The Application and challenge of Digital Twin technology in Ship equipment

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Abstract. Digital twin technology has been widely developed and very active in many areas of intelligent manufacturing in recent years. Due to the complexity of ship equipment, the impact of variable loads and the high salt spray environment of the ocean, performance degradation was rapid and failures occurred frequently. Its full life cycle operation and maintenance was the main problem that restricts its performance and affects the ship's ability to carry out its mission. Based on the analysis of the development status of digital twin technology and its application in the full life cycle of equipment, this paper proposes a framework for intelligent operation and maintenance of marine devices based on digital twin and discusses the challenges faced by digital twin technology in the application of marine equipment, so as to provide reference and reference for accelerating the role of digital twin technology as a combat multiplier in marine equipment.

1. Introduction

Large ship equipment or platform, such as the vital equipment in the ship power system, like steam turbine, pressurized boiler, is the crucial equipment of the power system. Its reliability and operation state directly affect whether the power system can be used normally, and directly restrict the performance of the ship. The key equipment, such as steam turbine and turbocharged boiler, are large and complex mechanical systems. These systems are gigantic and complicated, their working environment is harsh and the load changes frequently. Broadly speaking, the more complex the system is, the more serious the consequences of the accident would be. In reality, the failure of crucial equipment such as steam turbine unit and pressurized boiler unit often leads to the loss of power and the difficulty of the ship to accomplish the mission. At present, the intelligent operation and maintenance of key marine power equipment, such as operation management, accident warning, fault diagnosis, remaining useful life prediction and maintenance, are important problems to be solved urgently. Therefore, the application of key technologies based on Digital Twin (DT) can not only realize the intelligent operation and maintenance of ship equipment, but also carry out full life cycle management of ship equipment, which is of great significance to further optimize its use and maintenance strategies and improve the on-voyage rate and combat effectiveness of ships.

Based on the analysis of the developing trend of digital twin technology, combined with the strong demand for large-scale ship equipment or platform full life cycle management and intelligent operation and maintenance, this paper analyzes the application status of digital twin in intelligent manufacturing,
intelligent operation and maintenance. The intelligent operation and maintenance framework of key devices is discussed, and the challenges of digital twin technology in marine equipment are discoursed, which provides a reference for accelerating the role of digital twin technology as a force multiplier in marine equipment.

2. Overview of Digital Twin

2.1. The concept of digital twin

"What is the definition of DT?" Although the concept of DT has long been proposed, the definition surrounding DT is still evolving. The concept of DT can be traced back to the NASA "Apollo" project in 1969 [1], but the specific concept of DT was given on a speech by Grieves on Product Life Cycle Management (PLM) at the University of Michigan in 2003 [2] and Grieves officially named the concept DT in 2011 [3]. DT was first defined by the NASA—'Make full use of physical models, sensor updates, and operational historical data, integrate multi-disciplinary, multi-physical, multi-scale, and multi-probability simulation processes to complete the mapping in virtual space. So as to reflect the full life cycle process of the corresponding physical equipment' [5]. DT was first proposed with the aim of being able to predict the life of a vehicle. In the subsequent research work, concepts such as the full life cycle [6], the detection of task requirements [7], and the use of prediction or fault diagnosis [8], were gradually introduced. The digital twin has the following characteristics [9]:

(1) Real-time mapping. There are two spaces in the digital twin, physical space and virtual space. The virtual space has to be superbly synchronised and realistic with the physical space.

(2) Interaction and convergence. The digital twin is a fusion of the whole process, all elements, and all services. In the physical space, the data generated at each stage can be connected to each other. At the same time, historical data and real-time data can also interact and merge. There is a smooth connection channel between the physical space and the virtual space, which allows them to interact easily [10].

(3) Self-evolution. Digital twins can update data at every moment, and the virtual model can be continuously improved by comparing the virtual space with the physical space [11].

2.2. Research Trends in Digital Twin Research

In this paper, the Web of Science database was chosen to search and filter the literature, using ‘digital twin’ as the search field in the abstract, keywords, and paper title. The search results show that the cumulative number of relevant literature from 2000 to 2009 is only 14, so only those published and included from 2010 to 2020 are selected for analysis.
2,344 papers related to digital twins are published from 2010 to 2020 (data from Webofscience). As can be seen from Figure 1(a), the amount of relevant literature grew nearly exponentially each year from 2017 to 2019, the number of publications per year in order of 91, 166, 328, and 672. The number of documents published in 2020 has reached a new peak, it reaches 731. From the beginning of 2021 to February 24, 96 related articles have been published. It is clear that research on the digital twin is gaining momentum and the literature will continue to grow rapidly. From 2017 to 2019, related conference articles have grown rapidly, outpacing the number of journal articles. In 2020 journal articles regained their dominance, indicating that the current mainstream research on digital twins is becoming more in-depth and systematic.

From 2010 to 2020, the top three countries that published relevant documents were the United States, Germany, and China in order. The proportion of relevant documents published in the United States, China, and Germany accounted for 40% of the total number of relevant documents published in 85 countries. As can be seen from the cooperation mapping of individual countries, the initial interoperability and cooperation between the countries with the highest number of publications has been established, laying a good foundation for further research on digital twin technology later on.
Figure 2  Top 10 countries in digital twin-related literature

Figure 3  Mapping of cooperation in digital twins across countries

Figure 4  Mapping of collaboration between units and their researchers

The mapping of the units and their research collaborations shows that the top-ranked units are already taking shape in terms of the number of papers published. Meanwhile, the units publishing digital twin-related literature are dominated by universities, such as RWTH Aachen University, the University of California system and Beijing University of Aeronautics and Astronautics, but the top three publications are occupied by the Helmholtz Institute (Germany), the French National Center for Scientific Research,
and the Chinese Academy of Sciences. Siemens (Germany) ranks sixth with 38 papers. The top five institutions with the most cooperation with other institutions are the University of Sheffield, Pennsylvania State University, Cambridge University, Chinese Academy of Sciences, and Ohio State University. Professor Fei Tao, Professor Sehitoglu, Professor Soderberg and Professor Rossmann ranked the top four in terms of number of articles published, with Professor Fei Tao ranking first in terms of number of citations, with 1071. The concept of digital twins has received considerable international attention in both theoretical research and practical applications, but the cooperation between scholars leading the frontier research in the field of digital twins needs to be strengthened in order to further explore the heat, depth, and breadth of the field.

At present, digital twins involve more than 80 research directions, which shows the breadth of research. Among these research directions, engineering is the most popular and is the absolutely central. Computer science and materials science is the second and the third, respectively. Engineering is the hottest because the digital twin technology realizes the feedback from the real physical system to the digital model in the cyberspace. The application of information simulation, process analysis, data accumulation, knowledge mining, etc. based on the digital twin technology is crucial in the future engineering field, so scientific research and innovation in the field of digital twin technology will inevitably affect the development prospects and research directions of the engineering field [12]. Computer science is high because the use of computers to simulate and interact with physical entities is essential to achieve intelligent manufacturing and full cycle management of product design, manufacturing, optimization and operation and maintenance. Materials science is hot because of the extreme need for digital twins, where all anomalies that may affect the working condition of equipment must be accurately examined, evaluated and monitored, and new materials must be developed.

3. Application of digital twin in the full life cycle of equipment

For equipment, product design, processing and manufacturing are very significant parts. They are an important basis for realizing specific equipment functions and ensuring equipment reliability and are the basis for equipment operation and maintenance. Accurate fault warning and maintenance of equipment can further improve the use efficiency of equipment and optimize life cycle costs. In recent years, the application of digital twin technology in the full life cycle of equipment has advanced by leaps and bounds, providing strong support for the digital design, intelligent processing, fault warning and maintenance of marine equipment.

3.1. The application of digital twin in product design

Product design is the first step in the application of digital twin technology to intelligent manufacturing. The use of digital twin technology can shorten the product design cycle, especially for large ship equipment or platforms, where the design cycle is long and costly. As more functionally advanced ship equipment or platforms continue to be developed, traditional design methods have become difficult to adapt to their design needs.

To provide better design services to end users, people have conducted research on the application of digital twin in the product design. For example, in the function formulation stage, Cheng J et al. [21] proposed a systematic approach to feature recommendation that makes full use of information in the context of information flooding in order to help end-users better understand their needs. Tao Fei et al. [9,22-24] proposed several product design methods based on digital twin technology. For example, based on the management of product life cycle big data, the generated and integrated network data can be used to better serve the product life cycle to promote product design; at the same time, a method of using digital twin technology to drive the product design is proposed. Developed the Digital Twin-driven Product Design framework (DTPD), which can be used as a reference for establishing digital twins in CPS. Zhuang Cunbo [25] discussed the application of digital twin in product design, proposed a framework of intelligent production management and control methods for complex product assembly workshops based on digital twins, and elaborated on the four core technologies required by the framework. Schleich B [26] et al. proposed a comprehensive reference model based on the concept of
model surface shape, and solved the problems of conceptualization, representation, realization and product life cycle of the model.

3.2. Application of Digital Twin in Manufacturing

Traditional manufacturing systems rely on systems such as Manufacturing Execution Systems to sense real-time production data and monitor production status such as progress, quality and workload, while subsequent exception or error handling relies on manual supervision and reconfiguration. This centralized approach is inefficient. Such as turbine units, which are machined with such high precision that a slight defect in the machining of a component can lead to the scrapping of the whole part, thus placing high demands on the whole process of machining and assembly of the unit. Intelligent production technology is mainly to achieve effective management of production resources in the workshop or factory, thereby improving the production efficiency, product quality, and reducing production costs. The digital twin can describe the production process and the product performance [27]. By synchronising physical and virtual spaces, operators can monitor complex production processes via the digital twin and make timely adjustments and optimisations to the process [28].

Zhao P [29] et al. describe a method for building a digital twin process model (Digital Twin Process Model (DTPM)) in a manufacturing process and the data content of the digital twin, discussing the method of acquiring real-time data and the management of simulation data. They propose a hierarchical model and mapping strategy for processing multi-source heterogeneous data for data fusion in physical and virtual space, as a way to generate digital twin data, and analyse the role of DTPM in process design for guidance and visualisation. Tao Fei [30] et al. proposed a new concept of Digital Twin Shop-floor (DTS) based on digital twins, and discussed its four key components: physical workshop, virtual workshop, workshop service system and workshop digital twin data. The operation mechanism and the implementation method of DTS, the key technology and challenges of DTS, etc. are studied, providing a reference for enterprises to realise the digital twin shop-floor. Wang Y [31] et al. introduced the virtual-real fusion technology of the digital twin to integrate information and logic in the scheduling process as part of a manufacturing execution system-based production scheduling mechanism, improving the overall performance of the shop floor production scheduling system and providing a reference for the application of the digital twin on the production floor. Zhang H [32] et al. explored a Product Manufacturing Digital Twin (PMDT) system for the production phase of the smart shop and, based on PMDT, proposed a new Cyber-Physical Production System (CPPS) architecture and also discussed the possibility of using the digital twin for job scheduling during normal operation of CPPS.

3.3. The application of digital twin in the optimization of equipment production indicators

Equipment life cycle engineering is an iterative process, and a large amount of data is collected, processed and used at any stage of the equipment life cycle [33]. The digital twin allows the values from big data analysis to be compared and analysed with the real values over the full life cycle of the equipment, on the basis of which the entire life cycle of the equipment can be optimised at each stage. Zhang H [34] et al. established a multi-objective optimization digital twin model of the production line including a computing system and a simulation platform. Lynn [35] et al. proposed a CPS-based manufacturing system to achieve the process control and optimization. Luo W [36] et al. established a multi-domain unified modelling approach for digital twin machine tools to study CNC machine tools to make them more intelligent while optimising the operation mode, reducing the rate of sudden failures and improving the stability of CNC machine tools.

3.4. The application of digital twin in the early warning and maintenance of equipment failures

With the application of digital twin technology, it is possible to establish a visual remote monitoring model by reading the real-time parameters of the device's sensors or the control system, analyze the status of the device and give timely warnings, and can also give corresponding maintenance strategies. Digital twins provide a comprehensive method to integrate and interpret physical knowledge and data
measurements, instead of relying solely on sensor data to detect [37], digital twins can also simulate the mechanism of typical failure modes and analyze their root causes to predict the evolution of the process.

Wang J [38] et al. proposed a reference model for the digital twin of rotating machinery fault diagnosis, discussed the requirements for constructing the digital twin model, and proposed a model modification scheme based on parameter sensitivity analysis to enhance the adaptability of the model. Sivalingam et al. [39] developed a digital twin model for predicting the remaining useful life and damage accumulation of wind power converters. Soares [40] et al. developed a digital twin technology for multi-effect evaporation devices and successfully implemented them in actual industrial installation. The system is based on a simple fully automated infrastructure operation and does not require significant capital expenditure, while providing predictions of important processes. Seshadri [41] et al. describe physical objects by integrating sensor data, input data, and virtual data, and diagnose information such as damage size, location, and other faults. Bazilevs [42] et al. developed a digital twin framework for fatigue damage prediction that combines physical and sensor data, thereby improving prediction accuracy. Saikumar [43] et al. developed and demonstrated that a multi-scale, non-deterministic numerical twin framework for predicting fatigue cracks from emergence to failure successfully extends a microstructure-based probabilistic model of fatigue crack expansion to the full probabilistic prediction of fatigue life. Patrick [44] et al. proposed a general method to reduce the uncertainty of fatigue life prediction based on Saikumar’s method, giving the digital twin method a high prediction accuracy and confirming the feasibility of the digital twin method in fatigue life prediction. Zakrajsek et al. [45] established a digital twin model to predict tire contact wear and failure probability. Compared with traditional models, the digital twin model shows many advantages in predicting the probability of failure at different sinking rates, yaw angles and speeds. Luo W [36] et al. proposed a digital twin multi-domain unified modeling method for CNC machine tools, using sensor systems, digital twin machine tool description models, algorithm models and mapping models to achieve accurate simulation, self-sensing, self-adjusting, self-predicting and self-assessment. Krishnan [46] et al. realized the health monitoring and prediction of permanent magnet synchronous motors by creating an Intelligent Digital Twin (IDT) in MATLAB/SIMULINK. Reifsnider [8] established a high-fidelity digital twin model on the basis of multi-physical quantity simulation, which can be used for non-destructive testing. Aivaliotis [47] et al. proposed a method to calculate the remaining useful life (RUL) of mechanical equipment using a physics-based simulation model and the concept of digital twins to achieve predictive maintenance of equipment.

4. Intelligent operation and maintenance framework of ship equipment based on digital twin

The operation and maintenance of ship equipment is one of the most important aspects of the full life cycle. For large ship installations, on the one hand, online monitoring data and historical data need to be combined to enable timely diagnosis and prediction of faults in order to reduce the risk of accidents. On the other hand, there is a need to monitor and evaluate the technical status in real time and to assess its remaining useful life in combination with its performance degradation pattern, for use in the formulation of its maintenance strategy, etc. The application of digital twin technology provides a good technical support for the intelligent operation and maintenance of ship equipment.

Based on the problems and task requirements of ship equipment in the operation and maintenance, this paper adopts digital twin and artificial intelligence technology to propose an intelligent operation and maintenance framework for ship equipment. On the basis of in-depth study of the dynamic characteristics and interactions of the various components of ship equipment, the performance degradation laws and characteristics of components and devices can be obtained; on the basis of high-precision digital model, combined with new methods of finite element analysis, etc., digital simulation of ship equipment is carried out; based on historical data and existing data, the results of the integrated digital model are adopted, machine learning and other technologies are used to evaluate the state of ship equipment; finally, on the basis of inference and decision model, intelligent diagnosis, prediction and maintenance optimization of ship equipment are carried out to improve the intelligent operation and maintenance level of ship equipment.
Its main key technologies include:

1) Analysis of failure mechanism and performance degradation of ship equipment
Marine equipment such as turbines are high-speed rotating machinery with high operational management requirements, and as their service life extends throughout the ship's service life, they are susceptible to performance degradation and damage accumulation due to various factors, which can lead to accidents. For example, due to the alternating load caused by thermal stress, frequent working condition changes, centrifugal load, steam dynamic load, etc., the rotor parts are prone to high/low cycle fatigue. When working under high temperature steam for a long time, the cylinder and rotor components are prone to creep. Due to high-speed steam flow excitation and bearing oil film vibration, steam turbine components are vulnerable to damage and cracks. The combined effect of these factors will ultimately affect its reliability and operational stability.

2) Multi-scale 3D digital modeling and finite element analysis of ship equipment
Constructing a high-precision three-dimensional digital model of ship equipment is an important foundation for subsequent machine learning, intelligent diagnosis, and maintenance decision-making. Using ANASYS and other tools to build a multi-scale and high-precision three-dimensional model of ship equipment parts/components/devices to improve the calculation accuracy of the finite element model. On the basis of digital models, numerical calculations are carried out using elastoplastic mechanics, fracture mechanics, computational fluid dynamics, computational heat transfer theory, etc., to simulate the damage evolution process of ship equipment, as the basis of machine learning algorithms and reasoning decision models.

3) State evaluation of ship equipment based on machine learning
During the operation of ship equipment, a large number of monitoring signals are generated, such as temperature, pressure, oil pressure, vibration. These signals are related to the failure and performance of ship equipment, and reflect the law of ship equipment performance degradation. Through in-depth feature mining and extraction of these signals, combined with digital model calculation data, a database that can interact with digital entities is formed. Based on machine learning and other technologies, the timely interaction of data between the physical and digital bodies of ship equipment can be realised to quantitatively assess the degradation status of ship equipment, carry out fault detection and remaining life prediction, etc., which can effectively reduce system maintenance costs and avoid major accidents.

4) Intelligent diagnosis and prediction of ship equipment based on inferential decision model
Forecasting is a forward prediction in which the current state of the ship's equipment is used to predict the future and thus the state at a future point in time, taking into account future loads, or to predict the remaining useful service life for a given load profile. Diagnosis is based on existing faults or abnormal
signals to analyze the causes or root causes, which is a kind of reverse reasoning. Based on Bayesian theory, a Bayesian network reasoning model for ship equipment is established, and its two-way reasoning mechanism can be used to realize its intelligent diagnosis and prediction.

(5) Decision-making and optimization of ship equipment maintenance based on intelligent operation and maintenance

Based on information such as the evaluation of the ship’s equipment status and intelligent diagnosis, the goal is to consider the completion of tasks and the minimum cost within the full life cycle, and make automatic optimization decisions on maintenance, etc., and automatically formulate maintenance plans (such as reducing working conditions), repair plans, and replacement guarantee demand, etc.

5. Challenges faced by digital twin in marine equipment applications

The implementation of the digital twin in marine equipment is currently facing a number of challenges:

(1) Integration involves multiple technologies such as data collection, data transmission, data mining, and collaborative control. The robustness and applicability of the fusion algorithm should be improved. During the construction of the digital twin system, the data obtained in various forms, including structured data, semi-structured data, unstructured data, etc. Although information standardization has always been the focus of researchers, this problem is still prominent. The more types and numbers of machines that can autonomously perceive, the lower the reliability of information exchange [48]. Especially for marine equipment, the harsh working environment, frequent load changes, and mutual influence between systems provide higher requirements for data interaction and fusion.

(2) High-precision and effective digital twin construction.

In order to ensure that the digital twin can solve complex coupled collaborative optimisation problems, it is necessary for the digital twin to have sufficient model accuracy and the largest possible variable coverage interval, to integrate engineering models from multiple domains in the digital twin, to optimise cross-model collaboration, and to achieve simultaneous changes in physical and virtual models. For marine equipment, the characteristics of physical objects need to be considered from multiple dimensions such as geometry, physics, behavior, rules, and manufacturing attributes.

(3) The scalability of the model. It is relatively costly to develop a new digital twin model. Because the relevant manufacturers of ship equipment have not standardized the database, and obtaining data from the collected inventory data is a long and difficult operation, it was necessary to make the model scalable in such a way that it could be rapidly applied on similar installations. At present, researchers are already looking for feasible solutions to realize digital twins of various manufacturing systems [49].

(4) Application of machine learning. The current PHM method provides a solution that can automatically execute predictive maintenance plans based on work data, but when its predictions still rely on historical failure data and the characteristics of typical cases, their main advantages will disappear. With the rapid development of artificial intelligence technology, the application of machine learning technology in digital twins has achieved certain results. Deep digital twins can be a solution to this problem. It can make health predictions without relying on historical fault data. Although Booyse [48] et al. proposed a framework for deep digital twins, further exploration is needed to apply these learnings to diagnosis. How to use deep learning to continuously improve the device through the fusion of virtual data and physical data is still a challenge.

6. Conclusion

The digital twin is now emerging in a variety of fields, and while the digital twin is still behind a combination of technologies such as simulation, the combination of digital models and IoT behind it has attracted the attention of many academics. As we can see, the digital twin is currently in its formative years. Germany, as the country that proposed the Industry 4.0 strategy, and the United States, as the country that proposed the concept of the digital twin, both carried out research work around the digital twin earlier and are much ahead of other countries. At present, the application of digital twin technology
in equipment in China is mainly the fault prediction, but there is still a lack of systematic theory and mature application, especially in ship equipment. With the development of intelligent, unmanned, integrated and modular ship equipment, higher requirements are placed on its full life cycle management and intelligent operation and maintenance, etc. Accelerating the application of digital twin technology is one of the important means to develop new ship equipment or platforms. With the rapid development and integration of big data, IoT, artificial intelligence and other technologies, digital twin technology will certainly have a broader application prospect in the full life cycle management as well as the intelligent operation and maintenance of marine equipment.

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