An integrated condition-based opportunistic maintenance framework for offshore wind farms

Jiaxuan Luo[1], Xiaofang Luo*[1], Xiandong Ma*[2], Yingfei Zan[3], Xu Bai[4]

1. School of Economics and Management, Jiangsu University of Science and Technology, Zhenjiang 212003, China

2. School of Engineering, Lancaster University, Lancaster, UK

3. College of Shipbuilding Engineering, Harbin Engineering University, Harbin 150001, China

4. School of Naval Architecture & Ocean Engineering, Jiangsu University of Science and Technology, Zhenjiang 212003, China

Abstract: The maintenance strategies commonly used in offshore wind farms may lead to under-maintenance or over-maintenance activities. To address this issue, this paper proposes an integrated condition-based opportunistic maintenance (CBOM) framework for the offshore wind farm, to balance the maintenance cost and component condition. Component health index (HI) is calculated based on the P-F (potential failure to functional failure) intervals to divide the component health stages, and the component type with the highest proportion in the operation and maintenance (O&M) cost is selected to determine the maintenance time window for multiple components. A maintenance priority index (PI) is calculated by the data envelopment analysis method (DEA) to determine the maintenance mode and sequence of individual components. The component with the lowest maintenance cost rate is selected by an exhaustive search algorithm (ESA) to reduce the total O&M cost in one maintenance action. Finally, a case study is carried out to demonstrate the feasibility of the proposed framework with the specific calculation process, and a comparison analysis is given. The results show that the proposed framework is an effective method for balancing the O&M cost against condition for the offshore wind farms.

Keywords: Maintenance framework; Offshore wind farms; Condition-based opportunistic maintenance; Maintenance cost; Component condition

1 Introduction

Wind energy has been a prominent renewable energy source in recent decades, with its share in the total energy output experiencing rapid growth. Due to the increasing

*Corresponding author.
E-mail address: luoxiaofang@just.edu.cn (X. Luo); xiandong.ma@lancaster.ac.uk (X. Ma).

scarcity of land resources for onshore wind development, offshore wind power has garnered significant attention in the wind energy industry for its abundant wind resources, high power generation efficiency, minimal land occupation, and reduced noise pollution. According to the Global Wind Report 2024, the global cumulative installed capacity of offshore wind power increased from 8 GW in 2014 to 75 GW in 2023, representing an annual growth rate of approximately 28.2% (see Fig.1) [1][1]. The global installed capacity of offshore wind power is expected to reach 270 GW by 2030 and surpass 2,000 GW by 2050 [2]. To ensure the long-term and sustainable wind power operation, effective operation and maintenance (O&M) activities are essential, which can improve the reliability of wind power systems and reduce O&M costs [3][4][5]. Due to the continuous expansion of offshore wind farm deployment, more complex and demanding challenges are brought to their O&M activities.

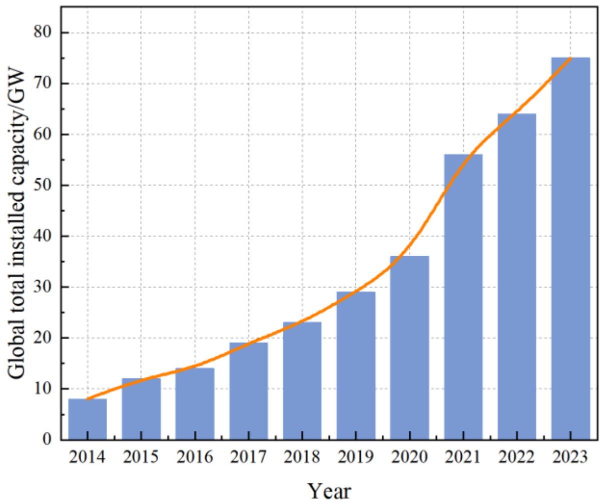

Fig. 1. Global total installed capacity of offshore wind power

Compared to onshore wind farms, offshore wind farm maintenance encounters numerous challenges. Due to prolonged exposure to humid and salty environments, the availability of offshore wind turbines is significantly lower than that of the onshore wind turbines. Typically, the availability of onshore wind farms ranges from 95% to 99%, whereas for offshore wind farms, it is estimated to be between 60% and 70% [11][6]. Furthermore, the remote location of offshore wind farms makes the O&M activities more difficult and expensive. Offshore wind farms are influenced by the surrounding wind and wave conditions, leading to greater volatility and randomness in the maintenance time windows [7]. When wind and waves surpass the safety threshold of the O&M vessel, maintenance tasks must be postponed, potentially resulting in longer maintenance waiting times and greater power generation losses. The lease or purchase of special O&M vessels and tools will increase the total O&M cost. Furthermore, the cost of installing and maintaining offshore wind turbines is much higher than that of the onshore wind turbines. Therefore, development of the cost-effective maintenance methods is crucial to maintain the success of offshore wind power [8].

To understand the current state-of-the-art maintenance strategies of offshore wind farms, we have performed a literature review on this topic, as summarized in Table 1. In the table, maintenance strategies are categorized in terms of strategy type, strategy level, and strategy composition.

Table 1 Literature review on the maintenance strategy of offshore wind farm

Literature		[12] **Error! Reference source not found.**	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	Our paper
Strategy type	CM			√	√	√	√	√				
	PM			√	√		√	√				
	OM	√	√							√	√	√
	CBM	√	√		√	√		√	√	√		√
Strategy level	Component level	√					√	√				
	Turbine level				√	√					√	
	Farm level		√	√					√	√	√	√
Strategy composition	Time/condition threshold	√	√	√	√	√	√	√	√	√	√	√
	Mode	√	√	√	√		√	√		√	√	√
	Sequence											√
	Components to maintain											√

A good maintenance strategy can ensure the reliable operation of offshore wind turbines and improve the economic competitiveness of offshore wind power. Existing maintenance strategies of offshore wind power can be broadly categorized into two types, namely corrective maintenance (CM) and preventive maintenance (PM) [9]. CM is a run-to-failure strategy carried out to restore the equipment to a normal operational state as quickly as possible [10]. PM usually refers to a periodic maintenance, that is, maintenance activities are carried out at the same time interval. Compared to CM, periodic maintenance cannot avoid unnecessary inspection and maintenance activities, although it has the advantage of effectively ensuring the system's reliability and power output [11]. And, the periodic maintenance is a maintenance strategy that has been obtained before the maintenance is implemented, and the strategy will not be dynamically adjusted according to the condition of the component or wind turbines. Considering the high O&M cost, periodic maintenance needs to be further optimized. Therefore, there is an urgent need for a maintenance strategy that runs through the implementation of the maintenance strategy and can be adjusted step by step based on the condition of the components or wind turbines at each moment.

In recent years, more advanced maintenance strategies such as opportunistic maintenance (OM) and condition-based maintenance (CBM) have emerged. Owing to its rapid advancement of continuous monitoring technologies, CBM has garnered increasing attention in the O&M of offshore wind turbines [20][22][23][24][25]. As a maintenance strategy, CBM integrates a data-driven approach with a condition monitoring system installed to assess the condition and degradation process of the wind turbines [26]. CBM has demonstrated its effectiveness in preventing unplanned failures and its superiority in reducing operational costs compared to traditional age-based or calendar-based PM maintenance practices [27]. Furthermore, opportunistic maintenance (OM), which emerged in recent years, has attracted extensive interest from academia and industry [22][28][29][30]. The offshore wind turbine is a typical multi-component system. Conducting maintenance on one component may create an opportunity to address other components eligible for maintenance activities within the wind farm [31]. This integrated maintenance approach reduces costs compared to individual component repairs, particularly when the expense of dispatching a maintenance team to the site is high. Cost is a fundamental factor considered by OM, with maintenance being scheduled often based on the operational condition or reliability level of the components [32]. This motivates the integration of CBM and OM, leading to the proposition of a Condition-Based Opportunistic Maintenance (CBOM) strategy. CBOM combines the strengths of both CBM and OM by considering not only the condition of each component but also maintenance opportunities for other components before one component fails. Maintenance strategies, which incorporate maintenance opportunities and component conditions, have gained increasing attention and hold promising applications, expanding from the individual component [12] to the entire onshore/offshore wind farms [13]. Our paper will therefore use CBOM as the target strategy framework to achieve a balance between the condition of components or wind turbines and the O&M costs.

The maintenance decisions of wind farms have been investigated based on component-level, turbine-level and farm-level [33]. Due to the long-term and high-intensity operations, crucial components, such as blades and gearboxes, often suffer from various damages [34]. Many scholars have investigated the maintenance strategy for individual components, such as [12][17][18], where each component is considered to be independent and the possible dependencies between components are ignored. On the contrary, the maintenance strategy at turbine level considers that the crucial components have a random dependence between each other. When optimizing maintenance decisions, ignoring component dependencies will lead to suboptimal solutions or even wrong solutions to the problem. Since the turbine is regarded as a series reliability system, any component failure in the system will cause the entire system breakdown. The maintenance strategy at wind turbine level have been studied in [15][16][21]. However, component-level and turbine-level maintenance strategies often focus only on their respective levels of condition, and are adjusted based on the condition of a single component or a single wind turbine. This may lead to a lack of comprehensive consideration of wind farm condition when formulating maintenance strategies. In the existing literatures, the maintenance strategy at farm level usually considers maintenance time window, maintenance threshold and maintenance mode [13][14][20]. However, there is no literature reporting the maintenance strategy of offshore wind farms involving determination of the priority of component maintenance to achieve multi-turbine maintenance activities. A comprehensive maintenance framework at farm level is therefore required to determine the maintenance time window, the maintenance priorities of components from different wind turbines and components that need to be maintained in a single dispatch.

Based on the discussions above, this paper proposes a novel maintenance framework for the offshore wind farm to achieve the goal of minimizing O&M cost while maintaining a high system availability. The contributions of this study can be summarized as follows:

(1) An integrated CBOM framework is proposed for the offshore wind farm, including the determination of maintenance time window, mode, sequence, and component to maintain. This framework forms a closed loop of offshore wind farm

maintenance so that the maintenance strategy can be dynamically adjusted step by step according to the condition of the components or turbines.

(2) Component health index (HI) is calculated based on the P-F intervals to divide the component health stages, and the component type with the highest proportion in the total maintenance cost is selected to determine the maintenance time window for multiple components.

(3) A maintenance priority index (PI) is calculated by the data envelopment analysis (DEA) method to determine the maintenance mode and sequence of components from different turbines.

(4) The component combination with the lowest maintenance cost rate is selected and optimized by an exhaustive search algorithm (ESA) to reduce the total O&M cost.

The rest of this paper is organized as follows: In Section 2, an integrated CBOM framework for the offshore wind farm is proposed, with the related concepts and methods being introduced. In Section 3, a case study of an offshore wind farm is presented, which presents the process of the P-F curves acquisition, the single-component maintenance results, and the optimization results of combined multi-component maintenance. In Section 4, a comparative analysis of existing offshore wind farm maintenance strategies is presented. The adaptability of the framework proposed in this paper is further discussed in Section 5, followed by the conclusions in Section 6.

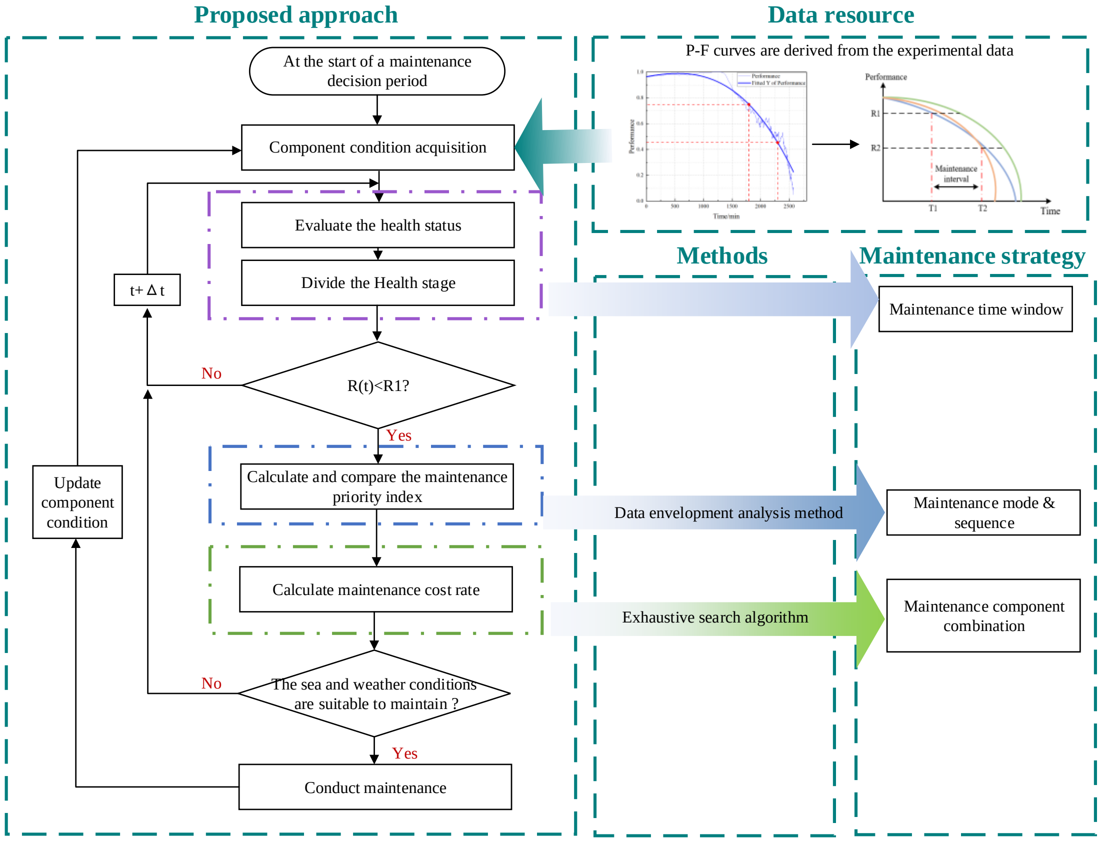

Fig. 2. The proposed maintenance framework

2 Proposed approaches

To address the issues in the current maintenance framework of offshore wind farms, such as inadequate maintenance structure and suboptimal effectiveness, this paper introduces an integrated CBOM framework to achieve the goal of the lowest maintenance cost and the highest availability. The critical steps in the framework are described as follows. Firstly, the component HI is proposed and calculated to evaluate multi-component operating states by utilizing P-F intervals, and the component type with the highest proportion in the total maintenance cost is selected to determine the maintenance time window for multiple components. Then, a maintenance PI is constructed and calculated by DEA to determine the maintenance mode and sequence of the individual components, taking into account a balance of cost and condition. Ultimately, to reduce fixed costs within the O&M cost, it is recommended to maintain multiple components during each maintenance outing operation. To solve this problem, the objective of minimizing the maintenance cost rate is set to select the optimal component combination, and an exhaustive search algorithm (ESA) is thus employed to identify the optimal component combination. Section 2.1 presents the relevant assumptions in the framework. Section 2.2 describes the three critical steps in the maintenance framework, i.e., determination of maintenance time window, determination of maintenance mode and sequence, and optimization of maintenance strategy. Section 2.3 presents the relevant concepts and methods used in the framework, including DEA and ESA. The proposed integrated CBOM framework is shown in Fig.2.

2.1 Assumptions

This paper considers an offshore wind farm comprised of m identical turbines. The turbines operate independently in the system, and the failure of any of the turbines will not affect the normal operation of the other turbines. Each turbine contains n components, which belong to different types. Assume that the total number of components in the system is N. All components in the turbines can be restored to full functionality through a single maintenance outing. Component matrix Q is constructed in Eq. (1). $\{A, B, C, \ldots\}$ represents the turbine in the offshore wind farm. $\{A_1, A_2, \ldots A_i, \ldots, A_n\}$ represents the component in the turbine A. $\{A_1, B_1, C_1, \ldots\}$ represents the first same type of component in different turbines. Component existence factor a_{ij} is introduced, indicating whether ith component is present in the jth turbine, where $i = 1,2,3, \ldots, n$ and $j = 1,2,3, \ldots, m$, as shown in Eq. (2).

$$Q = [A, B, C, \ldots]^T = \begin{bmatrix} A_1 & A_2 & \ldots & A_i & \ldots & A_n \\ B_1 & B_2 & \ldots & B_i & \ldots & B_n \\ C_1 & C_2 & \ldots & C_i & \ldots & C_n \\ \vdots & \vdots & \vdots & \vdots & \ldots & \vdots \end{bmatrix}_{m \times n} \tag{1}$$

$$a_{ij} = \begin{cases} 0, & j\text{th turbine does not contain } i\text{th component.} \\ 1, & j\text{th turbine contains } i\text{th component.} \end{cases} \tag{2}$$

Failure of any type of components will render the entire turbine inoperable. The turbines and components involved in the system are brand new at the beginning of the operation and after some time they inevitably experience condition degradation. The degradation will result in a reduction in the amount of power generated by the turbine. Therefore, timely and effective maintenance action must be taken to improve the efficiency of wind power generation. Considering the complexity and variability of the actual maintenance action in the offshore wind farm to simplify the calculation and ensure the adaptability of the proposed maintenance framework, the following assumptions are made. Some of them are cited in the literature, such as [35], [36], [37].

(1) The maintenance modes in this strategy are divided into two categories: minor repair and replacement. A minor repair can restore the condition of the component to a certain extent, while replacement can restore the component as well as a new one.

(2) Due to different degrees of recovery, the cost of minor repair and replacement is also different. The minor repair cost can be calculated according to a certain proportion of the replacement cost.

(3) Maintenance actions are unable to change the degradation path. The degradation path is regarded as an inherent characteristic of each component that remains unaffected despite the maintenance interventions.

(4) Various maintenance resources, such as spare parts, maintenance tools, and maintenance personnel, are ready in place to perform maintenance actions during the maintenance time window.

(5) Maintenance cycles are long enough to carry out maintenance actions.

2.2 A novel approach framework

2.2.1 Method for determining the maintenance time window

When carrying out maintenance actions on offshore wind turbines, the difficulty lies in the need to balance O&M costs against the condition of wind turbines. Too frequent maintenance may increase the total O&M cost and be a waste of the remaining useful life of the components, while too long maintenance intervals may lead to an increase in the turbine failure rate and a decrease in the condition of the whole offshore wind farm [38]. To address this issue, the P-F intervals of each component are first utilized to obtain the initial maintenance time window of multiple components in this section. Then, considering the differences in the O&M costs among various component types, HI is constructed and the health stages of components are classified to select the component type with the highest proportion in the total O&M cost. Finally, the initial maintenance time window and the maintenance time window for the selected component type in Stage 2 intersect to determine the common maintenance time window for the multi-component maintenance plan. The O&M operators of the offshore wind farms can perform maintenance actions within such a time window, taking into account the sea conditions.

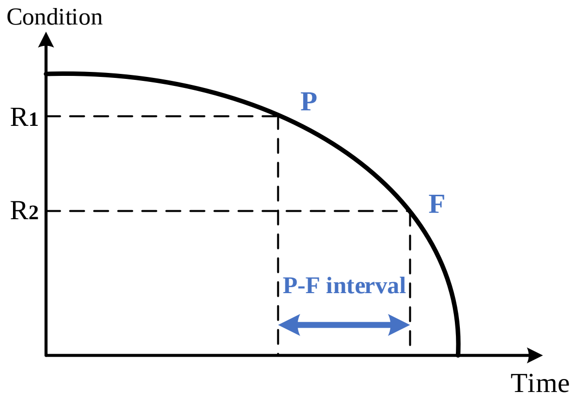

Fig. 3. A typical P-F curve

2.2.1.1 Component health index

The P-F curve was first proposed by Moubray in the 1990s, mainly in the context of reliability-centered maintenance (RCM) [39]. The term "P-F curve" is derived from its ability to identify the point at which the failure of monitored equipment becomes detectable. This specific point is called the potential failure point P in Fig.3. After this point, the condition of the equipment gradually degrades until it reaches the point where it finally completely loses its expected function, which is called the functional failure point F. In this paper, the maintenance thresholds corresponding to P and F points are named potential fault threshold R_1 and functional fault threshold R_2, respectively, as shown in Fig.3. The time interval between the P point and the F point is called the P-F interval. When formulating a maintenance strategy, the maintenance time should be set within the P-F interval to reduce the downtime caused by the failure of equipment or components, and to make full use of its useful life. The P-F interval can be estimated based on reliability, maintenance records, and expert empirical judgment, particularly for novel equipment [40]. The development of this kind of condition degradation and damage accumulation curves is based on several experiments, which should then be statistically processed to characterize the conservative curves for design purposes and to further support maintenance-related decisions.

Before performing maintenance on multiple components, the P-F intervals of multiple components need to be combined to obtain the initial maintenance time window for simultaneous maintenance of multiple components. First, the minimum time corresponding to the P point of multiple components is taken by the earliest time of the initial maintenance time window, denoted as t_1. Similarly, the minimum time corresponding to the F point of multiple components is taken by the latest time of the initial maintenance time window, denoted as t_2. Thus, the initial maintenance time window (t_1, t_2) for multiple components is obtained to ensure that the components with poor condition can be maintained before failure. To illustrate clearly, an example is shown. The P-F curves for components A, B, and C are shown in Fig.4. Here, threshold R_1 and R_2 are set to 75% and 45%, respectively. Therefore, the time corresponding to the P-points of components A, B, and C is 54 d(day), 62d, and 67d, and the time corresponding to the F-points is 83d, 85d, and 91d, respectively. Thus, the initial maintenance time window for these components is (54d,83d).

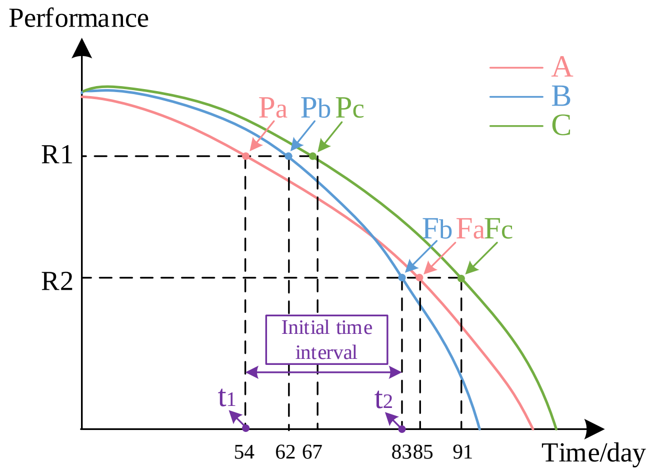

Fig. 4. An example for illustration of the initial time window

To accurately assess the condition of each component, HI is introduced, which is calculated in Eq. (3).

$$HI_{ij,T} = \frac{P'F_{interval_{ij,T}}}{PF_{interval_{ij,T}}} \tag{3}$$

where $HI_{ij,T}$ is the health index of ith component in the jth turbine at time T, $P'F_{interval_{ij,T}}$ is the duration of ith component from time T to the point F, and $PF_{interval_{ij,T}}$ is the length of P-F interval for ith component. HI enables the assessment of the condition of components characterized by different P-F curves. According to the value of this index, potential failures or abnormal conditions can also be promptly detected.

2.2.1.2 Component health stage

For this paper, three health stages are defined based on the HI, ranging from 0 to 1, which is healthy, good, and soon-to-fail, as illustrated in Table 2 [41]. To provide an intuitive example, let us consider a hypothetical case where the P-F interval for component A is 5 years, and for component B is 3 months. To quantize the health condition of the components, if sensor-monitored data suggest that at a certain time, component A has 1 year left and component B has 1 month left, the HI is 0.2 in case A, while it is 0.33 in case B, as calculated by Eq. (3). Thus, depending on the health stage division criteria, components A and B will both be categorized into the same stage: soon-to-fail.

Table 2 Health stage

Health stage	HI value	Condition
Stage 1	$0.75 < HI_{ij,T} \leq 1$	Healthy
Stage 2	$0.45 < HI_{ij,T} \leq 0.75$	Good
Stage 3	$0 < HI_{ij,T} \leq 0.45$	Soon-to-fail

Considering the O&M characteristics of offshore wind farms, this paper hypothesizes that the O&M cost of components in offshore wind turbines is related to their health stages. Components in Stage 1 are in good operating condition; while maintaining them can ensure continued stable operation. Premature maintenance may lead to unnecessary resource wastage and increased overall O&M costs, with limited improvements in component condition. In Stage 3, components experience significant wear and degradation, resulting in reduced power generation efficiency. Additionally, the repair and replacement work required for these components is complex and time-consuming, involving higher material and labor costs, as well as potential downtime losses, making the O&M costs the highest among the three stages. Compared to Stages 1 and 3, maintaining components in Stage 2 helps control maintenance costs while promptly restoring and maintaining the condition, thus avoiding the waste of remaining useful life due to premature maintenance and the high costs and power generation losses due to excessive wear. Therefore, this study hypothesizes that the maintenance cost of components is related to their health stages as follows.

$$C_{S_2} < C_{S_1} < C_{S_3} \tag{4}$$

where C_{S_1}, C_{S_2}, and C_{S_3} represent the O&M costs required for components in each of the three health stages, respectively.

Since this paper considers multiple components of various types with differing maintenance costs, the total O&M cost will be closely related to the maintenance costs and of each component type. The component type that accounts for the largest proportion of the total O&M cost is selected first. Then, the initial maintenance time window （t_1, t_2） and the maintenance time window for this component type in health stage 2 （t_1', t_2'） are combined to determine the common maintenance time window （T_1, T_2） for the multi-component maintenance plan. This is because this component type has the most significant impact on the O&M cost of offshore wind farms. Using the maintenance time window of such components as the maintenance time window for all components can achieve significant cost control. This component type is often crucial for the normal operation of the system. Adopting the maintenance time window of these components for all components can prevent operational risks caused by their failure, thereby enhancing the overall reliability and safety of the equipment and system. The equations for selecting the component type with the highest maintenance cost proportion are shown in Eqs. (5) - (9).

$$X_1 + X_2 + \cdots + X_\varphi + \cdots X_m = N \tag{5}$$

$$\sum_{g=1}^{3} X_{\varphi,S_g}(t) = X_\varphi \tag{6}$$

$$C_{\varphi,S_2} < C_{\varphi,S_1} < C_{\varphi,S_3} \tag{7}$$

$$C_\varphi = \sum_{g=1}^{3} C_{\varphi,S_g} \cdot X_{\varphi,S_g}(t) \tag{8}$$

$$k_\varphi = \frac{C_\varphi}{\sum_{\varphi=1}^{m} C_\varphi} \tag{9}$$

where X_φ is the number of components of type φ ($\varphi = 1,2,\cdots,m$). $X_{\varphi,S_g}(t)$ represents the number of components of type φ at time t in the stage g. C_{φ,S_g} denotes the O&M cost for components of type φ in the stage g. C_φ indicates the total O&M cost for components of type φ. k_φ is the impact factor of the maintenance cost for components of type φ on the total O&M cost. A higher value of k_φ indicates a larger proportion of the total O&M cost attributable to this component type.

2.2.2 Method for determining the maintenance mode and sequence

Offshore wind farms have a large number of turbines and there are a large number of components in each turbine. Based on the optimal maintenance time window, once the O&M staff arrives at the site to deal with a large number of components in urgent need of maintenance, if the maintenance sequence is disorganized, the opportunity for timely maintenance may be missed. In addition, the time and cost required for different maintenance solutions are different. Therefore, in this section, a component maintenance PI will be established, which is the ratio between the recovery degree of turbine condition before and after the maintenance of a component and maintenance cost under different maintenance modes. This ratio can be calculated by the DEA method. By comparing the maintenance PI of each component, the maintenance mode and sequence can be determined.

2.2.2.1 Maintenance cost

Maintenance costs are considered from four aspects in this paper, namely personnel, materials, transportation, and downtime loss.

(1) Personnel cost

Personnel costs are determined by factors like the duration of a single maintenance trip at sea, the number of maintenance personnel required for each trip, and the cost per unit of time for each maintenance personnel, which is related to the type of vessel being operated.

$$C_s^H = C_h \cdot T_v \cdot H_{ij} \tag{10}$$

where C_s^H is the total personnel cost required for the sth maintenance trip at sea. C_h is the per capita cost of maintenance personnel per unit of time with h-type maintenance vessel; T_v is the total traveling time for a single maintenance trip at sea. H_s is the number of personnel required for the sth maintenance trip at sea.

(2) Material cost

Material cost occurs when components need to be maintained, and these costs are independent of both the maintenance time window as well as maintenance route and can thus be simplified as a fixed value.

$$C_{ij,\theta}^o = \beta_{ij} C_{ij,\theta}^r + (1 - \beta_{ij}) C_{ij,\theta}^p \tag{11}$$

$$\begin{cases} \beta_{ij} = 0, \theta = \{\text{Replacement}\} \\ \beta_{ij} = 1, \theta = \{\text{Minor repair}\} \end{cases} \tag{12}$$

where $C_{ij,\theta}^o$ is the cost of material when maintenance personnel perform θ-type maintenance on the ith component in jth turbine. β_{ij} is the maintenance mode as given in Eq. (12). $C_{ij,\theta}^r$ is the cost of minor repair of the ith component in jth turbine. $C_{ij,\theta}^p$ is the cost of replacement of the ith component in jth turbine.

(3) Transportation cost

Transportation costs incurred by maintenance vessels are composed of the rental cost of the maintenance vessel and the voyage fuel expenditure. The rental cost is related to the length of transportation, while the voyage fuel expenditure is related to the voyage distance. Each maintenance vessel can carry different maintenance crews to the sea for maintenance. The length of each trip of the maintenance vessel consists of sailing time, personnel and material transfer time, and waiting time. The personnel and material transfer time of the maintenance vessel and waiting time for one trip are ignored here. The sailing time is related to the distance and speed. The distance includes the distance between the dock and the first turbine to be maintained, the distance between the other turbines to be maintained, and the distance between the last turbine and the dock. The sailing time should not exceed the maximum sailing time $T_{s_{max}}$ of the maintenance vessel.

$$C_v = C_{vr}T_v + C_f T_s C_p \tag{13}$$

$$T_v = T_s + T_m \tag{14}$$

$$T_s = \frac{D_{d,1} + \sum_{p=1}^{z-1} D_{p,p+1} + D_{z,d}}{V_h} \tag{15}$$

where C_v is the transportation cost incurred during maintenance. C_{vr} is the rental cost per unit of time. T_v is the total time of the maintenance vessel for one trip to the sea, as already defined in Eq. (10). T_s is the sailing time of the maintenance vessel for one trip to the sea ($T_s \ll T_{s_{max}}$). T_m is the total maintenance time required for components under poor condition in a single outing. C_f is the fuel consumption for each day. C_p is the oil price for each metric ton. $D_{d,1}$ is the distance from the dock to the first turbine to be maintained. $D_{p,p+1}$ is the distance from the pth turbine to the next turbine to be maintained ($1 < p < z-1$). $D_{z,d}$ is the distance from the zth turbine to the dock. V_h is the average speed of the maintenance vessel.

(4) Downtime loss cost

Downtime loss cost refers to the loss of generation due to downtime while maintaining jth turbine. For simplicity, the effect of wake effects on downtime loss is considered here.

$$C_{loss} = Q_0 t_{j,P'} \tag{16}$$

where C_{loss} is the cost of downtime loss. Q_0 is the average amount of electricity generated by each turbine. $t_{j,P'}$ is the average downtime of turbine caused by maintenance action.

(5) Overall maintenance cost estimation

In summary, the overall maintenance cost $C_{ij,\theta}$ is estimated in Eq. (17):

$$C_{ij,\theta} = \sum_{j=1}^{m} \sum_{i=1}^{n} \left(C_{ij}^{H} + C_{ij,m}^{O} \right) + C_v + C_{loss} \tag{17}$$

2.2.2.2 Maintenance priority index

To reduce the cost of single-trip maintenance, this paper introduces a maintenance PI to quantitatively analyze the importance of maintenance for each component. It can be used to help the O&M operators determine the maintenance mode and sequence of components. The larger the PI value, the higher the priority of the component to be maintained.

At the time t within （T_1, T_2）, the θ-type maintenance mode for the ith component in jth turbine is defined as the maintenance priority index $PI_{ij,\theta}(t)$ as follows.

$$PI_{ij,\theta}(t) = \frac{\Delta R_{ij,\theta}(t)}{C_{ij,\theta}} \tag{18}$$

where $\Delta R_{ij,\theta}(t)$ refers to the recovery degree of turbine condition after θ-type maintenance at time t (only component i is maintained). $\theta = \{1,2\} = \{\text{minor repair, replacement}\}$ is considered in this paper. $C_{ij,\theta}$ is the cost of θ-type maintenance of the ith component in jth turbine, as given in Eq. (17).

$\Delta R_{ij,\theta}(t)$ can be further represented by Eq. (19) as follows.

$$\Delta R_{ij,\theta}(t) = R'_{ij,\theta}(t) - R_{ij,\theta}(t) \tag{19}$$

where $R'_{ij,\theta}(t)$ is the condition of the ith component in jth turbine after maintenance. $R_{ij,\theta}(t)$ is the condition of the ith component in jth turbine at time t before maintenance.

A wind turbine is a complex equipment system composed of multiple types of components. Due to their significant differences in terms of the importance of the components within the turbine, this paper employs a weighted summation method to calculate the overall condition of the turbine, as given in Eq. (20). In evaluating the overall condition of the wind farm, it is assumed that changes in the condition of all turbines have an equal impact on the wind farm. Therefore, the condition of the wind farm is defined as the average of all turbine condition values, as given in Eq. (21).

$$C_j = \sum_{i=1}^{n} w_i \cdot c_{ij} \tag{20}$$

$$C = \frac{\sum_{j=1}^{m} C_j}{m} \tag{21}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{22}$$

where C_j is the condition of jth turbine $(j = 1,2,\ldots,m)$. c_{ij} refers to the condition of ith component in the jth turbine $(i = 1,2,\ldots,n)$. w_i represents the importance of the ith component, which is related to its maintenance cost. C is the condition of the whole offshore wind farm.

PI in Eq. (18) is more applicable to the offshore wind farm with the same type of turbines. However, for offshore wind farms with different types of turbines, only considering the performance recovery after component maintenance is insufficient. To tackle with this issue, the concept of component importance can be introduced. For wind farms with different types of turbines, the component importance should be prioritized when evaluating the maintenance priority. When the component importance is the same, the condition recovery degree after maintenance, as defined in Eq. (18), can then be considered. The DEA method can also be employed to calculate the component importance.

2.2.3 Method for optimizing the maintenance strategy

After analyzing the PI value, only the maintenance mode and sequence of components can be obtained. If large-scale maintenance is carried out, which means that all components are maintained at the same time, it will undoubtedly improve the overall condition of the turbine. But it will also result in excessive maintenance, which will increase the unnecessary maintenance cost and also sacrifice the remaining useful life of components. On the contrary, if only a small range of maintenance work is carried out, it will result in a significant increase in the maintenance frequency, which will in turn increase the maintenance cost. For this problem, an optimization model with the objective of the maintenance cost rate (CR) is constructed to select the optimal component combination. The relationship between the condition of components before the next maintenance $R_{ij,\theta}(t')$, after the next maintenance $R_{ij,\theta}(t' - \Delta t)$, and the potential failure threshold R_l is set to be constraints. The optimization model will be solved by exhaustive search algorithm (ESA), which is presented in Section 2.3.2.

The maintenance cost of the first μ components is as follows.

$$C_{ij,\theta}^{\mu}=\sum_{g=1}^{\mu}\sum_{j=1}^{m}\sum_{i=1}^{n}\left(C_{ij}^{H}+C_{ij,m}^{o}\right)+C_{v}+C_{loss} \tag{23}$$

where $C_{ij}^{H}, C_{ij,m}^{o}, C_{v}$, and C_{loss} is personnel cost, material cost, transportation cost and downtime loss cost, respectively. g refers to the maintenance sequence obtained in Section 2.2.2.

$$\begin{aligned} min \quad & CR=\frac{C_{ij,\theta}^{\mu}}{t'-t} \\ & R_{ij,\theta}(t')\leq R_{1} \\ s.t. \quad & R_{ij,\theta}(t'-\Delta t)>R_{1} \\ & \mu\geq 0, \mu=1,2,\cdots,N \end{aligned} \tag{24}$$

where CR refers to the maintenance cost rate of the first μ components, that is, the ratio of the maintenance cost of the first μ components to the time interval between two maintenance actions. $R_{ij,\theta}(t')$ and $R_{ij,\theta}(t'-\Delta t)$ represent the condition of components before and after the next maintenance of ith component in jth turbine, respectively. t and t' represent the current maintenance time and the next maintenance time, respectively. Δt is the time interval between two actions of maintenance. R_1 is the potential failure threshold, that is, once the performance of the component is lower than this threshold, the probability of potential failure will greatly increase.

To simplify the calculation, it is assumed that the degradation trend of the components remains unchanged before and after the maintenance is implemented. For the replacement operation, the condition is restored to a new state, and for the minor repair operation, the condition is restored to a certain degree. After a maintenance operation is performed at time t, the O&M operators will update the performance status of each equipment and component in time, predict the next maintenance time, mode, and sequence according to the proposed strategy, and arrange maintenance operations, to achieve dynamic adjustment of the maintenance time window. Considering the sea and weather conditions, the O&M operators can decide when to carry out maintenance actions within （T_1, T_2）.

2.3 Related methods in the framework

2.3.1 Data envelopment analysis method (DEA)

By observing Eq. (18), it is evident that the PI in this paper is influenced by the condition recovery degree of the turbine after maintenance and maintenance costs. However, these two factors possess distinct measurement scales, rendering direct comparisons unfeasible. Values, obtained through direct calculation or normalization, often fail to effectively reflect component priority degree. DEA is an efficiency evaluation method based on the concept of relative efficiency, which can directly estimate the relative relationships between the efficiencies of multiple decision-making units without considering dimensional normalization issues [42]. Therefore, in this paper, the maintenance mode and sequence of individual components are considered as a decision-making unit, with maintenance cost as an input indicator and the recovery degree of turbine condition after component maintenance as an output indicator. The aim is to achieve the maximum recovery degree of turbine condition with the lowest maintenance cost.

Assume that there are N components to be maintained, that is, there are N decision-making units. Thus, each decision-making unit has a corresponding maintenance efficiency evaluation index (E_z), as given in Eq. (25):

$$E_z = \frac{W^T \Delta R_{ij}^z}{U^T C_{ij}^z} \tag{25}$$

where $C_{ij}^z = \left(C_{ij}^{1z}, C_{ij}^{2z}\right)^T$ is the input vector. C_{ij}^{1z} and C_{ij}^{2z} refers to the input cost of the zth decision-making unit for the minor repair or replacement of the ith component in the jth turbine $(C_{ij}^{1z}, C_{ij}^{2z} > 0)$. $\Delta R_{ij}^z = \left(\Delta R_{ij}^{1z}, \Delta R_{ij}^{2z}\right)^T$ is the output vector. ΔR_{ij}^{1z} and ΔR_{ij}^{2z} refer to the recovery degree of component condition after the zth decision-making unit performs minor repair or replacement on the ith component in the jth turbine $(\Delta R_{ij}^{1z}, \Delta R_{ij}^{2z} > 0)$. $W = (W_1, W_2)^T$ is the input weight coefficient for α maintenance activities. $U = (U_1, U_2)^T$ is the output weight coefficient. $z = 1,2,\cdots,N$. The maintenance efficiency of the ith component in the jth turbine during the lth maintenance action is evaluated under different maintenance modes. The weighting coefficients W and U are set as variables. The maintenance efficiency evaluation index serves as the objective, while the maintenance efficiency indexes of all decision units are set as constraints. The evaluation model is formulated as follows.

$$max \qquad E_l = \frac{W^T \Delta R_{ij}^l}{U^T C_{ij}^l} \tag{26}$$

$$s.t \quad \frac{W^T \Delta R_{ij}^z}{U^T C_{ij}^z} \leq 1$$

$$W \geq 0, U \geq 0, z = 1,2,\cdots,N$$

There are two DEA expressions: (1) fractional programming model, as given in Eq. (25), and (2) linear programming model. The fractional programming model is the ratio of output and input, and the linear programming model is transformed from the Charnes-Cooper transform **Error! Reference source not found.**[43]. The calculation is more convenient; therefore, the linear programming model is generally used. Let

$$t = \frac{1}{u^T c_{ij}^z}, \quad \omega = tw, \mu = tu \tag{27}$$

The fractional programming model can be transformed into an equivalent linear programming model.

$$\begin{aligned} max \quad & E_l = \omega^T \Delta R_{ij}^z \\ s.t. \quad & \mu^T C_{ij}^z - \omega^T \Delta R_{ij}^z \geq 0, \\ & z = 1,2,\cdots,N \\ & \mu^T C_{ij}^l = 1 \\ & \omega \geq 0, \mu \geq 0 \end{aligned} \tag{28}$$

The dual model of the above linear programming model is given as follows.

$$\begin{aligned} min \quad & \varepsilon_l \\ s.t. \quad & \sum_{z=1}^{N} \alpha_z \Delta R_{ij}^z \geq \Delta R_{ij}^l \\ & \sum_{z=1}^{N} \alpha_z C_{ij}^z \leq \varepsilon_l C_{ij}^l \\ & \alpha_z \geq 0 \quad z = 1,2,\cdots,N \end{aligned} \tag{29}$$

To ensure that the dual model is effective for the DEA of the first decision-making unit, the residual variable μ^+ and the slack variable μ^- are introduced for each output and input. The dual model is improved.

$$\begin{aligned} min \quad & \varepsilon_l \\ s.t. \quad & \sum_{z=1}^{N} \alpha_z \Delta R_{ij}^z - \mu^+ = \Delta R_{ij}^l \\ & \sum_{z=1}^{N} \alpha_z C_{ij}^z + \mu^- = \varepsilon_l C_{ij}^l \end{aligned} \tag{30}$$

$$\mu^{+} = [\mu_1^{+}, \mu_2^{+}, \cdots, \mu_z^{+}] \geq 0$$

$$\mu^{-} = [\mu_1^{-}, \mu_2^{-}, \cdots, \mu_z^{-}] \geq 0$$

$$\alpha_z \geq 0 \quad z = 1,2,\cdots,N$$

where ε_l is the utilization efficiency index of maintenance cost for the lth decision-making unit. C_{ij}^{l} is the maintenance cost for the evaluated lth decision-making unit. ΔR_{ij}^{l} is the condition recovery degree of the evaluated lth decision-making unit after maintenance. α_z is the proportion of maintenance cost or recovery degree of condition for the zth decision-making unit and $z = 1,2,\cdots,N$.

Due to the possible 'degradation' of linear programming, it is sometimes difficult to obtain the optimal solution by using the above model. Therefore, Charenes [44] introduced a non-Archimedean infinitesimal ε, and equivalently transformed the model into a form commonly used in practical evaluation.

$$\begin{aligned} min \quad & \varepsilon_l - \varepsilon(\hat{e}^T\mu^{-} + e^T\mu^{+}) \\ s.t. \quad & \sum_{z=1}^{N} \alpha_z \Delta R_{ij}^{z} - \mu^{+} = \Delta R_{ij}^{l} \\ & \sum_{z=1}^{N} \alpha_z C_{ij}^{z} + \mu^{-} = \varepsilon_l C_{ij}^{l} \\ & \mu^{+} = [\mu_1^{+}, \mu_2^{+}, \cdots, \mu_z^{+}] \geq 0 \\ & \mu^{-} = [\mu_1^{-}, \mu_2^{-}, \cdots, \mu_z^{-}] \geq 0 \\ & \alpha_z \geq 0 \quad z = 1,2,\cdots,N \end{aligned} \tag{31}$$

where $\hat{e} = (1,1,\dots,1)^T \in R^k$, $e = (1,1,\dots,1)^T \in R^{\mu}$. The validity of the decision unit is judged by this dual programming. The proof process of these theorems is referred in [45].

By utilizing the above model, the maintenance efficiency evaluation index ε of different maintenance modes for the ith component in the jth turbine can be obtained. The efficiency index ε is typically defined in a range between 0 and 1. The closer the index ε is to 1, the higher the maintenance efficiency of the component is, which indicates a higher priority for its maintenance. To determine the maintenance mode and sequence of components, the following steps can be followed. Firstly, the PI of individual components is compared under minor repair and replacement operations to select the maintenance mode with a higher PI. Then, the components are ranked based on the PI values corresponding to the selected maintenance mode, to determine the maintenance sequence of the components. If the maintenance efficiency index ε of multiple components is 1, the optimal value ε^* can be obtained by comparing μ^{*+} and μ^{*-} based on the Theorem 1 and 2, which is supplemented in the Appendix [46].

2.3.2 Exhaustive search algorithm

The exhaustive search algorithm is a traversal-based solving algorithm. Given the known maintenance sequence of components, it can explore and evaluate all possible combinations of maintenance components, comparing their maintenance cost rates to find the combination with the minimum rate. This algorithm demonstrates good robustness and is capable of avoiding situations where it gets stuck in local optima. The flowchart of the ESA is shown in Fig.5, and the specific steps are described as follows.

Step1:

Taking into consideration of the sea and weather conditions, the maintenance time *t* can be determined by the O&M operators in the maintenance time window （T_1, T_2）, and only the components whose performance is lower than the threshold R_l at *t* can be maintained. By calculating the maintenance PI, the maintenance sequence of each component is determined and labeled with i.

Step2:

(1) $i = 1$.

(2) Solve $CR\,(t, i)$ and assign $CR^*\,(t, i^*\,) = CR\,(t, i)$; refer to Eq. (24) for CR;

(3) $i = i + 1$, solving $CR\,(t, i)$;

(4) Judge $i \;<\; i_{max}$. If yes, go to Step (5), otherwise the program ends;

(5) Judge $CR^*\,(t, i^*\,) < CR\,(t, i)$. If yes, then $CR^*\,(t, i^*\,) = CR\,(t, i)$, $i^* = i$, go to Step (3); otherwise, record $CR^*\,(t, i^*\,)$, i^*, go to Step (5).

Step3:

Through Step 2, the maintenance cost rate $CR\,(t, i)$ of different maintenance combinations can be obtained. Record all $CR\,(t, i)$ to find the minimum maintenance cost rate $CR^*\,(t, i^*\,) = \min\limits_{1 \le i \le i_{max}} \{CR\,(t, i)\}$ and the best maintenance combination (t, i^*).

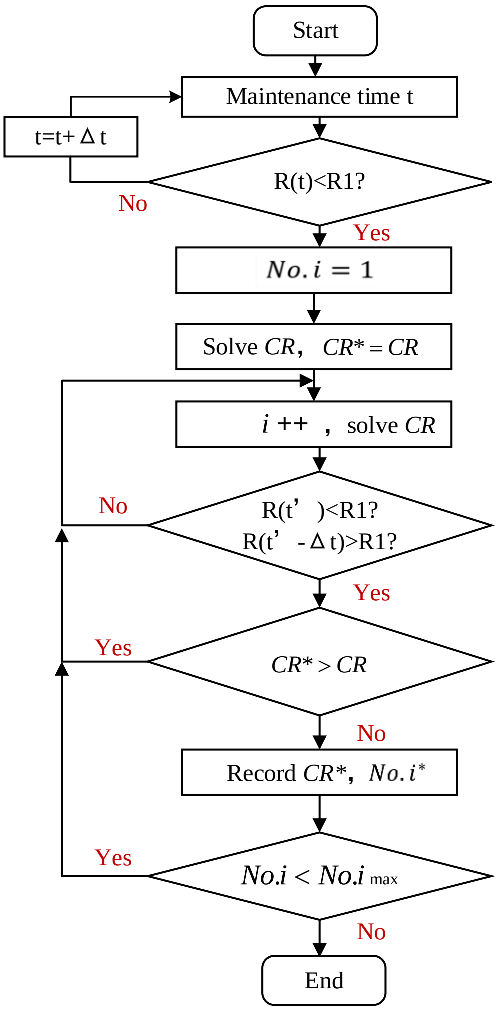

Fig. 5. The flowchart of ESA

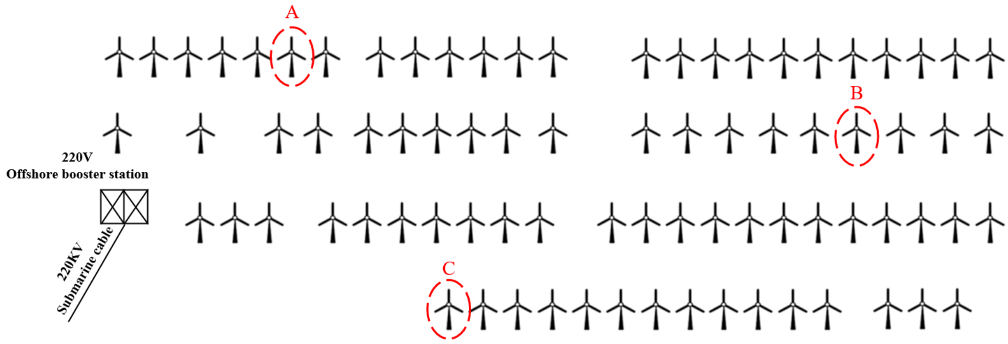

Fig. 6. The layout of the offshore wind farm

3 Case study

In this section, we take an offshore wind farm located along the eastern coast of China as a case study to validate the proposed maintenance framework. This offshore wind farm is equipped with 80 turbines, and the capacity of a turbine is 4.2 MW. The distance from the west of the offshore wind farm to the coastline is about 24 km. Turbines are arranged in a linear arrangement with a spacing of 300 m, and the layout of the offshore wind farm is shown in Fig.6. Due to being cost-effective in medium and high wave areas, jack-up vessels are the most utilized vessel for major maintenance operations in offshore wind energy market. Therefore, the jack-up vessel is chosen as the O&M vessel for the transportation of maintenance personnel and components.

Blades, generators, and gearboxes have been chosen as the critical components in turbines because failure of these components can cause a considerable period of downtime [47]. The component matrix Q is constructed from Eq. (1) and given in Eq. (32), where 1 means that the turbines all contain these key components.

$$Q = [A, B, C]^T = \begin{bmatrix} A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \\ C_1 & C_2 & C_3 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{32}$$

Table 3 Detailed information of experts

Expert	Position	Experience
1	Senior Engineer	More than 22 years of experience in offshore wind farm operation, maintenance, and fault diagnosis.
2	Intermediate Engineer	More than 16 years of experience in offshore wind farm operation and maintenance.
3	Junior Engineer	More than 8 years of experience in condition monitoring, operation, and maintenance of wind turbines.
4	Professor	Engaged in operational optimization and maintenance strategy research for offshore wind farms over 15 years
5	Associate Professor	Engaged in offshore wind power industry research over 9 years.

The values of thresholds R_1 and R_2 are estimated by expert survey based on historical operational data, maintenance records, and their professional experience. Furthermore, the values of thresholds R_1 and R_2 for different types of components are assumed to be the same. In this paper, we invited 5 experts from the offshore wind power field to estimate the values of R_1 and R_2 through a questionnaire survey. The details of these experts are provided in Table 3. Based on the expert evaluations, the values of R_1 and R_2 can be calculated through Eqs. (33) and (34).

$$R_1 = \sum_{\tau=1}^{5} w_\tau \cdot r_1^\tau \tag{33}$$

$$R_2 = \sum_{\tau=1}^{5} w_\tau \cdot r_2^\tau \tag{34}$$

where r_1^τ is the evaluation value of expert τ to R_1, while r_2^τ is the evaluation value of expert τ to R_2. w_τ is the weight of expert τ, which is related to their position and work experience. The evaluation criteria of expert weight are shown in Table 4. The expert weight is calculated by Eq. (35).

$$w_\tau = \frac{P_\tau + E_\tau}{\sum_{\tau=1}^{5} P_\tau + E_\tau} \tag{35}$$

where w_τ is the weight of expert τ. P_τ denotes the position score of expert τ. E_τ represents the work experience score of expert τ.

After calculation, the threshold R_1 is set to 0.75, and the threshold R_2 is set to 0.45.

Table 4 Expert weight evaluation criteria

		Score
Position	Senior engineer/ Professor	6
	Intermediate engineer/ Associate professor	4
	Junior engineer/ Lecturer	2
Work experience	More than 20 years	6
	Between 11 and 20 years	4
	Less than 10 years	2

Table 5 Component maintenance cost and time

Component	Maintenance cost/ £		Maintenance duration/day	
	Minor repair	Replacement	Minor repair	Replacement
Blade	75,000	150,000	1	2
Generator	120,000	240,000	3	6
Gearbox	400,000	800,000	6	12

Table 6 Input parameters

Parameter	Value	Unit
Operational speed	11	knot
Max operational wave height	2.8	m
Max operational wind speed	36.1	m/s
Fuel consumption	13.2	mt/day
Vessel charter cost	110,000	£/day
Technician cost	275	£/person/day
Required technician	6	person
Electricity price	140	£/MWh
Fuel price	300	£/mt

Maintenance modes are categorized into two types, including minor repair and replacement. The cost and time required for maintenance modes are shown in Table 5 [48]. The maintenance cost and time for the minor repair operation are assumed to be half of the replacement. The replacement operation restores the condition of the component as new, while the minor repair operation restores the condition of the component to 95% when it is in a brand-new condition. The value of 95% is obtained by expert survey with the same procedure when determining the thresholds for R_1 and R_2. The feasibility of the proposed framework is verified by using three wind turbines, the locations of which are marked in red in Fig.6. Other parameters used in the case study are shown in Table 6 [49].

3.1 P-F curves acquisition

The P-F curve in our study is obtained based on the degradation curve in Ref.[50]. The authors in [50] build an experimental platform to simulate the natural degradation process of the high-speed end bearing of the wind turbine gearbox from normal state to complete failure. Firstly, the time domain, frequency domain, and time-frequency domain indexes which are sensitive to bearing degradation are selected. Then, the live vibration data of the bearing are segmented. The corresponding degradation feature indexes are extracted from the segmented data to form the degradation feature matrix. Finally, the high-dimensional features are fused, and the principal component with the highest contribution rate is selected as the bearing degradation index, and the degradation curve is drawn, as shown in Fig.7.

The Y-axis of the degradation curve represents the degradation degree of the equipment while the Y-axis of the P-F curve represents the condition of the equipment. When the degradation increases, the condition value decreases, and vice versa. Therefore, the sum of the degradation value and the condition value is always 1, indicating that they are two different aspects of the same equipment. For example, when the degradation index is 0, it means that the equipment is brand new, and its condition value is the maximum value of 1. When the degradation index is 0.3, it means that the condition of the equipment has a certain degree of degradation, and its condition value decreases to 0.7. To facilitate the subsequent maintenance strategy, the P-F curve is polynomial fitted to obtain important maintenance information. The processed P-F curve is shown in Fig.8.

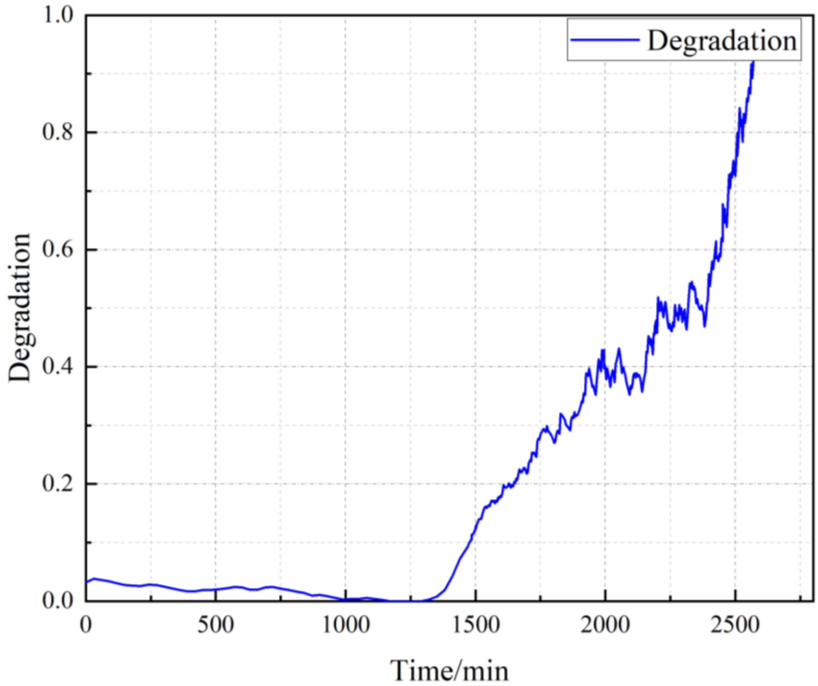

Fig. 7. A degradation curve from Ref. 46[50]

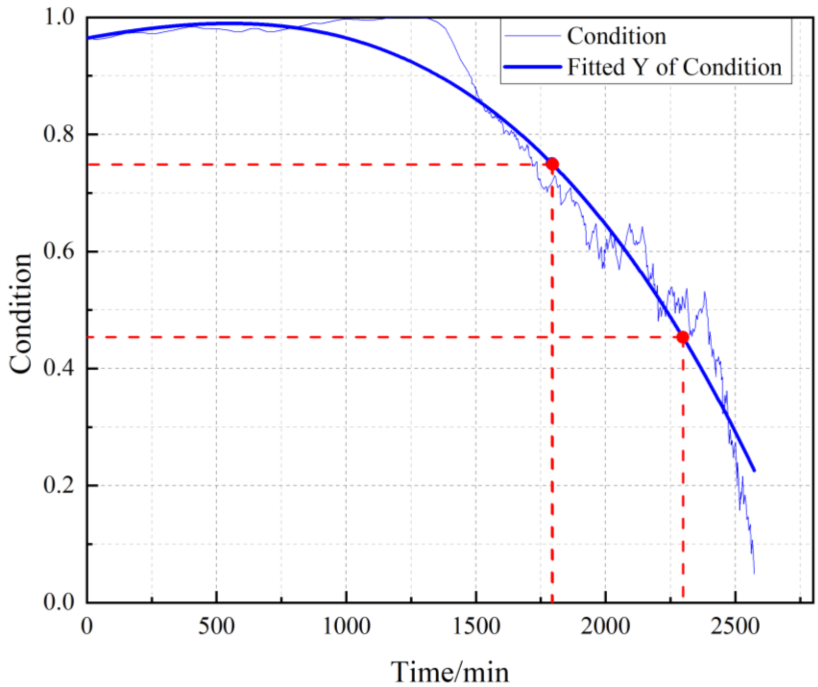

Fig. 8. The P-F curve of a bearing

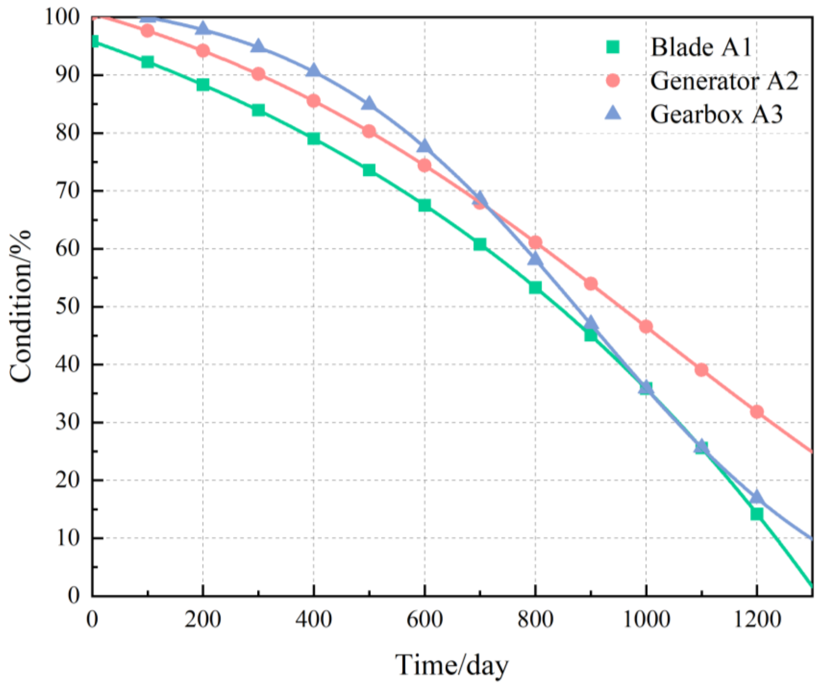

Fig. 9. P-F curves of turbine A

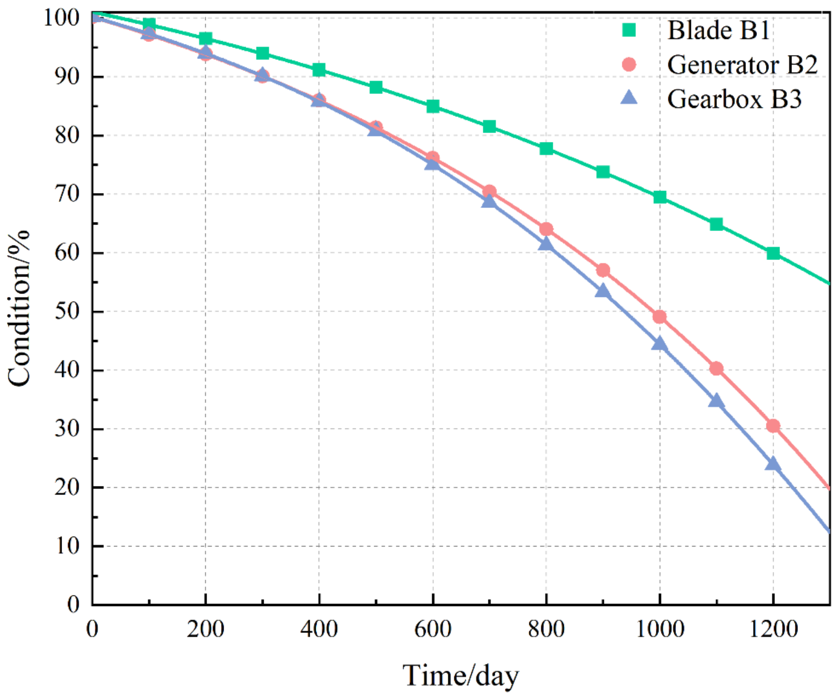

Fig. 10. P-F curves of turbine B

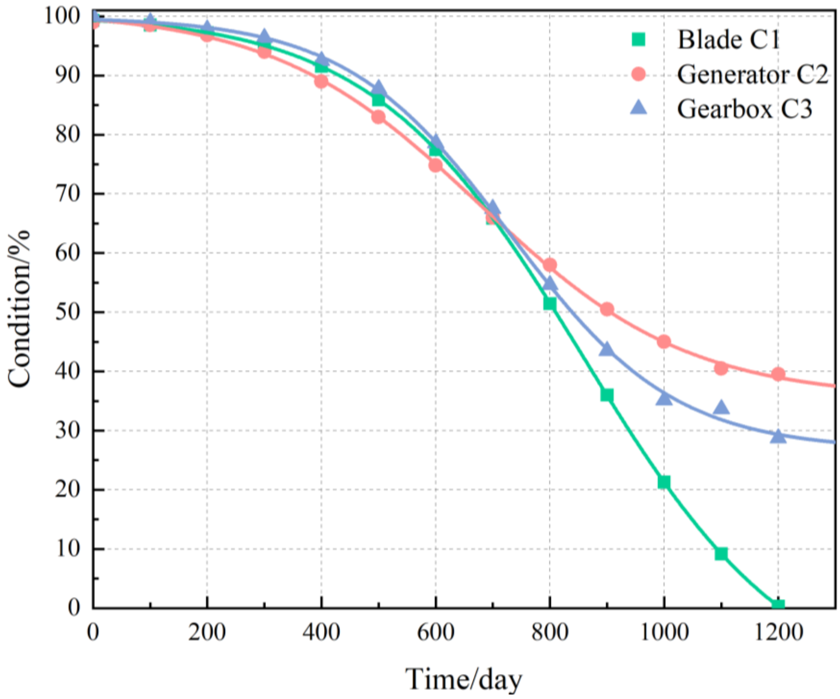

Fig. 11. P-F curves of turbine C

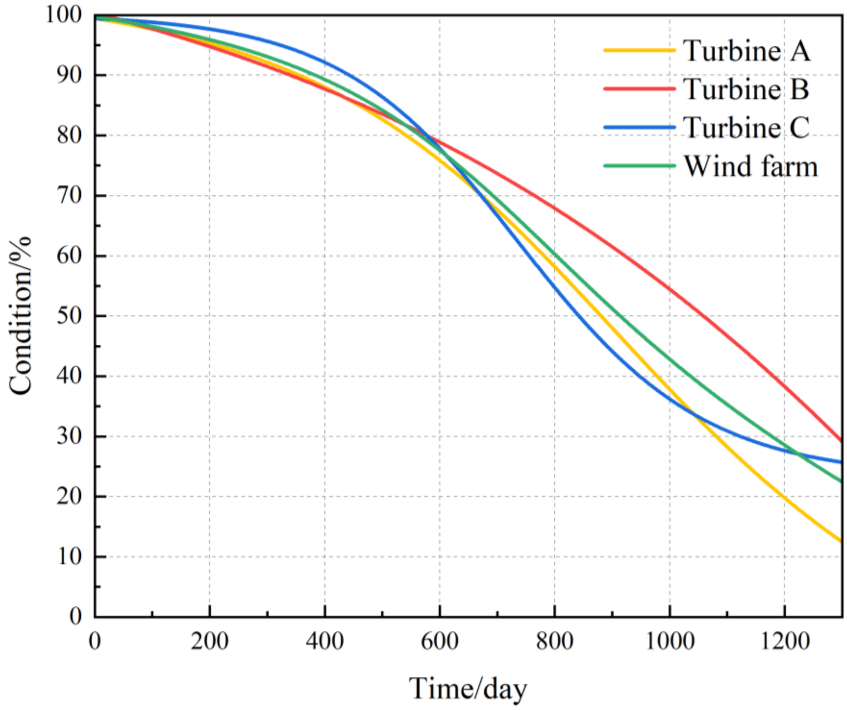

Fig. 12. P-F curves of wind farm

This paper sets the P-F curves for components such as generators, gearboxes, and blades based on the degradation curve of wind turbine bearings obtained from the reliability acceleration experiment detailed in Ref. [50], as shown in Figs.9-12. While the degradation trends for different types of components generally exhibit similar patterns, there may be some stochastic variability in the actual degradation trajectories. Therefore, the curves set in this paper show a consistent downward trend, but the degradation trajectories are different. The issue of P-F curve accuracy will be discussed in Section 5.1.

Table 7 Results of maintenance optimization for single component

Component	Maintenance time window/day	Maintenance timing/day	Time interval/day	Mode	Cost/ £
A1	(476,899)	774	481	Minor repair	187,680
A2	(589,1020)	687	662	Minor repair	236,682
A3	(630,917)	804	627	Minor repair	522,679
B1	(869,1481)	1175	917	Minor repair	187,574
B2	(621,1048)	834	669	Minor repair	236,580
B3	(600,993)	797	627	Minor repair	522,573
C1	(681,916)	773	400	Minor repair	187,655
C2	(595,1003)	798	382	Minor repair	236,657
C3	(671,874)	799	540	Minor repair	522,653

3.2 Maintenance optimization for single component

In this section, maintenance optimization is performed for each component without considering maintenance opportunities for other components. First, the maintenance time window for components is determined based on their P-F curves. Then, the O&M operators can decide when to carry out maintenance activities during such a time window. For each component, Table 7 presents the maintenance time window, the selected maintenance timing, the time interval to the next maintenance, and the maintenance mode. Fig.13 illustrates the time windows of components for the first maintenance. As shown in the figure, except for blade B1, there is a significant overlap in the maintenance time window for the other components. Therefore, a single maintenance trip can be utilized to simultaneously maintain multiple components, thereby reducing the total O&M costs of the offshore wind farms.

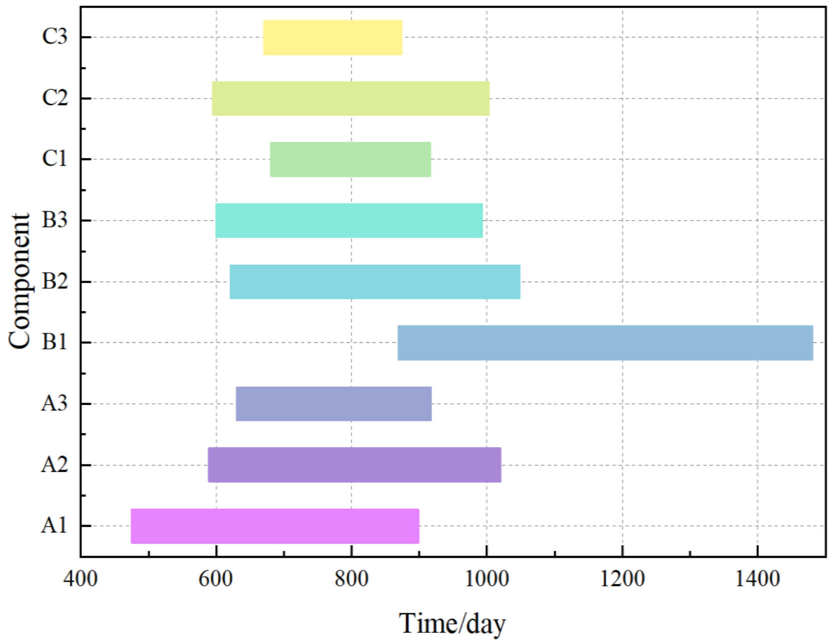

Fig. 13. Maintenance time windows for single component

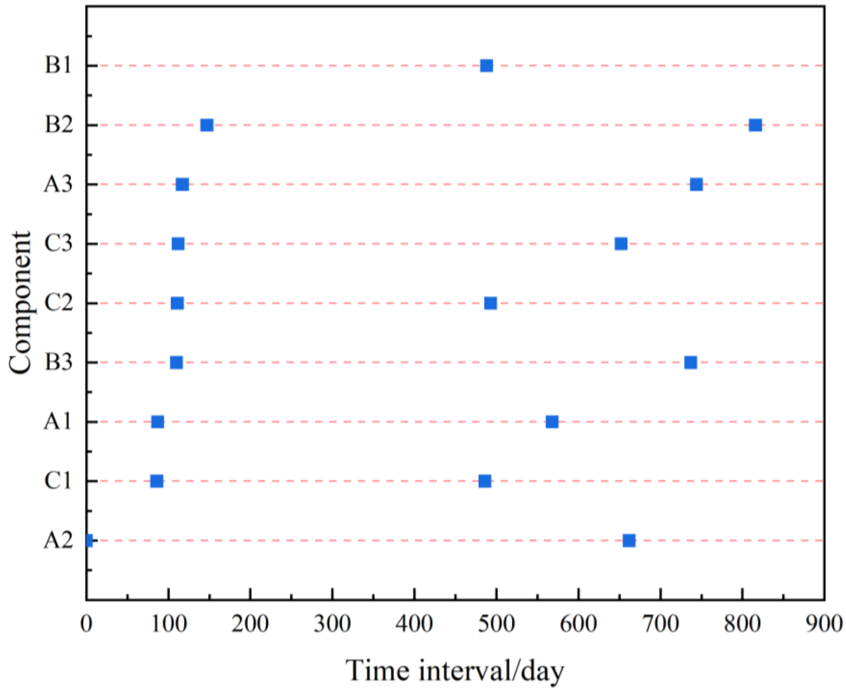

Fig. 14. Maintenance timing for single component

Considering the sea and weather conditions, the O&M operators can select the maintenance timing. Without considering maintenance opportunities, each maintenance trip only focuses on a single component, relying solely on the condition of individual components to make maintenance plans. Fig.14 illustrates the maintenance frequency for the three turbines when the maintenance cycle is set to five years. During the five-year maintenance cycle, all components except blade B1 require two maintenance visits.

In total, the O&M operators need to go out 17 times during the scheduled cycle to complete the maintenance tasks. The total O&M cost is £5,493,901, a large portion of which comes from the rental cost of the O&M vessels and the material cost of components.

3.3 Maintenance optimization for multiple components

3.3.1 Maintenance time window

In actual maintenance operations, it is more common to maintain several components at the same time. This section will incorporate the maintenance framework proposed in Section 2.2.1 to achieve a balance between maintenance cost and condition. Since the threshold R_1 and R_2 are set to 0.75 and 0.45, respectively, the initial maintenance time window of multiple components is (476d, 874d), which can be observed from Figs. 9-12.

From Table 5, it is evident that both minor repairs and replacement maintenance costs for gearboxes are higher than other types of components. Additionally, given that the quantities of each component type are equal, it can be inferred that gearboxes represent the largest proportion of maintenance costs. The common time window of three gearboxes in health stage 2 is (721d, 782d). The common time window of such maintenance window and the initial maintenance time window is (721d, 782d), too. Thus, the O&M operators will schedule the maintenance activities within this time window.

3.3.2 Maintenance mode and sequence

To simplify the calculation, we assume that the degradation trajectory of the components before and after the maintenance implementation remains unchanged. To study the relationship between the maintenance cost and the condition recovery degree of components after maintenance, we construct the maintenance PI and use the DEA method to measure the efficiency relationship between input and output, to obtain the maintenance mode and sequence of components. The maintenance mode of a single component can be obtained by comparing the maintenance PI corresponding to the replacement and minor repair. Based on this, the maintenance sequence of all components can be obtained by comparing the maintenance PI corresponding to the maintenance mode of multiple components. The maintenance mode and sequence provide the basis for finding the optimal maintenance opportunity.

Considering factors such as sea conditions and weather, it is assumed that the O&M operators decide to carry out maintenance activities at $t = 760d$ in the maintenance time window (721d, 782d). Table 8 shows the maintenance PI value and the maintenance mode and sequence of components at $t = 760d$. It can be seen from the table that when the maintenance actions are carried out at $t = 760d$, all components are maintained in a minor repair way. This is because, the maintenance cost and time of minor repair is only half of the replacement cost, and the degree of condition recovery provided by minor repair is only slightly lower than that of replacement. Therefore, compared with replacement, minor repair is a more cost-effective option.

Table 8 Maintenance priority index of components

Component	Recovery degree of wind turbine/%		Processed maintenance priority index		Maintenance mode and sequence
	Minor repair	Replacement	Minor repair	Replacement	
A1	4.85	5.48	1.0000	0.5650	Minor repair（1）
A2	6.27	7.00	0.8078	0.4510	Minor repair（6）
A3	21.81	25.17	0.8432	0.4865	Minor repair（5）
B2	5.02	6.03	0.6469	0.3885	Minor repair（8）
B3	17.98	21.34	0.6951	0.4125	Minor repair（7）
C1	4.72	5.35	0.9732	0.5516	Minor repair（2）
C2	6.89	7.91	0.8879	0.5097	Minor repair（4）
C3	23.94	27.31	0.9255	0.5279	Minor repair（3）

Table 9 Results of maintenance strategy optimization for the offshore wind farm

The combinations	Wind farm condition/%	Time interval/day	Cumulative cost/￡	Cost rate /(￡/day)
A1	65.53	15	107,653	7,176
A1, C1	67.11	28	194,695	6,953
A1, C1, C3	75.09	103	602,675	5,851
A1, C1, C3, C2	77.39	138	726,425	5,263
A1, C1, C3, C2, A3	**84.66**	**241**	**1,128,744**	**4,683**
A1, C1, C3, C2, A3, A2	86.75	264	1,254,723	4,752
A1, C1, C3, C2, A3, A2, B3	92.75	346	1,656,772	4,788
A1, C1, C3, C2, A3, A2, B3, B2	94.42	362	1,758,813	4,858

3.3.3 Maintenance optimization

To find the maintenance opportunities, we calculate the maintenance cost rate for different combinations of components. After arranging the components in the maintenance sequence, several different maintenance combinations are obtained, from which the combination of components with the lowest maintenance cost rate is selected. The maintenance cost rate of each component maintenance combination and the system performance after maintenance are presented in Table 9. From Table 9, it can be seen that as the number of components in the component combination increases, the overall performance of the system and the accumulated maintenance cost gradually increase, while the maintenance cost rate shows a decreasing and then gradually increasing trend. The maintenance cost rate is minimized when the combination of components is {C1, A1, A2, B2, C2, B3}. Therefore, the final maintenance schedule is to perform a minor repair operation on components in the sequence of {A1, C1, C3, C2, A3, A2} at $t = 760d$. It is suggested that the next maintenance interval is 174 days, which means that the next maintenance is performed at $t' = 934d$.

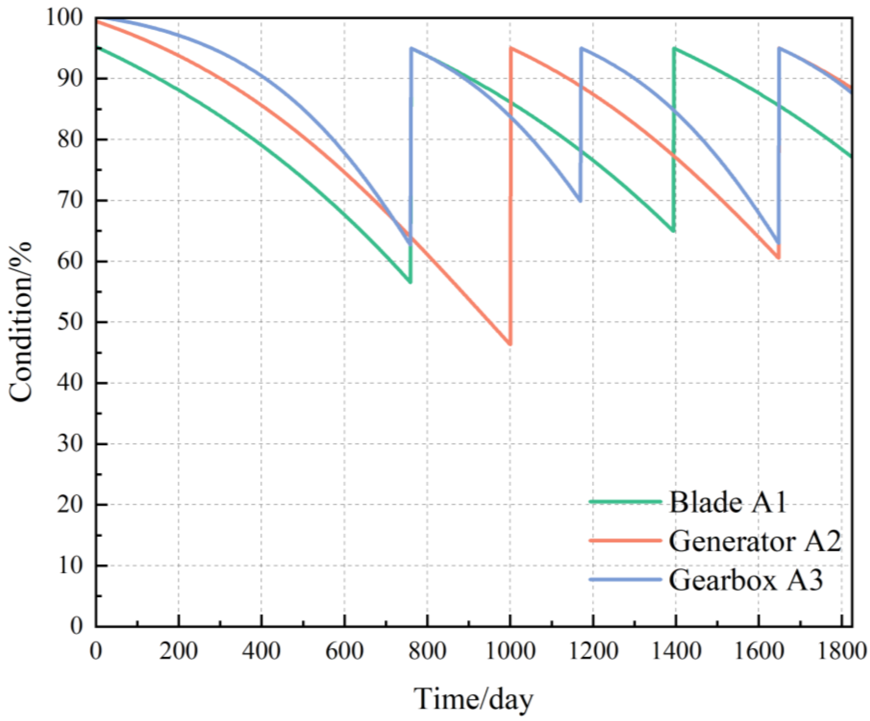

Fig. 15. Maintenance schedule of the turbine A

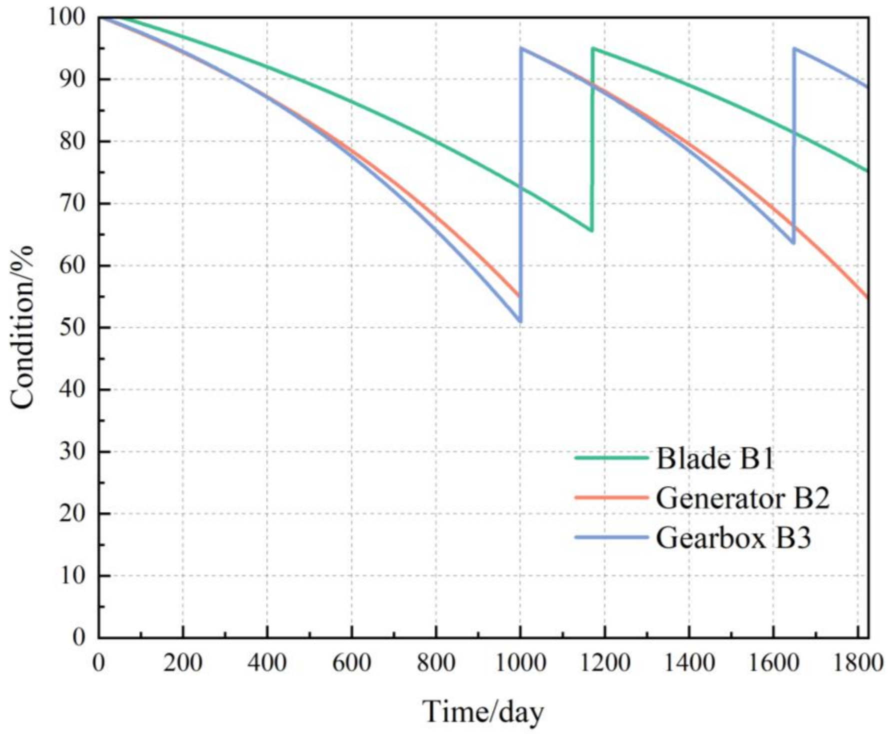

Fig. 16. Maintenance schedule of the turbine B

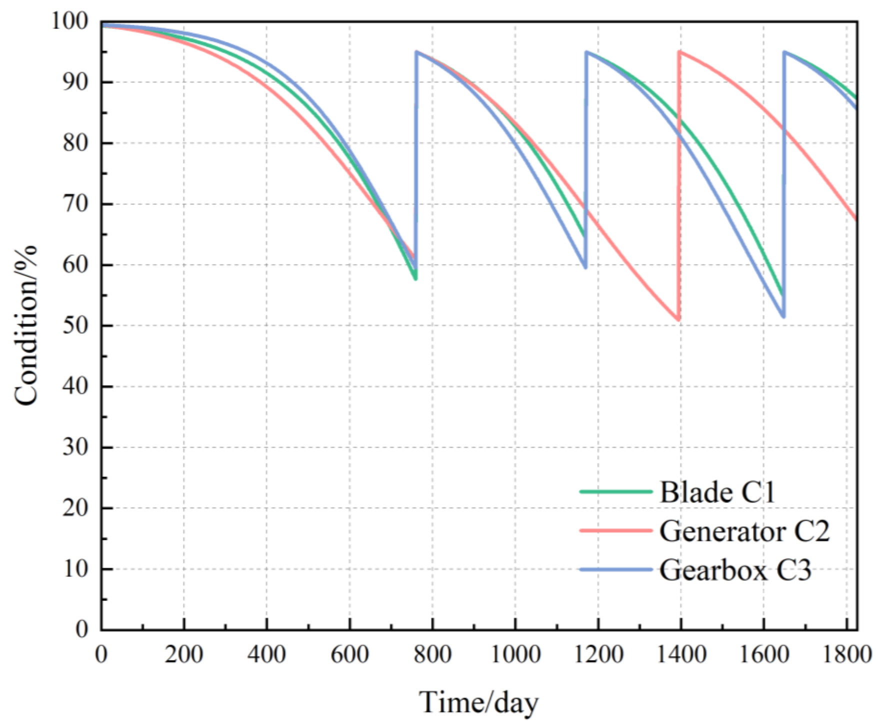

Fig. 17. Maintenance schedule of the turbine C

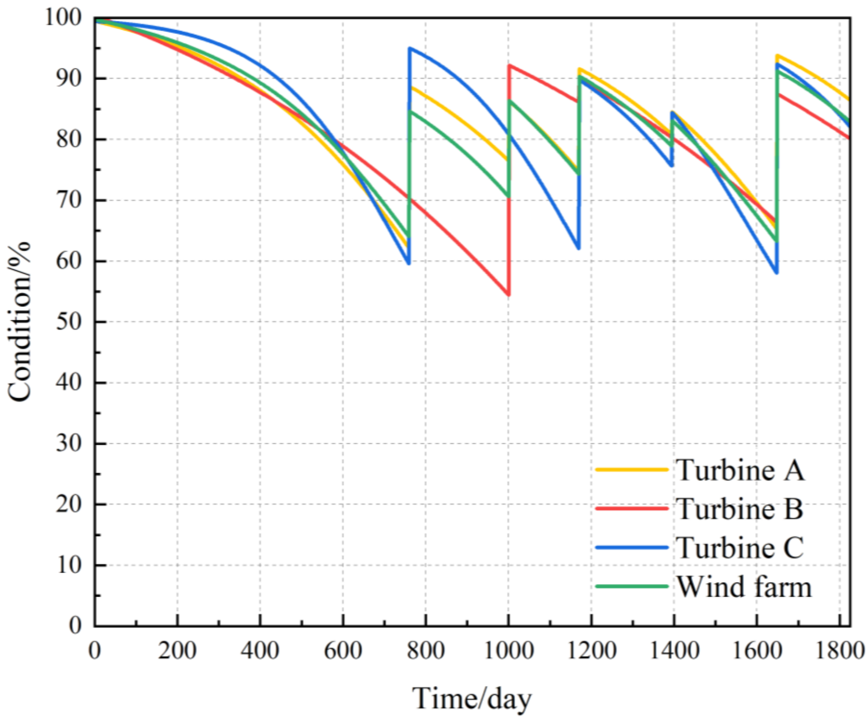

Fig. 18. Maintenance schedule of the whole wind farm

Figs.15-18 presents the maintenance schedule of turbines and the whole wind farm over five years. The O&M operators are required to carry out 5 offshore maintenance activities and the total O&M cost required is £5,103,625 within five years. Compared to the result from single component maintenance optimization, the total O&M cost is reduced by £390,276. The results show that seizing every opportunity to perform maintenance and maintaining as many components as possible can reduce the number of maintenance trips during the maintenance cycle, thus significantly reducing the total O&M cost of the offshore wind farm.

After the selected combination of components has been maintained, the condition of the components and turbines must be updated to ensure the accuracy and stability of the turbines and the wind farm. Subsequently, the next maintenance schedule is developed according to the key steps in the maintenance framework, forming a continuous, cyclical closed-loop maintenance. This closed-loop maintenance framework enables a continuous monitoring of system operation and timely identification and resolution of problems, thereby maximizing system reliability and maintainability.

4 Comparison analysis

The proposed maintenance strategy is compared with two benchmark maintenance strategies, corrective maintenance (CM) and the combination of corrective and preventive maintenance (CPM), both of which are widely adopted in the O&M of offshore wind farms. CM is a maintenance tool used when a turbine fails or becomes abnormal, which does not perform any preventive maintenance actions. CPM refers to the periodic maintenance of the turbines, and then if the turbine fails before periodic preventive maintenance, CM is applied.

The maintenance strategies for CM and CPM are further elaborated based on the case study in Section 3. In CM, a component failure is assumed when its condition value falls below the functional failure threshold R_2. The cost of CM includes the cost of replacement of the failed component, the personnel cost, the cost of transportation of the personnel and the replacement component to the maintenance site, and the downtime loss of the turbine. In CPM, the periodic maintenance cycle is one year. The costs include preventive maintenance costs or replacement of the failed components, personnel costs, transportation costs for personnel and replacement parts to the failure site, and turbine downtime losses.

Table 10 Results of comparison analysis

	CM	CPM	CBOM
Maintenance cost/ £	5,894,537	5,374,519	5,103,625
Reduction/%	13.42	5.04	-

The performance of the proposed strategy and the two benchmark maintenance strategies are reported in Table 10 concerning the maintenance cost reduction for the offshore wind farm when the maintenance cycle is five years. The CBOM strategy allows for approximately 13.42% and 5.04% reduction in the maintenance cost compared to CPM and CM, respectively. This study demonstrates that the proposed CBOM strategy provides a better reduction in maintenance costs than other maintenance strategies.

5 Discussions on the approach

5.1 Discussion on P-F curve accuracy

P-F curve is a characteristic curve describing the condition and time of the equipment, which is used to establish the initial maintenance time window. It can be obtained through accelerated experiments of reliability based on physical models, by knowledge-driven methods, or by data-driven methods with monitoring data. However, due to the lack of such monitoring data and data confidentiality, it is difficult to obtain

P-F curves from monitoring data.

Currently, research on the health condition degradation of key components such as bearings in wind turbines is mainly based on the reliability acceleration experiment. The natural degradation process of components from normal condition to complete failure is simulated by such experimental methods [51][52]. These experiments are rigorously validated and calibrated, providing detailed time-series degradation data that ensures the accuracy and reliability of RUL predictions and degradation process descriptions. Moreover, components typically undergo degradation during use, and these degradations show consistent and regular trends. Thus, it is scientifically sound and reasonable to set the P-F curves for various types of offshore wind turbine components on experimentally derived degradation from the wind turbine bearings, despite including some hypothetical implications in this process.

The goal of this paper is to propose a CBOM strategy based on the P-F curve. Compared with the periodic maintenance strategy commonly used in offshore wind farms, CBOM can avoid under-maintenance or over-maintenance, save O&M costs, reduce the number of downtimes, and improve the availability of components and turbines. Whether the P-F curve is based on experimental methods, knowledge-driven methods, or data-driven methods, it applies to the CBOM strategy proposed in this paper. We understand the use of real-time monitoring data can obtain dynamic P-F curves close to reality, thus facilitating a more accurate prediction of the health condition of wind turbines. The accuracy of the P-F curves can be improved in the future when the monitoring data are available and accessible.

5.2 The way of accessing the maintenance site

The significant difference in the O&M between offshore and onshore wind farms is that the maintenance personnel must use costly O&M vessels to access the offshore maintenance site. The cost of O&M vessels accounts for 73% of the total O&M cost in the offshore wind farm. Therefore, the selection of the O&M vessel can have a significant impact on the total O&M cost. In the case study, we select the jack-up vessel, which is the main O&M vessel in the offshore wind energy market, to verify the effectiveness of the proposed maintenance framework. To further explore the impact of O&M vessel type on the total O&M cost, the effectiveness of other types of O&M vessels, such as offshore access vessels (OAV) and crew transfer vessels (CTV), is also investigated. The parameters related to OAV, CTV, and jack-up vessels are presented in Table 11. Here, we illustrate the calculation of the total O&M cost for a single offshore maintenance voyage using the component combination, as discussed in Section 3.3.3. The maintenance costs under different O&M vessels are £875,635, £853,126, and £1,128,744, respectively.

Table 11 Parameters of OAV and CTV

Parameter	OAV	CTV	Jack-up	Unit
Number of vessels	1	2	1	vessel
Operational speed	13.5	24	11	knot
Max operational wave height	2	1.5	2.8	m
Max operational wind speed	25	25	36.1	m/s
Vessel charter cost	10,000	2,500	110,000	£ /vessel/day

Jack-up vessels have the highest total O&M costs due to their high chartering cost. Despite the high chartering cost, this type of vessel can navigate in more severe offshore environments and weather conditions and has a longer O&M window compared to other types of vessels. The utilization rate will be higher than other types of vessels, which does not show up in the results. Therefore, the chartering cost of a vessel can reflect the size of the vessel's navigable window to some extent. In future research, optimizing the O&M cost can be achieved by considering the selection of the O&M vessel type based on meteorological and navigation conditions at sea to ultimately optimize the maintenance strategy.

5.3 Sensitivity analysis of maintenance threshold

The maintenance threshold plays a crucial role in formulating a reasonable maintenance strategy. Therefore, this section will delve into the sensitivity analysis of thresholds R_1 and R_2. The value set of R_1 is {0.70, 0.75, 0.80, 0.85} and R_2 is {0.35, 0.4, 0.45, 0.5}. The O&M cost required for a single maintenance activity is calculated, as shown in Fig.19. The analysis results indicate that when the difference between the thresholds R_1 and R_2 increases, the cost of a single maintenance activity also rises. This phenomenon can be attributed to the expansion of the maintenance time window due to the increased difference between R_1 and R_2, which in turn increases the number of components that meet basic maintenance requirements. This finding aligns with the practical O&M scenarios of wind turbines.

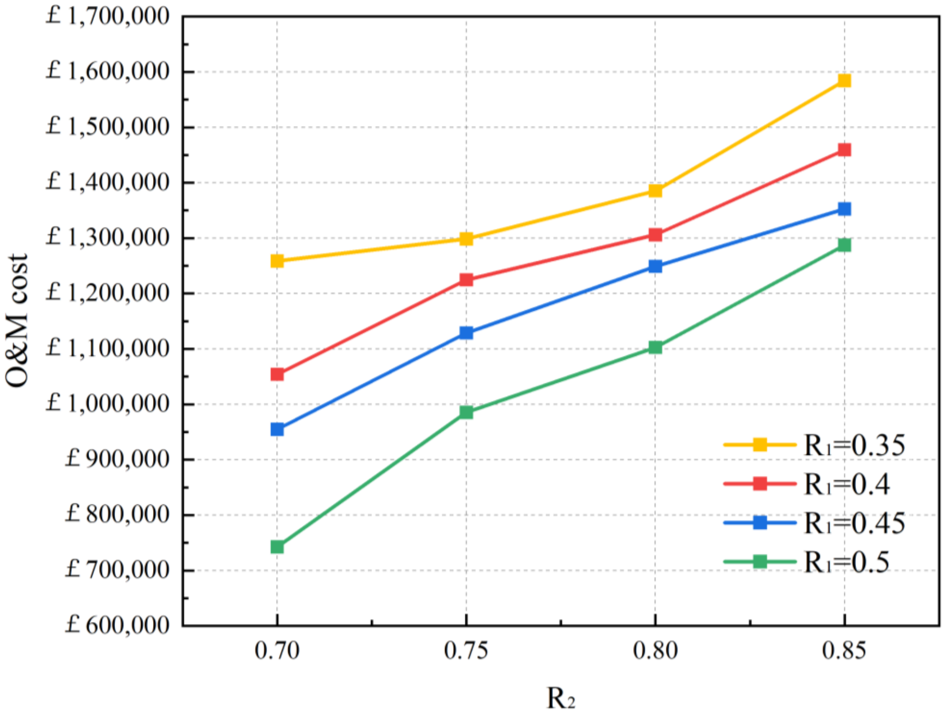

Fig.19. The results of sensitivity analysis for maintenance thresholds R_1 and R_2

Setting the potential failure threshold R_1 too low may prevent the timely detection of potential failures in turbines or their components, leading to severe faults, significant power loss, and safety risks. Conversely, setting R_1 too high will extend the maintenance time window and significantly increase maintenance frequency, resulting in longer downtime losses. In this case, even minor faults or slight performance declines during turbine operation might trigger maintenance requests, thus escalating maintenance costs. Similarly, setting the functional failure threshold R_2 too low will reduce its effectiveness in predicting failures. On the other hand, setting R_2 too high may classify early-stage failures as serious faults requiring urgent maintenance, leading to unnecessary downtime and wasting component residual life.

6 Conclusion

In this paper, an integrated condition-based opportunistic maintenance framework for the offshore wind farm is proposed, which contains the maintenance time window, mode, sequence, and component to maintain in a single dispatch to form a closed loop of maintenance. The maintenance strategies in the framework are carried out based on P-F curves and intervals, which provide a decision basis for the formulation of the maintenance strategies. First, component HI is constructed to divide the component health stages, and the component type with the highest proportion in the total maintenance cost is selected to determine the maintenance time window for multiple components. Then, the maintenance PI is calculated to evaluate the efficiency relationship between the maintenance cost and the recovery degree of the turbine before and after maintenance, which is solved through the DEA method to obtain the maintenance mode and sequence of the components. Finally, the ESA algorithm is adopted to select the combination of components to minimize the maintenance cost rate. Repeating the above steps to dynamically adjust the maintenance time window and schedule can tackle the drawbacks of conventional maintenance strategies.

The results via the case study show that maintenance optimization for multiple components by considering maintenance opportunities is more effective than maintenance optimization for single component. The number of maintenance trips and the total O&M cost in a given maintenance cycle are lower for multiple-component maintenance optimization. Taking into account both the health condition of the components and the availability of maintenance opportunities, the outcomes of the proposed strategy prove to be superior to the commonly used CM and CPM. Moreover, the attributes of the maintenance strategy and the effect of different ways to access the offshore maintenance site are further discussed. It can be found that the strategy proposed in this paper, online or offline, can be adapted depending on the type of used data. Additionally, the O&M cost is significantly influenced by the selection of O&M vessel type, where the chartering cost of the vessel can indicate the duration of the ship's navigational window. It is found that the maintenance thresholds R_1 and R_2 play a crucial role in formulating a reasonable maintenance strategy.

The proposed framework facilitates continuous improvement and optimization of O&M procedures, mitigating the risks associated with insufficient or excessive maintenance commonly encountered in offshore wind farms under traditional cyclic maintenance approaches. It significantly reduces the frequency of maintenance trips and turbine downtime, thereby lowering the overall O&M costs. This framework holds significant implications for advancing research in the optimization of offshore wind farm O&M practices.

In the future, optimizing the O&M cost can be achieved by considering the selection of the O&M vessel type, based on meteorological and navigation conditions at sea, to ultimately optimize the maintenance strategy. One of the limitations of this work is that there is no upper limit on the number of minor repair operations. To ensure the efficiency of the equipment, equipment may need to be replaced after exceeding a certain number of repair operations. In future research, the proposed maintenance framework can take into account the number of minor repair operations thresholds, to be in line with the actual maintenance situation. Presently, the P-F curves used to prove the effectiveness of the proposed framework in the case study is derived based on the reliability acceleration experimental data of bearings. In the future, when the real-time monitoring data of the wind turbine components become available and accessible, more accurate P-F curves can be used to provide a more accurate prediction for the health condition of the wind turbines.

Acknowledgments

The authors would like to thank the Royal Society International Exchanges under Grant IEC\NSFC\223091, the National Natural Science Foundation of China (No. 42276225), Natural Science Foundation of Heilongjiang Province of China (Grant No. LH2021E048) and the Postgraduate Research & Practice Innovation Program of Jiangsu Province (No. KYCX24_4055) for their financial supports. The authors wish to express their thanks to the reviewers for their useful and constructive comments.

Appendix

Theorem 1: The sufficient and necessary condition for the weak DEA efficiency of the decision-making unit is that the optimal value in the fractional programming in Eq. (25) or the dual programming in Eq. (30) is 1.

Theorem 2: The sufficient and necessary condition for the decision-making unit to be DEA efficient is that the optimal value of the dual programming in Eq. (28) is 1, and μ^{*+} and μ^{*-} of each optimal solution are 0.

Reference

[1] Global Wind Energy Council. Global Wind Report 2024; [Online]. Available. https://gwec.net/global-wind-report-2024/.

[2] Global Wind Energy Council. Global Wind Report 2020; [Online]. Available. https://gwec.net/global-wind-report-2020/.

[3] Saleh, A., Chiachío, M., Salas, J.F. and Kolios, A. Self-adaptive optimized maintenance of offshore wind turbines by intelligent Petri nets. Reliability Engineering & System Safety, 2023; 231, p.109013.

[4] Ghamlouch, H., Fouladirad, M. and Grall, A. The use of real option in condition-

based maintenance scheduling for wind turbines with production and deterioration uncertainties. Reliability Engineering & System Safety, 2019; 188, pp.614-623.

[5] Marugán, A.P., Chacón, A.M.P. and Márquez, F.P.G. Reliability analysis of detecting false alarms that employ neural networks: A real case study on wind turbines. Reliability Engineering & System Safety, 2019; 191, p.106574.

[6] Shafiee, M. Maintenance logistics organization for offshore wind energy: Current progress and future perspectives. Renewable energy, 2015; 77, pp.182-193.

[7] Zhu, W., Castanier, B. and Bettayeb, B. A dynamic programming-based maintenance model of offshore wind turbine considering logistic delay and weather condition. Reliability Engineering & System Safety, 2019; 190, p.106512.

[8] Lagaros, N.D., Karlaftis, M.G. and Paida, M.K. Stochastic life-cycle cost analysis of wind parks. Reliability Engineering & System Safety, 2015; 144, pp.117-127.

[9] Li, M., Wang, M., Kang, J., Sun, L. and Jin, P. An opportunistic maintenance strategy for offshore wind turbine system considering optimal maintenance intervals of subsystems. Ocean Engineering, 2020; 216, p.108067.

[10] Nielsen, J.J. and Sørensen, J.D. On risk-based operation and maintenance of offshore wind turbine components. Reliability engineering & system safety, 2011; 96(1), pp.218-229.

[11] Nguyen, T.A.T. and Chou, S.Y. Maintenance strategy selection for improving cost-effectiveness of offshore wind systems. Energy conversion and management, 2018; 157, pp.86-95.

[12] Shafiee, M., Finkelstein, M. and Bérenguer, C. An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks. Reliability Engineering & System Safety, 2015; 142, pp.463-471.

[13] Li, M., Jiang, X., Carroll, J. and Negenborn, R.R. A closed-loop maintenance strategy for offshore wind farms: Incorporating dynamic wind farm states and uncertainty-awareness in decision-making. Renewable and Sustainable Energy Reviews, 2023; 184, p.113535.

[14] Yeter, B., Garbatov, Y. and Soares, C.G. Risk-based maintenance planning of offshore wind turbine farms. Reliability Engineering & System Safety, 2020; 202, p.107062.

[15] Yan, R., Dunnett, S., and Jackson, L. Impact of condition monitoring on the maintenance and economic viability of offshore wind turbines. Reliability Engineering & System Safety, 2023; 238, 109475.

[16] Gonzalo, A. P., Benmessaoud, T., Entezami, M., and Márquez, F. P. G. Optimal maintenance management of offshore wind turbines by minimizing the costs.

Sustainable Energy Technologies and Assessments, 2022; 52, 102230.
[17] Hendradewa, A.P. and Yin, S. Comparative Analysis of Offshore Wind Turbine Blade Maintenance: RL-based and Classical Strategies for Sustainable Approach. Reliability Engineering & System Safety, 2024; p.110477.
[18] Van Horenbeek, A., Van Ostaeyen, J., Duflou, J. R., and Pintelon, L. Quantifying the added value of an imperfectly performing condition monitoring system—Application to a wind turbine gearbox. Reliability Engineering & System Safety, 2013; 111, 45-57.
[19] Yu, V. F., Le, T. H. A., Su, T. S., and Lin, S. W. Optimal maintenance policy for offshore wind systems. Energies, 2021; 14(19), 6082.
[20] Li, M., Jiang, X., Carroll, J. and Negenborn, R.R. A multi-objective maintenance strategy optimization framework for offshore wind farms considering uncertainty. Applied Energy, 2022; 321, p.119284.
[21] Kang, J., and Soares, C. G. An opportunistic maintenance policy for offshore wind farms. Ocean Engineering, 2020; 216, 108075.
[22] Luo, Y., Zhao, X., Liu, B., and He, S. Condition-based maintenance policy for systems under dynamic environment. Reliability Engineering & System Safety, 2024; 246, 110072.
[23] He, R., Tian, Z., Wang, Y., Zuo, M., and Guo, Z. Condition-based maintenance optimization for multi-component systems considering prognostic information and degraded working efficiency. Reliability Engineering & System Safety, 2023; 234, 109167.
[24] Mikhail, M., Ouali, M. S., and Yacout, S. A data-driven methodology with a nonparametric reliability method for optimal condition-based maintenance strategies. Reliability Engineering & System Safety, 2024; 241, 109668.
[25] Oakley, J. L., Wilson, K. J., and Philipson, P. A condition-based maintenance policy for continuously monitored multi-component systems with economic and stochastic dependence. Reliability Engineering & System Safety, 2022; 222, 108321.
[26] Li, H., Zhu, W., Dieulle, L. and Deloux, E. Condition-based maintenance strategies for stochastically dependent systems using Nested Lévy copulas. Reliability Engineering & System Safety, 2022; 217, p.108038.
[27] Wang, Y., He, R. and Tian, Z. Opportunistic condition-based maintenance optimization for electrical distribution systems. Reliability Engineering & System Safety, 2023; 236, p.109261.
[28] Lu, Y., Wang, S., Zhang, C., Chen, R., Dui, H., & Mu, R. Adaptive maintenance

window-based opportunistic maintenance optimization considering operational reliability and cost. Reliability Engineering & System Safety, 2024; 250, 110292.

[29] Zhang, C., Gao, W., Yang, T., & Guo, S. Opportunistic maintenance strategy for wind turbines considering weather conditions and spare parts inventory management. Renewable Energy, 2019; 133, 703-711.

[30] Li, H., Huang, C. G., & Soares, C. G. A real-time inspection and opportunistic maintenance strategies for floating offshore wind turbines. Ocean Engineering, 2022; 256, 111433.

[31] McMorland, J., Collu, M., McMillan, D., Carroll, J. and Coraddu, A. Opportunistic maintenance for offshore wind: A review and proposal of future framework. Renewable and Sustainable Energy Reviews, 2023; 184, p.113571.

[32] Chen, Y., Qiu, Q. and Zhao, X. Condition-based opportunistic maintenance policies with two-phase inspections for continuous-state systems. Reliability Engineering & System Safety, 2022; 228, p.108767.

[33] Shafiee, M., & Sørensen, J. D. Maintenance optimization and inspection planning of wind energy assets: Models, methods and strategies. Reliability Engineering & System Safety, 2019; 192, 105993.

[34] Chou, J. S., Chiu, C. K., Huang, I. K., & Chi, K. N. Failure analysis of wind turbine blade under critical wind loads. Engineering Failure Analysis, 2013; 27, 99-118.

[35] Liu, B., Xu, Z., Xie, M. and Kuo, W. A value-based preventive maintenance policy for multi-component system with continuously degrading components. Reliability Engineering & System Safety, 2014; 132, pp.83-89.

[36] Shi, D., Ma, H. and Ma, C. A dynamic maintenance strategy for multi-component systems using a genetic algorithm. CMES-Computer Modeling in Engineering & Sciences, 2023; 134(3).

[37] Xu, J., Liang, Z., Li, Y.F. and Wang, K. Generalized condition-based maintenance optimization for multi-component systems considering stochastic dependency and imperfect maintenance. Reliability Engineering & System Safety, 2021; 211, p.107592.

[38] Shafiee, M. and Sørensen, J.D. Maintenance optimization and inspection planning of wind energy assets: Models, methods and strategies. Reliability Engineering & System Safety, 2019; 192, p.105993.

[39] Moubray, J. Reliability-centered maintenance. 2001. Industrial Press Inc.

[40] Wang, K., Deng, C. and Ding, L. Optimal condition-based maintenance strategy

for multi-component systems under degradation failures. Energies, 2020; 13(17), p.4346.
[41] Ochella, S., Shafiee, M. and Sansom, C. Adopting machine learning and condition monitoring PF curves in determining and prioritizing high-value assets for life extension. Expert Systems with Applications, 2021; 176, p.114897.
[42] Abdullah A, Saraswat S, Talib F. Impact of Smart, Green, Resilient, and Lean Manufacturing System on SMEs' Performance: A Data Envelopment Analysis (DEA) Approach. Sustainability. 2023;15(2).
[43] Charnes, A. and Cooper, W.W. Programming with linear fractional functionals. Naval Research logistics quarterly, 1962; 9(3‐4), p.181-186.
[44] Charnes, A., Cooper, W. W., Golany, B., Seiford, L. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. Journal of econometrics. 1985; 30(1-2): 91-107.
[45] Duan Y R. Data Envelopment Analysis. Shanghai Science Publishing House, 2006.
[46] Ma Z X. Data envelopment analysis model and method. Beijing: Science Press. 2010.
[47] Anselm L, Michael K, Oliver M. Degradation model constructed with the aid of dynamic Bayesian networks. Cogent Engineering. 2017;4.
[48] Dalgic Y, Lazakis I, Turan O, Judah S, et al. Investigation of optimum jack-up vessel charting strategy for offshore wind farm O&M activities. Ocean Engineering. 2015; 95, 106-115.
[49] Dalgic Y, Lazakis I, Dinwoodie I, McMillan D, et al. Advanced logistics planning for offshore wind farm operation and maintenance activities. Ocean Engineering. 2015; 101, 211-226.
[50] Han Y ZH. Damage identification and state degradation prediction of large wind turbine gearbox bearings. Shenyang University of Technology, 2022. (in Chinese)
[51] Tian M, Su X, Chen C, An W. A Novel Method for Multistage Degradation Predicting the Remaining Useful Life of Wind Turbine Generator Bearings Based on Domain Adaptation. Applied Sciences. 2023; 13(22):12332.
[52] Soualhi A, Medjaher K, Zerhouni N. Bearing health monitoring based on Hilbert–Huang transform, support vector machine, and regression. IEEE Transactions on instrumentation and measurement. 2014; 64(1):52-62.