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HIGH-FIDELITY DIGITAL TWIN MODELLING FOR PREDICTIVE MAINTENANCE STATE-OF-THE-ART

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ABSTRACT

High-fidelity modelling techniques provide high-precision simulations required for the construction of digital twin (DT), facilitating high-level mapping of physical systems in virtual space. The integration of DT and high-fidelity modelling enables real-time monitoring, fault diagnosis, performance evaluation and optimization of physical entities. These techniques have been explored in different industrial sectors and on various topics in recent years, such as predictive maintenance (PdM). Existing literature on high-fidelity DT has extensively covered major aspects such as framework construction and applications, advances in applications in various fields, and integration with the Internet of Things (IoT) or machine learning (ML) technologies. However, there is limited research on how high-fidelity modelling methods interact with DT to aid and optimize PdM. To comprehensively analyze the state-of-the-art of high-fidelity DT modelling in PdM, this paper focuses on how high-fidelity DT modelling facilitates three key PdM tasks: health indicator estimation, remaining useful life prediction and fault diagnosis. For each task, discussion will be subdivided into two parts: 1) high-fidelity modelling methods, and 2) the process of integrating these methods into DT-driven predictive analytics. The advantages of high-fidelity DT modelling brings to PdM are also summarized. Finally, challenges and opportunities for future research are discussed.

Keywords: High-fidelity Modelling, Digital Twins, Predictive Maintenance, Real-Time Monitoring, Fault Diagnosis

1 INTRODUCTION

High-fidelity modelling not only provides a comprehensive portrayal of the system structure, but also details the interactions between the internal elements of the system and the environment. With the continuous advancement of manufacturing intelligence, the importance of high-fidelity modelling technology is becoming more and more apparent. In the construction process of digital twin (DT), this technology lays the foundation for accurate correspondence and synchronous updating between physical entities and their virtual counterparts by providing high-fidelity simulation models. By integrating high-fidelity modelling technology, the virtual entity constructed by DT is not only a one-to-one mapping and description of the physical object, but also effectively achieves real-time monitoring of the state of the physical entity, rapid diagnosis of maintenance faults, and comprehensive evaluation of the overall performance of the system through the seamless integration of the real-time data flow and dynamic feedback mechanism [1]. Relying on the precision and accuracy of high-fidelity models, DT technology accurately maps system states and response behaviors in the real world, building a virtual environment for simulation experiments, system optimization and decision support.

In recent years, high-fidelity DT has been utilized in several industrial sectors [2]. Particularly in the field of predictive maintenance (PdM), manufacturers use high-fidelity DT models to achieve accurate prediction of possible failures in equipment operation, to rationalize scheduled maintenance and reduce downtime, to optimize the re-engineering of production processes, and to greatly improve the operational efficiency of the entire production system [3]. This ability based on digital simulation and prediction not only greatly improves the maintainability and reliability of the production process, but also extends the life cycle of the physical assets, saves substantial maintenance costs and potential economic losses for the enterprise, and becomes an important technical support to ensure the competitiveness of the manufacturing industry.

A significant amount of existing academic research focuses on building comprehensive DT frameworks across multiple areas of expertise, exploring scenarios for their application in different industries, and examining the latest advances in DT across various domains. Additionally, existing research has paid considerable attention to the integration and intersection of DT with cutting-edge technologies, such as the Internet of Things (IoT), machine learning (ML), and cloud computing. These convergences not only advance the development of DT technology, but also offer the possibility of intelligent upgrading in many industries. However, despite the coverage of these topics in the literature, the question of which high-fidelity modelling approaches can be employed in DT for PdM and how high-fidelity modelling approaches work together with DT to assist and optimize PdM is still an area that has been relatively little explored in depth.

To comprehensively analyze the state-of-the-art in high-fidelity DT modelling in PdM, this review focuses on how high-fidelity DT modelling facilitates three fundamental PdM tasks: health indicator estimation, prediction of remaining useful life (RUL), and faults diagnosis [4]. Each of these tasks is critical to the effective implementation of a PdM strategy.

The paper is structured as follows: Section 2 includes the search framework used to review different high-fidelity DT modelling papers for PdM. Section 3 is a comprehensive review of the relevant literature on the integration of high-fidelity DT modelling with the three main objectives of PdM. Also included is a discussion of the key results of the important reviews. Section 4 explores the challenges and future opportunities for the application of high-fidelity DT modelling in PdM. Section 5 concludes the full paper.

2 RESEARCH METHODOLOGY

2.1 Research questions

Table 1 presents the research questions and their motivations for the systematic literature review.

Table 1: Research Questions and Motivations for the Review

Research Questions	Motivations
What are the strengths of integrating high-fidelity modelling with DT for PdM?	Helping researchers weigh the pros and cons of using high-fidelity based methods versus other approaches to solving the PdM problem.
What is the process of integrating high-fidelity modelling methods into DT-driven predictive analytics?	By presenting the integration process and highlighting key steps and considerations to help practitioners and researchers to effectively design, improve and implement these complex systems.
What are the challenges and opportunities for future research of high-fidelity DT modelling for PdM?	Motivating researchers to undertake targeted research efforts to address these challenges and advance the field, and point to promising directions for future research.

2.2 Search strategy

To assess the research status of DT on PdM, a comprehensive literature review was conducted using keywords such as "High-Fidelity Modelling," "Digital Twin," and "Predictive Maintenance." The search spanned five major databases: ScienceDirect, Springer Link, ACM Digital Library, IEEE Xplore Digital Library, and Scopus. Articles were excluded if they focused on low-fidelity or traditional modelling techniques, DT applications outside PdM, were not written in English, or lacked full text. Articles were included if they specifically addressed high-fidelity DT modelling for PdM and introduced innovative approaches. The initial search yielded 3898 results, which were filtered 1604 based on exclusion criteria. Further screening based on inclusion criteria resulted in 68 studies. Additional sources identified through snowballing and manual searches added 54 more publications [5, 6], with 41 finally meeting all criteria after quality assessment.

3 HIGH-FIDELITY DIGITAL TWIN MODELLING FOR PREDICTIVE MAINTENANCE

High-fidelity modelling involves the creation of detailed, accurate simulations that represent the physical and operational characteristics of real-world systems. It contains intricate details of physical phenomena and is capable of accurately reproducing real-world conditions. This contrasts with low-fidelity or simplified modelling techniques. The latter, while conducive to computational efficiency and shorter turnaround times, tend to ignore details that are critical to the overall behavior and performance of the system. High-fidelity modelling provides a powerful foundation for creating digital copies of physical systems [7]. These models are essential for the development of DT, which are dynamic and virtual counterparts of physical assets, integrating real-time data and advanced analytics to reflect and predict the behavior of these assets [8]. The synergy between high-fidelity modelling and DT improves the accuracy and reliability of DT, enabling them to effectively perform complex predictive tasks [9].

Meanwhile, the rapid development of big data analytics, the IoT and cloud computing technologies in recent years has further enhanced the capabilities of high-fidelity DT modelling techniques, enabling them to collect finer-grained data and enhance predictive analytics [10].
When applied to PdM, this synergy helps to provide insights into the health of an asset, leading to PdM decisions to pre-emptively address potential failures [11]. In contrast, DT with low-fidelity models may not be able to capture these nuances, which may lead to inaccurate predictions and suboptimal maintenance schedules. High-fidelity DT modelling leverages these detailed simulations to health indicator estimation, RUL prediction and diagnose failures in real-time [4]. In addition, high-fidelity DT can provide a comprehensive view of the equipment's operational status, which can help in the early detection and resolution of potential problems, leading to more accurate troubleshooting [12].
This chapter relies on the literature screened in 2.2 to provide an in-depth discussion of high-fidelity DT modelling in the field of PdM. Specifically, it covers the architecture of high-fidelity DT modelling applied to PdM and how it enhances research in the three core tasks of PdM, namely health indicator estimation, RUL prediction, and fault diagnosis.

3.1 High-fidelity DT framework for PdM

Several scholars have proposed reference frameworks for high-fidelity DT modelling applications [13-17]. The continuous improvement and development of high-fidelity DT technology provides an advanced and extensive technology platform for PdM. This platform integrates real-time data synchronization and analytics between physical devices and their digital copies for precise monitoring and management. Through the integration of PdM and high-fidelity DT modelling, specific high-fidelity DT-driven PdM frameworks are generated, including physical entities, virtual entities, and connecting components between them [13, 18-24]. To this end, the National Institute of Standards and Technology (NIST) is actively involved in the development of the ISO 23247 standard, which aims to provide a standardized framework for high-fidelity DT modelling and PdM [25, 26].
Based on the existing work [27], Figure 1 shows a framework of high-fidelity DT for PdM. This framework incorporates advanced high-fidelity modeling techniques alongside DT technology to span the entire PdM process—from initial data collection through to application. Data is first collected from the physical layer through sensor networks, including device data, process data, and product data. The data is delivered via wireless network to the edge devices and then uploaded to the cloud center. Next, the data is further analyzed by using high-fidelity modelling approaches to simulate the environment with high accuracy. Finally, the information provided by the DT is used, in conjunction with relevant modelling techniques like ML, to model physical equipment for RUL prediction and fault diagnosis. These results will optimize PdM decisions such as spare parts management, maintenance planning and operations scheduling, and improve the accuracy and reliability of PdM.

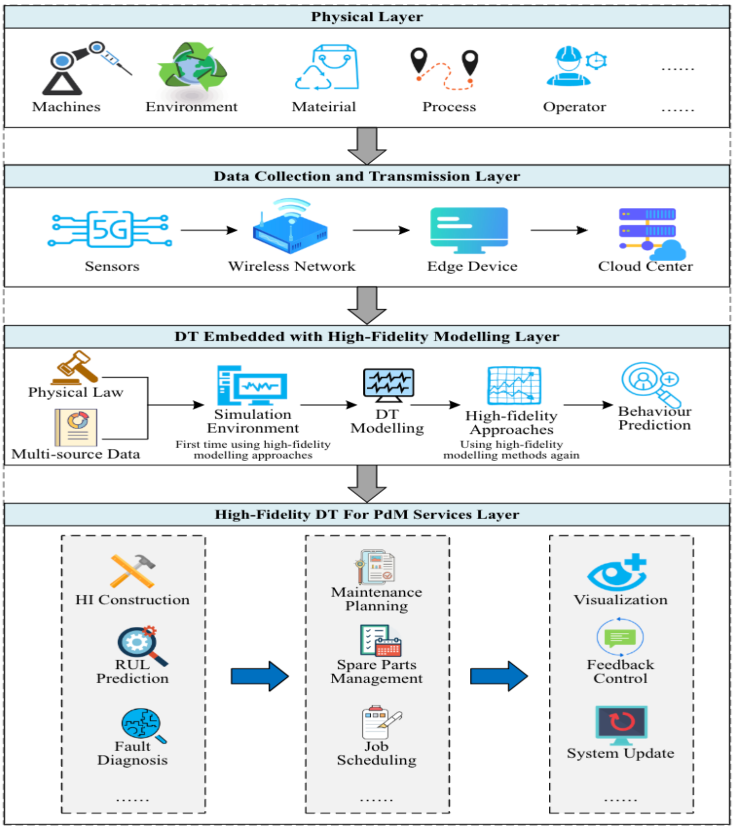

Figure 1: Framework for High-fidelity Modelling in DT for PdM

3.2 High-fidelity DT modelling for three core predictive maintenance tasks

3.2.1 High-fidelity DT modelling for health indicator construction and RUL prediction

Within the field of PdM, the prediction of health indicator and RUL is particularly critical. RUL prediction is used to estimate the remaining life of a machine, and health indicator prediction assesses the health of the equipment. health indicator can be used as a feature or an input of the RUL prediction model to take into account the current health of the equipment and to increase the precision of the prediction. Nagi et al. indicated that constructing multi-stage degradation trends based on health indicator to assist RUL prediction is effective, replacing a single model with lower accuracy by multi-model predictions [28]. The application of health indicator can exhibit three major attributes: detectability, separability and trendability [29]. Therefore, the construction of health indicator is particularly critical and can only be recognized as optimal when these three requirements are met.

Many scholars have proposed estimating health indicator by integrating high-fidelity modelling methods and DT. For example, Peng et al. outlined the health indicator that are available for each level of power converter, while the DT and physical model are used to estimate the circuit parameters using a particle swarm optimization algorithm [30]. Yu et al. proposed a health state assessment method for optoelectronic systems formulated with reference to the DT model and using the optical transfer function as a health metric [31]. Qin et al. are based on an exponential transient maintenance strategy to accurately locate essential components such as bearings [32]. This is done by analyzing statistical parameters obtained from monitoring signals to determine trend characteristics such as root mean square (RMS). RMS indicates energy or amplitude levels and is used in conjunction with DT as a measure of component health. Also, the use of ML techniques in conjunction with DT to build health indicator has become a prominent topic. Spectral amplitude modulation using Support Vector Machines (SVMs) and k-Nearest Neighbor (k-NN) is used to compute the impactivity of signals and to determine the health status of machines [33]. Most of the DL methods used to construct health indicator are based on autoencoder (AE) schemes, such as LSTM-AE [34], BiRNN-ED [35]. Additionally, a number of methods for RUL prediction that integrate high-fidelity modelling approaches and DT have also been proposed. For example, Lee et al. used DT with physical models from finite element analysis (FEA) to consider failure mechanisms [12]. Sikorska et al. focused on building statistical models (autoregressive (AR) models) from extensive empirical knowledge and deriving RUL models from observations [36]. Data-driven ML methods are also heavily used. For example, Zemouri et al. used Recurrent Neural Networks (RNN)) to predict the RUL of mechanical components [37]. Liu et al. utilized DT and convolutional neural network (CNN) approaches for gas turbine performance degradation assessment and RUL prediction from an airline operator's perspective [38]. Lv et al. used a combination of DT with BLS algorithm and deep learning algorithm to predict RUL of air source heat pumps [22]. Figure 2 illustrates the high-fidelity DT-driven health indicator and RUL prediction process.

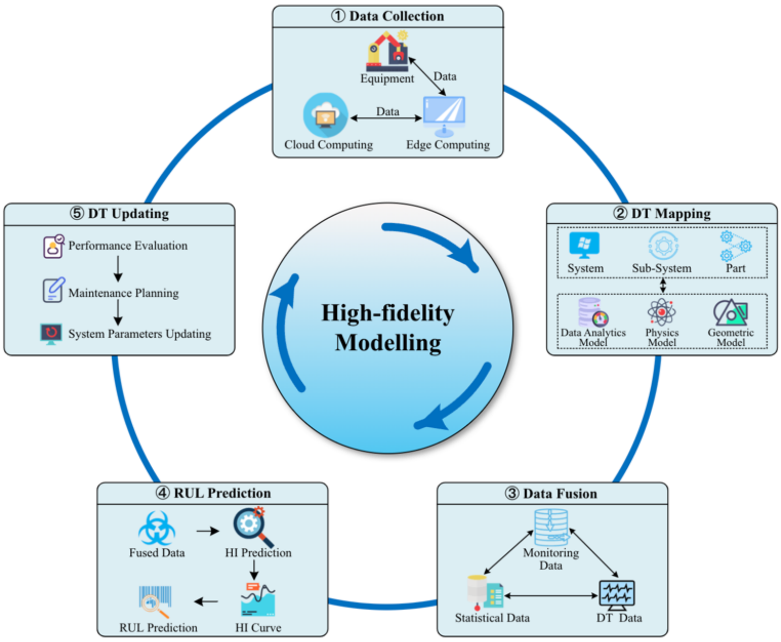

Figure 2: The Process of High-fidelity DT-driven Health Indicator and RUL Prediction

Firstly, it implements multi-source data collection, covering sensors, simulations, statistics and other types of data, and carries out data analysis and model construction. Based on the feature weights of the relevant algorithms, the cloud computing platform formulates the data collection programme, specifies the required feature set and sampling frequency, and conveys it to the edge computing devices for execution. After completing data collection, the high-fidelity data for analysis and processing is transmitted to the cloud platform. The next step focuses on updating and iterating the model, involving geometric, data analysis and physical models, with the aim of improving the model's high-fidelity and accurate representation of real-world assets. The third step is dedicated to data fusion processing, integrating multi-source high-fidelity data information. After updating the DT with high-fidelity using real-time monitoring data, the DT simulation is applied to analyze the predicted key features about the health of the asset. High-fidelity modelling techniques are applied to integrate and fuse the simulation results, monitoring data and statistical data for analysis. The fourth step is the construction of predictive models for health indicator and RUL based on the fused high-fidelity data. The health indicator model is constructed based on the fused data using relevant algorithms, and the RUL is predicted based on the health indicator curves constructed in the high-fidelity DT. Finally, based on the prediction results of health indicator and RUL, the performance of the assets in the DT is evaluated with high-fidelity and the optimal maintenance and operation plans are planned in the framework of the high-fidelity DT.

3.2.2 High-fidelity DT modelling for construction of fault diagnosis model

Fault diagnosis involves high-fidelity monitoring of the operating conditions of a machine and analyzing the mechanism in the event of a fault or anomaly. When a fault occurs, it can be visually located, isolated, diagnosed and analyzed based on the characteristics of the machine's high-fidelity DT model, thus determining the location of the faulty component and the root cause of the fault [39]. However, building such high-fidelity models relies heavily on rich domain knowledge. The use of ML and deep learning networks to model collected data with high-fidelity and adaptively learn machine diagnostic knowledge has become a popular approach for intelligent fault diagnosis [23]. For example, Convolutional Neural Network (CNN), which can efficiently extract key fault features from input data, have been successfully applied in the construction of fault diagnosis models for rolling bearings, gears, and hydraulic pumps in mechanical equipment [40]. Transfer learning, as a popular deep learning technique, has made a significant contribution to the field of fault diagnosis [41]. Cao et al. proposed a deep convolutional neural network (CNN) based transfer learning method [42]. Training with experimental data on gear failures shows that the method can perform adaptive feature extraction without preprocessing using a small dataset. DT have played an important role in advancing the fault diagnosis techniques, and have been particularly notable for building predictive model implementations [43]. Xu et al. explored a new methodology based on DT technology aimed at staged fault detection on an automotive body side manufacturing assembly line [18]. The initial phase of the approach relies on the simulation of a high-fidelity body model in a DT system from which data is extracted. Subsequently, transfer learning techniques are applied to a trained stacked sparse autoencoder (SSAE) model to implement real-time state monitoring of the system under test.
Referring to [18], Figure 3 shows the high-fidelity DT-driven fault diagnosis process. Relying on the high-fidelity DT model, this process is able to simulate the characteristics and analyze the performance of fault condition, so as to obtain high-fidelity fault data samples. Based on this, the relevant high-fidelity modelling algorithm (e.g. deep transfer learning) is then applied to construct an intelligent diagnostic model for both unknown and known faults.

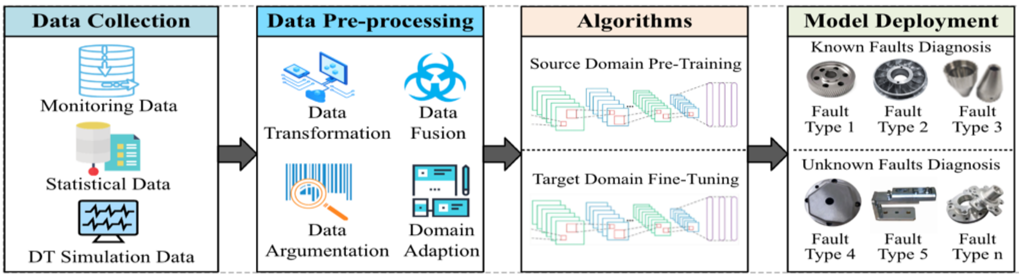

Figure 3: The Process of High-fidelity DT-driven Fault Diagnosis

4 CHALLENGES AND OPPORTUNITIES FOR FUTURE RESEARCH

The integration of high-fidelity DT modelling into health indicator estimation, RUL prediction, and fault diagnosis presents many challenges and opportunities for future research. This section will discuss key areas where further research is needed to improve the effectiveness and adoption of DT in PdM.

(1) **Data quality and completeness.** In performing high-fidelity DT model implementations, it becomes a major challenge to ensure the quality and integrity of the data. To perform predictive maintenance work accurately, one needs to rely on extensive and high-quality data sets. However, data collected in industrial equipment often suffers from high noise, missing values, and inconsistent formats [44]. To solve these problems, it is necessary to apply powerful data preprocessing techniques such as noise reduction processing, missing data estimation techniques, and data format normalisation.
(2) **Fusion of multi-source data.** The fusion of multi-source data is of key importance in building an integrated high-fidelity DT model that accurately reflects the state of physical assets. Multiple data types, such as sensor data, maintenance records, and operation logs, can provide different perspectives on equipment status[45]. Integrating these heterogeneous data sources presents significant challenges due to differences in data structure, sampling rate, and accuracy. Recent advances in machine learning such as convolutional neural networks (CNN) and recurrent neural networks (RNN) offer potential solutions for data fusion[38]. Future research should be devoted to exploring methods for seamlessly integrating data from multiple sources and using deep learning techniques to improve the fidelity and predictive power of DT models.
(3) **Standardisation of high-fidelity DT framework for PdM.** Another key challenge is the lack of standardisation of high-fidelity digital twin technology frameworks for predictive maintenance. Currently, digital twin technology exhibits significant inconsistencies in terms of model accuracy and reliability due to varying means of implementation adopted by different industries and organisations[46]. In order to promote consistency and interoperability of digital twins across different platforms and applications, it becomes particularly important to develop standardised protocols and frameworks developed specifically for digital twin technology. Such a standardisation process should cover specific guidelines for data collection, model validation and performance evaluation.
(4) **Comprehensive assessment methods.** Efficient evaluation mechanisms play an integral role in determining the performance of high-fidelity DT models for PdM applications. Recent research results tend to adopt hybrid evaluation methods, such as those incorporating statistical analysis and ML [47]. For future research directions, efforts should be focused on constructing a comprehensive evaluation strategy aimed at providing a comprehensive analysis of the performance of DT models and driving their continuous optimisation.

5 CONCLUSIONS

In conclusion, integrating high-fidelity modelling techniques with DT technology is essential to advance PdM across industries. This paper explores how high-fidelity DT modelling can enhance three key PdM tasks: health indicator estimation, RUL prediction and fault diagnosis. A detailed study of high-fidelity modelling approaches and their integration with DT-driven PdM analysis reveals the unique benefits these techniques offer. Specifically, their convergence can lead to a deeper understanding of system health and lifetime, as well as improved management efficiencies. Despite significant progress in the use of high-fidelity DT in PdM, challenges such as data quality and integrity, multi-source data fusion, the need for standardised high-fidelity DT frameworks, and comprehensive assessment methods still need to be overcome. Addressing these challenges will not only improve the effectiveness of PdM, but also expand the scope and applicability of high-fidelity DT in different industries.

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