

Research Progress in Predictive Maintenance of Offshore Platform Structures Based on Digital Twin Technology

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Abstract

Offshore platforms are large, complex structures designed for long-term service, and they are characterized by high risk and significant investment. Ensuring the safety and reliability of in-service offshore platforms requires intelligent operation and maintenance strategies. Digital twin technology can enable the accurate description and prediction of changes in the platform's physical state through real-time monitoring data. This technology is expected to revolutionize the maintenance of existing offshore platform structures. A digital twin system is proposed for real-time assessment of structural health, prediction of residual life, formulation of maintenance plans, and extension of service life through predictive maintenance. The system integrates physical entities, digital models, intelligent predictive maintenance tools, a visualization platform, and interconnected modules to provide a comprehensive and efficient maintenance framework. This paper examines the current development status of core technologies in physical entity monitoring, digital model construction, and intelligent predictive maintenance. It also outlines future directions for the advancement of these technologies within the digital twin system, offering technical insights and practical references to support further research and applications of digital twin technology in offshore platform structures.

Keywords Offshore platform; Digital twin; Physical entity monitoring; Digital model construction; Predictive maintenance

1 Introduction

Petroleum and gas resources are vital to the global economy. As onshore reserves can no longer meet current and future energy demands (Liu et al., 2020), offshore exploitation has become central to securing these critical resources. Offshore platform structures are characterized by high construction costs and significant technical challenges. To reduce

production costs, operation and maintenance strategies for these structures are continuously updated and optimized. These improvements aim to extend the actual service life of offshore platforms by at least 10 years beyond their design life (Aeran et al., 2017; Leng et al., 2023).

Offshore platforms face significant degradation over time owing to the harsh marine environment, leading to issues such as corrosion, fatigue, and cracking. Globally, there are approximately 12 000 offshore oil and gas installations nearing the end of their operational lifespans. In the North Sea alone, 1 500 platforms and facilities—averaging over 25 years of age—are included in this category. Similarly, in the Asia-Pacific region, approximately 2 500 platforms are expected to be decommissioned within the next decade (Knights et al., 2024). In China, more than one-third of offshore platforms continue to operate beyond their intended design life (Yan et al., 2021). The structural health of offshore platforms varies significantly owing to differences in their designs and operational characteristics. Consequently, it is crucial to implement online monitoring systems tailored to each platform and conduct regular safety maintenance to ensure their operational integrity throughout their service life.

In practice, the operation and maintenance phase of offshore platforms typically extends well beyond the design and manufacturing phase. Common maintenance strategies

Article Highlights

- A technical framework for a digital twin system is proposed to enable predictive maintenance of offshore platform structures, addressing the engineering requirements for structural condition prediction.
- An intelligent predictive maintenance module for offshore platform structures is proposed, featuring damage identification and residual life assessment as its core functionalities.
- The research status of key technologies within the digital twin framework for offshore platform structures is reviewed, and future development directions for advancing digital twin technology are identified.

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for large and complex equipment include reactive maintenance, preventive maintenance, condition-based maintenance, and predictive maintenance (Khan et al., 2016a; van Dinter et al., 2022). However, reactive maintenance can pose significant safety risks, while preventive maintenance may lead to unnecessary costs owing to excessive servicing. Therefore, the maintenance of offshore platform structures must be grounded in comprehensive condition assessments to optimize safety and efficiency.

State-of-the-art evaluation technologies for offshore platforms have evolved from early non-destructive testing to advanced structural health monitoring. With the integration of cutting-edge technologies such as big data and artificial intelligence (AI), the real-time evaluation and prediction of platform conditions have become feasible, offering robust technical support for intelligent predictive maintenance (Carvalho et al., 2019). The advent of digital twin technology enables more comprehensive and accurate predictions of structural conditions, transforming traditional passive maintenance into proactive services. This innovation revolutionizes the existing technical framework and enables “customized” intelligent predictive maintenance throughout the entire life cycle of each offshore platform structure.

Although digital twin technology has been widely adopted in various industries and has reached maturity in some sectors, its application in marine engineering remains in its early stages (Semeraro et al., 2021; Tao et al., 2019). Currently, research on the use of digital twin technology for the predictive maintenance of marine engineering structures is limited, and a standardized industry framework is yet to be established. In response to this gap, this paper proposes a digital twin system tailored to the predictive maintenance requirements of offshore platform structures. It examines the development status of the core technologies within each module of the system, identifies challenges, and outlines future directions for advancing these technologies within the digital twin framework.

This review is organized as follows: Section 2 provides an overview of the functions and interconnections of the modules within the technical framework of the digital twin

predictive maintenance system for offshore platform structures. Section 3 examines the key technologies involved in physical entity monitoring systems. Section 4 discusses critical technologies for constructing digital models in digital twin systems for offshore platform structures, while Section 5 explores essential technologies for predictive maintenance. Finally, Section 6 summarizes the main conclusions.

2 Predictive maintenance of offshore platforms enabled by digital twin

A digital twin-based predictive maintenance system for offshore platform structures has been proposed.

2.1 Introduction to digital twin technology

Digital twin technology enables the synchronous mapping, analysis, and optimization of physical entities in a digital space through testing, simulation, data integration, and data analysis. Its key development history is illustrated in Figure 1.

The concept of the digital twin was first applied in NASA’s Apollo project (Rosen et al., 2015). The digital twin model was initially proposed by Grieves in 2003 and is considered the prototype of the digital twin concept. At that time, it was not referred to as the “digital twin” (Grieves, 2014). Between 2003 and 2010, the concept was described as the “mirror space model” and the “information mirror model” (Githens, 2007; Grieves, 2005). It was not until NASA published its “Modeling, Simulation, Information Technology, and Processing” technology roadmap in 2010 that the term “digital twin” was officially introduced (Shafto et al., 2012). In 2011, Grieves (2011) introduced the term “digital twins” as an alternative to the “information mirror model” in his book, and the term gained widespread recognition in academia. A digital twin creates a virtual replica of a physical entity in the digital world, enabling the analysis, understanding, and optimization of physical objects. It facilitates full traceability, bidirectional data sharing, and

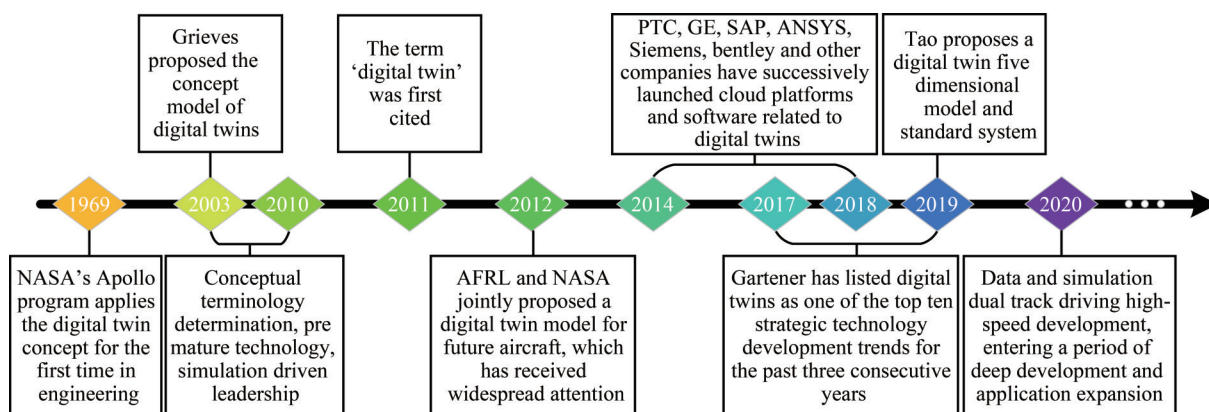


Figure 1 Development history of digital twin technology

interaction, ultimately establishing a closed-loop management system for data and models throughout the product life cycle.

Since NASA and the U.S. Air Force Research Laboratory jointly proposed a futuristic aircraft digital twin model (Glaessgen and Stargel, 2012; Tuegel et al., 2011), digital twin technology has garnered significant attention from various industries and quickly emerged as one of the most promising technologies in recent years (Errandonea et al., 2020; Rasheed et al., 2020; van Dinter et al., 2022). Companies such as PTC, GE, SAP, ANSYS, Siemens, and Bentley have launched cloud platforms and commercial software related to digital twin technology, accelerating its widespread application (Rasheed et al., 2020).

Owing to varying application requirements, different industries have developed diverse interpretations of the digital twin concept, and a standardized definition is yet to be established (Errandonea et al., 2020). While industry-specific needs have led to the creation of various technical frameworks, most of these frameworks are still based on Grieves' original model. This framework includes three key components: physical space, virtual space, and the interface between them (Errandonea et al., 2020; Semeraro et al., 2021). Tao et al. expanded Grieves' three-dimensional model by proposing a five-dimensional model for digital twins, offering a more detailed description of the digital twin concept, which has significant implications for the future

development of this technology (Tao et al., 2019).

Since the introduction of digital twin technology, it has undergone nearly 20 years of development. The foundational technologies and supporting infrastructure have now matured, laying the groundwork for rapid future advancements. The mode of technological development has evolved from being simulation-driven before 2010 to the current approach, where both data and simulation drive progress in tandem. In recent years, mature enabling technologies such as the Internet of Things, big data, machine learning (ML), blockchain, and cloud computing have provided crucial support for deeper technology integration and large-scale applications while also guiding the direction for further technological expansion.

2.2 Digital twin-based predictive maintenance system for offshore platform structures

According to the engineering requirements for predicting the structural condition of offshore platforms, a technical framework for a digital twin system has been proposed for their predictive maintenance. This system consists of five main components: 1) physical entity, 2) digital model, 3) intelligent predictive maintenance, 4) visualization platform, and 5) interconnections between modules, as illustrated in Figure 2.

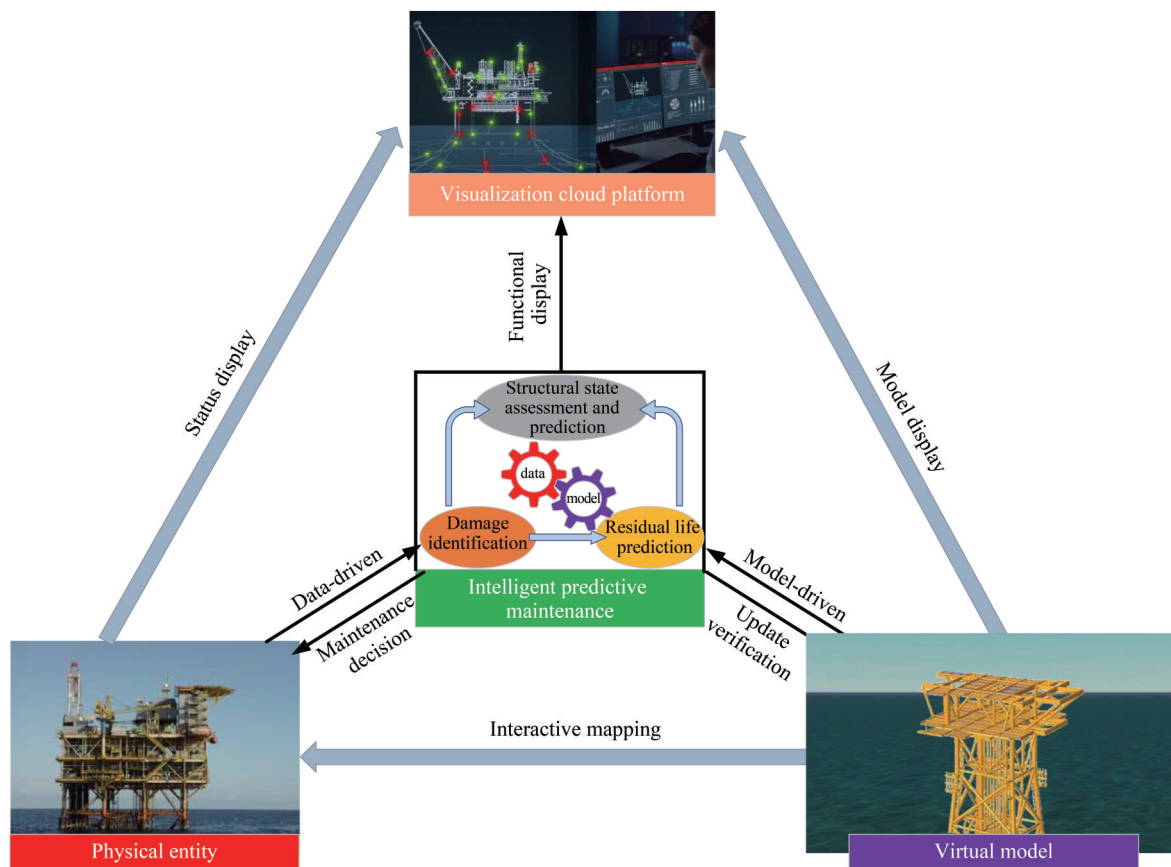


Figure 2 Predictive maintenance digital twin system for offshore platform structures

In the technical framework of the digital twin predictive maintenance system for offshore platform structures, illustrated in Figure 2, physical entities and digital models serve as the two core components, with an interactive mapping relationship. The updating of digital models relies on data provided by physical entities, with changes in physical entities reflected through updates to the digital models. The other components are extensions of the intended functions and connections between the modules. Physical entities and digital models enable interactive mapping through the operation of core functional modules and the multidimensional transfer of data.

The physical entity is the starting point of the digital twin system data chain for offshore platform structures. Its primary function within the system is to collect structural monitoring data and transmit it to other components through various sensors placed on the offshore platform structure.

The digital model is the starting point for simulation calculations in the digital twin system of the offshore platform structure and serves as the core module of the system. Its main function is to represent changes in the physical entity of the offshore platform structure within the physical space. This is achieved through the real-time updating of parameters such as geometry, physics, and state in the model. The digital model also provides model-driven support for intelligent predictive maintenance calculations and model visualization.

Intelligent predictive maintenance is the core functional module, and it is supported by physical entities through data-driven methods, while digital models provide the basis for model calculations through model-driven methods. Predictive maintenance for offshore platform structures is based on structural condition assessment and prediction. It can be achieved through structural damage identification and residual life prediction and provides valuable insights for future maintenance plans. This module supports intelligent operation and maintenance of physical entities in offshore platform structures and facilitates interactive verification of changes in geometry, physical, and other parameters in the digital model. The model is continuously updated based on changes in the physical entity.

The functionality of the cloud platform visualization throughout the system is similar to the application layer of computer software. It displays changes in the physical model status, real-time updates of digital models, predictive maintenance functions, and provides suggestions to users in an interactive format.

In conclusion, physical entities, digital models, intelligent predictive maintenance, and visual cloud platforms are interconnected through data transmission, ultimately forming a digital twin system for offshore platform structures, with predictive maintenance as its primary function.

In the digital twin system described above, data serves as the “foundation”, the model is the “core”, and the soft-

ware acts as the “carrier”. Physical entity monitoring provides the data source, digital model construction is the key focus of the model, and predictive maintenance is the function enabled by the software. The following section focuses on these three aspects.

3 Key technologies for physical entity monitoring

Data forms the foundation for the functioning of digital twins, and the key challenge in monitoring physical entities lies in acquiring comprehensive environmental and structural response data, as well as analyzing and processing it effectively. The physical entity of the offshore platform structure is the object to be twinned by the digital model in the digital twin system. Various types of sensors placed on the structure provide the data source for the entire system. The core objective of structural monitoring is to obtain load and response information from the structure based on test data. As illustrated in Figure 3, the function of physical entity monitoring is mainly achieved through the acquisition of load data from the offshore platform structure, the collection of structural response data, and the subsequent transmission, analysis, and processing of this data.

3.1 Acquisition of load and structural response data

Offshore platforms operate in a complex and dynamic marine environment over extended periods, subjected to various environmental loads such as wind, currents, waves, and ice. These forces can cause damage, including corrosion and cracks, which may not always be visible. As a result, deviations may arise between the digital twin system and the physical model. To improve the accuracy of the digital model, eliminating these deviations is crucial. Measured loads and structural response data are essential for achieving this correction.

3.1.1 Acquisition of structural load data for offshore platforms

For offshore platform structures, loads can be acquired either through direct measurement using sensors or via data mining based on historical measurement data. These loads can be classified into two categories: marine environmental loads and loads generated during service. Environmental loads are the primary cause of structural damage and reduced mechanical properties of offshore platforms, while loads generated by the production process are relatively fixed and typically follow a mass distribution method. To address the complexity of environmental load data, it is essential to focus on commonly used methods for measuring marine environmental load data, as shown in Table 1.

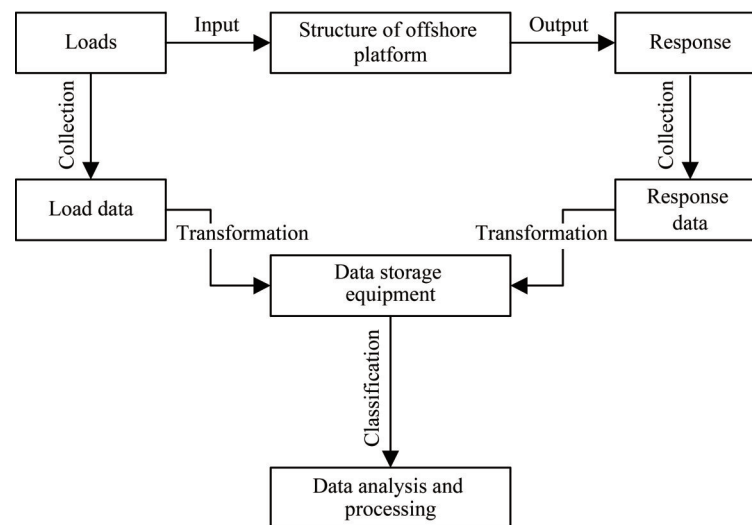


Figure 3 Key technologies for physical entity monitoring of offshore platform structures

Table 1 Environmental load data measurement instruments and their applicable working conditions

Environmental load	Instrument type	Principle of measurement	Field monitoring application
Wind load (Dhanak and Xiros, 2016)	Vane	According to the rotational speed of the vane	Low-precision measurement requires start-up wind speed
	Ultrasonic	According to the frequency of a vortex	Suitable for high-precision measurement, with minimal blind spots and no mechanical wear
	Hotwire	According to the measured current and resistance	Used for high-frequency response measurement, but easily damaged
	Laser Doppler anemometer	Doppler effect	Owing to its complex usage, high cost, and limited applicability in various scenarios
Wave load (Li et al., 2022)	Water pressure type	Water surface pressure	Long-period waves in shallow water
	Acoustic type	Acoustic signal	Nearshore and shallow water platforms
	Wave buoy	Acceleration integral	Open Water
	X-band radar	Scattering wave resonance	Operated in short pulse mode and measures the sea state from digitized sea clutter images
Current load (Gerner et al., 2007)	Image recognition	Image reconstruction	Various types of offshore platforms are susceptible to interference
	Buoy	GPS positioning	Deep sea, single measuring point
	Mechanical current meter	Propeller rotation	Any depth, a single measuring point, needs to consider the starting speed
	Electromagnetic current meter	Induced electromotive force	Single measuring point, influenced by geographical dimensions
	Acoustic current meter	Time difference, Doppler frequency offset	Near bottom flow, horizontal flow
Ice load (Wang et al., 2018)	ADCP	Pulse signal, Doppler frequency offset	Widely used, with good stability and blind spots in measurement
	Buoy	Motion trajectory and acceleration	Requires a certain placement density
	Radar image	Radio wave echo imaging	Measurement of regional sea ice density and flow velocity
	Satellite remote sensing	Spectral response characteristic analysis	Open sea areas, large sea ice
	Video image	Image recognition	Low cost, suitable for long-term monitoring

Direct measurement of wind load through sensors is the most commonly used technique. The key variables include

wind speed and direction, as shown in Table 1. Typical sensor types include vane, ultrasonic, hotwire, and laser Doppler

anemometers (Wang et al., 2018).

Several wave-measuring instruments are commonly used for offshore platform structures, and their applications are shown in Table 1. Acoustic-type instruments, image-recognition instruments, and X-band radar-type instruments are mainly used for water measurement. Underwater measurements mainly use mechanical current meters and acoustic sensors, while wave buoys are employed for measuring the water surface.

In addition to direct measurement, using wave spectra for empirical estimation is another essential method for obtaining structural wave loads on offshore platforms. Most wave spectra are based on empirical, semi-empirical, and semi-theoretical data. Owing to varying wave conditions in different sea areas, accurately describing waves with existing wave spectra is challenging. Therefore, it is necessary to adjust these spectra using field measurements. The corrected wave parameters can provide more reliable wave environment data for future structural safety designs of offshore platforms (Pedersen et al., 2019).

Ocean current load is one of the primary forces acting on underwater structures. As shown in Table 1, the acoustic Doppler current profiler (ADCP) is the most commonly used instrument for measuring ocean currents at various depths. However, because the ADCP measures currents in only one direction, multiple sensors are often used together to provide a complete profile of the currents (Cook et al., 2006). Current parameters are characterized by randomness, uncertainty, and variation with depth. Simplified models, such as uniform flow, shear flow, and gradient flow, are insufficient to accurately capture these complexities. Consequently, ML algorithms have gained popularity as a technical approach for classifying sea current data in recent years (Liu et al., 2018; Wu et al., 2019).

Ice monitoring is mainly used in low-temperature sea areas and includes measurements of ice parameters and loads. As shown in Table 1, radar imaging is commonly used

to measure ice density and flow velocity, while satellite remote sensing is employed to determine its size. Video imaging technology is used to observe the cross-sectional thickness of ice, and buoys are used to measure its trace and acceleration. For measuring ice loads, pressure boxes are used for direct measurement.

3.1.2 Acquisition of structural response data for offshore platforms

Monitoring environmental loads alone cannot directly reflect changes in the mechanical properties of offshore platform structures, and thus, the monitoring needs to be complemented by the measurement of structural response data. Structural response monitoring on offshore platforms combines global and local monitoring techniques. As shown in Table 2, the main parameters for global structural response monitoring include acceleration, inclination, angular velocity, and position information, while local monitoring mainly focuses on strain.

In acquiring global parameters, the GPS and differential global positioning system (DGPS) are used to determine position information, while the inertial navigation system (INS) measures the angular velocity of the structure rotation. The angular rate sensor tracks the tilt changes, and the acceleration sensor measures both the motion and vibration accelerations of the structure.

In the acquisition of local parameters, strain monitoring is commonly used to detect local structural changes. The most widely used sensor for this purpose is the strain gauge, which is typically placed in critical areas of the structure, such as the splash zone or key connection points.

3.2 Data analysis and processing

Through data, physical space and digital space can be linked in real-time. Data transmission, storage, analysis, and processing technologies are essential for constructing a digital twin system. Offshore platforms require long-term

Table 2 Platform motion and response data measurement instruments and applicable conditions

Response parameter	Instrument Type	Measuring principle	Applicability in the field
Position or motions of 6 degrees of freedom	GPS	Pseudo-range difference	Low-cost for global positioning
	DGPS	Pseudo-range difference, carrier phase difference principle	For the positioning of local areas, the accuracy is high.
Angular velocity	INS	Mechanical Gyroscope	Can be used underwater, working 24/7
Acceleration	Low-frequency acceleration sensor	Newton's Second Law, Electromagnetic Mutual Inductance	Long-term monitoring of structural acceleration in offshore platforms
Angle and curvature	Angular rate sensor	Solid pendulum, liquid pendulum, gas pendulum	Measurement of attitude of offshore platform structures
Strain	Strain gauge	Strain effect, piezoresistive effect	Low-cost, widely used for long-term monitoring
	Optical fiber sensor	The relationship between reflection wavelength and strain	Can be used in harsh environments such as humidity, corrosion, and high temperatures
	Piezoelectric material sensor	Piezoelectric effect	High sensitivity, high signal-to-noise ratio, and moisture resistance are required.

monitoring, which involves using a wide variety of sensors. The collected data comes in various formats and large volumes, making it susceptible to significant environmental interference. These factors create challenges for data transmission, storage, analysis, and processing (Hansen et al., 2024).

3.2.1 Data transmission

The data transmission mode for offshore platforms is classified into wired and wireless transmission. To ensure data reliability, wired transmission is mainly used on offshore platforms, while both wired and wireless transmission modes are employed for platform-to-land communication.

Submarine cable transmission is mainly used for platform-to-land wired communication, while satellite transmission is commonly used for platform-to-land wireless communication. Although submarine cable transmission offers fast data transfer and complete transmission, challenges include difficult installation and maintenance, limited transmission distance, and limited scalability. Despite these drawbacks, it is widely used on offshore platforms. Satellite transmission offers the advantage of long-range communication and 24/7 global coverage, but it suffers from lower transmission speeds and limited data capacity. Consequently, offshore platforms typically use a combination of both transmission methods, depending on the specific operational requirements.

3.2.2 Analysis and processing of monitoring data

The working environment of offshore platform structures is complex, and a wide range of sensors must be configured. The obtained data is characterized by multiple formats, large volumes, and significant implications for environmental monitoring. The primary task in data analysis for digital twin systems is to categorize and process real-world data so that the data can be related to the digital model. The fundamental objective of building digital twins is to classify various sensor data types for subsequent association with different functions in the digital model. To process structural response data for offshore platforms, it is necessary to correlate global vibration test data with the dynamic analysis of the numerical model and local response data with local stress calculations. Additionally, during the processing of environmental load data, sensor measurement data at specific locations must be correlated with environmental loads across the entire numerical model.

1) Analysis and processing of environmental load data

Environmental load data mainly includes oceanic environmental parameters such as wind, waves, currents, and ice, measured by various types of sensors. Wind load parameters include instantaneous wind direction, instantaneous wind speed, and average wind speed. According to different frequencies, wind can be classified into average wind and fluctuating wind. The average wind is processed through averaging, while the fluctuating wind requires statistical

processing, which involves analyzing turbulence parameters and combining them with the fluctuating wind speed spectrum for further statistical analysis (Wang et al., 2018).

Wave load parameters include instantaneous wave height, wave direction, and wave period. The effective wave height and equivalent period can be obtained through statistical methods, which can either directly describe the wave load or be used to modify the wave spectrum. Additionally, wave direction data can be used to adjust the direction spectrum (Tygesen et al., 2018).

The current loading parameter data include stratified flow velocity and direction obtained from ADCP measurements, which can be simplified by assuming non-time-varying stratification owing to the weak time-varying nature of the data. However, if more accurate analysis is required, ML techniques can be applied for clustering and predictive analysis of the measured parameters (Liu et al., 2018).

Measurement parameters for ice loads include geometry, motion, and load characteristics. Currently, acquiring complete real-time ice load data remains challenging. Statistical methods are employed to process the ice load data, which are then combined with structural response data to predict the impact of the ice load data on the offshore platform structure (Wang et al., 2018).

2) Analysis and processing of structural response data

Global structural response data are mainly derived from the analysis of acceleration data. However, the acceleration data acquired from the sensor often contain a considerable number of interference signals. The first step in processing the data is denoising. Signal denoising methods are mainly divided into filtering and decomposition. Filtering effectively handles noise generated during vibration experiments, while signal decomposition removes complex noise introduced by the measured environment (Huang and Liu, 2002). The processed acceleration data are mainly used for dynamic analysis of the structure, and correlation with the digital model is established through modal parameter identification.

Operational modal analysis (OMA) is mainly employed to analyze the dynamic characteristics of offshore platform structures based on their structural and operational characteristics. The data processing methods can be categorized into three types: frequency domain, time domain, and time–frequency domain methods. The frequency domain modal parameter identification methods for in-service offshore platforms include the peak picking method, frequency domain decomposition method, and least-squares complex frequency domain method. The time domain methods suitable for modal identification of in-service offshore platforms include the random subspace method, automatic moving average model time series method, random decrement method, Ibrahim time domain method, system feature realization method, and natural excitation technique. The two main time–frequency domain methods suitable for identi-

fying modal parameters of offshore platforms are the Hilbert–Huang Transform method and the wavelet transform method (Leng et al., 2017).

Local response data are mainly strain data collected by strain gauges. Considering that the offshore platform structure is pre-stressed when the strain gauge is installed, the gauge typically monitors relative changes in strain. The response has minimal effect on the test results of structural strain. To process the strain data, signal amplification and noise filtering are commonly applied.

3.3 Challenges and future research in physical entity monitoring

In terms of data acquisition, collecting load and structural response data from offshore platforms is a systematic task. The use of sensor-collected data, which are straightforward and direct, remains the main method at present. Although the data obtained largely meets the needs of the physical monitoring system, some technical limitations still need to be addressed.

1) The data of underwater structures are difficult to obtain through direct sensor measurements. To address this, underwater test data can be supplemented through the development of sensors and underwater measurement robots specifically designed for such conditions.

2) The local response data of the structure are insufficient. AI, ML, neural networks, and other algorithms can be used to deduce the local response data of the structure in the absence of sensors through the combination of historical test data with real-time sensor data.

3) The cost of sensor placement still needs optimization. The application of virtual sensor technology, based on historical data and digital models, can significantly reduce the number of sensors required for offshore platform structures, thereby lowering costs. The integration of ML, NN, and surrogate models, or the incorporation of Bayesian models into algorithms, is a promising direction for optimizing sensor placement in terms of both quantity and location.

In terms of data transmission, current information transmission methods have enabled more comprehensive transmission of offshore platform structure monitoring data. With the development of new transmission technologies and the continuous emergence of innovative transmission methods, future offshore platform data transmission will continue to evolve toward lower power consumption, reduced latency, higher efficiency, and enhanced security.

In terms of data analysis and processing, the existing noise reduction and analysis methods have become relatively mature. However, some technical challenges still need to be addressed.

1) The “information island” problem between various types of data. Establishing relationships between different data types and integrating them into a unified database is

the key direction for addressing this technical issue.

2) Environmental noise considerably impacts the overall structural response test data. Combining deep learning techniques, such as convolutional neural networks or recurrent neural networks, for noise reduction in test signals offers better handling of complex and nonlinear signal processing. This is a promising direction for future research.

3) For the analysis and processing of local structural response data, further research is needed on how to correlate it with the overall response data and how to eliminate the influence of structural residual stress.

4) For environmental load data, minimizing the interference of uncertain factors to obtain more accurate load measurements remains a key area of research.

4 Key technology for constructing digital models

The digital twin system requires interactive mapping between the digital model and the physical entity, requiring that the digital model exhibits high fidelity and real-time updatability (Purcell et al., 2024). According to these requirements and the characteristics of offshore platform structures, the key technologies for constructing the digital model of the offshore platform structure and the correlations between them are illustrated in Figure 4. These key technologies mainly include initial digital model modeling, model updating, and reduced-order modeling (ROM) techniques.

4.1 Initial digital model modeling technology

The establishment of the initial model serves as the foundation for constructing the digital model. The primary technical approaches include two directions: one involves creating a matrix model using mathematical methods, while the other involves developing a numerical model based on finite element theory. Because the matrix-based mathematical model is limited in reflecting changes in the physical parameters of the real structure, the finite element model is predominantly used for modeling offshore platform structures.

During the service life of an offshore platform, the degradation of mechanical performance due to changes in physical parameters becomes evident. These changes in physical parameters can be more effectively captured through the finite element modeling method. Therefore, the finite element model is employed to describe the offshore platform structure. Table 3 outlines the three main types of finite element modeling techniques for offshore platforms, categorized according to the specific problems they are designed to address. There are three types of modeling methods commonly used in offshore engineering. The first involves

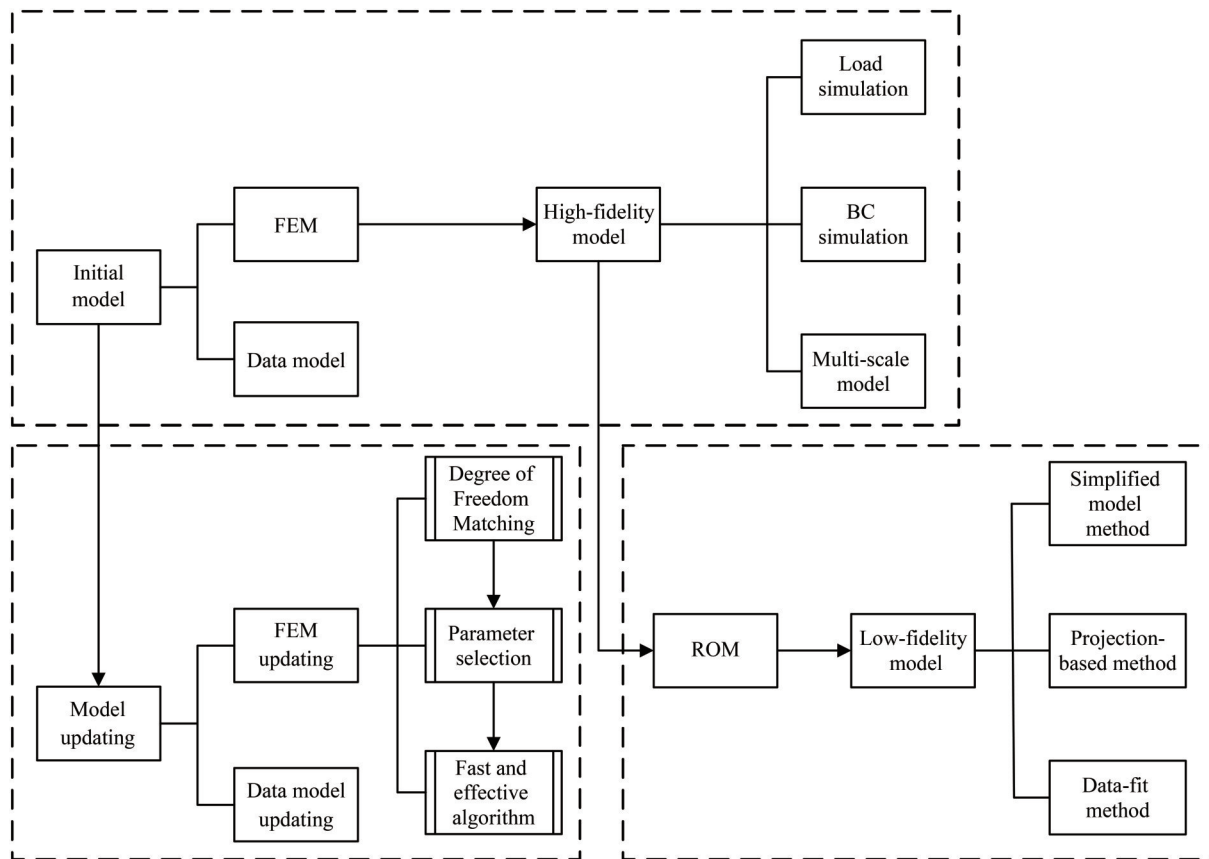


Figure 4 Key technologies for constructing digital models of Offshore Platform Structures

Table 3 Common design software for offshore platform structures

Finite element modeling methods	Applicable issues
Universal finite element software	Suitable for academic and engineering problems, used for establishing finite element models of common structures, materials, loads, and boundary conditions.
Specialized finite element software	Mainly used to solve engineering problems, marine engineering specialized software incorporates built-in calculation and evaluation standards that align with industry norms.
Self-compiled modeling	Suitable for problems that cannot be addressed by the existing elements and algorithms in general finite element software, such as describing special boundaries and constitutive relationships.

using general finite element software, such as ANSYS, ABAQUS, and NASTRAN. The second involves using specialized software designed for the offshore engineering industry, including SACS, SESAM, OrcaFlex, ENSA, and OPENFAST. The third method employs self-developed tools or programming languages, such as Fortran, MATLAB, Python, and UIDL.

The “fidelity” of the numerical model refers to its ability to accurately reflect the real physical model, and achieving high fidelity is a key goal in simulation work. Owing to the complexity of offshore platform structures; the diversity, randomness, and uncertainty of loads; and the complexity of boundary conditions, it is challenging to precisely capture the characteristics of the offshore platform. To enhance the fidelity of offshore platform structure modeling, research mainly focuses on three aspects: accurate load description,

precise representation of boundary conditions, and high-precision characterization of local model details.

4.1.1 Load simulation technology

Accurate load application, appropriate structural discretization, and rational simplified constraints are crucial for obtaining accurate finite element simulation results. The complexity of the marine environment, along with its high degree of randomness and uncertainty, makes it challenging to accurately simulate the service loading of the offshore platform structure, which can significantly affect the accuracy of subsequent finite element calculations (Arif et al., 2022; Renugadevi et al., 2021). Therefore, load simulation in the marine environment is a key component of high-fidelity modeling technology for offshore platform structures.

Wind loads on offshore platform structures are composed of both average and pulsating winds (Wang et al., 2018). In static analysis, the influence of the mean wind on the structure is mainly considered. In dynamic analysis, however, the combined effect of both the mean and fluctuating winds must be considered. When parameters such as wind speed and direction do not vary significantly, the wind can be approximated as average wind. Different standards provide various formulas for calculating the average wind (Veritas, 2000). Fluctuating wind simulation should be based on the wind speed spectrum, with the uncertainty described using statistical theory. The fluctuating wind load can then be incorporated into the finite element model through secondary development.

Wave load simulation is based on wave theory, and selecting the appropriate wave theory is crucial for accurate wave load estimation. For offshore platform structure simulation, most wave loads are ultimately applied to the finite element model in the form of wave forces and moments. In marine engineering, for small-scale structures such as marine risers, pipelines, and various piles, the influence of structural size on fluid motion can be neglected. In these cases, Morrison's formula can be used to calculate wave loads. The Morrison formula is a semi-empirical equation that considers the effects of different wave theories in the calculation of the velocity and acceleration of water points. The determination of hydrodynamic coefficients depends on experimental data (Morison et al., 1950). The calculation of wave loads based on the Morison equation is supported by both theoretical foundations and engineering experience. The terms and coefficients in the equation can be adjusted to address different engineering challenges. With high calculation accuracy over many years of engineering applications, the Morison equation remains the most commonly used method for simulating wave loads on small-scale marine structures (Ma et al., 2023).

In the design and calculation of marine structures, the current is typically treated as laminar to simplify the problem, with the influence of velocity and direction changes over time being ignored. The magnitude of the current load generally varies with depth, so a piecewise function is often used to represent the distribution of velocity and direction at different depths (He et al., 2024). For current load simulation, the velocity and direction at various depths are calculated separately and applied in segments to the offshore platform structure. Because the velocity and direction near the seabed exhibit significant changes, their impact on the structure is more pronounced than that of the current load near the sea surface. Therefore, the influence of the current load on the offshore platform structure near the surface can often be neglected (Khalifa et al., 2014).

4.1.2 Simulation technology for offshore platform structure boundary conditions

Different types of offshore platforms have distinct forms

of constraints. A common approach is to apply rigid constraints at the boundary between the pile foundation and the soil for jacket and jack-up platforms. However, this method does not effectively capture the interaction between the pile foundation and the soil, which can lead to inaccuracies in subsequent residual life calculations. A more accurate approach is the linear spring equivalent method, which is commonly used for boundary treatment (Yan et al., 2021). The constitutive relationship between soil and pile foundations is nonlinear, making the linear spring model an inaccurate representation. While a nonlinear spring can provide a more accurate description of the boundary, determining the constitutive relationship curve between soil and pile foundations requires extensive experimental data, which is difficult to obtain. Although finite element software (such as SACS) and general-purpose software (such as ABAQUS) have developed PSI elements to simulate the interaction between piles and soil, defining the nonlinear constitutive relation curve remains a challenging problem to resolve.

Another boundary condition that has been further studied is the simulation of connections between the internal components of offshore platforms. For jacket and jack-up offshore platform structures, the focus is mainly on the connection of complex joints. Various comparable techniques are used for these joints, including rigid connections, flexible connections, and substructures (Chen et al., 1990). However, these methods can introduce errors in dynamic calculations and fatigue life predictions for the structure (Dubois et al., 2013; Khan et al., 2016b). For complex joints, such as direct rigid connections between beam elements and pipe elements (Li et al., 2012; Wang et al., 2015), the high calculation efficiency of this method can lead to excessive local stiffness, resulting in overly conservative fatigue life predictions. The joint flexibility connection parameter equation based on the Buitrago method is only applicable to specific types and sizes of nodes (Morgan and Lee, 1998; Schaumann and Böker, 2008). Establishing a local high-order element model for the joint can not only accurately describe the stiffness of the connection but also capture the detailed stress distribution around the joint. This method is the most commonly used approach for simulating complex joints.

4.1.3 Multi-scale model simulation technology for offshore platform structure

In the simulation of offshore platform structures, tasks such as damage identification, residual life prediction, and crack propagation require an accurate representation of the local model during the modeling process. Offshore platforms are large and complex structures, and the scale of the local model is considerably different from that of the global model, as illustrated in Figure 5. When a detailed local model simulation is required, multi-scale modeling becomes essential. The modeling process progresses from

macroscale to micro-scale, transitioning from the global model to the local model. Specifically, the global model is simplified using low-order elements to calculate global deformation and behavior, while the local model is optimized using high-order elements to calculate stress–strain responses and crack propagation.

The multi-scale modeling method allows the selection of different dimensional units based on the scale of the research object and the type of analysis. In this method, elements of varying sizes are employed to discretize the structure. Through multi-scale modeling, the local model can be described in greater detail, and the degrees of freedom can be effectively reduced in the finite element model. This approach helps to reduce the computational effort of the finite element model while still achieving the desired calculations (Khandelwal, 2008; Ladevèze et al., 2002). According to the number of calculations and the coupling relationship between high and low scales, multi-scale modeling techniques are classified into two types: information-passing multi-scale methods (Michopoulos et al., 2005) and

information-concurrent multi-scale methods (Li et al., 2009).

The sub-model method and substructure method are the two most commonly used approaches in multi-scale information-passing modeling. Owing to their convenience and versatility, these methods have been integrated into various general finite element software. The technical approaches of these two methods are illustrated in Figures 6 and 7, respectively.

As illustrated in Figure 6, the sub-model method follows a global-to-local modeling approach, where the boundary conditions for the local model are derived from the global model. This method is suitable for analyzing local connection stresses, damage evolution, crack initiation and propagation, and local fatigue stress.

The sub-model method was used to establish the offshore platform structure and simulate local crack propagation (Zhao et al., 2019). Xu et al. (2020) developed a K-joint sub-model for an offshore platform structure and analyzed it for multiaxial fatigue, which more accurately reflects experimental life compared with uniaxial fatigue (Xu et al., 2020).

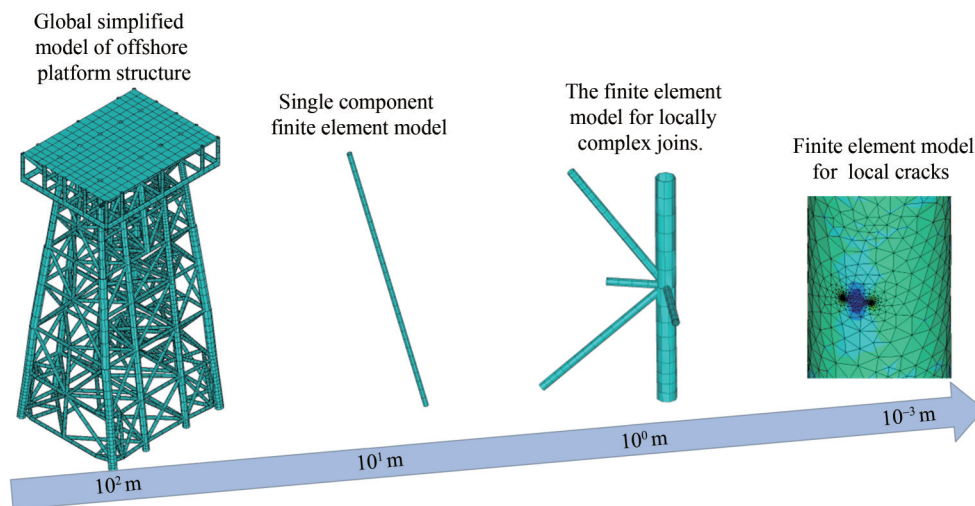


Figure 5 Schematic of multi-scale analysis modeling for offshore platform structures

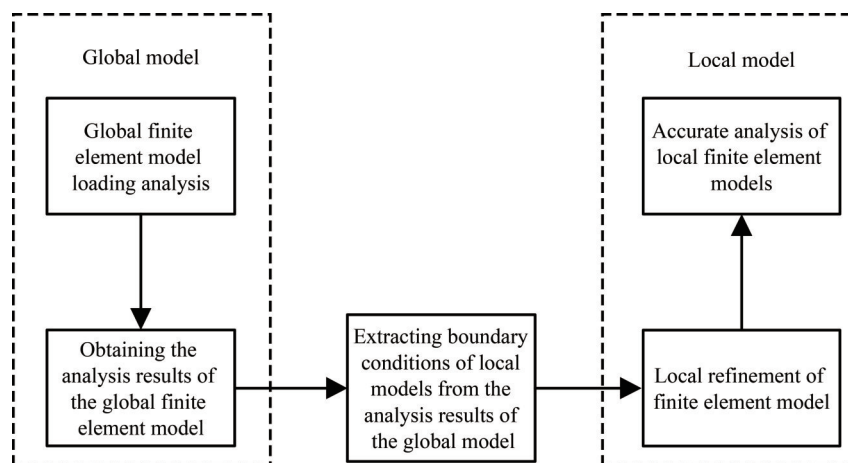


Figure 6 Flowchart of the sub-model technology

As illustrated in Figure 7, the substructure method follows a local-to-global modeling approach. The same local structure within the system is transformed into a super element, which is then inserted into the global model. This method is suitable for the simulation and calculation of large structures containing multiple local structures.

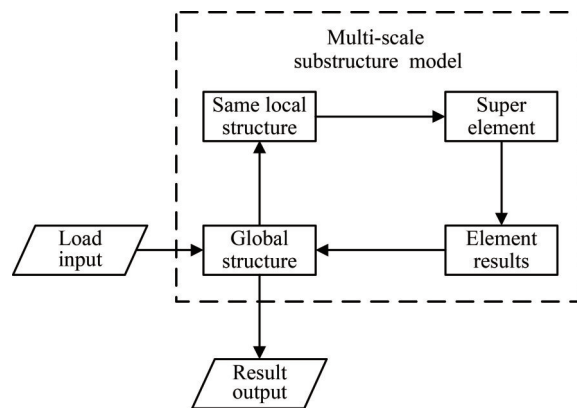


Figure 7 Flowchart of substructure method

Schaumann and Böker (2008) established a multi-scale model of the jacket structure and analyzed the influence of substructure modeling on the global dynamic characteristics and fatigue life simulation of the structure. Dubois et al. (2013) employed the substructure technique to model the complex joints of the offshore jacket structure as high-order elements, providing recommended truncated positions for different types of complex joints.

Unlike transfer multi-scale modeling, consistent multi-scale modeling has the advantage of not requiring secondary calculations, and it is widely used for modeling large equipment such as offshore platforms. However, the connection between different scale units remains a challenge that needs to be addressed in consistent multi-scale modeling.

Yu et al. (2012) extensively discussed the connection methods between different types of elements, establishing

the connection between beam and shell elements using constraint equations, and developed a uniform multi-scale model for beam–shell elements. Wang et al. (2016) created a multi-scale beam–shell element model for a jacket offshore platform structure. Wang et al. (2017) established a multi-scale beam–solid model for jacket structures and proposed a collaborative correction method for both the global and local models.

In summary, the technical approach of multi-scale modeling is well-suited for the development of finite element models of offshore platform structures. The multi-scale modeling analysis of offshore platform structures can be conducted using the analysis process outlined in Figure 8.

4.2 Model update technology

The regular updating of the finite element model for offshore platform structures ensures that the virtual entity is synchronized in real time with changes in the physical entity. Model updating technology serves as a bridge between the monitoring data from physical entities and the geometric, physical, and state parameters of digital models. According to the differences in model-building techniques, model updating technology is divided into finite element model updating technology and mathematical model updating technology. Because finite element technology is predominantly used in offshore platform structure modeling, this section focuses on the finite element model updating technology specific to offshore platform structures.

The causes of parametric errors in models are multifaceted. They include changes in the external environment, variations in manufacturing processes, simplifications of boundary and connection conditions, deviations in geometric dimensions, and inaccuracies in constitutive relationships (Jayanthan and Srinivas, 2015; Saidou Sanda et al., 2018). The purpose of finite element model updating is to reduce the discrepancy between the finite element model and the measured model by incorporating physical structure measurement data.

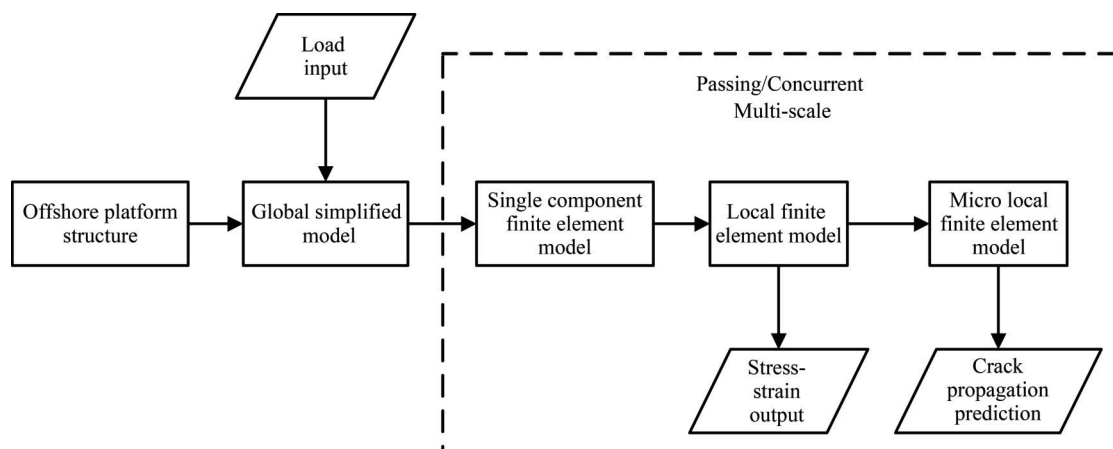


Figure 8 Simulation flowchart of the multi-scale model for offshore platform structures

The primary errors that occur during the offshore platform structure modeling process are related to model parameters, and the model corrections discussed in this section focus on addressing these errors. Owing to the structural characteristics and unique working conditions of offshore platform structures, the challenges faced in model updating research are mainly concentrated in three areas: 1) a considerably smaller number of measurable freedoms than the number of freedoms in the finite element model; 2) lack of methods for selecting appropriate updating parameters and defining their range; 3) lack of faster and more efficient algorithms.

4.2.1 Modal decomposition and expansion

Most finite element model updating methods use the measured modes as a reference for the modes of the numerical analysis model. For this approach, it is essential that the degrees of freedom in the measured modes match those of the analysis model. The finite element model of the offshore platform structure typically has considerably more degrees of freedom than the number of measured modes. Degrees of freedom that are not captured in the measured vibration modes are usually approximated using data from the analysis model. This requires that the deviation between the analysis model and the measured model is minimal; otherwise, the error may be too large, or ill-conditioned equations may arise. There are two approaches to address this issue: one is to reduce the degrees of freedom of the original analytical model, known as model reduction, and the other is to attempt to expand the degrees of freedom of the measured model, referred to as modal expansion (Friswell and Mottershead, 1995).

The model reduction method focuses on condensing the analysis model, serving as an approximation technique. Notable examples include Guyan's static condensation method (Guyan, 1965), the dynamic condensation method, O'Callahan's improved reduction system method (O'Callahan, 1989), and Kammer's exact modal condensation method (Kammer, 1987). However, owing to modal truncation errors, these methods can only ensure accuracy within the range of the highest intercepted modal frequencies (Friswell and Mottershead, 1995). In contrast, modal expansion targets the measured modes of each order. Given the presence of nonlinear damping, the measured modes are often complex. Preprocessing is employed to extract the main modes from the complex modes, after which modal expansion is performed. Modal expansion is mainly achieved through interpolation techniques. Notable methods include the iterative interpolation method (Berman and Nagy, 1983) and the optimal fitting method (Farhat and Hemez, 1993). Additionally, some modal reduction methods can also be adapted for modal expansion.

4.2.2 Selection of updating parameters

In structural finite element model updating, parameters

with real physical significance are typically chosen as updating parameters, and the changes in these parameters are used to predict the behavior of the physical structure. For offshore platform structures, updating parameters commonly include the elastic modulus, mass distribution, pipe thickness, moment of inertia, joint stiffness, density, pile foundation characteristics, and soil constraint stiffness (Ding et al., 2023; Li et al., 2011; Tygesen et al., 2018; Tygesen et al., 2019; Wang et al., 2015; Yan et al., 2021).

Among the physical parameters that can be used for updating, one or more parameters are typically selected based on the results of sensitivity analysis (Arora, 2011; Yuan et al., 2019). The number of parameters to be updated is often determined by the number of tests or the type of test data available.

Li et al. (2011) used the cross-model cross-mode method to modify the model of a jacket platform structure in the Bohai Sea, with the constraint connection between the pile foundation and soil as the updating parameter. Yan et al. (2021) used measured vibration and strain data from a jacket offshore platform structure monitoring system in the South China Sea. The stiffness of the pile foundation connection and the stiffness of key parts of the structure were selected as updating parameters, and the finite element model of the platform was updated twice.

Tygesen et al. (2018, 2019) proposed a five-level finite element model updating method for offshore platforms, with the model updating flow illustrated in Figure 9. The offshore platform structure model is updated based on local detection, finite element dynamic parameters, wave load calculation parameters, risk assessment parameters, and historical monitoring data. Decision gates are set between each level to ensure updating accuracy and prevent excessive computational effort during the updating process.

4.2.3 Fast and effective algorithm

Finite element model updating can be considered a structural optimization problem. The objective is to optimize the parameter arrangement to minimize the residual error between experimental measurements and theoretical simulation values. When the finite element model of the offshore platform structure is meshed, the number of elements and degrees of freedom increases, which also increases the number of parameters involved in the optimization, significantly raising the computational load of the model updating process. Improving the computational efficiency of finite element model updating can be achieved by reducing the number of parameters involved in the calculation, changing the calculation approach, and minimizing the number of iterations.

Reducing the number of degrees of freedom in the finite element model is the most direct approach for reducing the design parameters in the model updating process. The substructure method can achieve this by reducing the degrees of freedom in the global model, thereby lowering the com-

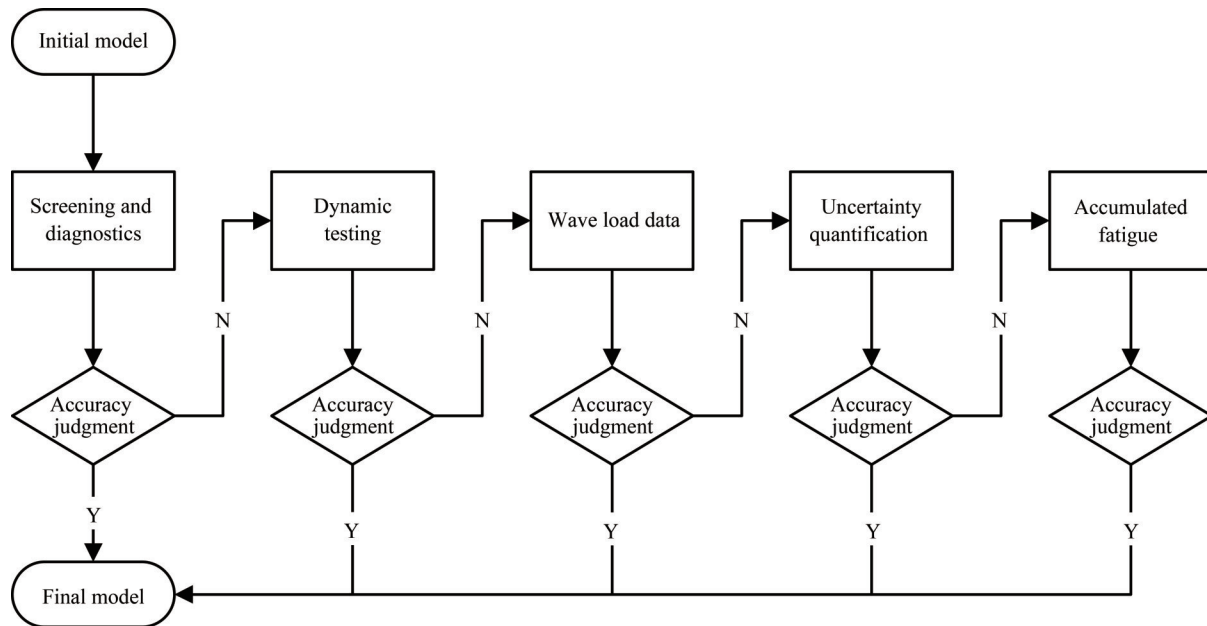


Figure 9 Five-level model updating process (Tygesen et al., 2018)

putational load of the model updating task (Weng et al., 2011; Zhu et al., 2021). Weng et al. (2011) divided the large structure into multiple substructures and performed model updating on the entire structure by modifying element parameters in one or more substructures, which significantly improved the efficiency of the model updating process. Zhu et al. (2021) proposed an improved method based on substructure response sensitivity, which accelerated the convergence speed of model updating and enhanced computational efficiency by more than 20 times compared with the global model updating method.

Choosing a suitable algorithm can significantly reduce the iterative calculation time for model updating and improve calculation accuracy. Ren and Chen (2010) replaced the conventional sensitivity analysis-based finite element model updating calculations with the response surface methodology, making the model updating process more efficient and faster to converge. Once the response surface is constructed, each optimization iteration no longer requires finite element calculations. The Kriging model was applied to update the finite element model of the jacket platform structure and a multi-objective genetic algorithm was introduced to enhance the accuracy of the Kriging model (Leng et al., 2019). Yin et al. (2019) employed the cuckoo algorithm to obtain the updating parameters and established an objective function with a minimum frequency response to optimize the traditional Kriging model, thereby improving both the accuracy and efficiency of the calculation.

4.3 Reduced-order modeling technology

The timeliness of computation is another crucial aspect in the establishment of virtual entities, and it serves as the

technical foundation for ensuring that virtual entities accurately reflect physical entities in real-time. As the “high fidelity” of a numerical model increases, the computational load often increases exponentially. An excessive focus on “high fidelity” can lead to unnecessary calculations, as non-essential information is incorporated into the model, resulting in a waste of resources (Zhang et al., 2021). Achieving lightweight computation while maintaining calculation accuracy has become a key research focus in the field.

The ROM technique simplifies key information and main influencing parameters in the high-fidelity model to considerably reduce both calculation time and the size of the computational file without compromising calculation accuracy or only with minimal loss of accuracy. There are three main types of model reduction methods: the simplified model method, the projection method, and the data fitting method (Peherstorfer et al., 2018).

4.3.1 Simplified model method

The simplified model method requires the application of specialized knowledge in the field. It involves adopting theoretical approximation assumptions based on the specific research object, making it a method grounded in physical models. Generally, the model is simplified by coarsening the mesh, converting nonlinear problems into linear problems, and reducing the complexity of detailed structures. This approach demands a high level of expertise from researchers and is less versatile for the analysis of specific problems (Peherstorfer et al., 2018).

According to the characteristics of the offshore platform structure and its operating environment, the model is typically simplified in the following aspects (Li et al., 2011; Ren et al., 2022; Yan et al., 2021):

- 1) For areas that do not require detailed focus, low-order elements can be used for modeling, and the mesh can be appropriately coarsened.
- 2) Nonlinear boundaries are simplified using linear equivalents.
- 3) Weld modeling at complex joints is simplified by replacing it with equivalent connection stiffness.
- 4) Equivalent reduction in pipe thickness due to corrosion damage.
- 5) Equivalent reduction in stiffness resulting from mechanical damage.
- 6) Equivalent pressure field of the fluid acting on the plate structure.
- 7) Current load is treated as a uniform flow for equivalence.
- 8) In certain special cases of dynamic calculations, the lumped mass method can be used to simplify the model.

4.3.2 Projection-based method

The projection method is a purely mathematical technique. Through the construction of a low-dimensional subspace that preserves the input–output mapping of the system, the control equation of the original structure is projected into this subspace to achieve ROM. It does not depend on engineering background or industry-specific knowledge, making it highly versatile. Commonly used methods include proper orthogonal decomposition, the Krylov subspace method, and the reduced basis method, among others (Peherstorfer et al., 2018).

Reduced basis finite element analysis (RB-FEA) combines the high computational efficiency of the reduced basis method with the detailed description of finite element components, making it suitable for simulating large-scale, complex engineering structures (Abdulle and Bai, 2013).

Eftang and Patera (2014) significantly reduced the number of degrees of freedom from 26 million to thousands by combining the reduced basis method with finite element analysis. As a result, computation time was reduced from one hour to just a few seconds, greatly enhancing computational efficiency. Ballani et al. (2018) applied the combination of finite elements and reduced basis methods to solve nonlinear problems, verifying their approach with several examples. This method can substantially improve computational efficiency for both nonlinear local model computations and large global model analyses.

Sharma uses RB-FEA technology to analyze the time-domain strength and fatigue life of the semi-submersible offshore platform structure. The calculation efficiency is more than 1 000 times higher than that of traditional finite element models (Sharma et al., 2018). RB-FEA is combined with fast full-load technology to construct a semi-submersible offshore platform and a digital twin FPSO, significantly improving calculation efficiency while ensuring accuracy (Knezevic et al., 2018). Several researchers, in collaboration with Shell Oil Company, integrated RB-FEA with a

physical sensing monitoring system to develop a “digital thread” that enables functions such as asset integrity management, risk assessment, and automatic operation optimization (Bhat et al., 2021; Podskarbi and Knezevic, 2020).

4.3.3 Data-fit method

The core idea of the data fitting method is to establish a complex mapping relationship between input and output parameters to replace intricate finite element calculations, thereby reducing computational workload. The advantage of this method is its ability to significantly reduce computational demands, making it particularly suitable for analyzing complex equipment or motion problems. However, a key disadvantage is that the accuracy of the calculation is highly dependent on the quantity and quality of the training samples. In practical engineering applications, many unique working conditions lack sample data, presenting challenges for the implementation of the surrogate model method.

Wang et al. (2021) and Zhang et al. (2021) combined the surrogate model method with the finite element method to analyze practical engineering problems, achieving promising results. Song et al. (2019) established a multi-fidelity model based on the radial basis function method, providing the scale factor for the response of different fidelity models in their study. Their example calculations demonstrated that the multi-fidelity model offers better accuracy and robustness compared with the single-fidelity model. Lai et al. (2021, 2022) developed a digital twin model that integrates the shape and performance of multiple devices using surrogate model technology. This model allows for the selection of various model calculations based on their relative importance, enabling intelligent optimization of computational effort.

4.4 Challenges and future research in constructing digital models

In high-fidelity modeling, multi-scale modeling has become the mainstream approach for offshore platform structure modeling, striking a balance between accuracy and computational efficiency. However, challenges remain in areas such as load simulation and displacement boundary simulation, which require further exploration.

1) For load simulation, finite element software typically uses its own marine load simulation module or a programming language to simulate complex marine environmental loads. Various methods are employed to directly apply wave loads in the form of force and moment. However, few studies have addressed the interaction between fluid and solid, and further research is needed in this area.

2) The simulation of displacement boundaries, the interaction between pile foundation and soil, and the connection at complex nodes has a relatively mature technology route. However, the accuracy of these simulations still requires substantial experimental data for validation.

In terms of model updating, the parametric finite element updating method effectively reflects the real physical changes of the measured structure and is commonly used for large structures. However, improving the accuracy and efficiency of the parametric correction method remains an area that requires further research in future updating calculations.

1) Multiple updates based on various updating parameters can effectively address the issue of low calculation accuracy in single updates, representing a key direction for improving updating accuracy.

2) Methods based on advanced computer algorithms, such as response surface, ML, NN, and total statistics, have been applied to finite element correction work, exploring future efforts to improve the efficiency of updating calculations.

3) Uncertainty in updating parameters and nonlinear issues in large structures are also important research topics for the future.

Regarding ROM, most current research focuses on simplified model and projection methods to enhance computational efficiency. Leveraging data fitting models to further improve computational efficiency represents a key direction for future development.

1) The accuracy of the surrogate model method heavily relies on the quantity and quality of training samples, making the acquisition of reliable training samples an urgent challenge to address.

2) Accurately capturing the physical characteristics of a structure using data fitting models for order reduction remains difficult. Combining the projection method with the surrogate model method offers a potential solution, enabling the generation of a reduced-order model that incorporates the physical characteristics of offshore platform structures.

5 Key technologies of predictive maintenance

The software serves as the foundation of a digital twin

system. For offshore platform structures, the primary challenge lies in leveraging software to implement predictive maintenance functionalities effectively. Predictive maintenance is a state-based approach with three principal methods for complex equipment maintenance: reliability-based statistical probability methods, model-driven methods, and data-driven methods (van Dinter et al., 2022). However, owing to the unique construction and operating conditions of offshore platforms, the reliability-based statistical probability method is not well-suited for these structures.

The primary focus of predictive maintenance for offshore platform structures is the continuous monitoring of their health status. This involves assessing how changes in the structural condition influence the overall load-bearing capacity, predicting trends in geometric and physical parameters, and proactively determining maintenance strategies. As illustrated in Figure 10, local damage often occurs during the service life of offshore platform structures. Accurately characterizing this damage and analyzing its impact on the remaining service life of the entire structure are critical aspects of predictive maintenance efforts.

5.1 Structural damage identification technology

During the operation of large structures, various types of damage are inevitable. If such damage is not detected promptly, it could lead to structural failure or collapse. Therefore, damage identification plays a crucial role in enhancing structural safety and reliability (Hou and Xia, 2021). Rytter categorized damage identification into four levels: 1) detection of structural damage, 2) localization of structural damage, 3) quantitative analysis of damage, and 4) prediction of structural damage (Doebeling et al., 1996).

In the digital twin of an offshore platform structure, maintaining real-time synchronization between the digital model and the physical model is essential (Tao et al., 2019). When the physical structure experiences damage, the form, extent, and location of the damage must be reflected in the digital model. This process creates an updated baseline model for subsequent predictions and calculations. To

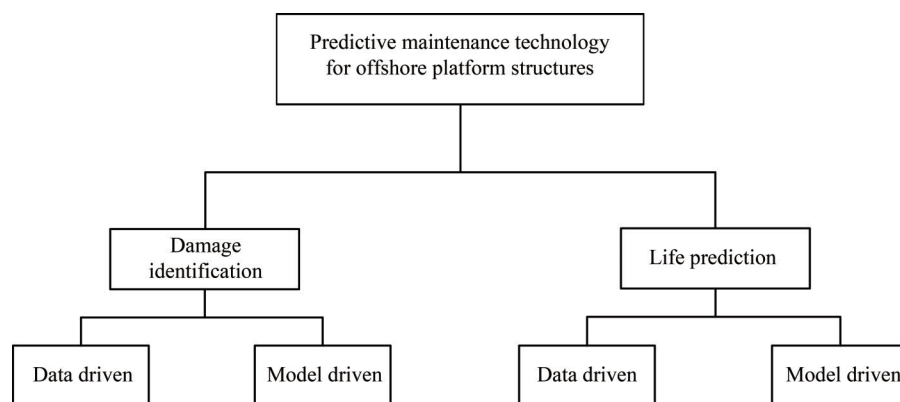


Figure 10 Technical workflow for predictive maintenance of offshore platform structures

achieve this, two primary methods are employed: 1) analyzing test data to detect changes in structural parameters and 2) calculating and updating the digital model to identify structural damage.

5.1.1 Data-driven damage identification technology

When the geometric, physical, and state parameters of an offshore platform structure change, the output from the physical monitoring system also changes. By correlating these changes in monitoring data with structural parameter variations, structural damage can be identified. This constitutes the core concept of data-driven damage identification. Monitoring data serve as the foundation for damage identification and act as a bridge between the physical monitoring system and the identification process. Compared with model-driven damage identification, the data-driven approach offers higher computational efficiency but is less effective in describing localized damage and predicting future damage.

The most commonly used method for data-driven damage identification in offshore platform structures is modal analysis. This approach involves determining the location and extent of damage by analyzing changes in structural modal parameters—such as natural frequency, vibration modes, and modal damping—and physical parameters, including mass, stiffness, and damping after the damage has occurred (Cevasco et al., 2022).

Owing to factors such as installation, environmental changes, and system time-varying conditions, the monitoring data and structural models of offshore platform structures are subject to significant uncertainties. Addressing the influence of uncertainty on damage identification is a key research focus in the field of offshore platform structural health monitoring. Techniques such as the Bayesian model (Li et al., 2017; Yin and Zhu, 2020), random finite element (Zhao et al., 2020), and statistical models have been introduced to mitigate uncertainty in damage identification. These approaches have shown promising results in identifying structural damage in offshore platforms (Xia et al., 2002; Yin et al., 2022).

Owing to the unpredictable variations in the strength and direction of marine environmental loads, the structural characteristics extracted from monitoring data over different periods may vary (Tang et al., 2015). Short-term monitoring data alone cannot fully capture the offshore platform's working conditions, and damage assessment must rely on long-term monitoring data. Given the large volume of long-term monitoring data, it is necessary to adopt data processing technologies. ML techniques, such as supervised learning (SL) and semi-supervised learning (SSL), are increasingly being applied in the damage identification of offshore platform structures.

5.1.2 Model-driven damage identification technology

Model-driven damage identification, also known as structural state assessment, plays a crucial role in evaluat-

ing the condition of a structure. The structural condition is an essential indicator for predictive maintenance, and real-time monitoring of the structure's health is a prerequisite for effective predictive maintenance.

The method of identifying damage using numerical models typically involves selecting a previous model as the reference model. The original reference model is usually considered to be intact, with physical parameters updated using test data and then fed back into the numerical model (Simoen et al., 2015). This process is carried out in two steps: the first step involves calculating the change in physical parameters through test data and a model updating algorithm. The second step updates the identified physical parameters in the numerical model to create a new benchmark model. Damage identification based on global model updating is mainly suited for damage localization and quantification, while damage prediction requires the establishment of a local model to calculate crack propagation.

The offshore platform structure is a large-scale system in long-term operation. Under the combined influence of complex environmental loads and its own loads, damage is inevitable. Research on model-based damage location and quantification for offshore platforms mainly focuses on the updating of finite element models. Compared with the structural matrix model, the finite element model more accurately reflects changes in the real physical parameters of the structure. Since damage identification based on finite element model updating is an inverse problem, it seeks to reverse-engineer the changes in the physical parameters of the structure using known structural test signals. However, the large number of nodes in the finite element model results in a substantial computational load. The use of surrogate model technology to establish the mapping relationship between the physical parameters of offshore platform structures and their structural response data has significantly reduced computational demands. In recent years, this approach has been extensively applied to damage identification research for offshore platforms.

5.2 Residual life prediction of offshore platform structures

The design life of offshore platform structures typically ranges from 20 to 30 years. However, varying operating environments can alter the remaining life over time. With proper maintenance, the service life of these structures can be extended by an additional 10 years (Aeran et al., 2017; Bhowmik, 2019).

Residual life is a critical indicator for evaluating the safety of offshore platform structures. Real-time prediction of residual life forms the foundation for implementing predictive maintenance strategies. The approaches to predicting structural residual life can be broadly categorized into two main methodologies: model-driven techniques based on finite element simulation and data-driven techniques

leveraging advanced data mining.

Indicators for evaluating the residual life of offshore platform structures include the corrosion margin derived from corrosion analysis, the reserve strength ratio and residual capacity ratio of the global structure based on strength analysis, the residual fatigue life obtained through fatigue analysis, and the probability of failure assessed using reliability analysis. Detailed calculation methods and coefficient values for these indicators are outlined in various industry standards, such as API (API RP 2A-WSD, 2014) and DNV GL (DNVGL-RP-C203, 2016).

Research has indicated that fatigue is one of the primary causes of damage to offshore platforms, with many platform failures attributed to fatigue-related issues. Consequently, the impact of fatigue on residual life has been extensively studied. Fatigue failure involves a progression from microcrack initiation to macrocrack propagation, ultimately compromising structural strength. At the macrolevel, fatigue analysis is typically conducted using two main approaches: the cumulative fatigue damage method based on SN curves and the fatigue crack propagation method based on fracture mechanics.

5.2.1 Residual life prediction using on model-driven model

Residual life prediction of offshore platform structures using model-driven approaches relies on finite element simulation technology. This method offers distinct advantages: it can effectively analyze large and complex structures compared with theoretical analysis and provides a cost-effective, time-efficient alternative to experimental research.

Shittu et al. (2021) developed a three-dimensional model of an offshore platform structure and a separate joint connection model, and the S-N curve and fracture mechanics were used to analyze fatigue life. Comparative results indicated that cumulative fatigue life analysis is more suitable for life prediction during the initial design phase, while fracture mechanics is more appropriate for evaluating structures nearing retirement. Dong et al. (2011) constructed a local welded toe model of a tubular joint in an offshore jacket platform located in the North Sea. Using the S-N curve, they analyzed the fatigue life of the structure through the local hot spot stress method, revealing that wind load significantly impacts the prediction of cumulative fatigue damage life. Similarly, Yeter et al. (2016) employed the finite element method and S-N curve to identify key hot spots experiencing the most severe fatigue damage in offshore platform structures. The prediction results of various fatigue spectra on fatigue damage were compared.

5.2.2 Data-driven residual life prediction

Data-driven life prediction relies on test data or finite element simulation data to predict the remaining life of a structure through in-depth analysis and data mining. Compared with model-driven approaches, it eliminates the need

for finite element analysis and local model calculations, significantly improving computational efficiency. However, since the process depends entirely on data, the accuracy of the prediction is heavily influenced by the quality and accuracy of the data used.

Bhowmik et al. (2019) developed a fatigue life prediction model for offshore platform structures using measured data and ML algorithms. They compared the results with finite element model calculations, achieving an error rate of 5%–10%, indicating both high accuracy and significant improvement in computational efficiency. Gulgec et al. (2020) proposed a method to predict the fatigue life of the global structure by using acceleration test data to deduce structural strain through deep learning techniques, which was validated through experiments. Leser et al. (2017) employed the surrogate model method to replace finite element calculations for the stress intensity factor and proposed a method for predicting the probability of fatigue crack propagation. Experimental results showed that this method demonstrated high accuracy. Mai et al. (2016) calculated the fracture failure probability of joints in the offshore platform structure by combining the fatigue assessment diagram with traditional simulation technology, predicting the residual life of the structure based on failure probability. Nabuco et al. (2020) used OMA and virtual sensing technology to predict fatigue stress in non-measured areas, utilizing both measured and predicted strain values as input data for the prediction model. A method for predicting the fatigue life of a jacket offshore platform structure based on test data was proposed.

5.3 Challenges and future research in predictive maintenance

In the field of damage identification research, damage detection and localization have matured, while damage quantification and prediction require further investigation due to their complexity.

1) Data-driven technology performs effectively in damage detection and localization. A key area of research is how to leverage new algorithms, such as ML, SL, and SSL (Dhiraj et al., 2021; Leng et al., 2024) to extract more effective damage information from existing data samples (Hou and Xia, 2021).

2) Model-driven damage identification is effective in damage localization and quantification. However, it involves a large computational workload, which fails to meet the computational efficiency requirements of digital twin systems.

3) Further investigation is needed to simplify the calculation model and improve computational efficiency while maintaining accuracy. Additionally, addressing the impact of uncertainties related to load and damage type, as well as conducting prediction research after damage identification, are key challenges in both technical directions. These are crucial areas of focus for damage identification in offshore

platform structures.

Residual life prediction, particularly fatigue life prediction for offshore platform structures, has become relatively mature after years of research, with the industry also establishing well-developed general engineering standards. The integration of cumulative damage prediction for the entire structure with crack propagation prediction for localized areas has become the primary technical approach. However, some aspects of these methods still have limitations and require further study.

1) Detecting local cracks in offshore platform structures is challenging. To address this, a data-fitting model can be developed to predict crack initiation and propagation.

2) The crack propagation process and the alternating loads during service involve significant uncertainty. Therefore, further research is needed to mitigate the impact of uncertainty on the accuracy of fatigue life predictions for offshore platform structures.

3) Owing to the limited strain testing areas, there are few known strain data points in the structure. Inferring the stress field of the large, unknown areas based on a small number of known strain regions to accurately predict fatigue life is an important research topic for the future.

6 Conclusions

Aiming to meet the engineering requirements for predictive maintenance of offshore platform structures, this paper proposes a digital twin system for predictive maintenance and explores the development status of key technologies. Currently, the construction of a digital twin for offshore platform structures is supported by basic technical frameworks. From a functional perspective, the core capabilities for the predictive maintenance of offshore platform structures through digital twin technology have been established. However, further optimization is necessary. Advanced functionalities, driven by practical engineering challenges, still need to be further developed and expanded. For the future application of digital twin technology in offshore platform structures, the following issues require further investigation:

1) In the physical entity monitoring system, the integration of direct measurement and historical data mining has become the main direction for the future development of offshore platform load and structural response data acquisition. Moreover, the development of virtual sensors based on historical data and digital models requires further study. In addition, data fusion from heterogeneous information sources, synchronous acquisition, and analysis of different excitation signals, as well as methods to mitigate the influence of environmental factors on monitoring data, still need to be explored in greater detail.

2) In digital model construction, accurately describing

the connection between the local and global structures requires more effective solutions. The complexity and uncertainty of the boundary conditions of the structure make precise modeling challenging and still require further research. Multi-field coupling simulation is also a key area of future research. Multi-parameter updating has become the primary focus of offshore platform structure model updating. Moreover, improving the calculation accuracy of reduced-order models and the hybrid application of multiple reduced-order models remain areas that require further investigation.

3) In the research of predictive maintenance technology for offshore platforms, combining model-driven and data-driven approaches to achieve more accurate damage quantification and prediction is an important area for future study. Further research is needed to extract more effective damage information using new algorithms such as ML, SSL, and SL. Additionally, real-time quantification of structural damage uncertainty and damage prediction, integrated with AI models, requires further exploration. The prediction of fatigue life for unknown parts derived from strain test results at known locations still needs to be investigated. The integration of data-driven and model-driven approaches for real-time residual life assessment also requires additional research support moving forward.

In addition, in the field of visualization technology research, a key focus is on how to achieve real-time updates in the application layer and build an industry-specific software framework tailored to marine engineering. These aspects are essential for completing the display of digital twin systems (Correa et al., 2023). Given the requirements for accuracy, real-time performance, consistency, and security in information transmission between modules, further research is needed in areas such as data analysis, real-time data preprocessing, multi-source data fusion, and unification, as well as encryption and decryption during the data transmission process.

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