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Review

The advance of digital twin for predictive maintenance: The role and function of machine learning

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ABSTRACT

The recent advance of digital twin (DT) has greatly facilitated the development of predictive maintenance (PdM). DT for PdM enables accurate equipment status recognition and proactive fault prediction, enhancing reliability. This shift from reactive to proactive services optimizes maintenance schedules, minimizes downtime, and improves enterprise profitability and competitiveness. However, the research and application of DT for PdM are still in their infancy, probably because the role and function of machine learning (ML) in DT for PdM have not yet been fully investigated by the industry and academia. This paper focuses on a systematic review of the role of ML in DT for PdM and identifies, evaluates and analyses a clear and systematic approach to the published literature relevant to DT and PdM. Subsequently, the state-of-the-art applications of ML in various application areas of DT for PdM are introduced. Finally, the challenges and opportunities of ML for DT-PdM are revealed and discussed. The outcome of this paper can bring tangible benefits to the research and implementation of ML in DT-PdM.

1. Introduction

The digital twin (DT) consists primarily of a physical entity, a digital copy, and a connection, to leverage virtual analytics to enhance the performance of the physical entity [1,2]. The concept of the DT emerged from NASA's Apollo program, integrating information and data from cyberspace and physical space [3]. The concept of DT was initially proposed by Michael Grieves and has since then become a widely used term [4]. Companies have applied various models to their systems engineering output, incorporating physical and mathematical models. In 2012, NASA conceptualized DT as "the integration of a multidisciplinary, multi-scale simulation process that makes full use of physical models, sensors, operational history, and other data, which serves as a mirror image of the physical product in virtual space and reflects the full life-cycle process of the corresponding physical entity product" [5]. However, the implementation of intelligent manufacturing based on DT is still in its infancy, as far as the concept, characteristics and general framework of DT are concerned [6]. DT is now widely researched in product lifecycle management. In particular, publications on DT for predictive maintenance (PdM) have gained a lot of attention in recent years. The DT application adopts a proactive approach to equipment management services by integrating real-time equipment sensor data such as temperature and vibration with environmental data, to update the DT model and prevent unplanned downtime. Therefore, the research on the current state of DT-PdM is crucial, which allows for precise equipment status validation, early fault detection, and ultimately contributes to enhanced stability and reduced costs for organizations.

PdM techniques are utilized to assess the condition of equipment in operation, thereby predicting when maintenance will be required. This approach not only saves costs compared to routine or regular preventive maintenance but also enhances operational efficiency [7,8]. As per a report by IoT analytics in Hamburg, Germany, the PdM market is presently valued at $6.9 billion and is projected to reach $28.2 billion by 2026. There are currently over 280 PdM solution providers in the market, which is expected to grow to over 500 by 2026. The ultimate goal of PdM is to enable condition-based maintenance by utilizing real-time or near-real-time data transmission and relevant modeling techniques to improve a company's operational reliability and facilitate continuous improvement [9–11]. As per a report by IoT analytics in Hamburg, Germany, the PdM market is presently valued at $6.9 billion

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and is projected to reach $28.2 billion by 2026. There are currently over 280 PdM solution providers in the market, which is expected to grow to over 500 by 2026. DT-PdM is an essential technology for fault diagnosis, remaining useful life (RUL) prediction, and health indicator (HI) construction. It has been applied in diverse domains such as computer numerical control (CNC) machine tools, bearing, and gearbox, utilizing multi-source datasets to construct virtual models for optimization of PdM applications. Data-driven models currently require the collection of large amounts of multi-source data and the construction of models from a variety of sources including internet of things (IoT) data, environmental data, operational data, simulation data, and control data [12–19]. Physics-based models are also an important modeling approach, such as finite element analysis (FEA) to construct DT models from components [20]. DT, as a new technology that takes advantage of both a physics-based approach and a data-driven approach, has gained increasing attention in PdM [9,21–23]. Fig. 1 illustrates a line graph showing the number of papers published on ML-PdM and DT-PdM indexed by Google Scholar from 2001 to 2022. It can be seen that both ML-PdM and DT-PdM have undergone rapid growth in recent years. ML-PdM has consistently had more publications than DT-PdM each year, while DT-PdM witnessed moderate growth. The current implementations of DT-PdM face challenges in building high-fidelity models and deploying them in the industry. One of the main reasons is that it is hard to integrate, analyze and model the multi-modal data and derive the information and knowledge for DT. Machine learning (ML), as the key technology in advanced data analytics, plays a critical role in DT-PdM. Therefore, it is worthwhile to collect review and analyze the recently published papers to identify the role and function of ML in DT-PdM.

ML is an essential technology to facilitate the development of DT-PdM [24]. It has been used in many fields such as manufacturing and aerospace [25,26]. With the development of sensor technology, data is collected, stored, and applied in a data-driven PdM. In addition, data combined with physical information is also becoming an effective modeling approach. ML uses valid data to reveal hidden knowledge and build complex correlations to improve model accuracy and help make decisions on problems [27]. In the context of industry 4.0, the topic of DT-PdM has received continued attention but still in its infancy. Therefore, many researchers have studied ML techniques to facilitate the development of DT-PdM, such as fault diagnosis and RUL prediction in virtual spaces [28,29]. However, existing review articles relevant to DT-PdM mainly focus on analyzing the application scenarios of DT-PdM,

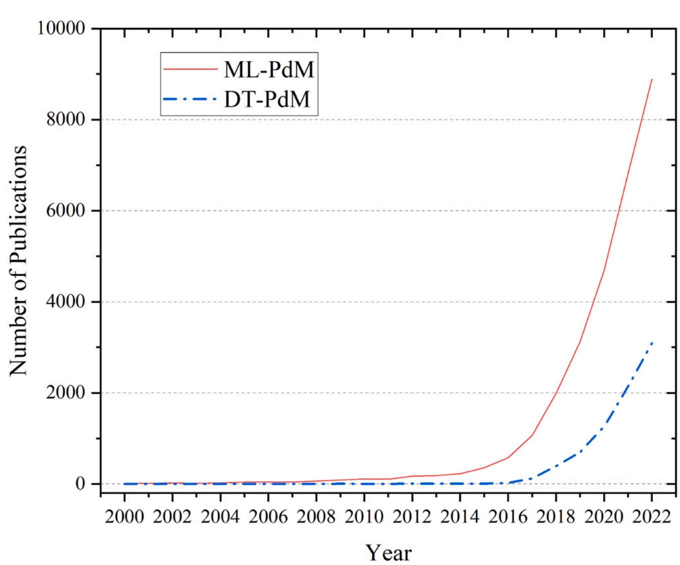

Fig. 1. Trends in ML-PdM and DT-PdM development: a Google Scholar publication analysis.

categorizing DT models, or researching specific components. There is still a lack of exploration of the role and function of ML [5,30,31]. Therefore, the main contributions of this paper are: (1) a framework for DT-PdM with ML techniques is proposed; (2) the role and function of ML in DT-PdM are identified through the critical review of relevant papers published in the last five years; (3) the research challenges and future opportunities to address implementation issues and proposing solutions in high-fidelity digital model construction, data fusion, physics informed-machine learning and cloud-edge collaboration when implementing DT-PdM are discussed. The rest of the paper is organized as followed: Section 2 introduces the state-of-the-art DT and PdM, including an introduction to DT and PdM respectively. Section 3 details the methodology of collecting review papers, and Section 4 introduces the role and function of ML in DT-PdM, as well as explaining the contribution of DT techniques in establishing applications. The opportunities are discovered and clarified in Section 5 and Section 6 concludes.

2. The state-of-the-art of digital twin and predictive maintenance

2.1. Digital twin in manufacturing

According to recent reports, the spending on DT has already reached $4.6 billion in 2022 and is expected to grow to around $34 billion in 2030. This includes various technologies such as computer-aided design (CAD) modeling, connectivity, cloud computing, industrial internet of things (IIoT) software platforms, remote monitoring, shop-floor worker hardware, physics-based simulation, ML, and systems integration, among others, all of which contribute significantly to the development of DT [32–38]. Essentially, the DT consists of three main components: the physical product in physical space, the virtual product in virtual space, and the interface for data and information interaction between physical and virtual space [5]. In essence, the DT is a reverse engineering feat in which everything that happens in the physical world is replicated in the digital space. A true full life cycle concept is realized through continuous tracking and feedback. The DT has several key features, including: (1) DT allows the collaboration and communication between physical entities and digital avatars [39]; (2) DT can generate insights and predictions about the behavior and performance of the physical asset; (3) The presence of DT allowing manufacturers to test and optimize their operations virtually before implementing changes in the real world; (4) DT can be continuously improved by collecting data, analyzing performance, and providing feedback for optimization.

DT are virtual models of physical entities that can be used to simulate their behavior and predict their performance. The development of technologies such as IoT, big data, and edge computing have paved the way for the development of DT modeling in the manufacturing industry. It can help optimize production processes, reduce downtime, and improve product quality by identifying and addressing issues before they occur. The origins and development of DT are deeply rooted in the industrial sector, initially to ensure reliable and stable equipment for the US Air Force, and later to improve efficiency in product design, development, and testing across various stages of the product lifecycle. Intelligent scheduling is an essential aspect of technology in the workshop. However, traditional algorithmic models, such as Markov models, may not always guarantee long-term stability and accuracy in workshop scheduling due to the presence of large coupling factors. Therefore, the use of DT technology, which combines real and virtual interactions to automatically optimize algorithms, can enhance production planning and scheduling, and reduce the impact of production downtime on site.

In recent times, the commercial landscape of DT in manufacturing has greatly improved, with companies pushing the boundaries of its application. An excellent embodiment of this shift is the foray into the "industrial metaverse". The cutting-edge technology companies such as Siemens has launched its take on the industrial metaverse. Their approach to the DT goes beyond mere mimicry of physical assets in a digital environment. Siemens' platform brings together the twin's representation with data analytics, artificial intelligence, and automation in a dynamic ecosystem. The ecosystem promotes collaborative design and operations, with real-time updates and integrations, which can promote the evolution of tools tailored for diverse manufacturing needs [40]. In recent years, Nvidia also has focused on the industrial metaverse. Nvidia's Omniverse platform—a collaborative and physically accurate simulation environment This platform allows manufacturers to visualize intricate processes and scenarios in high fidelity, ensuring that even the minutest of details can be reviewed and refined. Furthermore, Nvidia's prowess in AI plays a crucial role in analyzing data within this metaverse, driving predictive insights and performance optimizations [41]. The collaboration between Nvidia and Siemens in establishing an industrial metaverse represents a pivotal moment in the DT journey. It's not just about replicating the physical in the digital realm anymore. It's about building a comprehensive, interconnected, and intelligent virtual environment that can grow, adapt, and innovate alongside its physical counterpart.

In addition, DT technology has found its application in diverse industries such as machinery, logistics, the energy industry, weaponry, and others [5]. For instance, Rauscher et al. developed a DT-based simulation tool to minimize the duration of reactor downtime at the plant, which improves the quality and consistency of the input data and enables credible information to be derived from the simulation results to support the design and decision-making process [42]. Wu et al. [43] proposed an architecture of service platform for cold chain logistics using Internet of Everything and DT. Hu [44] proposed a mutual information-enhanced DT approach to promote the performance of vision-guided robotic grasping. CNC machine tools currently tend to affect production due to accuracy. Researchers have investigated DT for the condition monitoring of machine tools [45,46]. Building upon the versatility of DT, another significant application is PdM. PdM, backed by numerous academic studies, has become a sought-after approach in prognostic and health management [47–49], with many organizations embracing it for notable cost savings and efficiency enhancements.

2.2. Cutting-edge applications of predictive maintenance

PdM techniques are utilized to assess the condition of equipment in operation, thereby predicting when maintenance will be required. This approach not only saves costs compared to routine or regular preventive maintenance but also enhances operational efficiency [7,8]. The ultimate goal of PdM is to enable condition-based maintenance by utilizing real-time or near-real-time data transmission and relevant modeling techniques to improve a company's operational reliability and facilitate continuous improvement [9–11]. Currently, there are three primary PdM solutions: data-driven modeling, physical-based modeling, and hybrid modeling which combine both data-driven and physical-based methods. Data-driven modeling involves using multidimensional, large amounts of data gathered by sensors for research, exploration, and mining, along with domain knowledge to build models for PdM of equipment. Physical-based modeling is the study of the laws of motion of matter, combined with a variety of factors, and possibly the use of hypotheses and other methods to explore the laws and knowledge of PdM of equipment through simulation. In addition, the hybridization of data-driven and physical-based methods is an important approach to PdM, where data-driven models and physical models are combined to form hybrid models and make predictions. Further details are provided in the next section. Deep learning is the latest advanced technique in ML. Besides Deep learning, the classical ML algorithms also have been instrumental in the advancements of DT-PdM [3]. However, their applications and efficacies vary based on specific tasks and the data type [50]. The classical ML algorithms are efficient for datasets of moderate size. Classical ML algorithms like decision trees, support vector machines, or clustering techniques can be effective when the data structure is less intricate [51]. When deploying classical ML algorithms, feature engineering is needed. In contrast, deep learning algorithms require substantial amounts of data and large computational resources to train effectively. Deep learning can be effective in extracting features from complex internal structures like images, text, or high-dimensional sensor data without complex feature engineering [52]. The development of ML techniques has facilitated the data-driven method for PdM [53]. This approach has shown promising results in fault diagnosis and RUL prediction. For instance, Yu et al. employed a non-linear approach to degrade the intrinsic signal components and identified the dynamic matrix of different gear faults through the transfer function of gearbox vibrations under non-stationary conditions [54]. Chen et al. introduced the gcforest algorithm to PdM and built predictive models, which were implemented successfully [55]. Jamil et al. proposed a transfer learning model that extracts useful information from small training samples for similar working conditions and models, achieving high model accuracy in diverse environments [56]. Zuo et al. developed a probabilistic spike response model to facilitate multilayer network learning and improve the performance of the model for bearing fault diagnosis [57]. Among numerous studies of data-driven PdM, deep learning has gained increasing attention in recent years since it can automatically extract the key features relevant to the health status of assets.

Although data-driven PdM is the focus of current research and relatively easy to collect input information, physical modeling cannot be ignored to aid the development of PdM. The physics-based approach primarily employs physical principles to explore, summarize, and emulate the operation of a system [58]. Physical model-based PdM is also a crucial method, such as finite element methods, which use mathematical relationships to explore potential relationships [9,59]. Finite element models and Monte Carlo methods are utilized to reduce the uncertainty in life prediction and build life prediction models for predicting component life [9]. Numerical analysis is another alternative approach where the stress data collected from feedback sensors are modeled by analyzing the uncertainty of the crack from a microscopic perspective to study degradation trends and analyze the RUL of the component in conjunction with the crack length [9,60]. The hydraulic pump generates power in the machine, and da Silveira et al. used knowledge exploration and mapping to derive a physical model of the sub-process and a model based on vibration analysis to implement PdM on the hydraulic pump [61]. Aivaliotis et al. developed a method for calculating RUL based on physical simulation models for PdM of production equipment using predictive and health management (PHM) techniques. The resources of a production plant are modeled to enable the simulation of its functions and to identify maintenance activities for the machines [21]. Physical model development is based on interdisciplinary analysis of multiple physical fields in coupled systems. However, the current PdM-based approach primarily focuses on a single physical modeling approach, leading to inadequate exploration of the integration of multiple modes in the physical field. These modes include the kinematic field, chemical reactions, electrostatic interactions, and physical fields [22]. Hybridizing data-driven and physical methods have great potential in promoting the development of PdM-based physical modeling that considers these important factors.

The use of data-driven and physical hybridizations is becoming increasingly popular in enhancing data-driven models with physical models. This approach involves synthesizing data generated by a physical model with the original data to create a life prediction model with improved accuracy. Studies have demonstrated the effectiveness of this approach, especially in high-assurance models [9,62]. Optimization of physical models by ML requires appropriate and necessary conditions [63]. However, the optimization of physical models by ML requires certain necessary and sufficient conditions. The necessary conditions involve a causal relationship between the input and output parameters, while the sufficient conditions involve the theoretical construction of input parameters and output results [22,64]. Recent research has proposed various hybridization methods for improving the accuracy of reliability analysis. For instance, Zheng et al. developed a regularized deep polynomial chaos neural network to achieve iterative learning of expansion coefficients and used this method to improve the reliability of satellite systems [65]. Yu developed a hybrid DT-based physical and data-driven model to identify minor faults in gearboxes [66]. Similarly, Chi et al. proposed a systematic framework approach for dynamically analyzing the real-time reliability of information systems by constructing an extreme learning machine and simulating energy management system behavior based on a stacked autoencoder (AE) model [67]. Li et al. proposed a novel high-dimensional data abstraction framework for reliability dimensionality reduction using Gaussian functions to capture the limit state functions in the latent space for process regression [68].

To summarize, the integration of data-driven and physical-based approaches can be beneficial to the development of DT-PdM. Data-driven approach can be restricted by the limitations in data collection, and the quality of data may not meet the requirements of the specific application. On the other hand, a physical-based approach can address the lack of data samples, but integrating physical knowledge for the development of data-driven methods can be challenging. Thus, hybridizing data-driven and physical methods requires more attention in the future research.

3. Research methodology

In this section, a systematic literature review was conducted to investigate the use of DT-PdM. The methodology involved five steps: specifying research questions, identifying search sources, formulating criteria for article selection, classifying articles published within the last five years based on an extensive review, and providing a brief description of each article. The approach ensured a comprehensive and unbiased analysis of the existing literature. The review aimed to provide an overview of the current state of research and application of DT-PdM and to identify gaps and areas for future research.

3.1. Research questions

To address the aforementioned development challenges of DT for PdM, this section aims to investigate the role of ML technology in this context. The research questions, presented in Table 1, serve as the foundation for this inquiry.

3.2. Search strategy

3.2.1. Search terms identification

According to the research questions, the paper designs a search strategy that focuses on keywords, search resources, search criteria and a collection of qualified published articles related to the topic. The search query using Boolean operators is shown in Fig. 2.

3.2.2. Resources for searching

Six databases were selected for the search using keyword insertion, including IEEE Xplore Digital Library, Science Direct, Springer Link, Scopus, Google Scholar, and Taylor & Francis which are representative of scientific research databases and contain a large amount of literature with strong links to the topics of the review.

- IEEE Xplore Digital Library (http://ieeexplore.ieee.org).
- ScienceDirect (http://www.sciencedirect.com).
- SpringerLink (https://link.springer.com).
- Scopus (https://www.scopus.com).
- Google Scholar (https://scholar.google.com).
- Taylor & Francis (https://taylorandfrancis.com).

Table 1
Research questions posed for the systematic literature review.

Research questions
RQ1: What is the role and function of the ML in DT for PdM?
RQ2: What are the cutting challenges and opportunities of DT for PdM?

3.2.3. Inclusion and exclusion criteria for article selection

The inclusion and exclusion criteria are listed below for the selection process, and the exclusion criteria apply to the title, abstract, and keywords of the publication.

Exclusion criteria, sources that met the following restrictions were excluded from this study:

(1) Exclusion of review articles collected on databases using the search query.
(2) Exclusion of articles with no data source or experimental results were collected on the databases using the search query.
(3) Exclude articles where the DT for the PdM application does not match the topic of the article.
(4) Articles that were not written in English.

Inclusion criteria, sources that met the following restrictions were included in this study:

(1) All the articles, written in English, DT technologies for tackling PdM issues.
(2) Articles that introduce new techniques to improve the performance of existing DT technologies used for PdM.

3.2.4. Article selection and assessment process

A large number of publications were retrieved from the six main databases through keyword searches of the databases using Boolean-based operators and were selected based on inclusion and exclusion criteria. 26 publications were evaluated to meet the selection criteria. As shown in Table 2.

3.2.5. Classification of recent research work

In the previous section, recent research on DT for PdM was reviewed including the implementation process of different PdM applications using DT techniques. It is found that ML techniques play a crucial role in DT for PdM, but there is still a part where ML techniques are not applied. Table 2 classifies the articles of DT for PdM in the last five years. In Table 2, the main classification objectives include exploring the role of ML techniques in DT for PdM and whether ML techniques have been used to build the model. Another classification is the type of ML techniques used, including traditional ML algorithms, deep learning, and transfer learning. More than half of the studies have applied ML techniques to build DT for PdM models. In addition, data is an important aspect of ML but is often overlooked. Lastly, research objectives and tasks are included separately, as the results of the research are equally important. Several insights from Table 2 are listed as follows:

(1) **Data types:** The studies consider various types of data for analysis, such as sensor data, inspection data, force measurement data, acoustic data, vibration signals, images, text, simulation data, etc. ML plays a crucial role in identifying patterns, anomalies, and trends related to asset health and maintenance needs. However, how to comprehensively integrate these multi-source data for DT-PdM needs to be further explored.
(2) **The use of ML:** Various machine learning algorithms have been utilized, including deep learning, SVM and Random Forest. Among different types of algorithms, deep learning is the majority choice in these studies due to its capability to extract the senior features relevant to the asset health status from the multi-source data.
(3) **Research tasks:** The research tasks of these studies primarily focus on fault diagnosis, HI construction and RUL prediction. These are the main tasks in PdM, which aim to enhance

(("digital twin" AND "predictive maintenance") OR ("digital twin" AND "remaining use life") OR ("digital twin" AND "fault diagnosis") OR ("digital twin" AND "health indicator"))

Fig. 2. The search query for searching publications.

Table 2
The classification of research work of DT for PdM.

Reference	Deployment of ML	ML algorithm	Data type	Research object	Research task
Hosamo, et al.[28]	Y	ANN, SVM	Sensor data, inspection data	Stable air handling unit	Fault diagnosis
Luo, et al.[29]	Y	LR, RF, SVR	Force measurement data, acoustic data	CNC machine tool	Remaining useful life
Liu, et al.[9]	Y	Deep learning	Operation data, security data, life-time data	Bearing	Fault diagnosis
Georgoulias and Chryssolouris[21]	N		Controller data, sensor data	Gearbox	Remaining useful life
Shangguan, et al.[69]	Y	Clustering, SVM	Telemetry data	Satellite system	Fault diagnosis
Mahmoodian, et al.[70]	N		Telemetry data	Civil Infrastructure	Fault diagnosis
Lv, et al.[71]	Y	Deep learning	Vibration signals, images, text	Bearing	Fault diagnosis
Nguyen, et al.[58]	N		Sensor data, physics information	Thermal–hydraulic systems	Fault diagnosis
Xiong, et al.[35]	N		Operation data	PET open-circuit (O/C)	Fault diagnosis
Huang, et al.[72]	Y	Deep learning	Sensor data, engine data, simulation data	Aero-engine	Fault diagnosis
Hu, et al.[73]	Y	Deep learning	Vibration data, current data, acoustic data	Rotating machines	Health indicator
Hong and Pula[74]	Y	Deep learning	Images, simulation data	Photovoltaic	Fault diagnosis
Feng, et al.[49]	Y	Deep learning	Simulation data, surface measurement data	Bearing	Remaining useful life
Xie, et al.[36]	N		Sensor data, operation data	HVAC systems	Fault diagnosis
Wang, et al.[75]	Y	Transfer learning	Operation data, environment data,	Hydraulic electromechanical equipment	Fault diagnosis
Yu, et al.[66]	N		Simulation data, vibration data	Gearbox	Fault diagnosis
Xia, et al.[76]	Y	Transfer learning	Measured data, condition data	Pump	Fault diagnosis
Jain, et al.[77]	N		Solar irradiance and panel temperature data	Photovoltaic	Fault diagnosis
Darvishi, et al.[78]	Y	Deep learning	Sensor data	Sensors	Fault diagnosis
Liu, et al.[45]	Y	Monte Carlo tree	CWRU	CNC machine tool	Fault diagnosis
Jafari and Byun[79]	Y	XGBoost	Current data, voltage data, temperature data	Battery	State of charge
Moghadam, et al.[80]	N		Controller data	Gearbox	Remaining useful life
Xiong, et al.[10]	Y	Deep learning	Sensor data operating data, signal data	Aero-engine	Health indicator
Xue, et al.[46]	Y	CART	Vibration data	CNC machine tool	Fault diagnosis
Savolainen and Urbani [81]	N		Simulation data	Multi-unit system	Operations and maintenance
Wang et al.[82]	N		Vibration data	Rotating machinery	Fault diagnosis

maintenance decision-making by predicting and identifying potential faults or degradation in the assets.

Deep learning has emerged as the most prevalent ML technique in PdM applications. This is achieved through the collection of high-quality input data that includes different data types such as signals, text, and images [10]. Deep learning, such as convolutional neural networks (CNN) has been shown to be effective and has been applied to many industrial applications such as fault diagnosis, HI construction, and RUL prediction for different targets such as bearings, gearboxes, and pumps [9,66,76]. However, while deep learning has been widely applied to PdM, its impact on DT has not been extensively explored. The use of deep learning requires large amounts of training data. Moreover, deep learning algorithms require large computational resources for model training, which can be a challenge in the actual deployment. 'Black-box' models like deep learning also pose challenges for explaining ability, leading researchers to develop interpretable models for DT in PdM. Nonetheless, while most DT-PdM applications involve a large number of input data sources and use ML techniques, some of these data sources are poorly described, and multi-source data collection is often inadequate. It is challenging to construct a DT based on inadequate multi-source data to promote the performance of PdM. Therefore, exploring the role of ML in DT-PdM is crucial.

4. Machine learning for digital twin-driven predictive maintenance

The integration of information technology into manufacturing has facilitated significant advancements through digitization technology. It has led to the development of various practical applications, which have been focused on enhancing the role of information technology in manufacturing and achieving seamless data transfer and virtual-real relationships between the physical and virtual domains [21,79,83,84]. As a result, the industrial system's overall development strategy has prioritized the implementation of DT technology. DT has received increasing attention from the industry due to its ability to encompass all stages of structural design, manufacturing, assembly, and operational health management. This emerging set of concepts has been applied to manufacturing, including machinery and production lines, to enhance plant operations management. The technology enables real-time monitoring of operating equipment, leading to improved efficiency in the inspection and repair of faulty equipment, which can reduce productivity loss caused by equipment failure and regular maintenance requirements [74]. In the context of DT-PdM, ML plays a pivotal role in leveraging the power of DT. By analyzing the vast amounts of multi-source data such as monitoring data and maintenance data, ML algorithms can detect patterns and anomalies indicative of equipment failure or performance degradation. The essential tasks in PdM such as HI construction, RUL prediction, and fault diagnosis can be implemented via the modeling of multi-source data using ML. Before diving into how DT aids Predictive Maintenance (PdM), it's crucial to understand the key tasks integral to PdM:

1. **Health indicator estimation:** An aggregated metric or a set of metrics that give a snapshot of the current health or condition of a piece of equipment. This index allows operators to track the overall well-being of machinery and decide on appropriate actions based on its status.
2. **Remaining useful life prediction:** An estimate of the time left before a machine or equipment reaches the end of its effective operational life. This prediction helps plan maintenance activities and replacements in a timely manner.
3. **Fault diagnosis:** The process of identifying, isolating, and pinpointing the root cause of a malfunction or an anomaly in a system. It provides clarity on specific problems, facilitating targeted repair and maintenance actions.

With the aforementioned concepts clarified, the role of ML for DT-PdM can be better identified. PdM, at its core, revolves around the systematic use of HI, RUL, and fault diagnosis to predict the future condition of equipment and schedule maintenance accordingly. ML is the key component in this framework. By harnessing ML to sift through voluminous datasets from different data sources, it becomes possible to identify the degradation and faulty patterns of equipment issues.The relationship between the multi-source data and different tasks is illustrated in Fig. 3.

The advantage of DT-PdM is that it can guide the twin model's evolution in real-time according to changes in the physical object's operating state through the interaction of data between the physical object and the virtual model [28]. The simulation analysis feeds the prognostic results to the diagnostic control center of the DT, which helps the physical entity optimize and make decisions. ML in DT offers tremendous potential for revolutionizing of PdM. By leveraging the insights and capabilities of these technologies, organizations can optimize their maintenance practices, achieve greater asset reliability, and drive significant improvements in operational performance. With the ability to accurately diagnosis the faulty state and predict the equipment failures, ML empowers organizations to make data-driven decisions and take proactive measures to ensure the smooth operation of manufacturing processes and maximize productivity. In this section, a DT-PdM framework is first elaborated. Subsequently, the role and function of ML in DT-PdM are reviewed and discussed.

4.1. Digital twin-driven predictive maintenance framework

Implementing PdM applications has been a challenge for many scholars, as noted in previous research [77,78,85], However, the continued development of DT has provided a broad and acceptable technical framework for DT-PdM, which contains physical entities, digital entities, and connectivity-related components [12,73,86]. Despite this progress, integrating PdM into a common DT framework remains a formidable challenge that requires extensive research and development efforts to overcome. To address this challenge, the American National Institute of Standards and related research are designing

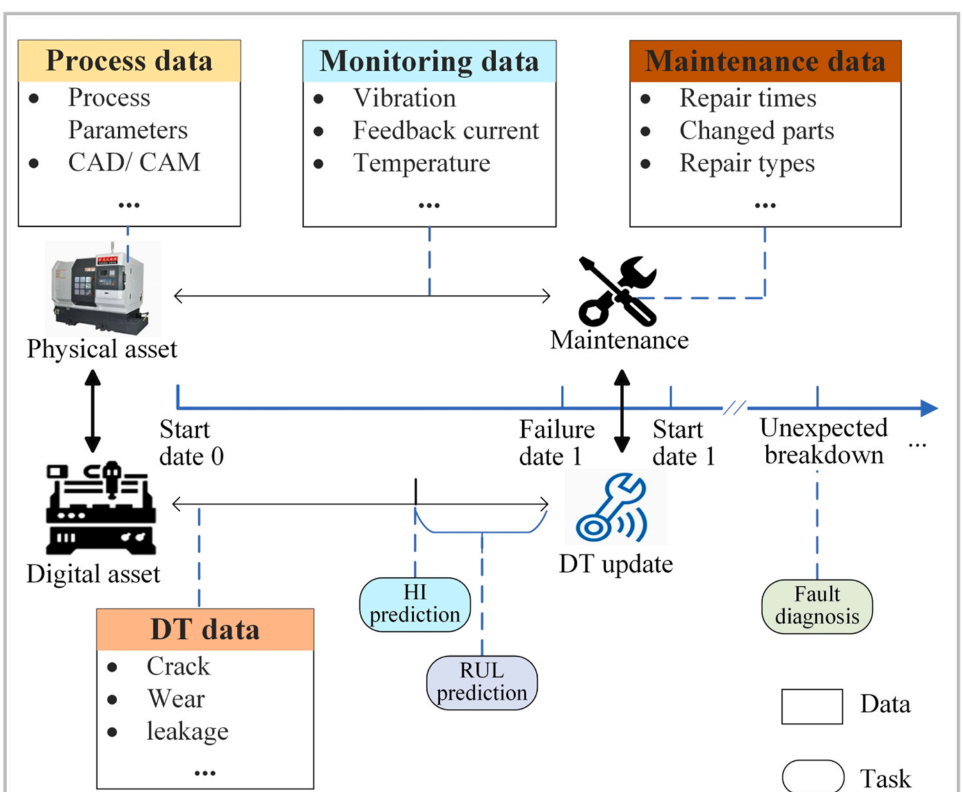

Fig. 3. The relationship of multi-source data and tasks in DT-PdM.

ISO 23247 to help standardize DT frameworks [69,87]. The standard provides a targeted integration of the DT framework and the PdM framework, clearly stating the general principles of the framework, the reference system, and relevant information, and proposing relevant reference models [2].

Based on the existing work [88], a DT generic framework for PdM is proposed in Fig. 4, which combines ML techniques and DT-PdM applications. Implementing DT-PdM in the framework of DT-PdM mainly involves three stages. First, the monitoring data in the physical layer is collected, including process data, equipment data, and product data, which is transmitted through wireless networks to edge devices and finally to the cloud. In this process, the transmission of high-volume multi-source data is a major concern due to the limitation of broadband and the computational cost of the cloud computer. Hence, the cloud-edge collaboration that adopts ML techniques can be a potential solution. In the cloud-edge collaboration of DT-PdM, the data sampling strategy can be optimized, and the sensor data can be pre-processed to extract the key features to lower the data transmission load.

Finally, with the information obtained from DT, advanced ML algorithms such as deep learning can be used for fault diagnosis and RUL prediction modeling. The results can be used to optimize the decision-making in PdM such as maintenance planning, spare parts management, and job scheduling. In the modeling of fault diagnosis and RUL prediction, several challenges such as data imbalance, the reasoning of the fault root cause, and the unseen tasks transfer learning can be addressed by the collaboration of ML and DT. DT can be used to simulate and generate data samples for the minority faulty class and the unseen tasks. Meanwhile, the DT can be used to verify the fault root cause identified by the ML algorithms.

4.2. Machine learning for health indicator construction and remaining useful life prediction

4.2.1. Overview of health indicator and remaining useful life prediction

Both HI and RUL prediction are essential in PdM. RUL prediction is concerned with estimating the remaining operational lifespan of a machine, whereas HI prediction focuses on quantifying the overall health condition. The RUL prediction provides a time-based estimation, indicating how much time is left before failure, while the HI provides a numerical value representing the health level. HI construction can be used as an input or feature for RUL prediction models. By considering the HI value along with other relevant features, RUL prediction models can consider the current health condition of the machine to improve the accuracy of the remaining life estimation. The construction of HI relies heavily on subjective assessments which can reveal the damage level of the component or system. The problem of ambiguity leads to challenges in the accuracy of the RUL prediction. Therefore, the construction of multi-stage equipment degradation trends through HI to aid RUL prediction may be a suitable approach [89], by splitting the multi-stage degradation state and using multi-model predictions instead of single-model predictions with low accuracy, so this section will illustrate the construction of a combined HI and RUL model based on DT. In conjunction with the application of HI, HI consists of three main attributes:

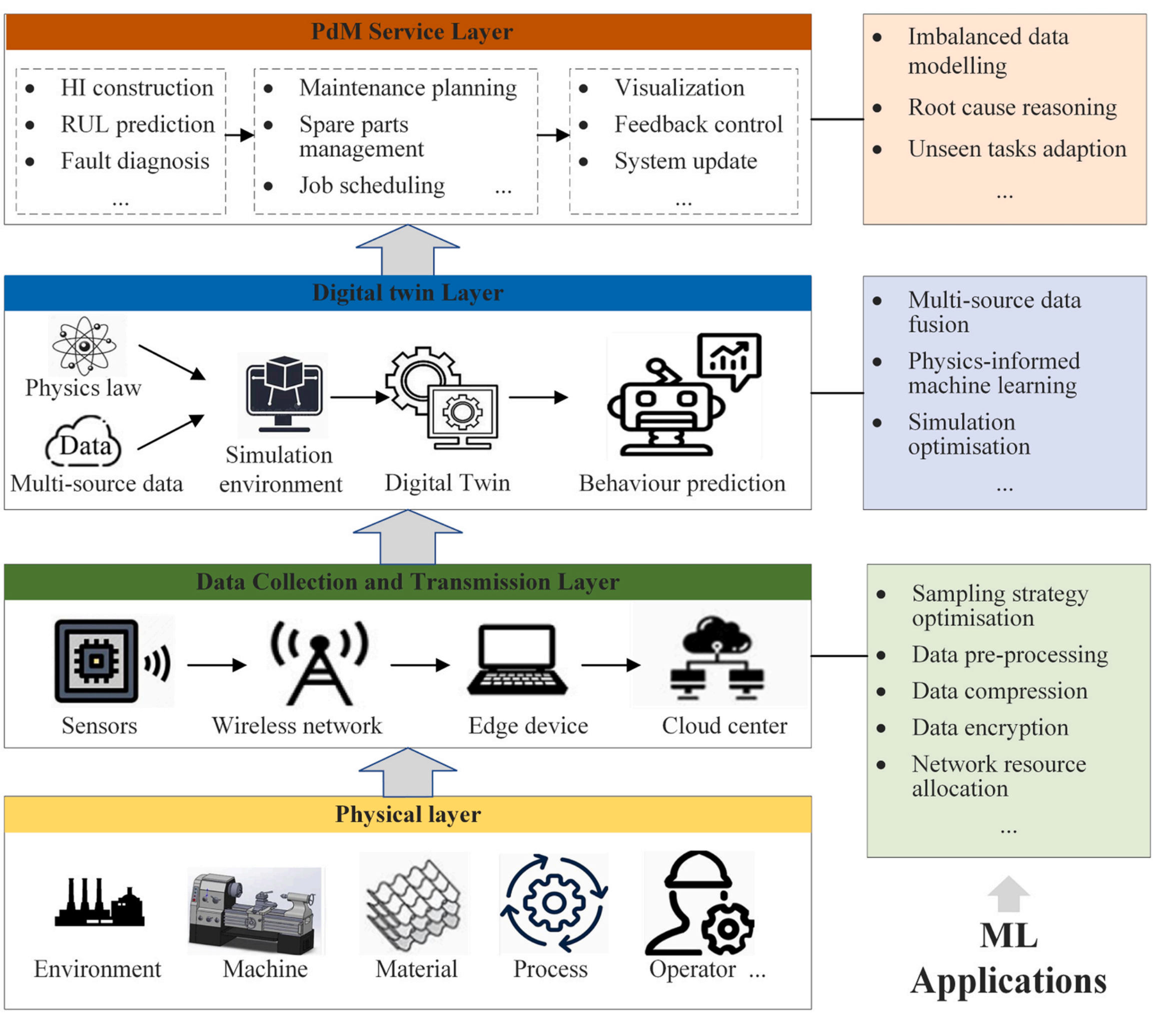

Fig. 4. A framework for ML in DT-PdM.

(1) **Detectability:** As different fault levels reflect different HI knowledge, the sensitivity of the HI is important and the best HI is assessed by the ability to detect the smallest fault type, which is often related to the construction of the fault characteristics [90].
(2) **Separability:** The aim is to distinguish between fault and non-fault types and to have realistic and reliable results [90].
(3) **Trendability:** the degradation of a component after a failure can be positively correlated with the running time and the fitting error is within acceptable limits, and the results are optimized continuously using a suitable evaluation matrix [91]. The construction of an HI is therefore essential and is considered to be optimal once it has achieved the requirements of detectability, separability, and Trendability.

4.2.2. *Machine learning for health indicator construction*

There are two primary types of HI-based construction: statistical-based models and ML-based models. Historically, HI was based on a statistically driven approach to modeling. For example, index-based transient maintenance targets simple components like bearings by extracting statistical parameters from monitoring signals to derive trend characteristics like root mean square (RMS), which reflects energy or amplitude and represents the health state [92]. However, researchers have found that RMS is affected by various operating conditions and is not very resistant to interference, making it unsuitable as a direct indicator of component HI [93]. The statistical-based approach to HI construction requires researchers to make human observations or discoveries of degradation trends, which can be time-consuming and subject to the variability of the parts being studied. To overcome these challenges, ML techniques can be employed to mine correlated degradation knowledge for HI.

ML techniques are currently a popular research topic for building HI. However, due to the limitations of current statistical parameters, the knowledge-mining presentation of the mechanisms may be incomplete. To address this, researchers have proposed constructing HI using a fusion of ML techniques. For example, Widodo fused peak, kurtosis, and entropy using principal component analysis for dimensionality reduction to construct HI [94]. Saidi et al. established a filtered detection method and successfully applied it to the HI construction of wind turbine bearings [95]. Moshrefzadeh et al. proposed spectral amplitude modulation that uses SVM and subspace *k*-Nearest Neighbor (*k*-NN) to calculate the impulsivity of signals and determine the state of health of the machine [96]. Mosallam et al. used features extracted in the time domain frequency domain and used principle component analysis models to construct HI [97]. These ML-based approaches demonstrate the ability to bridge gaps in statistical knowledge mining and information fusion, highlighting their potential in addressing HI construction methods. In DT-PdM, DT can generate key features that are relevant to the machine's health status. By simulating the behavior of the physical asset in a virtual environment, DT captures and represents various aspects of the machine's operation, performance, and condition. These captured features can be further used in HI estimation modeling. Meanwhile, the HI is a virtual metric that is hard to be directly evaluated. The simulation and visualization function of DT can be helpful in the evaluation of HI.

4.2.3. *Machine learning for remaining useful life prediction*

On the other hand, RUL prediction is a crucial technique in equipment management, which involves building mathematical and simulation models to predict the future state and operating trends of a system by combining various observations [80,98]. According to Salunkhe et al., RUL is the time remaining before the equipment fails in operation, obtained by building models based on the current age, condition, and past operating conditions of the equipment [99]. Initially, researchers classified these approaches as physical model-based, data-based, and hybrid-based. However, as research on RUL prediction continued, researchers further classified data-driven approaches as artificial intelligence model-based and statistical methods [100]. Currently, statistical-based models, physically-driven models, and data-driven models are being explored by researchers. The core principle of physical models for RUL prediction is to develop a mathematical model of the degradation trend of a mechanical component by considering its failure mechanism or damage principle. This requires the consolidation of various sources of information, including physical experiments and FEA. While physical-based models require a complete understanding of the failure mechanism of the equipment and the setting of effective parameters to achieve accurate estimation, they may limit the extension and application of the method for some complex mechanical systems. Statistical model-based RUL prediction focuses on building a statistical model from a large amount of empirical knowledge and deriving the RUL model from observations. The classical approach is autoregressive (AR) model which assumes future state values and measures the error of a linear function of observed and run values [101].

The data-driven RUL prediction focuses on utilizing ML techniques to uncover trends in mechanical degradation rather than relying on physical or statistical models. Various deep learning techniques have been used for RUL prediction. Recurrent neural networks (RNN) are widely used for RUL prediction because of their ability to handle explicit time series data. Zemouri et al. proposed a recurrent radial basis function network and used it to predict the RUL of mechanical components [102]. Hybrid method-based RUL prediction has also been proposed, integrating the advantages of different methods to construct integrated degradation models. However, there are relatively few studies in this category. Some researchers have used multiple prediction methods by fusing different strategies to build hybrid integrated prediction frameworks. For example, Zemouri et al. combined ANN with AR models to develop a hybrid approach [102].

Fig. 5 illustrates a line graph showing the number of papers published on developing HI and RUL prediction models using ML indexed by Google Scholar from 2001 to 2022. Although this data may not capture all publications and could potentially include non-academic publications, this proportion provides a valuable reference, indicating a significant increase in the importance of ML in developing HI and RUL prediction models. It can be seen that 2010 and 2017 are two accelerating points. The publication trends of both HI and RUL prediction are similar to the developing trend of deep learning in this period. Meanwhile, it is obvious that the research of RUL outweighed that of HI in the last decades. With the development of DT, the research of HI can be beneficial and the number of publications can be promoted.

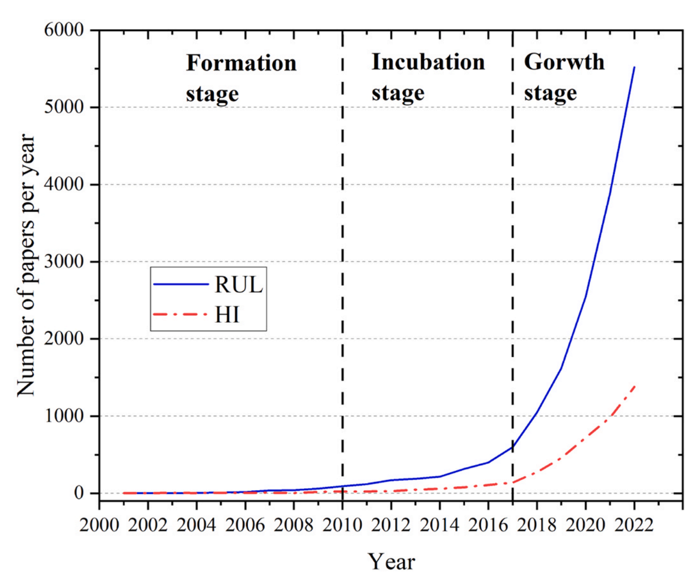

Fig. 5. Trends in ML-based RUL prediction model development: a Google Scholar publication analysis.

4.2.4. Leveraging health indicator construction and remaining useful life prediction with digital twin

HI construction and RUL prediction are the main tasks in PdM. The application of DT techniques can enhance the accuracy of HI and RUL prediction, as production environments can vary significantly, resulting in low model accuracy [49]. Fig. 6 illustrates the process of DT-driven HI and RUL prediction. The figure encompasses five distinct stages: data collection, communication, DT mapping, behavior prediction, and DT updating. Each stage plays a vital role in facilitating accurate and efficient PdM practices.

Stage 1: Multi-source data including sensor data, simulation data, and statistical data is collected for analysis and modeling. The cloud computer set up the data collection plan according to the feature importance in ML. The collection plan is then sent to the edge device including the required features, and sampling frequency. Finally, the specific data required by the cloud platform is transmitted to the cloud platform.

Stage 2: Updating different models including geometric model, data analytics model and physics model to achieve high fidelity mappings with the real-world asset. The geometric model can be updated via the analysis of the shape data such as point-cloud data. The data analytics models can be calibrated and updated via incremental learning or continuous learning. Meanwhile, ML can be used to discover new knowledge of physics which can update the physics model.

Stage 3: Data fusion is implemented to fuse the data from different sources. After the monitoring data is used to update the DT, the key features relevant to the asset health status such as wear degree and crack dimension are estimated using DT simulation. The simulated data, monitoring data and statistical data is then fused using advanced ML technique.

Stage 4: The fused data is then used for HI and RUL prediction modeling. The prevailing deep learning algorithm is then deployed to construct a HI model based on the fused data. Then the predicted HI is used to estimate the RUL based on the HI curve construed in DT.

Stage 5: Based on the HI and RUL prediction, the asset performance in DT is evaluated and the optimal maintenance plan and the job schedule are determined in DT. ML techniques such as reinforcement learning can be adopted to optimize maintenance planning, which can achieve the lowest maintenance cost and machine down time.

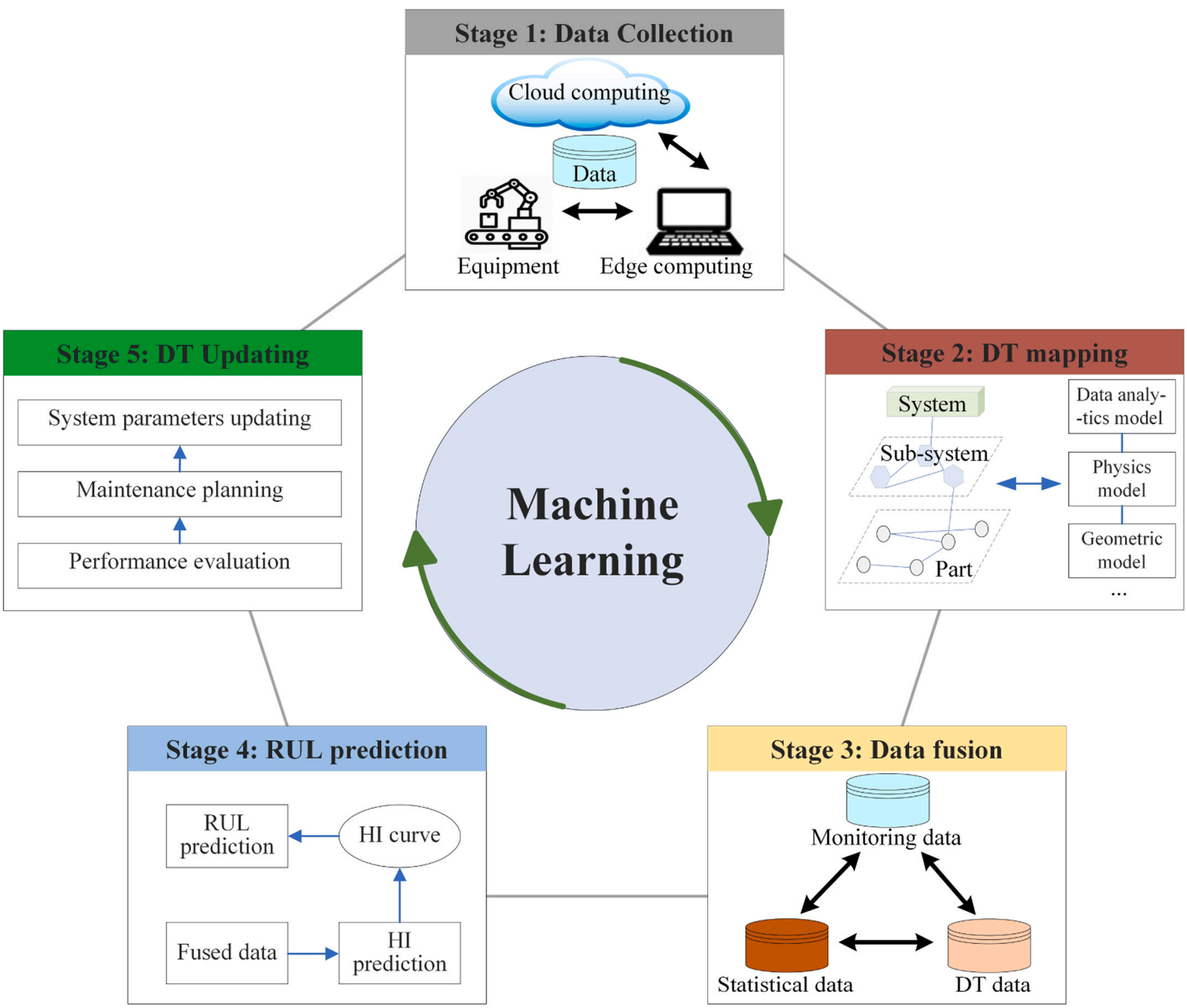

Fig. 6. The process of DT-driven HI and RUL prediction.

4.3. *Fault diagnosis based on machine learning*

With the increasing use of smart devices, health management technology has become crucial for building fault diagnosis models using monitoring data. Fault diagnosis involves monitoring equipment's operating status and analyzing the failure mechanism after a fault or anomaly has occurred. Anomaly detection has been widely studied in PdM. However, it's worth noting that anomaly detection often overlaps with fault diagnosis [103]. Both are essentially classification tasks: while anomaly detection classifies operational data into 'normal' or 'anomalous', fault diagnosis often extends this by classifying the specific type or cause of the anomaly. Hence, the anomaly detection tasks were classified into fault diagnosis in this study. Advanced fault prediction using intelligent technology can help enterprises manage and reduce costs [13]. However, building such models requires a combination of experienced domain knowledge. ML has emerged as a prevalent approach for intelligent fault diagnosis, utilizing ML and deep learning networks to model collected data and learn machine diagnostic knowledge adaptively. This approach replaces the previous reliance on engineer experience and knowledge for equipment maintenance [104].

4.3.1. *Machine learning for fault diagnosis*

ML-based fault diagnosis was one of the early applications of intelligent fault diagnosis. For instance, Wong et al. proposed an improved self-organizing mapping for bearing fault diagnosis. With the advance of deep learning, the performance of fault diagnosis has improved greatly. Liu et al. and Lu et al. used stacked sparse AE and stacked denoising AE to apply fault diagnosis to bearings with higher accuracy than SVM and other methods [105,106]. CNN can capture the key faulty features from the input data. CNN was successfully constructed for diagnostic models of rolling element bearings, gears, motors, and hydraulic pumps [107]. The attention mechanism is also a hot topic in the development of fault diagnosis. The introduction of an attention mechanism can help models autonomously assign learning weights and offsets to learn important information and ignore unimportant information, such as spatial attention [108–110] and channel attention [111,112].

In real industrial scenarios, healthy data can be easily collected, but the amount of faulty data often falls short of the requirement, which poses a challenge for building reliable diagnostic models. Therefore, transfer learning has been introduced to facilitate the application of fault diagnosis in engineering scenarios, such as transfer component analysis [113], joint distribution adaptive [114], and novel sparse de-noising AE [76]. The role of ML in fault diagnosis applications has become increasingly important and has evolved toward general-purpose models [115]. This section mainly reviews the development of ML in fault diagnosis from conventional ML-based fault diagnosis to deep learning-based fault diagnosis.

Transfer learning is a prevailing deep learning technique, which is helpful in fault diagnosis [116]. It is also expected to extend from academic research to industrial scenarios, reducing the cost of large amounts of labeled data by reusing diagnostic knowledge across multiple related domains to solve problems [75,113]. TrAdaboost is a transfer learning algorithm that originated from Adaboost, and Shen et al. used cross-domain features to train a set of k-NN- based diagnostic models through the TrAdabost algorithm [117]. Similarly, Cao et al. proposed a deep CNN-based fault diagnosis model for gearboxes, where the authors constructed a 24-layer CNN model and trained it using ImageNet datasets, and used transfer learning techniques to select parameters to pre-train themselves on another CNN diagnostic model [118].

In summary, the application of ML-based fault diagnosis methods has grown exponentially over time, with a gradual shift from traditional statistical methods to ML methods in the construction of fault diagnosis models. The widespread interest and application of transfer learning techniques suggest a potential shift towards the development of more generic models that can be used across multiple related domains. As the field continues to evolve, it is expected that the development of more sophisticated algorithms and models will lead to even more accurate and efficient fault diagnosis systems, ultimately improving the safety and reliability of industrial equipment.

4.3.2. *Leveraging fault diagnosis model construction with digital twin*

The construction of fault diagnosis models using ML faces various challenges, such as data imbalance and poor data quality. The emergence of DT has played a significant role in addressing these challenges by assisting in data pre-processing. This has, in turn, facilitated the development of fault diagnosis based on DT applications, with a particular focus on the role of DT techniques in predictive model establishment [72,119]. DT-based fault diagnosis may be able to provide effective observation data and facilitate data fusion techniques such as knowledge graphs to build models based on field environmental monitoring observations of field exploration relationships [71].

In terms of data pre-processing, traditional data collection may lead to missing values, data interruptions and other problems due to many technical reasons such as hardware equipment, and transmission protocols. DT can address these problems to some extent through virtual worlds instead of traditional methods such as replacing missing values with mean values to improve accuracy. Additionally, insufficient fault data is a great challenge in fault diagnosis modeling using ML. DT can generate faulty samples to address the unbalanced number of fault types instead of traditional modeling using over-sampling [120] and under-sampling [121] to improve model accuracy. With the advance of deep transfer learning, few-shot fault diagnosis can be achieved, while it still cannot address the unseen fault diagnosis challenge. However, DT-driven fault diagnosis can address this issue by generating faulty samples based on DT. The process of DT-driven unseen fault diagnosis using deep transfer learning is illustrated in Fig. 7. With the high-fidelity DT, the characteristic and performance of unseen fault can be simulated and the high-quality data samples for the unseen fault can be obtained. Then deep transfer learning can be deployed for the unseen fault diagnosis modeling.

DT-based fault diagnosis also facilitates the fault root cause reasoning. In a complex asset, it is challenging to identify the root cause. In DT, the correlation between the components and the sub-system can be identified, which can be transformed into a graph representation. Advanced graph neural network algorithms can then be used to build a node classification model so to identify the root cause of the fault. Meanwhile, external knowledge from the fault diagnosis knowledge graph also can be introduced into DT to enhance the fault root cause reasoning capability [122]. With the introduction of knowledge graph, DT-driven fault diagnosis can benefit from a comprehensive and interconnected understanding of the system. The knowledge graph serves as a powerful tool for root cause analysis by capturing and organizing domain knowledge and enabling the exploration and discovery of complex fault mechanisms.

5. Challenges and opportunities

Based on the analysis and discussion in the previous sections, there are some challenges identified in DT-PdM. (1) The complexity of DT-PdM systems requires high-fidelity modeling, but only a few studies have considered and explored this, with most researchers only modeling DT-PdM for a single component without considering the high-fidelity of the model; (2) Most of the articles collected data from a variety of sources including physical information collection, but there are few descriptions of data fusion for different levels of DT-PdM, only integrating and modeling the data collected from multiple sources; (3) To improve the generality of the model, some of the articles use physics knowledge for modeling but do not effectively combine ML techniques, which may not effectively establish an ML model; (4) Most researchers mainly focus on ML modeling, while a suitable low-latency interactive cloud-edge collaboration solution to deploy DT-PdM applications has not been considered. Therefore, in response to the above issues raised in

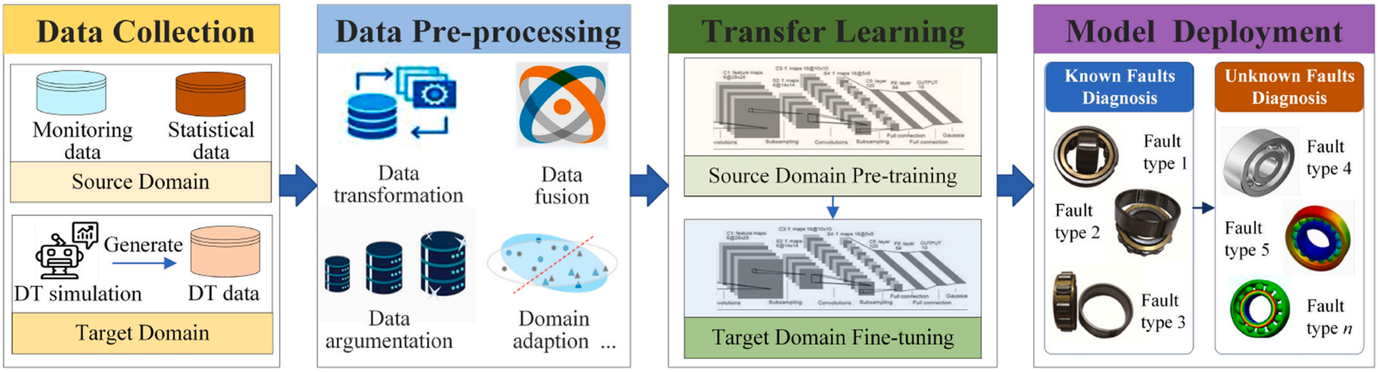

Fig. 7. The process of DT-driven unseen fault diagnosis using deep transfer learning.

the collected articles, this section presents future challenges and opportunities in four areas: ML for high-fidelity digital model construction, multi-source data fusion, physics-informed machine learning (PIML) for DT-PdM and cloud-edge collaboration for low latency interaction to address the current research gaps.

5.1. Machine learning for high-fidelity digital model construction

This section outlines an approach for developing high-fidelity models of DT for PdM, while also summarizing the current challenges and opportunities in this field. The process of modeling high-fidelity DT for PdM can be divided into three main steps: geometric model annotation, high-fidelity reality mapping, and qualitative and quantitative evaluation of high-fidelity models.

The first step involves accurately representing the true geometry of the physical space using aids such as CAD and computer-aided manufacturing (CAM) techniques for geometry annotation. Different types of annotation, including product design information, definition information, basic metadata information, functional information, parametric information, and static structure, can be utilized to achieve an accurate representation of the physical space. The existing studies have conducted the data synthetic using the virtual geometric model, which can be used for the tasks in PdM [9,10,21,28,29,35,36,45,46,49,58,66,69–82]. Furthermore, ML algorithms can facilitate continuous learning and adaptation of the DT as new data from the physical asset is available. By updating the models and retraining them with the latest information, the DT can continuously improve its performance and fidelity over time. This allows for a dynamic and evolving representation of the physical asset's behavior. Meanwhile, ML can be applied to learn and optimize the behavior of the DT. By training the models on historical data and observed outcomes, ML algorithms can discover complex patterns, relationships, and dependencies within the system. This enables the DT to simulate and predict the behavior of the physical asset with higher fidelity and accuracy. Meanwhile, the construction of a high-fidelity model must be evaluated. Since the virtual model differs from the physical entity in general and the DT model usually consists of several sub-models, evaluating the results of the ML model with a single quantitative indicator can be challenging. Therefore, the high-fidelity DT model construction needs to be further investigated.

5.2. Multi-source data fusion in DT-PdM

In the DT-PdM, the collected data comes from various sources such as sensors, IoT devices, maintenance logs, and external databases. After the multi-source data is collected, the data needs to be integrated and analyzed. However, none of the existing studies identifies the approaches for integrating the multi-source data and extracting the salient features for DT-PdM. By fusing data from multiple sources, the DT can provide a more comprehensive view of the asset's health status, which can bring tangible benefits to the PdM.

There are several challenges in the multi-source data fusion for DT-PdM. Firstly, these data sources may have different formats, structures, and quality levels. Handling the heterogeneity of data requires advanced ML techniques for data pre-processing, normalization, and transformation to ensure compatibility and consistency across different sources. Secondly, the quality and reliability of data from different sources can vary significantly. Some sources may provide accurate and reliable data, while others may be prone to errors, noise, or missing values. Dealing with data quality issues and developing methods to identify and handle unreliable or faulty data is crucial for accurate data fusion and subsequent predictive maintenance analysis. Thirdly, the data fusion of multi-sources data while maintaining synchronization and temporal coherence is essential for accurate analysis. Different data sources may have different sampling rates, time stamps, and event triggers. Aligning and synchronizing data from various sources is critical to ensure meaningful fusion and analysis. In the multi-source data fusion, a potential tool in facilitating this integration is the Asset Administration Shell (AAS) [123]. The AAS provides a standardized interface for integrating data and services across various sources, ensuring seamless data fusion by encapsulating assets in information models, thus addressing different information contexts with uniformity. Furthermore, another useful tool in multi-source data fusion is manufacturing middleware [124], which can play a substantial role in bridging the heterogeneous data environments. Manufacturing middleware ensures that disparate data formats, structures, and quality levels are homogenized, providing a consistent platform for further analysis in the DT-PdM framework. Overall, it is worthwhile to investigate multi-source data fusion in the DT for PdM, which can improve the accuracy, timeliness, and comprehensiveness of maintenance decisions.

5.3. Physics-informed machine learning for digital twin-driven predictive maintenance

To address the challenge of insufficient data volume in PdM for equipment failures, as well as to improve model generalization and ensure the physical soundness of results, PIML is a promising approach. In this section, the advantages of PIML-driven models and the challenges that may arise in the future from three perspectives [125] are introduced.

The training of ML models for PdM may require several components, including data, model architecture, optimization algorithms, and inference methods. Physical priors can be integrated into one or more of these components to improve performance. Firstly, for problems with constraints or related equations, data can be augmented or integrated, models can learn from this generated data, and physical knowledge can be reused to improve predictions compared to using only raw data. Additionally, the integration of physical knowledge may lead to a reduced need for data in the training process when applying PIML methods. Secondly, as the integration of physical knowledge may exhibit periodic or other physical patterns, the generality of the problem-solving can be enhanced, enabling the construction of a generic network model architecture. Finally, in model optimization, the optimization objective can integrate physical knowledge to reshape the optimization space and help the training process converge.

However, despite these advantages, PIML still faces several challenges in the future. Firstly, PIML requires relevant knowledge about the domain of PdM to select the appropriate physical knowledge for integration and to promote flexibility in the selection of physical knowledge. Secondly, due to the complexity of the equipment system architecture and fault information, there is a lack of evaluation of PIML methods for equipment failures and a lack of evaluation of various fault knowledge integration methods. Finally, in PIML, the loss function and optimization approach need to be designed to incorporate and enforce the physical laws or governing equations of the problem being solved. A suitable loss function and optimization approach can ensure that the neural network learns and respects the underlying physics, leading to more accurate and physically consistent predictions. Hence, PIML is a promising approach for addressing challenges in DT-PdM, but several challenges need to be further researched.

5.4. Cloud-edge collaboration for low latency interaction

When deploying ML in DT-PdM, concerns over latency and cloud-edge collaboration arise. DT-PdM relies on timely and accurate information to make informed decisions regarding asset health and maintenance actions. Low latency allows for rapid data processing, analysis, and decision-making at the edge, enabling real-time responses to critical events and minimizing downtime. This is particularly important in scenarios where immediate actions are required to prevent equipment failure or mitigate potential risks. Edge computing brings computational resources closer to the data source, reducing the latency involved in sending data to the cloud for processing. By leveraging the capability of data analytics in edge devices, data can be processed and analyzed locally, enabling faster insights and reducing the dependency on cloud resources. Low latency facilitates efficient utilization of edge computing capabilities, enabling quick response times and reducing the need for extensive data transfers to the cloud.

In order to achieve low latency in the cloud-edge collaboration of DT-PdM, several challenges need to be addressed. Firstly, edge devices often have limited computational power, memory, and energy resources. Running sophisticated machine learning algorithms on resource-constrained devices can be a challenge, requiring optimization techniques and efficient resource allocation strategies. Hence, lightweight and effective ML algorithms need to be explored. Secondly, DT-PdM involves processing and analyzing a large volume of data generated by numerous edge devices. Distributed ML algorithms for numerous edge devices can be a potential solution to achieve satisfactory performance with lower latency. The scheme of distributed ML in the DT-PdM deserves more attention in the future. Finally, the security and privacy of data in a cloud-edge collaboration are crucial. The need to transmit sensitive data between the cloud and edge devices while ensuring secure communication and preventing unauthorized access adds complexity to achieving low latency. Overcoming these challenges requires leveraging technologies such as advanced ML and edge computing techniques to achieve low latency in cloud-edge collaboration for DT-PdM.

6. Conclusions

ML techniques have made considerable contributions to DT for PdM applications, such as fault diagnosis, RUL prediction, HI construction and, to varying degrees, to DT techniques and PdM applications. This paper explores the role and function of ML techniques in DT for PdM applications. The results are then presented and further explained in the framework of DT techniques for PdM applications and ML. The latest ML techniques used in the three main application areas of DT for PdM are analyzed and classified. Furthermore, the main aspects of ML that contribute to the construction of virtual spaces and physical models are explored in depth for DT for PdM applications in different domains. Finally, the main research challenges are described and the opportunities and various prospects for DT for PdM ML techniques are discussed. Based on the foregoing, this paper provides insight into the research and implementation of DT for PdM, which can bring tangible benefits to the operation and maintenance of the industry.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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