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Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch

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ABSTRACT

Operation & maintenance (O&M) costs account for a large portion of total life cycle cost for onshore wind energy, and the amount is estimated to be more for offshore wind energy. Developing a sound opportunistic maintenance strategy is a solution to reduce O&M costs and enhance wind energy's competitiveness. When the wind farm is located offshore, turbines are not only subject to degradation but also the impact from the harsh marine environment. However, the degradation is mainly regarded as the only cause of the failure in the existing opportunistic maintenance models for the offshore wind energy sector. At the same time, too frequent preventive dispatch of maintenance teams exists on some occasions. This paper proposes a maintenance strategy for offshore wind farms integrating three types of maintenance opportunities. In addition to the maintenance opportunities created by degradation failures and incidents, an age-based opportunity is introduced to improve the trigger of preventive dispatch. A numerical example is presented to illustrate the effectiveness of the proposed strategy. The comparative analysis shows 2.6% and 1.5% annual cost can be reduced respectively when compared with two traditional opportunistic maintenance strategies in the base scenario.

1. Introduction

The increasing population in recent decades brings a growing global demand for energy, resulting in a serious effect on the environment. Considering the global warming and environmental pollution, renewable energy is being investigated as an sustainable and reliable option to replace conventional, fossil energy sources. In particular, wind energy trends to be one of the most widely explored renewable and sustainable energy resources in the future. According to the Global Wind Energy Council (2019), over 355 GW of new capacity will be added all over the world in the next five years, that is approximately 71 GW of new installations each year until 2024. Compared with onshore wind energy, the power installed offshore is still relatively small. However, offshore wind is more promising on the long term, due to the steadier and faster wind speeds at sea. In Europe only, about 20 GW of offshore wind has been installed nowadays. The European Commission estimates that an installed capacity of between 230 and 450 GW could be needed by 2050 (Wind Europe, 2019), meeting 30% of Europe electricity demand in 2050.

As wind energy systems are growing both in capacity and complexity, there are ongoing efforts to improve reliability, availability, maintainability and safety, aiming to enhance its marketability and competitiveness (Marugán et al., 2018). O&M costs account for 12%–30% of the total life cycle cost for onshore wind farms (Izquierdo et al., 2020), and the portion is estimated to rise to more than 32% for offshore wind farms (Martin et al., 2016; Lin et al., 2020). As shown in Fig. 1, the cost categories of O&M with estimated percentages are: land rent (18%), insurance (13%), regular maintenance, repair and spare parts (43%), administration costs (21%) and power from the grid (5%) (El-Thalji et al., 2009). This means that the maintenance activities account for almost half. Optimizing the O&M strategy, especially maintenance activities, is thus an effective pattern to reduce O&M costs and gain more profits.

As a strategic decision made by decision makers, the determination of the long-term maintenance strategy has a straightforward influence on wind farm O&M. Fig. 2 demonstrates the decision-making process of the farm maintenance. The decision maker, such as offshore wind farm owner and operator or the independent service provider, decides if the maintenance cycle should start according to the state of components/turbines. In the past decades, a large amount of research has focused on the development of the maintenance for wind energy. So far, corrective maintenance and time-based maintenance have been the main maintenance strategies applied in wind power industry (Nguyen and Chou,

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Nomenclature and acronyms denition

k	Index for turbine
i	Index for component
n	Index for maintenance cycle
K	Total number of turbines in the offshore wind farm
I	Total number of components at the offshore wind turbine
M	Total number of maintenance levels
N	Total number of maintenance cycles
C_{annual}	Annual cost during lifetime
S	Lifetime of offshore wind farm
l_m	mth maintenance level
σ_{ik}	Scale parameter
ε_{ik}	Shape parameter
$\lambda_k(t)$	Intensity function
p_k^1	Occurrence probability of critical impact
p_k^2	Occurrence probability of influential impact
p_k^3	Occurrence probability of minor impact
b_c	Age increase of component at cth stage due to influential impact
u_{ik}	Age of component i in turbine k
v_{ik}	Failure age of component i in turbine k
f_{ik}	Failure time of component i in turbine k
L_{ik}	Lifetime of component i in turbine k
T_Z^{period}	zth time period
$A^{\min}$	Minimum age percentage threshold
$A^{\max}$	Maximum age percentage threshold
w_k	Occurrence time of environmental impact on turbine k
ζ	Percentage threshold of number of aged components
T_n	Starting time of nth maintenance cycle
A^y	yth age threshold
θ_{l_m}	Maintenance quality of mth maintenance level
X_k^{TR}	Binary variable for transportation
X_{ik}^{PR}	Binary variable for preventive replacement
X_{ik}^{CR}	Binary variable for failure replacement
X_{ik}^{MR}	Binary variable for major repair
X_k^{EI}	Binary variable for environmental impact
X_k^{c}	Binary variable for critical impact
X^{i}	Binary variable for incident-based opportunity
X^{a}	Binary variable for age-based opportunity
X^{f}	Binary variable for failure-based opportunity
M_{ik}^{CR}	Cost of failure replacement of component i at turbine k
M_{ik}^{PR}	Cost of preventive replacement of component i at turbine k
M_{ikm}^{MR}	Cost of mth level of major repair of component i at turbine k
M^{f}	Fixed cost to trigger a cycle of maintenance
M_k^{TR}	Transportation cost to turbine k
$M_{\text{total}}^{\text{TR}}$	Total cost of transportation
$M_{\text{total}}^{\text{CR}}$	Total cost of complete replacement
$M_{\text{total}}^{\text{PR}}$	Total cost of preventive replacement
$M_{\text{total}}^{\text{MR}}$	Total cost of major repair
M_{total}	Total maintenance costs generated in one maintenance cycle

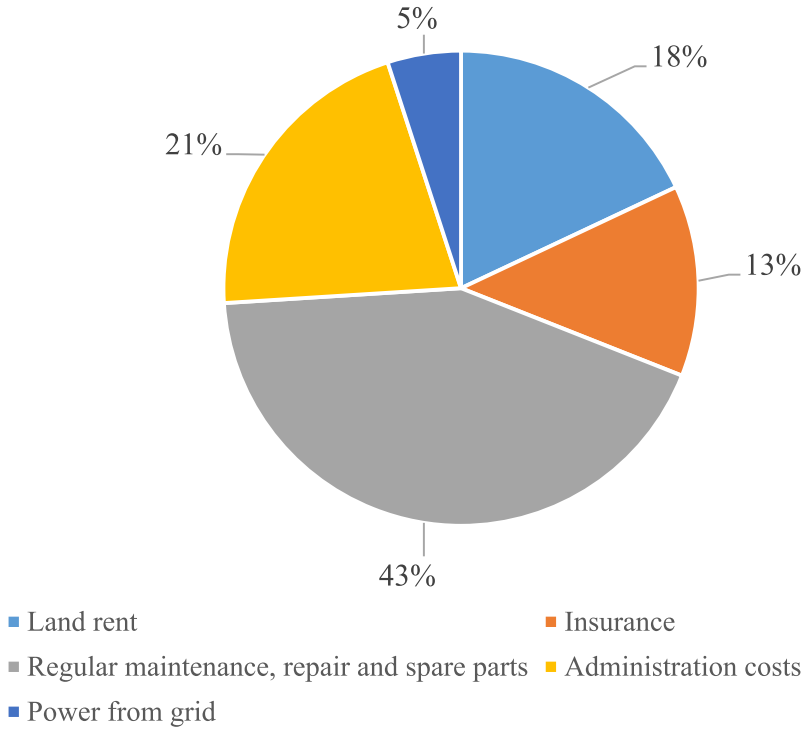

Fig. 1. Cost categories of O&M.

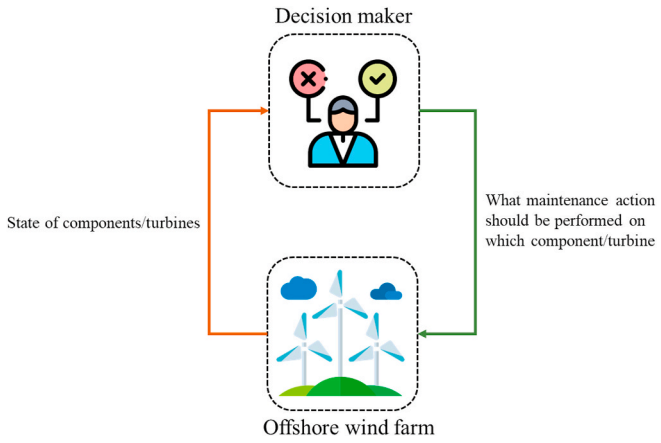

Fig. 2. Decision-making process of offshore wind farm maintenance.

2018; Li, Jiang, Polinder and Negenborn, 2020b). Condition-based maintenance is catching people's attention owing to rapid development of continuous monitoring and inspection techniques (Márquez et al., 2012). Relying on the collected signals, such as vibration, acoustic, temperature, magnetism, and current signals, fault diagnosis and prognosis are performed for developing the condition-based maintenance strategy(Merizalde et al., 2020).

A large-scale offshore wind farm is made up of a number of turbines. Besides, as a type of complicated electromechanical system, an offshore wind turbine system is composed of hundreds of components and subsystems (Qiao and Lu, 2015). The economic dependence among turbines and components applies when the combined maintenance leads to a different cost than repairing separately (Izquierdo et al., 2019). It plays a positive role when travelling to the location where maintenance activities have to be executed is costly (Keizer et al., 2017). Simultaneously performing several maintenance activities is more cost-effective than repairing turbines respectively. The opportunistic maintenance is a type of strategy taking advantage of the economic dependence to reduce maintenance cost. The concept of opportunistic maintenance was firstly introduced and applied in a case study of the rocket engine of a hypothetical ballistic missile (McCall, 1963; Radner and Jorgenson, 1963). There are no norms, standards or consensual accepted meanings of 'opportunistic maintenance' (Thomas et al., 2008). It is a systematic research to determine what time to perform maintenance activities for what reason, and what components or turbines can be repaired by making use of the opportunities.

1.1. Previous research

In 2009, Besnard et al. (2009) applied the opportunistic maintenance strategy to offshore wind energy. Opportunistic occasions appear when power production is unsatisfying because corrective maintenance has to be performed on a wind turbine or the wind speed is low. The case study shows taking these opportunities can effectively reduce maintenance costs. Due to the considerable potential, the number of literature focusing on opportunistic maintenance of wind energy sector is increasing in the following years. We make a comparative analysis after reviewing the following representative papers, as shown in the Table 1.

1.1.1. Degradation and environmental impact

Ding and Tian (2011) proposed an opportunistic maintenance model with two-level repair actions for wind turbine systems. The failures of the components are caused by the degradation. The failure times are modelled as Weibull distribution. Perfect and imperfect maintenance actions are performed depending on component states. Then, Ding and Tian (2012) introduced different maintenance thresholds in their model to distinguish the failed turbines and working turbines.

Instead of the two-level maintenance threshold, Sarker and Faiz (2016) proposed the concept of multi-level maintenance in their work. Degradation results in the component failure. The interval between maximum and minimum maintenance thresholds is divided into multiple groups. After discussing the relationship between maintenance costs and the number of maintenance levels, the optimal number of level is selected to minimize the total costs. Similarly, the failures of the components are also assumed to be caused by degradation processes in the literature (Abdollahzadeh et al., 2016; Atashgar and Abdollahzadeh, 2016; Erguido et al., 2017; Lu et al., 2018; Zhou and Yin, 2019).

Zhang et al. (2017) introduced the hybrid hazard rate method into the opportunistic maintenance model. The method describes the degradation processes causing the failures, where the increase of operation time will accelerate the degradation and weaken the maintenance improvement.

Li et al. (2020c) used Nonhomogeneous Continuous-Time Markov Process to represent the multi-state model of offshore wind turbine subsystems. The subsystems transfer from one state to another state as the operation time increases. The most cost-effective combination of qualified components is selected to reduce the maintenance costs when compared with individual maintenance.

It is remarkable that in these models, the wind turbines only experience the degradation. The system deteriorates over time due to wear, erosion, fatigue, corrosion and so on. This normal degradation process applies when the operation condition is ideal. However, the offshore structures suffer from the impact resulting from the harsh marine environment (e.g. sea ice, atmospheric icing, typhoon, sea wave, lightning strike, sudden change in wind speed or direction). The harsher the environment is, the random impact will arrive more frequently and the influence will be more serious. When the turbine works in the practical environments, it is not only subjected to degradation processes but also the random environmental impact throughout the whole service life.

Table 1
Previous research of the opportunistic maintenance for the wind energy.

Reference	Main contribution	Scope modeling	Failure modeling	Environmental impact	Maintenance levels	Preventive dispatch
Ding and Tian (2011)	Two-level maintenance	Wind farm	Degradation model	Not considered	Two-level	Not considered
Ding and Tian (2012)	Distinguish running/ failed turbines	Wind farm	Degradation model	Not considered	Two-level	Not considered
Sarker and Faiz (2016)	Multi-level maintenance	Wind farm	Degradation model	Not considered	Multi-level	Not considered
Abdollahzadeh et al. (2016)	Multi-objective	Wind farm	Degradation model	Not considered	Two-level	Single component
Zhang et al. (2017)	Hybrid hazard rate model	Single turbine	Degradation model	Not considered	Two-level	Single component
Lu et al. (2018)	Life prediction by ANN	Single turbine	Degradation model	Not considered	Two-level	Single component
Li, Wang, Kang, Sun and Jin (2020c)	Markov process	Single turbine	Multi-state model	Not considered	Not considered	Not considered

The presence of these environmental impact on the critical components, especially rotor blades, has effect on the performance of O&M and the overall economics of a wind energy project (Battisti et al., 2006; Pastromas et al., 2018). Only a few paper considered degradation and environmental impact simultaneously when developing opportunistic maintenance for wind energy. Shafiee, Finkelstein and Bérenguer (2015) proposed an opportunistic condition-based maintenance policy for a rotor-blade system. The multi-blade system is subjected to stress corrosion cracking and environmental impact. In order to avoid the expensive failure replacement, a maintenance team is dispatched to repair critical blade before the failure occurs, and other blades are preventively repaired as well.

The maintenance model considering random environmental shocks has been increasingly concerned in the field of reliability and engineering in the past years. Many industrial systems operate in the random shock environment and suffer from the damage of these shock which triggers the state transitions of the system. The shock models investigated in the literature include cumulative shock model, extreme shock model, run shock model, delta shock model, and mixed shock model (Wang et al., 2020). In addition, for some complicated systems, various dependence exists between the shock and degradation, namely shock-degradation dependence and degradation-shock dependence (Che et al., 2018). When considering the shock-degradation dependence, the assumptions are made that these impact may result in the abrupt increase of degradation (Ruiz-Castro, 2016), the increasing degradation rate (Rafiee et al., 2014), or even the sudden incidents. When considering the degradation-shock dependence, many studies assume that the intensity or the magnitude of shock is dependent on the degradation process of the system (Fan et al., 2017; Fan et al., 2000). Che et al. (2018) developed a Facilitation model where the mutual degradation-shock dependence and shock-degradation dependence are simultaneously considered. A case study of a jet pipe servo valve is presented to demonstrate the established model.

1.1.2. Maintenance opportunities

As the description of the opportunistic maintenance models for wind energy in the Table 1, Ding and Tian (2011, 2012); Sarker and Faiz (2016); Li et al. (2020c) assumed that the occurrence of a component degradation failure can be considered as a type of maintenance opportunity (failure-based opportunity). It is a very common assumption when developing opportunistic maintenance strategy. This failure-based maintenance opportunity can trigger a maintenance cycle, where the maintenance teams are correctively dispatched to simultaneously replace the failed components and perform preventive maintenance on the components needing repair.

As we know, the failure should be avoided as much as possible given the fact that the cost of failure replacement is very expensive. Therefore, it is not necessary to start a maintenance cycle only waiting for the occurrence of the turbine failure. In the literature (Zhang et al., 2017; Lu et al., 2018; Zhou and Yin, 2019), a preventive maintenance threshold is set to determine if the turbine component is in a defective or almost unacceptable state. In addition to the maintenance cycle triggered by failure, a maintenance cycle can also be triggered if any turbine component in the farm exceeds this preventive maintenance threshold. Actually, this preventive maintenance decision can be regarded as the preventive dispatch of maintenance teams. In the literature (Abdollahzadeh et al., 2016; Atashgar and Abdollahzadeh, 2016; Erguido et al., 2017), the preventive dispatch of maintenance teams is clearly addressed, meaning not until the failure occurs, the maintenance opportunity can also emerge to dispatch the maintenance teams preventively when a component satisfies the maintenance requirement (reach the threshold). Generally, the maintenance opportunity will appear in these two occasions: a failure occurs; a component reaches the preventive maintenance threshold.

However, although the preventive dispatch of maintenance teams has been introduced in the models, this action may not be as cost-effective as we expect. The maintenance team has to move to the wind site if even the single component reaches the predetermined threshold. It may be feasible when the farm is located onshore. Considering the effort and cost to dispatch the vessels and staff to the remote location away from the shore, the execution of preventive dispatch triggered by single component is not economic enough for offshore wind farms. These maintenance decisions may induce over frequent but unnecessary maintenance activities. Furthermore, in these existing opportunistic maintenance models for wind energy, the consequences of environmental impact have not been considered, as discussed in Section 1.1.1. For example, the critical impact may also result in the incident that the suffering turbine stops operating and requires maintenance, which can also provide the opportunity to repair the other turbines in the farm.

Table 2
Opportunistic maintenance model considering external shock.

Reference	Failure model	Number of systems	Maintenance trigger
Cui and Li (2006)	Cumulative shock model	Single	Failure
Zhang (2019)	Degradation and shock-degradation dependence	Single	Failure/ preventive maintenance
Zhao et al. (2019)	Mixed shock model	Single	Failure/ preventive maintenance
Hu et al. (2020)	Degradation and degradation-shock dependence	Single	Failure/ preventive maintenance
Zhang and Yang (2020)	Degradation and shock-degradation dependence	Single	Failure /preventive maintenance /unscheduled events

In the Table 2, an extensive literature review is made for the opportunistic maintenance with impact of external factors(shocks), not limited to the area of wind energy. Cui and Li (2006) developed an opportunistic maintenance for a multicomponent cumulative damage shock model. When the cumulative damage exceeds the predetermined threshold, the component will fail and create a maintenance opportunity for the system. Zhang (2019) developed a delay time model for an industrial system considering the external shocks. The impact of shocks on system may result in the random hazard rate increments (shock-degradation dependence). The developed model is demonstrated on a critical steel convertor plant in a steel mill. A series system which consists of two components with multi-stage accelerated damage is studied by Zhao et al. (2019). When the state of components gets worse, the shocks with the same magnitude may have more severe influence on the component state. A numerical example of a two-rolling bearing system is presented to demonstrate the proposed model. Hu, Shen and Shen (2020) studied the situation that the system consisting of two independent components is subjected to the degradation and external shock. The shock rate will increase as the increase of the degradation level of the component (degradation-shock dependence). The maintenance will be carried out when the degradation exceeds the preventive maintenance threshold or a fatal shock occurs. A hydraulic system consisting of two valves in series is used as the example to illustrate the proposed maintenance strategy. Zhang and Yang (2020) proposed a state-based opportunistic maintenance for industrial assets exposed of environmental impact. The impact of environmental stress on system deterioration is various based on the state of the system, resulting in the increments on the hazard rates (shock-degradation dependence). The unscheduled events due to several factors, including production shortage and desired tasks can also be regarded as the window to perform maintenance besides replacement.

Although these studies considered the influence of environmental impact when developing opportunistic maintenance model, the

limitations still exist. The models considered opportunities existing in a simple system (such as a series system consisting of two components), not extending the model to multiple systems (such as an offshore wind farm). Every turbine can be regarded as a multi-component system. The maintenance performed on a component should provide maintenance opportunities for all the turbines in the farm, instead of only the located turbine. Moreover, some of the models assume that once one component reaches a preventive maintenance threshold, a maintenance cycle will be initiated. This maintenance decision may not be reasonable enough when applied to a wind farm. As the farm size enlarges and the number of the component increases, the maintenance team has to move to the offshore location frequently because the occasion easily happens that one component reaches the threshold. As discussed above, the problem also exists in the opportunistic maintenance models for wind energy, but has not been studied before.

1.2. Proposed strategy

To address the above issues, we consider the influence of environmental impact when developing the maintenance model, and analyse the trade-off between the frequency of preventive dispatch of maintenance teams and maintenance costs. The purpose of this paper is to propose an opportunistic maintenance strategy that reduces maintenance costs over an offshore wind farm's service life. The attempt is integrating multiple types of maintenance opportunities into the maintenance strategy. Based on the shock-degradation dependence, the impact can be generally categorized into three types depending on the severity, that is critical impact, influential impact and minor impact. Critical impact is so fatal to induce the occurrence of incidents, then the undergoing component fails and the failure replacement is required. The influential impact leads to a sudden increase of the degradation. The minor impact may cause a negative influence on operation, such as the reduction of power generation, but the system will recover soon without any failure. When the dispatch of maintenance teams is caused by degradation failures or incidents, these maintenance opportunities are called the failure-based opportunity and incident-based opportunity respectively. Furthermore, the maintenance team is dispatched preventively when a portion of components reach the age thresholds, which can be called the age-base opportunity. The simulation technique is used to evaluate the annual maintenance costs during the whole service life. A numerical example is provided to illustrate the proposed maintenance model. A comparative study with the conventional opportunistic maintenance strategy is used to demonstrate the advantage of the proposed strategy in reducing maintenance cost.

1.3. Outline

The remainder of the paper is listed as follows. In Section 2, the proposed opportunistic maintenance strategy is formalized. The failure of components and turbines, as well as the maintenance process are described and analytically derived. In Section 3, a numerical example is used to illustrate the proposed strategy. The optimization results and comparative study are presented. Finally, conclusions and future works are presented in Section 4.

2. Model description

In this section, a mathematical model is developed to formalize the proposed opportunistic maintenance strategy. In the model, three types of maintenance opportunities can trigger maintenance cycles where the maintenance team is dispatched to the site to repair or replace the components satisfying the maintenance requirements. After finishing the maintenance actions on qualified components, the maintenance cycle will end until the maintenance opportunity appears next time. The total costs represent the sum of money generated from repair activities during the maintenance cycles.

2.1. Assumptions

In the offshore wind farm, we assume that all the turbines are of the same type. After a wind farm maintenance decision is made, sufficient preparation is done to ensure the execution of maintenance activities is as successful as we expect. Therefore, the following assumptions are made on the offshore wind farm:

1. A specific component is of similar nature for all the turbines in the farm. The same maintenance activity performed on the specific component spends the same money, no matter the component is contained at which turbine.
2. The time spent on performing maintenance activities is negligible when compared to the long service time of farms.
3. The maintenance resource and capacity, including staff, tools, spare parts, transportation means, etc., are always available to complete all the maintenance tasks in the farm.
4. The accessibility to the location of the farm will not be affected by any negative factor such as weather conditions.

For an individual offshore wind turbine, it can be regarded as a series system, because the failure of subsystem may result in the entire system break down. For the mechanical or electromechanical components in the turbine, Weibull distribution is appropriate to model the failure times. Poisson process is a completely random process and each point is stochastically independent of all the other points in the process. Impact from marine environment arrives randomly with the average rates varying with time, so non-homogeneous Poisson process is suitable to describe this process. Hence the following assumptions are made on every individual turbine:

1. Offshore wind turbine system is simplified to a series system of critical components.
2. The degradation failure times of components are modelled as a two-parameter Weibull distribution with scale parameter and shape parameter. The arrival times of the environmental impact are modelled as a non-homogeneous Poisson process.

2.2. Failure of component

Suppose that there are K offshore wind turbines consisting of I critical components connected in series. The particular type of components in different turbines would undergo the same degradation process if they operate under the same ideal condition. This process can be defined as the normal degradation process. The environmental impact arriving at the turbines may have an influence on the component degradation or failure. Considering degradation and environmental impact at the same time can describe the degradation mechanism of components more accurately (Zhou et al., 2016). It is assumed that the arrivals of environmental impact and the deterioration of the system are independent (Caballé and Castro, 2017).

2.2.1. Degradation

In the whole lifetime, the component gradually degrades as the age increases until failure. Assuming that the failure time of component i at turbine k is modelled as a Weibull distribution with scale parameter σ_{ik} and shape parameter ε_{ik}, the component has the probability density function $f_{ik}(t)$ as

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

The reliability function can be expressed as

$$R_{ik}(t) = e^{-\left(\frac{t}{\sigma_{ik}}\right)^{\varepsilon_{ik}}} \tag{2}$$

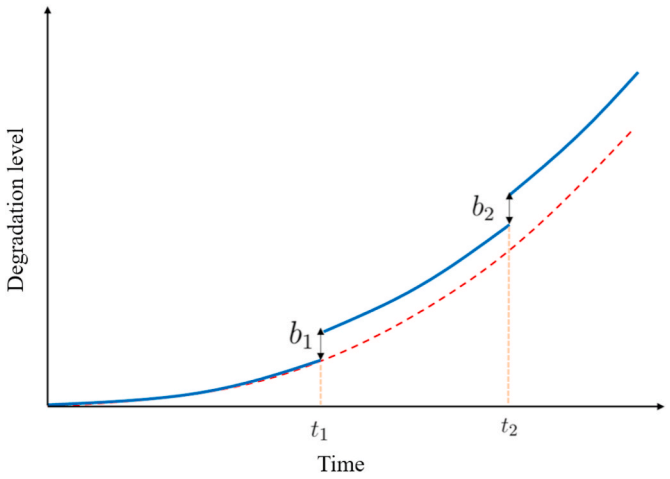

Fig. 3. Abrupt increases of degradation caused by influential impact.

The degradation degree increases as the time passes. The mean time to failure, $MTTF_{ik}$, denotes the expected time to failure for the component, and can be represented as

$$MTTF_{ik} = \int_0^{\infty} tf_{ik}(t) = \sigma_{ik}\Gamma\left(\frac{1}{\varepsilon_{ik}}+1\right) \tag{3}$$

with $\Gamma(*)$ denoting the Gamma function. The lifetimes of components are randomly generated by employing the Weibull distribution. Let $\alpha_{ik} = \sigma_{ik}^{-\varepsilon_{ik}}$, inverse Weibull model is used to generate Weibull distributed random numbers. We could begin with the random number, γ, which is in the range from 0 to 1. Then we can use the following equation to obtain new independent random numbers which have the Weibull distribution with the mean and variance depending on shape and scale parameters (De Gusmao, Ortega and Cordeiro, 2011). These random numbers will be assigned to corresponding components to represent their lifetimes (Tian et al., 2011).

$$t_{ik} = \left[-\frac{1}{\alpha_{ik}}\ln(1-\gamma)\right]^{\frac{1}{\varepsilon_{ik}}} \tag{4}$$

The degradation process of components may also be affected by some factors, such as environmental impact. For example, at time point t_1 and t_2, two times of impact arrive, resulting in the component degradation increases abruptly with the magnitude of b_1 and b_2 respectively (Fig. 3).

2.2.2. Environmental impact

We assume that the impact arrives somewhat randomly, modelled as a non-homogeneous Poisson process. A non-homogeneous Poisson process $\{N_k(t) : t \geq 0\}$ is a counting process where $N_k(t)$ is the number of load arrivals during time $(0, t]$, and the intensity function $\lambda_k(t)$ varying with time is a non-negative, integrable function satisfying the Poisson postulates (Leonenko et al., 2017). The Poisson random variable having mean is given by:

$$\Lambda_k(t) = \Lambda_k(0,t) = \int_0^t \lambda_k(z)dz \tag{5}$$

In order to simulate the occurrence times of impact, we can use the thinning algorithm to simulate the points in the non-homogeneous Poisson process (Kim and Singh, 2009; Xu and Dowd, 2010). The procedure starts with the determination of the maximum intensity value λ and with the generation of a realization of a homogeneous Poisson process with intensity value equal to this maximum intensity value. After that, the generated points of the homogeneous Poisson process at location t are retained and discarded based on the probability $\lambda_k(t)/\lambda$ (Lewis and Shedler, 1979).

2.3. Failure of offshore wind turbine

Considering the offshore wind turbine is a series system, the system fails once a component failure occurs. In other words, the component failures caused by degradation and environmental impact will force the turbine where the component is located to stop working immediately.

Not every environmental impact must induce the failure of turbines. The impact can be generally categorized into three types depending on the severity, that is critical impact, influential impact and minor impact. The critical impact means the impact is so disastrous that the turbine will break down until the failed component is completely replaced. The influential impact will cause an abrupt increase of the degradation. The minor impact will not make the turbine break down. It may affect the operation or production of wind turbines temporarily, so it is not necessary to perform maintenance. Correspondingly, the occurrence probability of critical impact p_k^1 $(0 \leq p_k^1 \leq 1)$ is the least, because this incident rarely happens. The probability of minor impact p_k^3 $(0 \leq p_k^3 \leq 1)$ is the most, and the probability of influential impact p_k^2 $(0 \leq p_k^2 \leq 1)$ is intermediate. The sum of p_k^1, p_k^2 and p_k^3 is equal to 1.

2.4. Opportunistic maintenance model

After studying the failure mechanism of turbines in the offshore wind farm, the opportunistic maintenance model will be developed to determine what time to activate maintenance activities and how the components will be repaired. The money spent on these maintenance-related activities will generate the corresponding maintenance costs.

2.4.1. Maintenance opportunities

There are three types of maintenance opportunity in the model, namely failure-based opportunity, age-based opportunity, and incident-based opportunity. The maintenance opportunities emerge when the corresponding situations happen. Every type of maintenance opportunity can initiate a maintenance cycle in the offshore wind farm. In Fig. 4, the detailed flow chart of the proposed opportunistic maintenance strategy is introduced. Only in the case that no opportunities happen, the system is determined to be without maintenance.

1. Failure-based opportunity. When the component i at turbine k breaks down because of the degradation, the maintenance opportunity will be triggered.
2. Age-based opportunity. No component fails, but a certain number of components reach the specific age threshold, the maintenance opportunity will arrive.
3. Incident-based opportunity. If the arriving environmental impact is critical so that the component fails, the maintenance opportunity will appear.

When the offshore wind farm begins to operate, all of the components are brand new, their ages u_{ik} are certainly 0. The inverse Weibull model is adopted to generate the random lifetime L_{ik} of each component. The failure age v_{ik} of the component equals its lifetime. Once the age reaches the failure age, this components will break down due to degradation. After every period of time $\left\{T_1^{\text{period}}, T_2^{\text{period}}, \ldots T_Z^{\text{period}}, \ldots\right\}$, the information of system is updated to determine if maintenance actions are needed.

During time T_{Z-1}^{period} to T_Z^{period}, the environmental impact is firstly checked. For each component subject to the environmental impact, the arrival time of impact is w_k. If $T_{Z-1}^{\text{period}} < w_k \leq T_Z^{\text{period}}$, the turbine k has to endure the environmental impact (X_k^{EI}=1). Considering the impact is critical, influential or minor, the Binomial distribution can present whether the impact can induce the incident. If the impact is minor, the turbines will maintain in the previous state. If the impact is influential, an abrupt increase of component age will be caused with the value b_c .

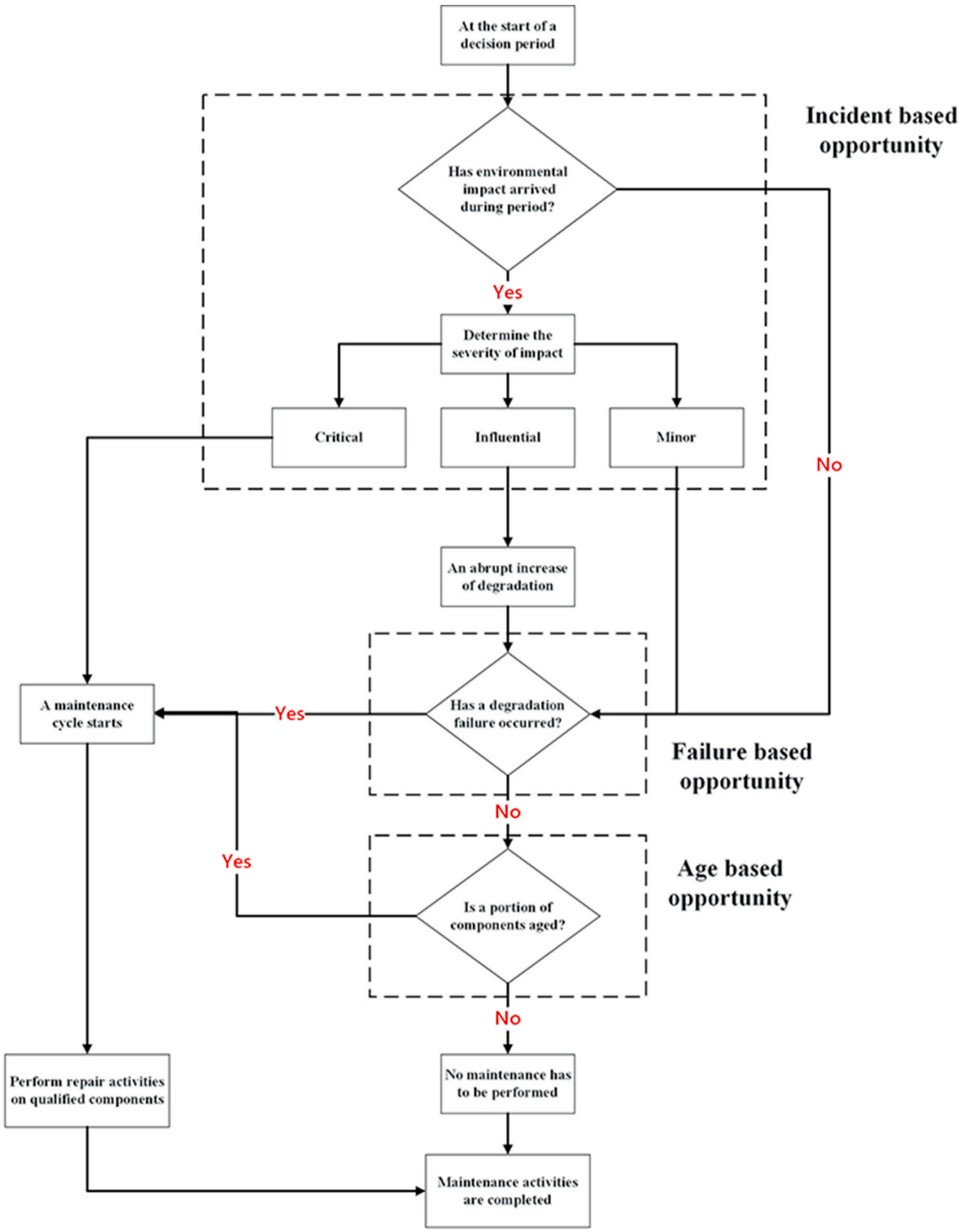

Fig. 4. Flow chart of the proposed opportunistic maintenance model.

We separate the interval between maximum age percentage threshold $A^{\max}$ and minimum age percentage threshold $A^{\min}$ into groups of equal lengths, $\{A^{\min}, \ldots, A^{y}, \ldots, A^{\max}\}$. If the component is younger than $A^{\min}$, there will an age increase with b_1. The age will be updated to $u_{ik}(1 + b_1)$. The age of components in the group between $A^{\min}$ and A^{1} will increase with b_2, and so on. The younger component is, the age increase will be less, because it is in a better state to withstand the impact. If the impact is so catastrophic to destroy the turbine ($X_k^{c} = 1$), the incident-based opportunity is generated (X^{i}=1).

If no incident happens, then the failure times f_{ik} are compared with the real time. If $T_Z^{\text{period}} < f_{ik}$, that means the component won't fail during this period and no failure replacement is needed, the binary variable X_{ik}^{CR} is equal to 0. Only for all the components, the $X_{ik}^{\text{CR}} = 0$, the value of X^{f} is 0. Otherwise, the $T_{Z-1}^{\text{period}} < f_{ik} \leq T_Z^{\text{period}}$, the degradation failure occurs on one component. In this case, $X_{ik}^{\text{CR}} = 1$, the failure-based opportunity

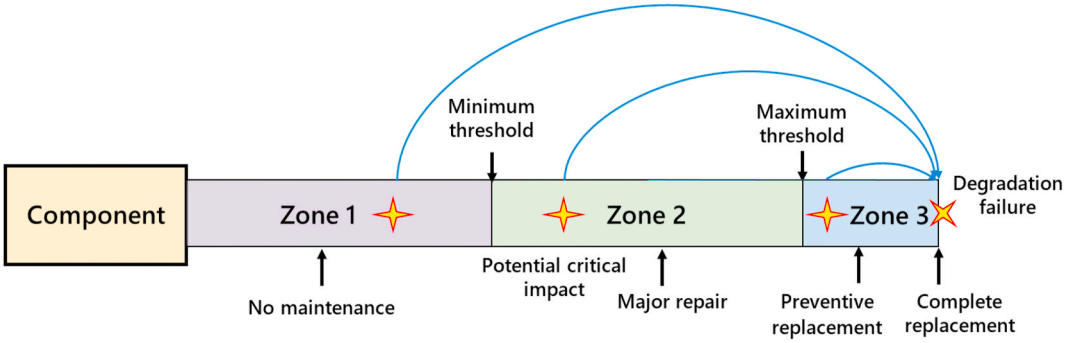

Fig. 5. Maintenance actions for the components of different stages.

appears (X^{f}=1) and one maintenance cycle will launch. If it is lucky that no failure occurs during this time period, the third maintenance opportunity, age-based opportunity, should be estimated. For component i at turbine k, if its age u_{ik} is more than a specific percentage of failure age v_{ik}, the component is regarded as an aged component. In other words, the component is judged as aged because it exceeds the maximum age threshold A^{max}. We assume ζ is the percentage threshold of number of aged components. If the total number of aged components in the wind farm is greater than or equal to U, $U = \zeta I$, the age-based opportunity is triggered (X^{a}=1). If X^{a}, X^{i}, $X^{f} = 0$, no maintenance is needed during the period. The time moves to next period, and values of time and age are updated.

2.4.2. Maintenance actions

Three maintenance actions are included in one maintenance cycle. Failure replacement is conducted on the failed component due to degradation or critical impact. The failure replacement means the component is completely replaced to a component of similar nature, implying the component is brand new with the age reset to zero. If the component is to fail because of the degradation, it is qualified for a preventive replacement. The preventive replacement can also restore the age of component to zero. Because it is preventively carried out before the failure to avoid potentially serious damages, so the cost is less when compared with failure replacement. The major repair will be carried out on the components satisfying the requirements (between maximum and minimum age threshold). The major repair can effectively improve the component health. The maintenance actions for components of different stages are illustrated as Fig. 5.

The nth maintenance cycle begins after the maintenance opportunity emerges. The starting time of this cycle is T_n. The component states in the site can be classified into four cases: failed, aged, mature, and young.

1. Failed component.

As introduced above, the failed components no matter due to degradation or critical impact should be completely replaced, their corresponding binary variables $X_{ik}^{CR} = 1$. Accordingly, their ages are reset to 0, as follows:

$$u_{ik}^{new} = 0 \tag{6}$$

By sampling from Weibull distribution, the lifetimes of these new components are obtained, L_{ik}, then their new failure ages (equals to the lifetime), v_{ik}^{new}, is known. The next failure times can be obtained as:

$$f_{ik} = v_{ik}^{new} + T_n \tag{7}$$

2. Aged component.

In the maintenance cycle, the ages of running components are compared with the predetermined age thresholds. We assume two percentages of failure ages as basic thresholds, A^{max} and A^{min}. If $u_{ik}^{old} > v_{ik}^{old} A^{max}$, it is determined as the aged component to be replaced and X_{ik}^{PR} is equal to 1. Similar to failed component, the age will be restored to 0 after preventive replacement, as follows:

$$u_{ik}^{new} = 0 \tag{8}$$

The new lifetimes L_{ik} and failure ages of these components v_{ik}^{new} are obtained. The occurrence time of next failure can be obtained as:

$$f_{ik}^{new} = v_{ik}^{new} + T_n \tag{9}$$

3. Mature component.

For the running components with ages between maximum and minimum thresholds, namely $v_{ik}^{old} A^{min} < u_{ik}^{old} \le v_{ik}^{old} A^{max}$, these components are judged as mature components which major repair should be conducted on (X_{ik}^{MR}=1). The components in the group between A^{min} and A^{1} will undergo the l_1 level maintenance action. The l_2 level maintenance action is performed on the components between A^{1} and A^{2}, and so on. For the mth maintenance level, l_m, there is a maintenance quality, θ_{l_m}. The maintenance quality means the age of components can be improved to a fixed percentage (Moghaddam and Usher, 2010). Therefore, the ages of component will be updated after major repair as follows:

$$u_{ik}^{new} = \theta_{l_m} u_{ik}^{old} \tag{10}$$

The failure age is updated as follows (Sarker and Faiz, 2016):

$$v_{ik}^{new} = v_{ik}^{old} \theta_{l_m} + (1 - \theta_{l_m}) L_{ik} \tag{11}$$

The occurrence time of next failure is as follows:

$$f_{ik}^{new} = v_{ik}^{new} - u_{ik}^{new} + T_n \tag{12}$$

4. Young component.

For the components younger than the minimum threshold ($u_{ik}^{old} \le v_{ik}^{old} A^{min}$), there is no need to maintain them. They are left there to continue operation, and no money is spent on them. During the maintenance cycle, they still retains the previous state, so the degradation process and failure age don't change, as follows:

$$v_{ik}^{new} = v_{ik}^{old} \tag{13}$$

After the maintenance cycle, their ages are updated as follows:

$$u_{ik}^{new} = u_{ik}^{old} \tag{14}$$

The occurrence time of next failure is as follows:

$$f_{ik}^{new} = v_{ik}^{new} - u_{ik}^{new} + T_n \tag{15}$$

2.4.3. Maintenance costs

The objective is to reduce the total maintenance costs of offshore wind farm. After developing the maintenance model, the cost generated in the procedure is calculated to estimate economic. The first step is to calculate the money spent on four types of components (failed, aged, mature, young) in each maintenance cycle.

For the failed component, it should be completely replaced, so the total cost of failure replacement of the wind farm, $M_{\text{total}}^{\text{CR}}$, is as follows:

$$M_{\text{total}}^{\text{CR}} = \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ik}^{\text{CR}} X_{ik}^{\text{CR}} \tag{16}$$

where M_{ik}^{CR} represents the cost of failure replacement of component i at turbine k, and X_{ik}^{CR} is the binary variable to determine whether this component needs to be replaced.

For the aged components reaching the maximum age threshold, they are replaced as well. The money spent on activities of preventive replacement, $M_{\text{total}}^{\text{PR}}$, is calculated as:

$$M_{\text{total}}^{\text{PR}} = \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ik}^{\text{PR}} X_{ik}^{\text{PR}} \tag{17}$$

where M_{ik}^{PR} represents the cost of preventive replacement of component i at turbine k, and X_{ik}^{CR} is the binary variable to check if preventive replacement is required.

The mature components with ages between the maximum and minimum age thresholds are qualified for major repair. In the present work, it is commonly assumed that the cost M_{ikm}^{MR} of intermediate maintenance level performed on component is function of the expected value θ_{l_m} of the improvement coefficient of l_m in addition to the age and the operating state of the component (Pandey et al., 2013). According to literature (Khatab and Aghezzaf, 2016; Duan et al., 2018), the cost of major repair can be obtained as:

$$M_{ikm}^{\text{MR}} = r_{ikm} M_{ik}^{\text{PR}} (1 - \theta_{l_m})^{d_{ikm}\eta_{ikm}} \tag{18}$$

where r_{ikm} and d_{ikm} are the characteristic constants that determine how the improvement coefficient affects the corresponding intermediate maintenance cost. Variable η_{ikm} represents the stability level of the maintenance quality. The $d_{ikm}\eta_{ikm}$ is smaller, then the major repair will be more expensive. Therefore, the total costs of major repair is:

$$M_{\text{total}}^{\text{MR}} = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ikm}^{\text{MR}} X_{ik}^{\text{MR}} = \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{I} r_{ikm} M_{ik}^{\text{PR}} (1 - \theta_{l_m})^{d_{ikm}\eta_{ikm}} X_{ik}^{\text{MR}} \tag{19}$$

where X_{ik}^{MR} is the binary variable to indicate if major repair is necessary.

For the young components, they aren't maintained in the maintenance cycle. Consequently, no cost is consumed for these components. Moreover, some extra cost exists along with the cost for maintenance tasks when conducting maintenance. Fixed cost M^{f} is the money used to make some preparation and trigger maintenance activities (Dalgic et al., 2015; Martin et al., 2016). M_k^{TR} is the transportation cost to turbine k in one maintenance cycle, thus more turbines are visited and repaired, the transportation cost is higher. Therefore, the total transportation cost is:

$$M_{\text{total}}^{\text{TR}} = \sum_{k=1}^{K} M_k^{\text{TR}} X_k^{\text{TR}} \tag{20}$$

where X_k^{PR} is the binary variable to indicate if the turbine is visited.

Finally, the total cost of one maintenance cycle is calculated as follows:

$$M_{\text{total}} = M^{\text{f}} + M_{\text{total}}^{\text{TR}} + M_{\text{total}}^{\text{PR}} + M_{\text{total}}^{\text{CR}} + M_{\text{total}}^{\text{MR}} = \tag{21}$$

$$M^{\text{f}} + \sum_{k=1}^{K} M_k^{\text{TR}} X_k^{\text{TR}} + \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ik}^{\text{PR}} X_{ik}^{\text{PR}} + \sum_{k=1}^{K} \sum_{i=1}^{I} M_{ik}^{\text{CR}} X_{ik}^{\text{CR}} + \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{i=1}^{I} r_{ikm} M_{ik}^{\text{PR}} (1 - \theta_{l_m})^{d_{ikm}\eta_{ikm}} X_{ik}^{\text{MR}}$$

It is assumed that the offshore wind farm operates for S years (lifetime) which N cycles of maintenance are carried out during. We can calculate the total costs during S years, and further obtain the annual cost C_{annual}, as follows:

$$\begin{aligned} \min \quad C_{\text{annual}}\left(A^{\min}, A^{\max}, \zeta\right) &= \frac{\sum_{n=1}^{N} M_{\text{total}}}{S} \\ &= \frac{1}{S}\sum_{n=1}^{N}\left(M^{\text{f}} + \sum_{k=1}^{K} M_k^{\text{TR}} X_k^{\text{TR}} + \sum_{k=1}^{K}\sum_{i=1}^{I} M_{ik}^{\text{PR}} X_{ik}^{\text{PR}} + \right. \\ &\left. \sum_{k=1}^{K}\sum_{i=1}^{I} M_{ik}^{\text{CR}} X_{ik}^{\text{CR}} + \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{i=1}^{I} r_{ikm} M_{ik}^{\text{PR}} (1 - \theta_{l_m})^{d_{ikm}\eta_{ikm}} X_{ik}^{\text{MR}}\right) \end{aligned} \tag{22}$$

$$\text{s.t.} \quad 0 < A^{\min} < A^{\max} < 1$$

where $A^{\min}$ (minimum age percentage threshold), $A^{\max}$ (maximum age percentage threshold), and ζ (percentage threshold of number of aged components) are the decision variables of the proposed model. Actually, the values of $A^{\min}$ and $A^{\max}$ can be regarded as the criterion to determine whether a component is qualified for the repair. If it is older than $A^{\min}$ but less than $A^{\max}$, a major repair is needed. If it is more aged than $A^{\max}$, it should be preventively replaced. By varying the thresholds, the number of components which should be repaired will change accordingly. The variable, ζ, can determine how many aged components can trigger the age-based opportunity. The objective is to determine the optimal combination of variables which can minimize the annual maintenance cost during the whole lifetime.

3. Numerical example

In order to illustrate the effectiveness of the proposed opportunistic maintenance method, a numerical example of the offshore wind farm is used in this section. The optimization results of three strategies are represented. A comparative study with the conventional opportunistic maintenance strategies under the same parameters demonstrates the advantage of the proposed strategy in reducing the maintenance cost.

3.1. Scenario set-up

We assume that there is an offshore wind farm containing 50 offshore wind turbines following a design life of 20 years. It is noted that the numerical example is generic, instead of a real and specific wind farm operating. Considering the turbine is a type of complicated electromechanical system containing hundreds of components, it is difficult to take every subsystem into account. Previously published results in peer-review journals (Shafiee and Dinmohammadi, 2014; Arabian-Hoseynabadi et al., 2010; Kang et al., 2019; Zhang et al., 2016; Kang, Sun, Sun andWu, 2017; Zhou et al., 2015; Scheu et al., 2019; Li, Teixeira and Soares, 2020a) have revealed the criticality ranking of wind turbine components by using the methods, such as Failure modes and effects analysis (FMEA), Failure mode effects and criticality analysis (FMECA), two-stage Failure Mode and Effect Analysis, etc. In our model, every turbine is simplified to a multi-component series system with five critical subsystem (gearbox, generator, rotor&blade, pitch system, and main bearing). Due to the extremely low failure rates, tower and support structure are not considered in our model. The blade is the component more subject to the environmental impact, and the influence of critical

Table 3
Failure distribution and cost parameters for critical components.

Component	Shape parameters	Scale parameters (days)	Failure replacement (k€)	Preventive replacement (k€)
Rotor&blade	3	1847	215	55
Bearing	2	1811	60	15
Gearbox	3	1477	260	65
Generator	2	1594	90	25
Pitch system	3	1144	46	10

impact on other components are ignored because of the protection of cabin. Carroll, McDonald and McMillan (2016) collected the maintenance information of operational data of 1768 turbines years. The data is based on 350 offshore wind turbines which are from between 5 and 10 wind farms throughout Europe. The ages of turbines are between from 3 to 10 years. The capacity is between 2 and 4 MW and the rotor diameter is between 80m and 120m. Santos, Teixeira and Soares (2015); Le and Andrews (2016) also collected and estimated the failure distribution and maintenance cost from several studies in the literature focusing on the O&M for European wind energy. The basis of the input information of the model is mainly estimated from these papers (Table 3), which represents the properties and parameters of the example of the offshore wind farm.

The decision moments are assumed to be periodic (20 days). The fixed cost M^{f} and transportation cost M_k^{TR} are 50k€ and 10k€ respectively. The intensity function of external factor is assumed to be $2/27*(t/27)$ (Shafiee et al., 2013, 2015). The value of p_k^1, p_k^2, p_k^3 is assumed to be 0.001, 0.005 and 0.994. Three age thresholds, maximum threshold A^{max}, intermediate threshold A^{y}, and minimum threshold A^{min}, are considered in the model. The maintenance improvement of two

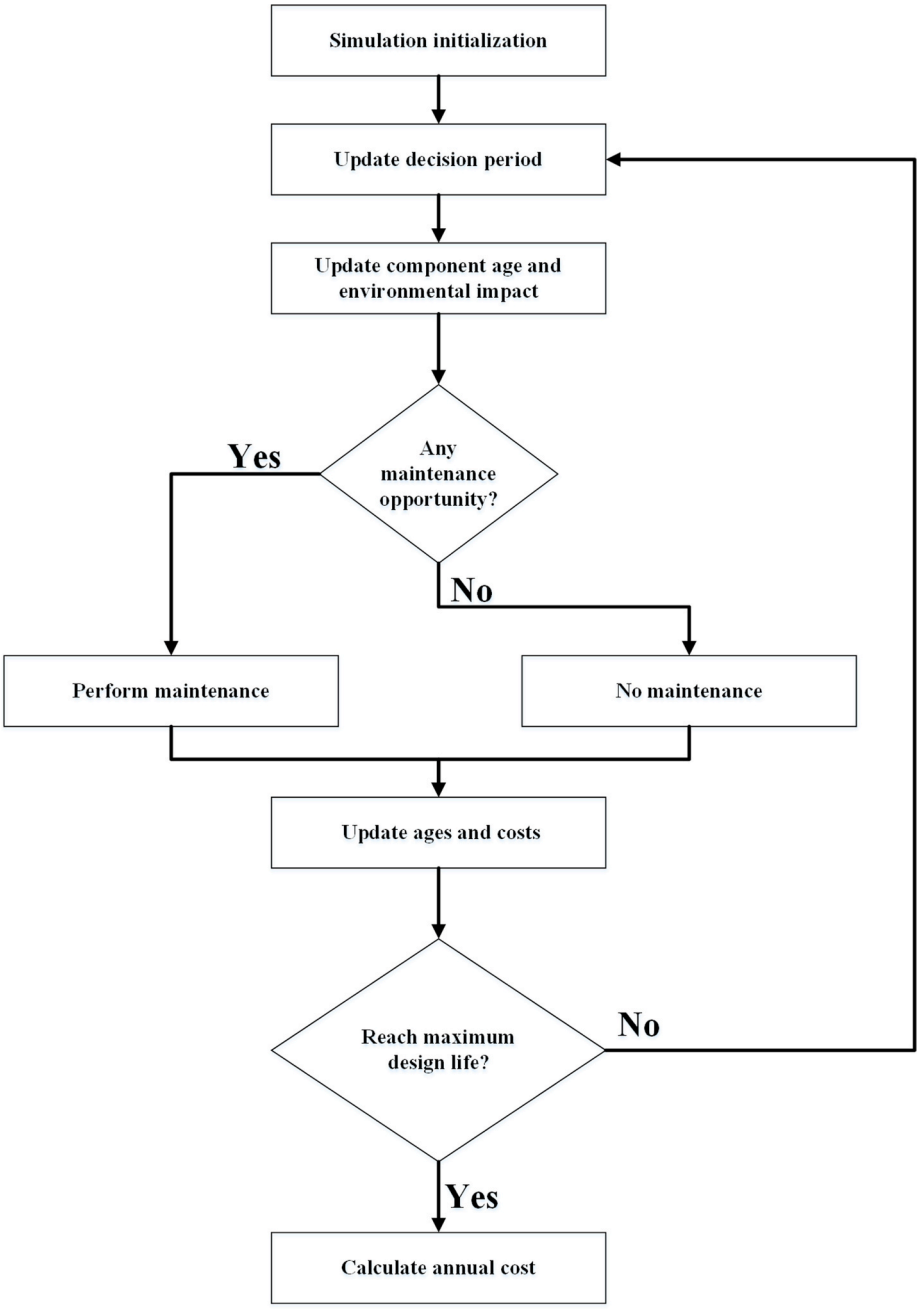

Fig. 6. Simulation process of the maintenance strategy.

levels, l_1 and l_2, are 0.5 and 0.7 respectively, indicating the maintenance quality will be more significant for older components. Accordingly, the maintenance task of higher quality is more costly. The values of $b_1 b_2$, b_3 and b_4 are 0.025, 0.05, 0.075 and 0.1 respectively. The values of r_{ikm} and η_{ikm} are both 1, and d_{ikm} is 2.

3.2. Optimization results

The possible maintenance optimization techniques include operations research models, analytical approaches, Markov models, simulation models, Petri net models, Bayesian networks and so on (Shafiee and Sørensen, 2019). In recent years, increasing attention has been directed towards improving and optimizing maintenance for industrial systems using the simulation method. One main reason is that many practical cases are too complicated to be given tractable mathematical formulations. The simulation method has the potential to tackle these challenging optimization problems involving nonlinearities, combinatorial relationships, and uncertainties (April et al., 2003). In addition, it allows experimenting and better understanding of systems with increasing complexity (Alrabghi and Tiwari, 2015). This method has been used in many studies about maintenance strategy optimization (Do et al., 2015). In this paper, the simulation frame work is established for the maintenance model of the offshore wind farm, as shown in Fig. 6. The simulation algorithm is presented in Algorithm 1. The Monte Carlo simulation method is implemented to evaluate the outcome of the proposed maintenance strategy.

There have been three strategies, NABO Strategy, SABO Strategy, and MABO strategy, as follows:

1. NABO Strategy

In the first strategy, only failure and incident can trigger the maintenance opportunities and the age-based opportunity is not considered, similar as the model in some papers (such as Sarker and Faiz (2016)).

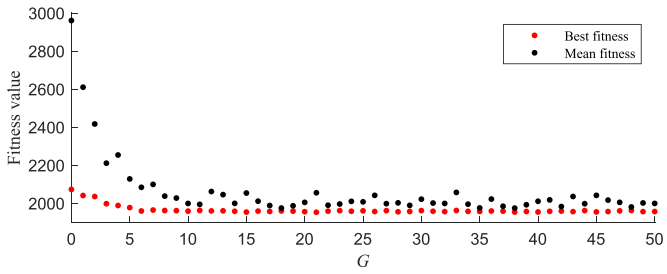

Fig. 7. The genetic algorithm optimization process results.

This kind of strategy is called as NABO Strategy (none age-based opportunity).

2. SABO Strategy

Failure and incident can trigger the maintenance cycle. Besides, if any component age reaches $A^{\max}$, the age-based opportunity will arise, like the model in some papers (such as Lu et al. (2018)), the model is called SABO Strategy (single age-based opportunity).

3. MABO Strategy

We call the developed model in the present paper is MABO Strategy (multiple age-based opportunity). Failure-based, incident-based, and age-based opportunities exist in the strategy. If a predetermined number of components are aged, the maintenance decision can also be made to maintain the wind farm.

Algorithm 1: Simulation procedure for the maintenance model of the offshore wind farm

Step 1: Initialize the simulation; Specify all the parameters involved, including scenario parameters, S, K, I; failure parameters, σ_{ik}, ε_{ik}, $\lambda_k(t)$, p_k^1, p_k^2, p_k^3, b_c ; cost parameters, M_{ik}^{CR}, M_{ik}^{PR}, M_k^{TR}, M^{f}; maintenance parameters, $A^{\max}$, $A^{\min}$, ζ, A_y, M, θ_{l_m} ;

Step 2: Randomly generate the failure ages v_{ik} and occurrence times w_k of environmental impact; Determine the nature of the impact;

Step 3: Update the decision moment T_Z^{period};

Step 4: **if** $T_{Z-1}^{\mathrm{period}} < w_k \le T_Z^{\mathrm{period}}$ **then**

  X_k^{EI}=1; Environmental impact arrives ;

  if $X_k^{\mathrm{c}} = 1$ **then**

    $X^{\mathrm{i}} = 1$; Incident-based opportunity appears; Maintenance cycle begins ;

else if $T_{Z-1}^{\mathrm{period}} < f_{ik} \le T_Z^{\mathrm{period}}$ **then**

  $X^{\mathrm{f}} = 1$; Failure-based opportunity appears; Maintenance cycle begins ;

else if $\sum_{k=1}^{K} \sum_{i=1}^{I} X_{ik}^{\mathrm{MR}} \ge \zeta I$ **then**

  $X^{\mathrm{a}} = 1$; Age-based opportunity appears; Maintenance cycle begins ;

else

  No maintenance activities;

end

Step 5: Update ages u_{ik} and cost M_{total} ;

Step 6: **if** $T_Z^{\mathrm{period}} < S$ **then**

  Return to Step 3;

else

  Export the annual maintenance cost C_{annual};

end

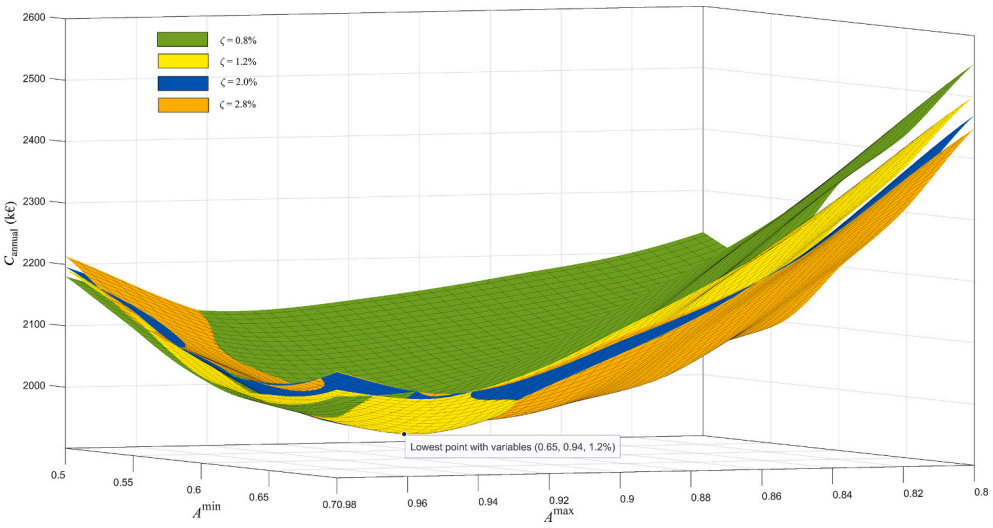

Fig. 8. Annual costs versus combinations of decision variables A^{min}, A^{max}, ζ

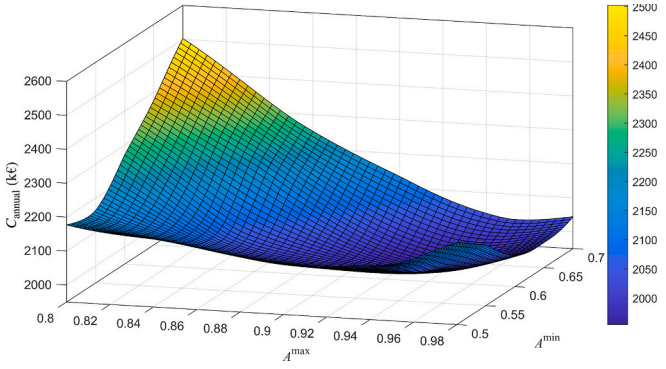

Fig. 9. Annual cost with different age thresholds under MABO Strategy when ζ = 1.2%.

As introduced above, the decision variables of the model (MABO Strategy) are A^{min}, A^{max}, ζ. The annual maintenance cost is the function of these decision variables. Genetic algorithm (GA) is a metaheuristic proposed according to the evolution of organisms in nature, which has been widely used to tackle the maintenance optimization issue (Compare et al., 2015). GA has its advantages when compared with other optimization methods, such as: avoid being trapped in local optimal solution by searching parallel from a population of points; use probabilistic selection rules instead of deterministic ones, etc. In this paper, we adopt GA to find the optimal combination of variables. The algorithm was configured with a population size of 40 individuals and a maximum number of generations (*G*) of 50. The fitness value of each individual is evalauted by Monte Carlo simulation with 500 times. With

Table 4
Optimized results of three strategies.

Strategy	A^{min}	A^{max}	ζ	Annual cost (k€)
MABO	0.65	0.94	1.2%	1956
SABO	0.64	0.96	-	1984
NABO	0.60	0.90	-	1996

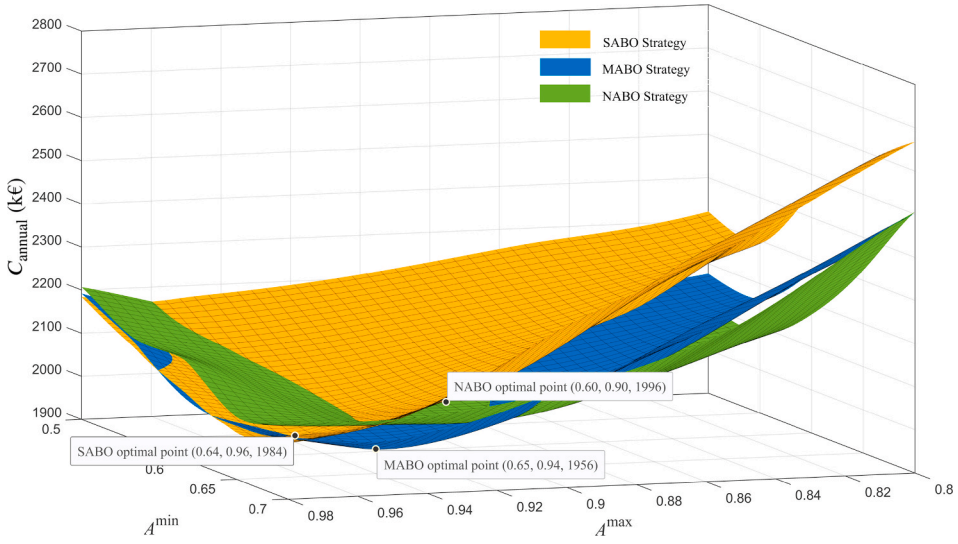

Fig. 10. Annual cost with different age threshold under three strategies.

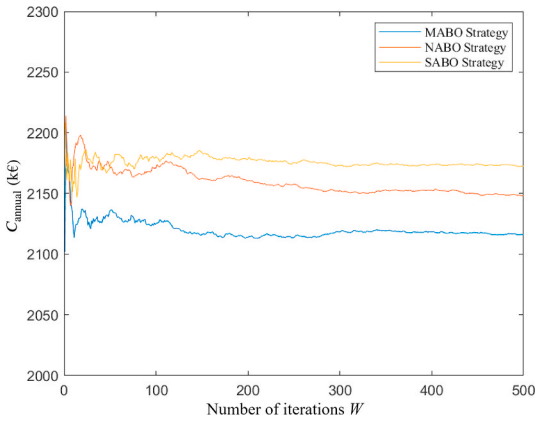

Fig. 11. Comparison of different opportunistic maintenance strategy.

this setting, the simulation in Fig. 6 should be run 1×10^6 times, which is implemented in MATLAB software. The GA optimization process results are represented in Fig. 7. The optimal combination of three decision variables is about (0.65, 0.94, 1.2%), with the lowest value 1956k€.

In order to illustrate how the varying variables affect the annual cost, we further test various combinations in Fig. 8 and show the effects of age percentage threshold under MABO Strategy when ζ equals 1.2% in Fig. 9. In Fig. 8, there exists an optimal combination of the decision variables which can minimize the annual maintenance cost. The variable ζ determines the exact number of the 'multiple' in the MABO Strategy. We select and present four faces ($\zeta = 0.8\%, 1.2\%, 2.0\%, 2.8\%,$) in the figure where the lowest point is on the yellow face ($\zeta = 1.2\%$). The lowest point means the optimal combination of the variables (0.65, 0.94, 1.2%). In Fig. 9, when changing $A^{\min}$ or $A^{\max}$, the trend is similar: the annual cost gradually drops as the increase of age threshold until the bottom, then increases to a high value. For the former, it can be explained that resulting from the lower threshold, more components are determined to be repaired in one maintenance cycle, contributing to more money. Then as the increase of threshold, the number of qualified components decreases, but the state of wind farm becomes worse due to less frequent repair. For the latter, the lower threshold indicates more components need to preventively replaced. More components are likely to fail due to insufficient preventive maintenance if the threshold is set at a higher percentage of the failure age.

In Fig. 10, the comparison among three strategies under different thresholds is illustrated. The MABO Strategy is the most cost-effective strategy after optimization as shown in Fig. 10 and Table 4. In the figure, the blue face (MABO Strategy) is the lowest in almost half of the area. However, we can find that it is not always the most cost-effective when varying the maintenance thresholds. When $A^{\max}$ is very high, MABO and SABO both perform better than NABO, because the expensive failure replacement can be avoided due to the benefit of age-based opportunity. When $A^{\max}$ begins to decrease, it will become gradually easier to trigger the age-based opportunity, causing the increasing

Table 5
Breakdown of maintenance costs of different strategies.

	Annual cost (k€)	Failure replacement (k€)	Preventive replacement (k€)	Major repair (k€)	Transportation and fixed cost (k€)
NABO strategy	2149	271	67	1070	741
SABO strategy	2173	126	54	1148	845
MABO strategy	2116	198	63	1089	766

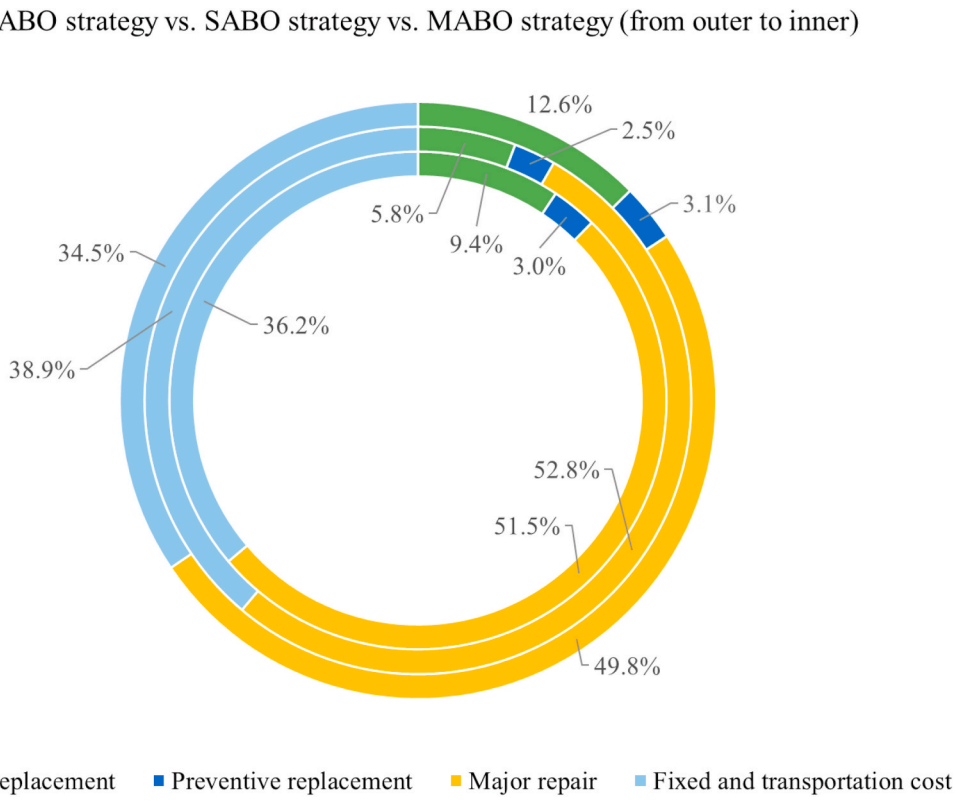

Fig. 12. Comparison of maintenance cost percentage for different maintenance strategies.

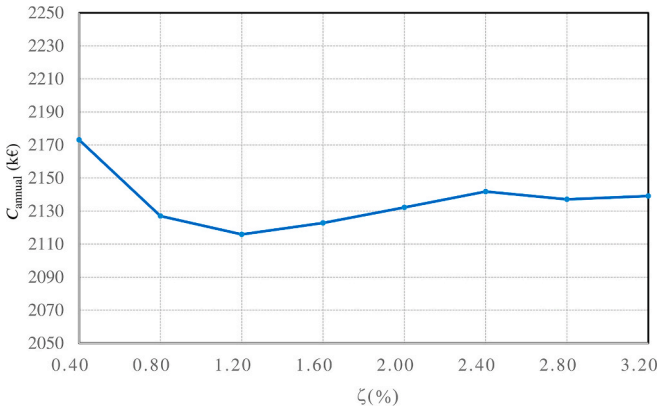

Fig. 13. Annual cost with different percentage thresholds.

maintenance frequency and cost, especially for SABO (yellow face). In these occasions, the NABO Strategy has a better performance to reduce costs. Compared with MABO and SABO, the variance of annual cost is relatively stable when changing threshold for NABO Strategy (as shown in green face), because the change of thresholds does not affect the trigger of age-based opportunity.

3.3. Comparative analysis

In order to study the differences among three strategies and discuss the reasons, all the parameters should be assumed the same, and the strategies are applied on the following base scenario: $A^{\max} = 0.95$, $A^{\min} = 0.5$, $\zeta = 1.2\%$.

In Fig. 11, the Monte Carlo simulation of three strategies is presented, where the number of iterations is presented by W. The simulation is run independently in each iteration. The convergence analysis for the Monte Carlo simulation is conducted. After running the Monte Carlo simulation for 500 iterations, it can be seen that no significant variations of the intermediate mean value are obtained. It indicates that the 500 iterations provide a sufficiently accurate statistical analysis of the results. The final results at the 500 simulation times are used to estimate the economic of different strategies. As shown in Table 5 and Fig. 12, these results suggest that MABO strategy shows the economic advantage compared with other two strategies. By introducing the age-based opportunity, the cost of failure replacement decreases accompanied by a increase in the cost of major repair, fixed cost and transportation cost. In SABO strategy, the triggering condition is set as single component. The corresponding result is the offshore wind farm can be maintained to a good state, with the lowest costs of replacing failed components. However, more maintenance cycles and activities make the costs of major repair, fixed and transportation cost grow, inducing the strategy doesn't perform satisfactorily in the aspect of economic. The age-based opportunity reduces the occurrence of failure events at the expense of triggering preventive repair more frequently. The MABO strategy found a balance to reduce the replacement costs with a slight increase of the major repair, fixed and transportation costs. Overall, the proposed MABO opportunistic maintenance strategy can lower the total maintenance costs compared with the other two strategies.

We further show the effects of following parameters on the MABO strategy: percentage threshold of number of aged components, ζ; the occurrence probability of critical, influential and minor impact, p_k^1 , p_k^2, p_k^3 ; the size of the offshore wind farm K. The value of these parameters will change gradually and all other parameters remain fixed.

In Fig. 13, as the increase of percentage threshold ζ, the annual cost drops at first until the bottom, then gradually grows with slight fluctuation. The size of the wind farm is 50 turbines with 250 critical components. The range of percentage thresholds from 0.4% to 3.2% indicates the number threshold of aged components is from 1 to 8. When the number is 1, that means once one component is determined to be aged, the age-based opportunity will make the maintenance cycle start. The number is 2 means two or more than two aged components can trigger the maintenance. And so on, for each set of percentage threshold. At the threshold of 0.4%, the failure occurrence can be avoided as much as possible, but the frequency of maintenance is also the highest resulting from the easily triggered conditions. The frequent maintenance results in the highest total cost. Then, as the increase of threshold, the negative influence of maintenance frequency weakens, but component failure is more likely to occur, resulting in the costly repair. A balance considering these two factors is find out until the lowest point at 1.2%.

Table 6
The cost savings under different size of offshore wind farm.

Farm size	NABO strategy (k€)	SABO strategy (k€)	MABO strategy (k€)	Cost savings (%)
10	463	408	408	11.9%/-
20	865	816	816	5.7%/-
50	2149	2173	2116	1.5%/2.6%
80	3574	3692	3507	1.9%/5%
100	4572	4731	4547	0.5%/3.9%

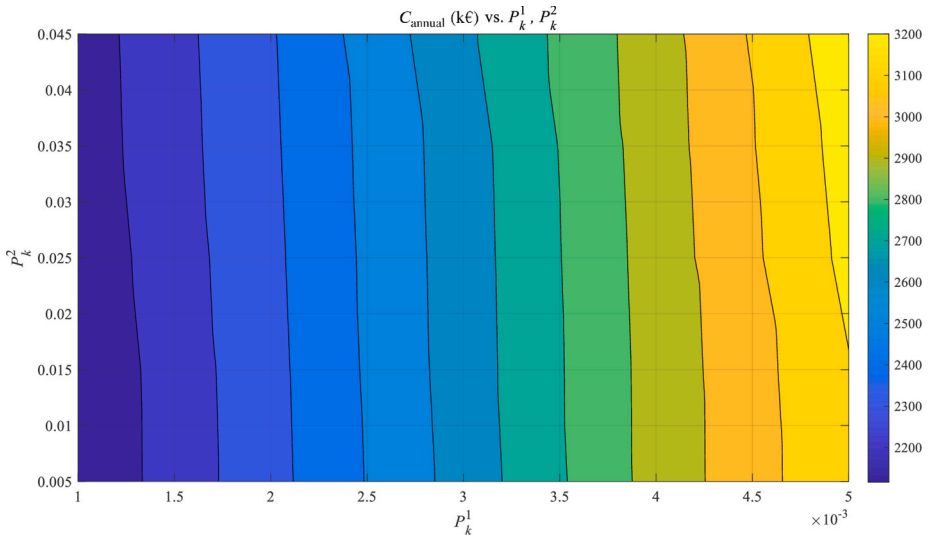

Fig. 14. The effect of varying probability of impact on annual maintenance cost.

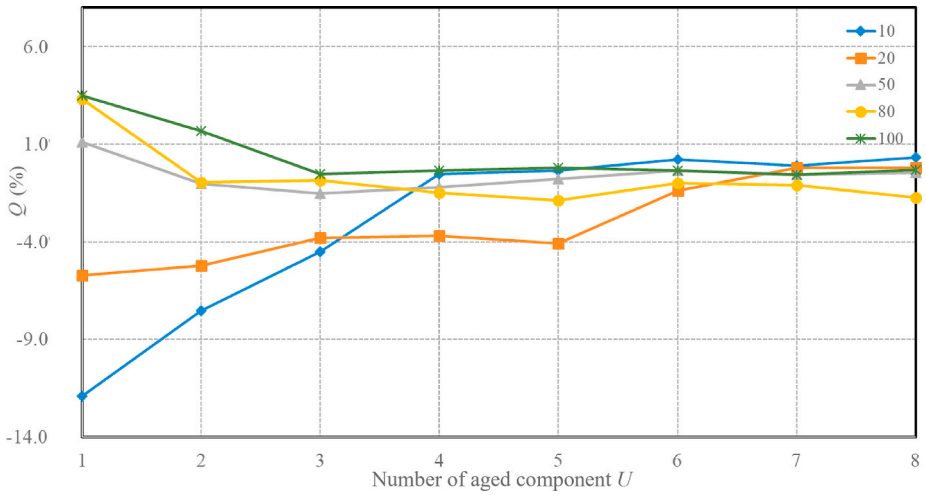

Fig. 15. Strategy improvement under different size of offshore wind farm.

Afterwards, the effect of failure occurrence becomes significant, causing the rise of annual cost.

Setting of the parameters of the environmental impact presents the harshness of the marine environment. In Fig. 14, it clearly shows that the annual cost rises as the increase of the probability of critical impact and influential impact. The value of p_k^1 has the most significant influence. The higher probability results in more components have to be completely replaced, so the cost of failure replacement will increase obviously. The influential impact can only accelerate the degradation, so its effect is less significant.

As shown in Table 6, we have applied the opportunistic maintenance strategy to the offshore wind farms with different number of turbines. When comparing MABO strategy with NABO strategy, for the small-scale farm, the results reveal that the cost saving is the most significant, as high as 11.9%. However, as the expansion of farm the reduction of maintenance costs become less considerable. It is largely explained by the more occurrence of failure-based opportunities and incident-based opportunities with the increase of farm size. The number of failure and incidents is less for a small-scale farm. In this case, the age-based opportunity is more promising to trigger the preventive maintenance and avoid failure replacement, then save more money. When the farm gets larger with even 100 turbines, the failure because of degradation or environmental impact have provided a number of opportunities to start the maintenance cycles. The age-based opportunity could make the strategy perform better on this condition, but not as substantial as small-scale farm. When the size is small, the cost savings of SABO strategy and MABO strategy is the same, because the single component is the best option to trigger preventive dispatch. However, the execution of SABO strategy becomes more costly as the increase of the farm size, even exceeding the NABO strategy. More turbines mean the number of aged component is more, so the over frequent maintenance activities may result in much unnecessary costs. In summary, the MABO and SABO strategy can reduce maintenance costs for a small-scale offshore wind farm when compared with NABO strategy. As the increase of turbine number, the MABO strategy is still the best option, followed by NABO strategy and SABO strategy.

In Fig. 15, we change the number threshold of aged components, U, under the MABO strategy when the size of wind farm is different. The annual cost of NABO strategy is seen as the comparison criterion, and the cost saving is presented by Q. When the threshold is only 1, the maintenance cost is minimized for the 10-turbine and 20-turbine farm. The preventive dispatch can significantly avoid the severe failure occurrence and high replacement costs. Furthermore, the case is also difficult to happen that more than 1 components reach the maximum age threshold at the same time for a small-scale farm. The more thresholds can only make the age-based opportunity happen more impossibly and the improvement weaken successively. When the number of turbines increase to 50, 80 and 100, the optimal number thresholds are obtained as 3, 5 and 7 respectively, showing that the optimal number of aged components increases as the wind farm enlarge.

4. Conclusion & Future research

The opportunistic maintenance strategy has been studied for the wind energy sector in recent years. A common assumption is made that the failure is mainly caused by degradation, ignoring the influence of environmental impact. Furthermore, the preventive dispatch of the maintenance team triggered by the occasion that a single component reaches the predetermined threshold probably induces much excessive cost. In this paper, an opportunistic maintenance strategy is developed for offshore wind farms. The offshore wind turbines operating in the harsh marine environment do not only suffer from degradation, but also impact from environment. The impact may result in the abrupt increase of degradation or the sudden incidents. The failures due to ultimate degradation and critical impact will create maintenance opportunities, namely failure-based opportunity and incident-based opportunity. Another maintenance opportunity considering the number of aged components, age-based opportunity, is also considered to balance costly failure replacement and over frequent maintenance cycles. The simulation method is used to represent the maintenance scenarios and evaluate the average annual maintenance costs.

In the NABO strategy, only failure and incident can create the maintenance opportunities. The SABO strategy assumes that if any component becomes aged and requires preventive replacement, another maintenance opportunity (age-based opportunity) will also arise. The developed strategy in the paper (MABO Strategy) considers the number of aged components. The age-based opportunity will be created when the number of aged components reaches a predetermined value. The comparative analysis under the based scenario shows the MABO and SABO strategies can both reduce about 11.9% cost than NABO strategy for a 10-turbine farm,. When the scale of the farm enlarges, the MABO strategy still has the best performance. An economic benefit of 2.6% and 1.5% respectively can be achieved for a 50-turbine farm when compared with SABO and NABO strategy. When the number of turbine increases to 100, MABO strategy saves 3.9% and 0.5% costs respectively in comparison to SABO strategy and NABO strategy. It is noted that the numerical example is generic, instead of a real offshore wind farm. In future work, if more detailed data can be collected from a real wind farm, the calculation results will be more realistic and contributive.

There are several potential extensions of this study. The O&M of

offshore wind farm is a complicated task involving failure, repair, spare parts management, transportation, weather prediction, and so on. In this paper, the assumption is made that the maintenance resource are always sufficient to perform maintenance activities and the accessibility to the location of the turbines will not be affected by any negative factor. However, the resource limitation and uncertain accessibility are significant problems during O&M for wind energy sector. The introduction of these factors into opportunistic maintenance model is worth further studying. Moreover, the developed model is based on the assumption that the parameters of the model are certain. For instance, the failure time of components is modelled as a Weibull distribution with parameters we have known even before the operation. However, these parameters should be uncertain due to the lack of knowledge of the actual use and maintenance of the equipment, and inaccurate historic data and records. These uncertain parameters will affect the performance of the maintenance strategy. It is necessary to further consider uncertainty when improving the O&M for offshore wind energy.

CRediT authorship contribution statement

Mingxin Li: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Xiaoli Jiang:** Supervision, 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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