

Framework for the Application of Digital Twin Technology in Intelligent Production Line Condition Monitoring and Predictive Maintenance

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Abstract: This paper addresses the urgent needs of intelligent manufacturing for highly reliable equipment operation and precise maintenance and delves into the innovative application of digital twin technology in production line condition monitoring and predictive maintenance. By systematically reviewing the core theories of digital twins, multi-source heterogeneous data acquisition and processing technologies, and predictive maintenance methodologies, a five-dimensional integrated framework comprising a physical layer, data layer, model layer, functional layer, and application layer is constructed. This framework innovatively achieves real-time dynamic mapping and bidirectional interaction between physical and virtual spaces, establishes a data-model hybrid-driven mechanism for equipment health status assessment and remaining life prediction, and forms a closed-loop optimization system from condition perception and fault early warning to maintenance decision-making. To verify the effectiveness of the framework, this study conducts a case study using a precision CNC gear machining production line. The results show that the framework can control the latency of critical equipment condition monitoring within 200 milliseconds, improve the accuracy of remaining life prediction by approximately 15% compared to purely data-driven methods, successfully achieve early fault warning, reduce unplanned downtime by 65%, and save maintenance costs by 28%. The research findings provide theoretical guidance and practical examples for achieving precise and forward-looking equipment health management in the context of intelligent manufacturing and have important reference value for promoting the digital transformation of the manufacturing industry.

Keywords: Digital twin; Intelligent production line; Condition monitoring; Predictive maintenance; Framework construction

1 INTRODUCTION

With the wave of the Fourth Industrial Revolution sweeping the globe, industrial transformation and upgrading led by intelligent manufacturing has become a core strategy for countries around the world to seize the commanding heights of future manufacturing. Against this backdrop, intelligent production lines, as the physical embodiment of the intelligent manufacturing concept, directly determine the competitiveness of the manufacturing industry through their operational efficiency, stability, and flexibility. However, the increasing intelligence of production lines has also brought unprecedented complexity. The increasingly

sophisticated and interconnected equipment systems make their failure modes more concealed and their propagation chains more complex, posing a severe challenge to transparent control of the production process and reliable operation and maintenance of equipment [1]. Traditional passive maintenance and periodic preventive maintenance models, due to their inherent defects such as delayed response and susceptibility to over-maintenance or under-maintenance, are no longer able to meet the stringent requirements of modern intelligent production lines for "zero downtime," high output, and low cost. Therefore, exploring an innovative technological paradigm that can deeply integrate information space and physical entities, achieving panoramic insight into the production process and forward-looking management of equipment health, has urgent practical needs and significant theoretical value.

Digital twin technology, as a key enabling technology for achieving deep integration of information and physical systems, provides a new perspective and powerful tools for solving the above challenges. It creates a holographic mirror image of a physical object in digital space by constructing a digital twin that dynamically interacts with and maps the physical entity to the real world. In recent years, theoretical research on digital twins has moved from conceptual definition to system construction, and its connotation has expanded from the initial three-dimensional geometric model to an integrated system covering data, models, services, and connections [2]. At the same time, research in the field of condition monitoring and predictive maintenance has also deepened, from early fault detection based on vibration analysis to intelligent diagnosis and life prediction that integrates machine learning and deep learning. Domestic and foreign scholars have begun to try to introduce the concept of digital twins into industrial operation and maintenance scenarios and have initially explored its application potential in equipment health management, fault tracing, and maintenance guidance [3]. However, existing research focuses on local technical verification or conceptual description and lacks a systematically integrated application framework that can run through the entire process of data acquisition, model construction, condition perception, predictive analysis, and decision feedback. This, to some extent, limits the full realization of the value of digital twin technology in intelligent production line operation and maintenance.

In view of this, this study aims to systematically construct a digital twin application framework for condition monitoring and predictive maintenance of intelligent production lines. This study will first sort out the core theoretical and technical foundations of digital twins, condition monitoring and predictive maintenance, and lay a solid theoretical foundation for the framework construction. On this basis, we will focus on designing layered and modular overall architecture, elaborate on its constituent elements, interaction logic and operation mechanism from the physical layer to the application layer, and deeply analyze the core mechanism and key technology for achieving accurate condition monitoring and effective predictive maintenance. To verify the feasibility and effectiveness of the proposed framework, this study will select typical industrial scenarios for case application and evaluate its practical benefits in improving the real-time performance of monitoring, the accuracy of prediction and the scientific nature of maintenance decisions through comparative analysis. The whole paper will follow the technical route of "problem statement - theoretical foundation - framework design - mechanism analysis - practical verification", and comprehensively use literature research, system modeling, case analysis and comparative research and other methods to gradually develop the discussion [4]. The structure of the subsequent sections of this paper is

as follows: Section 2 introduces the relevant theories and technologies, Section 3 elaborates on the design of the application framework, Section 4 deeply analyzes the core implementation mechanism of the framework, Section 5 conducts case verification, and finally Section 6 summarizes and looks forward to the whole paper.

2 RELEVANT THEORETICAL AND TECHNOLOGICAL FOUNDATIONS

To build an effective digital twin application framework, it is essential to first deeply understand the core theories and key technologies upon which it is based. Digital twins are not a single technology, but a comprehensive conceptual system integrating knowledge from multiple disciplines. Its core idea lies in creating a high-fidelity dynamic virtual model for a physical entity through digital means. This model can achieve bidirectional mapping and interaction with the physical entity with the help of real-time data. From a structural perspective, a complete digital twin typically includes four elements: physical entity, virtual model, connecting data, and service applications. These elements together constitute a closed loop, continuously iteratively optimized intelligent system [5]. Unlike traditional 3D simulation or digital prototypes, digital twins possess key characteristics such as real-time synchronization, closed-loop optimization, and full lifecycle management. Their maturity can gradually evolve from early static description to advanced stages of dynamic interaction and even autonomous decision-making, providing a theoretical ladder for their deep application in complex industrial scenarios.

Realizing the status monitoring of intelligent production lines is the perceptual basis for digital twins to realize their value. This process highly depends on a technological system capable of capturing information from the physical world in real time and with precision. In modern smart factories, various sensors (such as vibration, temperature, and vision sensors) and control systems (such as PLCs and CNCs) distributed throughout the production line constitute the source of data acquisition. Together, they generate massive amounts of operating parameters, environmental data, and process information with diverse structures [6]. The Internet of Things (IoT) technology acts like a nervous system, seamlessly transmitting this multi-source heterogeneous data to the digital space through high-speed and reliable protocols such as Industrial Ethernet, 5G, and TSN. However, raw data often contains noise and has many dimensions, limiting its direct usability. Therefore, it must undergo preprocessing processes such as data cleaning, noise reduction, alignment, and normalization, and further extract key features that characterize the health status of equipment through time domain, frequency domain, or time-frequency analysis methods, providing high-quality data fuel for subsequent in-depth analysis.

After obtaining accurate status information, predictive maintenance theory provides action guidelines for decision-making. The essence of predictive maintenance is an advanced maintenance strategy based on condition monitoring and data analysis. Its core process lies in accurately planning maintenance activities before failure occurs by assessing the current health status of equipment and predicting its future degradation trend. The realization of this goal is inseparable from the support of two core models: one is the fault diagnosis and health assessment model, which uses methods such as pattern recognition and deep learning to match the extracted features with known fault modes, realize the early detection and accurate

diagnosis of abnormal equipment status, and comprehensively calculate the overall health index of the equipment; the other is the remaining service life prediction algorithm, which is usually based on physical models, statistical models or data-driven models, and extrapolates its performance degradation curve by analyzing the historical operating data and degradation trajectory of the equipment, and predicts the remaining time from the current moment to functional failure [7]. These two together constitute a complete cognitive chain from "current status perception" to "future prediction", which is the intelligent core of digital twins to realize forward-looking decision support.

3 DESIGN OF A DIGITAL TWIN FRAMEWORK FOR CONDITION MONITORING AND PREDICTIVE MAINTENANCE

Based on thorough theoretical and technical preparation, this section aims to systematically construct a digital twin application framework for intelligent production line status monitoring and predictive maintenance. The framework is designed to achieve several core objectives: firstly, to achieve high-precision dynamic mapping and real-time interaction between the physical production line and its virtual twin, ensuring that the digital world can truly reflect every moment of change in the physical entity; second, to build a predictive analysis engine with forward-looking capabilities, capable of discerning the degradation trend of equipment performance and potential failure risks; and finally, to form a closed-loop optimization system from perception and analysis to decision execution, capable of autonomously or assistedly generating optimal maintenance strategies and feeding them back to the physical world. To achieve these objectives, the framework construction will follow the basic principles of modularity, scalability, and openness, ensuring that each functional component of the system can be flexibly configured and independently upgraded, and compatible with access to new data sources, algorithm models, and external applications, thereby adapting to the dynamic needs of different production scenarios and the development of future technologies [8].

Based on the above objectives and principles, this paper proposes a five-layer overall architecture. The foundation of this architecture is the physical layer, which consists of real equipment, mechanical units, control subsystems, and sensor networks distributed throughout the production line. It is the ultimate source and destination of all data and interactive behaviors. Above it is the data layer, which acts as the "blood system" of the framework. It is responsible for aggregating multi-source heterogeneous data streams from the physical layer and integrating, cleaning, storing, and managing them in a unified manner through technologies such as data lakes or time-series databases, providing clean and reliable data fuel for upper-layer applications. The model layer is the "digital heart" of the framework. It builds a multi-dimensional digital twin model of the production line and its equipment. This includes not only geometric and physical models that describe the geometric appearance and physical relationships, but more importantly, behavioral models that incorporate equipment dynamics and fault evolution mechanisms, enabling the virtual entity to realistically simulate the operating state of the physical entity [9]. The functional layer is the "intelligent brain" of the framework. It carries core services such as status monitoring, predictive analysis, and decision support. By calling the lower-layer models and data, it realizes real-time health assessment, fault warning, remaining life prediction, and generates maintenance plan suggestions. The top layer is the application layer, which serves as the human-computer interaction interface. Through methods such as cockpits, 3D visualization, and virtual reality, it presents complex internal data and analysis results to managers in an intuitive way, supporting them in making accurate decisions and interventions.

To ensure the effective operation of this architecture, several key modules need to be designed in depth. The virtual-real synchronization and data-driven module is the guarantee of the dynamics of the entire system. It is responsible for establishing and maintaining a two-way data channel between the physical entity and the virtual model, ensuring that any change in the state of one side can trigger a response and update of the other side in near real time [10]. The high-fidelity simulation and model update module is dedicated to making the digital twin "come alive." It must not only be able to perform high-fidelity dynamic simulation based on physical laws and mechanisms, but also have self-learning capabilities, and be able to use the continuously flowing real-time data to calibrate and optimize the model parameters to reduce the deviation between simulation and reality. The intelligent analysis and prediction algorithm module is the core of the predictive maintenance function. It integrates advanced machine learning and deep learning algorithms to deeply mine the preprocessed feature data, realizing accurate prediction from intelligent fault diagnosis to remaining service life. Finally, the decision support and feedback control module constitutes both the endpoint and the new starting point of closed-loop optimization. Based on the prediction results, combined with the knowledge base and optimization algorithm, it generates specific maintenance work orders, resource scheduling schemes or control instructions, and securely sends them to the execution system at the physical layer, thereby completing the complete value closed loop from virtual cognition to physical action.

4 CORE IMPLEMENTATION MECHANISM AND KEY TECHNOLOGIES OF THE FRAMEWORK

The effectiveness of the constructed framework depends on breakthroughs in a series of core implementation mechanisms and key technologies. Among them, achieving real-time and accurate mapping of the state between the physical production line and the virtual model is a fundamental prerequisite. This mechanism is not a simple data transmission, but a dynamic, two-way interactive process. Through sensor networks and real-time data acquisition systems deployed at key nodes of the equipment, the operating parameters, environmental data, and control signals of the physical entity are continuously captured and transmitted to the virtual space via high-speed industrial networks, driving the digital twin to evolve synchronously [11]. At the same time, the simulation results or optimization instructions based on the model in the virtual space can also be applied back to the physical entity through this channel, such as adjusting equipment operating parameters or triggering specific actions, thereby forming a continuous closed loop from perception to decision-making and then to execution, ensuring the continuity and consistency of the digital thread throughout its entire life cycle.

Based on obtaining massive amounts of real-time data, how to effectively integrate it and transform it into an accurate understanding of the equipment's health status becomes the next key link. Due to the diverse sources, varying formats, and noise inherent in production line data, multi-source data fusion technology is required. Under the premise of spatiotemporal alignment, methods such as Kalman filtering, Bayesian estimation, or deep learning are comprehensively utilized to integrate complementary and redundant information, generating a more consistent and reliable equipment status description than any single data source. Based on this, equipment health assessment can be achieved [12]. This is typically accomplished by constructing a comprehensive health index that integrates the degradation characteristics of key performance parameters, historical maintenance records, and expert experience. It then uses models such as fuzzy logic, support vector machines, or deep autoencoders for

quantitative calculation, thereby dynamically and intuitively reflecting the continuous health status of the equipment from normal to failure.

To predict future trends from the current state, the framework introduces a fault early warning and remaining service life prediction mechanism based on digital twin simulation. Unlike purely data-driven prediction methods, this mechanism's advantage lies in its ability to integrate physical mechanism models into the analysis process. By modeling and simulating the internal fault propagation path and evolution law of the equipment, the digital twin can "pre-enact" various fault scenarios in virtual space, revealing early signs of potential faults and their development speed. Building upon this foundation, a data-model hybrid forecasting approach is employed. Statistical or machine learning models trained on historical operational data are integrated with mechanistic models reflecting the physical degradation process of equipment. This approach leverages data to compensate for model uncertainties while simultaneously constraining the predictive biases of data, thereby significantly improving the accuracy, interpretability, and robustness of RUL (Recovery Duration and Upgrade) predictions.

Ultimately, the value of all analysis and forecasting lies in the optimization and execution of maintenance decisions. When a potential failure risk or performance degradation is predicted, the framework's decision support module is activated. It doesn't provide a single maintenance recommendation but comprehensively considers multiple constraints, including equipment health, RUL prediction results, production plans, spare parts inventory, and maintenance costs. It uses multi-objective optimization algorithms to generate a set of alternative maintenance strategies and evaluates their overall effectiveness. The resulting final decision is then transmitted to the physical layer through a closed-loop feedback control strategy. This might involve automatically triggering a maintenance work order, adjusting the production cycle to await a maintenance window, or directly sending instructions to the control system to isolate the faulty equipment. This closed-loop process, from analysis and prediction in virtual space to precise execution in physical space and then using feedback on execution results to correct models and strategies, constitutes the core driving force for the self-iteration and continuous optimization of the predictive maintenance system driven by digital twins.

5 CASE ANALYSIS AND APPLICATION VERIFICATION

To verify the feasibility and effectiveness of the proposed framework, this study selected a precision CNC gear machining production line of an automotive parts manufacturing company as the application verification object. This production line consists of multiple five-axis CNC machine tools, industrial robots, and a conveyor system. Its machining accuracy and continuous stable operation capability are crucial to the entire production system. Among them, the spindle unit, as the core component of the CNC machine tool, directly determines the machining quality and equipment safety, and historical data shows that bearing degradation is the main cause of unplanned downtime. Therefore, this case study focuses on the critical CNC machine tool spindle system on this production line, aiming to achieve real-time status monitoring and predictive maintenance of the remaining bearing life by constructing its digital twin.

In the specific implementation process, vibration, temperature, and acoustic emission sensors were first installed on the spindle system at the physical layer, and operational data was collected in real time through an IoT gateway. In the digital space, a multi-dimensional

digital twin containing a geometric model, a physical model, and behavioral rules were constructed. The geometric model accurately reflects the spindle structure; the physical model embeds the bearing dynamics and degradation mechanism; and the behavioral model defines the normal and abnormal operating logic under different working conditions. The data layer utilizes a time-series database for unified management of sensor data and CNC system parameters. The functional layer deploys a vibration feature extraction algorithm based on convolutional neural networks and a data-model hybrid RUL prediction model combining a physical degradation model and a long short-term memory network. Finally, a 3D visualization monitoring interface was developed at the application layer to display the spindle health status, early warning information, and maintenance suggestions in real time.

After the system was put into trial operation, its key performance characteristics were continuously monitored and analyzed. Regarding the real-time performance of status monitoring, the end-to-end latency from sensor data acquisition to virtual model status updates was stably controlled within 200 milliseconds, successfully capturing multiple instances of instantaneous excessive spindle vibration caused by sudden load changes, demonstrating the timeliness and effectiveness of the virtual-real mapping. In terms of fault prediction accuracy, the hybrid-driven RUL prediction model reduced the prediction error by an average of approximately 15% compared to the pure data-driven model, successfully providing an early warning of a progressive degradation fault caused by insufficient bearing lubrication 42 hours in advance, leaving ample window for planned maintenance. In the maintenance decision effectiveness assessment, the system, while issuing an early warning, automatically generated a decision report including "It is recommended to replace the spindle bearing during the next planned downtime window; the required spare parts inventory is sufficient; the estimated impact on production capacity is 4 hours." This recommendation was adopted and successfully implemented by the operations and maintenance team, avoiding potential losses from sudden downtime.

To quantify the application benefits, this study compared key operational indicators for six months before and after applying this framework. Compared to the traditional scheduled maintenance model, the unplanned downtime of this CNC machine tool decreased by 65%, and spare parts costs due to over-maintenance were reduced by 28%. More importantly, through precise predictive maintenance, two potential batch product quality defects and severe spindle damage accidents were avoided, with estimated direct economic losses exceeding one million yuan. These data demonstrate that the digital twin framework constructed in this study is not only technically feasible in practice but also brings significant economic and operational benefits to enterprises, effectively enhancing the resilience and overall competitiveness of intelligent production lines.

6 CONCLUSION AND OUTLOOK

This study systematically explores the application path of digital twin technology in condition monitoring and predictive maintenance, focusing on the core needs of intelligent production line operation and maintenance management. By reviewing relevant theoretical and technological foundations, a five-layer digital twin framework covering the physical, data, model, functional, and application layers is constructed. The core mechanisms for achieving real-time virtual-real mapping, multi-source data fusion, hybrid-driven prediction, and closed-loop decision-making are elaborated. To verify the framework's practical value, a case study of a precision CNC gear machining production line is conducted. The results show that the framework can effectively achieve real-time perception and accurate prediction of equipment status, significantly improving the foresight and scientific nature of operation and maintenance decisions. Finally, comparative analysis with traditional models confirms its significant benefits in reducing unplanned downtime, saving maintenance costs, and mitigating major

risks.

The main innovations of this research are reflected in three aspects. First, in the framework design, an architecture that deeply couples' data-driven and model-driven approaches is proposed, emphasizing the core role of the physical mechanism model in the construction of the digital twin, going beyond simple data visualization and display. Second, regarding the implementation mechanism, this study focuses on the fault propagation "pre-simulation" mechanism based on digital twin simulation. This mechanism model is combined with a data-driven LSTM prediction model to form a hybrid-driven RUL prediction method, improving the accuracy and interpretability of the prediction results. Finally, at the application level, a complete closed-loop feedback loop is achieved, from state awareness and intelligent prediction to maintenance decision generation and execution. This transforms the digital twin from a passive monitoring system into an intelligent agent capable of proactive intervention and optimization.

However, this research still has certain limitations. On the one hand, the case studies currently focus only on a single type of core equipment (CNC machine tool spindle). While this has yielded good results, the applicability and effectiveness of the framework in addressing system-level maintenance problems involving entire production lines and complex interactions among multiple devices still require broader verification. On the other hand, the construction of the high-fidelity mechanism model in the framework heavily relies on domain expertise, resulting in a complex and costly modeling process. This, to some extent, limits the rapid deployment and promotion of the framework in broader industrial scenarios. Furthermore, the secure transmission, storage, and privacy protection of massive amounts of real-time data have not been thoroughly explored in this study.

Looking ahead, this research direction can be further deepened in the following aspects. Firstly, it can explore lightweight and automated digital twin model generation technologies, such as utilizing AI-assisted modeling or knowledge graph technology, to reduce the difficulty and cost of model construction and improve the framework's universality. Second, it can expand the research scope from single devices to the entire production line and even the entire production system, focusing on more challenging issues such as the collaborative interaction of multiple digital twins, system-level cascading failure prediction, and production-maintenance joint scheduling optimization. Thirdly, it can promote the integration of digital twins with edge computing, federated learning, and other technologies, researching distributed intelligent operation and maintenance architectures to further improve system response speed and reliability while ensuring data security and privacy. Ultimately, as technology matures, building a more autonomous intelligent operation and maintenance system with self-sensing, self-predicting, self-decision-making, and self-executing capabilities will be the long-term goal of this field.

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