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Original research article

A closed-loop maintenance strategy for offshore wind farms: Incorporating dynamic wind farm states and uncertainty-awareness in decision-making

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ABSTRACT

The determination of maintenance strategies is subject to complexity and uncertainty arising from variable offshore wind farm states and inaccuracies in model parameters. The most common method in the existing studies is to adopt an open-loop approach to optimize a maintenance strategy. However, this approach lacks the ability to capture periodic operational state of the wind farm and the awareness of eliminating uncertainty. Consequently, the determined strategy is inadequate to instruct maintenance activities, inducing excessive revenue losses. In this paper, a closed-loop maintenance strategy optimization method is proposed for decision-makers to identify a more profitable manner of wind farm maintenance management. The life-cycle maintenance optimization problem is decomposed into a sequence of sub-optimization problems covering multiple time periods by using a rolling-horizon approach. Each sub-optimization problem is intentionally designed based on the monitored state of the wind farm and the available reliability, availability, and maintainability (RAM) database. Meanwhile, the decision maker consciously mitigates the parameter uncertainty in the maintenance model gradually by updating the current database. Compared to conventional strategies covering the entire lifetime of wind farms, the proposed maintenance strategy is periodically adjusted to provide a series of sub-strategies. The proposed approach was applied in a simulation experiment, a generic small-scale offshore wind farm, to assess its performance. Computational results show that adapting maintenance strategies based on the current state of the wind farm can reduce revenue losses in comparison to conventional open-loop strategies. In addition, the benefits of updating the RAM database in decreasing revenue losses is revealed.

1. Introduction

Due to the past negative impact on environment, humans are in a time of environmental crisis, including air pollution, global warming, ocean acidification, etc. The COP26, the United Nations Climate Change conference in 2021, emphasized the urgency of curbing greenhouse gases through enhancing climate action in order to effectively address the climate crisis. The development of renewable energy can massively cut carbon emissions and help to mitigate climate change.

As one of the most significant renewable technologies, wind energy is experiencing a rapid growth all over the world [1]. Compared to onshore, the offshore wind energy sector has the advantages of higher wind speed, more wind consistency, less visual impact [2]. In Europe, the Netherlands is one of the leading countries in new installation of offshore wind energy. The Dutch Government has raised the offshore wind energy target to about 21 GW around 2030 [3]. By then, offshore wind energy is expected to supply 16% of the Netherlands' energy needs and 75% of current electricity requirements.

The water depth of the majority of existing offshore wind farms is no more than 10 m and the location is no greater than 10 km away from shore [4]. However, the future trend is that the farm site is moving towards greater distances and deeper water depth [5], which brings huge challenges to operation and maintenance (O&M) activities [6,7]. The maintenance cost is estimated to account for about 30% of the total life cycle cost of an offshore wind farm [8–10]. In order to increase the cost-effectiveness of the offshore wind sector, it is necessary to competently manage maintenance activities to reduce costs.

The maintenance management for the offshore wind energy sector is generally categorized into three echelons, depending on the length of the planning horizon: namely strategic level, tactical level, and operational level [11]. As a type of strategic decision instructing O&M activities for offshore wind farms over the long lifespan, the determination of the optimal maintenance strategy is a complex optimization problem. The variation in decision variables, such as maintenance thresholds, represents difference in maintenance criterion, bringing

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Nomenclature and acronyms definition

O & M	Operation and Maintenance
RAM	Reliability, Availability and Maintainability
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
CMS	Condition Monitoring System
HLV	Heavy Lift Vessel
FSV	Field Support Vessel
CTV	Crew Transfer Vessel
K	Set of offshore wind turbines
I	Set of components
S	Length of wind farm lifetime
U	Set of time period
Δs	Length of time periods for wind farm state
$(\bullet)(u)$	Parameter at period u
$(\dot{\bullet})$	Parameter in the maintenance model
$(\bullet)_{ik}$	Parameter of component i at turbine k
$(\bullet)^{\mathrm{f}}$, $(\bullet)^{\mathrm{p}}$, $(\bullet)^{\mathrm{a}}$, $(\bullet)^{\mathrm{i}}$	Parameter of failure replacement, preventive replacement, major repair, basic repair
$(\bullet)_{ikm}$	Parameter of component i at turbine k under maintenance level m
$\boldsymbol{R}$	State of wind farm system
$\boldsymbol{\xi}$	Start state of wind farm system
$\boldsymbol{\omega}$	End state of wind farm system
$\boldsymbol{\kappa}$	Interior state of wind farm system
$\boldsymbol{w}$, $\bar{\boldsymbol{w}}$	Cumulative time matrix in start state and end state
$\boldsymbol{f}$, $\bar{\boldsymbol{f}}$	Current age matrix in start state and end state
$\boldsymbol{v}$, $\bar{\boldsymbol{v}}$	Real lifetime matrix in start state and end state
$\hat{\boldsymbol{v}}$, $\bar{\hat{\boldsymbol{v}}}$	Predicted lifetime matrix in start state and end state
$\boldsymbol{e}$, $\bar{\boldsymbol{e}}$	Failure state matrix in start state and end state
$\boldsymbol{g}$, $\bar{\boldsymbol{g}}$	Failure moment matrix in start state and end state
${}^{1}\boldsymbol{O}$, ${}^{2}\boldsymbol{O}$, ${}^{3}\boldsymbol{O}$	Binary variable matrix for degradation failure, incident failure, ageing stage
$\boldsymbol{\theta}$	Maintenance quality matrix
$\boldsymbol{q}$	Occurrence moment matrix for impact
$\boldsymbol{b}$	Influence matrix for impact
σ, ε	Weibull parameters for component lifetime in the wind farm system
λ	Intensity function of environmental impact
P^{C}, P^{I}, P^{M}	Probability of critical, influential, minor impact
b	Abrupt increase of degradation due to environmental impact
θ	Maintenance quality
$\hat{\psi}$	Health state indicator
$\psi_{\max}$	Decision variable 1: Maximum maintenance threshold
$\psi_{\min}$	Decision variable 2: Minimum maintenance threshold
ϑ	Decision variable 3: Number threshold of aged component
d	Binary variable determining whether a maintenance cycle is trigged
ψ	Life percentage
$\bar{E}$	Average prediction error
E, μ, δ	Prediction error, and the corresponding mean and standard deviation
μ_{PE}, δ_{SD}, χ_{PE}, χ_{SD}	Basic error and positive coefficients in modelling prediction error
α, β, μ_{θ}, σ_{θ}	Shape parameters, expected value, variance of maintenance quality
M^{o}	Mobilization cost in the maintenance cycle performed
T_k, F_k^{T}	End time of maintenance and failure moment of wind turbine k
L	Price of the generated electricity per turbine per day
R	Spare part costs of maintenance
x	Binary variables determining whether the maintenance action is performed
Q^{J}, Q^{S}, and Q^{C}	Daily cost of HLV, FSV, and CTV
N	Repair time
r^{p}	Daily personnel cost
h	Number of required technicians for maintenance
η_{c}, μ_{c}, δ_{c}	Coefficient estimating major repair cost, and the corresponding mean and standard deviation
η_{t}, μ_{t}, δ_{t}	Coefficient estimating major repair time, and the corresponding mean and standard deviation
ΔT	Time interval for decision making
ϱ	Number of covered wind farm state in a decision-making step
A_{r}	Annual revenue loss in the wind farm system
ℓ	Revenue loss in the wind farm system
P_z	Sub-optimization problem at decision-making step z
T_z	Future horizon at decision-making step z
$c(z)$	Maintenance strategy at step z
$\boldsymbol{c}$	A series of maintenance strategy during lifetime
${}^{1}\boldsymbol{X}$	Original component lifetime database
${}^{2}\boldsymbol{X}$	Original RUL prediction performance database
${}^{3}\boldsymbol{X}$	Original maintenance implementation database
${}^{1}\boldsymbol{X}^{z,D_1}$, ${}^{1}\hat{\boldsymbol{X}}^{z,D_1}$	New component lifetime data sample and updated database at step z
${}^{2}\boldsymbol{X}^{z,D_1}$, ${}^{2}\hat{\boldsymbol{X}}^{z,D_1}$	New RUL prediction performance data sample and updated database at step
${}^{3}\boldsymbol{X}^{z,D_1}$, ${}^{3}\hat{\boldsymbol{X}}^{z,D_1}$	New maintenance implementation data sample and updated database at step z
$\boldsymbol{\theta}^{D_1}$, $\boldsymbol{\theta}^{D_2}$, $\boldsymbol{\theta}^{D_3}$	Probability distribution parameters D_1, D_2, D_3 in maximum likelihood estimation
$x_{\lambda}(\varpi)$, $y_{\lambda}(\varpi)$	Position and velocity of λth particle in ϖth iteration
β_1^{o}, β_2^{o}, η^{o}	Acceleration coefficients and constriction coefficient in PSO

about different maintenance frequencies as well as ranges of components/turbines qualified for different types of maintenance actions. Accordingly, the estimated maintenance costs, production losses, and

Table 1
Comparative analysis of the reviewed maintenance strategy studies for the wind energy sector.

		[13]	[14]	[16]	[17]	[18]	[19]	[20]	[21]	[15]	[22]	[23]	[24]	[25]	[26]	This paper
Maintenance strategy	Corrective	×	×	×	×	×	×	×	×	×	×	×	✓	✓	×	×
	Opportunistic	×	✓	✓	✓	✓	×	×	✓	×	×	✓	×	×	✓	✓
	Condition-based/predictive	✓	✓	×	×	×	✓	×	×	✓	✓	✓	×	×	×	✓
	Group	×	×	×	×	×	×	✓	×	✓	✓	×	×	×	×	×
Decision-making approach	Open-loop	✓	✓	✓	✓	✓	✓	×	×	×	×	✓	×	×	×	×
	Reactive	×	×	×	×	×	×	✓	✓	✓	✓	×	×	×	×	×
	Closed-loop	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓
State-based dynamic adjustment	Component-level	×	×	×	×	×	×	✓	✓	✓	×	×	×	×	×	×
	Turbine-level	×	×	×	×	×	×	×	×	×	✓	×	×	×	×	×
	Farm-level	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓
Impact of parameter uncertainty	Quantification	×	×	×	×	×	×	×	×	×	×	✓	✓	✓	✓	✓
	Mitigation	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓

availability, these performance indicators representing decision-maker's objectives and preferences, also vary under various combinations of decision variables. Finally, the optimal maintenance strategies are determined to satisfy a single objective or balance multiple possibly conflicting objectives.

A sound maintenance strategy can ensure the reliable operation of offshore wind turbines and enhance economic competitiveness of offshore wind energy. Corrective maintenance and time-based maintenance are widely applied in real wind farms [12]. In recent years, some novel strategies have been proposed and developed, such as condition-based maintenance [13], predictive maintenance [14], group maintenance [15] and opportunistic maintenance [16]. Table 1 shows the similarities and differences among some state-of-the-art studies on maintenance strategies for wind energy. The comparison is based on the following four aspects: adopted maintenance strategies, decision-making approaches, state-based dynamic adjustments, and research on the impact of model parameter uncertainty.

When determining solutions to optimization problems, a distinction can be made to distinguish between open-loop, reactive and closed-loop approaches [27,28]. An open-loop approach is to find the optimal maintenance strategy at the beginning of operation and to implement it over the entire lifetime. This open-loop approach is the most widely used in the past studies, such as [17–19]. Compared to the open-loop strategy that is applied over the entire optimization horizon blindly, a reactive strategy is determined step by step, with the capacity of making decisions based on the present state. A dynamic adjustment in the strategy is made on the basis of the current state, and it is implemented until the next step in which a new strategy is determined again. This method has been used in the past research [15,20–22]. However, these studies only focus on component-level and turbine-level states. The adjustment of maintenance strategies is based on the states of individual components or turbines within the wind farm, leading to the lack of a comprehensive consideration of the overall wind farm-level state in the formulation of maintenance strategies.

[29] pointed out that designing maintenance strategies covering the long lifespan involves a high degree of uncertainty. The strategic maintenance plan largely relies on accuracy and completeness of the available database, but vendor guidelines may not be fully compatible because of lack of knowledge of the actual use and maintenance of the wind turbine [30]. Additionally, maintenance records and historic failure data are usually not complete and accurate enough [31]. The uncertainty in model parameters may lead to a maintenance strategy that is incompetent for target wind farms. Up to now, the limited number of papers paying attention to strategic wind energy maintenance considering uncertainties still adopt a passive manner [23–26]. The passive manner means the influential uncertainties are identified and their influence on maintenance performance or decisions is quantified. However, no solution is proposed to gradually mitigate the negative influence of uncertainty. In comparison, a proactive manner is to consider the feasibility of gradually mitigating or eliminating uncertainty.

In addition to open-loop and reactive approaches, a closed-loop approach refers to a process from information and feedback collection, to decision-making, action taking, and back again to information. This approach has been commonly used in other areas, such as vessel control [32,33], energy management [34], and transportation planning [35], but has never been proposed for use in wind energy maintenance. In the context of determining maintenance strategies for offshore wind farms, the closed-loop approach is able to respond to the feedback information originated from the offshore wind farm when compared to open-loop and reactive approaches. This feedback information can be new Reliability, Availability and Maintainability (RAM) data that is gradually generated during the long-term O&M of wind farms. Moreover, in order to address the limitations of the current reactive approach, the development of the closed-loop approach should incorporate the wind farm state for adjusting the strategy.

The research gaps can be concluded according to the literature review. First, when determining a wind energy maintenance strategy, decision-makers are confronted by uncertainties in model parameters, caused by inaccurate and insufficient data. Most of the existing models still assume that input parameters are accurately known ahead of time. The limited number of studies paying attention to uncertainty have rarely attempted to consciously mitigate its negative influence. Second, the operational state of the offshore wind farm is constantly changing over time. This dynamic change brings about a challenge in maintenance optimization. Models proposed so far commonly employ an open-loop approach ignoring the varying wind farm state, and the papers using a reactive strategy never pay attention to the entire wind farm state and reveal the economic benefit of capturing its changes.

Considering the above research gaps, the objective of this paper is to propose a closed-loop approach for offshore wind farm maintenance strategy optimization with the capacity to mitigate the uncertainty in the model parameters and capture the operational state of the wind farm. With the awareness of the model uncertainty, the decision-maker is able to intentionally adjust the maintenance strategy once more reliable data is collected during wind farm operation. Additionally, the adjustment is made considering the dynamic state of the offshore wind farm, leading to a more targeted maintenance strategy. To the best of the authors' knowledge, there is no paper before that proposes this closed-loop maintenance strategy that captures the overall wind farm state and mitigates model parameter uncertainty. This forms the main contribution of this research.

In this paper, first of all, the concept of the closed-loop decision-making is proposed to connect the decision-maker's virtual maintenance model and the target offshore wind farm in reality. Then, a mathematical model is developed to use a series of matrices to represent the discrete wind farm states under a predictive opportunistic maintenance strategy. Moreover, the information about the component condition received by the decision-maker and the maintenance actions performed are modelled, and the potential uncertainties involved are identified. Then, the maintenance model on which the decision-maker relies is formalized. This model serves as a tool to predict the maintenance performance, namely revenue losses, when a specific maintenance strategy is conducted. Compared to the real wind farm, the prediction produced by this maintenance model is inaccurate as there is a discrepancy between the model parameters derived from the database and the actual parameters. The inaccurate parameters in the maintenance model are gradually updated by utilizing the maximum likelihood estimation method to analyze the data accumulated with the operation of the offshore wind farm. After that, the maintenance optimization problem is modelled repeatedly. The entire maintenance optimization problem covering the overall lifetime is decomposed into a finite sequence of sub-optimization problems covering multiple time periods. Finally, the maintenance strategy is adjusted periodically to form a series of maintenance strategies on the basis of the current monitored wind farm state while making use of the updated parameters.

The remainder of this paper is organized as follows. In Section 2, the proposed method is presented and the individual models within it are introduced. In Section 3, a generic offshore wind farm is used as a representative case study. A comparative study of five strategies is performed to highlight the performance of the proposed method. Moreover, practical implications of this study are discussed to provide insights for real-world applications and future research. Finally, conclusions are provided in Section 4.

2. Methodology

In this section, he closed-loop maintenance strategy covering the wind farm service life is formally introduced in detail, as illustrated in Fig. 1. The decision-maker formulating the maintenance strategy is the wind farm owner and operators. As a crucial strategic decision in the maintenance management, the maintenance strategy consists of several thresholds. These thresholds act like maintenance criteria, which determine the triggering of maintenance cycles and the maintenance actions required for components in different health states in maintenance cycles. Before the operation of the wind farm, the decision-maker employs a maintenance model and an optimization model to determine the optimal maintenance strategy in view of the preferred objective. The resource for values of input model parameters can be from vendor guidelines, maintenance records, historic failure data, or even expert survey. Although uncertainty and inadequacy in the data is a serious problem for decision makers, the development of the current maintenance strategy still has to rely on these available data.

The sensors installed on the operating wind turbines record the various kinds of signals including vibration, temperature, and acoustic emission, depending on the type of the component that is monitored. Then the signals are transferred to a remote monitoring and control center where the experts perform fault prognosis for wind turbine remaining useful life (RUL) estimation. The health state of components is assessed according to the estimated RUL, and the decision-maker decides on whether to initiate a cycle of maintenance or not according to the current maintenance strategy. In the maintenance cycle, the spare parts, maintenance vessels, and technicians are organized to perform maintenance.

With the accumulation of failure data and maintenance records over the lifespan, new data can be delivered to the decision-maker's databases. The previous uncertain input parameters of the maintenance model are updated using the new data. The decision-maker periodically adjusts the pre-determined maintenance strategy, and then the new strategy is delivered to guide the maintenance in the following periods. The entire process introduced above is regarded as the framework of closed-loop maintenance strategy optimization.

2.1. Dynamic offshore wind farm states

In this section, a mathematical model is developed to represent the dynamic states of the offshore wind farm system. The model is extended based on the previous study [23]. It is supposed that there is an offshore wind farm consisting of K turbines of the same type. Each turbine is simplified as a series system consisting of I components.

The maintenance strategy is a type of long-term plan covering the whole lifespan. The length of the offshore wind farm lifetime is represented by S. From the moment a wind turbine begins to operate and produce power, the components gradually degrade until degradation failure. In order to maintain a turbine in a good state, maintenance actions are carried out to recover or restore the component state. In other words, the state of a farm at different time points over the lifespan is varying due to constant degradation and occasional failures and repairs. A discrete manner is used to represent this process, where the information of the wind farm state is updated every time period of Δs. The number of the discrete time periods, represented by U, is obtained by $U = S/\Delta s$

For the time period u, where $u \in \{1, \ldots, U\}$, the wind farm state $\boldsymbol{R}(u)$ has a set of variables representing the start state $\xi(u)$, the end state $\boldsymbol{\omega}(u)$, and the interior state $\boldsymbol{\kappa}(u)$, as:

$$\boldsymbol{R}(u) = \begin{bmatrix} \xi(u) & \boldsymbol{\kappa}(u) & \boldsymbol{\omega}(u) \end{bmatrix}. \tag{1}$$

The interior state is neither start state nor end state, but performs as a transition. The start state $\xi(u)$ and the end state $\boldsymbol{\omega}(u)$ connect the current time period and the previous or subsequent time period as:

$$\xi(u+1) = \boldsymbol{\omega}(u). \tag{2}$$

The state $\boldsymbol{R}(u)$ incorporates the effects of the failures and repairs that the wind farm system experiences during the period u. It is necessary to model this process in order to demonstrate how the system state transforms successively with the time going. The state $\xi(u)$ is represented by:

$$\xi(u) = \begin{bmatrix} \boldsymbol{w}(u) & \boldsymbol{f}(u) & \boldsymbol{v}(u) & \hat{\boldsymbol{v}}(u) & \boldsymbol{e}(u) & \boldsymbol{g}(u) \end{bmatrix}, \tag{3}$$

where $\boldsymbol{w}(u) = \left[w_{ik}(u)\right]_{I\times K}$ contains the variables representing the cumulative time of component i at turbine k at the beginning of period u; $\boldsymbol{f}(u) = \left[f_{ik}(u)\right]_{I\times K}$ represents the current age of components; $\boldsymbol{v}(u) = \left[v_{ik}(u)\right]_{I\times K}$ represents the real lifetime of components; $\hat{\boldsymbol{v}}(u) = \left[\hat{v}_{ik}(u)\right]_{I\times K}$ represents the predicted lifetime of components; $\boldsymbol{e}(u) = \left[e_{ik}(u)\right]_{I\times K}$ are the binary variables implying whether the component is in a failure state; $\boldsymbol{g}(u) = \left[g_{ik}(u)\right]_{I\times K}$ represents the failure moment of the turbine component if it is in the failure state.

The end state at period u is given by:

$$\boldsymbol{\omega}(u) = \begin{bmatrix} \bar{\boldsymbol{w}}(u) & \bar{\boldsymbol{f}}(u) & \bar{\boldsymbol{v}}(u) & \bar{\hat{\boldsymbol{v}}}(u) & \bar{\boldsymbol{e}}(u) & \bar{\boldsymbol{g}}(u) \end{bmatrix}, \tag{4}$$

where $\bar{\boldsymbol{w}}(u)$, $\bar{\boldsymbol{f}}(u)$, $\bar{\boldsymbol{v}}(u)$, $\bar{\hat{\boldsymbol{v}}}(u)$, $\bar{\boldsymbol{e}}(u)$, and $\bar{\boldsymbol{g}}(u)$ contain the corresponding variables at the end of period.

The updating of variables between the start state and the end state relies on the interior state $\boldsymbol{\kappa}(u)$, represented by:

$$\boldsymbol{\kappa}(u) = \begin{bmatrix} {}^1\boldsymbol{O}(u) & {}^2\boldsymbol{O}(u) & {}^3\boldsymbol{O}(u) & \boldsymbol{\theta}(u) & \boldsymbol{q}(u) & \boldsymbol{b}(u) \end{bmatrix}, \tag{5}$$

where ${}^1\boldsymbol{O}(u) = \left[{}^1O_{ik}(u)\right]_{I\times K}$contains the binary variables meaning whether a repair action is needed for the degradation failure of component i at turbine k; ${}^2\boldsymbol{O}(u) = \left[{}^2O_{ik}(u)\right]_{I\times K}$ contains the binary variables meaning whether a repair action is needed for the incident failure of component i at turbine k; ${}^3\boldsymbol{O}(u) = \left[{}^3O_{ik}(u)\right]_{I\times K}$ contains the binary variables meaning whether the component i at turbine k is at the ageing stage; $\boldsymbol{\theta}(u) = \left[\theta_{ikm}(u)\right]_{I\times K}$ contains the variables representing the quality of potential maintenance actions performed on the component i at turbine k; $\boldsymbol{q}(u) = \left[q_{ik}(u)\right]_{I\times K}$ contains the variables representing the occurrence time of environmental impact on the component i at turbine k; $\boldsymbol{b}(u) = \left[b_{ik}(u)\right]_{I\times K}$ contains the variables representing the influence of environmental impact on the component i at turbine k.

Assuming that the failure time of component i located at turbine k follows a two-parameter Weibull distribution with scale parameter σ_{ik} and shape parameter ε_{ik}. The Weibull distribution with these two parameters is used to model the failure characteristic and degradation behaviour of the components in reality. The inverse Weibull model is used to produce the actual component lifetime v_{ik} [36] as:

$$v_{ik} = \sigma_{ik}[-\ln(1-\gamma)]^{\frac{1}{\varepsilon_{ik}}}, \tag{6}$$

where γ is a random value between 0 and 1.

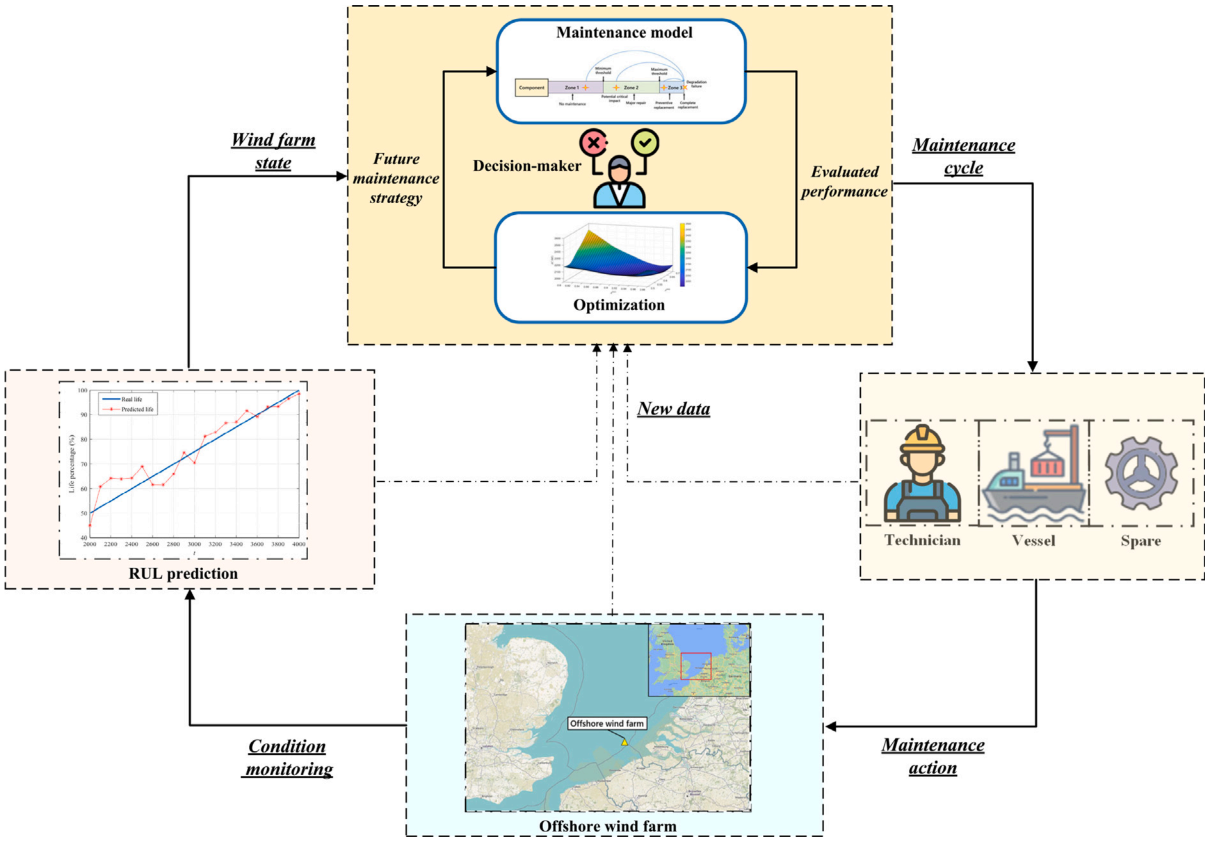


Fig. 1. Schematic diagram of the closed-loop maintenance decision-making process.

Considering the offshore wind farm is located in a typical harsh marine environment, it is assumed that the wind turbine, especially rotor and blade, is subject to a degradation process and environmental impact simultaneously. The arrival of environmental impact is assumed to follow a non-homogeneous Poisson process with the intensity function $\lambda_{ik}(t)$. The impact is categorized into critical, influential, and minor impact. The critical impact makes the turbine fail immediately. The influential impact causes an abrupt increase b_m of actual age, where m is the degradation stage. The minor impact brings a relatively moderate influence on operation, thus the turbine will recover soon without necessary maintenance actions. The probability of three types of impact is P^{C}_{ik}, P^{I}_{ik}, and P^{M}_{ik} respectively, and the sum is equal to 1.

When the farm begins to operate at the beginning, the cumulative time $w_{ik}(u)$ is equal to 0. All the components in the farm are brand new, thus the component ages are set as $f_{ik}(u) = 0$. By sampling the distribution as Eq. (6), the failure age of each component $v^{\mathrm{a}}_{ik}(u)$ can be obtained. The turbine just begins to operate, so the binary variable $e_{ik}(u)$ is 0, and the value of $g_k(u)$ is null.

With the operation of the turbine, the component state is affected by internal degradation, environmental impact, and maintenance actions. At the beginning of u period, the cumulative time is calculated as:

$$w_{ik}(u) = (u-1)\Delta s. \tag{7}$$

The cumulative time of the end of u period is calculated as:

$$\bar{w}_{ik}(u) = w_{ik}(u) + \Delta s = u\Delta s. \tag{8}$$

The component age increases as the wind farm operates. The interior state $\boldsymbol{\kappa}(u)$ is categorized into two types according to the degradation and operational states of wind farm system, that is, normal operation or under maintenance. If the wind farm normally operates without any maintenance, the change between $\boldsymbol{\xi}(u)$ and $\boldsymbol{\omega}(u)$ is resulted from degradation and environmental impact. If the impact is not so severe to cause abrupt degradation or failure, the age is updated as:

$$\bar{f}_{ik}(u) = f_{ik}(u) + \Delta s. \tag{9}$$

If the environmental impact causes an abrupt degradation $b_{ik}(u)$, then

$$\bar{f}_{ik}(u) = \bar{w}_{ik}(u) - q_{ik}(u) + b_{ik}(u)\left[f_{ik}(u) + \left(q_{ik}(u) - w_{ik}(u)\right)\right]. \tag{10}$$

The value of $b_{ik}(u)$ is set as an enormous positive number if the impact is critical, and the age $\bar{f}_{ik}(u)$ increases to be much higher than its real lifetime. If a maintenance cycle occurs during this period, the current age of the component subject to maintenance actions will change. Suppose that the quality of the mth level maintenance action is $\theta_{ikm}(u)$, the influence of maintenance actions is modelled using a Kijima type II model as in [37]:

$$\bar{f}_{ik}(u) = f_{ik}(u)\theta_{ikm}(u) + \bar{w}_{ik}(u) - w_{ik}(u). \tag{11}$$

The lifetime $\bar{v}_{ik}(u)$ remains the same as $v_{ik}(u)$ if the component is not replaced by a new one, otherwise a new lifetime is generated following Eq. (6). During the period u, a condition monitoring technology is used to record sensor data, and the RUL of critical components is predicted based on collected data. The value of $\hat{v}_{ik}(u)$ is close to the real lifetime but not equal, because of unavoidable prediction error. The predicted lifetime $\hat{v}_{ik}(u)$ is estimated based on the real lifetime $v_{ik}(u)$, with the generated error introduced in Section 2.2. It is worth stating that the actual life of a component is unknown in practice, and only the predicted lifetime is the information that can be known and used as basis for maintenance decisions.

Variable $\bar{e}_{ik}(u)$ is binary, determined by the magnitude of the values of $\bar{f}_{ik}(u)$ and $\bar{v}_{ik}(u)$, as:

$$\bar{e}_{ik}(u) = \begin{cases} 0, & \bar{f}_{ik}(u) < \bar{v}_{ik}(u) \\ 1, & \bar{f}_{ik}(u) \geq \bar{v}_{ik}(u). \end{cases} \tag{12}$$

When $\bar{e}_{ik}(u)$ equals 1, the value of $\bar{g}_{ik}(u)$ is obtained according to the cause of the failure. The moment of the failure caused by critical impact is equal to the occurrence time of the impact ($\bar{g}_{ik}(u) = q_{ik}(u)$). If the failure is caused by degradation, then

$$\bar{g}_{ik}(u) = \bar{\omega}_{ik}(u) - \bar{f}_{ik}(u) + \bar{v}_{ik}(u). \tag{13}$$

After defining how the start state and the end state are inter-connected, the next part of this section is to introduce the interior state. As stated above, the update between $\boldsymbol{\xi}(u)$ and $\boldsymbol{\omega}(u)$ is decided by the performed maintenance actions and the environmental impacts during the period, which is represented by $\boldsymbol{\kappa}(u)$.

A predictive opportunistic maintenance strategy with three decision variables ($\psi_{\max}$, $\psi_{\min}$, ϑ) is applied to the wind farm system. The component that has failed is determined to be completely replaced. For the running components, their health state is determined by a indicator $\psi_{ik}(u)$ that is calculated by:

$$\hat{\psi}_{ik}(u) = \frac{f_{ik}(u)}{\hat{v}_{ik}(u)}. \tag{14}$$

By comparing the health indicator with the decision variable $\psi_{\max}$ and $\psi_{\min}$, the component is judged to be in a different state. In the case where $\psi_{ik}(u)$ is higher than $\psi_{\max}$, the component is close to failure, requiring a preventive replacement. If the indicator $\psi_{ik}(u)$ is lower than $\psi_{\min}$, the component is regarded to be in good condition and requires basic maintenance. The components between $\psi_{\max}$ and $\psi_{\min}$ require a major repair. These components are categorized into $(M-2)$ levels as [38]:

$$\begin{aligned}&\hat{v}_{ik}(u)\left[\psi_{\max} - \frac{\psi_{\max}-\psi_{\min}}{M-2}(m-1)\right]\\ &\quad \le f^{a}_{ik}(u) < \hat{v}_{ik}(u)\left[\psi_{\max} - \frac{\psi_{\max}-\psi_{\min}}{M-2}(m-2)\right],\end{aligned} \tag{15}$$

where $m = 2, 3, \ldots, M-1$.

In order to count the number of aged and failed components in the wind farm, ${}^{1}\boldsymbol{O}(u)$, ${}^{2}\boldsymbol{O}(u)$, ${}^{3}\boldsymbol{O}(u)$ are used in the model. A binary variable $d(u)$ in Eq. (16) is used to decide whether a maintenance cycle should be initiated. In the case that a critical incident arises, or a degradation failure occurs, or a sufficient number of components are aged, a maintenance cycle is determined to be triggered, and the available maintenance resources are organized to support the implementation of the determined maintenance strategy (see Fig. 1).

$$d(u) = \begin{cases} 1 & \text{if } \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{1}O_{ik}(u) \ge 1 \text{ or} \\ & \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{2}O_{ik}(u) \ge 1 \text{ or } \sum_{i=1}^{I}\sum_{k=1}^{K} {}^{3}O_{ik}(u) \ge KI\vartheta \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

2.2. Condition monitoring and remaining useful life prediction

The applied predictive opportunistic maintenance strategy greatly depends on the RUL prediction of components. The purpose of this section is modelling the performance of the RUL prediction technique and explaining its function as a decision-making basis. More details on how to analyze the real-time signals and develop prognostic approaches to predict the wind turbine RUL can be found in [39].

Data from Supervisory Control and Data Acquisition (SCADA) and condition monitoring systems (CMS) are the most common data as input to the RUL method. The types of the data are various (vibration, acoustic emission, strain, torque, temperature, lubrication oil parameter, etc.), as concluded in [40]. After measuring these signals, the subsequent RUL methods are generally categorized into physical models, artificial neural networks, knowledge-based models, and life expectancy models [41]. The RUL of the target component is then predicted to foresee when a failure will occur.

It is assumed that a reliable RUL prediction technology is used during O&M. The prediction performance is evaluated by the average prediction error, which is defined as [42]:

$$\bar{E} = \frac{1}{UIK}\sum_{u\in U}\sum_{i\in I}\sum_{k\in K}\left|\psi_{ik}(u) - \hat{\psi}_{ik}(u)\right|, \tag{17}$$

where $\psi_{ik}(u) = f_{ik}(u)/v_{ik}(u)$ represents the component life percentage and $\hat{\psi}_{ik}(u)$ is the predicted value in Eq. (14).

As revealed in [43], the prediction error usually decreases as a component degrades. In this study, the error between $\psi_{ik}(u)$ and $\hat{\psi}_{ik}(u)$ is assumed to follow a Normal distribution as:

$$E_{ik}(u) = \left|\psi_{ik}(u) - \hat{\psi}_{ik}(u)\right| \sim N(\mu_{ik}(u), \delta_{ik}(u)^2). \tag{18}$$

Here, the expected value $\mu_{ik}(u)$ and standard deviation $\delta_{ik}(u)$ both tend to decline with the decrease of RUL. It is supposed that $\mu_{ik}(u) = \mu_{\mathrm{PE}} + \chi_{\mathrm{PE}}(1-\psi_{ik}(u))$ and $\delta_{ik}(u) = \delta_{\mathrm{SD}} + \chi_{\mathrm{SD}}(1-\psi_{ik}(u))$. The parameters μ_{PE} and δ_{SD} are the basic error which always exists. The positive parameters χ_{PE} and χ_{SD} represents the rising tendency of error with the increase of RUL. Therefore, by using Eqs. (14) and (18), the RUL prediction results of the offshore wind farm at the point u is generated, representing the performance of the applied RUL technology.

2.3. Consequences of maintenance implementation

The above sections describe the process from the operation of offshore wind farm to the wind turbine RUL prediction. After receiving the estimation of potential failure time of all critical components in the farm, the maintenance implementer compares these health condition with the currently executed maintenance strategy to decide whether to initiate a maintenance cycle as Eq. (16). In this study, the consequences of the maintenance cycles include two aspects, i.e., the improvement in wind farm health condition, and the loss of the revenue consisting of maintenance related costs and production losses.

In terms of improving the wind farm condition, the influence of maintenance actions on a wind farm is recovery or restoration of component state. According to the component state, different degrees of maintenance actions is performed. A replacement indicates the component has been changed to a complete new one. The component age is restored to 0, thus the maintenance quality $\theta_{ikm}(u)$ is equal to 0. On the contrary, a basic repair maintains the operation of component without any influence on component health, so the maintenance quality $\theta_{ikm}(u) = 1$. The quality of intermediate maintenance action, namely major repair, is assumed to be a stochastic value between 0 and 1, as it is unstable under the influence of practical factors including technician's expertise, operating environment, investment budget. A Beta distribution is used to model the maintenance quality, as:

$$f(\theta_{ikm}(u)) = \frac{\Gamma(\alpha_m+\beta_m)}{\Gamma(\alpha_m)\Gamma(\beta_m)}\theta_{ikm}(u)^{\alpha_m-1}(1-\theta_{ikm}(u))^{\beta_m-1}, \tag{19}$$

where α_m and β_m are two positive shape parameters. The expected value of maintenance quality $\mu_{\theta_{ikm}(u)}$ and the variance $\sigma_{\theta_{ikm}(u)}$ are:

$$\mu_{\theta_{ikm}(u)} = \frac{1}{1+\frac{\beta_m}{\alpha_m}}, \tag{20}$$

$$\sigma_{\theta_{ikm}(u)} = \left[\frac{\alpha_m\beta_m}{(\alpha_m+\beta_m)^2(1+\alpha_m+\beta_m)}\right]^{\frac{1}{2}}. \tag{21}$$

The maintenance quality represents the level of repair service implemented by the maintenance service provider. The analysis of the maintenance historic database containing the maintenance records will provide a basis to estimate the component health recovery and the stability of repair quality.

Another important indicator the decision-maker is concerned about is the revenue loss. As shown in Fig. 1, maintenance vessels, technicians, and spare parts are mobilized and organized in the maintenance cycle. These maintenance related costs account for a large portion of the revenue losses. Meanwhile, the downtime of wind turbines during failure states and maintenance implementation induces production losses.

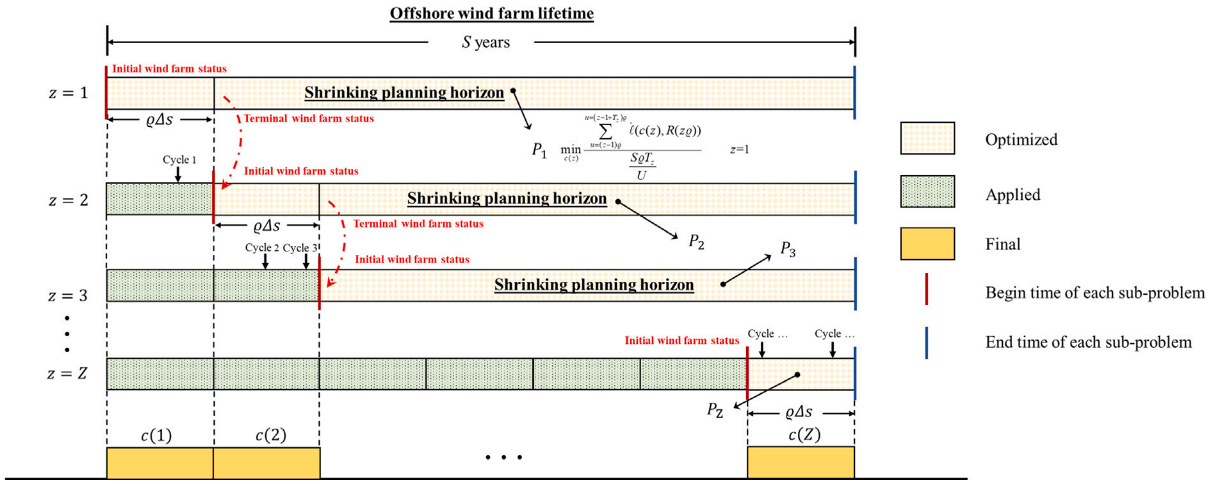


Fig. 2. Schematic representation of the shrinking planning horizon over the wind farm lifetime.

The total revenue losses during period u, represented by $\ell(u)$, composed of spare part cost, vessel cost, technician cost, and cost of production loss, are defined as

$$\ell(u) = d(u)\Big\{ M^{\mathrm{o}}(u) + \textstyle\sum_{k\in K}\Big\{ \left(T_k(u) - F_k^{\mathrm{T}}(u)\right) L + \sum_{i\in I}\Big\{ \left[R^{\mathrm{f}}_{ik} + N^{\mathrm{f}}_{ik}\left(Q^{\mathrm{J}} + h^{\mathrm{f}} r^{\mathrm{p}} + L\right)\right] x^{\mathrm{f}}_{ik}(u) + \left[R^{\mathrm{p}}_{ik} + N^{\mathrm{p}}_{ik}\left(Q^{\mathrm{J}} + h^{\mathrm{p}} r^{\mathrm{p}} + L\right)\right] x^{\mathrm{p}}_{ik}(u) + \left[R^{\mathrm{i}}_{ik} + N^{\mathrm{i}}_{ik}\left(Q^{\mathrm{C}} + h^{\mathrm{i}} r^{\mathrm{p}} + L\right)\right] x^{\mathrm{i}}_{ik}(u) + \sum_{m=2}^{M-1} x^{\mathrm{a}}_{ikm}(u)\left[R^{\mathrm{a}}_{ik}(u) + N^{\mathrm{a}}_{ikm}(u)\left(Q^{\mathrm{S}} + h^{\mathrm{a}} r^{\mathrm{p}} + L\right)\right]\Big\}\Big\}\Big\}, \tag{22}$$

where $M^{\mathrm{o}}(u)$ represents the mobilization cost in the maintenance cycle performed at period u; $T_k(u)$ is the end time of maintenance on turbine k; $F_k^{\mathrm{T}}(u)$ is the failure moment of wind turbine k; L is the price of the generated electricity per turbine per day; R^{f}_{ik}, R^{p}_{ik}, $R^{\mathrm{a}}_{ikm}(u)$, and R^{i}_{ik} is the cost of failure replacement, preventive replacement, mth major repair, and basic maintenance of component i at turbine k; $x^{\mathrm{f}}_{ik}(u)$, $x^{\mathrm{p}}_{ik}(u)$, $x^{\mathrm{a}}_{ikm}(u)$, $x^{\mathrm{i}}_{ik}(u)$ are binary variables determining whether the corresponding maintenance action is performed; Q^{J}, Q^{S}, and Q^{C} is the daily cost of heavy lift vessel (HLV), field support vessel (FSV), and crew transfer vessel (CTV) respectively; N^{f}_{ik}, N^{p}_{ik}, $N^{\mathrm{a}}_{ikm}(u)$, and N^{i}_{ik} is repair time of failure replacement, preventive replacement, major repair and basic maintenance; r^{p} is daily personnel cost; h^{f}, h^{p}, h^{a} and h^{i} is the number of required technicians.

The cost and time consumed for major repair usually increases when the maintenance quality is better. The relationship between maintenance quality, cost, and time is given by [44]:

$$R^{\mathrm{a}}_{ikm}(u) = R^{\mathrm{p}}_{ik}(1-\theta_{ikm}(u))^{\eta_{\mathrm{c}}(u)}, \tag{23}$$

$$N^{\mathrm{a}}_{ikm}(u) = N^{\mathrm{p}}_{ik}(1-\theta_{ikm}(u))^{\eta_{\mathrm{t}}(u)}, \tag{24}$$

where $\eta_{\mathrm{c}}(u)$ and $\eta_{\mathrm{t}}(u)$ are the coefficients determining the relationship between maintenance quality and corresponding repair cost and time.

The coefficients $\eta_{\mathrm{c}}(u)$ and $\eta_{\mathrm{t}}(u)$ influence the amount of cost and time for implementing major repair, which are assumed to be random values following a Normal distribution, thus the coefficient $\eta_{\mathrm{c}}(u)$ is represented as $\eta_{\mathrm{c}}(u) \sim N(\mu_{\mathrm{c}}, \delta_{\mathrm{c}}^2)$ and the coefficient $\eta_{\mathrm{t}}(u)$ is represented as $\eta_{(u)} \sim N(\mu_{\mathrm{t}}, \delta_{\mathrm{t}}^2)$.

2.4. Decision-maker's virtual maintenance model

The state transition of the actual offshore wind farm and the execution of the maintenance cycles are modelled in Section 2.1- Section 2.3, which can be considered as the real O&M situation of the wind farm under a specific maintenance strategy. The strategy is a kind of control action that is decided on by the decision-maker. In order to design a sound maintenance strategy, the decision-maker relies on a virtual maintenance model to simulate the O&M in the real offshore wind farm and predict the expected annual revenue losses $\dot{A}_{\mathrm{r}}$ under the specific maintenance strategy.

Running such a maintenance model requires input parameters which are derived from the database available to the decision-maker. In the decision-maker's maintenance model, the wind farm states are represented as:

$$\dot{\boldsymbol{R}}(u) = \begin{bmatrix} \dot{\boldsymbol{\xi}}(u) & \dot{\boldsymbol{\omega}}(u) & \dot{\boldsymbol{\kappa}}(u) \end{bmatrix}. \tag{25}$$

The state $\dot{\boldsymbol{R}}(u)$ is different from $\boldsymbol{R}(u)$ due to the uncertainty in the parameters. These uncertainties induce an incorrect estimation of the system state. In this paper, the uncertain parameters include component lifetime parameters, RUL prediction error parameters, and maintenance consequence parameters. In the maintenance model, the component lifetime is also modelled following a two-parameter Weibull distribution as:

$$\dot{\upsilon}_{ik} = \dot{\sigma}_{ik}[-\ln(1-\gamma)]^{\frac{1}{\dot{\varepsilon}_{ik}}}, \tag{26}$$

where the shape and scale parameters $\dot{\sigma}_{ik}$ and $\dot{\varepsilon}_{ik}$ are unequal to the parameters in Eq. (6), which represent the actual component failure information is still not fully recognizable by the decision-maker.

The decision-maker has realized the possible error between the predicted and real component age when developing the maintenance model. The prediction error modelling is based on the past performance of the adopted RUL prediction technology. However, once the RUL technique is applied in practice, it is very likely that the real prediction accuracy is far from the expected result given the negative influences from the actual operating environment. In this situation, the prediction error in the maintenance model is modelled as:

$$\dot{E}_{ik}(u) \sim N(\dot{\mu}_{ik}(u), \dot{\delta}_{ik}(u)^2). \tag{27}$$

The modelling of the maintenance consequences represents the decision -maker's estimation of maintenance effect, cost, and time, that result from the execution of the maintenance action. This estimation is dependent on the historic maintenance database. As discussed before, the historic database may be inaccurate and incomplete to derive the explicit estimation. Therefore, the coefficients input to the maintenance model is $\dot{\eta}_{\mathrm{c}}(u) \sim N(\dot{\mu}_{\mathrm{c}}, \dot{\delta}_{\mathrm{c}}^2)$ and $\dot{\eta}_{\mathrm{t}}(u) \sim N(\dot{\mu}_{\mathrm{t}}, \dot{\delta}_{\mathrm{t}}^2)$. The maintenance quality is $\dot{\theta}_{ikm}(u)$ with the parameters $\dot{\alpha}_m$ and $\dot{\beta}_m$. The expected value and the variance is $\dot{\mu}_{\theta_{ikm}(u)}$ and $\dot{\sigma}_{\theta_{ikm}(u)}$, respectively.

2.5. Rolling horizon and information updating

As introduced in Section 1, the existing wind energy maintenance models mostly adopt a kind of open-loop method for decision-making. For a large time horizon, such a fixed strategy is likely to be inappropriate due to the ignorance of periodic properties and accumulated data. As a decomposition based approach, the rolling horizon method is used to exploit the temporal structure and decompose the entire optimization problem into multiple optimization problems.

The decision-maker is assumed to employ a time interval ΔT for decision making, where $\Delta T = \varrho \Delta s$. On the basis of the maintenance model proposed in Section 2.4, the decision-maker here uses a so-called shrinking-horizon approach [45] and decomposes the optimization problem into finite sub-problems $\{P_1, \ldots, P_Z\}$, as illustrated in Fig. 2. Each optimization problem belongs to a step of decision-making z, where $z \in \{1, \ldots, Z\}$, and is only dependent on the maintenance strategy and the present monitoring state of the wind farm. The maintenance strategy is designed for future T_z steps at zth decision-making step.

At the step z, the maintenance strategy that controls the maintenance management is implemented, and the process starts over when the step is at $(z+1)$. The strategy $c(z)$ is represented as:

$$c(z) = \left[\psi_{\max}(z), \psi_{\min}(z), \vartheta(z)\right]. \tag{28}$$

A series of consequent strategies $\boldsymbol{c} = \mathrm{col}(c(1), \ldots, c(z), \ldots, c(Z))$ constitute the overall maintenance strategy during the wind farm lifetime, controlling maintenance timing and actions. A strategy consisting of two phases is used as an example, as shown in Fig. 3. Compared to Fig. 3(a), the maintenance thresholds are separated into two phases in Fig. 3(b), where the thresholds keep the same in period 1 and change in period 2. The moments of maintenance cycle 3 and 4, as well as the determined maintenance actions on component 1 and 2, are consequently different from Fig. 3(a).

The problem P_z defined to start at step z and cover the future horizon from z to $(z+T_z)$, can be formulated as Eq. (29) to find the optimal solution $c(z)$. In Eq. (29), the optimization objective, the annual revenue loss in the horizon, is calculated by dividing the sum of losses over by the horizon length. The final result, that is also the performance of the developed maintenance strategy, is the annual revenue losses A_r in reality when the maintenance strategy $\boldsymbol{c} = \mathrm{col}(c(1), \ldots, c(z), \ldots, c(Z))$ is implemented.

$$\min_{c(z)} \frac{\sum_{u=(z-1)\varrho}^{u=(z-1+T_z)\varrho} \acute{\ell}(u, c(z), R(z\varrho))}{\frac{S\varrho T_z}{U}}. \tag{29}$$

The different optimization processes between open-loop and reactive/closed-loop strategy are illustrated in Fig. 4. In the open-loop maintenance strategy, the maintenance strategy is determined based on the optimization results and is applied to a number of stochastic scenarios generated by using Monte Carlo methods. The expected performance of the maintenance strategy, i.e., annual revenue losses, is estimated by averaging the performance of each scenario. In the reactive or closed-loop maintenance strategy, the wind farm is divided into a series of phases in each scenario. The end of the previous phase is the beginning of the next phase. A specific sub-strategy is formulated based on the optimization results for each phase. The overall performance is also estimated by averaging the performance of each scenario.

The input parameters for the optimization problem are estimated using the existing wind farm failure and maintenance databases. The decision-making is inevitably influenced by the lack of data, especially in the early operational phase of the wind farm. The design of the maintenance strategy is based on limited useful information, including the life test data from the original equipment manufacturer (OEM) and subjective judgement of maintenance experts. In addition to the incompleteness of data, as [11] pointed out, much of the available field data may be inaccurate, undetailed, or redundant, leading to a negative effect on the estimation of maintenance model parameters.

The amount of wind turbine failure and maintenance data gradually increases as the offshore wind farm operates. Although the raw data gathered from the wind farm is not always ready and useful, it is assumed that it has been well-prepared to identify the relations among the data variables. At the beginning of operation, the original database the decision-maker has known is $\boldsymbol{X} = [{}^1\boldsymbol{X}, {}^2\boldsymbol{X}, {}^3\boldsymbol{X}]$. The sub-dataset ${}^1\boldsymbol{X} = \{{}^1x_1, {}^1x_2, \ldots, {}^1x_{\epsilon_1}\}$, ${}^2\boldsymbol{X} = \{{}^2x_1, {}^2x_2, \ldots, {}^2x_{\epsilon_2}\}$, ${}^3\boldsymbol{X} = \{{}^3x_1, {}^3x_2, \ldots, {}^3x_{\epsilon_3}\}$ contains component lifetime data, RUL prediction performance data, and maintenance implementation data respectively.

The initial lifetime parameters input into the maintenance model are derived from the database ${}^1\boldsymbol{X}$. The new lifetime sample consists of n_1 observations before decision-making step z is ${}^1\boldsymbol{X}^{z,D_1} = \{{}^1x_1^{z,D_1}, {}^1x_2^{z,D_1}, \ldots, {}^1x_{n_1}^{z,D_1}\}$. Hence the updated database is:

$$\begin{aligned} {}^1\hat{\boldsymbol{X}}^{z,D_1} &= \{{}^1\boldsymbol{X}, {}^1\boldsymbol{X}^{z,D_1}\} = \{{}^1x_1, \ldots, {}^1x_{\epsilon_1}, {}^1x_1^{z,D_1}, \ldots, {}^1x_{n_1}^{z,D_1}\} \\ &= \left\{{}^1\hat{x}_1^{z,D_1}, {}^1\hat{x}_2^{z,D_1}, \ldots, {}^1\hat{x}_{\epsilon_1+n_1}^{z,D_1}\right\}. \end{aligned} \tag{30}$$

The probability distribution D_1 is associated with a vector $\boldsymbol{\theta}^{D_1} = \left[\theta_1^{D_1}, \theta_2^{D_1}\right]$ of parameters. The probability that the sample can be observed is:

$$P({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = f_{D_1}({}^1\hat{x}_1^{z,D_1}, {}^1\hat{x}_2^{z,D_1}, \ldots, {}^1\hat{x}_{\epsilon_1+n_1}^{z,D_1} \big| \theta_1^{D_1}, \theta_2^{D_1}). \tag{31}$$

The maximum likelihood estimation is used to update the parameters used in the maintenance model. The likelihood function is obtained as:

$$L({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = \prod_{\tau=1}^{\epsilon_1+n_1} f_{D_1}({}^1\hat{x}_\tau^{z,D_1}; \boldsymbol{\theta}^{D_1}). \tag{32}$$

The maximum likelihood estimation aims to find the values of the model parameters which can maximize the likelihood function, namely:

$$\hat{\theta} = \arg\max L({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}). \tag{33}$$

The lifetime of components is modelled as a Weibull distribution with shape parameter $\dot{\epsilon}$ and scale parameter $\dot{\sigma}$. The probability density function is:

$$f({}^1\hat{x}_\tau^{z,D_1}) = \frac{\dot{\varepsilon}}{\dot{\sigma}} \left(\frac{{}^1\hat{x}_\tau^{z,D_1}}{\sigma}\right)^{\varepsilon-1} e^{-\left(\frac{{}^1\hat{x}_\tau^{z,D_1}}{\sigma}\right)^{\varepsilon}}. \tag{34}$$

Then, the likelihood function of the sample is:

$$L({}^1\hat{\boldsymbol{X}}^{z,D_1}; \boldsymbol{\theta}^{D_1}) = \prod_{\tau=1}^{\epsilon_1+n_1} \frac{\varepsilon}{\dot{\sigma}} \left(\frac{{}^1\hat{x}_\tau^{z,D_1}}{\sigma}\right)^{\dot{\epsilon}-1} e^{-\left(\frac{{}^1\hat{x}_\tau^{z,D_1}}{\dot{\sigma}}\right)^{\dot{\epsilon}}}. \tag{35}$$

It is usually more convenience to use the natural logarithm of the likelihood function [46], which is called the log-likelihood:

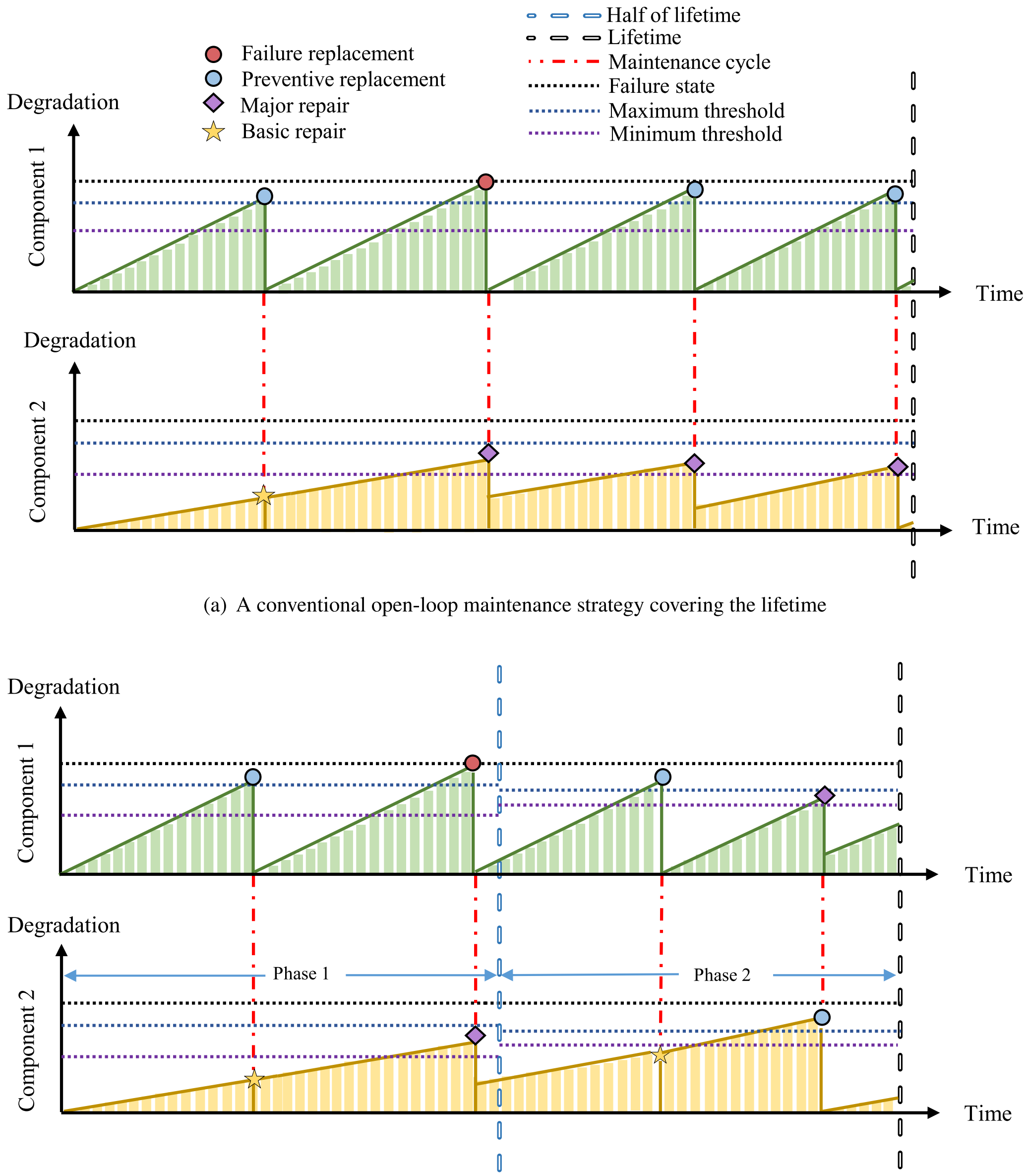
$$\begin{aligned} \ln(L({}^1\hat{\boldsymbol{X}}^{z,D_1}; \dot{\epsilon}, \dot{\sigma})) &= (\epsilon_1 + n_1)\ln(\dot{\epsilon}) - (\epsilon_1 + n_1)\dot{\epsilon}\ln(\dot{\sigma}) \\ &\quad + (\dot{\epsilon} - 1)\sum_{\tau=1}^{\epsilon_1+n_1} \ln(x_\tau^z) - \sum_{\tau=1}^{\epsilon_1+n_1} \left(\frac{{}^1\hat{x}_\tau^{z,D_1}}{\dot{\sigma}}\right)^{\dot{\epsilon}}. \end{aligned} \tag{36}$$

The score equations are:

$$\frac{\partial \ln L}{\partial \dot{\sigma}} = -\frac{(\epsilon_1 + n_1)\dot{\epsilon}}{\sigma} + \frac{\dot{\epsilon}}{\dot{\sigma}^{\dot{\epsilon}+1}} \sum_{\tau=1}^{\epsilon_1+n_1} ({}^1\hat{x}_\tau^{z,D_1})^{\dot{\epsilon}} = 0, \tag{37}$$

$$\begin{aligned} \frac{\partial \ln L}{\partial \dot{\epsilon}} &= -\frac{\epsilon_1 + n_1}{\dot{\epsilon}} - (\epsilon_1 + n_1)\ln\dot{\sigma} + \sum_{\tau=1}^{\epsilon_1+n_1} \ln({}^1\hat{x}_\tau^{z,D_1}) \\ &\quad + \frac{\ln\dot{\sigma}}{\dot{\sigma}^{\dot{\epsilon}}} \sum_{\tau=1}^{\epsilon_1+n_1} ({}^1\hat{x}_\tau^{z,D_1})^{\dot{\epsilon}} - \frac{1}{\dot{\sigma}^{\dot{\epsilon}}} \sum_{\tau=1}^{\epsilon_1+n_1} ({}^1\hat{x}_\tau^{z,D_1})^{\dot{\epsilon}} \ln({}^1\hat{x}_\tau^{z,D_1}) = 0. \end{aligned} \tag{38}$$

Thereby, the parameters of lifetime of components are estimated at step z through calculating Eqs. (37) and (38). In the similar way, the updated databases for RUL prediction performance and maintenance



(b) Adjusting the maintenance strategy between phase 1 and 2

Fig. 3. Influence of fixed and adjustable maintenance thresholds on maintenance actions.

implementation are:

$$ {}^2\hat{\boldsymbol{X}}^{z,D_2} = \{{}^2\boldsymbol{X}, {}^2\boldsymbol{X}^{z,D_2}\} = \left\{ {}^2\hat{x}_1^{z,D_2}, {}^2\hat{x}_2^{z,D_2}, \dots, {}^2\hat{x}_{\epsilon_2+n_2}^{z,D_1} \right\}, \tag{39} $$

$$ {}^3\hat{\boldsymbol{X}}^{z,D_3} = \{{}^3\boldsymbol{X}, {}^3\boldsymbol{X}^{z,D_3}\} = \left\{ {}^1\hat{x}_1^{z,D_3}, {}^1\hat{x}_2^{z,D_3}, \dots, {}^1\hat{x}_{\epsilon_3+n_3}^{z,D_3} \right\}. \tag{40} $$

The parameters in the Normal distribution of the prediction error or repair cost/time coefficient are updated as:

$$ L({}^2\hat{\boldsymbol{X}}^{z,D_2}; \boldsymbol{\theta}^{D_2}) = \left(\frac{1}{\sqrt{2\pi\dot{\sigma}}} \right)^{\epsilon_2+n_2} \exp\left(-\sum_{\tau=1}^{\epsilon_2+n_2} \frac{({}^2\hat{x}_\tau^{z,D_2} - \dot{\mu})^2}{2\dot{\sigma}^2} \right), \tag{41} $$

$$ \frac{\partial \ln L}{\partial \dot{\mu}} = \frac{1}{\dot{\sigma}^2} \sum_{\tau=1}^{\epsilon_2+n_2} \left({}^2\hat{x}_\tau^{z,D_2} - \dot{\mu} \right) = 0, \tag{42} $$

$$ \frac{\partial \ln L}{\partial \dot{\sigma}} = -\frac{\epsilon_2+n_2}{2\dot{\sigma}^2} + \frac{\epsilon_2+n_2}{2\dot{\sigma}^4} \sum_{\tau=1}^{\epsilon_2+n_2} \left({}^2\hat{x}_\tau^{z,D_2} - \dot{\mu} \right)^2 = 0. \tag{43} $$

The parameters modelling the maintenance quality, which follows a Beta distribution, is estimated as:

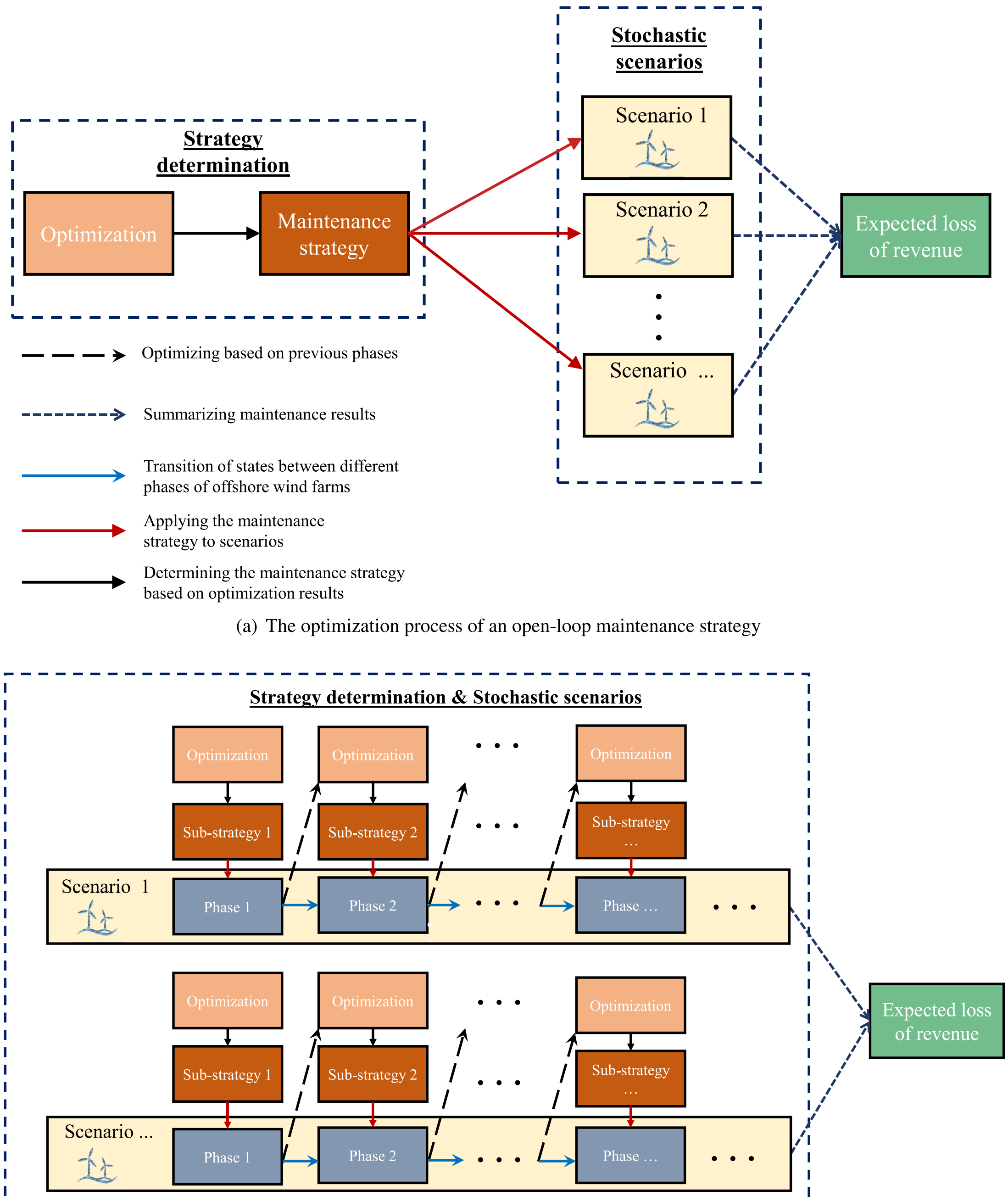
$$ L({}^3\hat{\boldsymbol{X}}^{z,D_3}; \boldsymbol{\theta}^{D_3}) = \left(\frac{\Gamma(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha})\Gamma(\dot{\beta})} \right)^{\epsilon_3+n_3} \prod_{\tau=1}^{\epsilon_3+n_3} {}^3\hat{x}_\tau^{z,D_3\,\dot{\alpha}-1} \prod_{\tau=1}^{\epsilon_3+n_3} (1 - {}^3\hat{x}_\tau^{z,D_3})^{\dot{\beta}-1}, \tag{44} $$

$$ \frac{\partial \ln L}{\partial \dot{\alpha}} = \frac{(\epsilon_3+n_3)\Gamma'(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha}+\dot{\beta})} - \frac{(\epsilon_3+n_3)\Gamma'(\dot{\alpha})}{\Gamma(\dot{\alpha})} + \sum_{\tau=1}^{\epsilon_3+n_3} \ln({}^3\hat{x}_\tau^{z,D_3}) = 0, \tag{45} $$

$$ \frac{\partial \ln L}{\partial \dot{\beta}} = \frac{(\epsilon_3+n_3)\Gamma'(\dot{\alpha}+\dot{\beta})}{\Gamma(\dot{\alpha}+\dot{\beta})} - \frac{(\epsilon_3+n_3)\Gamma'(\dot{\beta})}{\Gamma(\dot{\beta})} + \sum_{\tau=1}^{\epsilon_3+n_3} \ln(1 - {}^3\hat{x}_\tau^{z,D_3}) = 0. \tag{46} $$

2.6. Optimization method

The maintenance optimization problem here is complicated, involving nonlinearities, combinatorial relationships, and uncertainties, and it is more efficient and feasible to use a heuristic algorithm to solve it. The



(a) The optimization process of an open-loop maintenance strategy

(b) The optimization process of a reactive/closed-loop maintenance strategy

Fig. 4. An illustration of different optimization processes in open-loop and reactive/closed-loop maintenance strategies.

optimization method used to find the optimal solution is the Particle Swarm Optimization (PSO) algorithm with constriction coefficient. PSO algorithm was first proposed in [47], with the advantages including simple concept, easy implementation, robustness to control parameters, and computational efficiency [48]. The PSO algorithm has been widely used in solving maintenance optimization problems [49,50]. The algorithm was originally inspired by the regularity of flocking activity of birds, which led to a simplified model using swarm intelligence. After that, new elements are introduced to improve its performance, such as constriction coefficient [51]. Compared to the original PSO algorithm, the particle converges over time due to a constriction coefficient. The amplitude of a particle's oscillation decreases as it concentrates on the local and neighbourhood previous optimal points. The convergence of the algorithm can be insured by using the constriction factor.

PSO has two primary operators: velocity update and position update. At the beginning, initial random positions and velocities are possessed to all the particles in the space. During each generation, every particle moves towards its previous best position and the best position found so far by the whole swarm. In iteration ϖ, the position of λth particle is changed as:

$$x_\lambda(\varpi) = x_\lambda(\varpi-1) + y_\lambda(\varpi), \tag{47}$$

while the velocity of λth particle is updated as:

$$y_\lambda(\varpi) = \eta^{o}\left[y_\lambda(\varpi-1) + \beta_1^{o}v_1^{o}\left(x_\lambda^{\mathrm{IB}} - x_\lambda(\varpi-1)\right) + \beta_2^{o}v_2^{o}\left(x_\lambda^{\mathrm{GB}} - x_\lambda(\varpi-1)\right)\right], \tag{48}$$

Table 2
Failure and maintenance parameters for critical components.

Component	Distribution parameters		Maintenance cost (k€)		
	Scale (days)	Shape	Failure replacement	Preventive replacement	Basic repair
rotor and blade	3000	3	185	60	4
bearing	3750	2	45	15	1
gearbox	2400	3	230	75	5
generator	3300	2	60	20	1.5
pitch	1858	3	14	5	0.5

Table 3
Parameters for three types of maintenance vessels.

Vessel	Mobilization cost (k€)	Daily cost (k€)	Technician number	Daily technician cost (k€)
HLV	57	50	8	
FSV	–	18	4	0.6
CTV	–	8	2	

$$\eta^{o} = \frac{2}{\left|2-(\beta_1^{o}+\beta_2^{o})-\sqrt{(\beta_1^{o}+\beta_2^{o})^2-4(\beta_1^{o}+\beta_2^{o})}\right|}, \tag{49}$$

where β_1^{o} and β_2^{o} are two acceleration coefficients, η^{o} is constriction coefficient, υ_1^{o} and υ_2^{o} are two positive random numbers uniformly sampled from [0,1], x_{λ}^{GB} is the neighbourhood best state found so far, and x_{λ}^{IB} is the individual best state found so far.

The velocity and position of each particle is updated in iterations where the position of each particle is evaluated by the Eqs. (47) and (48). This process repeats until the maximum iteration number to capture the optimum solution. It is clarified that improving the performance of the selected algorithm by varying configuration parameters is also interesting but out of the scope of the study.

3. Results and discussion

In this section, the proposed methods are applied to a generic offshore wind farm with a designed 20-year lifetime, located at the North Sea, the Northwest of the Netherlands. The farm consists of a group of five 3-MW wind turbines individually containing five critical components. The technical parameters of each turbine are: (1) 3-blade rotor configuration, diameter 90 m; (2) hub height 80 m; (3) cut in speed 3 m/s, cut-out speed 25 m/s, rated speed 12 m/s.

Failure and maintenance parameters are derived from the past reports and papers [38,52–54], as listed in Tables 2 and 3. The unit price of power generation is 0.128 k€/MWh [55]. The daily wind speed data for this location from 1979 to 2012 is available in Royal Netherlands Meteorological Institute (KNMI) [56]. The mobilization time is 21 days, and the repair time of failure replacement, preventive replacement, and basic repair is respectively 70 h, 50 h, and 6 h [53], and working shift is 12 h. The accuracy of the RUL technique is about 87.2% under the error parameter μ_{PE} and δ_{SD} are both 0.01, and the value of χ_{PE} and χ_{SD} are 0.02. The variance of maintenance quality is 0.01. The value of μ_c and μ_t is 2, and δ_c and δ_t is 0.5.

3.1. Computational results and comparative performance

A comparative study is performed to compare the performance of five strategies in which assumptions and conditions are different. The computation is implemented in Matlab®, using one node with 48 cores, 2x Intel XEON E5-6248R 24C 3.0 GHz, and 192 GB memory at DelftBlue (TU Delft supercomputer) [57]. The parameter setting of the PSO optimization method is: (1) maximum number of iterations is 40, the swarm size is 30; (2) acceleration coefficients β_1^{o} and β_2^{o} are 2.05, constriction coefficient η^{o} is 0.73. The computation time for the strategies using an open-loop approach is about 0.2 h. The time for each other strategy is about 150 h, much higher than open-loop approach. The reason is that the optimization is performed once in the open-loop approach while the optimization is performed much more times in the other strategies.

Below is a list of the five different maintenance strategies:

- O-K strategy: An open-loop maintenance strategy disregarding wind farm states and uncertainty
  This strategy demonstrates an ideal situation where the model parameters are accurately known by the decision-maker, which is an assumption commonly used in the existing maintenance models. Once the maintenance strategy is optimized at the beginning phase, it will be implemented over the entire lifetime.
- O-U strategy: An open-loop maintenance strategy considering uncertainty and disregarding wind farm states
  A common situation in actual O&M is that the decision maker's information is deviated from the actual information. The inaccurate parameters input into the model are: RUL accuracy is about 93.1%, under the value of χ_{PE} and χ_{SD} is 0.01; the variance of maintenance quality is 0.001; the value of δ_c and δ_t is 0.3. The determined strategy is also employed over the entire lifetime without any adjustment.
- R-K strategy: A reactive maintenance strategy considering wind farm states and disregarding uncertainty
  A strategy similar to O-K strategy, supposes the model parameters are known. The difference is that the decision-maker periodically updates the maintenance strategy. The number of decision-making step is set as $Z = 4$. In other words, the maintenance strategy is adjusted every five years according to the current monitoring state of the wind farm. The prediction horizon for decision-making steps gradually shrinks from 20 years to five years.
- R-U strategy: A reactive maintenance strategy considering wind farm states and uncertainty
  Instead of the open-loop optimization method, the maintenance strategy is also re-designed every five years. The decision-maker

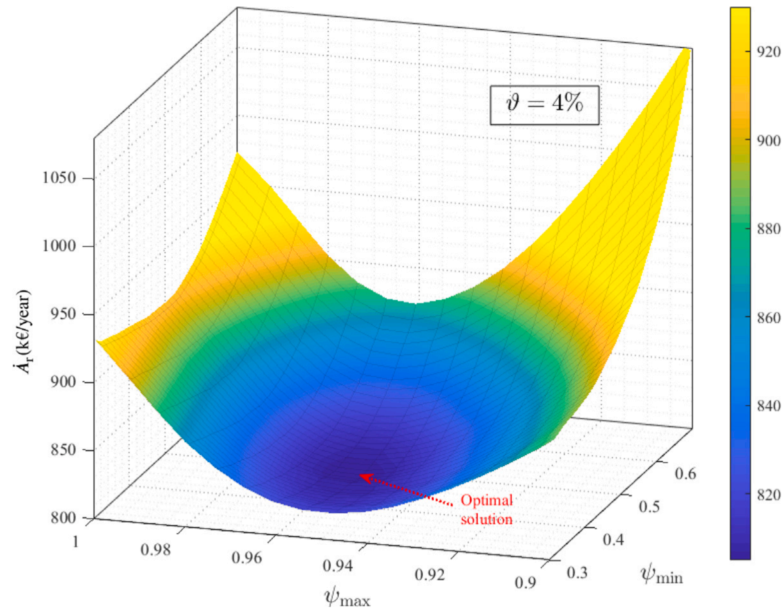


Fig. 5. Annual revenue losses versus different combinations of decision variables in O-K strategy.

ignores the potential parameter uncertainties, only considering the monitoring state of the wind farm and using the initial but inaccurate parameters to optimize the maintenance strategy.

- C-U-A strategy: A closed-loop maintenance strategy considering wind farm states and uncertainty-aware decision-making
The decision-maker has been aware of the model parameter uncertainty and consciously change the strategy based on an updated database containing historic O&M data and new cumulative data. Until a sufficient amount of new data is collected, the decision-maker cannot update the decisions as there is no basis to support the update. The volume of data in the database expands at a rate of 5% per year, and the strategy is updated every five years in line with the expanded database.

The expected annual revenue losses in O-K strategy, as a function of the maintenance thresholds and the number threshold of aged components, are given in Fig. 5. The surface has convexity, indicating there exists an optimal solution. By using the optimization model to solve the optimization problem, the optimal combination of the decision variables is given by (0.451, 0.962, 4%). In O-K strategy, the parameters in the model are accurate, thus the model output is the corresponding optimal result 806.4 k€/year.

Fig. 6 shows the estimated annual revenue losses in O-U strategy. In comparison with Fig. 5, the expectation of the revenue losses is lower due to the inaccuracy of the model parameters. The optimal solution (0.409, 0.925, 4%) corresponds to the minimum annual revenue losses in the maintenance model. The actual performance of the solution is estimated by inputting the solution into the wind farm system with accurate parameters, given by 826.4 k€/year.

The revenue losses of R-K, R-U, and C-U-A strategies and a comparison of five strategies are shown in Fig. 7. The annual revenue losses in the strategies under unknown parameters are greater than the strategies where the parameters are known accurately. This can be understood that the inaccurate parameters induce negative influence on decision-making, leading to a non-optimal solution and corresponding worse performance. The benefits of reactive approach are mainly reflected in two aspects. Firstly, the revenue loss decrease by 1.0% and 1.6%, regardless of whether the parameters are known or not, and the performance is better under unknown parameters. Moreover, compared with the open-loop method, the negative impact of parameter uncertainty on revenue losses is smaller, approximately 3.2% which is less than 3.7%.

R-K, R-U, and C-U-A strategies represent the best, the worst, and the intermediate consequences if the maintenance strategy is periodically adjusted. When decision-makers are aware of the potential uncertainty in the model parameters, they will attempt to remove this uncertainty in pursuit of the optimal consequence, which is represented by R-K strategy. As shown in Fig. 7, a reduction around 1.8% has been realized owning to the new collected data. A further reduction about 1.2% is hopefully be achieved if more data are available to realize the ideal case. As discussed before, O-U strategy is the situation the decision maker is most likely to face in reality. In comparison to it, the C-U-A strategy proposed in this study achieves a 3.4% reduction.

The O-K and O-U strategies assume that the model parameters are known to the decision-maker, which is an ideal situation cannot be realized up to now. However, this is the decision-making environment pursued, where the prior knowledge is sufficient to support the estimation of the parameters. On the contrary, the other strategies where the original model parameters differ from the practical information are more real O&M situations. Until more new data is added to the database, it is difficult to make a judgement on how to adjust the strategy. Once the enough amount of reliable data is accumulated, the new decisions based on the updated parameters are able to achieve a further cost reduction.

The O-K and O-U strategies adopt an open loop where the optimization model is run once, so that only one optimal solution is obtained. In R-K, R-U, and C-U-A strategies, the number of decision-making step is set as four, indicating the global maintenance strategy consists of four sub-strategies in one simulation. Hence a total of 4 × 400 optimizations are performed in each strategy, as the number of Monte Carlo simulation is 400.

Fig. 8 illustrates the variety of the maintenance thresholds in C-U-A strategy. The number of the optimal combination of decision variables derived is 1600, belonging to four different phases, and the duration of each phase is five years. In Fig. 8(a), the thresholds mostly concentrate in the range 0.38 to 0.48. The reason for the various thresholds at first phase is that the PSO is a heuristic algorithm, so the near-optimal solutions with close performance are obtained. Then the range of fluctuation increases over time in the following phases. In phase 4, the minimum thresholds even fluctuate from about 0.28 to 0.65. In addition, in the region composed of light blue dots at different phases, the shade of blue represents the concentration of the thresholds. The graph shows that the thresholds become more diverse

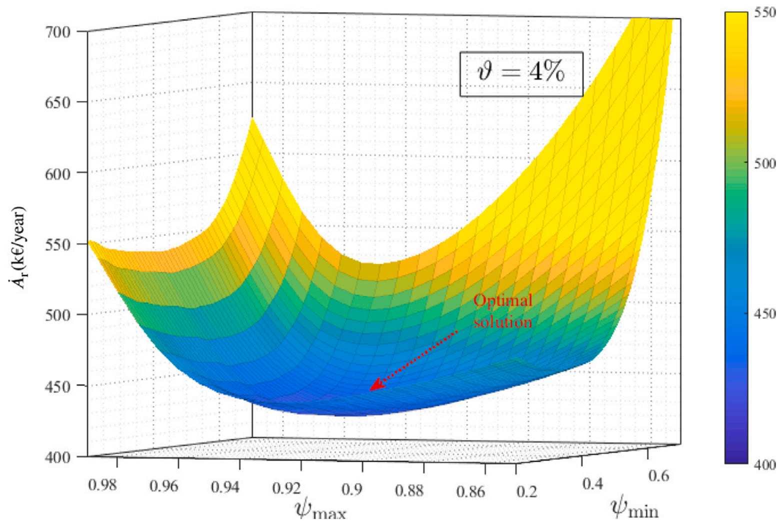


Fig. 6. Annual revenue losses versus different combinations of decision variables in the maintenance model in O-U strategy.

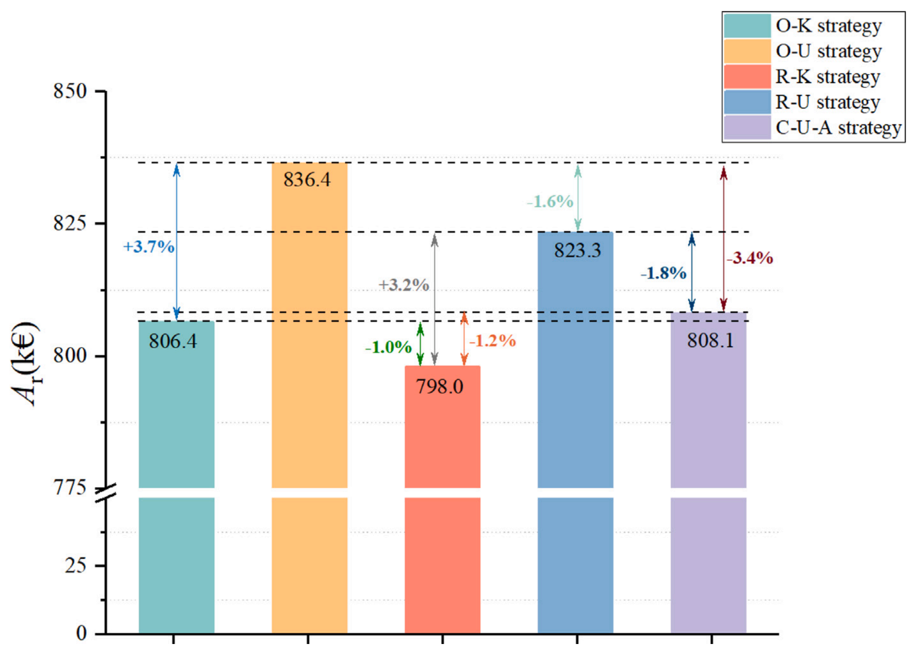


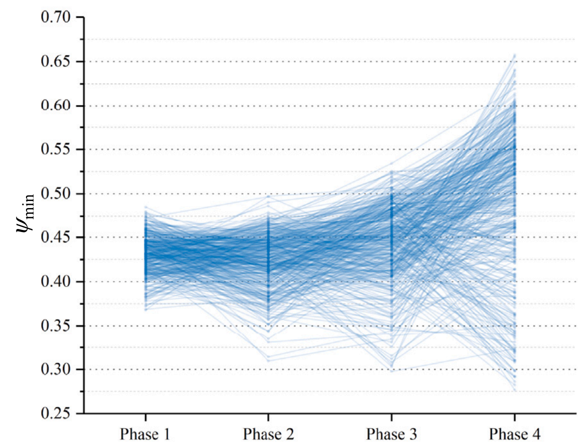
Fig. 7. Comparison of annual revenue losses of five strategies.

as the operational time increase, because the state of the wind farm is more various, and the thresholds are determined according to the state.

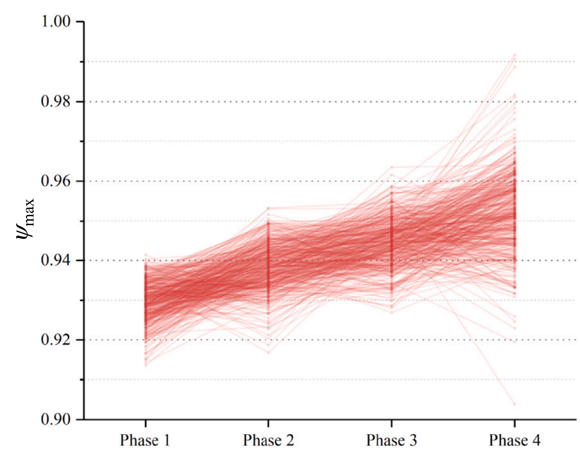
Fig. 8(b) reveals a similar trend: the maximum thresholds become more fluctuating. Compared to the minimum thresholds, the range of maximum thresholds is smaller, around 0.92–0.98 in phase 4. That can be explained by the different feature of these two thresholds. Minimum threshold ψ_{min} is more relevant to the determination of major repairs, while maximum threshold ψ_{max} controls the component replacement. For different wind farm states, it is more cost-effective to adjust the scope of application of the major repair rather than extending the scope of replacement. It should be explained here that the value of the third decision variable ϑ is always equal to 4%, because the case is a small-scale offshore wind farm and the change of ϑ is not influential.

The comparison of annual revenue losses over the lifespan and different phases is shown in Table 4. The utilization of reactive approach is able to reduce the cost in O-K strategy and O-U strategy from 806.4 k€/year and 836.4 k€/year to 798.0 k€/year and 823.3 k€/year in R-K strategy and R-U strategy respectively. If the parameters are updated in the process, the annual revenue losses further decreases from 823.3 k€/year in R-U strategy to 808.1 k€/year in C-U-A strategy.

Fig. 9 illustrates the annual revenue losses in different phases of the wind farm. No matter the wind farm is maintained in which strategy, the highest revenue losses always arise in the phase 2, followed by phase 3 and phase 4, and the losses are always lowest in the first phase. The reason for this situation is related to component failure modelling. In this paper, Weibull distribution is used to randomly generate the component lifetime, and the failure parameters determine the rough time to failure. In the early phase of the wind farm, the components are mostly in a healthy state. The impact of deterioration and failure is therefore small, and the revenue losses are lowest. In the later phases,



(a) Minimum maintenance threshold $\psi_{\min}$ changes with phase in different scenarios



(b) Maximum maintenance threshold $\psi_{\max}$ changes with phase in different scenarios

Fig. 8. Fluctuation of maintenance thresholds in C-U-A strategy.

Table 4
Comparison of different strategies in different phases of the wind farm.

		O-K strategy	O-U strategy	R-K strategy	R-U strategy	C-U-A strategy
Revenue loss (k€/year)	Phase 1	723.0	732.4	722.2	733.8	731.2
	Phase 2	886.1	914.7	881.4	906.4	900.3
	Phase 3	824.1	856.2	815.9	840.4	824.8
	Phase 4	792.4	842.1	772.4	812.4	776.1
	Lifespan	806.4	836.4	798.0	823.3	808.1

especially the phase 2, the ageing of the wind farm leads to a peak in maintenance, so the revenue losses are higher. Then after that, the state of the wind farm improved and therefore the losses in phase 4 are relatively low.

From the beginning to the end, O-U strategy always lead to the highest revenue losses, and R-K strategy gives the best performance. In phase 1, the performance of O-K, R-K is similar, and the results in O-U, R-U, and C-U-A are close. The slight deviations in the calculation results are due to the randomness in the simulation. In this phase, the implemented strategy is determined at the beginning, and the uncertain parameters induce a higher revenue losses. In phase 2, C-U-A strategy is located in the midstream. With the continuous revision of the parameters, its performance gradually surpasses R-U strategy and finally approaches R-K strategy.

3.2. Practical implications of this study

The results are relevant and beneficial for decision-makers and practitioners in wind energy industry. The maintenance strategy is recognized as health management criteria providing decision-makers

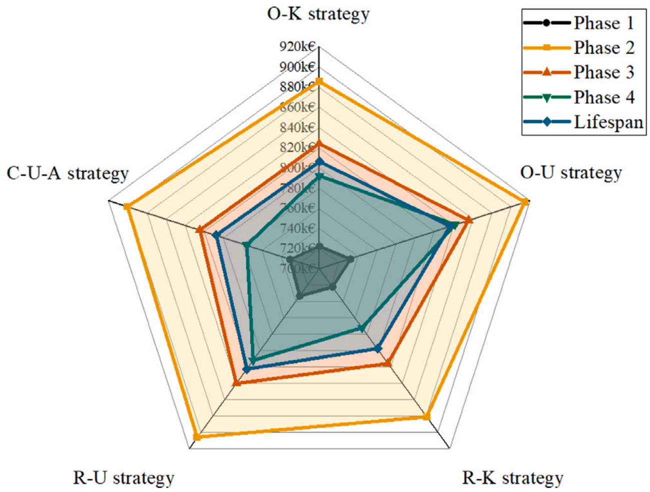


Fig. 9. Change of annual revenue losses of five strategies in different phases.

basis to determine when maintenance cycles are triggered and which component requires what kind of maintenance. It is known that the availability of RAM data has been the biggest challenge bringing about obstacles in O&M studies of wind energy. Without accurate and precise information, maintenance decisions are determined on the basis of unreliable data, which may lead to sub-optimal or even inappropriate strategies.

The introduction of advanced condition monitoring and fault prediction technologies has the capability to provide high quality data and wind farm state to assist the decision-maker to determine maintenance strategies. This paper shows that a sound maintenance strategy cannot be determined at one blow. It is beneficial to periodically adjusting the maintenance strategy according to the monitoring state of the wind farm and new data. Instead of a static and fixed one, the maintenance strategy should be more flexible and dynamic. A closed-loop approach can help the wind farm owners or operators to reduce revenue loss and gain more profit. The value of information and the significance of a reliable RAM database is revealed.

The case study is set as a five-turbine wind farm in this research. In the future, offshore wind farms will be large-scale. The improvement in small wind farms is relatively insignificant, as the overall state is not very various and the dependence on parameters is not strong enough. Considering the offshore wind farm tend to be much bigger in the future, the potential of the proposed method in terms of reducing revenue loss is expected to be more significant.

In addition, it can be noticed that the negative influence which non-optimal solutions bring about is not so notable. It can be attributed to the benefits of the applied preventive opportunistic maintenance strategy, where most of the maintenance actions are performed before the component failure. Variations in thresholds control the range of maintenance. Higher thresholds lower the number of the components subject of maintenance, indicating that the corresponding maintenance costs are lower. However, less maintenance is not beneficial to the wind farm state, perhaps result in more failure in the future. The results are the opposite when the thresholds are lower. In other words, changing thresholds is a double-edged sword. That can explain the revenue losses are not very sensitive when slightly changing the combinations of thresholds. In other words, the application of the maintenance strategy using the failure prognosis of component as the decision basis is robust and reliable from the perspective of economics.

However, there are still limitations in the current research. More future work is still necessary in order to improve the proposed method and gain further insight into its impact. The proposed closed-loop process brings much higher workload than the open loop as hundreds of optimizations have to be performed. Even though this research was carried out with the help of the supercomputer, the size of the offshore wind farm in the case study is still relatively small, only five turbines. One of the significant future trends of offshore wind energy is the wind farm size will become larger. It would be a feasible direction to ease the heavy workload in simulation and test the performance on a large offshore wind farm. In addition, much of the RAM data in wind farm databases may be incomplete, dubious, and redundant in reality. For instance, the failure data may be right-censored, interval-censored, and left-censored. In this paper, the new data used to update model parameters is assumed to be clean and well-prepared. Efforts should be made to introduce more data in real cases. Finally, the amount of new data per year as a percentage of the size of the original database, and the interval between updates for the maintenance strategy are fixed in the paper. More research should be done to answer the questions, such as 'Is it more cost-effective to update the maintenance strategy more or less frequent?' and 'Is there any better solution to adjust the maintenance strategy when the amount of the new data is limited?'.

4. Conclusions

The development of new real-time monitoring and fault prediction for offshore wind turbine systems creates the opportunity to understand the wind farm state more accurately and to build a more complete RAM database. The existing maintenance models for wind energy typically employ an open-loop or reactive approach to determine the maintenance strategy which assumes the model parameters are known and ignores the changes in the entire wind farm states, resulting in irrational and ineffective strategies.

This paper proposes a closed-loop maintenance strategy optimization approach to deliver feedback information and connect the offshore wind farm system, the maintenance model, and the optimization model. The maintenance optimization problem is decomposed into a finite sequence of sub-problems which cover multiple time periods. During this process, the database used to derive the model parameters is expanded to gradually eliminate uncertainty in model parameters. The maintenance strategy consisting of a series of sub-strategies is intentionally designed for the specific wind farm state and the updated database.

The proposed method is applied to a generic offshore wind farm located at North Sea to test its performance in terms of revenue losses. The five strategies in the comparative study have revealed that a reactive maintenance strategy which captures the changeable wind farm state is more cost-effective than conventional open-loop maintenance strategies, reducing about 1.6% of revenue loss. A closed-loop maintenance strategy which further exploits feedback from offshore wind farm system to mitigate model parameter uncertainty reduces about 3.4% of revenue loss in comparison to open-loop strategies. The results also revealed that the range of fluctuations in maintenance thresholds enlarges over time. It can be explained that the decision-making horizon is gradually shrinking, meanwhile the subsequent wind farm state is more various compared to the original state. Moreover, the revenue loss is various in different phases, from the beginning of operation until the end-of-life phases, representing the change in wind farm state under the maintenance strategy.

CRediT authorship contribution statement

Mingxin Li: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Xiaoli Jiang:** Supervision, Writing – review & editing. **James Carroll:** Writing – review & editing. **Rudy R. Negenborn:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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