Journal of
*Marine Science and Engineering*

*Review*

# An Overview on Structural Health Monitoring and Fault Diagnosis of Offshore Wind Turbine Support Structures

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**Abstract:** The service environment of offshore wind turbine (OWT) support structures is harsh, and it is extremely difficult to replace these structures during their operational lifespan, making their failure a catastrophic event. The structural health monitoring (SHM) of OWT support structures is a crucial aspect of operational maintenance for OWT support structures, aiming to mitigate significant financial losses. This paper systematically summarizes the current monitoring methods and technologies for OWT support structures, including towers and foundations. Through the review of monitoring content and the evolution of monitoring techniques for supporting structures, it delves deeper into the challenges faced by wind turbine monitoring and highlights potential avenues for future development. Then, the current damage identification techniques for OWT towers and foundations are analyzed, exploring various methods including model-based, vibration-based, artificial intelligence and hybrid fault diagnosis methods. The article also examines the advantages and disadvantages of each approach and outlines potential future directions for research and development in this field. Furthermore, it delves into the current damage identification techniques for OWT towers and foundations, discussing prevalent challenges and future directions in this domain. This status review can provide reference and guidance for the monitoring design of OWT support structures, and provide support for the fault diagnosis of OWT support structures.

**Keywords:** structural health monitoring; fault diagnosis; offshore wind turbine; support structures; tower; foundation

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**Citation:** Yang, Y.; Liang, F.; Zhu, Q.; Zhang, H. An Overview on Structural Health Monitoring and Fault Diagnosis of Offshore Wind Turbine Support Structures. *J. Mar. Sci. Eng.* **2024**, *12*, 377. https://doi.org/10.3390/jmse12030377

Academic Editors: João Miguel Dias, Carlos Guedes Soares, Markes E. Johnson, Rafael J. Bergillos, Naomasa Oshiro, Alvise Benetazzo and Kamal Djidjeli

Received: 10 January 2024
Revised: 5 February 2024
Accepted: 20 February 2024
Published: 22 February 2024



## 1. Introduction

Wind energy is a clean and renewable energy source with vast reserves. The offshore wind power generation industry is experiencing exponential growth. At the end of 2022, the global installed capacity of offshore wind power has reached an impressive 64.3 GW. The support structure of OWTs (tower and foundation) must withstand loads transferred from the upper nacelle and blades, along with extreme and fatiguing environmental forces. It is, therefore, imperative to conduct comprehensive health monitoring and damage diagnosis for the supporting structures of OWT. This provides vital technical support for ensuring the safe operation and maintenance of offshore wind power projects, ultimately promoting the long-term sustainability and viability of this renewable energy source.

The monitoring of OWTs encompasses several key components, including nacelles, blades, towers, and foundations. While nacelles and blades often receive the most attention [1–4], OWT supporting structures are essential but often overlooked. Given the significant economic losses caused by OWT damage, operation and maintenance account for 30% of the total life cycle cost. Reasonable OWT monitoring can save operation and maintenance expenses [5,6]. However, the monitoring of OWT support structures does not cover all OWTs, and the number of OWTs being monitored is generally about 10% of the total number of OWTs in an entire wind farm. The potential damage to these supporting structures during operation and maintenance can range from changes in modal parameters to soil strength degradation, erosion, fatigue, cracks, and corrosion [7]. The complex service environment is a primary factor in the degradation of these structures, with fatigue accounting for 80% of structural damage [8,9]. The first offshore wind farm in China began generating electricity in 2010 and has a service life of approximately 25 years. As the wind farms approach the end of their service life, it is essential to consider end-of-service options. For OWTs adopting re-operation plans (which refers to the process of repairing, modifying or upgrading wind turbines that have been stopped or abandoned, so that they can resume operation and continue to provide services to the power system) the performance evaluation of their foundations relies heavily on monitoring data. In summary, the monitoring of OWT supporting structures is crucial for ensuring safe operation and maintenance. The assessment of an OWT service status relies heavily on these monitoring results, making it paramount for wind farm operators to prioritize regular monitoring and damage diagnosis.

Structural health monitoring (SHM) techniques produce abundant data captured from in situ structures, e.g., structural responses and environmental status, offering the potential for fault detection and condition assessment [10,11]. An SHM system produces abundant data captured from the in situ structure; these recorded data are transferred to servers and stored. Then, data analysis methods are conducted to assess structural conditions or detect anomalous changes. Note that more sensors obtain more detailed structural information; however, a large number of sensors would increase the system budget and bring about data redundancy [12]. Thus, considerable efforts have been devoted to optimizing sensor layouts. In addition, methods for assessing structural condition or detecting anomalous changes are also continuously reviewed by civil engineers. Accordingly, an SHM system provides a reliable reference for structural maintenance, as shown in Figure 1, and this article mainly summarizes data acquisition and fault diagnosis in the condition assessment of structural health monitoring. Initially, it delves into the monitoring content of tower and foundation structures within the supporting structure, emphasizing the significance of employing diverse monitoring methods for specific purposes. This section can serve as a practical guide for professionals involved in OWT monitoring. Subsequently, the article examines the evolving fault diagnosis methods for current OWT supporting structures. The increasing popularity of offshore wind power and the advancement of artificial intelligence have significantly improved fault diagnosis, making it more intelligent and efficient. In conclusion, this article wraps up by discussing and projecting the current status of industry development. It offers valuable insights for the offshore wind power monitoring industry, providing technical support for offshore wind farm operation and maintenance.

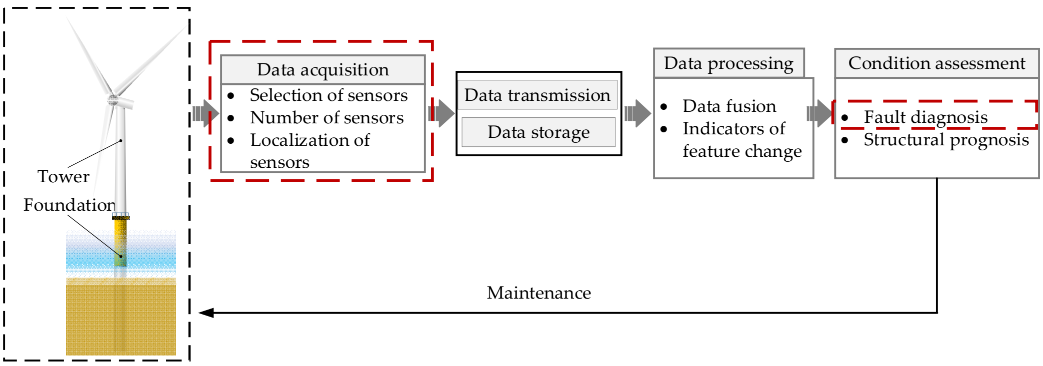


**Figure 1.** Diagram of SHM of OWT support structures.

## 2. Strategies and Challenges in SHM of OWT Support Structures

The service environment of the offshore wind turbine (OWT) support structures is harsh, as they must withstand inertial forces transmitted from the nacelle and blades, wind loads, waves, currents, and soil–structural interactions, as well as potential seismic events. SHM can detect the service status of the OWT supporting structures, enabling intervention to avoid the failure of the OWT supporting structure affecting the operation of the wind farm. The SHM techniques of OWT includes acoustic inspection, thermal imaging inspection, visual inspection, strain monitoring, and fatigue and modal characteristics inspection [6]. The OWT with monopile foundation fault types are shown as an example in Figure 2 [13]. The left side of Figure 2 illustrates the loads that may be encountered throughout the service life of OWTs, while the right side depicts the various types of potential damages to the support structure, which may include changes in modal parameters, soil strength degradation, scouring, and more. For an OWT in service, the monitoring fatigue types and technique of the tower and foundations will be illustrated in the following part.

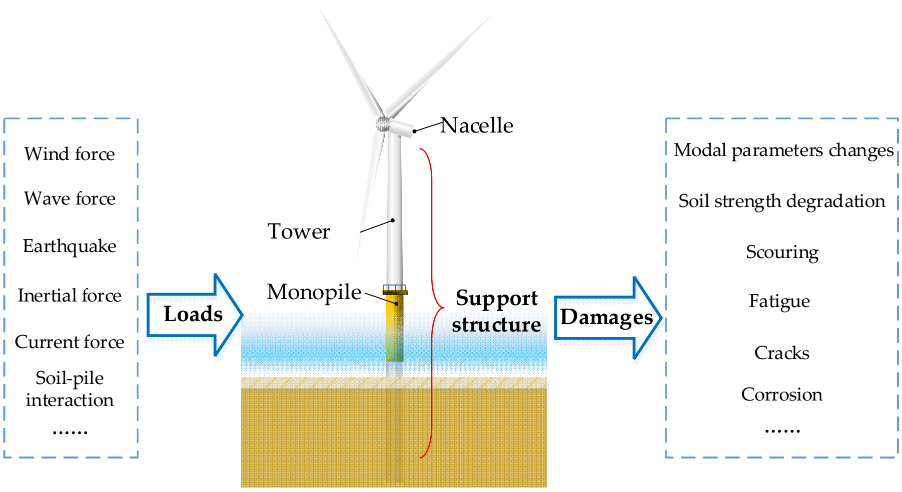


**Figure 2.** Fault types of OWT with monopile foundation.

### *2.1. SHM Strategies of OWT Towers*

The tower of OWTs serves as the connection between the nacelle and the foundation. As the length of the OWT blades increase, the tower height also escalates. However, in complex operation environments, there have been instances of tower collapse, leading to significant economic losses [14,15]. Consequently, it is imperative to implement SHM of OWT towers to assess their service condition and minimize the occurrence of OWT accidents. The monitoring system of tower is supposed to include the following parts:

1. Vibration

Generally, damage (e.g., crack, bolt loosening, and corrosion) decrease structural stiffness. Accordingly, the loss of stiffness leads to the change in structural dynamic characteristics (e.g., frequency, damping ratio and mode shapes) [16]. Thus, operational modal analysis (OMA) has been employed for damage detection and condition assessment. Herein, modal parameters are compared between the intact and damaged conditions [17,18]. In particular, natural frequency always decreases with damaged conditions. To assess the operational status of the tower, accelerometers are equipped to capture vibration data, which are utilized to identify the modal parameters. Zhou et al. positioned five wireless accelerometers at varying heights on the tower [19]. By examining vibration signals under different excitations, they conducted modal analysis on an OWT with a monopile foundation. The research results indicate that modal parameters derived from controlled ship impacts are more accurate compared to those obtained from data collected under environmental loads.

2. Cracks

During the service period of OWTs, the tower is subjected to repeated cyclic loads; studies have found that 80 percent of structural damages are caused by fatigue [8,9]. Monitoring crack depth and length at critical locations such as the tower and weld joints is crucial for evaluating tower integrity. Gansel et al. evaluated the performance of DY butt welds under tensile loads using five eddy current differential sensors [20]. The data obtained from crack monitoring can serve as a predictive indicator for OWT service life. Strain sensors are utilized in critical parts to detect cracks [21]. Cicero et al. (2009) delved into how welding defects in the tower influence its fitness throughout its service life, revealing that once the tower exceeds the maximum acceptable lack of penetration defects, it necessitates repair to uphold its structural integrity [22]. Capaldo et al. (2020) examined how cracks impact the capacity of a tower to withstand buckling, analyzing the effects of factors like crack location and length on its strength. Their findings revealed that cracks in the compression zone of the tower have a more significant impact compared to those in the tension zone. When the crack reaches a size of 30–40 cm, the critical load is reduced by approximately 8% [23]. Additionally, visual inspection [24], either manual or assisted by AI, is a widely used method for crack detection. Traditional methods rely heavily on inspector expertise, while AI-assisted approaches leverage computer vision technologies such as digital cameras to enhance crack identification accuracy. However, it should be noted that visual inspection is limited to surface crack detection.

3. Tower bending moment

The measurement of tower bending moment is typically achieved through strain gauges, often located on the inner wall of the tower. However, it is noteworthy that only a subset of OWTs is equipped with strain gauges for monitoring tower bending moments. Santos et al. (2022) adopted acceleration data, supervisory control and data acquisition (SCADA) to estimate the tower fore–aft bending moment damage equivalent loads, utilizing artificial neural networks [25]. Jay et al. (2016) compared the yield strength of traditionally welded tower sections with those spirally welded and found that the former had a lower yield strength, confirming that the method of connection between different tower sections significantly affects the bending capacity of towers [26]. Additionally, as thin steel cylindrical shells, the bending properties of towers are greatly influenced by strain-hardening models, which have a significant impact on curvature and bending capacity [27]. Fajuyitan et al. (2018) conducted research on the imperfection sensitivity of cylindrical shells under uniform bending, examining the effects of cylinder length, end support conditions, forms, and amplitudes of geometric imperfections. They also utilized a novel automation strategy for analysis, but the research was primarily numerical simulation and further analysis with field measurements is required [28]. The bending capacity and buckling behavior of towers are closely related to their diameter–thickness ratios. OWTs towers typically have a diameter–thickness ratio exceeding 150, and as this ratio increases, local buckling can affect the bending properties of tubular cross-sections [29]. The continuous monitoring of bending capacity can help detect potential safety hazards in towers and take measures to ensure the long-term stable operation of OWTs.

4. Tower flange connection bolts inspection

OWTs are constantly exposed to cyclic loads, and if a bolt or flange bolt loosens and falls off, it can have a significant impact on the stress of other bolts [30]. It is difficult to manually identify bolt loosening, and it is one of the main reasons for structural collapse [31,32]. Liang et al. (2015) proposed an intelligent bolted joint failure monitoring approach to achieve the real-time monitoring of bolt loosening. This method utilizes monitoring data and combines the developed decision fusion system with Lamb wave propagation. However, more complex bolt structures are needed to verify the reliability of this method [33]. Ji et al. (2023) analyzed the impact of initial flatness divergence, indicating that tower-sided gapping and flange-sided gapping conditions result in more severe fatigue damage to bolts compared to parallel gapping [34]. Cheng et al. (2023) studied C1 wedge connections in towers and found that the contact surface friction coefficient and bolt pretension level significantly affect the local deformation capacity and stress range of the connection [35]. Li et al. (2023) proposed a damage monitoring method capable of identifying the loosening location of flange bolts. This method is primarily based on dynamic strain responses, but the work conditions studied had a limited number of bolts, and further research is needed to evaluate its applicability to OWTs with hundreds of bolts [36]. Other studies have examined the impact of flange bolt loosening on turbine responses, showing that bolt loosening has little effect on the first-order frequency, damping ratio, and mode shape of the turbine. However, it has a significant impact on the absolute value of the phase difference between the upper and lower plates. When the bolt loosening rate is 6%, there is a noticeable increase in numerical values [37]. Due to the large number of flange connection bolts in tower sections, some studies have begun to use artificial intelligence methods [38,39] to solve the problem of bolt stress distribution prediction. Nguyen et al. (2016) proposed an image processing technique for identifying bolt loosening. The main principle is to identify the rotation angle of the nut from images. This method was primarily validated in indoor tests and lacks practical engineering applications and verification [40]. Dai et al. (2023) used machine learning to predict the stress distribution of Circular Hollow Section Tube of flexible high-neck flange joints [41].

5. Tower weld seam monitoring

Due to the limitations of the manufacturing process, traditional OWT towers usually contain circumferential welds perpendicular to the tower height and longitudinal welds parallel to the tower height. The quality of tower welds has an important impact on the overall strength and service life of the tower [42]. The commonly used three weld monitoring methods include ultrasonic phased array detection, TOFD detection and the magnetic memory method. Each of the three methods has its advantages and disadvantages. Ultrasonic phased array detection is more suitable for structures that are difficult to access, has limitations in repeatability accuracy, and finds is difficult to calculate the defects quantitatively; TOFD detection can achieve the quantified calculation of flaws, and has blind spots in surface detection; the magnetic memory method is cost-effective, yet the signal it generates is relatively feeble and susceptible to various influencing factors [43]. Farhan et al. (2022) studied the optimal monitoring time and repair strategy for OWT weld from the early stage of its service life. It was found that the inspection should be carried out around the midpoint of the service life of the welding joint, and the fatigue crack should be repaired at the same time [44]. With the continuous development of technology, the monitoring and detection methods for tower weld seams are also continuously improving and being perfected. Monitoring tower weld seams can enable the timely discovery of problems such as fatigue, damage, or aging, and avoid tower safety accidents.

6. Bolt inspection of tower and foundation connection

The bolts connecting the tower and foundation, during their service, are constantly subjected to cyclic loads transmitted from the upper tower, which makes them prone to fatigue failure. Weijtjens et al. (2021) used the monitoring data of bolts in the monopile to the transition piece bolted flange connection and strain gauges of wind turbines to study the load transfer behavior and predict the fatigue life of the bolts. By comparing the field monitoring data with finite element analysis results, they found that the load transfer coefficients obtained from field monitoring data were larger than those from finite element simulations. Therefore, when using finite element simulations, consideration should be given to the flange tilt [45]. The piezoelectric impedance method can be used to monitor flange bolt looseness. This method utilizes the piezoelectric effect and is sensitive to structural parameters, but it is also easily affected by environmental factors [46,47]. In addition, due to the harsh service environment, the bolts connecting the tower and foundation also need to be monitored for bolt corrosion and stress. Damaged or ineffective bolts should be replaced in a timely manner to detect and address potential safety hazards.

### *2.2. SHM Strategies of OWT Foundations*

Since the first offshore wind farm project, the Vindeby project in Denmark in 1991, the offshore wind power industry has developed rapidly, and OWTs have also developed towards large-scale and deep-sea areas. The types of OWT foundations include monopile, gravity-based, jacket, tripod, tripole, spar type, tension-legged and semi-submersible foundations [8]. The service life of OWTs is generally 20–25 years. To ensure the safety of OWT foundations during the service period, health monitoring is required. The current types and methods of monitoring are listed below.

1. Vibration

Abnormal vibration of the foundation poses a significant threat to the operation of the OWT, and vibration of the foundation should be monitored [48]. Currently, a monopile foundation generally has equipped accelerometers at the top of the monopile to monitor the vibration of the foundation during service period. It is well known that OWTs have strict frequency requirements for the foundation, and to avoid resonance, the natural frequency of the foundation, one and three times of the blade rotation frequency, must be avoided. The accelerometers deployed on the OWT foundation can obtain the vibration condition of the foundation and provide monitoring data for the analysis of the frequency of the foundation. In addition, for the floating OWT foundation, the monitoring of the OWT vibration is also particularly important [49,50].

2. Displacement

For a fixed-base foundation, the displacement monitoring includes settlement and inclination. Under environmental loads, self-weight loads, and long-term vibration during the service life of an OWT, the foundation soil consolidates the settlement and inclination is of great importance to ensure the safety of OWTs. In addition, for floating OWTs, the rotation of foundation must be monitored during service life [50].

3. Axial forces and bending moments

For monopile foundations, the axial forces and bending moment of the monopile is monitored by strain gauges placed at the bottom of the tower and at the top of the monopile [51,52]. The weighted average recorded at the same height represents the axial strain; the strain difference of opposite sides at the same height produces the bending moments. For composite bucket foundations, in addition to monitoring the bending moment at the top of the foundation, reinforcement gauges and concrete strain gauges are used to monitor different parts of the foundation, including the transition section, main beams, and secondary beams [53]. For jacket foundations, strain gauges are used to measure different jacket members [54,55]. The marine environment has high requirements for strain gauges, necessitating excellent resistance to corrosion, water, and shock, ensuring long-term stable operation [56]. Furthermore, due to the confidentiality requirements surrounding OWT data, there have been limited published studies on on-site axial and bending moment monitoring. Nevertheless, as monitoring technology continues to advance, there will be a gradual increase in relevant research aimed at ensuring the safety of wind turbine foundations.

4. Corrosion and cracks

Due to harsh conditions, such as high salt and high humidity in the marine environment, OWT foundations are prone to corrosion, which is one of the main reasons for foundation damage. Recently, many corrosion detection techniques have been applied to OWT foundation monitoring, such as corrosion coupons, electrochemical sensors, magnetic sensors, acoustic sensors, thermal cameras, radio frequency identification sensors, radiography, and visual inspection [57]. The monitoring of cracks in the foundation is equally important to that of crack monitoring in the tower. However, offshore wind turbine foundations are located underwater for long periods of time, and welding joints are the weakest part of the foundation. Under the action of long-term cyclic loads, it is necessary to monitor the fatigue behavior of the weld seams. The weld seam location is prone to stress concentration, which can cause local cracks [58]. Kolios et al. (2019) proposed a method for calculating the stress concentration factors of weld seams by combining 3D laser scanning technology with finite element analysis cameras and critical points where fatigue cracks may occur [59]. Additionally, utilizing corrosion and crack monitoring results is very important for OWT operation and maintenance as well as predicting the remaining service life.

5. Scouring

Scouring can be measured by single-wave velocity and multi-wave velocity instruments to detect changes in the terrain near the foundation at different locations, obtaining information about foundation erosion. However, the underwater terrain measurement method has high costs, is highly influenced by sea conditions, and cannot provide real-time erosion information. Recently, wind farms have begun to adopt a local scouring real-time monitoring technology based on sonar image processing technology, which can achieve the continuous, unattended, real-time monitoring of underwater terrain data around the foundation.

In addition, scouring decreases the buried depth of the OWT foundation; accordingly, structural dynamic properties change due to the scouring. Thus, structural dynamic characteristics (e.g., frequency, the damping ratio, and mode shapes) are employed as an indicator of the scouring [60–62]. Weijtjens et al. (2017) analyzed the modal parameters of OWTs and found that the resonance frequency of the second-order mode is most closely related to OWT scouring [62]. It can be used to quickly assess scouring conditions. Wang et al. (2023) used finite element models to analyze the characteristics of vibration frequencies at different scouring depths and proposed a scouring depth warning method based on changes in natural frequencies [63]. It is recommended to issue warnings when the decrease in operational frequency reaches 0.01 Hz.

6. Grouted connections

For OWTs, there is a layer of grout in the overlapping part of the tower and the OWT foundation connection. The grout quality must be checked to avoid the risk of slippage in the transition section, which can be monitored by electromechanical impedance spectroscopy [64]. Brett et al. (2018) adopted a swept frequency ultrasonic technique, which can map the resonances characteristic of the structure and its various fault conditions [65].

7. Marine growth

Marine growth can produce hydrodynamic effects [66] and affect the modal characteristics of OWTs. Jahjouh conducted research on the impact of marine growth on OWT modal parameters to distinguish the differences between modal parameters caused by marine growth and structural damage, providing a reference for analyzing abnormal modal parameters of OWTs [67].

### *2.3. Challenges in SHM of OWT Support Structures*

The offshore wind power industry continues to thrive and expand into deeper and further seas, foreshadowing a promising future for the operation and maintenance market of offshore wind farms. The above review part delved into the current monitoring items associated with SHM strategies for OWT support structures. Upon analyzing current SHM strategies for foundations and towers, the following challenges have been identified:

1. The challenging offshore environment leads to a significant probability of sensor failures within the monitoring system, resulting in data loss and posing formidable challenges for subsequent data analysis and processing. It is imperative to enhance the reliability of the monitoring system and design a resilient monitoring system.
2. Monitoring typically involves the assessment of parameters such as acceleration, strain, and displacement, leading to the generation of highly diverse monitoring data. This poses a significant challenge for data analysis and makes it arduous to assess the service status of OWTs using multi-source heterogeneous monitoring data.
3. The health monitoring of OWT support structures can slash operation and maintenance costs while reducing the number of days required for troubleshooting and repairs.
4. The number of OWT support structures being monitored in wind farms is restricted, and the monitoring process may not be continuous. The monitoring cycles of various projects vary distinctly, ranging from testing intervals of 1 to 5 years. Long-term real-time monitoring needs to be paid more attention for future progress.

5. The offshore real-time data transmission network limits the intelligent development of the monitoring system. Currently, there is limited real-time and intelligent capability, with only a few wind farms achieving the automated real-time monitoring of OWT support structures.
6. Given the current primitive state of intelligence in this field, the data processing for wind farm health monitoring and maintenance necessitates a high degree of professionalism from personnel. Currently, there is a scarcity of specialized teams capable of meeting these demands.

## 3. Fault Diagnosis of OWT Support Structures

Health monitoring data hold valuable insights into environmental effects, structural response, and performance evolution. It is crucial to diagnose the service status of OWT support structures based on these data. Given the current research landscape, fault diagnosis can be broadly categorized into four distinct methods: model-based fault diagnosis, vibration-based methods, artificial intelligence methods, and hybrid fault diagnosis methods. A comprehensive overview of the research status of these four fault diagnosis methods is provided below.

### *3.1. Model-Based Fault Diagnosis*

The monitoring of OWT support structures typically only covers about 10% of the total number of OWTs in a wind farm. How can fault diagnosis be effectively conducted for the unmonitored OWTs? Furthermore, with the installation of OWT health monitoring systems, how can fault alarm thresholds be accurately set? Addressing these challenges may require the integration of numerical simulation. The service status of unmonitored OWTs can be generated utilizing validated OWT numerical models, introducing real external loads, analyzing the OWTs response through numerical simulation, and performing fault diagnosis. For the second scenario, models are employed to analyze the OWT potential responses under various damage conditions, enabling the extraction of pertinent response parameters such as changes in modal parameters under varying erosion depths and acceleration responses under potential earthquake loads. The flowchart for model-based fault diagnosis is outlined below in Figure 3 [68]. By using the OWT design parameters to establish numerical model and inputting environmental loads, static and dynamic analyses of the wind turbine can be conducted to obtain the response of the OWT support structure. Based on the response results, the service status of the wind turbine can be evaluated. Tewolde et al. (2017) utilized a validated finite element model, incorporating monitoring data, to analyze parameter indicators under different damage conditions of the OWT, thus aiding in determining health detection thresholds [69]. Li et al. (2020) utilized finite element analysis to analyze the static and dynamic responses of a tower, providing valuable engineering recommendations for monitoring [70]. It is noteworthy that during service, the stiffness of the OWT foundations may vary due to structural damage or soil strength degradation. McAdam et al. (2023) proposed a method to estimate foundation stiffness based on field monitoring modal characteristics [71].

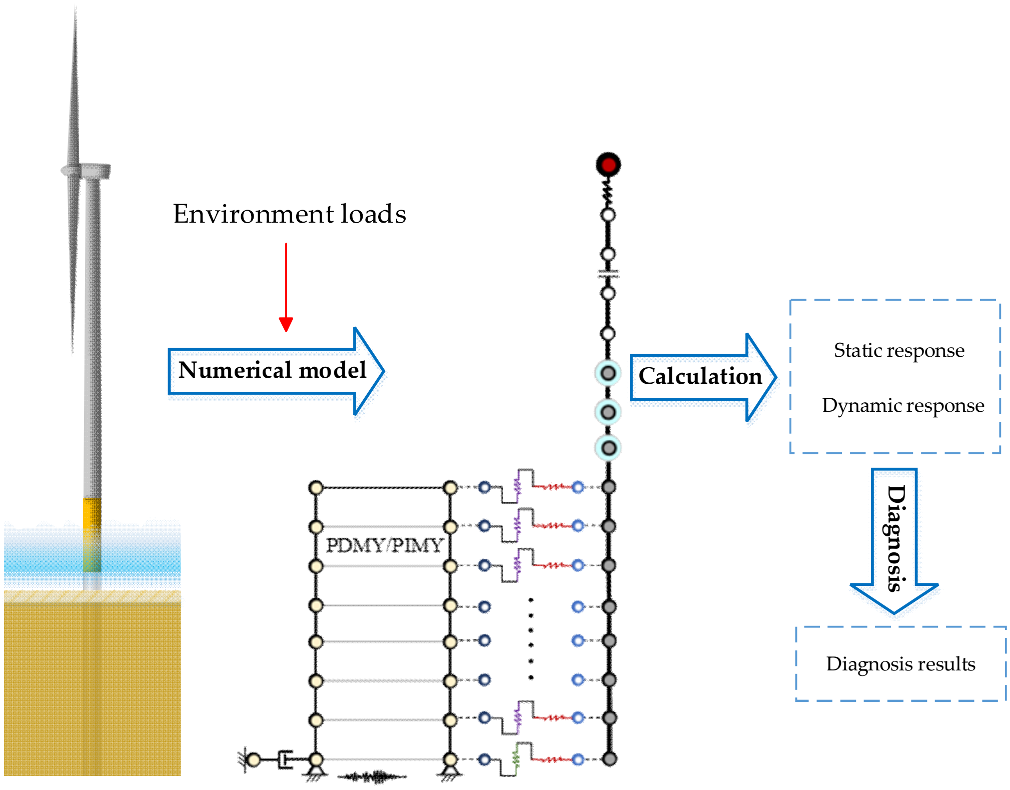


**Figure 3.** The flowchart of model-based fault diagnosis (the data were from [72,73]).

### 3.2. Vibration-Based Fault Diagnosis Methods

The vibration-based fault diagnosis method was adopted in the civil engineering sector in the 1980s [74]. The fault diagnosis may be called signal-based fault diagnosis by some researchers, as it includes electrical signals, vibration, sound signals. However, in the OWT monitoring area, the most commonly used signals are the vibration data. Figure 4 illustrates how vibration data can be utilized for fault diagnosis. Initially, the acceleration data captured by the accelerometers on site undergo preprocessing. Subsequently, modal parameters are identified using a Stochastic Subspace Identification method or other reliable methods. By utilizing the frequency obtained from modal identification, a comparison is made with the OWT required frequency for conducting fault diagnosis. Valencia and Fassois (2017) carried out analysis of an OWT model and collected the vibration data from the tower top and blades [75]. The results showed that the vibration–based damage diagnosis method for structures appears to be appealing and promising. However, the vibration sensors located mainly at the tower top and blades [76] could not generate the modal parameters of the OWT system and the review in this paper mainly focused on the fault diagnosis based on the vibration data collected from different heights of the tower. The on-site vibration monitoring data of OWTs are typically not publicly accessible, and there is a scarcity of publicly available databases. Dong et al. (2018) utilized OWT vibration monitoring data to analyze the structural vibration response characteristics of OWTs, providing technical support for OWT fault diagnosis [77]. Weijtjens et al. (2017) employed OWT acceleration data to investigate the modal parameter characteristics of OWTs and employed resonance frequency to monitor scour damage of OWTs [62]. Jeong et al. (2020) presented a multisensory data fusion-based damage detection method utilizing wireless smart sensors for OWT support structures [78]. They validated the proposed method using numerical simulation and indoor experiments. Currently, there is a lack of support from actual OWT monitoring data.

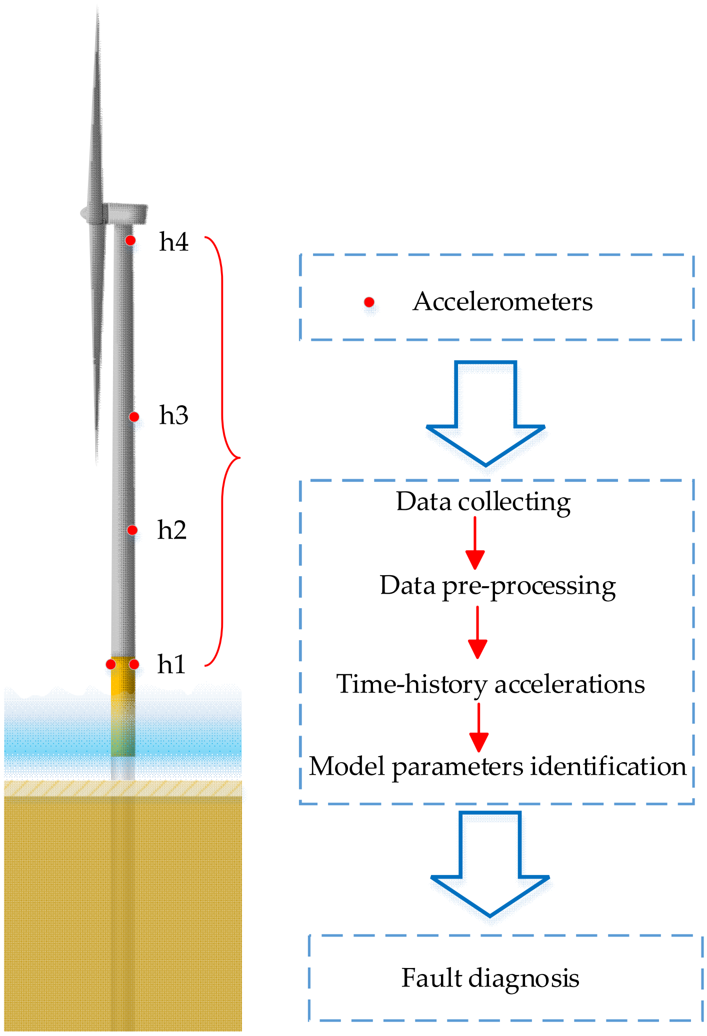


**Figure 4.** Schematic diagram of vibration-based fault diagnosis methods.

### *3.3. Artificial Intelligence Methods*

With the development of artificial intelligence, more and more researchers are exploring the use of machine learning methods to solve the problem of fault diagnosis for OWTs [79–81]. Relying on intelligent robots for data collection and intelligent algorithms for damage identification, the accuracy rate can reach up to 90% [13]. Santos et al. (2022) utilized a large amount of monitoring data from OWTs to train a two-tier neural network model to obtain damage equivalent loads for tower fore–aft (FA) bending moments [25]. Puruncajas et al. (2020) proposed a method based on acceleration and deep convolutional neural networks using acceleration data collected from indoor scaled model tests [54]. This method can achieve the intelligent identification of different damage conditions with an accuracy rate of up to 99%, and it is expected to be used for damage identification of future jacket support structures for OWTs. Guo et al. proposed an unsupervised statistical estimation method to detect structural damage, but this method only considers two static parameters: inclination and displacement [82]. Feijóo et al. (2021) utilized monitoring data from healthy OWTs to train a neural network model for fault diagnosis [55]. Some scholars have also used machine learning methods to evaluate the service performance of OWT foundations, including cracks and corrosion, in order to achieve life-extension classification [83]. Additionally, digital twin technology is currently a popular area for scholars and wind power practitioners [6]. The digital twin intelligent operation and maintenance diagram for OWTs is shown below in Figure 5. The digital twin technology utilized by OWTs creates a virtual model based on the physical model, mirroring its actual behavior.

This process begins by establishing a numerical model using design data. Subsequently, the response characteristics of the OWTs are analyzed through monitoring data, enabling the extraction of modal parameters. To ensure the accuracy of the virtual model, the frequency calculation results from the numerical model are compared with those obtained from analysis results using monitoring data and then update the numerical model. Ultimately, a robust virtual model that faithfully reflects the actual behavior of the OWT is established. This virtual model serves as a powerful tool for numerical simulation analysis, fault diagnosis, and structural prognosis, and it also offers valuable insights for wind turbine operation and maintenance. Furthermore, throughout the operational lifecycle of OWT, both the physical and virtual models can be updated in real time, enhancing the overall safety of the operation and maintenance system. With the development of artificial intelligence, enhanced digital twin technology is also emerging [83].

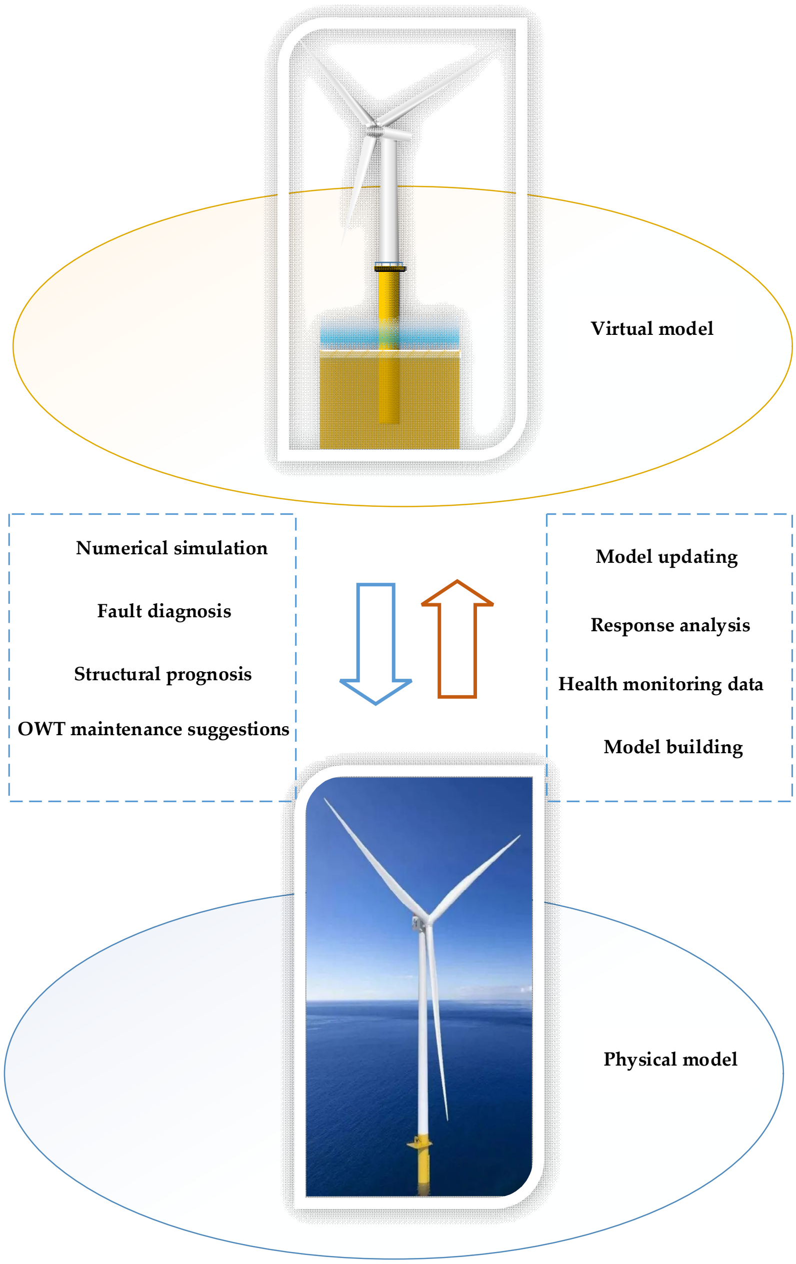


**Figure 5.** Digital twin intelligent operation and maintenance diagram for OWTs.

### *3.4. Hybrid Fault Diagnosis Methods*

With the current development and technological advancements in offshore wind power, an increasing number of methods are being used for OWT fault diagnosis [84]. As shown in Figure 6, the combination of monitoring data and numerical simulation was carried out to update the finite element model of OWTs, allowing for further analysis of their dynamic response and damage conditions [85,86]. During the simulation process, an integrated bounding surface model can be employed for the soil model under dynamic loads [87], while a simplified numerical model, such as the lumped parameter model [88], can be utilized for OWTs. Iliopoulos et al. (2016) utilized limited monitoring displacement and acceleration data in combination with finite element software to estimate the response at the unmonitored location [89].

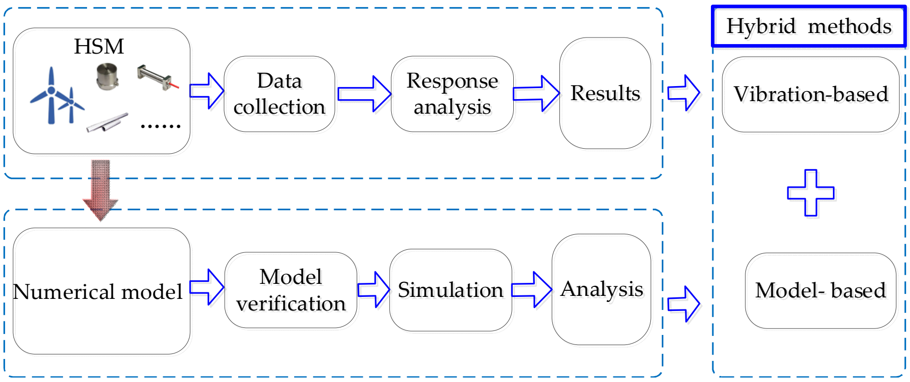


**Figure 6.** Combination of monitoring data and numerical model.

## 4. Discussion

The fault diagnosis methods of the OWT support structures were compared, as shown in Table 1.

**Table 1.** Advantages and disadvantages of various methods for fault diagnosis.

| Methods | Advantages | Disadvantages |
|---|---|---|
| Model-based fault diagnosis | Able to analyze the service status of unmonitored OWT support structures using numerical simulation; The SHM system has a limited number of measurement points and using validated models, information such as acceleration, displacement, and bending moment can be obtained for unmeasured points. | There is a high demand for numerical analysis skills for workers; Modeling takes a long time, as each OWT has a different structure, foundation, and ground environment, requiring separate modeling for analysis; Real-time OWT support structure service status cannot be obtained, requiring a long time for analysis and diagnosis. |
| Vibration-based fault diagnosis methods | It is able to quickly diagnose the service status of OWT support structures using monitoring data; Vibration data can be used to reflect the erosion status of OWT support structures; The vibration characteristics of OWT support structures can be obtained through ship collisions, allowing for multiple monitoring during service. | Only a small number of OWT support structures in wind farms have installed health monitoring systems, limiting health diagnosis to only monitored OWT support structures; The harsh service environment of sensors leads to a high probability of sensor failure and data loss; The modal parameters of OWT support structures are difficult to accurately identify due to environmental loads and rotor rotation. |
| Artificial intelligence methods | It can achieve multi-source and heterogeneous data fusion to determine the service status of OWT; There is significant room for future development, with the potential for real-time intelligent monitoring. | The large volume of data results in time-consuming calculations for machine learning models; A significant amount of data are required for support, yet currently, most offshore wind farm support structure monitoring data remain undisclosed. |
| Hybrid fault diagnosis methods | Combining the advantages of data-driven and physics-based models to compensate for their respective disadvantages; There is significant room for future development. | It is challenging to achieve real-time diagnosis; Professional personnel are required to diagnose faults by combining monitoring data with numerical simulation results. |

Based on the above analysis, the following are some comments on future development:

1. While the monitoring of OWT farms may be not conducted in real time, it serves as an assessment of the operational and maintenance status of OWT support structures using monitoring data. However, there is a lack of research on long-term vibration monitoring to evaluate OWT support structures safety, indicating significant potential for future development in this area.
2. The current level of real-time diagnosis and alarming is relatively low. Current monitoring or fault diagnosis only assesses the current OWT support structures status and lacks the ability to predict potential future failures. Predicting failures based on current monitoring data is crucial and there is ample room for future advancements.
3. It is also crucial to combine diagnosis results to develop reasonable overhaul or operation and maintenance strategies. This can significantly reduce operation and maintenance expenses and time for offshore wind farms.
4. The current level of real-time monitoring is limited. It requires a significant amount of time to diagnose OWT support structures using monitoring data, numerical simulations, or artificial intelligence. This results in a delay in fault diagnosis and an inability to promptly address the service status.
5. Current research mainly focuses on monitoring damage through frequency changes, but there is still a lack of research on how to quantify the relationship between frequency and damage, such as cracks. In addition, further research is needed on foundation stiffness during storms and the distinction between temporary and permanent changes, in order to obtain data on permanent stiffness changes, which is crucial for evaluating the status of OWT support structures.
6. OWT support structure monitoring data provide important data support for its remaining lifespan and strategic choices after decommissioning it. Therefore, it is essential to conduct in-depth exploration of the characteristics of OWT support structures, utilizing the monitoring data.
7. In the future, artificial intelligence technology holds great potential for OWT support structures monitoring and fault diagnosis, particularly in the development of remote intelligent monitoring and fault warning platforms. These platforms can assist wind power operation and maintenance personnel in quickly assessing the operational status of wind turbines, issuing advance warnings for OWT support structure malfunctions, and ultimately preventing significant economic losses.

## 5. Conclusions

In this paper, an overview of SHM and fault diagnosis for OWT support structures was presented. SHM and fault diagnosis for OWT support structures are crucial to reducing maintenance costs in offshore wind farms. The monitoring strategies for tower and foundation structures can provide valuable insights for the design of monitoring strategies for OWTs support structures. Additionally, the field of fault diagnosis in OWTs has developed significantly with the application of artificial intelligence techniques. Based on the reviewed literature, the following conclusions are drawn:

1. The monitoring and fault diagnosis of OWTs are of utmost significance, as they not only reduce operational and maintenance costs for OWT farms, but also provide technical support for the performance evaluation of supporting structures at the end of their service life [90].
2. Utilizing modal parameters changes for OWT support structure fault identification is widely adopted; however, the accuracy of modal parameter identification requires stringent conditions, and identification is greatly influenced by environmental interference and OWT operational loads.
3. The real-time monitoring and fault diagnosis of wind farms are essential and require further development in the future. Digital twin holds great potential for growth. Utilizing machine learning for fault recognition can be time-consuming and the processing and utilization efficiency of real-time data remains relatively low. Furthermore, there

is a scarcity of databases accessible to all parties involved in wind power, hindering the optimization of fault diagnosis methods.

**Author Contributions:** Conceptualization, F.L. and Y.Y.; methodology, Q.Z.; investigation, Y.Y.; writing—original draft preparation, Y.Y.; writing—review and editing, Q.Z.; visualization, H.Z.; supervision, F.L.; project administration, F.L.; funding acquisition, F.L. and Y.Y. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the National Natural Science Foundation of China (Grant No. 52178346), the Top Discipline Plan of Shanghai Universities-Class I (Grant No. 2022-3-YB-02), the Fundamental Research Funds for the Central Universities, the Shanghai Post-doctoral Excellence Program (Grant No. 2022588), the China Postdoctoral Science Foundation (Grant No. 2023M742666), and the Soft Science Project of Shanghai Science and Technology Innovation Action Plan (Grant No. 23692122600).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors are deeply grateful to the anonymous reviewers for their invaluable feedback. Their comments and suggestions have significantly enhanced the quality of the paper.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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