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Dynamic opportunistic maintenance framework for offshore wind farms in deregulated electricity markets

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Abstract

The economic viability of offshore wind farms (OWFs) is heavily constrained by exorbitant operation and maintenance (O&M) costs and significant revenue losses during system downtime. While opportunistic maintenance (OM) strategies have been widely adopted to share the high fixed costs of vessel dispatch, existing frameworks largely rely on static degradation models and fail to account for the extreme short-term volatility of modern deregulated electricity markets. To bridge these gaps, this paper proposes a dynamic OM framework driven by day-ahead locational marginal prices (LMPs). Firstly, a hybrid multi-component degradation model is established. A stochastic process is developed to capture the complex crack initiation and propagation mechanisms of wind turbine blades, while the progressive aging of electromechanical components is characterized by Weibull distributions. Secondly, a dynamic and price-responsive OM thresholding mechanism is introduced. By integrating day-ahead weather forecasts and LMPs, the proposed strategy proactively groups preventive maintenance tasks during low-price windows and tightens thresholds during price spikes, thereby minimizing the expected maintenance cost. Numerical case studies based on real-world OWF configurations and historical market data demonstrate that the proposed dynamic strategy significantly outperforms traditional static OM approaches, reducing the expected lifecycle maintenance costs by 18.4% and substantially mitigating financial risks associated with electricity price volatility.

Keywords: offshore wind farms, opportunistic maintenance, day-ahead electricity market, dynamic scheduling

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1. Introduction

The rapid expansion of offshore wind farms (OWFs) plays a critical role in the global transition toward renewable energy [1]. However, the harsh and highly variable marine environment, characterized by high wind speeds, salt spray, and complex wave conditions, accelerates the degradation of wind turbine components [2]. Consequently, operation and maintenance (O&M) costs remain high, typically accounting for 20%–30% of the levelized cost of energy (LCOE) for offshore wind projects [3, 4]. To mitigate these exorbitant expenditures, opportunistic maintenance (OM) has emerged as a prevailing strategy. By leveraging the economic and structural dependencies among multiple components and turbines, the OM strategies group coordinates activities among various components [5–8]. This grouping mechanism effectively shares the substantial fixed setup costs of dispatching specialized O&M vessels and reduces the overall downtime of the wind farm [9].

Regarding the O&M management of OWFs, scholars have conducted research centered on issues such as condition assessment, environmental forecasting, and maintenance decision-making, aiming to provide actionable guidelines for wind farm operators. Existing studies predominantly focus on the health monitoring and maintenance policies for individual turbine systems and their critical components. These approaches scientifically schedule tasks based on the operational states of critical components to prevent both over-maintenance and under-maintenance [10–12]. Furthermore, for multi-state complex systems, current research incorporates various interventions, such as repairs and replacements, utilizing joint decision-making to enhance system reliability and reduce lifecycle costs [13]. Considering that wind turbines operate continuously in complex environments characterized by gusty winds, alternating aerodynamic loads act on the blades and are transmitted through the drivetrain's critical components. This continuous stress makes the drivetrain highly susceptible to failures during its service life. To address this, Yang *et al* [14] proposed a wind turbine O&M strategy that accounts for dynamic wind conditions, comprehensively quantifying both the positive impacts (maintenance opportunities) and negative impacts (operational delays) of wind variations to determine the optimal maintenance timing by minimizing costs and production losses. Similarly, Zheng *et al* [15] formulated an optimal policy that integrates preventive maintenance, replacements, and minor repairs to minimize the long-term average cost rate. Expanding the scope, Bakir *et al* [16] explored composite maintenance opportunities across three levels, establishing a sensor-driven adaptive strategy that continuously updates maintenance schedules based on degradation predictions and system topology. Addressing the inherent uncertainties in O&M services, Li *et al* [17] considered the stochastic nature of component failure times, actual turbine faults, and practical repair efficacies, proposing a Monte Carlo-based multi-objective optimization framework to guide the long-term management of OWFs.

Nevertheless, while existing OM frameworks have demonstrated theoretical maturity, their practical application in modern, market-driven OWFs is hindered by two limitations in their underlying modeling assumptions. The first major limitation lies in the simplification of component degradation models. The majority of existing OM literature frequently utilizes generic statistical distributions (e.g., the Weibull distribution) to characterize the lifetimes of all turbine components. While such data-driven static models may suffice for certain mechanical or electrical parts, they fail to capture the distinct physical failure mechanisms of wind turbine blades. For example, blades are highly susceptible to aerodynamic loads and environmental erosion, and their degradation is inherently a multi-stage physical evolution rather than a simple aging process [18–20]. It typically begins with the random initiation of surface micro-cracks, followed by continuous crack propagation under alternating stress, ultimately leading to catastrophic fracture [21]. Relying on static probability distributions obscures the early-stage micro-damage states and nonlinear propagation trajectories, resulting in inaccurate remaining useful life (RUL) estimations. Consequently, traditional OM algorithms often miss the optimal grouping windows for blade maintenance. Therefore, embedding physics-informed stochastic processes into the underlying degradation models is imperative for accurate OM decision-making.

Besides, another critical limitation is the disconnect between the economic evaluation models used in current OM strategies and the operational realities of deregulated electricity markets. In formulating the objective functions for maintenance scheduling, existing studies predominantly calculate downtime penalties (i.e. production losses) based on a constant annual average electricity price or a fixed penalty rate per unit of time [22–24]. In practice, as shown in figure 1, modern OWFs participate in wholesale electricity markets (e.g., the day-ahead markets), where the locational marginal prices (LMPs) exhibit extreme short-term volatility. Driven by weather fluctuations, grid congestion, and peak demand, day-ahead prices can experience severe spikes or even drop to negative values during off-peak hours with high wind generation [25, 26]. Executing maintenance during a price spike incurs massive opportunity costs, whereas scheduling downtime during low-price periods results in negligible revenue loss. Ignoring these short-term price signals renders static OM schedules economically suboptimal and exposes wind farm operators to significant financial risks.

Beyond the aforementioned conditions, the sheer temporal scale of offshore wind operations presents a formidable logistical challenge. A typical OWF possesses a design lifecycle of approximately 25 years, during which the multi-component systems will inevitably require multiple maintenance interventions [27, 28]. These activities range from preventive maintenance (PM) and minor *in-situ* inspections to corrective maintenance (CM) and major component overhauls. Given the degradation trajectories of different critical components, their maintenance demands emerge at vastly different frequencies. If these varied PM and CM tasks are treated as isolated events over the long term, the cumulative fixed costs of frequent vessel mobilizations and the resulting cumulative downtime would render the project economically unviable.

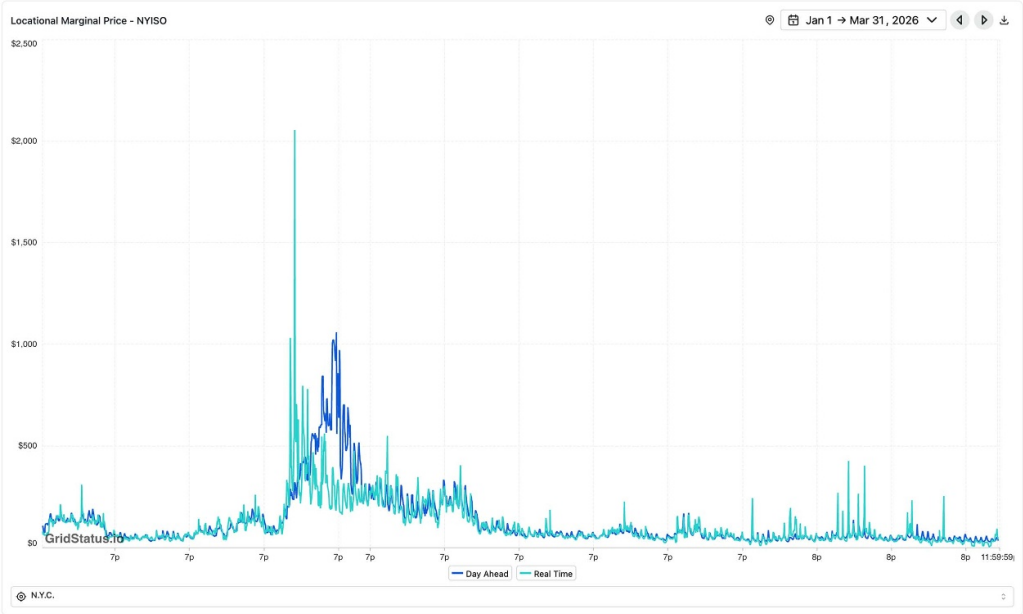


Figure 1. Day-ahead and real-time LMPs in New York City.

To bridge the research gap, this paper proposes a dynamic OM framework for OWFs. It should be emphasized that OM is not an independent maintenance paradigm parallel to PM, but rather a coordinating mechanism established upon an underlying PM policy. In this study, the PM foundation is formulated as a hybrid policy, in which condition-based maintenance (CBM) is adopted for the blade based on its real-time crack length, while time-based maintenance (TBM) is adopted for the rotor, main bearing, gearbox, and generator based on their optimized age-based PM intervals. Departing from traditional long-term static scheduling, the proposed framework adopts a daily sequential decision-making mechanism that aligns with the information clearing schedule of day-ahead markets. The dynamic day-ahead LMP signals then modulate the opportunistic grouping thresholds on top of this PM foundation. Specifically, upon acquiring the day-ahead weather forecasts and LMPs, it evaluates the real-time health states of multi-component systems. The algorithm then dynamically adjusts the OM grouping thresholds based on the price signals: proactively grouping potential PM tasks during low-price windows to capitalize on cheap downtime, while strictly tightening maintenance thresholds during price peaks to maximize generation revenue. The main contributions are summarized as follows:

- We propose a hybrid degradation approach for five critical components. Specifically, the blade degradation is captured through a physics-informed model that integrates crack initiation, crack propagation, and a damage rate to quantify its structural failure mechanism. Concurrently, the degradation of the remaining four components is characterized by Weibull distributions.
- We develop a dynamic maintenance mechanism driven by day-ahead market LMPs. By integrating the highly volatile 24-hour electricity prices into the downtime penalty, the strategy dynamically adjusts the OM thresholds. This allows the system to proactively group potential multi-component preventive maintenance tasks during low-price windows, effectively minimizing opportunity costs without relying on long-term, error-prone price forecasting.
- We establish an optimization model that simultaneously optimizes the opportunistic grouping of the multi-component tasks. The model rigorously incorporates practical constraints, offering a comprehensive and economically viable O&M paradigm for market-participating OWFs.

2. Problem description

Before delving into the empirical data and mathematical formulations, this section outlines the configuration of the multi-component offshore wind turbine and the operational logic of the proposed decision-making framework. It establishes the structural baseline for the dynamic OM strategy.

This study considers an OWF consisting of N wind turbines, participating in a deregulated day-ahead electricity market. As shown in figure 2, each wind turbine is treated as a multi-component system comprising five critical sub-assemblies: the blade, rotor, main bearing, gearbox, and generator. Due to their distinct operational environments and physical characteristics, these components exhibit heterogeneous degradation behaviors.

Specifically, the blade, which is directly exposed to alternating aerodynamic loads and harsh marine environments, undergoes a complex structural degradation process. Its deterioration is modeled via a physics-informed approach that captures crack initiation, crack propagation, and a comprehensive damage rate. In contrast, the degradation of the remaining four mechanical and electrical components (rotor, main bearing, gearbox, and generator) is characterized by

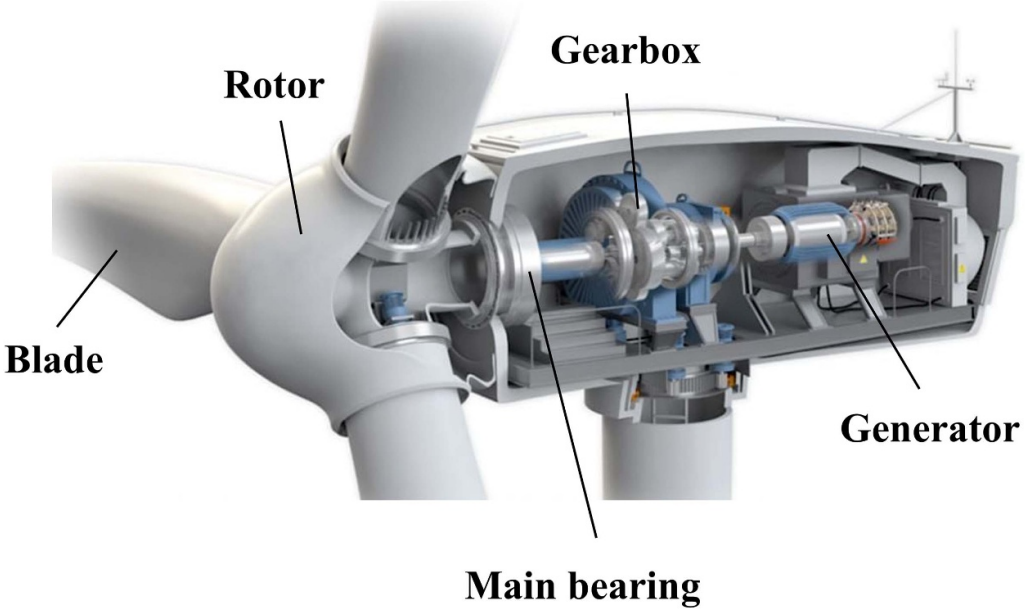


Figure 2. The basic configuration of wind turbine.

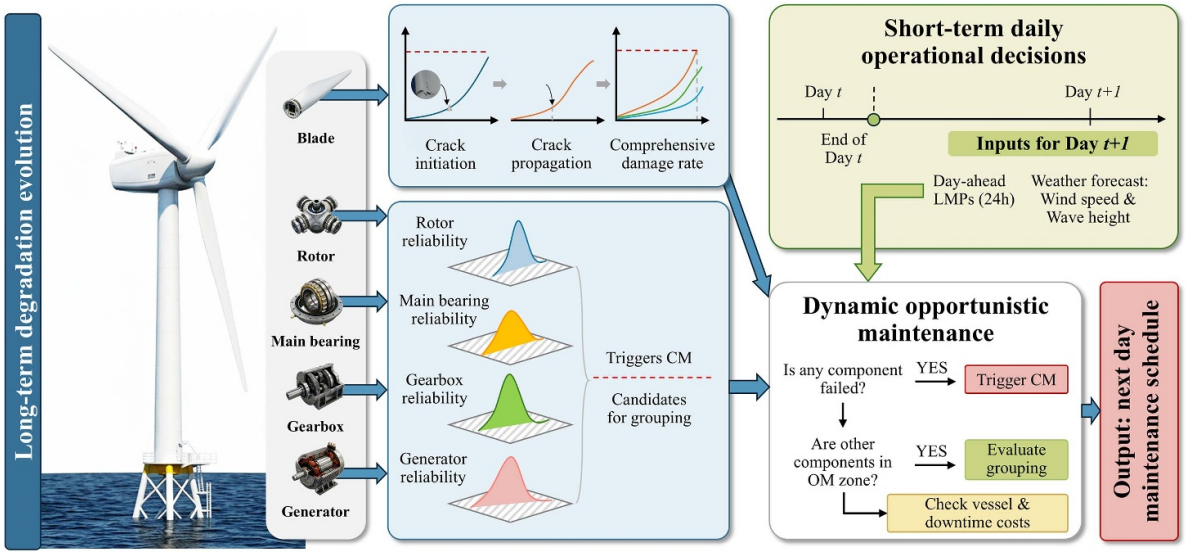


Figure 3. The proposed dynamic opportunistic maintenance framework.

component-specific Weibull distributions. The failure of any single component leads to the shutdown of the entire wind turbine, necessitating immediate CM to restore its functionality. To mitigate the high fixed costs associated with vessel dispatch and the severe downtime penalties during price spikes, PM for other degrading components can be opportunistically grouped with the required CM tasks.

As shown in figure 3, our proposed framework operates through a dual-timescale decision-making process, integrating long-term degradation evolution with short-term market and weather dynamics. Over the long term, the health state of each component evolves continuously. The system monitors and updates the cumulative damage of the blades and the reliability levels of the Weibull-distributed components. This long-term tracking provides the fundamental physical baseline for maintenance requirements. When a component's degradation reaches its failure threshold, a CM task is triggered. Simultaneously, components whose degradation levels have crossed a predefined OM threshold become candidates for opportunistic grouping. Meanwhile, the core optimization occurs at the short-term, daily operational level, strictly aligning with the clearing schedule of the day-ahead electricity market. At the end of each day t, the OWF operator receives the 24-hour weather forecast (wind speed and wave height) and

the day-ahead LMPs for day $t+1$. Based on these short-term deterministic inputs and the current long-term degradation states, the operator makes the decisions for the upcoming day.

3. Data-driven component degradation and maintenance analysis

While section 2 establishes the conceptual framework, it is imperative to ground the component heterogeneity in empirical evidence. Therefore, to accurately characterize the distinct degradation processes, this section conducts a data-driven analysis. By referencing real-world operation and failure data from 313 turbines in the LGS-Offshore database, we statistically analyze the failure frequency, mean time to failure (MTTF), and failure severity of the five key components to determine their different roles within the OM framework.

To accurately characterize the degradation process of the offshore wind turbines, this study referenced real-world operation and failure data from 313 turbines in the LGS-Offshore database. The five key components of the system exhibited significant differences in failure frequency, MTTF, and failure severity, determining their different roles within the OM framework.

As shown in figure 4, generators and gearboxes have high failure rates, with MTTFs of 87 640 h and 76 025 h, respectively. Failures in these electromechanical and transmission components often manifest as progressive wear or aging (e.g., abnormal gearbox wear, generator cooling system failure), making them suitable for long-term reliability modeling using the Weibull distribution. Due to their frequent failures, they are the primary candidates for dynamic maintenance strategies. Conversely, the main bearing has an extended MTTF of 701 120 h, classifying it as a low-frequency failure component. However, according to failure severity statistics, rotor components experience an extremely critical failure rate as high as 19%, significantly higher than other components. Consequently, a main bearing or critical rotor failure typically necessitates immediate turbine shutdown and triggers mandatory CM actions, thereby creating a crucial time window for executing OM on other degrading components. Besides, the blade's MTTF is approximately 101 775 h. Unlike electromechanical components, blades are directly exposed to harsh marine weather conditions, and their failure modes are mostly structural damage, such as cracks and delamination. Blade degradation is a long-term, cumulative physical process, and routine maintenance rarely involves the replacement of the entire blade.

Therefore, the maintenance operations executed over the 25-year lifecycle of these turbines highlight the necessity of a differentiated and grouped maintenance strategy. Over this extended operational horizon, the five components exhibit distinct temporal maintenance trajectories and resource requirements. Gearboxes and generators typically undergo multiple major overhauls or complete replacements throughout the 25-year lifespan, demanding frequent mobilization of crew transfer vessels (CTVs). In contrast, main bearings are fundamentally designed to last the turbine's entire lifecycle; however, when a rare failure does occur, it requires the deployment of costly heavy-lift jack-up vessels. The rotor system requires periodic, moderately frequent interventions, such as lubrication, sensor calibration, and pitch actuator replacements. Meanwhile, long-term blade maintenance primarily consists of scheduled surface inspections and minor *in-situ* repairs rather than full component replacements. Because a single offshore vessel dispatch incurs exorbitant fixed costs and significant downtime, treating these lifecycle maintenance actions in isolation is economically unviable. By aligning the frequent, predictable interventions of gearboxes, generators, and rotors with the mandatory, high-cost CM of critical components like main bearings, the proposed OM framework effectively capitalizes on shared vessel mobilizations and overlapping downtime, thereby minimizing the total O&M costs over the lifecycle.

4. Mathematical model

In this section, a comprehensive mathematical framework is formulated to quantify the heterogeneous degradation processes of the offshore wind turbine components and to optimize the dynamic OM strategy.

4.1. Assumption

To formulate the maintenance optimization model for the OWF, several necessary assumptions regarding the system structure, degradation processes, and maintenance actions are established as follows:

(i) The wind turbine is considered a multi-component series system. The failure of any single critical component results in the shutdown of the entire turbine system.
(ii) Maintenance actions are classified into two categories: CM and PM. CM is a reactive action performed when a component completely fails. CM is assumed to be a perfect replacement, which completely replaces the failed component and restores it to an 'as good as new' state. PM, on the other hand, is a proactive action triggered when the degradation level of a component reaches a predefined preventive threshold (e.g., the crack length reaches d).
(iii) Unlike CM, PM is assumed to be imperfect. It mitigates the degradation and improves the condition of the component, but it cannot fully restore the component to a new state. Thus, after PM, the component is in a state that lies between 'as good as new' and 'as bad as old'.
(iv) The degradation processes of different components within the wind turbine are statistically independent. On the one hand, the failure processes in different blades are assumed to be statistically independent. Besides, the crack initiation and propagation on the blades do not affect the wear process of the gearbox, and they develop independently over time.
(v) Each maintenance action incurs a specific cost. The cost of CM is significantly higher than the cost of PM, due to

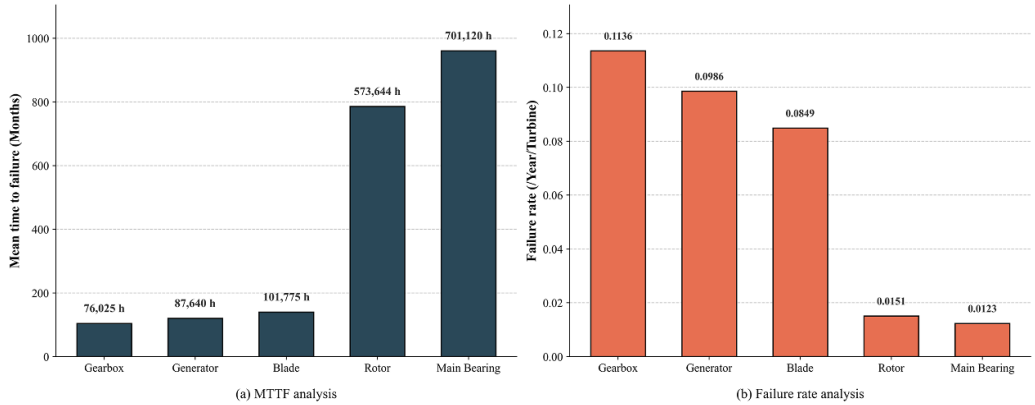


Figure 4. Degradation and maintenance analysis of each component.

the severe consequences of unexpected failures, including system downtime, secondary damage, and emergency logistics.

(vi) Short-term meteorological conditions (wind speed and wave height) and day-ahead electricity prices can be reliably forecast within the scheduling horizon.

(vii) The availability of maintenance vessels and spare parts is known, and each vessel has a maximum operational capacity and strict weather limits for safe accessibility.

4.2. Multi-component degradation model

4.2.1. Comprehensive damage model for the blade. The degradation of a wind turbine blade is a complex process involving both the random initiation of cracks and their continuous stochastic propagation. Specifically, a wind turbine typically contains three blades. Although the three blades are structurally identical and share the same crack degradation model, the crack propagation process of each blade is modeled as a statistically independent process. Consequently, the three blades generally reach their respective degradation thresholds at different time instants, and each blade is therefore treated as a separately monitored and maintained degrading unit. The generation of cracks on the surface of a blade follows a non-homogeneous Poisson process (NHPP) with an intensity function $m(t)$. Let $N_1(t)$ denote the number of cracks initiated in the interval $[0,t)$. The mean value function $M(t)$, which represents the expected number of cracks up to time t, is given by:

$$M(t)=\int_0^t m(y)\,\mathrm{d}y, \quad t\geqslant 0 \tag{1}$$

Accordingly, the probability that exactly j cracks are initiated on a blade by time t is expressed as:

$$P(N_1(t)=j)=\frac{[M(t)]^j}{j!}\mathrm{e}^{-M(t)}, \quad j=0,1,2,\ldots \tag{2}$$

Once a crack is initiated, its length expands continuously over time. A homogeneous Gamma process is adopted to describe this degradation process due to its suitability for modeling monotonic, gradual deterioration. Let $X(t)$ denote the length of a crack at time t after its initiation. The crack length $X(t)$ follows a Gamma distribution with a time-dependent shape parameter αt and a scale parameter β. The probability density function (PDF) of the crack length $X(t)$ is given by:

$$f_{X(t)}(x)=\frac{\beta^{\alpha t}}{\Gamma(\alpha t)}x^{\alpha t-1}\mathrm{e}^{-\beta x}, \quad x>0 \tag{3}$$

where $\Gamma(\cdot)$ is the standard Gamma function.

Let U^x denote the time elapsed from the crack initiation until its length first reaches a specific size x (i.e. the first passage time), defined as $U^x=\inf\{t\geqslant 0: X(t)\geqslant x\}$. Based on the properties of the Gamma process, the cumulative distribution function (CDF) of the first passage time, $G_{U^x}(t)$, is equivalent to the probability that the degradation level at time t exceeds x:

$$G_{U^x}(t)=P(X(t)\geqslant x)=\frac{\Gamma(\alpha t,\beta x)}{\Gamma(\alpha t)}, \quad t\geqslant 0 \tag{4}$$

where $\Gamma(\alpha t,\beta x)=\int_{\beta x}^{\infty} z^{\alpha t-1}\mathrm{e}^{-z}\mathrm{d}z$ is the upper incomplete Gamma function. The corresponding probability density function $g_{U^x}(t)$ can be obtained by taking the derivative of $G_{U^x}(t)$ with respect to t.

Furthermore, since cracks are continuously generated and each propagates independently, it is crucial to determine the probability that the length of a crack on a certain blade exceeds the threshold x for the first time. Let $N_{S_i}^x(t)$ denote the total number of cracks on the ith blade whose length exceeds x in the interval $[0,t)$. This counting process is also an NHPP. The intensity function $\theta_x(t)$ of this process is given by the convolution of the crack initiation rate and the first passage time density of the crack, which is expressed as:

$$\theta_x(t)=\int_0^t m(y)\,g_{U^x}(t-y)\,\mathrm{d}y=m(t)*g_{U^x}(t) \tag{5}$$

where the symbol $*$ denotes convolution, the intensity function is obtained as the convolution of the crack-initiation intensity $m(\cdot)$ and the crack-propagation density $g_{U_x}(\cdot)$

When the length of a crack reaches a critical threshold D, the blade breaks and requires a costly corrective replacement. To prevent this, a major repair is triggered when the crack length reaches a preventive threshold d ($d<D$).

4.2.2. Degradation model for other components. For the other components (the rotor, main bearing, gearbox, and generator), their degradation manifests as progressive wear and aging. As established by historical failure data, their lifecycles are accurately captured by the Weibull distribution. For component k (where $k \in \{1,2,\ldots,K-1\}$), the reliability function $R_k(t)$ at operational time t is defined as:

$$R_k(t) = \exp\left(-\left(\frac{t}{\eta_k}\right)^{\beta_k}\right) \tag{6}$$

where β_k is the shape parameter indicating the aging rate, and η_k is the scale parameter representing the characteristic life. The corresponding hazard rate $\lambda_k(t)$, which is derived as $\lambda_k(t) = \frac{\beta_k}{\eta_k}\left(\frac{t}{\eta_k}\right)^{\beta_k-1}$, is used to monitor the degradation state of these components.

To determine the PM interval T_k^{PM}, a classic maintenance cost rate model is utilized. Specifically, T_k^{PM} is obtained by minimizing the long-term expected maintenance cost (EMC) per unit time for the individual component. Once T_k^{PM} is optimized, the real-time effective age $v_k(t)$ of component k is continuously tracked to judge whether a PM action is required. The effective age $v_k(t)$ is updated depending on the type of maintenance action performed:

$$v_k(t+\Delta t) = \begin{cases} 0, & \text{if CM is performed} \\ \rho v_k(t), & \text{if PM is performed} \\ v_k(t)+\Delta t, & \text{otherwise.} \end{cases} \tag{7}$$

(1) After a CM action, the effective age of the component is reset to zero ($v_k = 0$), and the hazard rate $\lambda_k(t)$ restarts from its initial baseline.
(2) If a PM action is executed when the component reaches an effective age $v_k(t)$, its effective age immediately after the PM is reduced to $\rho v_k(t)$, where $\rho(0 < \rho < 1)$ is an age reduction factor. Consequently, the hazard rate drops to $\lambda_k(\rho v_k(t))$, and the component resumes its progressive aging from this partially restored state in the next operational cycle.

4.3. Optimization model

To bridge the gap between the long-term lifecycle degradation and the short-term day-ahead operational scheduling, an optimization framework based on a rolling horizon approach is proposed. Over the 25-year lifecycle T_{life} of the OWF, components will undergo multiple degradation-maintenance-restoration cycles. Therefore, attempting a single global optimization for the entire lifecycle is computationally intractable and practically infeasible due to the stochastic nature of weather, electricity prices, and component degradation. In this paper, the system state is continuously updated at discrete time steps Δt. When any component reaches its mandatory CM or PM threshold, a scheduling optimization is triggered.

4.3.1. Decision variables. Due to the distinct degradation mechanisms of the various components within the wind turbine, two state-based thresholds are utilized to govern maintenance activities. In this study, the PM thresholds for all components are predetermined parameters known in advance. Specifically, for the blades ($k = K$), the PM threshold d is a given parameter. When the crack length $X(t)$ reaches d, mandatory PM must be triggered. For the other components ($k \in \{1,\ldots,K-1\}$), the PM threshold T_k^{PM} is obtained in advance by minimizing the expected cost rate function of each individual component. Mandatory maintenance is triggered once the virtual age $v_k(t)$ of component k reaches its respective T_k^{PM}.

Based on the predetermined PM thresholds, the core decision variables to be optimized in the proposed model are the OM thresholds:

- OM threshold of blade d_{OM}: When the system is shut down for other reasons and $X(t) \geqslant d_{\mathrm{OM}}$ ($d_{\mathrm{OM}} \in \mathbb{Z}^+$), OM can be performed on the blades.
- OM thresholds for the other components $T_{OM,k}$: When the system is shut down and $v_k(t) \geqslant T_{OM,k}$ ($T_{OM,k} \in \mathbb{Z}^+$), OM is executed.

Consequently, the set of decision variables to be optimized in this model consists solely of these OM thresholds, which can be mathematically expressed as:

$$\boldsymbol{X} = \{d_{\mathrm{OM}}\} \cup \{T_{OM,k} \mid k \in \{1,\ldots,K-1\}\} \tag{8}$$

4.3.2. Maintenance logic. = At any given time t, the maintenance requirements of each component are determined jointly by its degradation state and the predefined decision thresholds. Let $I_k^{\mathrm{CM}}(t)$, $I_k^{\mathrm{PM}}(t)$, and $I_k^{\mathrm{OM}}(t)$ denote the binary indicator variables for CM, PM, and OM of component k, respectively. For the blades ($k = K$), the indicators are defined based on the degradation thresholds D (failure), d (PM), and d_{OM} (OM):

$$\begin{aligned} I_K^{\mathrm{CM}}(t) &= \begin{cases} 1, & \text{if } X(t) \geqslant D \\ 0, & \text{otherwise} \end{cases} \\ I_K^{\mathrm{PM}}(t) &= \begin{cases} 1, & \text{if } d \leqslant X(t) < D \\ 0, & \text{otherwise} \end{cases} \\ I_K^{\mathrm{OM}}(t) &= \begin{cases} 1, & \text{if } d_{\mathrm{OM}} \leqslant X(t) < d \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{9}$$

For the other components ($k \in \{1,\ldots,K-1\}$), the indicators are defined based on the virtual age thresholds T_k^{PM} (PM)

and $T_{OM,k}$ (OM):

$$I_k^{\mathrm{CM}}(t)=\begin{cases}1, & \text{if component } k \text{ fails}\\ 0, & \text{otherwise}\end{cases}$$
$$I_k^{\mathrm{PM}}(t)=\begin{cases}1, & \text{if } v_k(t)\geqslant T_k^{\mathrm{PM}}\\ 0, & \text{otherwise}\end{cases} \tag{10}$$
$$I_k^{\mathrm{OM}}(t)=\begin{cases}1, & \text{if } T_{OM,k}\leqslant v_k(t)<T_k^{\mathrm{PM}}\\ 0, & \text{otherwise.}\end{cases}$$

A vessel dispatch request $Z(t)\in\{0,1\}$ is generated by the wind farm immediately if any component reaches the threshold for mandatory CM or PM. Therefore, the explicit expression for $Z(t)$ is formulated by aggregating the indicator variables of all components:

$$Z(t)=\begin{cases}1, & \text{if } \sum_{k=1}^{K}\left(I_k^{\mathrm{CM}}(t)+I_k^{\mathrm{PM}}(t)\right)\geqslant 1\\ 0, & \text{otherwise.}\end{cases} \tag{11}$$

The generated request $Z(t)$ cannot be executed immediately under severe sea conditions. A binary weather window indicator $W(t)$ is defined as:

$$W(t)=\begin{cases}1, & \text{if } w(t)\leqslant W_{\mathrm{safe}} \text{ and } h(t)\leqslant H_{\mathrm{safe}}\\ 0, & \text{otherwise}\end{cases} \tag{12}$$

where $w(t)$ and $h(t)$ are the wind speed and wave height at time t, respectively. A state variable $B(t)\in\{0,1\}$ is introduced to represent the backlog state of maintenance tasks (i.e. waiting for a weather window). Its recursive update is given by:

$$B(t)=\max\left(Z(t),B(t-1)\cdot(1-Y(t-1))\right). \tag{13}$$

The final actual vessel dispatch decision $Y(t)\in\{0,1\}$ is triggered only when there is a backlogged request and the weather permits:

$$Y(t)=B(t)\cdot W(t). \tag{14}$$

Once the vessel is successfully dispatched (i.e. $Y(t)=1$), the system determines the actual maintenance action $a_k(t)$ executed on component k based on its current indicator variables:

- If $I_k^{\mathrm{CM}}(t)=1$, then $a_k(t)=\mathrm{CM}$.
- If $I_k^{\mathrm{PM}}(t)=1$, then $a_k(t)=\mathrm{PM}$.
- If $I_k^{\mathrm{OM}}(t)=1$ and $Y(t)=1$ (i.e. the vessel is dispatched due to the failure or PM requirements of other components), the grouping strategy is triggered, and $a_k(t)=\mathrm{PM}$ (OM is executed).
- If none of the above conditions are met, then $a_k(t)=\emptyset$ (No action is taken).

Through this rigorous logical framework, the degradation states of individual components are explicitly mapped to specific maintenance actions $a_k(t)$. These actions subsequently serve as the fundamental inputs for calculating the direct maintenance cost $C_{\mathrm{direct}}(t)$ and the downtime $T_{\mathrm{maint}}(t)$ in the objective function.

4.3.3. Objective function. The objective is to find the optimal combination of OM thresholds, denoted as $\boldsymbol{X}^*$, that minimizes the EMC over the entire lifecycle. The EMC comprises four components: the fixed vessel dispatch cost C_{ves}, the direct maintenance cost $C_{\mathrm{direct}}(t)$, the dynamic downtime generation loss $C_{\mathrm{loss}}(t)$, and the risk penalty cost for delayed maintenance $C_{\mathrm{risk}}(t)$. The objective function is formulated as follows:

$$\min \mathrm{EMC}=\sum_{t=1}^{T_{\mathrm{life}}/\Delta t}\big(C_{\mathrm{ves}}\cdot Y(t)+C_{\mathrm{direct}}(t)+C_{\mathrm{loss}}(t)+C_{\mathrm{risk}}(t)\big). \tag{15}$$

Firstly, the fixed vessel dispatch cost is incurred every time a maintenance vessel is dispatched to the offshore site. It is calculated as $C_{\mathrm{ves}}\cdot Y(t)$, where C_{ves} is a constant representing the mobilization and daily charter rate of the vessel, and $Y(t)$ is the binary actual dispatch decision variable.

Secondly, the direct maintenance cost accounts for the material, labor, and equipment costs associated with the specific maintenance actions executed on the components. It depends entirely on the actual maintenance action $a_k(t)$:

$$C_{\mathrm{direct}}(t)=\sum_{k=1}^{K}\left(C_k^{\mathrm{CM}}\cdot I_{\{a_k(t)=\mathrm{CM}\}}+C_k^{\mathrm{PM}}\cdot I_{\{a_k(t)=\mathrm{PM}\}}\right) \tag{16}$$

where C_k^{CM} and C_k^{PM} are the costs for CM and PM of component k, respectively. $I_{\{\cdot\}}$ represents the indicator function that equals 1 if the condition inside the braces is met, and 0 otherwise. Note that OM is executed as a PM action, thus incurring the PM cost C_k^{PM}.

Thirdly, the dynamic downtime generation loss quantifies the revenue lost due to turbine downtime during maintenance or failure. Unlike traditional static models, this model captures the dynamic nature of wind power generation and electricity markets:

$$C_{\mathrm{loss}}(t)=(1-A_{\mathrm{sys}}(t))\cdot P_{\mathrm{gen}}(t)\cdot p_{\mathrm{e}}(t)\cdot\Delta t \tag{17}$$

where $P_{\mathrm{gen}}(t)$ is the theoretical output power determined by the dynamic wind speed at time t, and $p_{\mathrm{e}}(t)$ is the day-ahead market electricity price. $A_{\mathrm{sys}}(t)\in\{0,1\}$ denotes the system availability state, which is constrained by component failures and the actual maintenance duration $T_{\mathrm{maint}}(t)$. The system is unavailable ($A_{\mathrm{sys}}(t)=0$) if any component is in a failed state or undergoing maintenance. The power output $P_{\mathrm{gen}}(t)$ depends on the dynamic wind speed $w(t)$:

$$P_{\mathrm{gen}}(t)=\begin{cases}0, & \text{if } w(t)<w_{\mathrm{in}} \text{ or } w(t)>w_{\mathrm{out}}\\ P_{\mathrm{r}}\cdot\dfrac{w(t)^3-w_{\mathrm{in}}^3}{w_{\mathrm{r}}^3-w_{\mathrm{in}}^3}, & \text{if } w_{\mathrm{in}}\leqslant w(t)\leqslant w_{\mathrm{r}}\\ P_{\mathrm{r}}, & \text{if } w_{\mathrm{r}}<w(t)\leqslant w_{\mathrm{out}}\end{cases} \tag{18}$$

where w_{in}, w_{out}, w_{r} are the cut-in, cut-out, and rated wind speeds, respectively. And P_{r} is the rated power.

Finally, due to harsh offshore weather conditions, a generated maintenance request may be backlogged. During this

waiting period, a component that has reached its PM threshold faces a continuous risk of degrading into a sudden failure (CM state). This penalty cost quantifies the expected financial risk of such deterioration:

$$C_{\text{risk}}(t) = \sum_{k=1}^{K} I_k^{\text{PM}}(t) \cdot (1 - Y(t)) \cdot P_k^{\text{fail}}(t) \cdot \left(C_k^{\text{CM}} - C_k^{\text{PM}}\right) \cdot \Delta t \tag{19}$$

where $I_k^{\text{PM}}(t) \cdot (1 - Y(t))$ indicates that component k requires PM but the vessel has not been dispatched. $(C_k^{\text{CM}} - C_k^{\text{PM}})$ represents the additional cost incurred if the component fails before the PM can be executed. And $P_k^{\text{fail}}(t)$ denotes the probability of component k failing within the next decision interval Δt:

$$P_k^{\text{fail}}(t) = \begin{cases} P(X(t+\Delta t) \geqslant D \mid X(t)), & \text{for } k = K \\ \lambda_k(t) \cdot \Delta t, & \text{for } k \in \{1, \ldots, K-1\}. \end{cases} \tag{20}$$

For the blades ($k = K$), the failure probability is the conditional probability that the crack length exceeds the failure threshold D within Δt, given its current state $X(t)$. And for the other components ($k < K$), the failure probability is approximated using their dynamic hazard rate $\lambda_k(t)$ derived from the Weibull distribution.

4.3.4. Constraints. To guarantee the logical feasibility of the maintenance strategy and ensure the safety of offshore operations, the optimization model is subjected to the following constraints:

(1) Threshold logic constraints:

To ensure the logical hierarchy of maintenance triggers and avoid premature interventions, the OM threshold should start at a significant proportion of its PM threshold and be strictly less than the PM threshold. Let γ ($\gamma \in (0,1)$, typically set between 0.7) denote the minimum degradation ratio for OM eligibility.

$$\lfloor \gamma \cdot d \rfloor < d_{\text{OM}} < d < D \tag{21}$$

$$\lfloor \gamma \cdot T_k^{\text{PM}} \rfloor < T_{OM,k} < T_k^{\text{PM}}, \quad \forall k \in \{1, \ldots, K-1\}. \tag{22}$$

(2) Vessel dispatch and safety constraints:

Offshore maintenance is strictly limited by meteorological conditions and task demands. A vessel can only be dispatched if a safe weather window is open ($W(t) = 1$) and there is at least one backlogged mandatory maintenance task ($B(t) = 1$):

$$Y(t) \leqslant W(t) \tag{23}$$

$$Y(t) \leqslant B(t). \tag{24}$$

(3) OM grouping constraint:

OM is designed as a strategy to share fixed vessel dispatch costs. Therefore, an OM action on any component k can only be executed if the vessel has already been dispatched due to the mandatory CM or PM requirements of other components. It also ensures that OM indicators alone cannot trigger a vessel dispatch; they merely take advantage of an existing dispatch $Y(t) = 1$.

$$I_{\left\{a_k(t)=\text{PM} \mid I_k^{\text{OM}}(t)=1\right\}} \leqslant Y(t), \quad \forall k \in \{1, \ldots, K\}. \tag{25}$$

4.4. Solution approach

To evaluate the EMC and solve the optimization model, a rolling horizon framework is developed. The entire lifecycle of the OWF is discretized into sequential daily decision steps. At each decision point, the real-time health states of all components are evaluated first. For the blades, the current crack length $X(t)$ is observed. For the electromechanical components, the effective age $v_k(t)$ is updated. If any component reaches its PM threshold (d and T_k^{PM}), a maintenance opportunity is triggered. Then, the model ingests the day-ahead forecasts, including the LMPs $p_e(t+1)$ and meteorological conditions (wind speed $w(t+1)$ and wave height $h(t+1)$). Based on these inputs, the optimal vessel dispatch $Y(t)$ and the task conducting indicators ($I_k^{\text{CM}}(t)$ and $I_k^{\text{PM}}(t)$) are determined. Then, the algorithm optimizes the OM thresholds to achieve a trade-off between ensuring component lifespan utilization and avoiding unnecessary losses during the long-term lifecycle.

Once the scheduled maintenance actions are executed, the system states are updated. Components undergoing CM are reset to an 'as good as new' state ($v_k = 0$). Components undergoing PM update their effective ages using the reduction factor ρ. For components not maintained, their degradation processes continue to evolve. The simulation horizon then rolls forward to the next day, and the process repeats until the end of the lifecycle. The optimization model formulated is a mixed-integer nonlinear programming (MINLP) problem. To efficiently solve this, we propose a hybrid optimization algorithm integrating a genetic algorithm (GA) with an iterated local search (ILS) [29].

5. Case study

To verify the effectiveness of the proposed maintenance strategy, a numerical experiment is conducted based on a real-world OWF. The parameters, including meteorological data, wind farm topology, and component reliability, are calibrated using industrial databases and historical observations.

5.1. OWF configuration and meteorological data

The OWF for this case study is configured based on the layout of Empire Wind 1, located in the New York Bight area, as shown in figure 5. This facility comprises 54 wind turbines and one offshore substation, interconnected by approximately 214 km of inter-array cables. Crucially, the offshore substation aggregates the generated power and transmits it via high-voltage export cables to the onshore point of interconnection located at the Gowanus substation in Brooklyn, New York.

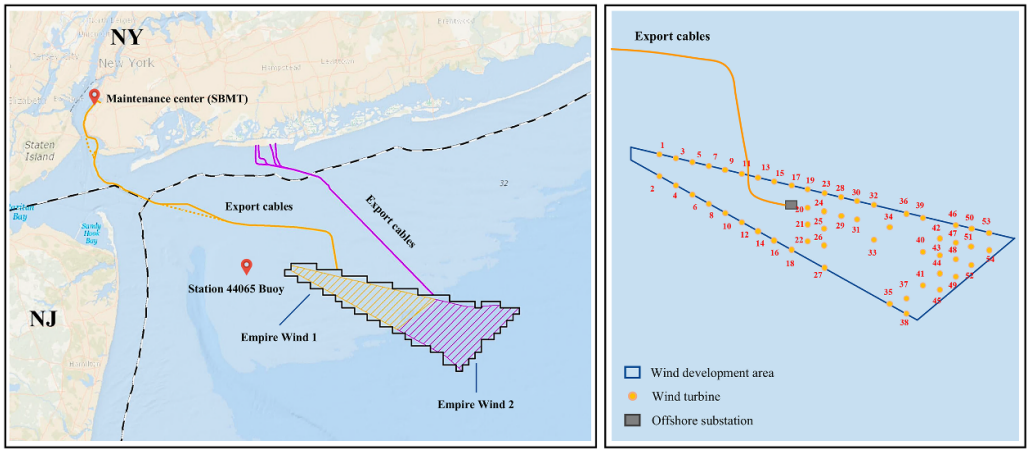


Figure 5. The topology of Empire Wind 1.

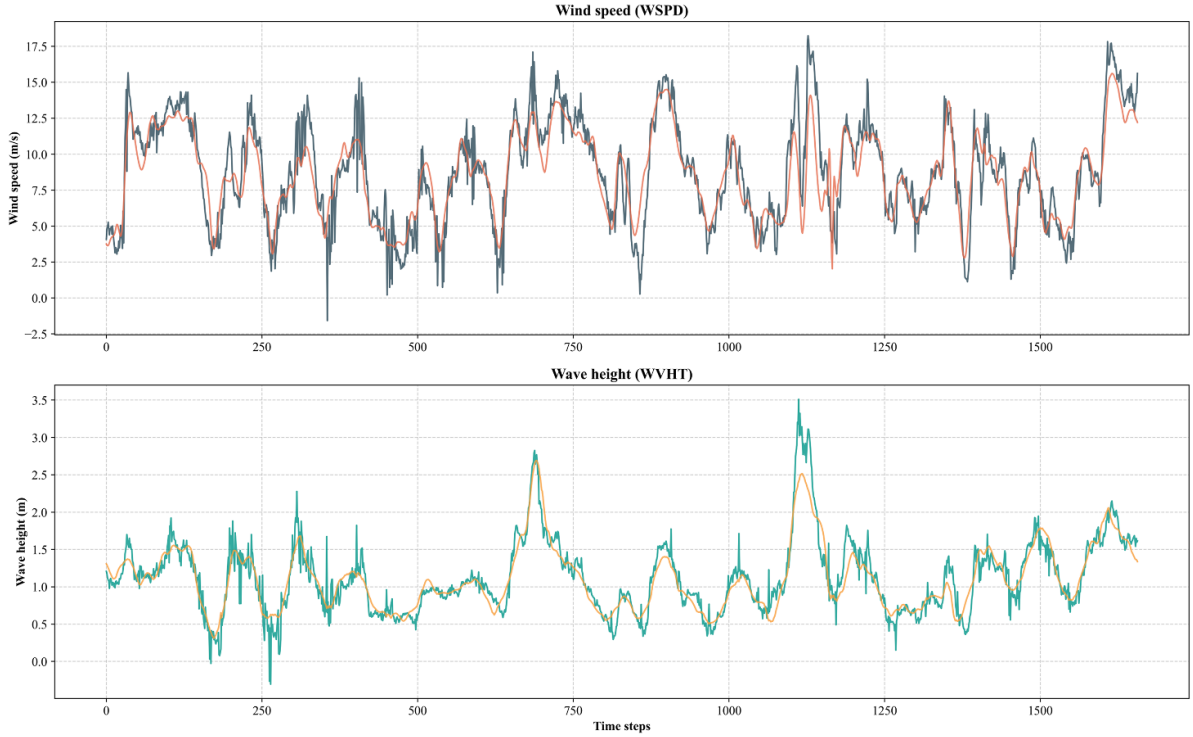


Figure 6. Time-series data of wind speed and wave height.

Meanwhile, vessel accessibility and maintenance execution are constrained by local weather conditions. Historical meteorological data, specifically wind speed and wave height, are extracted from Station 44 065 from the National Data Buoy Center (available at: https://www.ndbc.noaa.gov/). To support proactive maintenance planning, these weather time-series data are fed into the proposed SMD-LSTM forecasting module to determine day-ahead safe working windows. Specifically, the SMD decomposition approach combines the Seasonal and Trend decomposition using LOESS (STL) and VMD. The raw time series undergoes a two-stage decomposition, where STL is used to separate trend and seasonal components, followed by VMD to decompose the complex residual component into multiple intrinsic mode functions (IMFs). By decomposing the non-linear and non-stationary characteristics of the marine environment, SMD-LSTM yields accurate day-ahead forecasts, thereby providing reliable weather inputs for dynamic scheduling.

Since this study aims to evaluate the maintenance strategy over the entire life-cycle, relying solely on a limited historical dataset is insufficient. Therefore, the long-term wind speed and wave height profiles for the entire 25-year simulation are stochastically generated based on the statistical distributions and seasonal transition probabilities derived from the historical data. Figure 6 presents a test set consisting of a representative one-year snapshot of time-series data spanning the period from 1 January, 2025, to 31 December, 2025, sampled at a frequency of 30 min. It should be emphasized that this

specific one-year dataset is utilized exclusively for the training, testing, and validation of the SMD-LSTM forecasting model to demonstrate its learning efficacy, while the stochastically generated long-term profiles are employed for the life-cycle maintenance assessments.

Specifically, the decomposed components are fed into an LSTM network to capture temporal dependencies. Based on established configurations in recent literature [29], the SMD parameters are set as follows: the periodicity of the sequence in STL is 24 h, the length of the seasonal smoother is 13, and the number of IMFs in VMD is set to 3. For the LSTM architecture, the hidden dimension size is set to 64, with 2 stacked LSTM layers and a dropout rate of 0.1 to prevent overfitting. The dataset is chronologically partitioned into 70% for training, 10% for validation, and 20% for testing. The sliding time window size is set to 24 time steps. The model is trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 256. The training process spans 50 epochs, incorporating an early stopping mechanism with a patience of 15 epochs based on the MSE loss. All experiments were conducted on a hardware configuration featuring a 22-core AMD EPYC 7T83 CPU and a single NVIDIA GeForce RTX 4090 GPU with 24 GB of VRAM. The software environment was built on Python 3.12 and PyTorch 2.5.1.

5.2. Component degradation and reliability modeling

To accurately characterize the degradation processes formulated in section 4.2, this study extracts and calibrates the reliability parameters using real-world operation and failure data. The five key components of the system exhibit significant differences in failure mechanisms and degradation trends. Besides, each turbine also experiences slightly different operating conditions. Accordingly, the degradation parameters for the components across different turbines are modeled as uniformly distributed random variables within a specified range.

For the rotor, main bearing, gearbox, and generator, the degradation manifests as progressive wear and aging, which is modeled using the Weibull distribution as defined in equation (6). The scale parameter η_k and shape parameter β_k for each component are estimated using the maximum likelihood estimation (MLE) method based on historical failure records. Furthermore, considering the imperfect nature of preventive maintenance, the age reduction factor ρ is calibrated based on historical maintenance logs. The specific parameters for these four components are summarized in table 1, and $\mathcal{U}(a,b)$ denotes a continuous uniform distribution bounded by a and b.

The degradation of each blade is driven by structural damage, primarily the initiation and propagation of surface cracks. Following the model described in section 4.2.1, the crack initiation is governed by an NHPP with a power-law intensity function $m(t) = abt^{b-1}$. Once initiated, the crack propagation follows a homogeneous Gamma process with shape parameter α and scale parameter β. To reflect the varying aerodynamic loads experienced by different blades across the wind farm, the parameters for the blade degradation model are defined within variation ranges, as listed in table 2. The critical failure threshold D and the preventive repair threshold d remain deterministic, as they are governed by strict industry safety standards.

5.3. Economic parameters and operational settings

To evaluate the EMC formulated in the optimization model, the relevant parameters are further defined in alignment with the actual configuration of the OWF. Regarding the power generation model, the Empire Wind 1 is equipped with 15MW wind turbines. The rated power is set to $P_r = 15\text{MW}$. The power curve parameters are set as follows: the cut-in wind speed $v_{\text{in}} = 3.0\ \text{m s}^{-1}$, the rated wind speed $v_r = 11.0\ \text{m s}^{-1}$, and the cut-out wind speed $v_{\text{out}} = 25.0\ \text{m s}^{-1}$.

To quantify the dynamic production losses $C_{\text{loss}}(t)$, the day-ahead electricity price $p_e(t)$ is required. Similar to the long-term meteorological data, it is impossible to obtain deterministic electricity prices for a 25-year lifecycle. Therefore, historical LMP data is extracted via GridStatus.io for the NYISO N.Y.C node (available at: https://www.gridstatus.io/live/nyiso). Based on this historical dataset, a stochastic price capturing both diurnal patterns and seasonal volatility is developed to simulate the long-term dynamic electricity price profile.

Meanwhile, Offshore maintenance execution is heavily dependent on vessel availability and weather conditions. Based on CTV specifications, the safe weather thresholds are set to a maximum safe wind speed $V_{\text{safe}} = 12.0\ \text{m s}^{-1}$ and a maximum safe wave height $H_{\text{safe}} = 2.5$ m. The fixed vessel dispatching cost C_{ves} is exorbitant in offshore environments and is estimated at \$30 000 per dispatch. This high fixed cost underscores the necessity of the proposed opportunistic grouping strategy, which aims to share the dispatch cost across multiple components.

Finally, when a vessel is successfully dispatched ($Y(t) = 1$), the direct maintenance costs $C_{\text{direct}}(t)$ and the required maintenance durations $T_{\text{maint}}(t)$ are determined by the specific actions executed on the degraded components. The expected costs (C_k^{CM}, C_k^{PM}) and durations (T_k^{CM}, T_k^{PM}) for CM and PM of each component are calibrated based on offshore industry standards and are summarized in table 3.

5.4. Dynamic maintenance results

To demonstrate the effectiveness of our proposed dynamic OM framework, a representative operational window is extracted from the 25-year lifecycle simulation. The scheduling logic strictly follows the day-ahead market-clearing timeline. As shown in figure 7, during a peak-demand week, the day-ahead LMPs exhibited severe volatility, with prices spiking to over 180 \$/MWh during evening hours and dropping below 15 \$/MWh during late-night periods with high wind speeds. On Day 420 of the simulation, Turbine 12 experienced a main bearing failure, triggering a mandatory CM request. Simultaneously, the gearbox of Turbine 12 and the generator of Turbine 14 can be maintained by utilizing this opportunity.

Table 1. Weibull degradation parameters for components

Component	Scale parameter η_k (h)	Shape parameter β_k	Age reduction factor ρ
Generator	$\mathcal{U}(83\,200, 92\,000)$	$\mathcal{U}(2.05, 2.25)$	0.15
Gearbox	$\mathcal{U}(72\,200, 79\,800)$	$\mathcal{U}(2.28, 2.52)$	0.20
Rotor	$\mathcal{U}(142\,500, 157\,500)$	$\mathcal{U}(2.95, 3.25)$	0.10
Main bearing	$\mathcal{U}(666\,000, 736\,000)$	$\mathcal{U}(1.75, 1.95)$	0.25

Table 2. Degradation parameters and thresholds for blades.

Parameter	Notation	Value
NHPP scale parameter	a	$\mathcal{U}(1.1 \times 10^{-4}, 1.3 \times 10^{-4})$
NHPP shape parameter	b	$\mathcal{U}(1.28, 1.42)$
Gamma process shape parameter	α	$\mathcal{U}(0.80, 0.90)$ (cm year^{-1})
Gamma process scale parameter	β	$\mathcal{U}(2.00, 2.20)$ (1/cm)
Preventive maintenance threshold	d	15.0 cm
Critical failure threshold	D	35.0 cm

Table 3. Maintenance costs and durations for components.

Component	PM cost $C_k^{\mathrm{PM}}(\$)$	CM cost $C_k^{\mathrm{CM}}(\$)$	PM duration T_k^{PM} (h)	CM duration T_k^{CM} (h)
Blade	15 000	300 000	24	96
Generator	15 000	120 000	12	48
Gearbox	20 000	150 000	16	72
Rotor	10 000	80 000	10	40
Main bearing	12 000	100 000	14	60

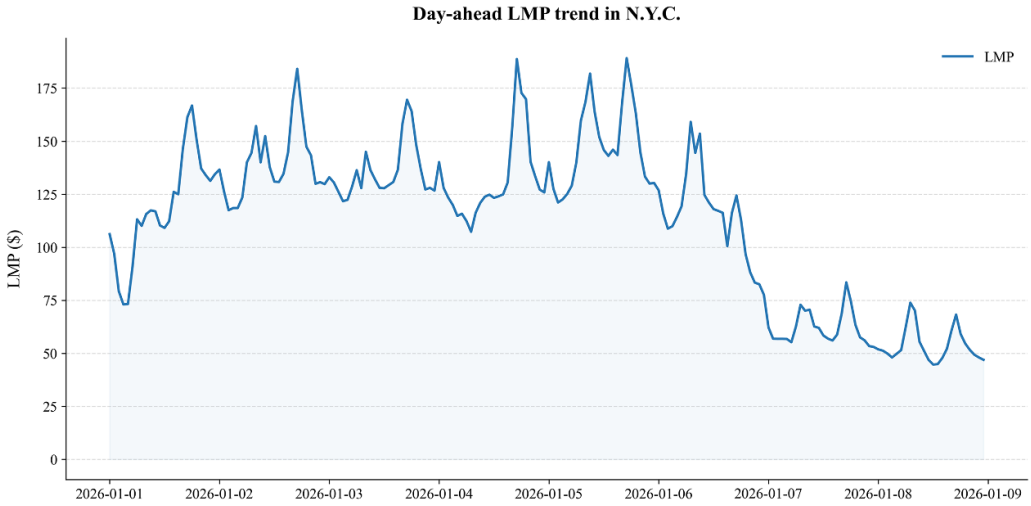


Figure 7. Day-ahead LMPs during a week.

Under the traditional OM strategy, the required CTV will be dispatched to execute the CM and both PM tasks, resulting in a continuous 120 h downtime that overlaps with the evening price spikes. In contrast, the proposed framework dynamically evaluated the day-ahead LMPs and weather windows. Recognizing the impending price spikes, this framework tightened the OM threshold, deferring the PM on Turbine 14"s generator that had a low immediate failure risk to a subsequent low-price window. Furthermore, it optimized the departure time of the vessel to execute the CM on Turbine 12 during the off-peak hours, avoiding the high-opportunity-cost periods. This dynamic adjustment preserved approximately $42 500 in generation revenue over a single week compared to the traditional strategy.

Table 4. Performance comparison of different maintenance strategies.

	Total CTV dispatches	Total EMC	Average availability	Production loss
Policy A	842	48 600 000	88.4%	15 200 000
Policy B	1105	42 100 000	93.1%	11 800 000
Policy C	615	31 400 000	95.2%	8500 000
Proposed	588	25 600 000	96.8%	4900 000

5.5. Strategy comparison

To further validate the performance of our proposed framework, it is benchmarked against three maintenance policies over the 25-year lifecycle:

(i) Policy A (CM-Only): Components are only replaced upon functional failure. No preventive or OM is performed.
(ii) Policy B (Traditional PM without Grouping): PM is executed strictly when a component reaches its predefined degradation limit. Each maintenance task triggers an independent vessel dispatch.
(iii) Policy C (Static OM): PM and CM tasks are grouped based on fixed degradation thresholds, utilizing a constant average electricity price to calculate penalties.

To account for the random weather, component degradation, and electricity markets, the average of 10 simulations and maintenance execution is taken, and the comparison results are summarized in table 4. It can be noted that Policy A has the highest loss due to extended downtimes caused by severe component failures and subsequent weather delays. Policy B improves system availability but suffers from exorbitant vessel dispatch costs due to the lack of task grouping. Policy C significantly reduces vessel mobilizations by grouping tasks, lowering the total cost to $31.4 million. In comparison, the proposed framework achieves the most remarkable economic performance. By dynamically aligning maintenance downtime with low-electricity-price windows, this strategy reduces the total cost to $25.6 million, achieving an 18.4% cost reduction compared to Policy C. Furthermore, this strategy can defer non-urgent PM tasks during lucrative high-price periods, which directly contributes to a 42.3% reduction in production loss compared to Policy C. These results confirm that integrating short-term market volatility into long-term degradation management is economically imperative for modern OWFs.

To further clarify the source of the economic improvement, the four benchmarked policies are designed as a stepwise ablation that isolates each mechanism. The grouping effect, reflected in the transition from Policy B to Policy C, reduces the vessel dispatches from 1105 to 615 and lowers the total EMC from $42.1 million to $31.4 million by sharing the fixed vessel cost across multiple tasks. The price-responsive scheduling and downtime reduction, jointly reflected in the transition from Policy C to the proposed framework, reduce the production loss from $8.5 million to $4.9 million (42.3%) and improve availability from 95.2% to 96.8%, contributing the dominant share of the 18.4% total cost reduction. Meanwhile, the risk mitigation embedded in $C_{risk}(t)$ guarantees that the price-driven deferral of non-urgent tasks does not compromise reliability, as evidenced by the further reduction of dispatches from 615 to 588.

5.6. Discussion

In the preceding subsections, the optimization model is evaluated based on deterministic day-ahead forecasts. However, in practical OWF operations, predictions for wind speed, wave height, and LMPs contain uncertainties. The magnitude of these forecast errors is directly associated with the design and selection of the forecasting models, as well as the prediction horizon. As the prediction step increases, the accuracy naturally deteriorates. Consequently, in practical applications, when wind farm operators select and implement an O&M strategy, it is imperative that they evaluate the performance and reliability of the underlying forecasting algorithms, as the efficacy of the maintenance strategy is coupled with forecast quality.

Furthermore, it is crucial to note that the impact of these uncertainties on the proposed maintenance strategy cannot be adequately captured by simple averaged metrics. Forecast errors manifest in diverse forms, such as underestimation, overestimation, and extreme fluctuations. Each type of error affects the optimization model and the optimal solution differently. For example, an underestimation of wave height may result in a futile vessel dispatch where maintenance crews cannot safely access the turbine, leading to wasted logistical costs and delayed repairs. Conversely, an overestimation of LMPs or an underestimation of wind speeds might trigger premature OM, causing the operator to miss more lucrative generation windows. Extreme fluctuations in market prices further complicate the threshold-setting mechanism for dynamic maintenance.

Despite these challenges, our proposed dynamic OM framework exhibits inherent structural robustness. Unlike static maintenance schedules that are highly vulnerable to sudden weather or market shifts, the proposed dynamic thresholding mechanism can be continuously updated as new, shorter-horizon forecasts that possess higher accuracy become available. By continuously rolling forward the decision-making horizon, the model can correct previous sub-optimal decisions caused by long-horizon forecast errors. Future work will focus on integrating stochastic optimization or robust optimization techniques to explicitly quantify and hedge against these asymmetric forecast risks within the mathematical formulation.

6. Conclusion

This paper presents a dynamic OM framework for OWFs operating in deregulated electricity markets. By employing an NHPP and a Gamma process, the crack initiation and propagation mechanisms of turbine blades are quantified, while Weibull distributions capture the progressive degradation of electromechanical components. Moreover, the framework introduces a dynamic thresholding mechanism driven by day-ahead LMPs. This allows the OWF operator to proactively group maintenance tasks during low-price windows and avoid costly downtime during price spikes. Extensive numerical simulations based on real-world data demonstrated that the proposed framework outperforms traditional static strategies, yielding an 18.4% reduction in expected lifecycle maintenance costs and maximizing generation revenue under volatile market conditions.

While the proposed framework provides a solution for market-driven maintenance scheduling, several avenues remain for future exploration. In this study, the degradation processes of identical components across different turbines were assumed to follow similar statistical distributions with bounded variations. However, in large-scale OWFs, turbines situated in different locations experience highly distinct wind profiles and turbulence intensities due to wake interactions. The alternating aerodynamic loads and stress frequencies exerted on critical components (e.g. the blades and rotors) vary depending on the spatial position relative to the prevailing wind direction. Future work will integrate high-fidelity wake models into the physics-informed degradation framework to capture these localized load variations.

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