Offshore wind turbine operations and maintenance: A state-of-the-art review

Zhengru Ren[a], Amrit Shankar Verma[b,c], Ye Li[d,*], Julie J.E. Teuwen[b], Zhiyu Jiang[e]

[a]*Department of Marine Technology, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway*
[b]*Faculty of Aerospace Engineering, Delft University of Technology, Delft, the Netherlands*
[c]*SINTEF Ocean AS, Trondheim, Norway*
[d]*School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiaotong University, 200240, Shanghai, China*
[e]*Department of Engineering Sciences, University of Agder, NO-4879 Grimstad, Norway*

Abstract

Operations and maintenance of offshore wind turbines (OWTs) play an important role in the development of offshore wind farms. Compared with operations, maintenance is a critical element in the levelized cost of energy, given the practical constraints imposed by offshore operations and the relatively high costs. The effects of maintenance on the life cycle of an offshore wind farm are higly complex and uncertain. The selection of maintenance strategies influences the overall efficiency, profit margin, safety, and sustainability of offshore wind farms. For an offshore wind project, after a maintenance strategy is selected, schedule planning will be considered, which is an optimization problem. Onsite maintenance will involve complex marine operations whose efficiency and safety depend on practical factors. Moreover, negative environmental impacts due to offshore maintenance deserve attention. To address these issues, this paper reviews the state-of-the-art research on OWT maintenance, covering strategy selection, schedule optimization, onsite operations, repair, assessment criteria, recycling, and environmental concerns. Many methods are summarized and compared. Limitations in

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[*] Corresponding author

Email addresses: `zhengru.ren@ntnu.no` (Zhengru Ren), `A.S.Verma@tudelft.nl` (Amrit Shankar Verma), `ye.li@sjtu.edu.cn` (Ye Li), `j.j.e.teuwen@tudelft.nl` (Julie J.E. Teuwen), `zhiyu.jiang@uia.no` (Zhiyu Jiang)

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the research and shortcomings in industrial development of OWT operations and maintenance are described. Finally, promising areas are identified with regard to future studies of maintenance strategies.

Highlights

- Review of strategies, planning, operations, and environmental effects of offshore wind turbine operation and maintenance.
- Maintenance strategies are introduced, including corrective, proactive, and opportunistic.
- The development and limitations of the optimal scheduling problem are discussed.
- The crew and equipment transferring, docking, and lifting operations are analyzed.

Keywords: Offshore wind turbine, operation and maintenance, maintenance strategy, onsite maintenance, maintenance scheduling, environmental issues

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List of abbreviations

CapEx	Capital expenditure
CMS	Condition monitoring system
CTV	Crew transfer vessel
DecEx	Decommissioning expenditure
DP	Dynamic positioning
GHG	Greenhouse gas
LCOE	Levelized cost of energy
O&M	Operations and maintenance
OWT	Offshore wind turbine
OpEx	Operational expenditure
RAMS	Reliability, availability, maintainability, and safety
SCADA	Supervisory control data acquisition

Contents

1. Introduction

1.1. Background

Among different renewable energy sources, wind power shows great promise due to its relatively high technological readiness level, abundant availability, and relatively low environmental footprint. Energy harvesting via conventional wind turbines is achieved by converting the kinetic energy of the wind into mechanical power through blade rotation, and then into electrical power through generators. Based on their locations, wind turbines can be categorized as onshore or offshore wind turbines (OWTs). Although definitions exist for nearshore wind turbines [1] or unconventional turbine technologies such as airborne wind energy systems [2], we broadly consider any off-the-coast turbines to be OWTs and focus on three-bladed horizontal-axis technologies in this paper.

With rapid growth in wind power demand over the past decade and the depletion of land resources, OWTs have become the focus of wind technology development. Compared with onshore wind turbines, OWTs have many advantages, e.g., abundant wind resources, lower turbulence, substantial space for establishment, lower transmission and distribution losses, less visual impact, and less noise pollution. Given these notable advantages that guarantee reliable energy production, there has been a rapid increase in the demand of OWTs in the last two decades; see Figure 1. The first OWT was constructed in Sweden in 1990 [3]. Since then, OWT projects have proliferated across Sweden, Denmark, the Netherlands, and the UK [4]. Europe has always been at the front runner of OWT development, and the evolution of offshore wind capacity in Europe can be clearly seen from Figure 1(b). By the end of 2019, the UK had the highest total installed capacity of 9945 MW (representing 45.0% of the total installed capacity in Europe), followed by Germany with 7445 MW installed capacity [5].

Despite the steady growth of the OWTs in recent years, their development lags far behind that of onshore turbines likely due to the high cost of power production from OWTs. The levelized cost of energy (LCOE), which represents the average life-cycle price of the electricity generated from a given power source per megawatt-hour, is employed to compare different power sources. As of 2018, the LCOE for offshore wind power is higher than that of other competitive energy resources, such as coal, hydro, and nuclear power [9]. Figure 2 compares the LCOE of offshore wind power to that of onshore wind power. This figure shows that the cost of energy produced from onshore wind is still much lower than that of offshore wind, though the deviation is becoming smaller. Several strategies have been considered to reduce the LCOE related to offshore wind power, for example, installing turbines in deep waters farther from shore, as well as installing wind turbines with increased power capacity and rotor sizes. Although the trend to install larger wind turbines provides a number of benefits, these would be counterbalanced by higher failure rates, thereby contributing to higher repair and maintenance cost [10].

The advancement of offshore wind farms is hindered by the harsher conditions to which offshore installations are exposed [13, 14], difficult and expensive maintenance [15], and the inherently unpredictable nature of wind. Minimizing the total lifetime expenditure of offshore wind power is crucial to enhance their competitiveness. As shown schematically in Figure 3, the total costs that contribute to the total lifetime expenditure of a wind turbine can be divided into three components, i.e., capital expenditure (CapEx), operational expenditure (OpEx), and decommissioning expenditure (DecEx). CapEx can be further divided into the cost associated with wind turbine components and the cost of associated power production components; OpEx can be subdivided into operating and maintenance costs.

1.2. Importance of maintenance

Operating and maintenance (O&M) costs accounts for a large portion of the LCOE of an offshore wind farm, constituting 23% of their total investment cost, compared to only 5% for onshore wind turbines [18, 19]. Hence, reducing O&M costs is an effective way to control the LCOE.

Compared to operating costs, maintenance costs are more important in controlling the LCOE. In the composition of O&M costs, equipment costs are highest, followed by revenue losses. These two costs are explicitly associated with maintenance costs, with the former representing the direct cost of maintenance, and the latter being associated with the cost resulting from a lack of maintenance [18].

Maintenance has a strong influence on downtime duration over the lifetime of an offshore wind farm and consequently contributes considerably to the LCOE. Maintenance activities of any engineering structures involve regular inspections and repairs to correct any failure or replace faulty components. OWT maintenance costs vary with foundation type and location. In general, the maintenance costs are two to three times higher than those of onshore wind farms [20]. High maintenance costs are a vital factor that restricts the development of offshore wind farms. Though the performance of a wind farm degrades over time, reasonable and efficient maintenance strategies and procedures can reduce the downtime caused by aging equipment [21, 22]. Hereafter, we focus on OWT maintenance.

1.3. Challenges to OWT maintenance activities

Maintenance activities are considered one of the most critical tasks for OWTs, and the challenges associated with them are due to many reasons. First, the distance from an offshore wind farm to a port or shore reduces the accessibility and increases the downtime. The ownership or hiring of a maintenance fleet and an increased number of technicians is costly. In addition, the complexity of OWTs is high due to the introduction of bottom-fixed and floating foundations. Moreover, weather conditions, especially significant wave heights and wind speeds, limit the accessibility of OWTs for service vessels and personnel transfer from the vessel to the OWT. Offshore access systems with motion-compensated gangways have been widely applied together with service operation vessels in the past decade, although such devices are still heavy and costly [23]. If a maintenance task must be postponed due to weather issues, a longer waiting period and greater loss of power generation during downtimewill likely occur. Even without considering the effects of weather, OWT maintenance costs are higher than that of equivalent tasks onshore due to the specialized equipment required. Furthermore, a severe offshore working environment, higher wind speed, wave-induced motions, and structural vibrations result in higher failure rates of OWT components. Additionally, the growing size of OWTs in recent decades, which aim to improve power generation efficiency, requires larger and more specific devices for offshore maintenance and repairs.

Given that it is expected that 50% of electricity demand will be fulfilled by wind energy by 2050, significant amounts of maintenance and repair activities will be required in future decades [24]. Accordingly, it is equally important to explore the effect of OWT maintenance on environmental impact. Hence, the overall aim of a suitable repair and maintenance strategy must balance maximizing profitability and minimizing environmental impacts, thereby contributing to the sustainable development of offshore wind energy over the long run. Based on the above discussion, it is clear that OWT maintenance is challenging, and proper maintenance will ensure a decrease in downtime while reducing losses in energy output.

The broad topic of OWT O&M can be separated into several unrelated research questions, such as overall cost management and logistics planning, onsite operations and mechanical designs for specific operations, and forward-looking evaluation of potential effects. Although each subproblem has been studied by the researchers and engineers from corresponding disciplines, an amalgamation of these technologies is still in its infancy. Therefore, the target of this review is to provide a comprehensive framework for interested researchers and engineers with different backgrounds to gain a broad picture of OWT O&M.

1.4. Scope of this review

This paper reviews the state-of-the-art research of OWT operations and maintenance, including strategies, planning, onsite operations, and assessment criteria. Promising areas are identified concerning the future development of maintenance strategies. Furthermore, the negative impacts of offshore maintenance on greenhouse gas emissions marine wildlife, and waste recycling are discussed. This review presents a comprehensive overview of the literature on OWT maintenance (see Figure 4) and provide a basis for the development of maintenance strategies in the future for offshore wind power facilities. Research gaps are also identified through gathering and comparing many scientific publications, technical reports, and open databases.

The review is structured as follows. In Section 2, several maintenance strategies are introduced and discussed, including their development, benefits, shortages, and challenges, and critical factors that affect maintenance costs are analyzed. Based on the selected maintenance strategy, optimal maintenance routing and scheduling are discussed in Section 3. Several aspects of the associated optimization problem are discussed including their developments and limitations. Onsite maintenance activities are summarized in Section 4. Three onsite operations are introduced, i.e., transferring, docking operation, and lifting operation. Maintenance and repair of two vulnerable components, namely, the blade and the gearbox, are highlighted.

Numerical analyses are conducted to evaluate the operational safety and critical environmental conditions. In Section 5, the environmental impacts of OWT O&M are discussed, such as greenhouse gas emissions, negative impacts on marine wildlife, and waste recycling. In Section 6, further discussion is presented and conclusions are drawn regarding these maintenance-related issues.

2. Maintenance strategies

An effective and reliable maintenance strategy is an indispensable part of OWTs' daily operations. Since technicians have to visit the wind farm from a port, it is impossible to achieve around-the-clock operations without any interruptions of onsite maintenance. To prevent a failure from occurring, a maintenance team should visit the wind farm frequently. However, unnecessarily frequent visits, on the one hand, are inefficient and expensive due to the high amount of maintenance vessels and personnel required. On the other hand, a lower visit frequency may result in a higher failure rate and, consequently, longer downtime. Therefore, maintenance frequency is a trade-off among risks, vessel capacities, human resources, and so forth. A successful maintenance strategy aims to maximize economic benefit, extend components lifespans, reduce the number of emergency repairs, decrease overtime labor costs, and relieve the working stress of unpredictable equipment failures.

Maintenance strategies are typically categorized as corrective (reactive) maintenance, proactive maintenance, and opportunistic maintenance according to when maintenance is conducted [25]. These classifications are shown in Figures 5 and 6. The meanings of the color changes between the different lines are:

- From green to red: the wind turbine stops due to a failure;
- From red to green: the wind turbine is repaired and can continue to work;
- From blue to orange: a maintenance vessel is used to execute tasks;
- From orange to blue: a maintenance vessel is back at the port and waits for new tasks.

Details of these classifications are explained and discussed in sections 2.2–2.4.

2.1. OWT failure modes

Failures can be categorized into two sources; i.e., some are caused by long-term operation and aging, and others are caused by short-term overload and sudden breakdown [26]. Since the rotor and drivetrain rotate, and the structures are exposed to waves, the failure rates are frequently caused by wear and fatigue during operation, and some failures are considered to happen randomly without explicit trends and predictions. The major failures of these components are listed as follows:

- Rotor and blade: deterioration, adjustment error, rotor imbalance, blades and hub corrosion, crack, and serious aeroelastic deflections [27–29];
- Shaft: shaft imbalance, shaft misalignment, shaft damage, and broken shaft [30];
- Gearbox: wearing, fatigue, pitting, gear tooth damage, braking in teeth, eccentricity of toothed wheels, displacement, oil leakage, insufficient lubrication, high oil temperature, and poor lubrication [31];
- Generator: overspeed, overheating, wearing, excessive vibration, rotor asymmetries, bar break, electrical, problems, insulation damage, slip rigs, winding damage, and abnormal noises [32];
- Bearings: overheating, spalling, wear, defect of bearing shells, and bearing damage [33];
- Nacelle: fire and yaw error [34];
- Tower: fatigue, vibration, foundation weakness, and crack formation [35–37];
- Electrical system: short circuit, component fault, bad connection, contamination, and arcs [38];
- Mooring system: mooring line breakage and fatigue [39].

There are many critical components in OWTs, and their failure rates vary. The failure rates depend on the location of the wind farm, foundation type, and drivetrain type. The failure rate increases and reliability decreases with the application of less mature techniques, i.e., larger scale and more complex drivetrain. The total failure rates for direct-drive and indirect-drive systems are nearly identical, but the failure rates for different components vary. Compared with a direct-drive wind turbine, the failure rates of the gearbox, inverters and electronics, and generator in an indirect-drive wind turbine are higher, lower, and lower, respectively [40].

2.2. Corrective maintenance strategy

Corrective maintenance, or reactive maintenance, is a failure-based maintenance strategy in which maintenance is carried out only when a failure has already occurred; see Figure 6(a). The corrective maintenance strategy can effective achieve high availability while avoiding unnecessary maintenance visits and inspection. It is thus suitable for a system with negligible downtime loss. However, the corrective maintenance strategy turns out to be impractical and undesirable for large-scale offshore wind farms due to a high failure rate and relatively low system reliability [41]. Unexpected failures may cost more than expected downtime. In addition, the marine environment reduces accessibility and decreases reliability; for example, a failure may be noticed by the maintenance team after a long downtime (see Figure 6(a)).

2.3. Proactive maintenance strategy

Proposed in the early 1970s, proactive maintenance is a more advanced approach [42] where scheduled inspection and replacement is carried out before failure to prevent minor faults from developing into a major failure. Major failures (only 25% of all failures) contribute to 95% of downtime [43]. Proactive maintenance is a relatively mature technique, and proactive maintenance strategies mainly comprise preventive and condition-based maintenance strategies.

2.3.1. Preventive maintenance strategy

A preventive strategy usually refers to scheduled maintenance that takes place at (i) a predetermined period, or (ii) a given level of power generation.

(i) The selection of a planned intervention depends on the reliability of each component and the overall cost. If a failure happens between two intervention intervals, the wind turbine will remain out of operation until the next planned visit, as shown in Figure 6(b). Thus, it is possible to carry out repairs and regular maintenance in the meantime, which achieves efficient use of resources. Because the maintenance cost of different components varies markedly, increasing reliability and mitigating expensive maintenance tasks will help minimize maintenance cost. The number of planned intervention intervals in a year is calculated by considering capacity factors, weather-related accessibility, and levelized production cost of each site [41].

(ii) A preventive maintenance strategy that considers power generation considers the effect of power generation rate on the degree of deterioration on the turbine and consequently on the maintenance strategy [44].

The goal of preventive maintenance strategy is to optimize the production plan and the economic maintenance plan. Compared with corrective maintenance, the advantages of this strategy are (1) elimination of unplanned maintenance, (2) availability of a sufficient maintenance weather window, (3) minimization of the effect of unpredictable weather, (4) reasonable use of service vessels, (5) avoidance of excessive spare stock, (6) combined maintenance and repairs, (7) optimization of maintenance tasks, and (8) contribution to an effective asset maintenance plan[45].

Preventive maintenance tasks can be planned based on the age groups of different components. An optimum selection of extreme age thresholds and a number of age groups allows maintenance costs to be minimized by reducing the setup and labor costs of repeated visits. This approach is preferred for large offshore wind farms that require repetitive maintenance. This age-based method is also used by Santos et al. [46] with imperfect repairs and is compared with a corrective maintenance strategy and a classic preventive maintenance strategy with fixed time intervals. In that study, the preventive maintenance strategy considered that the age reduction ratio contributes to cost reduction with regard to the use of large vessels (55.51%) and replacements (60.28%). Although the cost of the supply vessels and crew increased by 166.4%, the overall benefits are significant, yielding a total cost reduction of 24.2%.

Some efforts have been made to improve the preventive maintenance strategy. Dui et al. [47] proposed a cost-based measure to identify the maintenance priority of a component based on the joint effect of component reliability and maintenance cost on system reliability. Nejad et al. [48] applied a the reliability-based maintenance strategy to gearbox components that have a higher probability of fatigue failure and a lower level of reliability. The authors proposed a “vulnerability map” to reduce downtime and increase the efficiency of finding faulty components during routine inspection and maintenance.

Preventative maintenance strategies can frequently be described as an optimal maintenance scheduling problem, which should aim to reduce the maintenance cost and increase OWT availability without threats to the system, ship crews, or the environment [49]. One effective method is to optimize the selection of the preventive maintenance interval, which will be reviewed on more detail in Section 3.

2.3.2. Maintenance strategy using sensors

2.3.2.1. Condition-based maintenance strategy. OWTs are prone to deterioration due to fatigue, corrosion, erosion, and wear. Combined with a risk-based life-cycle approach based on the per-posterior Bayesian decision theory, condition-based maintenance, which is also referred to as predictive maintenance, can be used to observe the degree of the deterioration and thus increase the reliability of predictions [50, 51].

Condition-based maintenance is a strategy that combines relevant information measured by a condition monitoring system (CMS) and the results of an online or offline health diagnosis or fault analysis system. This type of maintenance is also guided by the status of the components. Maintenance repairs occur when a failure occurs, as shown in Figure 6(c). The aim is to prevent major failures from happening [52]. Maintenance repairs are used in the prospective health condition maintenance, and allow the planning and selection of the most effective repair methods based on the wind turbine's condition, faults, the costs of maintenance, resource depletion, and production efficiency. Asensio et al. [53] evaluated the economic viability of a predictive maintenance strategy from the perspective of the life-cycle cost of CMS. The model takes account of the investment costs and O&M of the CMS and the cost reduction due to CMS implementation. Walgern et al. [54] compared a condition-based maintenance strategy with corrective and preventative maintenance strategies and found it to achieve the best performance of many methods. Combining CMS with weekly scheduled maintenance was shown to be the most cost-effective approach. Condition-based maintenance strategies minimize maintenance costs and increase OWT reliability, while the monitoring devices require extra costs. Many condition monitoring techniques applied to monitor and inspect the components in a wind turbine are listed in Table 1, and include vibration, acoustic emission, ultrasonic measurement, and thermography techniques [55].

Sensors play a significant role in CMS. Many types of sensor systems have been introduced to analyze OWT system performance, and their prices have gradually decreased in recent decades. Sensor measurements provide technicians with a clear and comprehensive image of the OWTs' real-time conditions. The topics of structural health monitoring, feature extraction, and fault detection have been intensively reviewed in early studies, e.g., [30, 55–57]. Surveys of specific wind turbine components are proposed, e.g., bearing [58], generators [59], gearbox [60], energy conversion systems [61], and drivetrain [62] have also been proposed.

Table 1: The monitoring and analysis methods to different components.

	Nacele	Tower	Blade	Bearings	Shaft	Gearbox	Generator
Vibration analysis	✓		✓	✓	✓	✓	✓
Torsional vibration					✓	✓	
Acoustics Emission		✓	✓	✓	✓	✓	
Oil analysis				✓		✓	✓
Strain measurement		✓	✓				
Optical fiber monitoring			✓				
Electrical effects				✓			✓
Temperature	✓			✓		✓	✓
Ultrasonic testing techniques		✓	✓				
Thermography	✓		✓	✓	✓	✓	✓
Visual inspection	✓		✓	✓		✓	✓
Radiographic inspection.		✓	✓				
Generator power output							✓

According to measured data, frequency-frequency analysis is widely used in fault detection and isolation, e.g., Fourier transformation and wavelet transformation. The costs and levels of and deployment of these techniques are presented in Figure 7. Visual inspection cannot achieve on-line monitoring since it is impossible for a technician to remain at an OWT. It is noted that the level of deployment declines with the cost. Hence, attention should be placed not only on newly developed technologies but also on the budget reduction of existing solutions.

The advanced data collection techniques provided by supervisory control data acquisition (SCADA) and CMS are significant due to their roles in the supervising operational conditions, thereby increasing reliability and optimizing maintenance plans [65]. In addition, the involvement of condition monitoring can improve planning and avoid over-maintenance or under-maintenance. For example, the remaining useful life could be predictive based on condition monitoring data [66].

Many factors affect the performance of a condition-based maintenance strategy, such as the CMS detection rate and the false alarm rate. May and Mcmillan [67] investigated the effects of these two factors and pointed out that an increase in the number of false alarms resulting from a decrease in the reliability of the CMS will lead to a reduction in the availability of the wind farm. One way to improve the fault detection success rate is to add more CMSs to the system. May et al. [68] performed an economic analysis of improvements in the use of CMS. Among various approaches in which CMSs are added to the drivetrain, gearbox, and generator, or the tower or the blades, only the additional blade CMSs improve the cost-effectiveness of the maintenance strategy [69]. There is a 95% improvement compared with the use of a CMS on the drivetrain alone, taking both fault detection and the extra expense of the additional CMS into consideration. In [70], the geographical clustering of OWTs, such as the layout of the wind farm, is considered in order to optimize a condition-based maintenance strategy. Dividing wind turbines into different clusters based on the optimum offshore wind farm layout leads to further improvements in the convenience of maintenance.

The level of automation and intelligence is thus improved. Data-driven approaches, e.g., machine learning, has become popular in recent years, and it has been applied to optimal maintenance scheduling [71]. Supervised learning is the most widely used approach. A black-box neural network model is trained to fit the labeled data, and the network can be applied to conduct various analyses, classification monitoring, and prediction [71]. This approach is especially suitable for scenarios that are difficult to model due to high complexity and uncertainty. However, there are a few shortcomings of learning approaches. First, the method highly relies on the quality and quantity of measured data. A lack of necessary measurements degrades the neural network. Additionally, it is hard to prove stability. The network architecture influences the computational speed and robustness. If the failure scenarios are not included in the trained data, failure can hardly be detected. There is no guarantee that the key parameters tuned in the design period work well in practical applications since neural networks are not good at extrapolation.

2.3.2.2. Predictive maintenance strategy. Compared with condition-based maintenance, another similar but more advanced proactive maintenance strategy is predictive maintenance. According to sensor measurements, parametric analyses are conducted to determine when maintenance should be performed before a failure occurs; see Figure 6(d). The main idea is to minimize the downtime and maximize the reliability; i.e., the maintenance events are conducted when they are indeed necessary. Though the associated equipment cost is higher, the benefits of this strategy include reduced maintenance frequency and time, downtime, and cost of spare parts and supplies.

Digital-twin platforms are the latest popular research topic and are used to predict the remaining useful life of OWT components [72]. Practical physics and virtual models are paired to predict when maintenance should be performed. By combining measured data and virtual models, failures can be predicted before they occur. This method can be applied to both OWTs and service vessels. Although several digital-twin platforms have been proposed [73–77], systematic and convincing research is still lacking.

2.3.2.3. Limitations. The use of sensors in practical applications is challenging due to their growing number. Although, more sensors markedly improve the measurement accurately and redundancy, they also markedly increase system cost and complexity, and introduce new problems, such as sensor failures and misreporting. Studies of effective and robust approaches to fuse sensor signals and handle fault conflicts are remain to be performed. Wang et al. [78] introduced a monitoring system for use in a condition-based maintenance strategy with a SCADA database to collect and analyze monitoring information. The former provides low-resolution monitoring to supervise the operation of the wind turbine, collects data, and alarms; the latter is employed to diagnose and predict subassembly faults through high-resolution monitoring [65]. However, it is challenging to distinguish whether a fault is real or fake using SCADA analysis; thus, accuracy and robustness should be improved by employing more advanced fault detection algorithms and artificial intelligence.

The extensive monitoring of turbine conditions and supervision of mechanical performance generates large quantities of data, in addition to the O&M information recorded during the turbine lifespan. The problems of collecting, filtering, analyzing, and storing these large amounts of information have received much attention.

One shortcoming of existing data-collection schemes is the lack of detail that they record: merely recording failed components is far from satisfactory. Reliability, availability, maintainability, and safety (RAMS) databases have been proposed to provide more detailed information, such as the causes of failure, corresponding maintenance tasks, and the effects on future failure behaviors. This database serves as a basis for condition-based maintenance by determining the periods of preventive maintenance and contributing to maintenance planning, scheduling optimization, life-cycle cost minimization, and profit analysis [79]. Data stored in a RAMS database will also serve as essential input to determine and design a function-behavior-state model and functional redundancy designer [79].

Regarding the incompleteness of current operational data collection and the loss of valuable data resulting from the rescaling of traditional databases, methods designed for big data are used to manage detailed operational data collection and reuse [80]. All data can be stored in a data chain. The streaming data processing tools employed allow the use of more sophisticated wind-farm-level alarms and warnings. The scalability of these methods allows all historical data to be considered with no need for data archiving. Hence, these methods can manage growing wind farms predictably due to the comparatively simple and cost-effective features of the extended distributed big data systems compared with the traditional databases.

Cyber-security is another critical issue in practical applications, e.g., remote sensing. The digital network and rapid development of remote communication have significantly enhanced OWT O&M convenience and efficiency. However, cyber-security in the wind industry is relatively unexplored, and issues of concern likely include information disclosure and cyber attacks. The system puts the reliability of the grid at a major risk. Systematic improvement and design are needed.

2.3.3. Summary

A summary of different maintenance strategies is tabulated in Table 2.

Table 2: Comparison among different maintenance strategies.

	Corrective maintenance	**Preventive maintenance**	**Condition-based maintenance**	**Predictive maintenance**
Trigger	Failure	Planned date	Real-time measurement	Real-time measurement
Initial cost	Low	Medium	High	High
Operating cost	High	Medium	Medium	Low
Number of failures	High	Low	Medium	Low
Unnecessary visits	High	Medium	Low	Low to medium
Unplanned maintenance	Low	Low	High	Medium
Maintenance regarding failures	After	Before or after	Shortly after	Before
Downtime	High	Medium	Medium	Low
Level of automation	Low	Low to medium	Medium to high	High

2.4. Opportunistic maintenance strategy

The first opportunistic maintenance strategy was proposed in the 1960s [81], and the concept has since been extended and developed since then. However, its definition is still not consensually defined [82]. The notion of opportunistic maintenance is often referred to as a grouping of diverse planned preventive maintenance tasks or the combination of preventive and corrective maintenance actions. Different types of maintenance tasks are typically scheduled within the same period, or even during the same visit [83]. For example, additional unplanned service actions that should be undertaken in the future are carried out together with a planned service at its corresponding downtime when a failure occurs or when the reliability of a component reaches its predetermined preventive maintenance threshold. The maintenance team can take the opportunity to maintain other healthy components whose maintenance thresholds have not yet been reached. By taking advantage of wind forecasts and corrective maintenance of low power generation periods or of unexpected failures to perform preventive maintenance, the opportunistic preventive maintenance strategy leads to a 43% reduction in preventive maintenance cost [84]. Zhang et al. [85] calculated a scheduled time for preventive maintenance based on reliability requirements and determined the opportunistic maintenance interval by optimizing the total maintenance cost. This method reduced downtime and overall maintenance costs compared to the classic preventive maintenance strategy.

The opportunistic preventive maintenance strategy replaces failed components and takes the opportunity to replace or maintain operating components preventively when onsite [86]. Group maintenance planning is determined by the optimal maintenance plan for each individual components[87] and maintenance cost[88].

OWTs often suffer from the internal system deterioration and external damages due to the harsh offshore environment. Shafiee et al. [66] proposed an opportunistic condition-based maintenance strategy for multiple-blade OWTs subjected to deterioration and environmental shocks and verified that the strategy can reduce maintenance setup costs, greenhouse gas emissions, and O&M costs. Data collected by a SCADA system was also used to verify the proposed algorithm.

Both opportunistic preventive maintenance [85, 86, 89–91] and opportunistic condition-based maintenance [66, 91, 92] are described in the literature. Based on monitoring systems, condition-based maintenance has recently been extended to become opportunistic. Maintenance should be conducted when the designed maintenance index reaches a given threshold. If this threshold varies, the strategy is called dynamic opportunistic maintenance [91]. Maintenance costs can be dynamic. Zhang et al. [91] reported that the dynamic opportunistic maintenance strategy yields 11% and 18%

decreases in life cycle O&M costs compared with a static opportunistic maintenance strategy and a strategy that does not consider opportunistic maintenance, respectively. Grouping periodic maintenance planning and reactive maintenance is studied in Zhu et al. [93].

3. Optimization models for maintenance planning

Ensuring system reliability and minimizing the maintenance LCOE represents a complex management problem with a number of uncertainties when considering a long-term perspective. There are many time-varying, unpredictable, or partly unpredictable factors, including the environment and climate, management, aging, supply chain, electricity price fluctuations, technology advancements, risk analysis, interest rates, political tendencies, and the global market. Therefore, most maintenance policies and decision-making algorithms tend to model and maximize short-term benefits, i.e., ensuring that the maintenance fleet and OWTs work efficiently.

The optimum scheduling of maintenance tasks and fleet routing must consider costs, weather, maintenance intervals, personnel, downtime, repair time, and fleet size. (i) Maintenance scheduling refers to the detailed arrangement of maintenance tasks for a set of target OWT during recommended periods while considering environmental conditions, resource availability, and the loss of revenue due to turbine failure. (ii) Route planning refers to the choice of an optimum route for each service vessel to perform maintenance tasks for a group of target OWTs within a specified weather window. The service objective expands from one O&M base and one wind farm to multiple O&M bases and multiple wind farms while considering the number of available technicians and spare parts, and the capacities of the service vessels. Once the schedule has been determined, service vessels are selected; routes are planned for each vessel to access the corresponding wind turbines, and personnel are assigned. Optimal route planning is achieved by balancing energy efficiency and time consumption. Sea currents and winds are the primary environmental parameters that affect this problem. The environment is typically assumed to be steady [94] or spatiotemporally variant Niu et al. [95]. Some other problems can include, e.g., the optimal vessel fleet composition [96].

Maintenance strategies can be solved as optimization problems. In this section, cost functions and constraints are discussed, and the development and limitations of associated methods are reviewed.

3.1. Optimization problem

The core of route planning and maintenance scheduling is a constrained optimization problem. A standard form is given by

$$\begin{aligned} \min_{x} \quad & f(x) \\ s.t. \quad & g_i(x) \leq 0, \quad i = 1, \cdots, m \\ & h_j(x) = 0, \quad j = 1, \cdots, n \end{aligned} \tag{1}$$

where $m \geq 0$ and $n \geq 0$. Two parts are elementary to the constrained optimization problem in eq. (1), i.e., the cost function(s) ($f(x)$) and constraints ($g_i(x)$ and $h_j(x)$). According to the objective functions, the optimization problems can be categorized into single-objective and multi-objective optimizations. The optimum solution minimizes the cost functions under a number of inequality ($g_i(x)$) and equality constraints ($h_j(x)$). In this way, a maximization problem can be transferred to a minimization problem.

The quantitative model is based on a series of assumptions and simplifications and must be simplified with an educated guess. Significant amounts of models have been proposed to describe this process [97], and most are deterministic linear models that can be solved with commercial solvers. While some considerations introduce nonlinearities to a part or parts of the cost functions and constraints. Quantitative coefficients are determined based on project experiences and historical data. However, other aspects are difficult to evaluate if they are time-varying, uncertain, or nonlinear. Table 3 lists the similarities and differences among some state-of-the-art decision support algorithms that perform optimal maintenance scheduling with respect to the optimization problem/solutions.

3.1.1. Cost function

This section begins by discussing single-objective optimizations. Single-objective cost functions are time-based [98], cost-based [83, 86, 87, 99–105], reliability-based [106], or sometimes availability-based. For an OWT, reliability and availability are related and similar, but not equivalent. The most widely used cost functions are cost minimization and reliability maximization.

The most widely studied optimum assignment is determined in terms of total maintenance costs, which are a sum of revenues and penalty costs. Zhang [100] and Dai et al. [83] only consider the fundamental travel cost and downtime penalty cost. The travel cost relates to travel distance and vessel capacity. The lost revenue in the downtime is influenced by the types of maintained components, technician skills, electricity price, wind speed, and OWT size. Additionally, the cost of a repair or replacement is considered in the cost function in some studies. The costs of the service fleet and associated personnel can be categorized into fixed and variable costs. Fixed costs, which are independent of the vessel usage, can include the cost of lease contracts, onshore/offshore bases, and the maintenance team; variable costs depend on how much the vessel is used. Adjustment cost is related to schedule uncertainties due to the weather changes or other unexpected situations. Unplanned downtime and speed losses are considered in Krokoszinski [107]. Compensation cost for incomplete tasks is studied in some studies [85, 87, 101]. Raknes et al. [104] proposed a mathematical model that can model several work shifts and corresponding vessels, and accurately calculate revenue losses resulting from turbine failures. This model can also be employed to evaluate decisions regarding vessel size and mix, as well as the consequences of these decisions. Startup cost and customer relationship management cost are only considered in Zhong et al. [108] and Hajej et al. [109]. Unlike a hydroelectric or a thermal power plant, the startup cost of OWT maintenance scheduling is not significant since a wind turbine can startup in 60 seconds [110]. From a long-term perspective, the spare-parts inventory cost affects the OWT life cycle cost and is related to the ordering, purchasing, and holding costs [91].

In other studies, reliability criteria are considered. There are several critical components and services for each component in an operational wind turbine. The system reliability can be calculated as the average of components' individual reliabilities [108] or using fuzzy system reliability [111].

However, reliability (or availability) maximization and cost minimization are inversely related, resulting in the abovementioned optima being partial and circumscribed in only one aspect. To overcome these limitations, another type of single-objective cost function that minimizes the cost/reliability (or cost/availability) ratio can be used. As an alternative approach, multi-objective optimization has been used in recent studies, where cost functions are cost-reliability-based [106, 108, 111], cost-power-based [90, 112], and cost-reliability-availability-based [113].

3.1.2. Constraints

The cost functions are restricted by specific constraints to achieve specific considerations and ensure the practical meanings of optima. The number of constraints grows with the number of considerations and requirements. To satisfy a specific requirement, several constraint inequations/equations are needed. Table 3 summarizes the most widely used selection of requirements. For a specific vessel, its maximum offshore travel and maintenance time is affected by its loading capacity, and the total number of onboard technicians are known. The accessibility of each wind farm depends on the vessel capacity and environmental conditions. The frequency of leaving and entering harbors is also constrained in the optimization in case of unnecessary high-frequency fluctuations in the optima. The total number of serving vessels must be predetermined. For overnight service, whether technicians will be back to onshore or accommodated onboard was to be determined. Seasonal constraints also exist because maintenance is not allowed during certain periods. Environmental effects, e.g., greenhouse gases and seabirds, are taken into account in only a small part of works [108, 112].

3.1.3. Solver

After constructing the optimization problem, the next step is to solve the problem and find the optima. Most linearly constrained programming problems are solved by commercial solvers, such as Xpress, using mixed-integer programming. However, nonlinear cost functions are used some works [108]. Multi-objective optimization problems can be solved using many approaches, including duo-Ant colony optimization [100], a nondominated sorting genetic algorithm [108], a genetic algorithm [105], and ε-constraint method [112]. Optimal results can be verified by simulations. The offshore wind farm O&M process can be simulated by, for example, distributed simulation using a multi-agent system [114] and business process simulations [115]. A hybrid simulation model is proposed by [116] to combine a continuous system dynamics model, a discrete agent-based simulation (ABS), and a discrete-event simulation (DES) [117, 118].

3.2. Development

The optimal-scheduling problem is modeled and solved using a more realistic and flexible perspective. A decade ago, this problem was still modeled using static and deterministic parameters, while dynamic and stochastic methods become increasingly popular. In addition, the complexity of the optimal scheduling problem grows in time due to the increasing number of considered factors.

Table 3: Comparison of optimal routing and scheduling approaches (Duo-ACO:duo-ant colony optimization, MIP:mixed integer programming, MO:Multi-objective optimization, GA:genetic algorithm).

		[99]	[100]	[83]	[101]	[102]	[103]	[86]	[106]	[104]	[87]	[108]	[105]	[96]	[112]
Cost	Downtime cost	✗	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	-	✓	✗
	Cost of vessels + personnel	✗	✗	✗	✓	✓	✓	✗	✗	✓	✓	✓	-	✓	✓
	Travel/transportation cost	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
	Fixed cost	✗	✗	✗	✓	✓	✗	✓	✗	✗	✗	✗	-	✓	✓
	Incompleted maintenance	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	-	✓	✗
	Equipment maintenance cost	✗	✗	✗	✗	✗	✗	✓	✓	✗	✓	✗	-	✗	✓
	Adjustment cost	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	-	✗	✗
	Startup + CRM cost	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	-	✗	✗
	Mother ship cost	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	-	✗	✗
Consideration	Multiple vessels	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓
	Multiple ports	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗
	Multiple services/components	✗	✗	✗	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✗
	Multiple OWT farms	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓	✗	✗
	Multiple technician types	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
	Weather condition	✗	✗	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓
	Parallel maintenance tasks	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗
	Sensor update	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗
	opportunistic	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗
Constraints	Visit every farm only once	✗	✓	✓	✓	✗	✗	✗	✓	✓	✗	✓	✓	✗	✗
	Limited Leave and return harbor	✗	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗
	Vessel capacity	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✗	✓	✓	✓
	Maximum offshore/travel time	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	✓	✗	✓
	Personnel onboard	✓	✓	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓
	Total vessels in base	✗	✗	✗	✓	✗	✗	✗	✓	✓	✗	✓	✓	✓	✗
	Waiting period	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Greenhouse gas emission + wildlife	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓
	Seasonal constraints	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Total no. of constraints	16	17	19	29	-	17	-	10	62	-	16	-	8	14
Loss function	Cost	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Reliability	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗
	Power generation	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
	Solver	-	Duo-ACO	MIP	MIP	-	MIP	-	-	MIP	-	MO	GA	MIP	MO

Possible realistic operations and issues were not considered in early studies. The research was extended to multiple port bases [83, 105], multiple types of maintenance services [86, 87, 89, 101, 103–105], and multiple types of technicians [101]. All these factors greatly increase the optimization complexity, resulting in more complex cost functions and increasing numbers of variables and constraints; see Table 3. For example, Irawan et al. [119] overcame the limitations of previous models, that are restricted to a single O&M base and a single wind farm, by proposing a model and solution for multiple O&M bases and wind farms at different locations, which is more representative of real OWT developments. Dai et al. [83] considered only small cases, in which only four, six, or eight OWTs required maintenance. In another study of this topic, Zhang [100] considered the priority of the maintenance tasks and suitable environmental conditions, and proposed the application of a duo ant colony optimization method to the scheduling and routing of a maintenance fleet for offshore wind farms. This method performs well, even with many OWTs. The most popular approach currently is to decompose the routing problem into a master problem (allocating routes to each vessel) and subproblems (producing new routes) [119]. Spare-parts inventory management is sometimes considered [91, 120], because spare parts are not always available.

Cooperative maintenance and fleet sharing enhance overall maintenance efficiency. Maintenance tasks in parallel are studied in Raknes et al. [104]. The fleet leaves maintenance personnel at a specific OWT and continues onto other wind turbines/farms. The technicians are then picked up after finishing their maintenance tasks. Some studies consider reliability with [99] or without costs [106, 108]. A study uit het Broek et al. [121] showed that the vessel and harbor sharing policy greatly reduces overall maintenance costs.

Time-varying parameters have been considered in recent studies, such as time-varying power harvesting [109], time-varying maintenance cost [122], and the time-varying reliability threshold of maintenance [91]. Since the failure rate of an OWT increases over its lifespan, these factors grow linearly or exponentially with time. The problem can be solved by transforming continuous variables in a discretized set.

More realistic environmental models have been developed, where significant wave heights and wind speeds are critical parameters. The weather forecast can be assumed to be perfect for occasional travel, but its uncertainty surges with a longer time windows. A one-time route and regular routes may not be the same due to weather uncertainties. Stochastic modeling and Monte Carlo simulations are thus widely adopted, more variations appear in the windy environment. In addition to the mean wind speed, gust measurement and estimation are introduced to minimize the total duration of scheduled tasks [98]. Wind direction and wake effects are modeled to improve the local OWT maintenance order in a specific wind farm [112]. The benefits of weather measurement and prediction reduces uncertainty during modeling. Improving predictions within a given weather window reduces uncertainty in maintenance schedules. Considering wave height, autoregressive models and artificial neural networks with different lookahead time steps are compared based on a data mining approach[123]. Online monitoring is integrated into planning in Zhu et al. [93].

One trend is from deterministic modeling to stochastic modeling; i.e., the considered uncertainties of OWT maintenance scheduling enhance in the state-of-the-art studies. These uncertainties come from several aspects, e.g., OWT component failure, weather condition, technician skills, defective repair, and vessel conditions. In deterministic models, failures are assumed to happen periodically according to historical data. Stochastic failures occur randomly based on a predefined probability distribution function using the collected data, such as the Weibull distribution [101, 124], Bernoulli distribution, and binomial distribution [125]. It is possible to extend the deterministic algorithm by probabilistic modeling, such as [101]. The stochastic optimization problem could be solved by transforming the stochastic programming formulation into its deterministic equivalents [126, 127]. The effects of government subsidy are studied in Nguyen and Chou [124]. Due to a limited number of studies, the stochastic modeling of the uncertainties should be studied and discussed in future research [91].

To sum up, research on optimal scheduling has been intensively developed to improve planning performance and complexity. The number and size of maintenance fleets and wind farms continue increasing with time, and more complete considerations and subtle factors have been investigated. Maintenance activities are becoming more diverse and flexible, and stochastic and time-varying models are being used to describe the environment more accurately.

3.3. Limitations

However, there are some shortages and limitations in existing algorithms, including a lack of online updates, vessel failures, lack of vessel interaction and cooperation, extreme weather conditions, a large number of constraints, and limited flexibility.

First, the project schedule is normally decided offline without real-time updating. The coefficients and parameters in the models are predetermined by statistical metrics and project experience. Inaccurate parameters result in misplanning. However, it is impossible to correct the parameters and coefficients by online update. Due to advances in remote-sensing and communication techniques, more knowledge and information are available, e.g., the health of technicians, vessel failures, weather windows, project delays, and emergency issues. Real-time adjustment and replanning have the potential to improve solution robustness.

Second, the failures of maintenance vessels and devices are not included in literature. An offshore supply vessel approaches an OWT using a dynamic positioning (DP) system. Since the DP system has a relatively high failure rate, delays and other issues caused by maintenance vessels should be considered [128].

More realistic cooperative planning among several vessels is not considered in most studies. Instead of going back to the ports repeatedly or using more vessels, interactions among vessels can improve the efficiency of all maintenance tasks and use vessel capacities fully. Considering the following example. A normal-size vessel (A) is adopted to conduct a complex maintenance task, and its deck space (or crane capacity) is not enough for some components (or operations). It is possible to use another larger vessel (B) to carry the other components (or conduct the corresponding tasks). After unloading these components (or accomplishing the tasks), vessel (B) leaves and continues to its next project at another wind farm. If so, then there is no need to assign two normal-size vessels to the project. However, all studies neglected such a possibility due to the correspondingly high variations and complexity. Hence, the cooperation among vessels can improve the overall maintenance efficiency.

Moreover, some extreme weather conditions are disregarded in current research. For example, a failure caused by ice in a cold climate requires special icebreakers to conduct maintenance. A powerful typhoon not only threatens wind turbines but also influences maintenance safety.

The number of constraints in the optimization problem reduces the solver's robustness and computational speed. For example, there are 62 constraints in Raknes et al. [104]. A longer duration is needed to tune the models, and the model uncertainty can be amplified by the improper selection of model coefficients.

The flexibility of current approaches remains limited. The optimization is performed according to some specific requirements; however, these requirements may change over time, and these changes are typically unforeseen. The performance and robustness of a specific algorithm in unconsidered scenarios are not guaranteed. Hence, a mechanism to reasonably and intelligently switch or fuse among all these algorithms is valuable.

4. Onsite maintenance

After maintenance tasks are planned, three operations related to the onsite maintenance make up a considerable proportion of maintenance cost, i.e., (1) the delivery of personnel and equipment to an offshore wind farm, (2) the docking operation to transfer onboard technicians between the service vessel and the wind turbine, and (3) the lifting operation when large components such as blades and the generator need replacement or maintenance. Since blades and gearbox are the two most vulnerable components of an OWT, their maintenance needs to be specified further. Innovative remote self-maintenance has become increasingly popular.

4.1. Equipment and crews transfer

It is essential to choose a suitable maintenance fleet that provides sufficient accessibility while minimizing the extra costs of power generation. As offshore wind farms become larger and farther away from shore, the demands imposed on service vessels will increase.

Various modes of transport are employed for different maintenance purposes, i.e., transport of crews, the shipment of large spare parts, and implementation of lifting operations; the corresponding vessels are crew transfer vessels (CTVs), supply vessels, multipurpose vessels, and floating cranes. Wind speed and significant wave height are representative parameters that limit the accessibility of helicopters or service vessels and therefore maintenance. The use of each vessel type is limited by environmental conditions [126]. CTVs are limited by environmental conditions. Climbing up a turbine is not allowed when the wind speed is higher than 20 m/s. In addition, helicopters are employed for maintenance, but their use is limited by wind speed (which usually must be under 20 m/s) and visibility [83]. In the absence of timely maintenance, the downtime of a wind farm will be prolonged, resulting in massive losses of power generation, especially given the increasing capacities of OWTs.

The sea states can be measured and detected by several measurement instruments, such as onsite wave buoys, onboard wave radars, and satellites. Although wave buoy and wave radar can provide real-time sea state information, they are costly due to the extra costs of their measurement instruments. Satellite signals also have an hour-level delay. However, an interesting research topic is to estimate real-time directional wave spectrum based on vessel responses, which is called the wave buoy analogy [129, 130]. However, this estimation's accuracy strongly depends on the calculated response amplitude operators (RAOs). Conversely, the vessel model can be tuned by vessel motions and environmental data [131]. A decision support system based on a wave height forecaster is proposed in Catterson et al. [132]. Concerning the environmental conditions of offshore wind farms, long-term average wind speed estimates based on a forecast dataset are studied in James et al. [133]. The estimate accuracy increases as the dataset widens, advanced physical models are used, and better data assimilation techniques are employed. Probabilistic forecasting is used in Taylor and Jeon [134] to calculate the probability of wave heights falling within the safety limit and to determine whether to send a service vessel. The results show that the proposed probabilistic method is more cost-effective than a deterministic approach based on point forecasting.

The optimum selection of a CTV plays a central role in organization of maintenance logistics. The main target is the maximization of overall economic benefits, and its capacity should provide sufficient support to the maintenance tasks with minimal cost. The economic benefits grow with the capacity of the CTV if it is below the optimum size. However, the benefits of using CTVs that are too large become decrease due to insufficient usage. Table 4 lists the factors that should be considered when selecting CTVs. Van Bussel and Bierbooms [135] investigated three access systems (rubber boats, an offshore access system, and helicopters) and showed that 90% availability could be achieved if rubber boats were not used alone. Environmental conditions, failures of turbine components, and assessment of the vessel's operation were also shown to affect maintenance tasks [102, 136].

There are several maintenance optimization models that have been developed individually. Sperstad et al. [137] employed six strategic decision support tools with different modeling methodologies to determine the best

Table 4: Factors related to CTV selection.

Environmental conditions	Failure characteristics	CTV specification	Financial attributes
• Wave height and period • Wind speed • Distance to port	• Number of components • Components configuration • Failure rates • Repair time	• Size • Capacities (fuel, accommodation, deck) • Speed • Operability	• Electricity cost • Fuel cost • Vessel & technician cost • Repair cost

maintenance vessel fleet and rank the sensitivity of the vessel fleet to various input assumptions. Their results show that the decision support tools generally agree on the best selection, partially on the overall ranking of each vessel fleet, and on the ranking of the sensitivity to input assumptions. Among the input assumptions, that of limiting significant wave height is the most important, while the vessel speed assumption is appreciably less important, and the assumptions of failure rates and vessel day rates are of intermediate importance. Since various tools yield similar results, decision makers should ensure that input assumptions are representative of a specific wind farm and try to reduce uncertainties in input data while ensuring the completion of preventive maintenance. Series games are used to help O&M planners, engineers, and researchers gain a better understanding of the effects of their decisions and to prevent revenue loss due to inadequate maintenance [138, 139]. Van Bussel and Zaaijer [15] pointed out that one of the main causes of high maintenance costs is using a large external crane vessel. Two methods are proposed to solve this problem. One approach is to design OWTs that can rely completely on built-in facilities to transfer failed parts and their replacements. The other approach is to adopt the offshore wind energy conversion system (Opti-OWECS) design solution, which involves expenditure on special maintenance facilities as an overall investment. In this approach, a self-propelled jack-up platform is modified to perform the required lifting actions and maintenance base.

4.2. Docking and lifting operation

4.2.1. Numerical simulations

Instead of time-consuming and costly model-scale and full-scale experiments, numerical simulation is an efficient and budget-friendly approach to evaluate marine operations. Using numerical simulations, it is possible to conduct an integrated aerodynamics-hydrodynamic-structural analysis of a maintenance project and identify operational limitations. Critical environmental conditions can be evaluated based on static results from finite element analysis.

In current commercial marine operation software, the vessel and the lumped-mass payloads are normally simplified to be rigid bodies in scenarios where structural flexibility is negligible. Furthermore, structural stiffness contributes to the local vibration and deformation of long structures, such as the crane boom and OWT blades. Multibody dynamics is used to simulate the dynamic system interaction.

Simulating environmental loads is computationally expensive because many simulations are required to calculate the critical environmental conditions in sensitivity studies. Therefore, hydrodynamics and aerodynamics loads are simplified and calculated by RAOs and the cross-flow principle [140–142]. To improve simulation fidelity, many theories have been developed to balance computational efficiency and accuracy when solving the Navier-Stokes equations. Real-time hybrid simulations are powerful when evaluating a complex system. These simulations separate the entire system into two parts, i.e., a numerical component that can be accurately simulated numerically and an experimental component that is difficult to model. Sensors and actuators are used as the interface between these two parts. However, these methods have not been adopted to simulate OWT O&M activities.

4.2.2. Docking operation

After approaching an OWT, a docking operation between a service vessel and an OWT is carried out. This operation uses a simple fender or an active motion-compensated access device. The aim of docking is to transfer personnel and equipment in an efficient and safe way. A passive gangway can also be also used to connect a jackup vessel and an OWT. Since there is no lifting crane on an OWT, typical personnel transfer methods used on oil and gas platforms, such as the Reflex Marine deliver, are not applicable in OWT maintenance.

A fender is the simplest type of docking device and is typically made of rubber or similar materials. The vessel's propulsion system provides a pushing force to keep the bow tightly attached to the tower, relying on friction to control the relative motion. The maintenance crew can then get onto the wind turbine from a ladder [143]. Fenders are inexpensive and easy to install on the service vessels. To improve boarding performance, automated control of air cushion pressure can be used to reduce vertical accelerations at bow [144]. The turbine is assumed to be vertical and rigid. The motions in only three degrees of freedom are taken into consideration, i.e., surge, heave, and pitch. The vessel and turbine interactions are modeled as a linear spring.

Active motion-compensation access devices, i.e., hydraulic gangways, can be installed on service vessels regardless of their size, providing sufficient deck space and weight capacity.These devices can cancel the relative motion of the vessel within the hydraulic system's limits, resulting in a higher working limit than a fender [23]. However, these devices are more expensive than fenders. Compared with heave compensators and DP systems, an active motion-compensation gangway must cancel all six of vessel degrees of freedom, including second-order wave motions [145]. The mechanical system is similar to an industrial robotic arm, but with a larger size and rated power. Due to wave-induced motions, the desired trajectory is calculated based on inverse kinematics and the relative motion between the vessel and wind turbine. Because gangway designs are normally over-actuated, the desired joint rotation angles can be calculated by the pseudo inverse method and other optimization approaches. The relative motion can be measured and estimated through an inertial measurement unit and LIDAR system [146, 147]. Feedback control can be achieved by many control methods, such as a typical linear PD controller with feedforward [148] and a model predictive controller [149]. Several companies have developed motion-compensation gangways that are available on the current market, e.g., Ampelmann, Barge Master, Kenz Figee Group, Royal IHC, Van Aalst Group, SMST, Uptime, ZTechnologies, Osbit, and Lift2Work [150, 151].

Because the docking operation is governed by the interactions of the vessel's structure, swell, and the relative motion of the docking device and the tower, simulating the docking operation and evaluating crew safety and the process of equipment transfer has become an important research topic. When the vessel is equipped with a fender at its bow to access the tower, Brändli et al. [152] presented a comprehensive framework to analyze the docking, in which a partitioned approach is proposed to solve the coupled motion while managing the governing fluid-structure interaction. González et al. [153] combined numerical simulations with experiments to investigate the landing maneuvers of a catamaran vessel. The simulation results were able to quantify the risk of a fender suddenly slipping during docking. König et al. [154] developed a software framework to implement a partitioned numerical solution strategy to optimize service vessel access to an OWT. Ren et al. [142] developed a MATLAB/Simulink toolbox to simulate complex marine operations for control purposes, where the crane module could be used to simulate the gangway. The crashworthiness and damage between several types of ships and different types of OWT foundations was also evaluated [155, 156], wh ere crashworthiness is determined by the mechanical properties of the foundation structures.

Attention must be paid to the risk of collision between maintenance vessels and other commercial vessels that pass close by at high speed, and to the risk of collision between a ship and an OWT. Severe damages can be caused to OWT foundations and to vessels. For example, an oil leak resulting from an oil tanker colliding with an OWT would cause environmental pollution.

Finite element analysis shows that the collision force is affected by the impact velocity, rubber hardness, and rubber thickness [157, 158]. The critical relative motions for structural collisions are found through finite element analysis. Wu [143] suggested that the docking capabilities of service vessels should be considered when evaluating operational limits. A linear frequency-domain method is proposed to assess the docking performance of various vessels employing either a fender or an active motion-compensated access device. Sperstad et al. [159] used such a method to derive multi-parameter wave criteria to analyze accessing systems. A numerical nonlinear finite element analysis method was used to investigate collisions between a vessel and OWTs with monopile or jacket fixed-bottom foundations. For collisions with a monopile foundation, the critical factors were found to be collision energy, the height of the vessel, and the impact area [160]. For collisions with a jacket foundation, vessel speed, and impact area are the dominant factors. Presencia and Shafiee [161] investigated the collisions of maintenance ships with OWTs from another perspective, comparing collision risks in terms of corrective maintenance and preventive maintenance strategies. The probability of occurrence of a collision is related to corrective repair and replacement, and an analysis of the damage magnitude found that collision risk is closely related to corrective replacement activities as part of a corrective maintenance strategy. In contrast to Dai et al. [156], in which considered factors included various external aspects related to the collision, such as personal characteristics of the crew and administrative controls, Moulas et al. [162] examined internal factors that are closely related to the collision and that determines the magnitude of damage, such as collision direction and angle, and type of ship.

A risk assessment is essential to assess the magnitude of the collision risk and to determine the critical factors involved. A specific risk analysis framework involves six main steps, i.e., initial analysis, hazard identification, probability analysis, consequence analysis, risk description and evaluation, and risk reduction [156]. The critical values of force and energy are identified to describe the likely structural damage in each case. Risk-influencing factors are analyzed using Bayesian networks. Based on the energy equation, the critical vessel speeds at which structural damage of the OWT could occur turned out to be very low, indicating that risk-reduction measures are essential.

4.2.3. Lifting operation

Lifting operations are widely used to execute the replacement and maintenance of large-scale OWT components, such as the generators, gearboxes, and blades (Figure 8). Compared with onshore lifting operations, offshore lifting operations are difficult owing to the unpredictable wind and wave conditions. Special, expensive, and sometimes scarce equipment is often required to perform lifting operations.

Offshore service vessels include crane vessels, flat-bottom sheer leg barges, and jack-up vessels [52]. The day rate for lifting equipment for offshore use is at least 10 times higher than that of onshore crane lifting for similar lifting heights because the cranes needed for offshore conditions must be sufficiently over-dimensioned in terms of lifting weight [15]. The trend of the day rate for crane vessels versus hoisting height shows that there is a sudden surge at around a height of 85 m [163]. Therefore, it makes sense to install built-in lifting facilities to reduce height requirements on external lifting equipment when replacing and maintaining large OWT components.

A relatively small built-in lifting device installed on an offshore wind tower from a floating vessel was proposed to reduce the maintenance costs by avoiding the need for a specialized maintenance vessel to replace the gearbox [164]. The crane would be attached to the tower by a clamping mechanism and fixed in position by friction. However, this approach provides only limited lifting capacity and has a limited scope of application. The use of a modified self-propelling jack-up platform is a cost-effective method for the comparatively large wind farms [165]. A crane mounted on one of the legs of the platform could draw itself up to the required working height, and the associated platform can serve as a base for the maintenance crew and tasks as well as a stock store.

Automated control theories were applied to enhance the efficiency of OWT maintenance. For example, an automatic lifting scheme was studied to reduce dynamic tension during lifting and lowering processes [166]. Active tugger line control was also proposed in Ren et al. [167, 168].

The risks related to lifting operations using offshore crane vessels were studied using numerical simulations [169]. As discussed before, the installation's weather window is an important constraint that is imposed during onsite maintenance. Currently, these weather windows are determined using experience-based operational limits; the typical allowable weather limit used in the industry is a 1.5 m significant wave height for crane-assisted lifting operation with a mean wind speed (U_w) below 10 m/s [12, 170]. A more scientific method is required to estimate these limits based on numerical modeling rather than just based on industrial experiences.

A response-based method to assess the operational limits of blade installation using an offshore crane vessel was proposed by [171–173]. The emphasis was placed on collision risk of the hoisted blade with surrounding structures, such as a hub or the turbine tower that could occur due to dynamic motion responses of the blade installation system [174]. A detailed list of factors and collision scenarios that can occur during blade installation was also identified [174, 175], and a blade root impact with the hub was deemed the most critical. For instance, Figure 9 presents different collision scenarios that could occur during the blade root mating phase [176] - a head-on impact that could occur due to misaligned wind-wave conditions; and a sideways impact that could occur due to collinear wind-wave conditions. Global motion responses were used to calculate the impact velocities for the hoisted wind turbine blade for different operational sea states, and damage assessments were performed to evaluate operational limits for blade installation using jack-up crane vessels. A sensitivity study [177] also used a tuned mass damper in the hub to control the vibrations of the hub during installation in the absence of aerodynamic damping. The tuned mass damper was found to be efficient at inhibiting resonance-induced vibrations in top of the tower, reducing impact velocities, while expanding the operational limits and weather window of the task. Other novel lifting operation concepts, e.g., [141, 178], have also been recently proposed. Nevertheless, the technology readiness levels of these concepts are low, and further research is required before they can be applied to onsite maintenance tasks.

4.3. Maintenance of the most vulnerable components

4.3.1. Blade

Due to complex long-term working conditions, OWT blades tend to experience many internal and external damages [179]. Damages include the fatigue failure of materials, wear, corrosion, erosion, and cracks induced by system degradation or deterioration [180]. Environmental conditions can cause damage to blades, both internal and external, e.g., rain/hail/ice, lightning, wave slamming, and wind gusts. For instance, rain causes erosion, which then decreases AEP and eventually leads to damage to the blades themselves [181]. Lightning could also cause splitting of the blade from the tip towards the inside. Blade failures make up a high proportion of all wind turbine failures [182].

Based on a database of 1013 wind turbine blades, the percentage breakdown of damage locations and types clearly shows that the majority of the damage is located on the coating surface and adhesive bonds, whereas the major blade structure damage modes are transverse cracks, spalling, leading edge adhesive bond failure, delamination in load-carrying laminate, sandwich/core debonding, and trailing edge adhesive bond failure [183]. Minor external damages tends to lead to a loss in AEP. Damage inspection and detection can be accomplished by acoustic emission sensors [184], visual cameras [185], tomography [186], and vibration-based estimation using accelerometers [187].

Among all damage types, leading edge erosion which involves the removal of material due to continuous exposure to rain, ice, insects, and dust, is a highly complex problem that degrades turbine performance [188]. As a result, blades are required to be regularly inspected, cleaned, and repair. A typical manual cleaning is conducted by fully stopping the turbine in a low-wind-speed environment. In recent years, automatic blade inspecting and cleaning robots have been developed, such as climbing robots that move along the tower [189], inchworm-type robots that move along the blade [190], and unmanned aerial vehicles [191]. Parallel cleaning was introduced in Deb et al. [192], and an artificial-rain cleaning device from BladeCleaning was equipped on a tower to spray water with detergent. While current technologies require rope access and manual repair of leading edges using solutions such as leading edge tapes from 3M [193], a large emphasis is currently being placed on drone-based applications [194] and robotic-assisted solutions [195]. Given that the current repair and maintenance cost of wind turbine blades requires millions of euros every year, more research and development are required on this topic.

The typical blade maintenance strategy currently is corrective maintenance. However, proactive maintenance becomes feasible with the fast development of various evolution algorithms and structural health monitoring techniques [84, 196]. Blade structural health and the interval between inspections can be estimated by the life-cycle model [196], an optimization model using knowledge-based force analysis [197], a crack length model using the stochastic gamma process [66], and predictive modeling using curve fitting [198].

An optimal opportunistic condition-based maintenance method was investigated in [66], and found that major maintenance needs to be carried out when the crack length in any blade exceeds a given threshold, and preventive maintenance could be performed on the other blades; otherwise, the scheduled preventive maintenance would be carried out for the pre-determined operational age. Optimal values were simultaneously determined by the model to minimize the average long-term maintenance cost per blade per unit time. To be more consistent with the practical operation, a two-level maintenance threshold (the preventive maintenance threshold and corrective maintenance threshold) were proposed [85].

Integrating in-situ structural health monitoring techniques based on acoustic emissions into a condition-based maintenance method have been shown illustrated to be practicable and promising [199, 200]. The knowledge-based methods for load analysis can also be employed to optimize proactive maintenance of OWT blades, which allows for monitoring blade performance in real-time, leading to advanced alarms when needed [197]. This process contributes to scheduling maintenance effectively. A fracture-mechanics-based model for estimating the remaining life of a blade was used for risk-based maintenance to improve the maintenance schedule for the blade lifetime [196]. Nichenametla et al. [198] used predictive analytics to optimize the operational life cycle cost and improve the reliability of the wind turbine blades to reduce maintenance costs. Machine learning was also used to extract blade features in Jiménez et al. [201].

4.3.2. Gearbox

A gearbox increases the rotational speed input to the generator and is the most vulnerable and expensive component of the wind turbine drivetrain due to its high work intensity and complex operation [202]. The gearbox is one of the OWT components with the highest failure rates [203], and its down-tower replacement requires the use of heavy lifting cranes and vessels, which are expensive. Fatigue damage is a major concern; thus, it is important to optimize its maintenance strategy. Increasing the gearbox reliability is particular important, as noted in the Gearbox Reliability Collaborative project, which was found in 2004 [204]. Kang [205] determined a reasonable interval to replace gearboxes to minimize the life-cycle cost of OWT gearboxes and discussed the relationship between transition rates and failure probabilities.

Deng et al. [206] proposed a model of the optimal maintenance interval for a gearbox to maximize its profit per unit time which contributes to the maintenance interval schedule for the preventive maintenance method. Li et al. [202] adapted a nonhomogeneous continuous-time Markov process to manage the gearbox as a multistate degrading system due to its performance degradation to analyze gearbox reliability and develop an optimal maintenance policy. Condition monitoring systems and models have been developed for gearboxes such as the Gaussian process gearbox temperature model [207] and nonlinear state estimation technique model [208]. The monitoring model, which is based on echo state network modeling and the dynamic threshold scheme, uses SCADA vibration data. The gearbox was also verified to improve unsatisfactory detection accuracy and the adaptability of traditional static monitoring methods [209]. A drivetrain vulnerability map can be calculated in numerical simulations according to the accumulative damage hypothesis [210]. Igba et al. [211] proposed using historical failure data for a specific module or subassembly to select an optimum preventive maintenance interval based on minimum maintenance cost and maximum availability to achieve the required reliability. This method was shown to be valid by applying it to the gearbox of a wind turbine.

4.4. Remote O&M and self-maintenance of OWTs

Instead of manned inspection and maintenance, remote O&M of OWTs is a promising solution to mitigate the issue of restricted accessibility caused by the harsh weather conditions and to reduce the number of maintenance tasks [212] and the costs incurred by manned maintenance. A remotely controlled robot prototype was perform inspections and the easiest maintenance tasks inside a wind turbine [213]. This device was tested and found to be reasonable and effective after comparison with manned inspections.

Making full use of system redundancies to decrease downtime is an effective way to reduce the costs of maintenance and energy generation. This concept improves the continuous operation capability of OWTs. Therefore, significant economic value can be gained by the development of fault-tolerant control; maintaining the operation of an OWT, even at a lower energy output, when faults occur in some components can be beneficial. An innovative maintenance system proposed in Echavarria et al. [214] could reconfigure the system or a subsystem to maintain OWT operations even at a reduced capacity, and determined a repair strategy until full maintenance was possible. This method was based on a qualitative approach and consisted of a fault diagnosis system composed of two modules, i.e., a functional redundancy designer and a model-based reasoner. When a fault occurs, the system analyzes the available information and reconfigures alternative components to perform the function of the faulty component. Both modules take advantage of a function-behavior-state model that provides information on potential existing system redundancies. This method forms a foundation for self-maintained wind turbines and is able to optimize the capabilities of OWT components, thereby enhancing system capabilities against faults.

5. Environmental issues

There is no denying that offshore wind farms contribute greatly to reducing reliance on fossil fuels, and wind power is more environmentally friendly than traditional energy resources. However, it is nevertheless associated with some environmental concerns, such as noise pollution, visual appearance, and consequences for nearby wildlife. Although their impact is minor at present, because wind energy is likely to become the main green energy source in the future, this may not always be the case, and there could be serious consequences [215]. Further investigations need to be carried out, and an optimum strategy should be developed for offshore wind farms so that wind energy can become an even more environmentally friendly and sustainable energy resource during its operation life. Noise and visual aesthetics account for about 39% of the total damage (excluding effects on global warming) for onshore wind farms but amount to less than 1% for offshore wind farms [216]. Therefore, only greenhouse gas (GHG) emissions, impacts on wildlife, and waste recycling related to OWT O&M are discussed here.

5.1. Greenhouse gas emission

GHG emissions are a critical environmental issue. According to Wang and Sun [217], the lifetime emission intensity of current wind farms from design to end-of-life is 5.0–8.2 g CO_2/kWh electricity. Regarding O&M, GHG emissions will result from the burning of diesel by the service vessels' engines and from the cleaning, repair, and replacement of OWT components. The required materials and equipment are transported from shore to the assembly base and are then delivered to the wind farm mainly by barges, tugboats, and deck barges. The amounts of CO_2 emitted from coal-, oil-, and gas-fired power plants are 154, 117, and 96 times that of wind power, respectively, with an average emission of wind power of 6.3 g CO_2/kWh. Significant reductions in GHG emissions have thus been achieved. However, with the rapid expansion of offshore wind farms, attention must be paid to the issue of GHG emissions to maintain sustainable development.

Life-cycle assessment was been widely adapted to quantify the relation of energy and environmental impacts within the whole life span of products and services [218, 219]. A process-based life-cycle inventory model has been used to analyze life-cycle environmental emissions [218].

Adopting more efficient maintenance arrangements can effectively reduce GHG emissions that are produced by grid connection and maintenance activities. A large reduction in the GHG produced during transport can be achieved by using alternative shorter transport routes. A case study showed that CO_2 emissions associated with the transport of OWTs and their components could be reduced by 33% with reasonable shorter transport routes; however, the operation only accounts for a very small portion of the emissions [217, 220]. The use of steel and the replacement of OWTs makes up a larger proportion (3% planned, 47% unplanned) of the GHG emissions during operation compared to vessel transportation [221]. Of this amount, approximately 33% of the GHG emissions results from the use of specialized vessels in the replacement of large components, while CTVs and helicopters account for only a minor part. A large percentage (46%) comes from the production and decommissioning of lubricants and spare parts.

During maintenance, failure rates are directly related to GHG emissions, because they determine the need for transportation and consequently affect fuel consumption. Arvesen and Hertwich [222] noted certain obstacles to future life-cycle assessments of wind power generation, including the lack of knowledge of toxic materials emitted, inadequate considerations of the details of the offshore wind farm operation, and insufficient experience of replacement of components. Greater attention must be paid to these factors to optimize the life-cycle environmental assessments and maintenance scheduling of offshore wind farm O&M.

5.2. *Effects on marine wildlife*

The effects of offshore wind farm operations on marine wildlife, e.g., fish, marine mammals, and seabirds, cannot be neglected. Sensitive creatures like cod and herring can detect piling noise at great distances (perhaps up to 80 km from the sound source), and dab and salmon are also sensitive to pile-driving pulses [223]. Their behaviors can thus be influenced by the presence of OWTs. Although the noise generated by normal turbine operation cannot be heard at water depths below 20 m [224], it has been found that this noise does have the potential to influence the physiology and behavior of harbor porpoises and seals at considerable range. Leaked oil and other waste during component replacement operations and from lubrication during maintenance are harmful to the wildlife [225]. The effects on birds resulting from OWT O&M include flight-route changes due to the visual stimulus provided by the turbines, physical habitat changes, and growing mortality rate resulting from collisions with the rotating blades or other superstructures [226]. Furthermore, transportation by boat or helicopter associated with maintenance may displace the activity space of birds. Therefore, more environmentally friendly designs should be investigated in future research.

5.3. *Waste inventory recycling*

Waste inventory happens in every stage in the life cycle of an OWT, i.e., transportation, installation, O&M, and disassembly and decommissioning. In this review, we focus on the waste that is produced during maintenance.

Among all OWT components, blade waste recycling and reuse are the most important topics [227–229]. The blades are made from composite materials, which are energy-intensive to manufacture and environmentally problematic. Therefore, the disposal and recycling of broken blades represent valuable research topics. Blade waste is predicted to significantly increase in upcoming decades; there is a clear linear trend between blade mass and power rating [227].

Blade recycling is achieved by mechanical, thermal, chemical approaches, e.g., decomposing the waste into other recyclable materials or raw materials for secondary use [229].

6. Discussion and conclusion

Maintenance of an offshore wind project is a broad topic. The cost of maintenance makes up a larger part of the total energy generation cost compared with onshore wind power. In this review, we present the state-of-the-art development of OWT maintenance with regard to strategy selection, schedule planning, onsite operations, and environmental threats. Analyzing the maintenance of OWTs and optimizing the procedures involved contribute to describing the status quo of offshore wind power. The major challenges of OWT maintenance include long distance from shore, weather uncertainty (including wind and wave conditions), a lack of information from remote monitoring, unpredicted failures, aging, and subjective factors (such as technicians' skills). Research in OWT maintenance involves a higher level of uncertainty and complexity to make calculations and analyses resemble reality more accurately. The core problem of OWT maintenance is to ensure operational safety, enhance economic profits, lower the LCOE, and minimize negative effects. Significant amounts of theoretical innovations and technical advancements have improved every aspect of OWT maintenance in the recent decades.

As the scale of offshore wind farms expands rapidly, a corrective maintenance strategy is no longer suitable and is gradually being replaced by proactive maintenance strategies. These strategies primarily involve preventive maintenance based on a predetermined period, together with condition-based maintenance based on the use of a condition monitoring system to supervise the health. Preventive maintenance strategies can be optimized by (1) optimizing the selection of the predetermined interval according to the failure probabilities of various components; (2) taking the opportunity to carry out preventive maintenance by replacing or maintaining faulty parts in the meantime; (3) dividing components into different age groups and applying the corresponding preventive maintenance tasks; and (4) employing queuing theory to determine the maintenance waiting time and carry out preventative maintenance according to the chosen maintenance priority. Condition-based maintenance strategies can be improved by (1) combining them with a risk-based life-cycle approach to monitor the degree of deterioration and thereby increase the reliability of prediction; and (2) carrying out condition-based maintenance according to the alert threshold of a given type of deterioration. Opportunistic maintenance strategies combine these maintenance strategies. However, it is very difficult to decide on the best maintenance strategy since the selection always yields corresponding optimal scheduling problems. To evaluate the safety and economy of scheduling, several assessment methods have been proposed, including economic assessment and risk assessment.

To carry out maintenance efficiently, maintenance tasks must be scheduled based on simple proper route planning and more complicated scenarios. Route planning for OWT maintenance has been achieved with one or multiple O&M bases by considering available crews and spares, as well as the capacity of the mode of transport. The aim of optimum route selection is simpler, i.e., highest efficiency and minimum transport cost, as well as reduced GHG emissions. Optimal scheduling should consider several more topics, including minimizing downtime, maximizing revenue, improving system reliability, and realizing cooperation among maintenance teams. The first step is to quantify the problem, and numerical deterministic and probabilistic models are used to describe the process. The scheduling problem can be converted into an optimization problem with a number of cost functions and constraints. According to the cost function, the problem can be further categorized into single-objective or multi-objective optimization problems. Cost, reliability, or their combinations makes up the cost functions. Maintenance strategies have been improved to cope with the limited weather window due to harsh offshore environmental conditions and thereby achieve high availability and reduce revenue loss caused by downtime. The complexity and reality of optimal scheduling algorithms has increased gradually. However, existing models still have their limitations. In addition, more practical, uncertain, and complex operations are still not considered.

Onsite maintenance is the next step after the scheduling, and is markedly different from that of an onshore turbine. First, unpredictable weather conditions limit the transport of crews and equipment and impose more stringent requirements on the modes of transport. Moreover, an extra docking operation is required, and docking devices have been reviewed in this paper, including active motion-compensated access devices and simple fenders. The risk of collision between service vessels and the turbine should be accessed while evaluating the importance of various critical factors related to collisions. The requirements for lifting operations are stricter for OWTs due to irregular wave heights. Specialized and expensive lifting equipment are often required, whose daily rates are considerably higher than for onshore lifting to similar heights. A built-in lifting device has been proposed for installation on OWT towers to reduce the height through which external cranes need to lift large components.

Numerical simulations are powerful tools to evaluate and predict the performance of onsite operations during planning. The critical impact velocity was found through finite element analysis, and the environmental limitations are calculated based on time-domain multibody dynamics simulations and FEM results. Both modeling approaches were based on a series of simplifications. FEM modeling only considered the instant impact, which is characterized by the impact area, impact speed, and impact direction. To ensure the computational speed, multibody dynamics models are commonly considered under the rigid-body assumptions. The flexible structures, such as the towers, blades, and wire ropes are simulated by one or a number of connected lumped-mass nodes. Wave-induced loads are also simplified to be a group of transfer functions, namely, response amplitude operators. Higher-fidelity simulations could be achieved by including computational fluid dynamics and aerodynamics [230–232].

The maintenance of OWTs can be optimized from two perspectives. One approach is to improve onsite maintenance by increasing the ability to predict the weather windows, which is fundamental for arranging onsite maintenance. The other approach is to replace onsite maintenance by remote-controlled maintenance through robots installed inside the tower to carry out simple maintenance tasks or to take advantage of redundancies in the system to maintain the operation of the wind turbine, even at a reduced capacity and thereby reduce maintenance frequency. Both perspectives require developments in data-collection capabilities.

The important environmental issues arising from OWT maintenance include GHG emissions and effects on wildlife. Improving route planning for transportation and employing reusable materials have been proposed to reduce GHG emissions. With regard to effects on wildlife, no suitable approach has been proposed. The recycling and reuse of OWT components are also of concern. The environmental issues related to the maintenance of OWTs, therefore, cannot be neglected.

The research on OWT maintenance has coevolved and accumulated with the technical advances and theoretical innovations in all relevant realms. The LCOE is gradually reduced by these technologies and their applications, which intensifies the market competition of offshore wind energy.

- Newly developed supply vessels and onboard equipment can improve the reliability and operational efficiency of maintenance tasks. Straightforward methods include improving wave and wind resistance, which could result in better accessibility and onsite operations in more strict offshore environmental conditions, yielding longer workable weather window for a specific operation and longer available maintenance time year-round for long-term planning. Hence, the maintenance costs, as well as the LCOE, are reduced due to the smaller number of required vessels and technicians.

- However, the involvement of specialized equipment increases the capital intensity of OWT maintenance. The scale and price of the devices increase with their sizes and OWT weights; for example, larger supply vessels, higher cranes, and more powerful tugboats have been developed and deployed. Owing to these challenges, the financial safety of the wind power industry is at risk and making companies less resistant to global economic fluctuations. Hence, accomplishing maintenance tasks with the cooperation of small-scale and commonly used equipment is a valuable issue.

- Given that the scales of offshore wind farms are growing, and equipment is becoming more effective, there is a major trade-off between renting and buying O&M services. Maintenance planners should evaluate many factors when deciding the percentage of self-operated maintenance, including budget and liquidity, outsourcing agreement, the occurrence of emergencies, scheduling flexibility, technique and management levels, and strategy selection.

- The quantification of environmental impacts might be itemized into LCOE and introduce extra costs. All O&M activities are influenced by climate and weather. Based on historical data and weather forecasts, this uncertainty could be minimized. However, a wind-farm planner should estimate the equivalent cost that the operator might encounter before the farm is designed, which can aid grid penetration in terms of cost competitiveness.

- Additional offshore technologies (e.g., service platform and unmanned system) might be developed to optimize future O&M processes. Although the automatic systems have significantly improved O&M efficiency, there is much more work to be done to enhance the levels of automation and intelligence in future research and applications. Before achieving fully intelligent operations, human operators must supervise and make crucial decisions. Hence, human-machine interaction and remote operations are meaningful. Therefore, unmanned or partly unmanned O&M exhibits along a significant potential to reduce human resource cost, resulting in a lower LCOE.

- An O&M friendly wind turbine design should be proposed to reduce O&M costs and the LCOE, although a wind turbine's capital cost might increase. For example, hydraulic transmission reduces the height of the drivetrain resulting in more efficient maintenance. The section of the tower that is Near water surface could also be redesigned for tug accessibility.

- Numerical simulations are widely used in onshore planning and onboard decision making. Simplified logistic models have been used to verify the proposed optimal scheduling approaches. Both FEM modeling and multibody dynamics modeling have investigated the criteria of the maintenance operations, such as docking, lifting, and mating operations. Compared with rigid-body dynamics, high-fidelity simulations could be achieved with more accurate modeling approaches, such as real-time computational fluid dynamics.

- Due to reductions of sensor prices, a more complete and precise image of OWT operational conditions could be built into maintenance planning and execution periods. System behaviors could be measured and predicted more accurately. Measurement availability, reliability, and accuracy improve with the development of data science, sensor fusion, and remote communication. A digital-twin platform was adopted to predict future performance and possible failure, combining the numerical models and various sensor data. In addition, large quantities of gathered data promote the development of both onshore and onboard decision support systems. State-of-the-art algorithms are of significant interest to analyze and utilize the collected data, such as via big data and machine learning approaches. The prediction of short-term weather and long-term climate conditions is useful in the operational and maintenance planning stages.

- Automatic control theories improve the operational efficiency of OWT maintenance. Currently, there are many studies of the autonomous systems applied during OWT maintenance, such as dynamic positioning systems, climbing robots, heave compensators, and actively controlled tugger lines. Automatic systems exhibit remarkable potential for unmanned maintenance in the future. The system redundancy can be improved by using fault-tolerant control.

Overall, this review provides a systematic knowledge set for wind farm operators and researchers, and provides guidance and suggestions to policy decision-makers and technology developers. Additionally, some information will be useful for related sister technologies such as tidal current energy farms and wave energy farms, which are being readied for commercialization but for which only a handful literature are available [233, 234].

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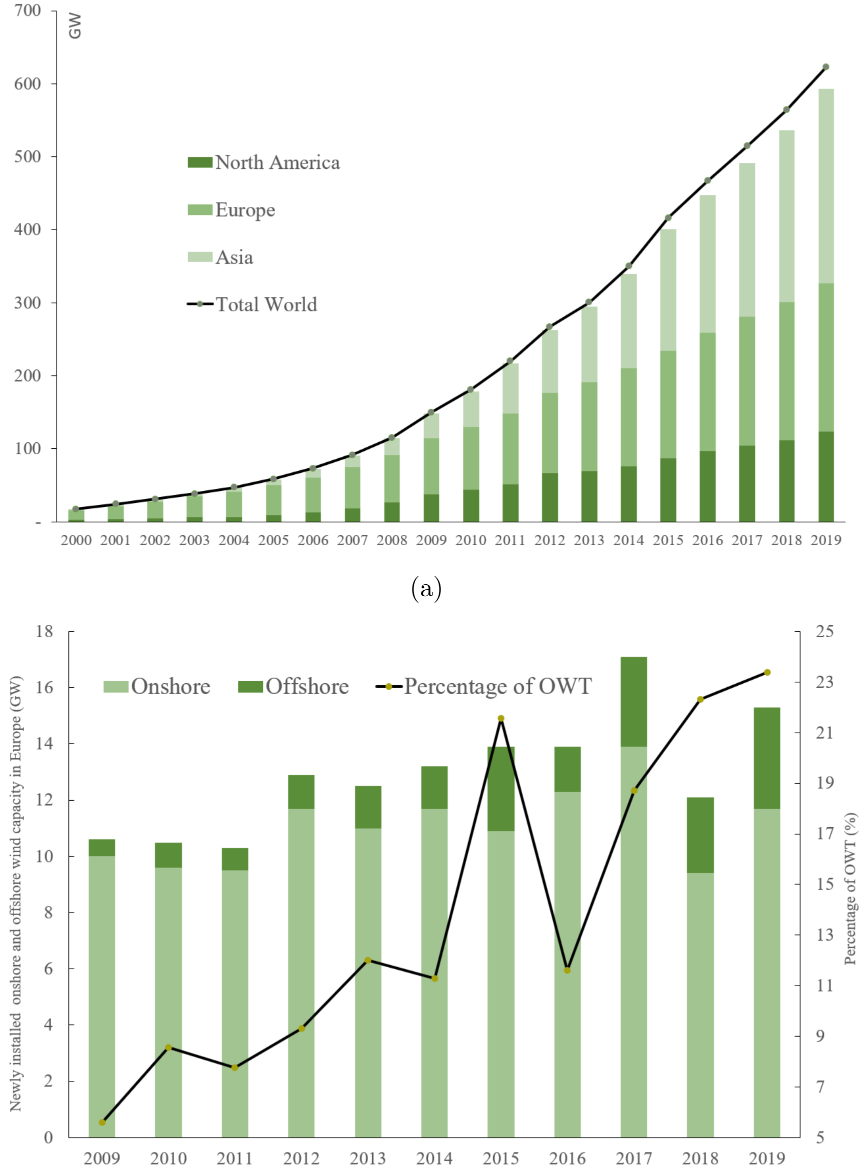


(a)

(b)

Figure 1: (a) Global wind capacity (data sourced from [6]) and (b) newly installed capability in European countries and the percentage of OWT between 2009–2019 (data sourced from [7, 8]).

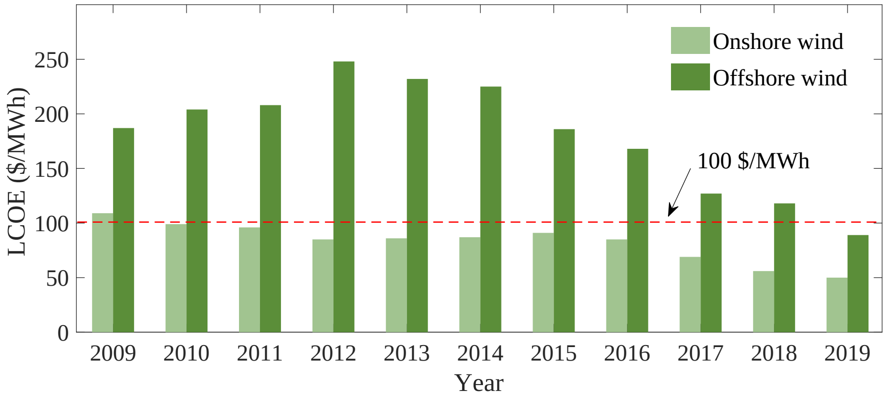


Figure 2: Comparison of LCOE for onshore and OWTs between 2009–2019 (data sourced from [11, 12]).

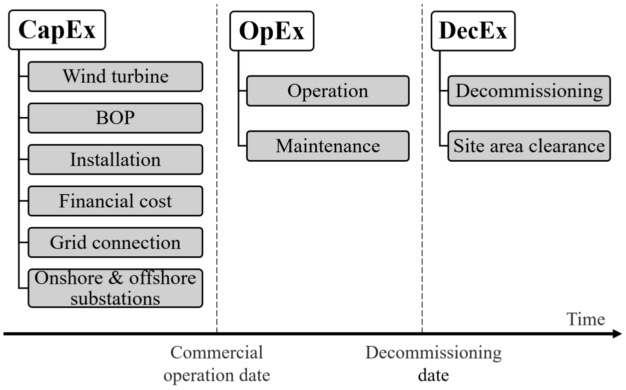


Figure 3: Cost breakdown of a floating wind turbine (sourced from [16, 17]).

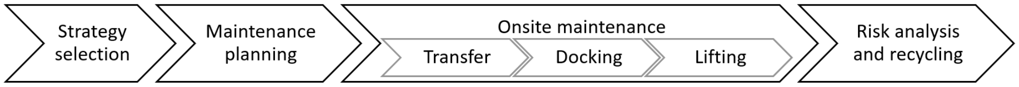


Figure 4: Development of maintenance strategies for an offshore wind farm.

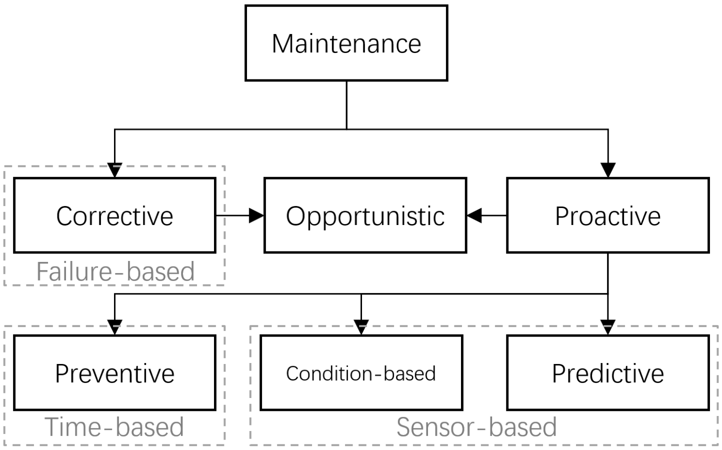
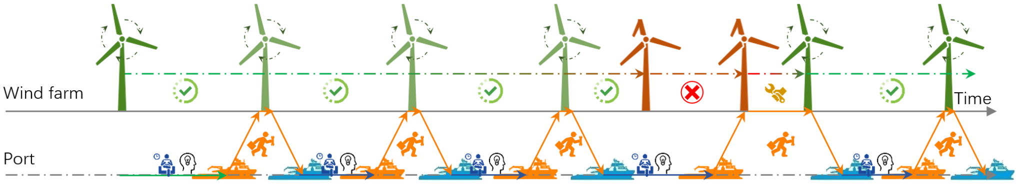
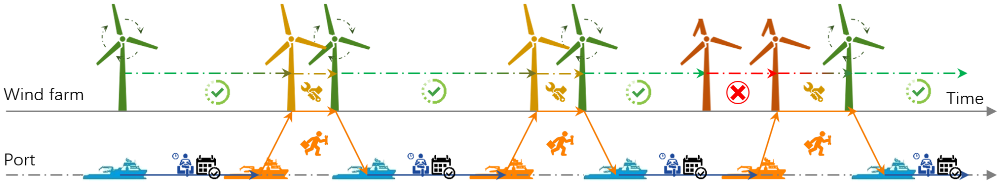


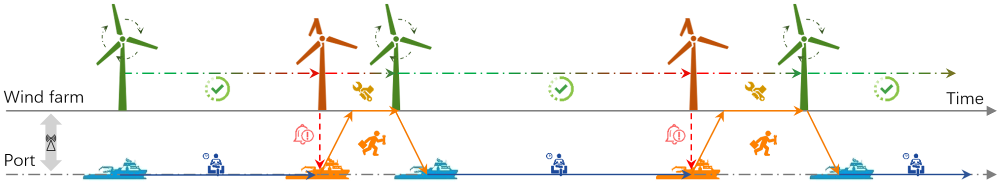
Figure 5: Classification of maintenance strategies.



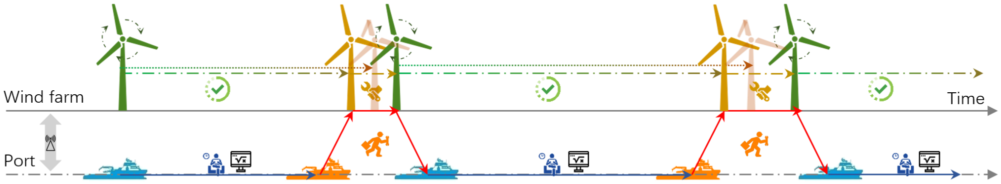
(a) Reactive maintenance



(b) Preventative maintenance



(c) Condition-based maintenance



(d) Predictive maintenance

Figure 6: Diagrams of maintenance strategies (The green, red, and yellow colors denote the normally operated OWT, the stopped OWT due to failures, and the stopped wind turbine due to maintenance, respectively. The blue and orange colors stand for the waiting maintenance vessel and the vessel performing tasks, respectively.).

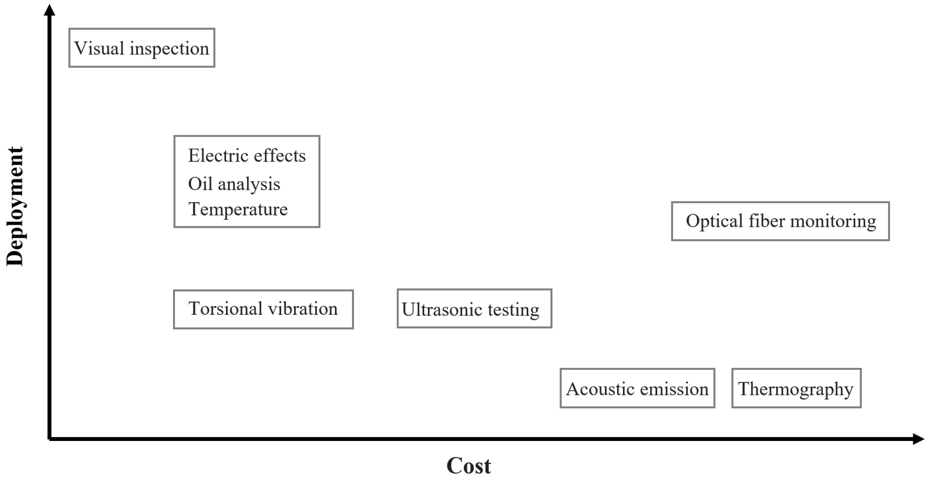


Figure 7: Costs and deployment levels of different wind turbine condition monitoring techniques (sourced from [56, 63, 64]).

Figure 8: Lifting operation [courtesy by Mrs Eva Boeckling of DEME].

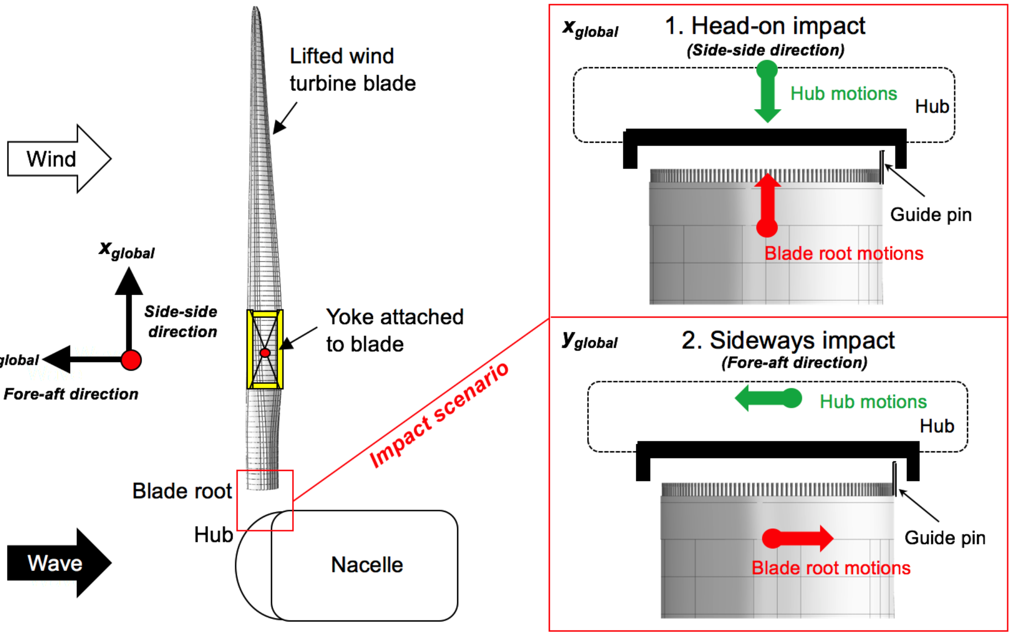


Figure 9: Blade root impact scenarios [175].