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Advances of Digital Twins for Predictive Maintenance

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Abstract

Digital twins (DT), aiming to improve the performance of physical entities by leveraging the virtual replica, have gained significant growth in recent years. Meanwhile, DT technology has been explored in different industrial sectors and on a variety of topics, e.g., predictive maintenance (PdM). In order to understand the state-of-the-art of DT in PdM, this paper focuses on the recent advances of how DT has been deployed in PdM, especially on the challenges faced and the opportunities identified. Based on the relevant research efforts recognised, we classify them into three main branches: 1) the frameworks reported for application, 2) modelling methods, and 3) interaction between the physical entity and virtual replica. We intend to analyse the techniques and applications regarding each category, and the perceived benefits of PdM from the DT paradigm are summarized. Finally, challenges of current research and opportunities for future research are discussed especially concerning the issue of framework standardisation for DT-driven PdM, needs for high-fidelity models, holistic evaluation methods, and the multi-component, multi-level model issue.

Keywords: Digital twin, Predictive maintenance, prognosis, diagnosis, review;

1. Introduction

Industry 4.0 is a new modernisation and computerisation trend of manufacturing driven by the advances of the Industrial Internet of things, cloud computing, edge computing and artificial intelligence [1]. The new paradigm promotes the adaption of these advanced technologies into the process and equipment in industrial manufacturing. PdM is a critical component of Industry 4.0 content. As production activities deeply rely on machines states, maintenance has obtained critical importance. To avoid an unexpected breakdown, there is a transformation from reactive maintenance to proactive maintenance. PdM is regarded as a cost-saving method, which aims to decide the

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maintenance time for equipment before the upcoming equipment failure by assessing the degradation condition and calculating the remaining useful life (RUL). With the implementation of PdM, the unplanned downtime cost can be reduced [2]. According to the report from McKinsey [3], the maintenance cost will significantly reduce by 18%-25% after implanting the PdM, and therefore the research on PdM appealed to lots of attention from both academia and industry in recent years.

Nowadays, large volumes of data that contain valuable information about the process and operations can be collected from industrial equipment. Industrial data are collected by heterogeneous sensors and then stored in the database. Data-driven methods are employed to analyse this data and get valuable insights for prognosis. Typically, data-driven methods [4] have two main scopes: machine learning approaches, and statistical approaches. Another mainstream method in PdM is the physical-based model [5], which assesses the degradation of components using physics laws. Besides, the hybrid approaches [6], which is a combination of data-driven methods with physical-based methods, is the third class of PdM methods.

With the development of sensor technology, AI, data science, and IoT, a new paradigm for engineering is developed, named digital twins (DT), which mainly consists of a physical entity, digital replica, and the connection. DT is targeted at improving the performance of the physical entity leveraging the analysis of the virtual counterpart [7]. DT is of importance in engineering by some scholars. Tao et al. [8] deemed that DT is a critical enabler towards Industry 4.0 and smart manufacturing. The research about DT is still in its primary. The main content of the current research is the concept, characteristics and framework of DT. Furthermore, DT is widely deployed in the product life cycle from the concept design to the logistic. Especially, the publication about the DT- driven PdM emerged and saw rapid growth in recent years. As a new technology, DT attained a growing interest, which arises a need to make it clear state-of-the-art in terms of concept, application, technology.

Although predictive maintenance is one of the important topics in the DT area, there lacks a common understanding of the trend, challenges and opportunities in both industry and academia. DT brings a new engineering solution for PdM, while the technological improvement and performance variation for a system in the new paradigm is not clear. Besides, to the best of our knowledge, there are two papers [9; 10] that reviewed the development of maintenance and DT, and the advances of DT for PdM has not been reported. Thus, a summary of the recent advance of PdM facilitating by DT is needed. In this paper, a systematic review for publications about PdM and DT is conducted where the trend is discussed to recognise research gaps and opportunities.

The rest of the paper is organised as follows: Section 2 reviews the state-of-the-art of DT in terms of concepts, technologies, and applications. Publications of DT and PdM are classified into four groups, and each category is analysed in section 3. Then, the gaps and corresponding opportunities are listed by analysing the trend of the topic. Section 5 concludes the paper.

2. Digital twins – A brief review

The concept 'digital twins' was coined in a presentation by Grieves in 2003 according to the white paper [7]. Until 2012, the first definition of DT was proposed as "an integrated multi-physics, multi-scale, probabilistic simulation" by Glaessgen [11]. Since then, DT has attracted attention from both academics and industry, and lots of efforts have been made. Some scholars defined DT from their perspectives to explore the concept, and their definition is quite similar to the first one [12]. In essence, digital twins mirror the operation and predict the state for the physical entity employing advanced technologies to improve the performance of a physical entity. DT is not a specific technique but a scheme, in which the modelling methods and purposes depend on the usage scenario. Digital twins have many characteristics.

- The communication between physical and digital replica is bi-direction, and it is a critical feature for distinguishing between the digital model, digital shadow and digital twin[12; 13];
- The fidelity of digital twins depends on its intended purpose [14], even though the level of fidelity of virtual models are not well clarified [15];
- DT is dynamic since it evolves with the physical entity by feeding the data in the product life cycle (PLC).

The development of DT takes benefits from numerous advanced technologies, such as IoT, big data, sensor technologies. Modelling is the basis of virtual twins. The digital model contains geometrical information, for example, the shape of objects. To make models more realistic, the product surface can be defined with texture mapping. The production characteristics and constraints information of products can be added to the digital model that can be used in manufacturing, assembly. Geometric models only represent the static information of the model. To imitate operations of a physical entity, simulation techniques engage in the digital twin. Physical simulation is based on selected physical laws, representing the key characteristics of objects, such as crack growth, kinetic models. The accuracy of the simulation model depends on the assumption within the model. Besides, another class of modelling methods [16], called the rule-based method, is used to extract knowledge and rules from historical data, expert knowledge to predict the behaviour of the physical entities. In rule-based methods, statistical methods and machine learning models are used to extract rules, and ontology methods are used to describe rules. Digital twins are dynamic, and model evolution techniques update the models according to the feedback of the physical twin to mirror the physical objects. Model verification and validation are critical to keeping the model fidelity and accuracy, which is quite critical to its performance. From the view of technologies, digital twins are the integration of existing methods and provide a novel paradigm for different sectors.

DT was originally developed for air force vehicles by NASA and the US air force to enable the safety and reliability of equipment [11]. After that, the application of DT sprung up over the different sectors and industries. In production engineering, DT technology is deployed in every phase in the whole lifecycle of products [17]. Based on design methods, DT improves the efficiency of product design processes. During manufacturing, DT automatically optimises production planning, scheduling and virtual commissioning [18]. DT also provides products service, such as products fault warnings and maintenance to lower the impact of production downtime. Besides, DT technology is widely employed in different sectors, including materials, railway, logistic, naval engineering, aerospace, the energy industry and manufacturing [9]. Particularly, maintenance research accounts for the largest proportion of all the DT academic publications. Furthermore, the most commonly used maintenance strategy in DT is PdM [9], which is applied to monitor equipment conditions to determine the next maintenance time. In industry, some companies, such as GE, Siemens, also adapt DT into the application and several patents were proposed [19; 20]. Though DT is quite popular in the industry, it is still in the infant stage. The impact of DT on the industry has yet to be explored due to the modelling methods and their intention varies. To reveal the impact of DT on PdM, a literature review is conducted to discuss the status in terms of framework, modelling techniques in the next section.

3. DT for PdM

To identify the research status of DT on PdM, a literature review on the related papers is conducted in this section. The methodology of the literature review is presented as follows. The journal papers are selected by searching ("digital twins" AND "predictive maintenance") in the title, abstract or author keywords among the mainstream database, including IEEE Xplore, Sciencedirect, Springer Link, ACM, Scopus, by 1st Jun 2021. In this stage, 194 papers were obtained. These papers were filtered according to the criterion that all articles, written in English, directly explored DT technologies to improve the performance of PdM. Finally, 30 papers are selected. The publication related to the DT-driven PdM are reviewed systematically and classified in terms of research objects, DT framework for PdM (Y: Have studied DT framework in the paper. N: Did not study framework in the paper), research methods ((1) diagnosis, (2) prognosis, (3) maintenance scheduling, and (4) literature review) and received benefits after implementing DT for PdM. The detailed contents are shown in Table 1.

It can be seen from the table that most of the research objects for PdM belong to mechanical components, and small parts are buildings and electrical systems. Seldom publication focused on the whole mechanical equipment and systems. The framework for DT for PdM is one of the most popular research points and many papers contributed to it. Nearly all research methods that were adopted in the paper solved diagnosis and prognosis problems, and only two papers contributed to maintenance optimization in DT. A further discussion follows in matters of DT-driven PdM framework, modelling methods and the interaction between these two parts. The perceived benefits of implementing DT for PdM are summarized at the end of this Section.

3.1. DT-driven PdM framework

In a system-level view of PdM, many researchers were inspired by the development of DT and explored the PdM framework driven by DT, to study the system architectures of PdM, enabling technologies, modelling methods, technical routes [21; 22].

Table 1 List of the recent research publications in the field of DT-driven PdM with the classifications

Reference	Research Objects	Framework	Research methods				Perceived benefits
			1	2	3	4	
Aivaliotis et al. [23]	gearbox	N		√			estimate RUL provides accurate results
Ding et al. [24]	shearer key parts	N		√			improving the accuracy of prediction
Liu et al. [25]	aero-engine bearing	Y	√				the prediction error is better.
Qiao et al. [26]	milling machine tool	Y	√	√			improving the accuracy of fault prediction
Short et al. [27]	rotating equipment	N	√				–
Xu et al. [28]	production line	Y	√				insufficient training data, different data distributions
Bigoni et al. [29]	complex structures	N	√				detecting and localizing crack
Booyse et al. [30]	sevral open cases	Y	√	√			–
Garza et al. [31]	eletric braking system	N	√				enhance its CBM capability
Karve et al. [32]	plate specimen	N	√	√	√		performing mission optimization.
Kim [33]	noise Barrier Tunnels	N		√			real-time diagnostics. improve sustainability
Li et al. [34]	cable-net structure	N		√			improving maintenance efficiency, reducing cost.
Lu et al. [35]	centrifugal pumps	Y	√				efficient and automated asset monitoring
Luo et al. [6]	CNC machine tool	Y		√			a more accurate result
Mi et al. [36]	bearings	Y			√		higher accuracy and reliability, the comprehensiveness of fault data is improved
Oluwasegun et al. [21]	control element drive system	Y	√				improve insight into system design
Shangguan et al. [22]	satellite System	Y	√				improve the accuracy and reliability of fault diagnosis
Szpytko et al. [37]	crane	N			√		simulations under various scenarios and conditions, accurate diagnostics and prognostics.
Huang et al. [38]	chiller	Y	√				low latency, real-time monitoring
Leser et al. [39]	specimen	N	√	√			predicting fatigue life, reduce uncertainty
Ye et al. [40]	load-bearing airframe	Y		√			real-time state monitoring, more accurately fault prediction
Aivaliotis et al. [41]	gearbox bearings	N		√			monitor the health status and convergence of the simulated to the actual robot
Moghadam et al. [42]	gearboxes	N		√			monitoring the remaining useful lifetime of the gears
Xiong et al. [43]	aero-engine	Y		√			the model prediction has high accuracy
Cavalieri et al. [44]	milling machines	N		√			achieve interoperability between different devices
Luo et al. [44]	CNC milling machine	Y		√			reduce sudden failure probability and improve stability
Zhidchenko et al. [45]	hydraulically actuated heavy equipment	N		√			–
Ritto et al. [46]	–	Y	√				realize the combination of different methods
Errandonea et al. [9]	Review					√	-
Khan et al.[10]	Review					√	-

For the DT framework, a basic, well-accept framework a three-dimension conceptual DT model was built based on the original definition, which contains a physical entity, digital entity and the connection [11]. Many researchers put efforts into the framework of the digital twin from different views. However, there is still a long way to the DT application. A generic framework normally contains the standards, technologies, and procedures of DT. To tackle the difficulties of DT application in enterprises, lots of organisations and researchers contributed to the framework of DT. The National Institute of Standards and Technology in the USA is working on the ISO 23247, which aims to standardize the DT manufacturing framework, and it is drafting currently [18]. This standard will have relative integrated contents, such as overview and general principles, reference architectures, digital representations, and information exchanges. Besides, some scholars proposed the reference model for DT applications [14; 47; 48; 49], such as the five-dimension DT model [50].

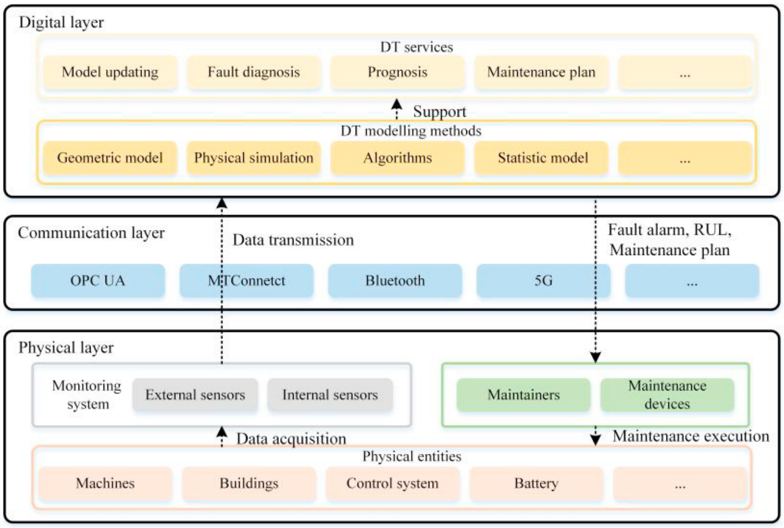

Figure 1 A generic model of DT for PdM

In the PdM application, many scholars combined the PdM and DT knowledge to generate the specific DT-driven PdM framework. Based on the current work, a generic framework of DT for PdM is illustrated in Fig. 1. In the physical layer, the conditional data of physical entities are captured by monitoring systems in real-time. The collected data are then transmitted to the digital twin enabling by the advanced communication layer. By leveraging on different technologies and data, the digital twin mirrors the state and behaviour of the physical twin. Furthermore, the digital twin provides diagnosis and prognosis services that detect faults and predict the RUL respectively. To minimize the cost and maximize the reliability of the system, maintenance optimisation is performed to generate a maintenance plan. The RUL and maintenance plan is transmitted back to the physical layer, and appropriate maintenance is then implemented.

The DT-driven PdM framework is constructed by enriching the DT model with PdM knowledge. Based on a three-part DT model [7], a DT-driven fault diagnosis framework was built by enriching the original model. Particularly, diagnosis and maintenance decisions were regarded as integrated services of virtual twin [22], and it is different from the five-dimension DT model [50], which regards the data and services as independent parts. Besides, Oluwasegun and Jung [21] also adopted a three-part DT model for the prognosis of the control element drive mechanism.

In addition to the DT-driven PdM framework, there are other frameworks, such as open system architecture for condition-based monitoring (OSA-CBM) [51], cloud enhanced PdM [52]. The DT-driven framework integrates the partial functions and features of other frameworks. For example, OSA-CBM, which is defined in ISO 13374, is comprised of six functional blocks that are data acquisition, data manipulation, state detection, health assessment, prognostics assessment, advisory generation, respectively. These functions are integrated into the DT-based framework directly or indirectly. By combining the knowledge of DT and cloud manufacturing, Mi et al. [36] proposed a multi-layer, cloud-based framework for PdM. The fault information and maintenance resource were shared among different enterprises for the same equipment to realise the real-time perception of maintenance information.

Normally, a standardised framework should provide the guidelines, key methods, and best practices for implementation [18]. In this respect, the research about the DT-based PdM framework is not detailed. The implementation of PdM applications with the DT paradigm requires that the framework should be compatible with various existing standards. Seldom papers mentioned the relationship between the proposed frameworks and the existing standards. More efforts should be put into the standardization of DT implementation.

3.2. Modelling methods of DT for Diagnosis and Prognosis

Many modelling methods are available for fault diagnosis and prognosis in the DT framework. Through summarize and classify the collected literature, the modelling methods can be categorized as data-driven methods, physical-based methods and hybrid methods. Based on the literature review, hybrid methods account for the biggest proportions of models both in diagnosis and prognosis.

3.2.1. Data-driven method

Data-driven methods play an important role in DT for PdM, and this type of method is normally regarded as a data-driven DT model which has the functions of faults classification, RUL predictions. For example, the artificial neural network was used for anomaly detection of control element drive system utilizing coil current data [21]. Besides, Bayesian change point detection methodology [35], deep learning [28] were adopted in studies. Some data-driven methods that used synthetic data were introduced in Section 3.2.3 hybrid methods.

3.2.2. Physical-based method

The physical-based method uses the physical laws to imitate system operations which relies deeply on mathematics and physics. The finite element method is the most widely employed method among the selected papers [39; 45; 53]. Using the finite element models and Monte Carlo methods, probabilistic estimates of the crack state for a geometrically complex test specimen calibrated the prognostic model and reduced the uncertainty in fatigue life prognosis [39]. Numerical analysis is another primary method in this area. By feeding the stress data collected by the gyro sensor, the numerical behaviour model was established to analyse the RUL of noise barrier tunnels [33]. A numerical example [40] showed the uncertainty of crack prediction from a micro view. The crack length was obtained by analysing observed crack data through Bayesian inference.

In [11], the multi-physics simulation was regarded as the foremost opportunity for the development of DT. Multi-physics simulation is considered more than one physical field that occurs in a coupled system and spans many scientific disciplines, such as mathematics, physicals and numerical analysis. In [6], a multi-physical simulation is constructed coupling dynamics and thermodynamics to imitate the milling process. However, the existing studies on PdM for DT mainly focused on single physical modelling.

In summary, the research on multi-physical simulation for DT is deficient currently. The physical fields explored in current studies are in the beginning stage, where only the stress and force for the mechanical structure were taken into consideration. The physical fields, such as heat transfer, pore water movement, concentration field, stress and strain, dynamics, chemical reactions, electrostatics and its interaction, have seldom been mentioned and considered.

3.2.3. The hybridisation of data-driven and physical methods

In this section, the common way to realize the hybridisation of different methods in DT is summarized. The most widely used hybridisation way [23; 25; 29; 32] is for data augmentation by generating synthetic data. For instance, a simulation of bearing was conducted combining domain knowledge and synthetic data were generated in the simulation. Critical features which were selected from sensor data and synthetic data were fed into a machine learning method to make the fault prediction of mechanical products. A case study was set to compare the prediction performance of the proposed method and the method without synthetic data, and the results verified the effectiveness of the hybrid method [25]. Transfer learning was adapted to migrate the equipment knowledge from virtual space to physical space by using synthetic data. A two-stage RUL prediction method is proposed to prognosis the equipment. At first, a deep neural network was trained using synthetic data. Then, the diagnosis model migrated from virtual to physical model by using the transfer learning method [28]. In addition to simulation data, generative learning is a way to augment data. In computer-aided engineering, machining learning methods were employed to enlarge computational fluid dynamics data, which covers the information of operational conditions [54].

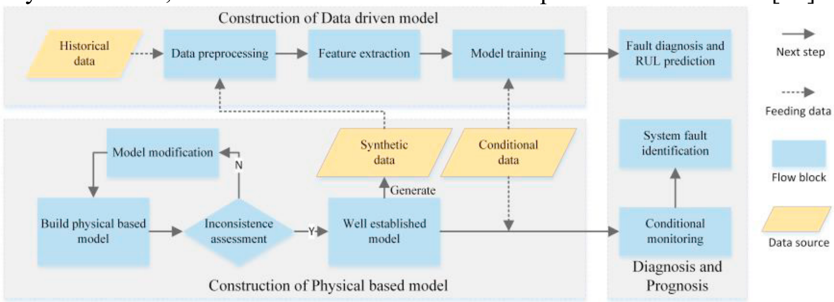

Figure 2. Flow chart of one of the hybridisation methods for PdM in DT

In industrial application, data insufficiency is the main concern, especially fault data, because equipment run in a healthy state most of the time. DT provides solutions for this problem by generating synthetic data. However, the quality of synthetic data depends on the fidelity of the digital model. Except for the model itself, the parameters of the digital model are key elements of the model fidelity. Some work studied tuning methods of the digital model by adjusting parameters. For example, when predicting the RUL of equipment machinery, the conditional data are used to synchronous tuning the digital model and equipment. After tuning, the quality of generating data was improved [23]. Based on the review work, the flow chart of the hybridization method is shown in Figure 2.

Another hybridisation way is running two methods parallelly, and the maintenance decision is made based on a synthesis of two analysis results. To predict the RUL of shearer key parts, a simulation and an autoencoder with bi-Gated Recurrent Unit methods were conducted simultaneously. To handle the two results, a strategy is adopted. If either result was abnormal, the inspection should be arranged for the equipment [24]. In another case, a particle algorithm was employed to make a more accurate RUL by combining the result of the data-driven method and state-space model [6].

3.3. Interaction between the physical entity and digital replica

The interaction between the physical-digital replica is bi-direction, and it is a remarkable feature to distinguish DT and digital model. In the PdM context, the physical-to-digital connection means that the conditional data of the physical entity is transmitted into the virtual environment in real-time. Then, the digital model tunes itself to stay the same as its counterpart, and conditional data are used to fault diagnosis and prognosis. The digital-to-physical connection refers to the transmission of maintenance information that is employed for maintenance decision making.

Most of the research in corpus focused on the physical-to-digital connection, papers seldom reported the opposite connection. The reason for the condition is the role of the human-in-the-loop [15]. Maintainers execute maintenance activities following the RUL and maintenance plan generated by digital twins. Thus, maintainers are the key elements in the digital-to-physical connection in DT.

In physical-to-digital connection, the digital model tunes itself to stay the same as its counterpart. For a physical-based model, the real data is provided as input for simulation, and parameters of simulation update so that the digital model mirror the behaviour of the physical model. Some shape-changing algorithms are used to reflect the changes of physical entities in real-time [33; 34]. For data-driven methods, real-time data is used for model training to realize fault diagnosis and prognosis. The infrastructure is the basis for data acquisition and transmission. The advance of sensor technology contributes to the collection of real-time data of system conditions where IoT plays an important role in data transmission [45]. Many protocols, such as OPC UA, were used in the process. The common tools and platforms in DT are well summarized in [16]. Besides, edge devices provide a decentralised, hierarchical solution for physical-to-virtual connection, and the advantages of this structure are the reduction of the data transfer amount. Huang et al. [55] proposed a framework that enables health monitoring in real-time and detects anomalies, and a concept prototype was developed to demonstrate the framework. Edge devices were employed for a fault detection system for rotating equipment [27]. The solutions for data structure [35] and data storage [6] were studied which are critical for data transmission and data processing. High accuracy fidelity models normally rely on a low latency network to provides real-time operational data, and the digital model is capable of updating itself.

3.4. Perceived benefits implementing DT for PdM

As a new paradigm, DT is expected to get improvement to different sectors. In terms of the maturity of DT for PdM, most of the studies in the corpus are assessed to be level 2 or level 3 according to the assessment method [56], which categorized digital twin into four-level, pre-digital twin, digital twin, adaptive digital twin and intelligent digital twin respectively. The reasons are that most of the digital models are characterized by the function of data acquisition from physical twin and machine learning methods were used in some of these studies. Besides, many studies demonstrated the improvement after implementing DT for PdM based on Table 1. The benefits are summarized as follows:

- DT provides a real-time communication architecture for PdM, in which real-time diagnostic and prognostic can be realized.
- By combining advanced algorithms and high-fidelity digital models, fault diagnosis and prognosis reach a higher accuracy and the reliability of equipment is enhanced.
- The digital model generates numerous synthetic data which augment data to solve data insufficient problems.

In addition to three improvements, there are other benefits, such as cost-saving, the hybridisation of different methods. Though many benefits after implementing DT are shown, a concern is that the improvement takes advantage of the included technology in DT rather than the DT paradigm. For example, real-time diagnosis benefits from the advance of communication techniques. Thus, the benefits of DT need to be demonstrated holistically.

4. Challenges and Opportunities

Though lots of efforts have been made for improving PdM through DT technologies, some limitations and restrictions still exist. Research gaps should be pointed out to provide promising directions for further research. Hence, in this section, four critical challenges in current research, as well as corresponding opportunities for future research, are discussed based on the previous literature review.

(1) **Framework standardisation for DT-driven PdM.** Although some researchers have studied the framework of PdM in DT, the proposed frameworks are either too generic to provide detailed hierarchies or only targeted on a specific application. The current research lacks a standardization framework for DT implementation. For example, when should the DT be implemented, how does the implementation schemes meet the requirement of the existing standards, and how do users choose the appropriate modelling methods for different machines? These questions remain to be solved for academic research and industrial applications. To solve these, a promising way is to standardise the DT framework for PdM that contains system architecture, workflow, and modelling methods. To give clear instructions for DT applications to users, more efforts should be put into the standardisation of the DT framework.

(2) **Needs of a high-fidelity digital model.** The digital model is the basis of DT. Normally, the higher fidelity of the digital model is, the more accurate diagnosis and prognosis results are. Accurate diagnosis and prognosis rise the increasing demands of high-fidelity digital models. Currently, many modelling approaches have been developed to attain higher fidelity models. However, these approaches have shortcomings and limitations. Multi-physical simulation can approximate real-world operations and phenomena, however, the heavy calculation burden impedes its application. Machine learning methods required numerous data for training, but fault data is typically hard to be acquired in some cases. New methods should be developed, and existing methods should be optimised for the high-fidelity digital model.

(3) **Holistic evaluation methods of DT-driven PdM.** Many studies showed the benefits of DT-driven PdM. However, it is confusing whether the performance improvement takes advantage of the included technologies in DT or the DT paradigm. A holistic evaluation of the DT paradigm is needed. The difficulty of the evaluation is the diversity of modelling methods. Future works need to set more experiments to validate its benefits.

(4) **Multi-component, multi-level model in DT-driven PdM.** Most research objects of DT are single-component models in the reviewed papers. The research objects may belong to a multi-component, multi-level system in the

industry. For example, a workshop may have many different machines in terms of type, function, and working principle. Single-component DT is hard to satisfy real needs in most cases. Some critical challenges such as how to construct a multi-component, multi-level model for a complex system, what is the coupling mechanism of different components in DT, and what is the maintenance strategy for a multi-component, multi-level system, remain to be tackled. It is deemed a promising direction for DT-driven PdM research.

5. Conclusion

The digital twin technology has emerged and attracted interest across a variety of application domains in the past decade. Many research efforts have been published recently to advocate introducing DT to improve the performances of PdM. In order to understand the challenges and opportunities of DT-driven PdM, this paper attempts to analyse the recent advances including its application framework, modelling methods, and interaction between the physical entity and virtual replica. Four challenges and their corresponding opportunities were discussed to provide insights for future research.

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