot and data mining algorithms, J. Soft Comput. Paradig. 3 (2021) 96–109.

[55] Z. Li, Y. Wang, K.-S. Wang, Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: industry 4.0 scenario, Adv. Manuf. 5 (2017) 377–387.

[56] K.S.H. Ong, W. Wang, D. Niyato, T. Friedrichs, Deep-reinforcement-learning-based predictive maintenance model for effective resource management in industrial iot, IEEE Int. Things J. 9 (2021) 5173–5188.

[57] Y. Hu, X. Miao, J. Zhang, J. Liu, E. Pan, Reinforcement learning-driven maintenance strategy: a novel solution for long-term aircraft maintenance decision optimization, Comput. Ind. Eng. 153 (2021) 107056.

[58] M.L.R. Rodríguez, S. Kubler, A. de Giorgio, M. Cordy, J. Robert, Y. Le Traon, Multi-agent deep reinforcement learning based predictive maintenance on parallel machines, Robot. Comput.-Integr. Manuf. 78 (2022) 102406.

[59] J. Lee, M. Mitici, Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics, Reliab. Eng. Syst. Saf. 230 (2023) 108908.

[60] L. Liao, W. Jin, R. Pavel, Enhanced restricted Boltzmann machine with prognosability regularization for prognostics and health assessment, IEEE Trans. Ind. Electron. 63 (2016) 7076–7083.

[61] J. Carrasco, D. López, I. Aguilera-Martos, D. García-Gil, I. Markova, M. Garcia-Barzana, M. Arias-Rodil, J. Luengo, F. Herrera, Anomaly detection in predictive maintenance: a new evaluation framework for temporal unsupervised anomaly detection algorithms, Neurocomputing 462 (2021) 440–452.

[62] B. Luo, H. Wang, H. Liu, B. Li, F. Peng, Early fault detection of machine tools based on deep learning and dynamic identification, IEEE Trans. Ind. Electron. 66 (2018) 509–518.

[63] A. Buabeng, A. Simons, N.K. Frempong, Y.Y. Ziggah, Hybrid intelligent predictive maintenance model for multiclass fault classification, Soft Comput. (2023) 1–22.

[64] Z. Xu, M. Bashir, Q. Liu, Z. Miao, X. Wang, J. Wang, N. Ekere, A novel health indicator for intelligent prediction of rolling bearing remaining useful life based on unsupervised learning model, Comput. Ind. Eng. 176 (2023) 108999.

[65] A. Kanawaday, A. Sane, Machine learning for predictive maintenance of industrial machines using iot sensor data, in: 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS), IEEE, 2017, pp. 87–90.

[66] M. Syafrudin, G. Alfian, N.L. Fitriyani, J. Rhee, Performance analysis of iot-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing, Sensors 18 (2018) 2946.

[67] B. Cline, R.S. Niculescu, D. Huffman, B. Deckel, Predictive maintenance applications for machine learning, in: 2017 Annual Reliability and Maintainability Symposium (RAMS), IEEE, 2017, pp. 1–7.

[68] A. Kara, Multi-scale deep neural network approach with attention mechanism for remaining useful life estimation, Comput. Ind. Eng. 169 (2022) 108211.

[69] M. Paolanti, L. Romeo, A. Felicetti, A. Mancini, E. Frontoni, J. Loncarski, Machine learning approach for predictive maintenance in Industry 4.0, in: 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications, IEEE, MESA, 2018, pp. 1–6.

[70] A. Ouadah, L. Zemmouchi-Ghomari, N. Salhi, Selecting an appropriate supervised machine learning algorithm for predictive maintenance, Int. J. Adv. Manuf. Technol. 119 (2022) 4277–4301.

[71] S. Arena, E. Florian, I. Zennaro, P.F. Orrù, F. Sgarbossa, A novel decision support system for managing predictive maintenance strategies based on machine learning approaches, Saf. Sci. 146 (2022) 105529.

[72] P. Bangalore, L.B. Tjernberg, An artificial neural network approach for early fault detection of gearbox bearings, IEEE Trans. Smart Grid 6 (2015) 980–987.

[73] R. Zhao, D. Wang, R. Yan, K. Mao, F. Shen, J. Wang, Machine health monitoring using local feature-based gated recurrent unit networks, IEEE Trans. Ind. Electron. 65 (2017) 1539–1548.
[74] W. Zhang, D. Yang, H. Wang, Data-driven methods for predictive maintenance of industrial equipment: a survey, IEEE Syst. J. 13 (2019) 2213–2227.
[75] W.L. Ng, G.L. Goh, G.D. Goh, J.S.J. Ten, W.Y. Yeong, Progress and opportunities for machine learning in materials and processes of additive manufacturing, Adv. Mater. (2024) 2310006.
[76] Y. Lei, N. Li, S. Gontarz, J. Lin, S. Radkowski, J. Dybala, A model-based method for remaining useful life prediction of machinery, IEEE Trans. Reliab. 65 (2016) 1314–1326.
[77] D.K. Sharma, S. Brahmachari, K. Singhal, D. Gupta, Data driven predictive maintenance applications for industrial systems with temporal convolutional networks, Comput. Ind. Eng. 169 (2022) 108213.
[78] Y. Lei, N. Li, J. Lin, A new method based on stochastic process models for machine remaining useful life prediction, IEEE Trans. Instrum. Meas. 65 (2016) 2671–2684.
[79] J.B. Ali, B. Chebel-Morello, L. Saidi, S. Malinowski, F. Fnaiech, Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network, Mech. Syst. Signal Process. 56 (2015) 150–172.
[80] A. Mosallam, K. Medjaher, N. Zerhouni, Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction, J. Intell. Manuf. 27 (2016) 1037–1048.
[81] Z. Zhao, B. Liang, X. Wang, W. Lu, Remaining useful life prediction of aircraft engine based on degradation pattern learning, Reliab. Eng. Syst. Saf. 164 (2017) 74–83.
[82] J. Wang, L. Zhang, L. Duan, R.X. Gao, A new paradigm of cloud-based predictive maintenance for intelligent manufacturing, J. Intell. Manuf. 28 (2017) 1125–1137.
[83] P. Strauß, M. Schmitz, R. Wöstmann, J. Deuse, Enabling of predictive maintenance in the brownfield through low-cost sensors, an iiot-architecture and machine learning, in: 2018 IEEE International Conference on Big Data (Big Data), IEEE, 2018, pp. 1474–1483.
[84] J.S. Rahhal, D. Abualnadi, Iot based predictive maintenance using lstm rnn estimator, in: 2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), IEEE, 2020, pp. 1–5.
[85] M. Calabrese, M. Cimmino, F. Fiume, M. Manfrin, L. Romeo, S. Ceccacci, M. Paolanti, G. Toscano, G. Ciandrini, A. Carrotta, et al., Sophia: an event-based iot and machine learning architecture for predictive maintenance in industry 4.0, Information 11 (2020) 202.
[86] A. Shamayleh, M. Awad, J. Farhat, Iot based predictive maintenance management of medical equipment, J. Med. Syst. 44 (2020) 1–12.
[87] M. Cakir, M.A. Guvenc, S. Mistikoglu, The experimental application of popular machine learning algorithms on predictive maintenance and the design of iiot based condition monitoring system, Comput. Ind. Eng. 151 (2021) 106948.
[88] R.M. Souza, E.G. Nascimento, U.A. Miranda, W.J. Silva, H.A. Lepikson, Deep learning for diagnosis and classification of faults in industrial rotating machinery, Comput. Ind. Eng. 153 (2021) 107060.
[89] M. Bhandari, B. Silwal, Development of machine learning model applied to industrial motors for predictive maintenance, in: 2022 International Interdisciplinary Humanitarian Conference for Sustainability (IIHC), IEEE, 2022, pp. 1632–1635.
[90] C. Liu, H. Zhu, D. Tang, Q. Nie, T. Zhou, L. Wang, Y. Song, Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in iot-enabled manufacturing, Robot. Comput.-Integr. Manuf. 77 (2022) 102357.
[91] S.F. Falkenberg, S. Spinler, The role of novel data in maintenance planning: breakdown predictions for material handling equipment, Comput. Ind. Eng. 169 (2022) 108230.
[92] Y.K. Teoh, S.S. Gill, A.K. Parlikad, Iot and fog computing based predictive maintenance model for effective asset management in industry 4.0 using machine learning, IEEE Int. Things J. (2021).
[93] E. Chung, K. Park, P. Kang, Fault classification and timing prediction based on shipment inspection data and maintenance reports for semiconductor manufacturing equipment, Comput. Ind. Eng. 176 (2023) 108972.
[94] J.C. Cheng, W. Chen, K. Chen, Q. Wang, Data-driven predictive maintenance planning framework for mep components based on bim and iot using machine learning algorithms, Autom. Constr. 112 (2020) 103087.
[95] F. Civerchia, S. Bocchino, C. Salvadori, E. Rossi, L. Maggiani, M. Petracca, Industrial Internet of things monitoring solution for advanced predictive maintenance applications, J. Ind. Inf. Integr. 7 (2017) 4–12.
[96] D. Kwon, M.R. Hodkiewicz, J. Fan, T. Shibutani, M.G. Pecht, Iot-based prognostics and systems health management for industrial applications, IEEE Access 4 (2016) 3659–3670.
[97] A. Chowdhury, S. Raut, A. Pal, Internet of things resource monitoring through proactive fault prediction, Comput. Ind. Eng. 169 (2022) 108265.
[98] S. Goundar, M. Pillai, K. Mamun, F. Islam, R. Deo, Real time condition monitoring system for industrial motors, in: 2015 2nd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), IEEE, 2015, pp. 1–9.
[99] R.C. Parpala, R. Iacob, Application of IoT concept on predictive maintenance of industrial equipment, in: MATEC Web of Conferences, vol. 121, EDP Sciences, 2017, p. 02008.
[100] M. Yaseen, D. Swathi, T.A. Kumar, Iot based condition monitoring of generators and predictive maintenance, in: 2017 2nd International Conference on Communication and Electronics Systems (ICCES), IEEE, 2017, pp. 725–729.
[101] A. Kadechkar, J.-R. Riba, M. Moreno-Eguilaz, J. Perez, Smartconnector: a self-powered iot solution to ease predictive maintenance in substations, IEEE Sens. J. 20 (2020) 11632–11641.
[102] L. Dong, R. Mingyue, M. Guoying, Application of Internet of things technology on predictive maintenance system of coal equipment, Proc. Eng. 174 (2017) 885–889.
[103] D. Mourtzis, J. Angelopoulos, N. Panopoulos, Design and development of an iot enabled platform for remote monitoring and predictive maintenance of industrial equipment, Proc. Manuf. 54 (2021) 166–171.
[104] D. Jung, Z. Zhang, M. Winslett, Vibration analysis for iot enabled predictive maintenance, in: 2017 IEEE 33rd International Conference on Data Engineering (ICDE), IEEE, 2017, pp. 1271–1282.
[105] P. Killeen, B. Ding, I. Kiringa, T. Yeap, Iot-based predictive maintenance for fleet management, Proc. Comput. Sci. 151 (2019) 607–613.
[106] L.C. Him, Y.Y. Poh, L.W. Pheng, Iot-based predictive maintenance for smart manufacturing systems, in: 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), IEEE, 2019, pp. 1942–1944.
[107] O.A. ElFar, C.-K. Chang, H.Y. Leong, A.P. Peter, K.W. Chew, P.L. Show, Prospects of industry 5.0 in algae: customization of production and new advance technology for clean bioenergy generation, Energy Convers. Manag. X 10 (2021) 100048.
[108] E. Commission, Directorate-General for Research and Innovation, M. Breque, L. De Nul, A. Petridis, Industry 5.0 – Towards a Sustainable, Human-Centric and Resilient European Industry, Publications Office of the European Union, 2021.
[109] M. Rada, Industry 5.0 definition, 2017.
[110] B. Friedman, D.G. Hendry, Value Sensitive Design: Shaping Technology with Moral Imagination, Mit Press, 2019.
[111] W. Shi, J. Cao, Q. Zhang, Y. Li, L. Xu, Edge computing: vision and challenges, IEEE Int. Things J. 3 (2016) 637–646.
[112] J. Schneible, A. Lu, Anomaly detection on the edge, in: MILCOM 2017-2017 IEEE Military Communications Conference (MILCOM), IEEE, 2017, pp. 678–682.
[113] Y. Lu, C. Liu, I. Kevin, K. Wang, H. Huang, X. Xu, Digital twin-driven smart manufacturing: connotation, reference model, applications and research issues, Robot. Comput.-Integr. Manuf. 61 (2020) 101837.
[114] Z. Jiang, Y. Guo, Z. Wang, Digital twin to improve the virtual-real integration of industrial iot, J. Ind. Inf. Integr. 22 (2021) 100196.
[115] E. Hämäläinen, T. Inkinen, Industrial applications of big data in disruptive innovations supporting environmental reporting, J. Ind. Inf. Integr. 16 (2019) 100105.
[116] M.H. Miraz, M. Ali, P.S. Excell, R. Picking, A review on Internet of things (iot), Internet of everything (ioe) and Internet of nano things (iont), in: 2015 Internet Technologies and Applications (ITA), 2015, pp. 219–224.
[117] J.E. Colgate, W. Wannasuphoprasit, M.A. Peshkin, Cobots: robots for collaboration with human operators, in: ASME International Mechanical Engineering Congress and Exposition, vol. 15281, American Society of Mechanical Engineers, 1996, pp. 433–439.
[118] N. Deepa, Q.-V. Pham, D.C. Nguyen, S. Bhattacharya, B. Prabadevi, T.R. Gadekallu, P.K.R. Maddikunta, F. Fang, P.N. Pathirana, A survey on blockchain for big data: approaches, opportunities, and future directions, Future Gener. Comput. Syst. 131 (2022) 209–226.
[119] M.Z. Chowdhury, M. Shahjalal, S. Ahmed, Y.M. Jang, 6g wireless communication systems: applications, requirements, technologies, challenges, and research directions, IEEE Open J. Commun. Soc. 1 (2020) 957–975.
[120] A.A. Murtaza, A. Saher, H. Mohyuddin, S.K.R. Moosavi, M.H. Zafar, F. Sanfilippo, Enhancing cardiovascular disease prediction via hybrid deep learning architectures: a step towards smart healthcare, in: 2023 2nd International Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering (ETECTE), IEEE, 2023, pp. 1–6.
[121] A. Armghan, J. Logeshwaran, S. Sutharshan, K. Aliqab, M. Alsharari, S.K. Patel, Design of biosensor for synchronized identification of diabetes using deep learning, Results Eng. 20 (2023) 101382.
[122] U. Singh, M. Rizwan, Scada system dataset exploration and machine learning based forecast for wind turbines, Results Eng. 16 (2022) 100640.
[123] M.K. Hassan, H. Youssef, I.M. Gaber, A.S. Shehata, Y. Khairy, A.A. El-Bary, A predictive machine learning model for estimating wave energy based on wave conditions relevant to coastal regions, Results Eng. 21 (2024) 101734.
[124] R.M.A. Velásquez, Bearings faults and limits in wind turbine generators, Results Eng. 21 (2024) 101891.
[125] P.K.R. Maddikunta, Q.-V. Pham, B. Prabadevi, N. Deepa, K. Dev, T.R. Gadekallu, R. Ruby, M. Liyanage, Industry 5.0: a survey on enabling technologies and potential applications, J. Ind. Inf. Integr. 26 (2022) 100257.
[126] T. Sahar, M. Rauf, A. Murtaza, L.A. Khan, H. Ayub, S.M. Jameel, I.U. Ahad, Anomaly detection in laser powder bed fusion using machine learning: a review, Results Eng. 17 (2023) 100803.
[127] L. Liu, F. Guo, Z. Zou, V.G. Duffy, Application, development and future opportunities of collaborative robots (cobots) in manufacturing: a literature review, Int. J. Hum.-Comput. Interact. (2022) 1–18.
[128] M.S. Kaiser, S. Al Mamun, M. Mahmud, M.H. Tania, Healthcare robots to combat covid-19, in: COVID-19: Prediction, Decision-Making, and Its Impacts, 2021, pp. 83–97.

[129] V. Rajasekar, M. Vaishnnave, S. Premkumar, V. Sarveshwaran, V. Rangaraaj, Lung cancer disease prediction with ct scan and histopathological images feature analysis using deep learning techniques, Results Eng. 18 (2023) 101111.
[130] M.H. Kashani, M. Madanipour, M. Nikravan, P. Asghari, E. Mahdipour, A systematic review of iot in healthcare: applications, techniques, and trends, J. Netw. Comput. Appl. 192 (2021) 103164.
[131] M. Baghalzadeh Shishehgarkhaneh, A. Keivani, R.C. Moehler, N. Jelodari, S. Roshdi Laleh, Internet of things (iot), building information modeling (bim), and digital twin (dt) in construction industry: a review, bibliometric, and network analysis, Buildings 12 (2022) 1503.
[132] A. Zabin, V.A. González, Y. Zou, R. Amor, Applications of machine learning to bim: a systematic literature review, Adv. Eng. Inform. 51 (2022) 101474.
[133] R. Niyirora, W. Ji, E. Masengesho, J. Munyaneza, F. Niyonyungu, R. Nyirandayisabye, Intelligent damage diagnosis in bridges using vibration-based monitoring approaches and machine learning: a systematic review, Results Eng. 16 (2022) 100761.
[134] F. Alhomaidat, M. Twaissi, et al., Unlocking insights from commercial vehicle data: a machine learning approach for predicting commercial vehicle classes using Michigan state data (1999–2017), Results Eng. 21 (2024) 101691.
[135] A. Alwabli, From data to durability: evaluating conventional and optimized machine learning techniques forbattery health assessment, Results Eng. (2024) 102445.
[136] F.P. Knebel, R. Trevisan, G.S. do Nascimento, M. Abel, J.A. Wickboldt, A study on cloud and edge computing for the implementation of digital twins in the oil & gas industries, Comput. Ind. Eng. 182 (2023) 109363.
[137] M. Bevilacqua, E. Bottani, F.E. Ciarapica, F. Costantino, L. Di Donato, A. Ferraro, G. Mazzuto, A. Monteriù, G. Nardini, M. Ortenzi, et al., Digital twin reference model development to prevent operators' risk in process plants, Sustainability 12 (2020) 1088.
[138] E. Goldin, D. Feldman, G. Georgoulas, M. Castano, G. Nikolakopoulos, Cloud computing for big data analytics in the process control industry, in: 2017 25th Mediterranean Conference on Control and Automation (MED), IEEE, 2017, pp. 1373–1378.
[139] P. Dutta, T.-M. Choi, S. Somani, R. Butala, Blockchain technology in supply chain operations: applications, challenges and research opportunities, Transp. Res., Part E, Logist. Transp. Rev. 142 (2020) 102067.
[140] M. Ben-Daya, E. Hassini, Z. Bahroun, Internet of things and supply chain management: a literature review, Int. J. Prod. Res. 57 (2019) 4719–4742.
[141] S.S. Kamble, A. Gunasekaran, H. Parekh, V. Mani, A. Belhadi, R. Sharma, Digital twin for sustainable manufacturing supply chains: current trends, future perspectives, and an implementation framework, Technol. Forecast. Soc. Change 176 (2022) 121448.
[142] A. Bousdekis, K. Lepenioti, D. Apostolou, G. Mentzas, A review of data-driven decision-making methods for industry 4.0 maintenance applications, Electronics 10 (2021) 828.
[143] D. Gorecky, M. Schmitt, M. Loskyll, D. Zühlke, Human-machine-interaction in the Industry 4.0 era, in: 2014 12th IEEE International Conference on Industrial Informatics (INDIN), IEEE, 2014, pp. 289–294.
[144] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, B. Qureshi, An overview of iot sensor data processing, fusion, and analysis techniques, Sensors 20 (2020) 6076.
[145] A. Adel, Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas, J. Cloud Comput. 11 (2022) 40.
[146] F. Varghese, P. Sasikala, Secure data transmission using optimized cryptography and steganography using syndrome-trellis coding, Wirel. Pers. Commun. 130 (2023) 551–578.
[147] A. Nain, S. Sheikh, M. Shahid, R. Malik, Resource optimization in edge and sdn-based edge computing: a comprehensive study, Clust. Comput. (2024) 1–29.
[148] T. Hautala-Kankaanpää, The impact of digitalization on firm performance: examining the role of digital culture and the effect of supply chain capability, Bus. Process Manag. J. 28 (2022) 90–109.
[149] H. Heinonen, J. Virtaluoto, T. Suomivuori, K. Forsman, T. Kangas, S. Siltanen, Minimalism for the win: user-centered design for guidance in industrial maintenance, IEEE Trans. Prof. Commun. 65 (2022) 485–501.
[150] V.S. Avvaru, G. Bruno, P. Chiabert, E. Traini, Integration of plm, mes and erp systems to optimize the engineering, production and business, in: IFIP International Conference on Product Lifecycle Management, Springer, 2020, pp. 70–82.
[151] J. Patalas-Maliszewska, M. Skrzeszewska, An evaluation of the effectiveness of applying the mes in a maintenance department–a case study, Found. Manag. 10 (2018) 257–270.
[152] B. Van Oudenhoven, P. Van de Calseyde, R. Basten, E. Demerouti, Predictive maintenance for industry 5.0: behavioural inquiries from a work system perspective, Int. J. Prod. Res. 61 (2023) 7846–7865.
[153] M. Javaid, A. Haleem, R.P. Singh, R. Suman, Substantial capabilities of robotics in enhancing industry 4.0 implementation, Cogn. Robot. 1 (2021) 58–75.
[154] C. Emmanouilidis, P. Pistofidis, L. Bertoncelj, V. Katsouros, A. Fournaris, C. Koulamas, C. Ruiz-Carcel, Enabling the human in the loop: linked data and knowledge in industrial cyber-physical systems, Annu. Rev. Control 47 (2019) 249–265.
[155] M. Numfu, A. Riel, F. Noël, Virtual reality based digital chain for maintenance training, Proc. CIRP 84 (2019) 1069–1074.
[156] V. Poosapati, V. Katneni, V.K. Manda, T. Ramesh, Enabling cognitive predictive maintenance using machine learning: approaches and design methodologies, in: Soft Computing and Signal Processing: Proceedings of ICSCSP 2018, vol. 2, Springer, 2019, pp. 37–45.
[157] A. Ucar, M. Karakose, N. Kırımça, Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends, Appl. Sci. 14 (2024) 898.
[158] A. Salonen, M. Bengtsson, Identification of maintenance performance indicators through stakeholder involvement, in: Proceedings of the 2nd Swedish Production Symposium, Stockholm, Sweden, 2008.
[159] A. Rahimazar, A. Nouri Qarahasanlou, D. Khanzadeh, M. Tavaghi, Assessing resilience in mechanical systems: an industrial perspective, Int. J. Qual. Reliab. Manag. (2024).
[160] K.T. Huynh, An adaptive predictive maintenance model for repairable deteriorating systems using inverse Gaussian degradation process, Reliab. Eng. Syst. Saf. 213 (2021) 107695.
[161] P.M.-G. Fernández, A.J.G. López, A.C. Márquez, J.F.G. Fernández, J.A. Marcos, Dynamic risk assessment for cbm-based adaptation of maintenance planning, Reliab. Eng. Syst. Saf. 223 (2022) 108359.
[162] S. Yoshikawa, Boiler feed pump (bfp), Ebara Eng. Rev. (2016) 11–20.
[163] M. Moleda, A. Momot, D. Mrozek, Predictive maintenance of boiler feed water pumps using scada data, Sensors 20 (2020) 571.
[164] A.D. Scaife, Improve predictive maintenance through the application of artificial intelligence: a systematic review, Results Eng. (2023) 101645.
[165] T. Tichy, J. Broz, J. Stefan, R. Pirnik, Failure analysis and data-driven maintenance of road tunnel equipment, Results Eng. 18 (2023) 101034.
[166] J.M. Fordal, P. Schjølberg, H. Helgetun, T.Ø. Skjermo, Y. Wang, C. Wang, Application of sensor data based predictive maintenance and artificial neural networks to enable industry 4.0, Adv. Manuf. 11 (2023) 248–263.
[167] U. Izagirre, I. Andonegui, I. Landa-Torres, U. Zurutuza, A practical and synchronized data acquisition network architecture for industrial robot predictive maintenance in manufacturing assembly lines, Robot. Comput.-Integr. Manuf. 74 (2022) 102287.
[168] S.-j. Wu, N. Gebraeel, M.A. Lawley, Y. Yih, A neural network integrated decision support system for condition-based optimal predictive maintenance policy, IEEE Trans. Syst. Man Cybern., Part A, Syst. Hum. 37 (2007) 226–236.
[169] S. Wellsandt, K. Klein, K. Hribernik, M. Lewandowski, A. Bousdekis, G. Mentzas, K.-D. Thoben, Towards using digital intelligent assistants to put humans in the loop of predictive maintenance systems, IFAC-PapersOnLine 54 (2021) 49–54.
[170] J. Moyne, J. Iskandar, P. Hawkins, T. Walker, A. Furest, B. Pollard, D. Stark, Deploying an equipment health monitoring dashboard and assessing predictive maintenance, in: ASMC 2013 SEMI Advanced Semiconductor Manufacturing Conference, IEEE, 2013, pp. 105–110.
[171] R. Siraskar, S. Kumar, S. Patil, A. Bongale, K. Kotecha, Reinforcement learning for predictive maintenance: a systematic technical review, Artif. Intell. Rev. 56 (2023) 12885–12947.
[172] P. Jain, E.N. Pistikopoulos, M.S. Mannan, Process resilience analysis based data-driven maintenance optimization: application to cooling tower operations, Comput. Chem. Eng. 121 (2019) 27–45.