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A multi-objective maintenance strategy optimization framework for offshore wind farms considering uncertainty

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ABSTRACT

While offshore wind energy is showing enormous potential, effective approaches to enhance its economics are being sought at the same time. The design of maintenance strategy is a type of strategic decision-making for offshore wind farms, aiming to improve energy production and reduce maintenance expenses. As a complicated and challenging task, the maintenance decision-making is confronted with various types of uncertainty in the model. The presence of uncertainty affects the estimation of maintenance performance, and renders the determined maintenance decisions sub-optimal or even inappropriate. In this paper, the authors propose an integrated decision-making framework incorporating i) a maintenance model which is applied to estimate maintenance performance, including maintenance costs and production losses, ii) a probabilistic uncertainty modelling approach which is used to characterize different types of uncertainty and a Monte Carlo method is adopted to generate stochastic scenarios, and iii) a multi-objective optimization method used to find the optimal decisions in the presence of conflict between multiple objectives. The uncertainties considered in the model include the stochastic attributes of time to failure, deviation between real and predicted failure times of components, and uncertain maintenance consequences. The proposed framework was applied in a generic 150MW-offshore wind farm located in the North sea. Results demonstrate that the deterministic scenario underestimates the maintenance costs and production losses, leading to the consequence that the developed maintenance strategy becomes unsatisfactory. A new series of solutions including priority solutions and trade-offs is provided for decision-makers to satisfy different goals while involving uncertainty. In addition, the influence of different uncertainties on the maintenance performance is quantified to assess the significance. The proposed optimization framework constitutes a useful decision-making tool to instruct the long-term maintenance strategy for offshore wind farms in a practical environment involving a high degree of uncertainty.

1. Introduction

Over past decades, rapid economic development and population growth has caused a continual increase in demand for electricity [1]. Meanwhile, consuming conventional fossil fuels results in about 75% of annual global anthropogenic GHG (greenhouse gases) emissions [2–4]. Energy shortages and climate change ensure renewable energy sources play a central role in the energy systems of the future [5–8], requiring global carbon dioxide emissions to be net-zero by 2050 [9–11]. In Europe, wind power is the fastest increasing renewable energy source and offshore wind market particularly achieves a high level of growth [12,13]. European offshore wind market enjoyed a 12% annual growth in the past decade (2011–2020), and annual new installations are expected to reach about 20GW in 2030 [4,14], expected to gradually realize the ambitious decarbonization goals [15].

Offshore wind energy is not more cost-effective than conventional power generation and other solutions to decarbonization [16]. In order to compete with other renewable energy sources, offshore wind energy still needs to strengthen the economic competitiveness which can be measured by comparing levelised cost of energy (LCOE) [17–19]. As one of the principal contributors of total cost of offshore wind energy, Operation and Maintenance (O&M) costs have been estimated to occupy around 14%–30% of life cycle cost (LCC) [20,21]. High O&M costs are negative factors restricting development of offshore wind energy. Availability of onshore wind farms has been shown to achieve a satisfying value (around 95%–97%) [22]. However, once wind turbines are placed offshore instead of onshore, the availability may decrease significantly to as low as 60%–70% [23]. The unavailability over the

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Nomenclature and acronyms definition

O&M	Operation and Maintenance
LCC	Life Cycle Cost
GHG	Greenhouse Gases
LCOE	Levelized Cost Of Energy
NSGA-II	Non-dominated Sorting Genetic Algorithm II
MTTF	Mean Time To Failure
RUL	Remaining Useful Life
$\mathscr{K}$	Total number of offshore wind turbines
$\mathscr{I}$	Total number of components at one turbine
$\mathscr{U}$	Total number of aged components
$\mathscr{S}$	Total number of maintenance cycles
$\mathscr{M}$	Total number of maintenance levels
k	Index for turbine
i	Index for component
s	Index for maintenance cycle
u_{ik}^{s}	Age of component i at turbine k in sth maintenance cycle
σ_{ik}	Failure parameter of component i at turbine k
ε_{ik}	Failure parameter of component i at turbine k
$\upsilon_{ik}(y)$	Real lifetime of component i at turbine k at yth decision point
$\lambda_k(t)$	Intensity function of environmental impact on turbine k
P_{ik}^{C}	Occurrence probability of critical impact on component i at turbine k
P_{ik}^{I}	Occurrence probability of influential impact on component i at turbine k
P_{ik}^{M}	Occurrence probability of minor impact on component i at turbine k
$\widetilde{\upsilon}_{ik}(y)$	Predicted lifetime of component i at turbine k at yth decision point
$u_{ik}(y)$	Age of component i at turbine k at yth decision point
T_s	Arrival time of maintenance cycle s
m	mth repair level
ψ_1	Maximum age percentage threshold
ψ_2	Minimum age percentage threshold
ζ	Percentage threshold of number of aged components
θ_{l_m}	Maintenance quality of mth maintenance level
b_m	Age increase of component at mth stage due to influential impact
C^{MAT}	Total cost of material for repair
C^{VES}	Total vessel cost
C^{TEC}	Total technician cost
C^{MOB}	Total mobilisation cost
M_s^{MOB}	Mobilisation cost in maintenance cycle s
O_s^{I}	Binary variable determining incident-based opportunity in maintenance cycle s
O_s^{F}	Binary variable determining failure-based opportunity in maintenance cycle s
O_s^{A}	Binary variable determining ageing-based opportunity in maintenance cycle s
X_{iks}^{FR}	Binary variable determining failure replacement of component i at turbine k in sth cycle
X_{iks}^{PR}	Binary variable determining preventive replacement of component i at turbine k in sth cycle
X_{ikms}^{MAR}	Binary variable determining mth level major repair of component i at turbine k in sth cycle
X_{iks}^{MIR}	Binary variable determining basic repair of component i at turbine k in sth cycle
R_{iks}^{FR}	Material cost of failure replacement of component i at turbine k in sth cycle
R_{iks}^{PR}	Material cost of preventive replacement of component i at turbine k in sth cycle
R_{ikms}^{MAR}	Material cost of mth level major repair of component i at turbine k in sth cycle
R_{iks}^{MIR}	Material cost of basic repair of component i at turbine k in sth cycle
Q^{J}	Daily cost of heavy-lift vessels
Q^{S}	Daily cost of field support vessels
Q^{C}	Daily cost of CTVs
N_{iks}^{FR}	Repair time of failure replacement of component i at turbine k in sth cycle
N_{iks}^{PR}	Repair time of preventive replacement of component i at turbine k in sth cycle
N_{ikms}^{MAR}	Repair time of mth level major repair of component i at turbine k in sth cycle
N_{iks}^{MIR}	Repair time of basic repair of component i at turbine k in sth cycle
T^{C}	Daily personnel cost
W^{FR}	Number of required technicians for failure replacement
W^{PR}	Number of required technicians for preventive replacement
W^{MAR}	Number of required technicians for major repair
W^{MIR}	Number of required technicians for basic repair
F_{iks}	Failure time of component i at turbine k before maintenance cycle s
F_{ks}^{T}	Failure time of turbine k before maintenance cycle s
N^{T}	Total downtime
w_{in}	Cut-in wind speed
w_{rated}	Rated wind speed
w_{out}	Cut-out wind speed

lifetime of an offshore wind farm directly results in a large amount of lost production and increased LCOE.

Maintenance management is a competitive factor which significantly affects profitability of offshore wind projects. Crespo Marquez and Gupta [24] suggested that contemporary maintenance management is classified into three echelons—strategic, tactical, and operational. A similar three-echelon architecture is also summarized in the area of offshore wind energy maintenance [25]. The strategic echelon focuses on the decisions affecting the O&M for a long period of time (e.g. the whole lifetime), such as maintenance strategy. The tactical echelon involves the decisions which are updated every 1–5 years, for example maintenance spare parts management and maintenance

P_{rated}	Rated capacity of wind turbine
w_t	Wind speed at day t
P_{kt}^{w}	Power production of turbine k at day t
L	Lifetime of offshore wind farm
C^{T}	Total costs related to maintenance effort
P^{T}	Total production losses
A_{p}	Annual production loss
A_{c}	Annual maintenance cost
Ω	Maximum number of generations
ω	Number of generation
Θ	Number of simulation
Y	Number of individuals
$\bar{e}$	Average Prediction Error
Y	Total number of inspection
$P_{ik}(y)$	Real remaining useful life percentage of component i at turbine k at yth decision point
$\tilde{P}_{ik}(y)$	Predicted remaining useful life percentage of component i at turbine k at yth decision point
$e_{ik}(y)$	Prediction error of component i at turbine k at yth decision point
$\mu_{ik}(y)$	Mean of prediction error of component i of turbine k at yth decision point
$\delta_{ik}(y)$	Standard deviation of prediction error of component i of turbine k at yth decision point
μ_{a}	Fixed parameter of mean of prediction error
δ_{a}	Fixed parameter of standard deviation of prediction error
a_{s}	Proportional parameter of standard deviation of prediction error
a_{p}	Proportional parameter of mean of prediction error
α_m	Shape parameter of mth level maintenance quality
β_m	Shape parameter of mth level maintenance quality
$\mu_{\theta_{l_m}}$	Expected value of mth level maintenance quality
$\sigma_{\theta_{l_m}}$	Standard deviation of mth level maintenance quality
η_c	Coefficient determining maintenance cost
η_t	Coefficient determining repair time
μ_c	Mean of coefficient determining maintenance cost
δ_c	Standard deviation of coefficient determining maintenance cost
μ_t	Mean of coefficient determining repair time
δ_t	Standard deviation of coefficient determining repair time

support organization. The operational echelon deals with the daily decisions, for instance routing and scheduling of maintenance vessels.

As a crucial issue in the strategic echelon, the maintenance strategy has a life-cycle effect on the project. The management of three echelons is usually determined from strategic to tactical and operational, implying the maintenance strategy influences the organization of medium-term and short-term maintenance plans as well. An unreasonable strategy may bring about negative consequences including high maintenance costs and tremendous production losses.

The optimization of maintenance strategy aims to provide decision-makers (offshore wind farm owner and operator or independent service provider) maintenance decisions to determine the necessary maintenance actions which should be performed on the qualified components and turbine. In reality, the decision-makers often focus on multiple maintenance objectives as opposed to a single objective such as minimum maintenance costs. These objectives may conflict with each other. In other words, it is difficult to find a solution making multiple objectives reach optimization at the same time. In addition, the maintenance optimization is a complex task replying on the development of maintenance model where various types of uncertainty are involved. For example, the exact values or distribution characteristics of input parameters are not deterministic due to insufficient information, but are assumed to be deterministic [26]. As another example, when the maintenance model is developed to explain real maintenance behaviours for offshore wind farms, the assumptions, simplifications, and generalizations involved make the maintenance model unable to accurately represent true characteristics [27]. The presence of uncertainty affects the estimation of maintenance performance along with the determination of maintenance strategy.

The maintenance optimization for offshore wind energy considering uncertainty is significant and challenging, but very few studies addressed this issue. Most of the existing research correlated to maintenance optimization is to build maintenance models in a deterministic scenario and perform optimization to purse a cost-effective solution. However, the maintenance objectives the decision-makers care about are often more than only maintenance costs. Moreover, the maintenance decision-making in reality is full of uncertainty. These uncertainties have an impact on different maintenance goals, and the magnitude of the impact is likely to vary with the degree of uncertainty. In the context, the determined maintenance strategy may become sub-optimal and need adjustment.

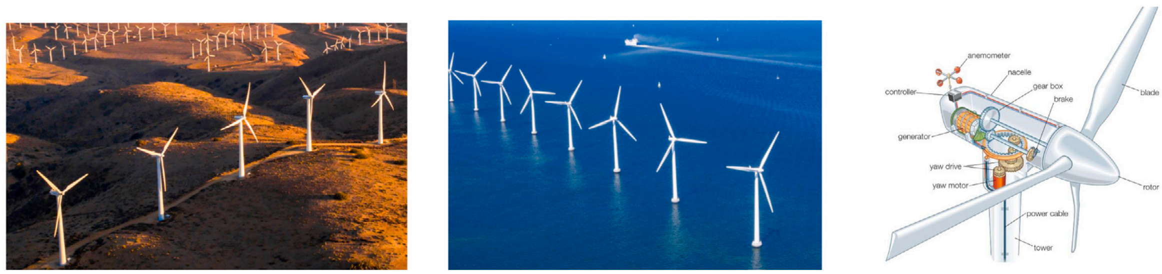
Considering the above research gap, in this paper, a holistic framework is developed to integrate maintenance strategy, decision-makers' objectives and uncertainty modelling. Compared to the existing research, this framework is designed for a more realistic maintenance decision-making environment, aiming to quantify the impact that uncertainty has on maintenance performance and provide a series of maintenance strategies meeting decision-makers' different demands while considering uncertainties.

Firstly, a long-term maintenance model is developed considering maintenance opportunities and condition prediction. The model is used to evaluate the maintenance performance. The outcome of the model includes costs related to maintenance effort and production losses resulted from downtime. In addition, the involved uncertainties are characterized and modelled by using a probabilistic method. Monte Carlo Simulation is adopted to generate stochastic scenarios representing the potential uncertainties. Furthermore, a non-dominated sorting genetic algorithm II (NSGA-II) method is used to derive a set of solutions balancing two maintenance objectives. Then, the conventional maintenance optimization model is set as the benchmark. The influence of different types of uncertainty is examined on the representative solutions, namely two priority solutions and a compromise solution. Finally, the integrated framework is performed to provide a series of optimal solutions considering uncertainty.

In summary, the contributions of the paper are:

(1) Developing a long-term maintenance model for offshore wind farms considering maintenance opportunities and condition prediction, as well as evaluating the maintenance performance including maintenance costs and production losses.

(2) Identifying and characterizing the potential uncertainties affecting the maintenance model, and quantifying the influence of different types of uncertainty on maintenance performance.



(a) (b) (c)

Fig. 1. Visual of wind farm and wind turbine system (a) Onshore wind farm [30] (b) Offshore wind farm [14] (c) Wind turbine system [31].

(3) Establishing a holistic framework integrating the maintenance model, the multi-objective optimization model, and multiple types of uncertainty, to design the maintenance strategy.

(4) Finding a series of solutions to satisfy decision-makers' different demands and preferences, as well as reflecting the adjustment of maintenance strategy when considering uncertainty.

The remainder of the paper is organized as follows: The literature focusing on the maintenance strategy, uncertainty and maintenance objectives is presented in Section 2. In Section 3, the maintenance model considering maintenance opportunities and component condition prediction is described. In Section 4, the concerned uncertainties are characterized and modelled. The optimization method which is used to find the balanced solutions between multiple objectives is presented in Section 5. In Section 6, the proposed framework is applied in a generic offshore wind farm. The results and discussion are also presented. In Section 7, concluding remarks and future research directions are provided.

2. Literature review

2.1. Maintenance strategy

Maintenance strategies for offshore wind energy are generally classified as corrective maintenance and preventive maintenance [28]. Corrective maintenance is carried out only after turbines break down. In order to avoid failure events, preventive maintenance is conducted at specific intervals, known as periodic maintenance. Corrective maintenance and periodic maintenance are still the dominated maintenance strategies applied in wind energy industry [29].

As an emerging maintenance strategy in recent years, opportunistic maintenance is capturing much attention from academia and industry. An offshore/onshore wind farm is composed of a number of turbines (as shown in Figs. 1(a) and 1(b)), and each turbine is a multi-component system consisting of many components (as shown in Fig. 1(c)). Performing maintenance on one component generates an opportunity window which can be taken advantage of to repair other components qualified for maintenance actions in this wind farm. Compared to repairing components individually, combined maintenance activities lower maintenance costs, especially when it is costly to send maintenance teams to the location. This characteristic is considered as economic dependence the opportunistic maintenance strategy exploits.

The decision variables in the opportunistic maintenance model are mostly set as maintenance thresholds related to component reliability [32,33] or mean time to failure (MTTF) [34]. However, these models did not connect the maintenance threshold with component condition. As it needs to be determined if a component qualifies for maintenance when a maintenance opportunity occurs, health condition prediction is significant to support the maintenance decisions. In past decades, condition monitoring technique has been developed to record diagnostic signals reflecting the health condition of critical components [35]. The remaining time before the component loses its operational ability is predicted by analysing the diagnostic signals, which is know as remaining useful life (RUL) prediction technology [36]. The RUL prediction provides a powerful basis for decision-makers to plan predictive maintenance based on future condition [37].

With potential for future application, the maintenance strategy considering maintenance opportunities and component condition has been gaining attention in recent years. The application of this strategy has been gradually extended from the rotor-blade system [38] to the entire onshore/offshore wind farm [39]. The health condition prediction provides the information associated with the possible failure times of components [40]. These components are then classified into different categories according to their health states, so that different maintenance actions can be carried out [41]. In this work, we adopt such a maintenance strategy as the target strategy in the framework.

2.2. Uncertainty

The formulation of a maintenance strategy during the long life span of wind farms is complicated. Various types of uncertainty are involved because of diversity of assets and their corresponding mechanisms [42], such as statistical uncertainty of component reliability estimations [43], inaccessibility for maintenance affected by weather variety [44], insufficient maintenance sources to support maintenance [45], etc. Therefore, it is important to develop the maintenance model capable of considering and incorporating the uncertainties.

Only limited papers paid attention to the maintenance models along with uncertainty. Dao et al. [46] mentioned the lack of reliability data and the vagueness of repair cost estimation have been widespread problems in the research community. A probabilistic sample method is used to derive failure data from reference reliability databases. Fuzzy numbers and a fuzzy inference system are used to model the uncertain repair related costs. The impact of uncertainty on performance indicators of an offshore wind turbine (availability, energy production, levelized cost of energy) is estimated. Scheu et al. [43] investigated the uncertainty in collecting reliability data for offshore wind turbine components. The uncertain component failure distributions are input in a O&M simulation tool. The results show that wind farm availability may vary in the range up to 20%.

However, these papers only study the impact of one or two types of uncertainty on the maintenance performance. Optimization is not involved, indicating that how the design of maintenance strategy is affected and then adjusted due to uncertainty is still unknown. In addition, these studies only paid attention to the scenarios where conventional corrective and time-based maintenance strategy is applied, novel maintenance strategies that industry may use in the future are not considered. Further, the estimation of performance of the maintenance strategy is distributed in a range because of uncertainty, but these papers cannot show how likely a specific value or range can be observed. Apart from the above papers, the prediction error of component health is mentioned in some literature [47,48]. However, these studies also cannot reflect the impact of varying degrees of uncertainty, and how maintenance decisions are altered because of uncertainty.

In general, the maintenance models cover the aspects including the modelling of the deterioration of the system, the description of the available information about the system state, the possible actions and consequences [49]. Various types of uncertainty are respectively associated with these aspects in the model, including stochastic attributes of time to failure [50], deviation between real and predicted failure times of components [51], and uncertain maintenance consequences [52,53], which we mainly concern in this study. The impacts of uncertainty such as accessibility affected by varying weather conditions, unpredictable availability of vessels and spare parts, etc., are also interesting topics worth investigation. However, these uncertainties are mainly studied in the tactical and operational echelon, which are beyond the scope of this paper and will be left to future research.

2.3. Maintenance objective

The maintenance strategy for industrial applications is usually concerned with maximizing equipment uptime and performance while balancing the resources and costs consumed [54]. Thus the objectives of maintenance strategy include reliability [55], safety [56], life cycle cost [57], carbon emission [58], etc., which depends on specific functions of equipment. In the area of wind energy, most of the work concentrates on a sole objective of reducing maintenance costs, whereas the decision-makers may have different interests and demands [59]. A comprehensive strategy is expected to provide a set of solutions satisfying decision-makers' multiple preferences.

Zhong et al. [60] proposed a non-linear multi-objective program for the maintenance of offshore wind farms. Two important goals are set as maximize system reliability and minimize maintenance cost. Erguido et al. [32] optimized maintenance strategy for onshore wind farms to maximize availability while minimizing cost. In addition, energy production and loss of load probability are also identified as the objective in [61,62].

We select two optimization objectives in the framework, minimum costs related to maintenance effort and minimum production losses caused by downtime. The objectives are directly associated with O&M cost and production performance for wind project, which are the primary concern of decision-makers. Considering the possible conflicts between objectives, it is impossible to make several objectives reach the optimal value simultaneously. A series of non-dominated solutions representing the trade-offs among objectives is expected to satisfy decision-makers as much as possible.

3. Maintenance model

In this section, a mathematical model is proposed to formalize the maintenance strategy for offshore wind farm considering maintenance opportunities and component condition. This model is developed from [63]. The purpose of the maintenance model is to evaluate the maintenance performance, including maintenance costs and production losses during the overall lifetime. The evaluation is then used in the optimization model to guide the search for the optimal solutions.

3.1. Assumptions

In the offshore wind farm, all turbines are assumed to be of the same type. Each turbine is simplified as a series system consisting of several critical components. Any failure of components causes breakdown of the whole system. The model focuses on long-term maintenance, so the maintenance decisions are at the strategic level. Once a strategic decision is made, the organization at tactical and operational level is assumed to be well-planned to support the strategic decisions. In other words, the maintenance decisions are ensured to be implemented successfully in time. During the lifetime of farm, the fluctuation in material cost for repair, daily cost for maintenance vessels and skilled technicians which may be caused by policy and market is not considered in the model. Hence the following assumptions are made:

1. All the turbines are of the same type. A particular component is of similar nature for all the turbines in the farm.
2. Each turbine is simplified to a series system where several critical components are connected.
3. The maintenance activities are ensured to be implemented successfully in time after the maintenance decisions are made.
4. The cost related to material, vessel, and manpower is constant during the lifetime, without considering the potential influence from changeable policy and market.

3.2. Failure modelling

Suppose that an offshore wind farm consisting of $\mathscr{K}$ turbines, and each turbine is composed of $\mathscr{I}$ critical components. The component gradually degrades as the age increases during the lifetimes, until the ultimate degradation failure. When decision-makers use the maintenance model, a specific lifetime distribution function and parameter values are input to model the degradation process and generate the failure events. In the wind energy sector, Weibull distribution is usually used, and it is presented here as an example. For the component i at turbine k, the used Weibull distribution is two-parameter with scale parameter σ_{ik} and shape parameter ε_{ik}. The failure probability density function is

$$f_{ik}(t) = \frac{\varepsilon_{ik}}{\sigma_{ik}}\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}-1} e^{-\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}}} \tag{1}$$

The $MTTF_{ik}$ denotes the expected time to failure, represented as

$$MTTF_{ik} = \int_0^{\infty} t f_{ik}(t) = \sigma_{ik}\Gamma\left(\frac{1}{\varepsilon_{ik}} + 1\right) \tag{2}$$

where $\Gamma(*)$ denoting the Gamma function. Knowing the distribution functions and parameter, the lifetimes of components are randomly generated by employing inverse distribution. Let $\alpha_{ik} = \sigma_{ik}^{-\varepsilon_{ik}}$ and γ is random value in the range from 0 to 1. The real lifetime of component v_{ik} is randomly generated as

$$v_{ik} = \left[-\frac{1}{\alpha_{ik}}\ln(1-\gamma)\right]^{\frac{1}{\varepsilon_{ik}}} \tag{3}$$

In addition to degradation, offshore wind turbines also suffer from impact resulting from harsh marine environment [64], such as atmospheric icing, lightning strikes, hurricanes, salty fog, changeable wind speed and direction, etc. The impact arrives randomly, which is modelled as a non-homogeneous Poisson process. Given the intensity function $\lambda_{ik}(t)$, the occurrence time of impact is obtained by using the inverse distribution.

The environmental impact is classified into three types depending on its severity: critical, influential, and minor. The component subject to the critical impact directly breaks down. The influential impact has an effect on the degradation of components, causing an abrupt increase of age b_m. The effect of minor impact is relatively small, only affecting the operation of turbine temporarily. Then, the turbine recovers to normal operational state after a short period of time. The occurrence probability of three types of impact is respectively P_{ik}^{C}, P_{ik}^{I}, and P_{ik}^{M}. Each probability is in the range from 0 to 1, and the sum of these probabilities equals 1. Considering the critical impact rarely happens, the value of P_{ik}^{C} is the least, following by P_{ik}^{I} and P_{ik}^{M}.

3.3. Maintenance opportunities and component condition

When a necessary maintenance action is required for single or multiple specific components, the maintenance opportunity emerges to repair the remaining components and turbines in the farm. The emergence of the maintenance opportunity triggers a maintenance cycle where all the planned maintenance actions are carried out. In the model, three types of maintenance opportunity are considered:

1. Failure-based opportunity. Failure-based opportunity appears when an offshore wind turbine breaks down due to degradation failure of a component.

2. Incident-based opportunity. Incident-based opportunity appears when an offshore wind turbine suffers from a sudden critical incident.

3. Ageing-based opportunity. No failure occurs in the farm, but a certain percentage of components reach a specific degree of ageing, the ageing-based opportunity appears.

The flow chart of the proposed maintenance model is shown in Fig. 2. Compared to the flow chart in [63], condition inspection is introduced to analyse the health state of components. At each decision point, the information of wind farm is collected to decide whether a maintenance cycle starts. If a critical impact arrives and causes a failure event, it is necessary to recover its operational state. The conduction of maintenance provides the opportunity for remaining components. Therefore, the incident-based opportunity emerges and a maintenance cycle starts, the binary variable O_s^{I} equals 1. Similarly, a maintenance cycle appears when a component breaks down due to degradation, the binary variable O_s^{F} equals 1.

If no degradation failure or incident happens, the ageing-based opportunity is determined based on component condition. Considering the real failure time is impossible to be known in advance, we have to estimate the condition based on predicted failure time. RUL is the time left before the failure occurs, which is a significant prognostics indicator [65]. It provides the useful basis for maintenance decision-making. It should be noted that how to analyse the collected diagnostic information and propose the approach to predict RUL is not the focus of the paper. This paper assumes that the failure time of component i at turbine k at yth decision point is predicted as $\widetilde{v}_{ik}(y)$. According to the predicted failure time, the component condition is estimated by comparing its age $u_{ik}(y)$ with prediction result $\widetilde{v}_{ik}(y)$. A percentage is set as threshold ψ_1. If the component is older than the threshold ($u_{ik}(y) > \widetilde{v}_{ik}(y)\psi_1$), it is regarded as an aged component. Another threshold ζ is introduced to denote the percentage threshold of aged components in the farm. The ageing-based opportunity arrives once $\frac{\mathscr{U}}{\mathscr{K}\mathscr{I}} \geq \zeta$, where $\mathscr{U}$ represents the number of aged components, then the binary variable $O_s^{\mathrm{A}} = 1$.

3.4. Maintenance categories

In a maintenance cycle, the components are performed different types of maintenance on depending on their conditions. Four types of maintenance actions are considered: failure replacement, preventive replacement, major repair, and basic maintenance. The Kijima type II virtual age model proposed in [66] and a multi-level maintenance model [67] are used to present the maintenance effect. The Kijima type II model assumes the age accumulates with time going, and the repair can remove the damages incurred before repair. The multi-level maintenance model classifies component condition into several groups to carry out maintenance actions. According to the component condition, $\mathscr{M}$ maintenance levels are introduced. The total number of maintenance cycles is $\mathscr{S}$, and the arrival time of sth maintenance cycle is T_s. After the sth maintenance cycle, the age of component i at turbine k is u_{ik}^s. The maintenance action of mth level in the $(s+1)$-th maintenance cycle updates the component age as [66]

$$u_{ik}^{s+1} = \theta_{l_m}(u_{ik}^s + T_{s+1} - T_s) \tag{4}$$

where u_{ik}^{s+1} is the new component age after repair; θ_{l_m} is maintenance quality for mth maintenance level.

Failure replacement is performed on the failed components due to critical impact or degradation. Preventive replacement is preventively replacing the components which are aged. These aged components reaching threshold ψ_1 are determined to be on the verge of failure and thus require preventive replacement ($m = 1$). Both failure replacement and preventive replacement reset the age of component to 0, which are regarded as perfect maintenance ($\theta_{l_m} = 0$).

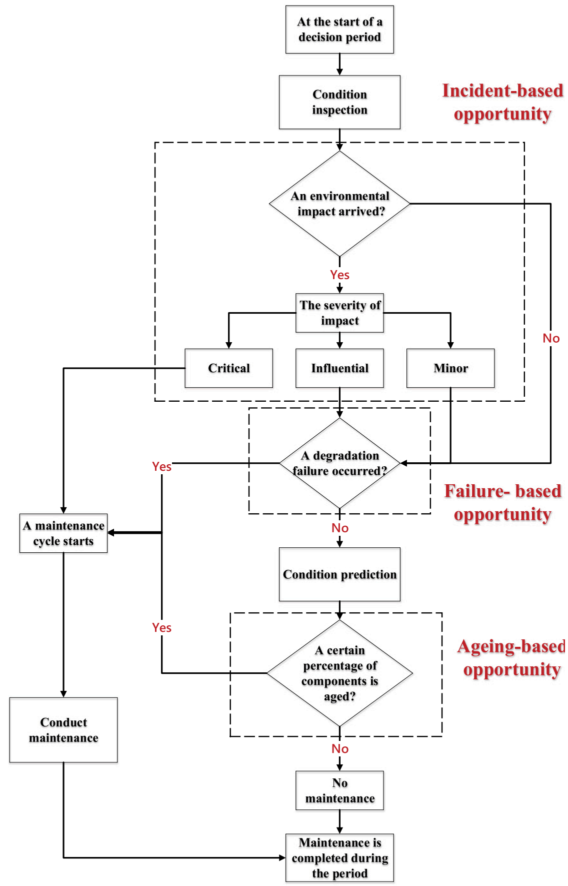


Fig. 2. Flow chart of the proposed maintenance model.

The young component which is in a good condition does not require maintenance actions. A maintenance threshold ψ_2 is introduced here. In the maintenance cycle, the component below ψ_2 is manually reset and checked with the capacity of ensuring the operation of components, such as lubricating, adjusting, tightening, and cleaning ($m = \mathscr{M}$). This basic maintenance does not improve the state of the undertaken components, indicating the value of θ_{l_m} is 1 and the component age does not change after repair.

The components between these two thresholds ψ_1 and ψ_2 are determined as mature components. The entire range between ψ_1 and ψ_2 is uniformly divided into $(\mathscr{M}-2)$ age groups. Component i at turbine k is performed the mth level of repair when the age falls into corresponding age groups [67]:

$$\tilde{v}_{ik}(y)\left(\psi_1 - \frac{\psi_1-\psi_2}{\mathscr{M}-2}(m-1)\right) \leq u_{ik}(y) < \tilde{v}_{ik}(y)\left(\psi_1 - \frac{\psi_1-\psi_2}{\mathscr{M}-2}(m-2)\right) \tag{5}$$

where $m = 2, 3, \ldots, \mathscr{M}-1$

3.5. Decision variables

There are three decision variables of the maintenance model: ψ_1, ψ_2, ζ. The variables ψ_1 and ψ_2 can be regarded as the criterion to determine whether a component is qualified for a specific type of repair. The number of different types of maintenance actions changes with the varying values of ψ_1 and ψ_2. In addition, the combination of ψ_1 and ζ determines the occurrence of ageing-based opportunity. Therefore, the decision vector is:

$$\vec{x} = [\psi_1, \psi_2, \zeta] \tag{6}$$

3.6. Model output

Two kinds of output are concerned in the model. The first one is maintenance related cost, including the cost of the materials used for repair, mobilisation cost, vessel costs and technician costs for the execution of maintenance tasks. In addition to maintenance related cost, another output is the production losses during the turbine downtime.

The total cost of the materials used for repair is obtained C^{MAT}as follows:

$$C^{\mathrm{MAT}} = \sum_{s=1}^{\mathcal{S}} \sum_{k=1}^{\mathcal{K}} \sum_{i=1}^{\mathcal{I}} \left(R_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} + R_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} + \sum_{m=2}^{\mathcal{M}-1} R_{iks}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}} + R_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} \right) \tag{7}$$

where R_{iks}^{FR}, R_{iks}^{PR}, R_{ikms}^{MAR}, and R_{iks}^{MIR} is the cost of failure replacement, preventive replacement, mth major repair, and basic maintenance of component i at turbine k in the sth maintenance cycle; X_{iks}^{FR}, X_{iks}^{PR}, X_{ikms}^{MAR}, X_{iks}^{MIR} determines whether the maintenance action is conducted.

Vessels are deployed to transport spare parts and technicians from shore to offshore sites. Considering the weight of the parts and maintenance requirements, different types of vessels are used for carry out maintenance. The replacement activities are implemented by using heavy-lift vessels, because the lifting capacity of large equipment is necessary. Heavy-lift vessel is a kind of self-elevating barge with the capacity of raising its hull for heavy lifting and heavy component replacements [45]. Field support vessel is needed to perform major repair considering its capacity to transport heavy spare parts. For basic maintenance, crew transfer vessel (CTV) is required to transport technicians and necessary tools.

In reality, maintenance service providers or asset owners usually own a number of specific vessels for O&M of offshore wind farms. When facing a high demand of vessels, service providers may also lease available vessels for a period of time from the market. Making purchasing/leasing decisions for vessels and optimizing fleet mix and size to support maintenance activities are usually regarded as tactical decisions in the O&M for wind energy. Further, the daily scheduling and routing of vessels is considered in the operational level. The tactical and operational decisions are not the concern of the paper. We approximately estimate the costs for vessels according to daily cost rate of specific vessels and repair time of different maintenance categories. The total vessel cost is denoted by C^{VES} as follows:

$$C^{\mathrm{VES}} = \sum_{s=1}^{\mathcal{S}} \sum_{k=1}^{\mathcal{K}} \sum_{i=1}^{\mathcal{I}} (N_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} Q^{\mathrm{J}} + N_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} Q^{\mathrm{J}} + N_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} Q^{\mathrm{C}} + \sum_{m=2}^{\mathcal{M}-1} N_{ikms}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}} Q^{\mathrm{S}}) \tag{8}$$

where Q^{J}, Q^{S}, and Q^{C} is the daily cost of heavy-lift vessels, field support vessels, and CTVs respectively; N_{iks}^{FR}, N_{iks}^{PR}, N_{ikms}^{MAR}, and N_{iks}^{MIR} is repair time of failure replacement, preventive replacement, major repair and basic maintenance.

Similar to vessel costs, the technician costs is estimated according to the daily personnel rate, the repair time of different maintenance categories, and the number of technicians needed to execute a maintenance task. The total technician cost C^{TEC} is calculated as:

$$C^{\mathrm{TEC}} = \sum_{s=1}^{\mathcal{S}} \sum_{k=1}^{\mathcal{K}} \sum_{i=1}^{\mathcal{I}} (N_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} W^{\mathrm{FR}} + N_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} W^{\mathrm{PR}} + N_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} W^{\mathrm{MIR}} + \sum_{m=2}^{\mathcal{M}-1} N_{ikms}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}} W^{\mathrm{MAR}}) T^{\mathrm{C}} \tag{9}$$

where T^{C} is daily personnel cost; W^{FR}, W^{PR}, W^{MAR} and W^{MIR} is the number of required technicians of failure replacement, preventive replacement, major repair and basic maintenance.

When using heavy-lift vessels to perform replacement, a large amount of cost is consumed to plan and prepare the marine operation before the vessel arrives at the wind farm, which is the mobilisation cost. In each maintenance cycle, the mobilisation cost of heavy-liftup vessels is only calculated for one time. The total mobilisation cost C^{MOB} is:

$$C^{\mathrm{MOB}} = \sum_{s=1}^{\mathcal{S}} M_s^{\mathrm{MOB}} \tag{10}$$

We consider the turbine downtime is mainly caused by turbine failure and maintenance execution. Once a failure occurs in the farm, the failed turbine stops operating until it is recovered in the upcoming maintenance cycle. The running turbines are required to stop operating during the maintenance execution, resulting in the production losses. Each turbine is assumed to be subject to one maintenance activity at the same time. The failure time of the component i at turbine k failing between $(s-1)$th and sth maintenance cycle is denoted by F_{iks}. Because the offshore wind turbine is a series system, the failure of one component makes the turbine stop operating immediately. The failure time of the located turbine is represented by F_{ks}^{T}. The total downtime thus can be calculated as

$$N^{\mathrm{T}} = \sum_{s=1}^{\mathcal{S}} \sum_{k=1}^{\mathcal{K}} (T_s - F_{ks}^{\mathrm{T}}) + \sum_{s=1}^{\mathcal{S}} \sum_{k=1}^{\mathcal{K}} \sum_{i=1}^{\mathcal{I}} (N_{iks}^{\mathrm{FR}} X_{iks}^{\mathrm{FR}} + N_{iks}^{\mathrm{PR}} X_{iks}^{\mathrm{PR}} + N_{iks}^{\mathrm{MIR}} X_{iks}^{\mathrm{MIR}} + \sum_{m=2}^{\mathcal{M}-1} N_{ikms}^{\mathrm{MAR}} X_{ikms}^{\mathrm{MAR}}) \tag{11}$$

The production loss is evaluated based on the wind speed data and the design parameters of the wind turbine, The wind turbine is designed to have a cut-in wind speed (w_{in}), a rated wind speed w_{rated}, and a cut-out wind speed (w_{out}). When the wind speed is too low, wind speed is not strong enough to make wind turbine operate. As the wind speed increases to w_{in}, the turbine starts to generate electricity by rotating blades. When the wind speed reaches the range between w_{rated} and w_{out}, the turbine operates in a rated capacity (P_{rated}). Once the turbine suffers from a wind speed higher than w_{out}, it shuts shown to avoid the potential damage and risk. The detailed relationship between wind speed (w_t) and turbine capacity (P_{kt}^{w}) is [68]:

$$P_{kt}^{\mathrm{w}} = \begin{cases} 0 & 0 \le w_t < w_{\mathrm{in}} \\ P_{\mathrm{rated}}(a + b w_t + c w_t^2) & w_{\mathrm{in}} \le w_t < w_{\mathrm{rated}} \\ P_{\mathrm{rated}} & w_{\mathrm{rated}} \le w_t < w_{\mathrm{out}} \\ 0 & w_{\mathrm{out}} \le w_t \end{cases} \tag{12}$$

where parameters a, b, and c are obtained as:

$$a = \frac{w_{\mathrm{in}}}{(w_{\mathrm{in}} - w_{\mathrm{rated}})^2} \left[(w_{\mathrm{in}} + w_{\mathrm{rated}}) - 4 w_{\mathrm{rated}} \left(\frac{w_{\mathrm{in}} + w_{\mathrm{rated}}}{2 w_{\mathrm{rated}}} \right)^3 \right] \tag{13}$$

$$b = \frac{1}{(w_{\mathrm{in}} - w_{\mathrm{rated}})^2} \left[4 (w_{\mathrm{in}} + w_{\mathrm{rated}}) \left(\frac{w_{\mathrm{in}} + w_{\mathrm{rated}}}{2 w_{\mathrm{rated}}} \right)^3 - (3 w_{\mathrm{in}} + w_{\mathrm{rated}}) \right] \tag{14}$$

$$c = \frac{1}{(w_{\mathrm{in}} - w_{\mathrm{rated}})^2} \left[2 - 4 \left(\frac{w_{\mathrm{in}} + w_{\mathrm{rated}}}{2 w_{\mathrm{rated}}} \right)^3 \right] \tag{15}$$

The offshore wind farms is designed with a L-year lifetime. During the overall lifetime, the total costs related to maintenance efforts is denoted by C^{T} which is estimated based on Eqs. (7)–(10), and the total production losses in the downtime is denoted by P^{T} which is estimated based on Eqs. (11)–(15).

3.7. Constraints

The constraints of the model are shown as follows:

$$X_{iks}^{\mathrm{FR}}, X_{iks}^{\mathrm{PR}}, X_{ikms}^{\mathrm{MAR}}, X_{iks}^{\mathrm{MIR}} \in \{0,1\} \qquad \forall i \in \mathscr{I}, \forall k \in \mathscr{K}, \forall m \in \mathscr{M}, \forall s \in \mathscr{S} \tag{16}$$

$$0 < \psi_2 < \psi_1 < 1 \tag{17}$$

$$\mathscr{K}\mathscr{I}\zeta \in \mathbb{Z}^{+} \tag{18}$$

$$O_s^{\mathrm{F}}, O_s^{\mathrm{A}}, O_s^{\mathrm{I}} \in \{0,1\} \qquad \forall s \in \mathscr{S} \tag{19}$$

$$F_{ks}^{\mathrm{T}} = \min\{F_{iks}\} \qquad \forall i \in I, \forall k \in K, \forall s \in \mathscr{S} \tag{20}$$

In constraint (16), the intermediate binary variables indicate whether the different type of maintenance action is performed on component i at turbine k in the sth maintenance cycle. Constraint (17) determines the decision variable triggering preventive replacement is higher than the decision variable triggering major repair. Constraint (18) determines the threshold of the number of aged components in the farm must be a positive integer. In constraint (19), the intermediate binary variables determines the occurrence of each type of maintenance opportunity. Constraint (20) determines the date of turbine breakdown. Once a component fails, the entire turbine consequently stops working.

4. Uncertainty modelling

The maintenance model illustrates the maintenance strategy which is designed in a deterministic scenario. In this section, three types of uncertainty are characterized and modelled by using a probabilistic method. Given the probability distribution, the Monte Carlo method is adopted to generate stochastic values. It should be noted that estimation of uncertainty by analysing available databases is not the concern of the section.

4.1. Stochastic attributes of time to failure

The failure rate of components is usually described as a shape of bathtub curve throughout the lifetime. Although the failure rate is not constant, the available maintenance models mostly rely on the simplification of assuming it is constant. This paper makes the same simplification. In order to model the degradation process and generate the failure events of each component, it is common to select and input a specific lifetime distribution and its parameter values which are estimated based on MTTF [69]. The lifetime distribution and parameters are typically assumed to be known with certainty in the conventional maintenance models.

However, the estimates of lifetime distributions and parameters may not be accurate. The reasons include the incompatible vendor guidelines due to lack of knowledge of actual use and repair, and unreliable collected maintenance records and historic failure data for years [70]. Given the same value of MTTF, the mean value of the distribution function estimating the probability of a failure occurrence corresponds to the MTTF, but the shape of different distribution and parameters results in different failure probabilities in certain intervals. In other words, the observations of failure data may not follow a clear pattern, then failure of components can be modelled in various lifetime distributions and parameters generating different failure behaviour of components, and consequently affect the model output [26]. This is a type of uncertainty in the lifetime distribution function and parameters under the same MTTF, which decision-makers are confronted with when designing the maintenance strategy.

Weibull, Exponential, Uniform, and Normal distributions are selected as the examples. As shown in Fig. 3, various lifetime distribution functions have the same value of MTTF (2679days). It means the simulated failure events occur every 2679 days on average, but failure characteristic follows different pattern. Even though we suppose the distribution function is certain such as Weibull distribution, the varying shape parameter in the range of [2.5, 3.5] still lead to different dispersion.

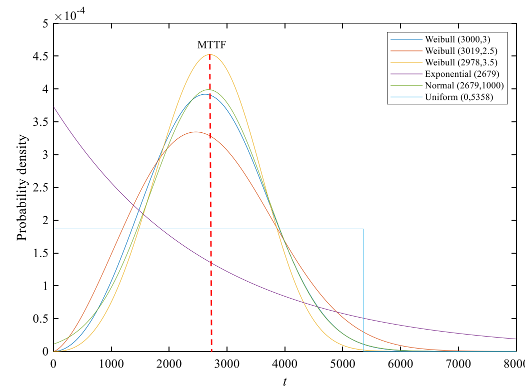


Fig. 3. Probability density of various lifetime distribution and parameter.

Decision-makers need to input the lifetime distribution functions and parameters into the maintenance model to model degradation process of components and randomly reproduce the time to failure. The occurrence of maintenance opportunities depends on failure and condition of components in the offshore wind farm. The uncertainty of distribution functions and parameters may result in different model performance, and then influence decision-making.

4.2. Deviation of predicted and real failure times

When a maintenance cycle is triggered, the number of components and turbines which are repaired or replaced is determined by comparing the component condition with maintenance thresholds. Because the real failure times of component is unknown in advance, people need to employ RUL prediction technology to make predictions which are regarded as the important decision basis for decision-makers to plan maintenance actions.

Diagnostic signals including vibration, acoustic emission, strain, torque, temperature, lubrication oil parameter, supervisory control and data acquisition (SCADA) system signals are provided by the sensors installed on critical components [71]. By analysing the signals, RUL prediction technology can provide information with respect to the time when the failure will occur. RUL prediction methods are basically classified into model-based methods and data-driven methods. Model-based methods use the knowledge of failure mechanisms to describe the system degradation process in a mathematical way. The operational data is collected to update the model parameters [36]. Data-driven methods use history data to derive the degradation process or match with history patterns to infer RUL [72].

These research mainly focuses on increasing the accuracy of prediction to provide more reliable information for the maintenance decisions. It would be ideal if the actual failure times can be accurately forecast, but the error between predicted and real failure times is inevitable. The inaccurate prediction indicates the component is maintained earlier or later than ideal timing, which is another type of uncertainty in the model.

The age of component i at turbine k at yth decision point is denoted by $u_{ik}(y)$. At the decision point, RUL prediction is performed to obtain the predicted failure age by analysing condition information of component. The predicted failure age is represented by $\widetilde{v}_{ik}(y)$. and the predicted RUL percentage $\widetilde{P}_{ik}(y)$ is obtained as $(\widetilde{v}_{ik}(y) - u_{ik}(y))/\widetilde{v}_{ik}(y)$. The real failure age of the component is represented by $v_{ik}(t)$, and the real RUL percentage $P_{ik}(y)$ is represented by $(v_{ik}(y) - u_{ik}(y))/v_{ik}(y)$.

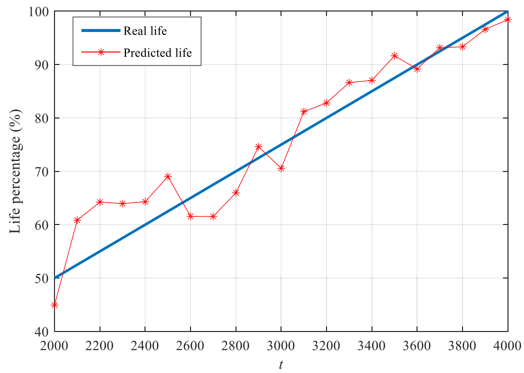


Fig. 4. Simulated deviation between real and predicted component life.

In order to quantify the prediction performance, an indicator called Average Prediction Error is usually used to evaluate the average prediction accuracy. If the total number of inspection during the lifetime is Y, Average Prediction Error $\bar{e}$ is calculated as [73]:

$$\bar{e} = \frac{1}{Y}\sum_{y=1}^{M}\left|P_{ik}(y) - \tilde{P}_{ik}(y)\right| \tag{21}$$

The Average Prediction Error is not constant during the lifetime of component. As the component gradually degrades, the component age is close to the failure age. The prediction results become more accurate as the component gets closer to failure [74]. The error between real RUL percentage $P_{ik}(y)$ and predicted RUL percentage $\tilde{P}_{ik}(y)$ is denoted by $e_{ik}(y)$, which is assumed to follow a Normal distribution:

$$e_{ik}(y) = \left|P_{ik}(y) - \widetilde{P}_{ik}(y)\right| \sim N(\mu_{ik}(y), \delta_{ik}(y)^2) \tag{22}$$

where $\mu_{ik}(y)$ is expected value and $\delta_{ik}(y)$ is standard deviation. With the decrease of RUL, the prediction accuracy increases, meaning the error $e_{ik}(y)$ gradually becomes lower. Thus the magnitude of error is positively correlated with the RUL. We suppose that $\mu_{ik}(y) = \mu_{\mathrm{a}} + a_{\mathrm{p}}P_{ik}(y)$ and $\delta_{ik}(y) = \delta_{\mathrm{a}} + a_{\mathrm{s}}P_{ik}(y)$. Parameter μ_{a} and δ_{a} indicates the error always exists no matter how close the component is to fail. Positive parameters a_{s} and a_{p} depicts that the error increases with the increase of RUL. Hence the deviation between predicted and real failure times is presented in this way, as shown in Fig. 4, thereby simulating the situation where the maintenance decision is not ideal due to the prediction error.

4.3. Uncertain maintenance consequences

After performing a maintenance action on the component, there is a corresponding cost and time consumed while the condition of the component is improved. These can be considered as the consequences of the maintenance action. The maintenance action is usually assumed to restore the state of component back to perfect, recover the stage with a certain degree, or not change the component age. However, the quality of maintenance is closely related to repairman's expertise, working environment, maintenance tools, etc., meaning the real value of maintenance quality varies from the expected maintenance effect. Meanwhile, the cost of the materials used for repair and the time spent on performing maintenance actions are closely related to maintenance quality, which are uncertain as well. The uncertain maintenance consequences is the third type of uncertainty concerned in the work.

Considering the consequences of replacement and basic repair are relatively stable, we mainly focus on major repair. The maintenance quality of major repair is often assumed as a fixed value in many studies of wind energy maintenance [34], indicating the major repair can successfully reduce the component age as expected. This assumption may disagree with the real-world maintenance situations. The real

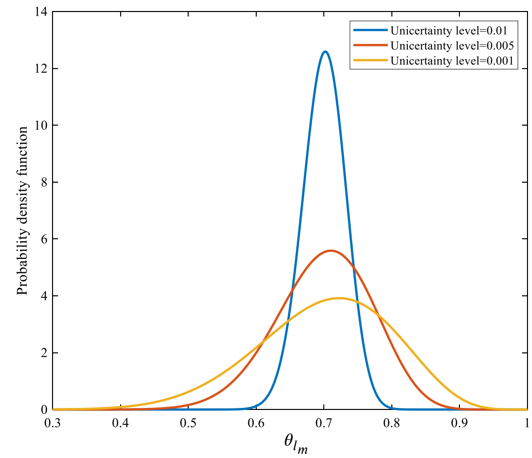


Fig. 5. Maintenance quality under different uncertainty level.

maintenance quality cannot be specified precisely as a fixed value. It is more reasonable and realistic to model it as a variable which is close to an expected value but is uncertain. The value of maintenance quality is between 0 and 1, because major repair can recover the component to an intermediate state between as good as new and as bad as old. In probability theory and statistics, the beta distribution has been applied to model the behaviour of random variables limited to interval [0,1]. We assume the random maintenance quality θ_{l_m} of mth maintenance level follows a beta distribution. The probability density function is:

$$f(\theta_{l_m}) = \frac{\Gamma(\alpha_m + \beta_m)}{\Gamma(\alpha_m)\Gamma(\beta_m)}\theta_{l_m}^{\alpha_m - 1}(1 - \theta_{l_m})^{\beta_m - 1} \tag{23}$$

where α_m and β_m are two positive shape parameters.

The expected value $\mu_{\theta_{l_m}}$ and the standard deviation $\sigma_{\theta_{l_m}}$ are:

$$\mu_{\theta_{l_m}} = \frac{1}{1 + \frac{\beta_m}{\alpha_m}} \tag{24}$$

$$\sigma_{\theta_{l_m}} = \left(\frac{\alpha_m\beta_m}{(\alpha_m + \beta_m)^2(1 + \alpha_m + \beta_m)}\right)^{\frac{1}{2}} \tag{25}$$

The value of $\mu_{\theta_{l_m}}$ is the age percentage which the component age is expected to reduce to. The value of $\sigma_{\theta_{l_m}}$ characterizes the instability of the maintenance quality. A higher standard deviation indicates the value of maintenance quality fluctuates in a larger range, as shown in Fig. 5.

The maintenance quality usually improves if more budget and time are allocated. In other words, the maintenance quality is positively correlated with the money and time spent on maintenance. The relationship between maintenance quality and cost is shown as [52,75]:

$$R_{ikms}^{\mathrm{MAR}} = R_{iks}^{\mathrm{PR}}(1 - \theta_{l_m})^{\eta_c} \tag{26}$$

where R_{ikms}^{MAR} is the cost of mth level major repair of component i at turbine k in the sth maintenance cycle; η_c is the coefficient determining the relationship between maintenance quality and corresponding repair cost.

Similarly, the relationship between maintenance quality and time is shown as [52,75]:

$$N_{ikms}^{\mathrm{MAR}} = N_{iks}^{\mathrm{PR}}(1 - \theta_{l_m})^{\eta_t} \tag{27}$$

where N_{ikms}^{MAR} is repair time of mth level major repair of component i at turbine k in the sth maintenance cycle; η_t is the coefficient determining the relationship between maintenance quality and corresponding repair time.

Eqs. (26) and (27) estimate the amount of cost and time invested in maintenance actions. The coefficients η_c and η_t influence how much more cost and time are needed with the increase of maintenance quality. In other words, larger η_c and η_t means a more efficient maintenance action with less cost and time [52]. However, if these parameters are set as constant, the cost and time invested must be the same as long as the same quality of maintenance is achieved, which may not be realistic. Furthermore, the value of η_c and η_t are not explicit enough considering quality and quantity of historical maintenance record in wind industry is still insufficient. Instead of a fixed value, the coefficients η_c and η_t are assumed to be random values following a Normal distribution. Therefore, the coefficient η_c is represented as $\eta_c \sim N(\mu_c, \delta_c^2)$ and the coefficient η_t is represented as $\eta_t \sim N(\mu_t, \delta_t^2)$.

5. Multi-objective optimization method

The section illustrates the process of searching for the optimal solutions among the universe of possible options, that is, the optimization problem needs to be solved. The two objectives of the optimization problem are identified as minimizing annual maintenance costs A_c and minimizing annual production losses A_p, which are shown in the following form:

$$\min A_\mathrm{c}(\psi_1, \psi_2, \zeta) = \frac{C^\mathrm{T}}{L} \tag{28}$$

$$\min A_\mathrm{p}(\psi_1, \psi_2, \zeta) = \frac{P^\mathrm{T}}{L} \tag{29}$$

It is very difficult or even impossible to find an optimal solution to satisfy multiple objectives simultaneously, especially when these objectives may be conflicting. In order to obtain solutions which are appropriate from different perspectives, a multi-objective optimization method is used to provide decision-makers with a better position to make maintenance decisions.

The multi-objective optimization methods can be broadly categorized into: scalarization approaches and Pareto approaches [76]. Scalarization approaches are to translate a multi-objective optimization problem into a single (or a series of) single objective optimization problem. The typical scalarization approaches include weighted sum approach, ε-Constraint Method, etc. Pareto approaches aim to generate a set of Pareto optimal solutions for decision-makers to choose from. NSGA-II method, a kind of Pareto approach, has been one of the most popular multi-objective optimization methods and widely used in many real-world applications [77]. NSGA-II was proposed by Deb et al. [78]. As an improved version of NSGA, NSGA-II has the advantages including a fast non-dominated sorting approach which reduces high computational complexity, a crowding distance technique which provides diversity in solution, and an elitist-preserving approach retaining the current optimal solution to the next generation. Considering its fast running speed and good convergence of the solution set, we select it as the multi-objective optimization method in the paper. More detailed description of the algorithm can be found in [78].

The proposed framework of optimizing maintenance strategy considering uncertainty is shown in Fig. 6, and the main steps are listed as follows:

Step 1: Initialize the necessary parameters for maintenance model, uncertainty model, and NSGA-II optimization method.

Step 2: The fist population containing Υ individuals are generated from the initial population after non-dominated sorting, selection, crossover, and mutation.

Step 3: Perform selection, crossover, and mutation to create the offspring population based on the first generation. The parent and offspring populations are merged as an intermediate population,

Step 4: Each individual containing decision variables is input into the maintenance model. In order to obtain reliable and stable results, the simulation of maintenance model is run for Θ times.

Step 5: In each simulation, the deterministic parameters are modelled by using a probabilistic method in the uncertainty model. The uncertainty scenarios are generated randomly by Monte Carlo method.

Step 6: The model outputs including annual maintenance cost A_c and annual production loss A_p is calculated in each simulation. After running the simulation for Θ times, the average results are calculated to represent the values of objective functions under a specific set of decision variables.

Step 7: Carry out fast non-dominated sorting and virtual crowding distance calculation for the merged population. The implementation of fast non-dominated sorting is based on the maintenance cost and production loss of individual, which is estimated in Step 6. The crowding-distance computation requires sorting the population according to each objective function value. The overall crowding-distance value is calculated based on the distance information of individual variables in the variable space.

Step 8: The new individuals are selected as the next generation according to fast non-dominated sorting and virtual crowding distance.

Step 9: The stopping criterion is checked. If the maximum generation is not reached, the population is updated with the new individuals. The updated population is expected to perform better than the previous generations. The new population undergoes the evolution process and is input to the maintenance model again. The number of generation increases until the maximum generation Ω.

Step 10: A set of non-dominated solutions is returned in the final step, which is regarded as the optimal solutions considering uncertainty.

6. Case study

6.1. Scenario set-up

The proposed approach is applied in a generic offshore wind farm with a capacity of 150 MW, designed for a 20-year lifetime. It is located in the North Sea, about 20 km away from the Netherlands shore, shown in Fig. 7. The scale of the farm is 50 turbines, and each 3-MW turbine is composed of five critical components (gearbox, generator, rotor&blade, main bearing and pitch system).

The technical specification of the turbine is shown in Table 1. Failure and cost parameters are collected and estimated from literature [67, 79,80], which is shown in Table 2. The input data for wind speed in the simulation is taken from the Royal Netherlands Meteorological Institute (KNMI). The generation of daily wind speed data is based on the 34-year from 1979 to 2012 [81]. The graph illustration of the wind data and turbine design parameter is provided in Fig. 8. The parameters of vessel and technician are derived from [80,82], as listed in Table 3. The number of periodic decision points in the lifetime is set as 120, indicating the interval of decision-making is two months. The intensity function of environmental factor is set as $2t/27^2$ [38]. The value of occurrence probability of critical, influential, and minor impact is respectively 0.0001, 0.03 and 0.9699. The blade suffers from the environmental impact, and the influence on other components is ignored due to protection of the hermetically sealed nacelle. The repair time of failure replacement, preventive replacement, and basic repair is 70 h, 50 h, and 6 h [80]. The value of maintenance level $\mathscr{M}$ is set as 4. The two maintenance improvement factors of major repair is $\theta_{l_2} = 0.5$ and $\theta_{l_3} = 0.7$. The value of age increase caused by influential impact is respectively 0.15, 0.12, 0.09, and 0.06 from maintenance level 1 to 4. These values indicate the older component is more vulnerable to environmental impact, and the maintenance action is more effective to recover its condition.

6.2. Optimization results disregarding uncertainty

In this section, the maintenance strategy is optimized disregarding the uncertainties. The deterministic input parameters have been provided in Section 6.1. Table 4 reports the parameter settings for the NSGA-II algorithm used to obtain optimal solutions. The algorithm is configured with a population size of 60 individuals and a maximum

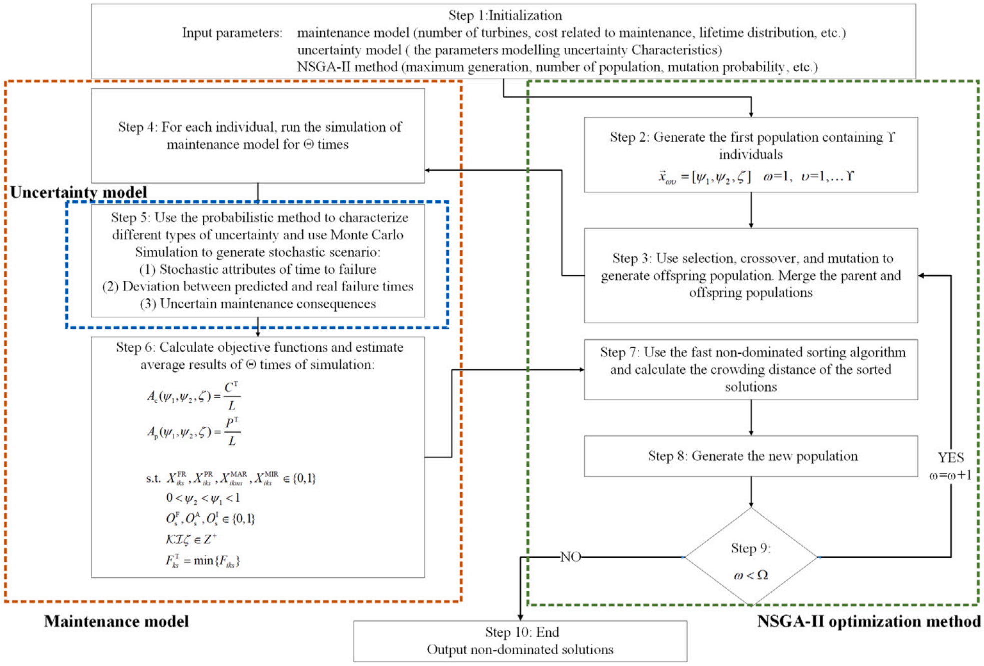


Fig. 6. Flowchart of the proposed multi-objective optimization framework of maintenance strategy considering uncertainty.

Fig. 7. Geographical localization of the offshore wind farm located in the North Sea.

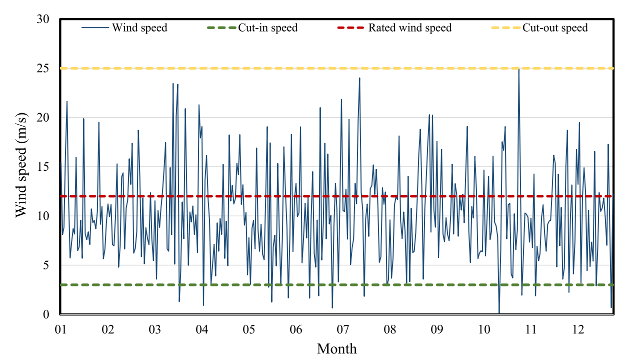


Fig. 8. Wind speed and turbine design parameter.

Table 1
Technical parameter of 3 MW offshore wind turbine.

Parameter	Value
Rated power	3 MW
Rotor configuration	3 blades
Drivetrain	High speed, multiple-stage gearbox
Rotor diameter	90 m
Hub height	80 m
Cut-in speed	3 m/s
Rated speed	12 m/s
Cut-out speed	25 m/s

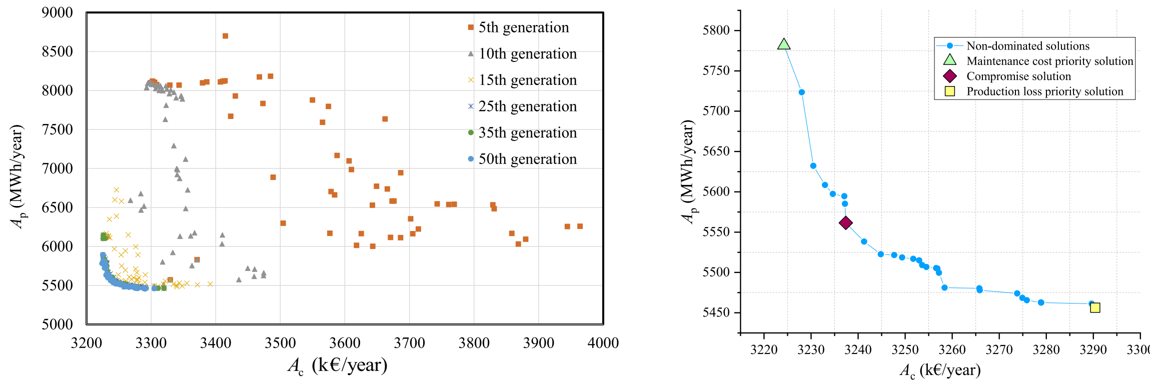
number of 50 generations. The fitness value of each individual is evaluated by Monte Carlo simulation with 5000 times. With this setting, the objective function of the maintenance model is evaluated 1.5×10^7 times in each implementation of optimization algorithm. The algorithm is implemented in Matlab®employed, using a computer equipped with 32 Intel Xeon Gold 5218 CPU 2.3 GHz and 192 GB of RAM. By implementing parallel computing, the time consumption is about 21 h.

Fig. 9 represents the populations and Pareto front obtained in selected generation. Fig. 9(a) illustrates the convergence plot of populations versus the number of generations. The populations gradually converge with the increase of generation. The figure indicates the front has converged well at the 50th generation.

All the non-dominated solutions at the 50th generation are shown in Fig. 9(b). A series of solutions are found when approaching the multi-objective optimization, addressing trade-offs among values of the objective functions. These solutions are non-dominated to each other, but dominate the rest of solutions. It is found that these two objectives do not completely conflict. In other words, the decrease of one objective function does not necessarily cause the increase of another objective function. The range of annual cost is from 3.22×10^3 k€ to 3.29×10^3 k€, and the annual production loss is in the range of 5.46×10^3 MWh to 5.78×10^3 MWh. These solutions are helpful for decision-makers to select a feasible solution so as to satisfy their preferences and requirements. Three representative solutions are highlighted on the front, namely a maintenance cost priority solution, a production loss priority solution, and a compromise solution. The decision instructions based on different solutions are discussed in Sections 6.3 and 6.4.

6.3. Influence of uncertainty

The three solutions marked in Fig. 9(b) represent the different preferences of the decision-maker. The solutions from cost priority to



(a) (b)

Fig. 9. Optimization results disregarding uncertainty: (a) Convergence of populations. (b) Non-dominated solutions at 50th generation.

Table 2
Parameters of critical components.

Component	Failure distribution and parameter		Repair cost (k€)		
	Weibull scale parameter (days)	Weibull shape parameter	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 of required vessels.

Vessel type	CTV	Field support vessel	Heavy-Lift vessel
Mobilisation cost (k€)	0	0	57
Daily vessel cost (k€)	8	18	50
Required technician	2	4	6–8
Daily technician cost (k€)		0.6	
Working shift (hours)		12 h	

Table 4
Configuration of NSGA-II algorithm.

NSGA-II parameter	Parameter value (type)
Maximum generation	50
Population size	60
Mutation operator	Gaussian mutation
Crossover operator	Intermediate crossover
Mutation probability	0.17
Crossover probability	0.67

production priority are named as Solution 1-3, which is considered as the benchmark. In Table 5, the cases are listed to represent different types of uncertainty. The detailed description of parameters is introduced in Section 4. From Case 1-1 to 1-4, the shape parameter σ gradually rises from 2 to 3, and Case 1-3 represents the value of σ is uniformly distributed in the range of [2,3]. Case 1-5 to 1-7 show the Uniform and Normal distribution. Cases from 2-1 to 2-6 generally represent the increasing error between real and predicted failure time. Case 3-1 to 3-3, we mainly concern about the uncertain maintenance quality, and Case 3-4 to 3-6 focus on the uncertain repair cost and time.

Figs. 10, 11, and 13 illustrate how the maintenance performance changes under different cases. Although minimum maintenance cost and minimum production loss are two different objectives, Fig. 9(b) has shown the conflict between the two goals is not serious, so the non-dominated solutions are located in a relatively small range. This results in the trend of Solution 1-3 changes similarly. In Fig. 10, from Cases 1-1 to 1-4, the values of A_c and A_p both tend downwards with the increase of shape parameter. In Weibull distribution, the shape with a higher shape parameters is more concentrated around the value of MTTF (shown in Fig. 3). In addition, the increase of standard deviation of Case 1-6 and 1-7 induces the increase of A_c and A_p. That reveals that when lifetime is modelled by using the distribution where the values tend to stay within a narrow range around MTTF, the model outputs are lower. It gives an explanation of the lower results when using the Weibull distribution with higher shape parameter and the Normal distribution with less standard deviation as the input. Moreover, when using Normal distribution and Uniform distribution, the outputs are both lower than benchmark which uses Weibull distribution. This result is generally consistent with the findings in the [43].

Fig. 11(a) illustrates the influence of prediction error on the maintenance cost. The values of A_c shows a growing trend when the deviation between real and predicted lifetime increases. Furthermore, the performance gap (A_c) between different solutions gradually widens, indicating the uncertainty strengthens the priority of the solutions. Solution 1 is the maintenance cost priority solution, and it always retain the lowest cost in the cases. However, this trend is not applicable in the aspect of production loss. As shown in Fig. 11(b), Solution 3 is the production loss priority solution with the lowest value of A_p. As the prediction error rises, Solution 3 gradually becomes the worst solution compared to Solution 1 and 2. Unlike maintenance cost, the performance gap of solutions in the aspect of production loss is reduced, even to the point where the priority solution becomes the worst solution.

The deviation between real value and prediction can be evaluated by using the Average Prediction Error $\bar{e}$. We use the symbol $\widetilde{E}$ to denote the deviation percentage between results of cases and benchmark. Fig. 12 represent how the maintenance performance of solutions changes with the increase of Average Prediction Error. It is found that as accuracy of prediction decreases (Average Prediction Error grows), the deviation between output and benchmark increase at a growing rate. Furthermore, in comparison with maintenance cost, the production loss of solutions is more sensitive to prediction error because its greater tendency to rise. These results can provide a basis for estimating the benefits of improved accuracy of fault diagnosis and life prediction techniques

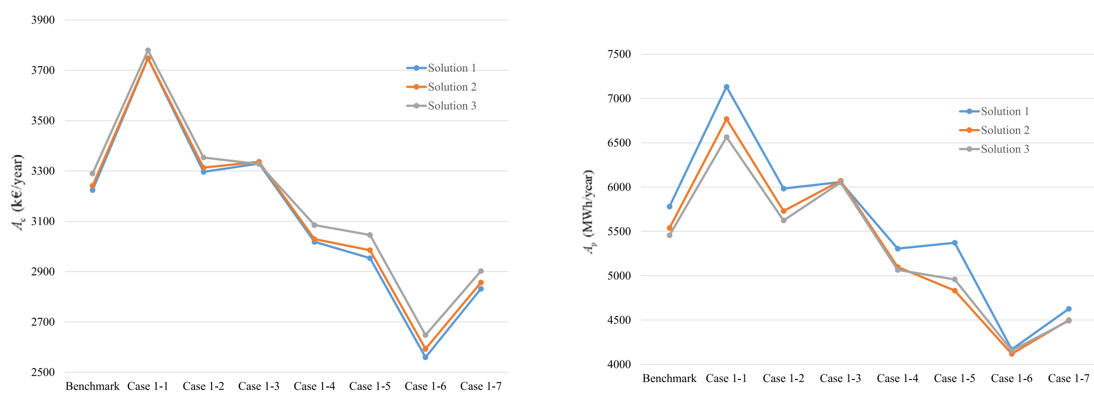
In Fig. 13, the benchmark represents the scenario where the maintenance actions can recover the component age with a fixed value as we

Table 5
Cases representing different types of uncertainty.

Case	Lifetime distribution and parameter	Case	Prediction error	Case	Maintenance consequences
Case 1-1	Weibull ($\sigma = 2$, $\varepsilon = \frac{\mathrm{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	Case 2-1	μ_a, $\delta_a = 0.005$, a_s, $a_p = 0.05$	Case 3-1	Quality ($\sigma_{\theta_{im}} = 0.001$)
Case 1-2	Weibull ($\sigma = 2.5$, $\varepsilon = \frac{\mathrm{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	Case 2-2	μ_a, $\delta_a = 0.005$, a_s, $a_p = 0.1$	Case 3-2	Quality ($\sigma_{\theta_{im}} = 0.005$)
Case 1-3	Weibull ($2 \le \sigma \le 3$, $\varepsilon = \frac{\mathrm{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	Case 2-3	μ_a, $\delta_a = 0.01$, a_s, $a_p = 0.1$	Case 3-3	Quality ($\sigma_{\theta_{im}} = 0.01$)
Case 1-4	Weibull ($\sigma = 3$, $\varepsilon = \frac{\mathrm{MTTF}}{\Gamma(1+\frac{1}{\sigma})}$)	Case 2-4	μ_a, $\delta_a = 0.015$, a_s, $a_p = 0.1$	Case 3-4	Cost and time (η_c, $\eta_t \sim N(2, 0.1^2)$)
Case 1-5	Uniform ($\frac{1}{2}$MTTF, $\frac{3}{2}$MTTF)	Case 2-5	μ_a, $\delta_a = 0.01$, a_s, $a_p = 0.15$	Case 3-5	Cost and time (η_c, $\eta_t \sim N(2, 0.3^2)$)
Case 1-6	Normal (MTTF, 500^2)	Case 2-6	μ_a. $\delta_a = 0.015$, a_s, $a_p = 0.15$	Case 3-6	Cost and time ($\eta_c, \eta_t \sim N(2, 0.5^2)$)
Case 1-7	Normal (MTTF, 700^2)				

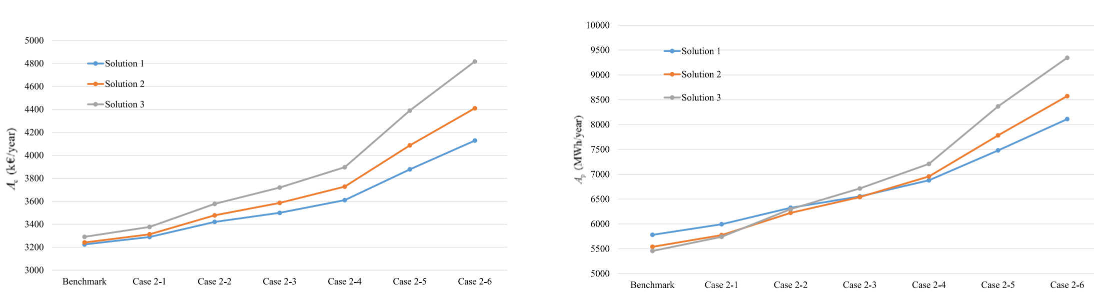
Table 6
Characteristics of solutions of different interest.

Solution	ψ_1	ψ_2	ζ	Cost (k€/year)	Production loss (MWh/year)	Loss of profit (k€/year)
Cost priority (certainty)	0.571	0.955	0.4%	3224.3	5781.5	3964.3
Compromise (certainty)	0.569	0.939	0.4%	3241.3	5538.3	3950.2
Production priority (certainty)	0.559	0.918	0.4%	3290.4	5456.3	3988.8
Cost priority (uncertainty)	0.538	0.979	0.4%	3828.2	8190.9	4876.6
Compromise (uncertainty)	0.511	0.955	0.4%	3868.9	7458.6	4823.6
Production priority (uncertainty)	0.433	0.894	0.8%	4047.9	7172.4	4966.0



(a) (b)

Fig. 10. Comparison of Cases 1-1 to 1-7: (a) Maintenance cost (b) Production loss.



(a) (b)

Fig. 11. Comparison of Cases 2-1 to 2-6: (a) Maintenance cost. (b) Production loss.

expect. And the relationship between maintenance quality, cost, and time is explicit, indicating we can accurately estimate the consumption according to maintenance effect. The maintenance quality becomes more unstable from Case 3-1 to 3-3 without considering the uncertain repair cost and time, then we can find the values of A_c and A_p go up. In practice, the effect of maintenance actions is always stochastic, worse

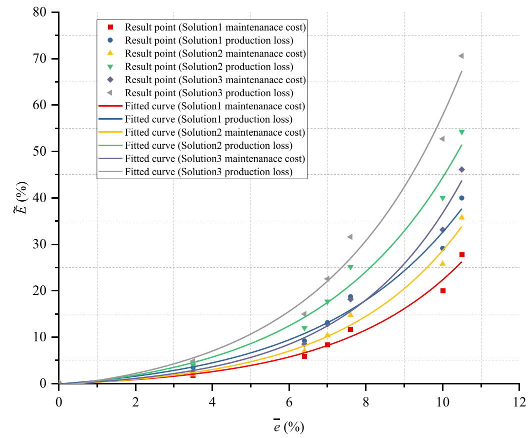


Fig. 12. Average Prediction Error $\bar{e}$ versus maintenance performance.

or better than the expectation. In order to reduce the consumption during maintenance activities, a suggestion is provided by enhancing the technicians' expertise, improving the maintenance conditions, and using more effective maintenance tools to ensure a more stable maintenance quality. Case 3-4 to 3-6 depict a growing uncertainty in the maintenance cost and time, representing a more ambiguous estimate of the maintenance resources expended to support the implementation of maintenance activity. Due to the functional relationship between maintenance cost and time and quality, this uncertainty can lead to an increase in maintenance consumption which cannot be ignored. Compared to the benchmark, the increase of A_c and A_p is notable, and this change is certain to impact the potential decision-making.

6.4. Optimization results under uncertainty

In this section, the proposed optimization framework incorporating three types of uncertainty model is implemented. The configuration of NSGA-II algorithm is the same as Section 6.2, and the time consumption is about 70 h. We consider the strategic decision-making environment includes the uncertainty represented in Case 1-3, 2-3, 3-2 and 3-5. Fig. 14(a) illustrates the trend of convergence of populations with the increase of generations. The Pareto front at 50th generation is provided in Fig. 14(b), which has converged well.

In Fig. 15, we make a comparison of the two Pareto fronts in Figs. 9(b) and 14(b). The Pareto front 1 (yellow line) is the optimal solutions disregarding uncertainty, and the Pareto front 2 (blue line) is obtained considering uncertainty. The Pareto front 2 lays to the upper right of the Pareto front 1, indicating the existence of uncertainty results in higher maintenance cost and more production loss. In addition, the range of front 2 is wider than front 1. Pareto front 1 shows that the maintenance cost and production loss are not completely conflicting objective functions, so the solution that is good for one objective may also be beneficial to another objective. However, uncertainty exacerbates the conflict between the two goals, indicating the maintenance decisions can no longer effectively reduce the two objectives at the same time. That results in the range of front 2 becomes wider. The red plots illustrate the performance of applying the solutions obtained in a certain environment (the non-dominated solutions on front 1) to an uncertain decision-making environment. It is found the points are located at the upper right of front 2, meaning the solutions are dominated by the solutions on front 2. The existence of uncertainty renders the maintenance decisions determined under certainty sub-optimal.

The solutions representing different interests are marked in Figs. 9(b) and 14(b). The top leftmost point corresponds to the solution with lowest maintenance cost and highest production loss, while the bottom rightmost point represents the highest maintenance cost with lowest production loss. A compromise solution is selected in the knee of the front.

These solutions can provide some instructions at the different strategic environment in which decision-makers manage an offshore wind farm project. (1) If the decision-maker adopts a cost priority strategy, the maintenance cost is set as the first consideration and it is reduced to the minimum. At the same time, the pursue of lowest cost indicates the production loss cannot reach the lowest value. The decision-maker is willing to execute the Solution 1 with the lowest cost and the high but acceptable production loss. (2) If both the maintenance cost and the production loss are equally significant for the decision-maker, the compromise solutions can be considered, such as Solution 2. The solutions implies to trade-offs between two objective functions. These trade-offs cannot reach the outstanding optimization in one direction, but provide a relatively comprehensive solution which does not sacrifice much on either objective function. (3) If the production is the priority objective, Solution 3 is the best maintenance strategy satisfying decision-maker's demand. In the situation, the decision-maker has the sufficient budget, so the cost expended on maintenance activities does not need strict control. Solution 3 can minimize the production losses and ensure the most efficient electricity production.

In Table 6, from cost priority solution to production loss priority solution, the maintenance thresholds (ψ_1 and ψ_2) both gradually decrease regardless of whether uncertainty is considered or not. The lower thresholds mean more frequent maintenance cycles, while repairing more components in each cycle, especially the number of aged components which are preventively replaced increases with the decrease of ψ_1. This change can effectively keep the wind farm in good condition, and the occurrence of failure events and related high material cost and long downtime can be reduced. Meanwhile, increasing the frequency of maintenance cycle and the number of repaired components also induces more cost and longer repair time. Comprehensively, the maintenance cost tend to increase and the production loss tend to decrease.

When considering uncertainty, the reduction of ψ_1 and ψ_2 of production priority solution is more significant compared to cost priority and compromise solution. In addition, the value of 0.4% increases to 0.8% with the purpose of balancing the relationship between the frequency of maintenance cycles and the maintenance thresholds. The increase means it is more demanding to trigger the ageing-based opportunity. Furthermore, the uncertainty makes the maintenances threshold decrease for the solutions with the same interest. In the decision-making environment considering the unknown lifetime distribution, the inaccurate prediction of component condition, and the unstable maintenance consequences, maintenance conditions are relaxed to allow as many components as possible to be repaired and replaced in order to ensure the good condition of the wind turbine and avoid the potential failure events.

The decision-makers have different interests when playing different roles. If the decision-maker is an independent service provider, the objective can be related to production losses or availability, depending on the target of maintenance contracts. Meanwhile, the service provider also concerns about the reduction of maintenance costs. Considering this point, the solutions following different preferences can provide the instruction in different directions. If the decision-maker is the asset owner or operator who may also be responsible for maintenance management, the most significant objective is to ensure the maximum profits. In this case, the maintenance costs and production losses can be merged to a single objective used to evaluate the maintenance strategy. The price of electricity refers to the first half of 2021 for the Netherlands, about 128€/MWh [83]. As shown in Table 6, the compromise solutions show a lower loss of profit, which the asset owner will be more interested in.

For each solution, the simulation of maintenance model is run 5000 times to estimate the average results. The distribution of the 5000 simulation results is shown in Fig. 16(a). Each solution has two marginal probability density functions of maintenance cost and

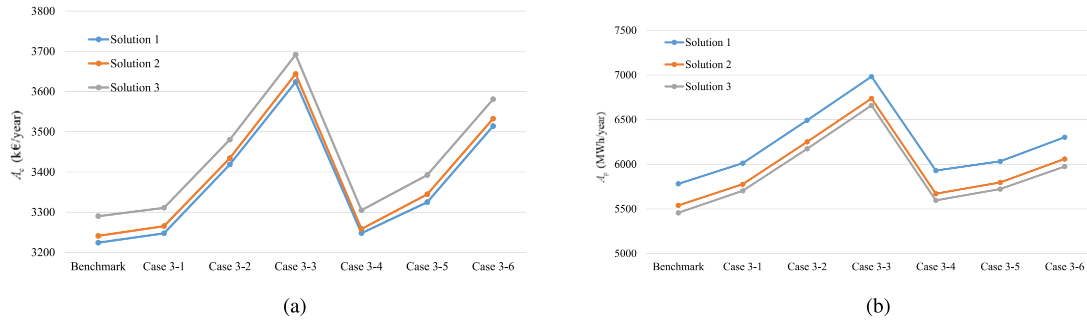


Fig. 13. Comparison of Cases 3-1 to 3-6: (a) Maintenance cost. (b) Production loss.

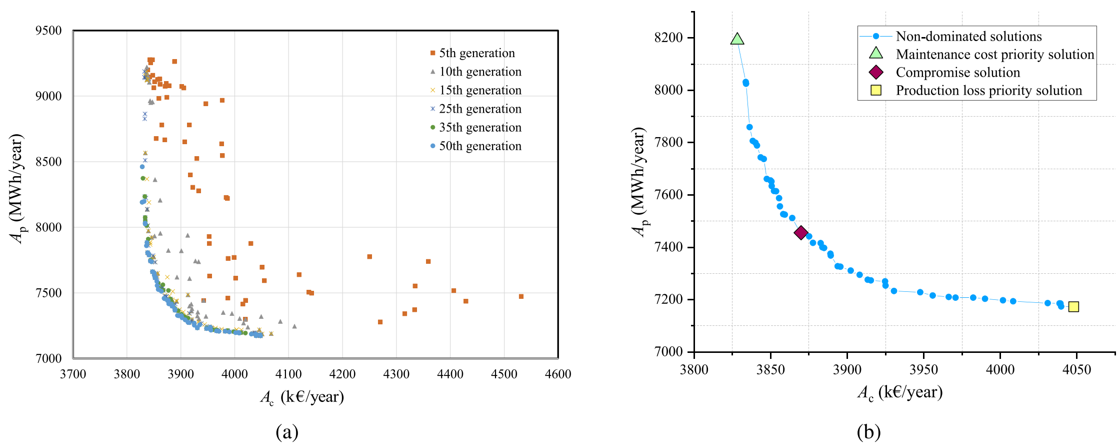


Fig. 14. Optimization results under uncertainty: (a) Convergence of populations. (b) Non-dominated solutions at 50th generation.

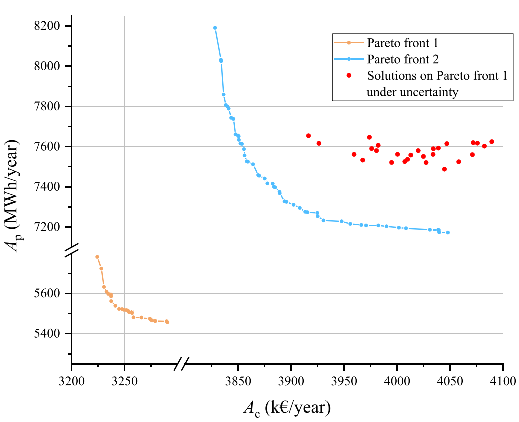


Fig. 15. Comparison of non-dominated solutions disregarding and considering uncertainty.

production loss, just as shown in Fig. 16(b). The probability density functions can inform the decision-makers how likely a specific value or range of model outputs can be observed.

The probability density functions of solutions is compared in Fig. 17, showing a clear representation of the variability of the solutions. Introducing uncertainty makes the solutions show greater dispersion, especially of the production loss in Fig. 17(b), because the solutions under uncertainty are observed in a larger range. In Fig. 17(a), the dispersion of solutions of different interests have a similar trend, that means the change of decision variables does not significantly influence the dispersion in the perspective of maintenance cost. In Fig. 17(b), the solutions with less production loss present less dispersion from Solution 1 to 3, indicating the solutions become more stable and robust when the decision-makers focus more on production loss.

In Table 7, we also show the worst scenario and risky scenarios of different solutions. As explained above, the maintenance costs and production losses vary in each simulation because of the stochastic processes, indicating the severe scenarios probably occur where the results are higher than our expectation. The worst scenario means the occurrence of the highest maintenance costs and production losses. In the worst scenarios, the Solution 3 under uncertainty displays a weak capacity to control risk about maintenance cost which is as high as 4844.9 (k€/year). Meanwhile, the robustness of Solution 1 under uncertainty is not ideal, because the production loss is 10 762 (MWh/year), higher than the other two solutions. We also introduce the risky scenarios from 1 to 3 representing the 95%, 90% and 85% of results are lower than a specific value. These results provide decision-makers with recommendations on risk limitation to more comprehensively evaluate the selected maintenance strategies.

6.5. Discussion of the results

(1) Most of the existing maintenance model optimization assumes the parameters are deterministic, and sets the reduction of maintenance cost as the sole objective. This is an ideal situation, differing much from the context decision-makers are confronted with. The results have shown the presence of uncertainty greatly impacts the estimation of maintenance performance, thus the predetermined solutions are not optimal anymore.

(2) The maintenance model heavily relies on the input lifetime distribution to represent real degradation process and generate discrete failure events. Under the same MTTF, the uncertain failure distribution and parameters result in different model outputs. The output tends to be less when the shape of distribution is more concentrated around MTTF. In order to eliminate the potential uncertainty as much as

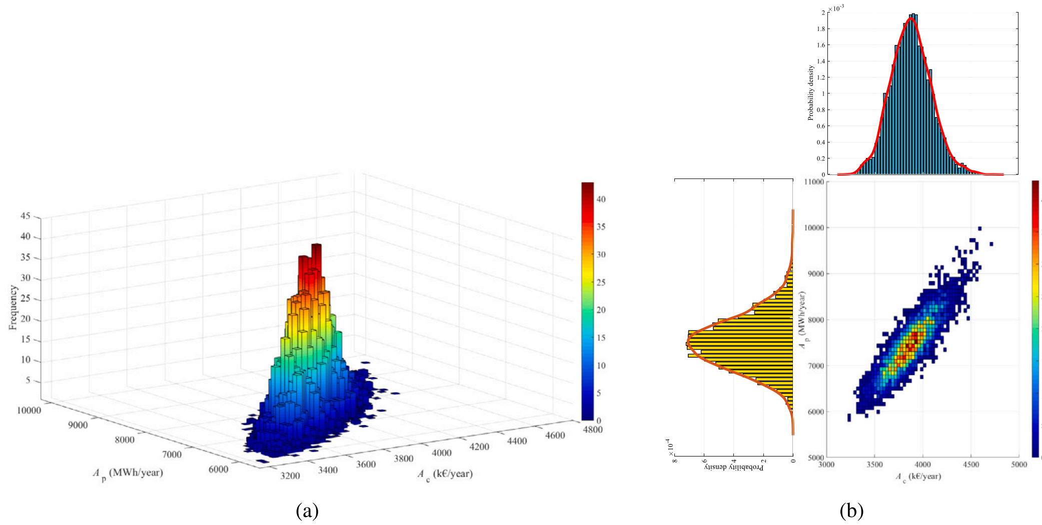


Fig. 16. Distribution of the derived results: (a) Bivariate histogram plot. (b) Plot with marginal probability density function.

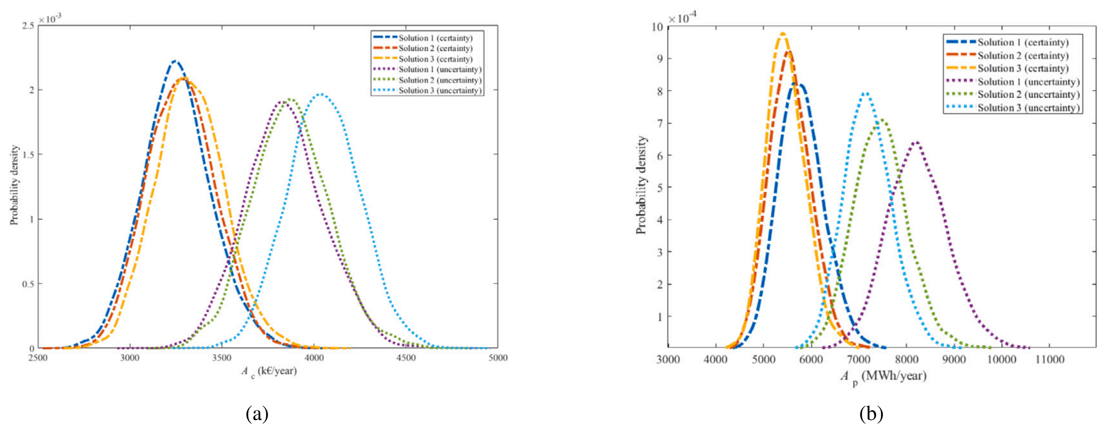


Fig. 17. Probability density functions: (a) Annual maintenance cost. (b) Annual production loss.

Table 7
Worst scenario and risky scenarios of solutions.

		Solution 1 (certainty)	Solution 2 (certainty)	Solution 3 (certainty)	Solution 1 (uncertainty)	Solution 2 (uncertainty)	Solution 3 (uncertainty)
Worst scenario (100%)	Cost (k€/year)	3941.2	4010.6	4091.9	4620.6	4727.3	4844.9
	Production loss (MWh/year)	7614.3	7282.5	7299.1	10 762.0	9708.6	9171.5
Risky scenario 1 (95%)	Cost (k€/year)	3574.2	3587.3	3635.4	4208.8	4222.8	4374.0
	Production loss (MWh/year)	6616.9	6305.8	6173.1	9314.6	8418.8	8062.2
Risky scenario 2 (90%)	Cost (k€/year)	3501.5	3520.2	3562.7	4127.5	4141.4	4306.8
	Production loss (MWh/year)	6428.2	6131.6	6013.4	9053.3	8199.0	7834.1
Risky scenario 3 (85%)	Cost (k€/year)	3447.7	3471.2	3515.4	4066.7	4087.8	4258.4
	Production loss (MWh/year)	6280.9	6017.6	5901.5	8879.2	8031.1	7697.2
Expected value	Cost (k€/year)	3224.3	3241.3	3290.4	3828.2	3868.9	4047.9
	Production loss (MWh/year)	5781.5	5538.3	5456.3	8190.9	7458.6	7172.4

possible, a database with more sufficient and reliable failure data is required to support maintenance decisions. Alternatively, the input parameters can be updated during the long lifespan of project to adjust the decision-making.

(3) The RUL prediction technology which can accurately evaluate the condition of components can provide significant decision basis of the maintenance strategy. The error between real and predicted failure times may result in higher maintenance costs and production losses according to the results. One reason is the lifetime of component is underestimated, thus the maintenance actions cannot be performed in a timely manner. More failure events are then caused due to the underestimation. Another reason is the underestimated lifetime of components. Preventive repair and replacement is planned in a premature way, resulting in the cost associated with changing out components that have remaining useful life and production loss. The improvement of prediction accuracy is significant to plan a sound maintenance strategy.

(4) The quality of maintenance actions is stochastic in the real maintenance situations, depending on the factors, such as environmental conditions, human factors, etc. The results have revealed that the more unstable maintenance quality causes an increase of maintenance costs and production losses. Therefore, the maintenance provider should enhance the technician training and improve the maintenance conditions and environment, in order to carry out maintenance in a more stable manner. Moreover, if a database related to repair cost and time is developed with good quality, a more explicit relationship between maintenance activities and corresponding consumption can be clarified and made an input to the maintenance model. Such an unambiguous input can assist the decision-maker to evaluate the maintenance performance more accurately.

(5) The framework is developed to provide a series of solutions considering uncertainty while satisfying decision-makers' multiple demands, but there are still limitations of this research. This study mainly focuses on the long-term maintenance strategy, so we make the assumptions which simplify maintenance logistics organization at the tactical and operational level and ignore the related uncertainty. Although the decisions are usually determined in the order of long-term to short-term, the organization at tactical and operational echelon has a impact on the long-term maintenance performance. The uncertainty, such as stochastic weather-dependent conditions, unpredictable spare parts demand, poor accessibility for maintenance and repair, may further worsen the O&M results. In addition, the uncertainty model used a probabilistic method to describe uncertainty and used a Monte Carlos method to represent uncertainty scenario. This kind of method still assumes the uncertainty follows a distribution function without analysing the real data. Considering these points, the decision-makers can integrate available databases and more types of uncertainty depending on the actual O&M process into the framework, and replace their targeted maintenance strategy as well as preferred objectives in future application.

7. Conclusions

The design of maintenance strategies for offshore wind farms is a complicated task where a high degree of uncertainty is involved, but the existing maintenance optimization approaches do not consider that uncertainty enough. This paper proposed a multi-objective optimization framework for maintenance strategy planning with consideration of uncertainty, which has several distinctive features compared to the conventional maintenance optimization approach. Firstly, the uncertainties affecting the maintenance strategy are quantified in a probabilistic method. Their influence on the performance of different representative solutions is estimated. In addition, a set of Pareto solutions is derived while considering several types of uncertainties simultaneously. These solutions represent reasonable trade-offs between conflicting maintenance objectives. Moreover, the proposed framework is a decision aid for wind farm owners and operators, as well as maintenance providers. Considering the actual wind farm situation, the available database, and the maintenance objectives, more feasible and reliable suggestions are provided for the decision-maker who manages maintenance in an uncertain decision-making environment. A case study from a generic offshore wind farm demonstrate that the performance of maintenance strategies worsen while considering uncertainty, and the solutions show greater dispersion. The maintenance decisions determined under certainty are not adequate in modern MW/GW scale offshore wind farms, so a new series of solutions need to be developed to cope with uncertainty.

Further research may be done by updating the uncertain parameters in the simulation process. The maintenance decisions can be periodically adjusted according to the new parameters. Moreover, maintenance strategy and tactical organization (e.g. inventory management) are interrelated. It would be beneficial to integrate the strategic maintenance model with the spare parts management model, and perform a joint optimization.

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:** 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.

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