Digital Twin-Driven Health Operation and Maintenance Strategies for Complex Equipment with Self-Healing Capabilities

ABSTRACT

With the development of the industrial level, the service-oriented transformation of the manufacturing industry has become a new growth point for the interests of the manufacturing industry recognized by all countries, and in this transformation process, the health operation and maintenance (HOM) of equipment has become a crucial link, especially for complex equipment, and its health operation and maintenance level directly affects the overall efficiency of the manufacturing industry. However, with the improvement of intelligence and complexity, a more general and complete set of methods and theories is needed for the healthy operation and maintenance of complex devices with self-healing states. Based on an in-depth analysis of the key issues of complex equipment health operation and maintenance, this paper introduces digital twin technology as a breakthrough. Digital twins provide new ideas for the healthy operation and maintenance of complex equipment. By defining a digital twin-driven PHM (Prediction and Health Management) framework, this paper not only solves the problem of mobility (i.e., virtual and real connection) of the cross-platform health operation and maintenance model, but also focuses on improving the accuracy and evaluation indicators of the model (the consistency between the virtual model and the entity). Addressing issues of strategy development and effectiveness evaluation. Based on the digital twin technology, a general model was established, and the self-healing phenomenon and different maintenance strategies were introduced to explore its impact on reliability. Based on the game idea, the reliability model is used to evaluate different maintenance strategies. So as to develop the optimal operation and maintenance strategy. This not only improves the accuracy and efficiency of O&M, but also provides a solid theoretical foundation and technical support for the intelligent and autonomous health O&M of complex equipment.

Keywords:Digital twin; virtual-real interaction; self-healing state; complex equipment; health maintenance and operation

1. INTRODUCTION

1.1 SOURCE OF THE TOPIC

The 20th Congress report of the party emphasizes the need to "accelerate the construction of a strong manufacturing nation, a quality nation, a space nation, a transportation nation, a network nation, and a digital China." As a micro-unit in the manufacturing system, the level of equipment development determines the shortcomings in the development of the manufacturing industry's "barrel effect." With the progress of globalization, urbanization, and industrialization, advanced technologies continue to emerge, and customer personalized demands are increasing. The equipment manufacturing industry presents characteristics of automation, diversification, intelligence, and complexity. In 2021, the basic principles of China's "14th Five-Year Plan for Intelligent Manufacturing Development" explicitly mentioned "adhering to integrated development, strengthening interdisciplinary and cross-domain cooperation, and promoting the deep integration of new generation information technology and advanced manufacturing technology[1]." In the column of intelligent manufacturing technology research, key issues such as "breaking through the digital twinning of equipment and production processes,""equipment fault diagnosis and predictive maintenance, dynamic production planning and scheduling in complex environments," and "the applicability of new technologies such as 5G, artificial intelligence, big data, edge computing in typical industry quality inspection, process control, process optimization, planning and scheduling, equipment operation and maintenance, and management decision-making" are addressed. In the column of breakthroughs in industrial software enhancement, "fault prediction and health management software (PHM), maintenance, repair, and overhaul (MRO) integrated guarantee management" are mentioned. According to the "Research on Intelligent Manufacturing Technology Forecasts and Roadmaps for 2035," digital twinning, equipment health assessment, and fault prediction are listed in the intelligent manufacturing technology roadmap for 2035[2].

1.2 RESEARCH BACKGROUND

As the total output of the manufacturing industry increases, the integration of equipment manufacturing and after-sales service gradually shifts from the unilateral business model of "manufacturing + sales" to the multidirectional business model of "manufacturing + sales + service". The emergence of large quantities of complex equipment has become the cornerstone of further development in the manufacturing industry. Ensuring the working quality of complex equipment, as well as the integrated service throughout its lifecycle, has become the focus and value-added point for various enterprises. It has also become an integral part of equipment services[3].

The most common equipment maintenance strategies currently employed are "planned maintenance" and "post-maintenance." The former overlooks the specific environment of equipment usage and individual differences in equipment, which can easily lead to situations of either over-maintenance or under-maintenance. Although there have been some explorations leading to the gradual development of "preventive maintenance," it can significantly reduce the likelihood of under-maintenance[4]. However, it still results in the waste of design life and an increase in operating costs. The latter inevitably leads to production stagnation, causing economic losses and even threatening production safety.

With the increasing complexity of equipment, more and more health monitoring methods are being applied to intelligent monitoring. This has given rise to the method of "condition-based maintenance," which involves executing different repair strategies while the equipment's health deteriorates rapidly, thereby extending its normal usage time. However, although condition-based maintenance can achieve better maintenance economy and have sufficient safety margin to adjust production plans, predicting spare parts, repair time, and predicting the remaining life after maintenance remain challenging tasks[5].

Therefore, condition-based maintenance is gradually evolving towards "predictive maintenance." Through various methods of predicting states, it aims to predict spare parts in advance and even eliminate future fault risks in the early stages of fault development through some control means. When facing future faults that require shutdown maintenance, early spare parts can be prepared to minimize the impact on production plans and maximize the utilization of equipment to achieve economic benefits. Various maintenance methods are illustrated in Figure 1, and with the increasing complexity and popularity of intelligent equipment, advanced predictive maintenance methods are continuously evolving. Therefore, the development of suitable and economically efficient health maintenance methods for complex equipment has become a hot issue in research worldwide[6].

1.3 RESEARCH PURPOSE, CONTENT, AND SIGNIFICANCE

1.3.1 RESEARCH PURPOSE

In response to the issue of poor generalization capability in current maintenance methods for complex equipment, we propose to investigate the characterization methods of the health status of complex equipment and the degradation mechanisms of their health status based on operational data from different equipment. Recognizing the health status of equipment is essential for its maintenance. Traditional methods for identifying the health status of complex equipment can only handle specific objects and cannot achieve real-time recognition. Therefore, this study intends to employ data analysis and normalization techniques, utilizing information fusion to construct an equipment health index[7]. This index will provide dimensional reduction of data input for the overall framework and serve as the basis for subsequent models.

In response to the underutilization of self-healing phenomena in complex equipment, we propose to investigate the role of self-healing states in equipment reliability models. Reliability models of equipment form a crucial foundation for effective maintenance. Traditional high-fidelity modeling based on analytical models fails to meet the practical demand for predictive maintenance of equipment at lower costs. Therefore, this study aims to establish a universal reliability model for complex equipment and devise updating rules tailored to different types of complex equipment, thus enabling a low-cost and low-sensor approach to reliability analysis.

Given the increasing occurrence of self-healing phenomena in complex equipment, we will introduce these phenomena into the existing reliability models and explore the impact mechanisms of different maintenance strategies on the entire lifecycle operation of complex equipment. This endeavor involves constructing reliability models for complex equipment that incorporate self-healing states. Currently, there is limited research on reliability models incorporating self-healing features. By defining various states, we can investigate how the timing of intervention with different maintenance and self-healing strategies affects reliability[8].

1.3.2 RESEARCH CONTENT

In response to the inadequacy of current maintenance strategies for complex equipment, we propose to initiate a quantitative evaluation of maintenance strategies based on the previously mentioned health maintenance model. Traditional approaches tend to fix the effects of maintenance without considering the individual differences in equipment usage. Therefore, this study aims to quantify the effects of self-healing and maintenance, employing a game-theoretical approach. Utilizing reliability models, different maintenance strategies will be assessed to derive the optimal strategy under given constraints.

Addressing the issue of the absence of a theoretical framework for health maintenance of complex equipment with self-healing capabilities driven by digital twins, we intend to start from the overall architecture of digital twin health maintenance models[9]. By integrating digital twin methods with health maintenance, incorporating reliability models driven by real-measured data, we will explore the adaptive deformations of reliability models in practical applications. This will entail constructing a digital twin knowledge base to model the effects of different strategies, facilitating rapid and efficient evaluation of maintenance strategies and aiding decision-making. Furthermore, this theory will be applied to 1-3 instances to further identify and address practical application issues.

1.3.3 RESEARCH SIGNIFICANCE

Research on the reliability models of complex equipment currently tends to focus primarily on the specific equipment itself, constructing models based on analytical reduction methods. However, such approaches suffer from poor universality. Achieving highly accurate analytical reduction models relies heavily on depicting multi-physics field coupling and control conditions, often resulting in substantial computational overhead and difficulty in achieving real-time operation and application migration across different equipment systems. Theoretically, constructing reliability models for complex equipment based on the theory of complex systems involves building reliability models based on state transitions, thereby addressing the transferability issues among different complex equipment[10]. Meanwhile, the interactive approach driven by digital twins provides initial conditions for reliability models and serves as a reference for evaluating the reliability of different complex equipment models, enriching the theoretical foundations of existing reliability assessments.

There is limited research on complex systems with self-healing capabilities, with current studies mainly focusing on how to add additional facilities to achieve self-healing. However, in practical applications, many complex equipment systems face challenges in adding extra devices. Hence, the research foundation for adjusting control strategies using existing sensor information to achieve equipment self-healing is relatively weak. This paper proposes describing self-healing states and different maintenance effects during the degradation process based on reliability models, thereby evaluating equipment self-healing and maintenance effects. This provides a new basis for the healthy operation and maintenance of complex equipment with self-healing capabilities[11].

The final framework of this paper integrates reliability models with the "service" digital twin complex equipment health maintenance model, where "service" refers to the formulation of maintenance strategies. Based on reliability models of complex equipment with self-healing capabilities, different maintenance strategies are evaluated to achieve optimal maintenance strategy formulation. While traditional maintenance strategies have an equal impact on models, this paper aims to further quantify equipment maintenance strategies using knowledge graphs, thus driving the updating of reliability models for complex equipment with self-healing capabilities to achieve more precise evaluation and formulation of maintenance strategies[12]. While knowledge graphs are commonly used to build triple data and develop knowledge bases, this paper extends their application by quantifying maintenance strategy knowledge bases, enriching the application of knowledge graphs, and providing theoretical references for service frameworks in the digital twin of complex equipment.

2. ARCHITECTURE OF DIGITAL TWIN CONTROL SYSTEMS

2.1 OVERVIEW

Currently, the study of sophisticated equipment's health maintenance strategies and methods primarily revolves around Prognostics and Health Management (PHM). PHM signifies a shift from traditional analytical diagnostic methods to intelligent diagnostics, enabling precise repairs at accurate times and locations, marking a transition from reactive communication to proactive maintenance activities. PHM for complex equipment has found wide-ranging applications, such as in rocket engines, satellite health maintenance, structural health monitoring, and gearbox health monitoring. Specific domains within PHM, including health and usage monitoring systems, integrated status assessment systems, equipment diagnostics, and predictive tool integration platforms, have seen significant development. Consequently, the interconnection of fault diagnosis, usage monitoring, and maintenance support systems has become increasingly crucial. The concept of PHM was initially introduced by the United States Joint Strike Fighter (JSF) program, notably the F-35, and has since undergone extensive military research. Over several decades of practice and application, significant breakthroughs have been achieved in both methodology and theory. Utilizing bibliometrics, an analysis of literature on equipment health maintenance from the Web of Science (WOS) database was conducted, constructing a dataset for bibliometric analysis. Figure 1 illustrates the thematic shifts in citation patterns across different years within this research direction[13].

Figure 1The evolution of key terms cited in this field is most strongly manifested in the emergence of specific themes.

The clustering analysis of the dataset reveals corresponding research themes. From the graph, it is evident that there is a close relationship among various research themes. However, the original clustering intertwines methods and objects. To delve further into the commonly used methods in the health maintenance of complex equipment, refinement of the clustering results is necessary. As shown in Figure 2, the clustered research primarily focuses on methods such as deep learning, risk and management, data modeling, fog computing, the Internet of Things, and deep reinforcement learning[14].

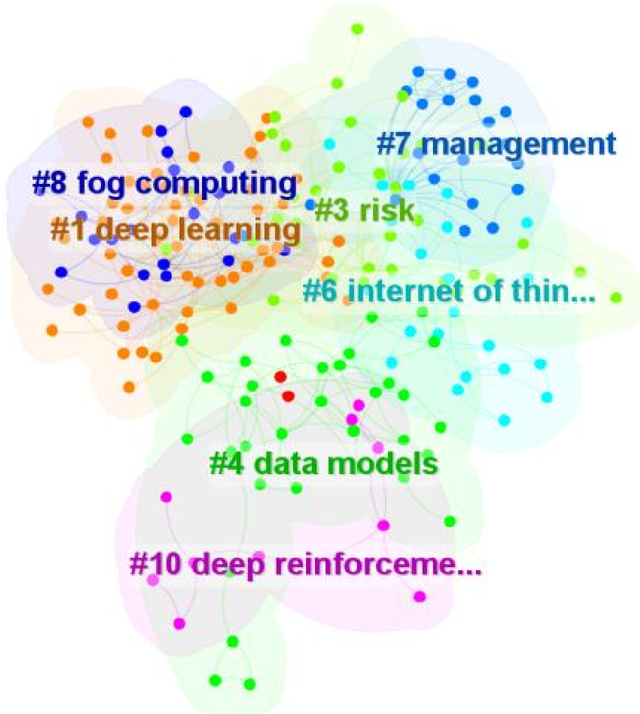

Figure 2Current Clustering of Health Maintenance Methods for Sophisticated Equipment

2.2 COMPLEX EQUIPMENT HEALTH STATE IDENTIFICATION

With the deepening of the complexity of equipment, the level of health operation and maintenance of equipment as a whole lags behind the design and development of equipment, as the main basis for equipment health operation and maintenance, how to realize the health operation and maintenance of complex equipment has become a key factor affecting the accuracy of the research results. Based on the data-driven complex equipment health state identification method based on condition monitoring data, mining which implies the fault characteristics of information for health state identification, based on operational data, interpretable and suitable for online monitoring, due to the development of sensing technology, communication technology and data storage technology, a large number of equipment operating state data is collected and stored for the rise of data-driven methods. Along with the development of signal processing, machine learning and deep learning technologies, data-driven methods for mechanical equipment health state identification and life prediction have been vigorously developed and applied. The research on data-based health state identification of complex equipment is mainly focused on variable working condition health state identification and cross-platform health state identification[15].

2.3 RELIABILITY PREDICTION OF COMPLEX EQUIPMENT WITH SELF-HEALING STATES

Self-healing phenomenon in engineering was firstly discovered in material discipline, in 1968 Briley, a scholar in the field of computer, proposed the concept of self-healing control, from then on, the researchers of self-healing phenomenon further expanded, and then people found self-recovering properties in complex network systems and studied them, and they were applied in complex systems such as power distribution systems. The concept of artificial self-healing of modern equipment was firstly proposed domestically and then developed internationally. The current research on self-healing mainly focuses on self-recovery action control and self-healing model construction[16].

Early research on equipment self-healing mainly focuses on equipment containing self-healing phenomenon, and gradually extends the research from self-healing polymer to mesh structure. For example, the application on energy storage equipment and smart grid has certain reference significance for the generalization model of complex network containing self-healing.

Domestic research in this area is almost synchronized with foreign countries, academician Gao Jinji team has been committed to the research of artificial self-healing equipment, and one of the main directions of his team is active artificial self-healing, that is, by increasing the components of the equipment to achieve the active recovery of a specific failure, such as the use of active exciter vibration of rotating machinery to actively control, so as to inhibit the shaft misalignment, motion imbalance failure, with the same team. YAO Jianfei, et al. HUANG Liquan, WANG Weimin, SU Yiru, et al. Automatic rotor balancing method and experimental research based on electromagnetic self-healing force [J]. Vibration and Shock, 2011, 30(01): 208-12. developed electromagnetic and pneumatic liquid-type automatic balancing device by means of electromagnetic actuator generating rotational electric power offset with rotor vibration, constructed a targeted self-healing regulation system, and effectively solved the vibration failure problem caused by rotor imbalance of the working condition that has been existed in the turbine.

Now the main direction for the degradation of complex equipment systems containing self-healing phenomena, that is, the use of complex systems containing self-healing modeling to reduce production costs or extend the life of the equipment, such as NASA's “Integrated Elastic Vehicle Control Project” through the intervention of the self-healing to enhance the comprehensive capabilities of the fighter aircraft[17]. In order to solve the problem of quay crane operation, which is easy to be disturbed by random shocks, thus affecting the production, Lim et al. further analyzed this system and constructed a self-healing operation scheme in the face of random shocks by using uncertain optimization, thus realizing a more efficient quay crane operation. Ben et al. believe that, for the current complex equipment, which is dynamic, multivariate, heterogeneous, and unpredictable in nature, it is important to enhance the autonomous behavior of these systems and predict their failures. behavior is as important as predicting their failures, and suggest that failure detection, recovery strategies, and reliability are essential to ensure continuous and correct operation even given the maximum number of faulty components, proposing a distributed formal model for the specification, validation, and analysis of self-repairing behaviors, from failure detection to self-recovery, in autonomous systems. This model allows the user to specify and apply the desired type of fault detection and recovery without the need for additional expertise, and provides qualitative validation primarily for the use of state space exploration tools, and quantitative properties can also be verified by statistical model checking.

3. METHODOLOGY

3.1 COMPLEX EQUIPMENT HEALTH OPERATION AND MAINTENANCE STRATEGY AND ASSESSMENT METHOD BASED ON STOCHASTIC PROCESS

Degradation trajectory-based and stochastic process-based are the two major directions for reliability modeling, however, the method by constructing product degradation trajectory also has considerable stochasticity, mainly in: measurement uncertainty, variability between samples and time-varying uncertainty. Moreover, the reliability models based on degradation trajectories mostly use the same parameters, so it is difficult to describe the individual characteristics of the object, and accurate degradation trajectory-based relies on the portrayal of physical details. The stochastic process-based model can well describe the individual degradation process due to vibration, temperature, humidity, variable amplitude load and other small environmental stress impact, the individual degradation process will show the characteristics of uncertainty, in the product time-varying uncertainty of the description of the product also has a good performance. Common models used for equipment reliability description are Gamma process, inverse Gaussian process, Wiener process and the promotion and correction forms of each process[18].

3.2 DIGITAL TWIN-DRIVEN HEALTHY O&M ARCHITECTURE FOR COMPLEX EQUIPMENT

In the development of equipment level, on the one hand, people found that the health operation and maintenance method based on analytical reduction is difficult to realize the formulation of accurate operation and maintenance plan in the equipment gradually complex, on the other hand, the development of computers and artificial intelligence also provides a more effective way of thinking for the health operation and maintenance of complicated equipments, and gradually forms a more comprehensive fault prediction and health management (PHM) which mainly includes the research on diagnostic logic and mathematical principles, and is mainly aimed at the research of diagnostic logic and mathematical principles. For the goal, mainly including diagnostic logic and mathematical principles of more comprehensive fault prediction and health management (Prognostics and Health Management, PHM). In engineering practice, it has been shown that PHM technology can further reduce the maintenance and security costs, improve the equipment integrity rate and mission success rate, which is reflected in the following: reducing the maintenance and security costs by reducing the demand for spare parts, security equipment, maintenance manpower and other security resources; shortening the maintenance time by reducing the number of repairs, especially the number of unplanned repairs; and reducing the risks caused by failures in the course of the mission through health perception, so as to improve the mission success rate. Success rate[19].

Combined with the development of informatics, health O&M has gradually changed from a model based on parsing to one based on online processing of diagnosis and maintenance strategy development for equipment. Online diagnostic methods received attention, and at this stage Predictive Maintenance (PdM), Condition Based Maintenance (CBM) and other methods were gradually developed[20].

The research of foreign PHM systems started relatively early, and there have been more industrialized cases, such as the F35 aircraft PHM system, helicopter health and use monitoring system (HUMS), Boeing's aircraft condition management system (AHM), NASA vehicle integrated health management (IVHM), the U.S. Navy's Integrated Condition Assessment System (ICAS), and Predictive Enhanced Diagnostic System (PEDS), etc.

4. INNOVATION POINT

4.1 A DIGITAL TWIN-DRIVEN METHODOLOGICAL FRAMEWORK FOR COMPLEX EQUIPMENT HEALTH OPERATIONS AND MAINTENANCE EXPLORATION

The model-based systems engineering approach can provide guidance for the construction of the overall system and the construction of functional objectives in the system, through the MBSE approach to the reliability, maintainability, security, testing, safety and environmental adaptability of complex equipment design, and pre-design of the objectives to be achieved in different processes. The main research content includes: using the model-based systems engineering approach to pre-design the digital twin-driven health operation and maintenance framework for complex equipment, and confirming the health operation and maintenance main line of "identification-prediction-operation and maintenance". Based on the requirements analysis and the implications of the digital twin framework, the objectives of each process are formulated.

4.2 EXPLORING METHODS FOR IDENTIFYING THE STATE OF HEALTH OF COMPLEX EQUIPMENT

The common problem of complex equipment health operation and maintenance is studied, mainly for the different signals across the platform for the dimensionless processing, such as vibration signals, voltage signals, etc., these continuous signals fault discrimination standards are different but to a certain extent reflect the degree of health and operational status of the equipment. Entropy provides ideas for cross-platform data normalization[21]. Since entropy does not rely on a priori knowledge, it does not require too much signal processing, and does not have a high dependence on the signal form, it is proposed to use entropy to process signals of different equipment and different time sequences in order to discriminate the state of the equipment. However, the basic entropy theory has the disadvantages of poor noise resistance, low computational efficiency, poor consistency, etc. In order to be more adapted to the health state recognition of complex equipment, it is proposed to further process the entropy through the improvement of entropy, such as symbolic dynamics filtering and other methods, so as to make it have better adaptability.

4.3 CONSTRUCTING OPERATION AND MAINTENANCE STRATEGIES AND STRATEGY EVALUATION METHODS FOR COMPLEX EQUIPMENT CONTAINING SELF-HEALING STATES

Reinforcement learning-based approach for the formulation of health operation and maintenance strategies for complex equipments. The health operation and maintenance of equipments involves the game between "benefit" and "life", and the reinforcement learning approach can be used to evaluate different strategies, so as to formulate the optimal strategy for a certain state under specific constraints. Reinforcement learning can be used to evaluate different strategies and formulate the optimal strategy for a certain state under specific constraints. Self-healing and maintenance strategies need to be processed by knowledge mapping, and the artificial definition of the effects of self-healing and maintenance will cause subjective bias in the reliability model. The quantitative processing of self-healing and maintenance strategies for complex equipment is constructed by means of knowledge mapping, and the effects of different self-healing and maintenance strategies on the health degree of the equipment are investigated by combining with the reliability model[22].

5. SUMMARY& CONLUSION

The application of digital twin technology in manufacturing has become an important trend, especially in the health operation and maintenance of complex equipment. As manufacturing grows, complex equipment plays a critical role in production and operations. Digital twin technology provides a new approach to manage and maintain these equipments, which enables real-time monitoring, prediction and optimization by building a virtual model of the equipment to interact with the actual equipment.

In this paper, based on digital twin technology, we propose a health operation and maintenance method for complex equipment that includes a self-healing state. First, a digital twin model of complex equipment is established, which is interacted with the actual equipment in a virtual and real way to realize the two-way transmission of information. Then, sensor data and real-time monitoring technology are utilized to track and monitor the state of the equipment in real time to identify potential failures and problems. Next, based on model prediction and optimization algorithms, the prediction and optimization of equipment health state, including the consideration of self-healing state, are realized. Finally, through the development of effective maintenance strategies and programs, regular maintenance and repair of equipment is achieved to minimize failures and downtime[23].

The establishment and maintenance of digital twin models require a large amount of data and resources, and how to improve the accuracy and precision of the models is a key issue. Second, the realization of the self-healing state requires more advanced algorithms and technical support to achieve rapid identification and resolution of equipment problems. Future research directions include further optimizing the digital twin technology to improve its application in complex equipment health operation and maintenance, as well as exploring new self-healing state realization methods to provide more reliable and efficient solutions for the development of manufacturing industry.

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