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Influence of uncertainty on performance of opportunistic maintenance strategy for offshore wind farms

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***Abstract*—The increasing capacity of offshore wind energy around the world brings challenges in Operation and Maintenance (O&M) management. Over the past years, many studies have focused on developing sound maintenance strategies in order to minimize maintenance cost or maximize availability. One of the promising maintenance strategies is opportunistic maintenance due to its potential to combine maintenance activities and save maintenance efforts. In these models, a common assumption is made that input parameters are deterministic and maintenance decisions are made based on these assumed deterministic input parameters. However, offshore wind farm maintenance in the practical world is a complicated task where multiple types of uncertainty exist. These uncertainties may affect evaluation or output of the maintenance model, making maintenance decisions sub-optimal or even inappropriate. In this paper, a probabilistic simulation-based approach integrating an uncertainty module and a simulation module is proposed to study the influence of the uncertainties on maintenance performance. We identify the primary input parameters which should be considered as uncertainty but are simplified to be deterministic values in offshore wind energy maintenance models. These deterministic parameters are modelled as stochastic values in the uncertainty module to generate uncertainty scenarios. The simulation module for opportunistic maintenance is developed to quantify the expected maintenance cost and lost production. The most influential uncertainties are identified. Valuable information and suggestions are provided to offshore wind farm owners for future decision-making and project management.**

***Index Terms*—maintenance strategy, uncertainty, offshore wind energy, operation and maintenance**

I. Introduction

Europe, the largest regional offshore wind energy market globally, is expected to devote more effort to developing offshore wind energy in the future. New annual installation in Europe is estimated to be more than 10 GW in 2026, and gradually increases to as much as 15 GW in 2030 [1]. With the increase of operational capacity, an effective Operation and Maintenance (O&M) strategy to increase wind farm availability with less cost is in urgent demand for industry.

As a type of complicated technical activity, O&M performed in offshore wind farm, is always affected by various factors including environmental conditions, technician expertise, maintenance source availability, etc. It means practical maintenance situations are always uncertain and varying, rather than deterministic or fixed. Although it is understood that the O&M should be organized under uncertain conditions and parameters, most of the existing O&M models still assume that the model inputs are deterministic and constant, disagreeing with the real world. Ignoring uncertainties possibly make the expected maintenance consequences considerably different, and the final decision making is largely influenced.

In recent years, some studies have noticed this gap. Reference [2] investigated the impact of uncertain component failure distributions at constant failure rates on the offshore wind farm availability. Reference [3] performed a sensitivity analysis to identify the most significant factors of O&M affecting operating cost and availability of offshore wind farms. Reference [4] used the probabilistic method to model reliability data uncertainty and the fuzzy logic to model failure cost uncertainty. The impacts of these uncertainties on operational and economic performance of offshore wind turbine are shown in the paper.

We can find the above literature solely studied the influence of one or two maintenance uncertainties on availability or cost, but no paper attempted to identify and conclude the primary uncertain input parameters affecting maintenance decisions, and then estimate the influence from the perspective of both availability and maintenance cost. In addition, these studies paid attention to the scenario where conventional time-based maintenance strategy is applied. People are seeking new maintenance strategies potential for future offshore wind farm, and one termed as opportunistic maintenance is attracting people's attention, where maintenance activities are combined according to the condition/age/reliability of turbine components [5]. No study before has focused on the influence of uncertainty on the performance of opportunistic maintenance model. Further, it is noted that the previous literature usually adopted non-probabilistic methods such as the deterministic sensitivity analysis and the fuzzy model. These methods are commonly used to model uncertainty of input parameters or examine impact of parameter uncertainty, but they can not inform the

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decision-makers how likely a specific value or range of values will be observed. Further, the range of input parameters chosen is often arbitrary in the deterministic sensitivity analysis, and no insight in effects at the margin can be provided [6].

Uncertainty deserves our attention during the entire O&M process, but it should be explained that the focus of this work is to study the influence of uncertain input parameters on the opportunistic maintenance model. O&M for offshore wind farms encompasses a broad spectrum of services, competencies, processes, and tools required to ensure turbines can operate as they were designed. A sound organization of O&M relied on good performance of different technologies and effective coordination of decision makers. The existence of uncertainty is inevitable during the application of technology and the process of decision-making. For instance, as a significant O&M technology, condition monitoring is developed to monitor operation parameters of machinery, so as to identify significant changes that indicate a fault, and then provide the preparation for making maintenance decisions. The uncertainties caused by limitation of unidentified degradation mechanism and measurement difficulties may result in inaccurate determination of machinery condition and unreasonable maintenance decisions [7]. Once a maintenance decision is made, maintenance logistics including spare part management, maintenance scheduling, vessel routing, etc., should be well organized to support the maintenance decisions. However, the predetermined maintenance logistics organization may suffer from the existence of the uncertainties. For instance, optimal schedule and routes for offshore wind farm maintenance determined under certain conditions may not be implemented successfully or even be cancelled due to uncertain metocean conditions [8], [9]. The maintenance model proposed in the paper only concerns the maintenance decisions, indicating the pre-preparation and post-support is not studied in the work. Such a model can be regarded as a decision making tool for decision-makers, especially offshore wind farm owners, who concern about production maximization and maintenance cost minimization in the whole lifetime of offshore wind farms.

Opportunistic maintenance for wind energy has been studied in some literature [5], [10], [11]. These models has many similarities in the process, which is presented as: discrete turbine failure events are generated by inputting the failure distributions and parameters; maintenance decisions are made based on the condition monitoring and predictive analytics of turbines; perform maintenance activities including replacement and major repair to improve condition of components; estimate the expected model outcome (maintenance cost or lost production). The focus of this paper is the influence of uncertainty on offshore wind energy opportunistic maintenance model, so the determination of the uncertainty sources is based on the process described above. Corresponding to each step, the following uncertainties are studied in the paper: (1)deviation of predicted and real failure times; (2)stochastic attributes of time to failure; (3)uncertain maintenance quality; (4)uncertain repair cost and time.

In this paper, we propose a probabilistic simulation-based approach integrating an uncertainty module where the input parameters are presented stochastically by using the probability distribution functions and a simulation module where an opportunistic maintenance model is proposed considering multiple types of maintenance opportunities. In the uncertainty module, the input parameters are represented by entailing the use of individual distributions to generate parameter values according to the probability density function. Then, the generated stochastic parameters are input into simulation module to derive the results when the corresponding maintenance uncertainty is considered.

II. Uncertainty module

In order to represent the uncertain model inputs in a more realistic pattern, they are quantified by utilizing a probabilistic method instead of conventional fixed and deterministic values in the uncertainty module. As discussed in the section of introduction, there are four main uncertainties considered in this paper:

A. Deviation of predicted and real failure times

In the existing maintenance models, an assumption is usually made that failure times of components are accurately known in advance, then maintenance decisions are made based on that accurate failure information. In order to realize such an assumption, we need to use condition monitoring and remaining useful life prediction (RUL) technology to monitor operational condition of machinery and predict the time left failure.

The past decades have witnessed an increasing attention on condition monitoring and RUL prediction for machinery. RUL prediction methods are generally categorized into two types, namely model-based method and data-driven method. Model-based method involves the knowledge of a system failure mechanisms to build a mathematical description of the system degradation process, and uses measured data to update the model parameters [12]. Common model-based method includes Winner process model, Gamma process model, Markov process model, random Gaussian model, etc. Data-driven method uses previously measured data to forecast the system state or match with history patterns to infer RUL [13]. It includes but is not limited to artificial intelligence method, statistical method, reliability functions [14]. The quality and quantity of history data measured during operation of machinery is important for ensuring accuracy of prediction.

Although a large number of studies have focused on the field and put effort into improving the prediction accuracy, an inevitable error between the prediction value and real failure time always exists, making the conduction of maintenance actions earlier or later than the ideal timing. Let us assume that the age of component i in turbine k is A_{ik}^m in mth inspection point. By using condition monitoring and RUL prediction method, the predicted failure time is $\widetilde{F}_{ik}$, then its predicted RUL percentage $\widetilde{P}_{ik}^m$ can be described as $\widetilde{P}_{ik}^m = (\widetilde{F}_{ik} - A_{ik}^m)/\widetilde{F}_{ik}$. If the real failure time is F_{ik}, its real RUL percentage P_{ik}^m is $P_{ik}^m = (F_{ik} - A_{ik}^m)/F_{ik}$.

The average prediction errors all over the degradation process, denoted by $\overline{e}$, is commonly used to estimate the prediction performance [15]. If the total number of inspection points is M, the error $\overline{e}$ is calculated as:

$$\bar{e} = \frac{1}{M}\sum_{m=1}^{M}\left|P_{ik}^{m} - \tilde{P}_{ik}^{m}\right| \quad (1)$$

Furthermore, it is noted that the prediction performance may not be completely constant throughout the degradation process. The RUL prediction is usually not reliable at an earlier stage. As the degradation process goes on, more data obtained may provide enough information and prediction results become more accurate when it gets close to the failure time [16].

In this study, at mth inspection point, the error between predicted RUL percentage $\widetilde{P}_{ik}^{m}$ and real RUL percentage P_{ik}^{m}, denoted by e_{ik}^{m}, is assumed to follow a Gaussian distribution:

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

where μ_{ik}^{m} is median and δ_{ik}^{m} is standard deviation. As the decrease of RUL, the prediction accuracy improves, indicating the error e_{ik}^{m} is gradually reduced. It is assumed that $\mu_{ik}^{m} = \mu_a + P_{ik}^{m}\mu_b$ and $\delta_{ik}^{m} = \delta_a + P_{ik}^{m}\delta_b$, which means the median and standard deviation of the error decreases as the reduction of RUL percentage. In this way, the deviation of predicted and real failure times is presented, and average prediction errors $\overline{e}$ can be estimated by varying values of $\mu_a, \mu_b, \delta_a, \delta_b$.

B. Stochastic attributes of time to failure (TTF)

Even if the deviation of predicted and real failure times can be perfectly eliminated by using advanced technology, stochastic attributes of TTF are still a type of uncertainty affecting estimation of the maintenance model. Although the bathtub curve is widely used to describe the hazard function of offshore wind turbines, most studies assumed that failure rates are constant during lifetime. Based on the constant failure rates, various failure distribution functions and parameters can be selected to produce random lifetimes representing the discrete failure events in time during simulation. The potential uncertainty in the distribution functions and parameters has a straightforward influence on the generated TTF values of components [17].

Reference [2] has investigated the influence of statistical uncertainty of component reliability estimations in the aspect of availability. It mainly focused on the failure distribution around a mean addressing the statistical uncertainty when the data collection method is not clear enough. The paper mentioned the uncertainty of failure distribution functions and parameters under the constant failure rates discussed above, but didn't reflect this time-based mechanism in that paper.

As shown in Table I, if the failure rate of a generator is 0.125/year [5], the mean time to failure (MTTF) can be computed as 2924 days. It means simulated failures occur every 2924 days on average, but the failure distribution and parameters may vary, then leading to different shapes of failure distribution. Weibull distribution is widely used in reliability engineering to represent failure characteristics of mechanical and electromechanical machinery. Further, some other distributions have also been selected to evaluate the failure behaviours, such as exponential distribution [18], Gaussian distribution [19], uniform distribution [2]. The various failure distribution and parameters will affect the generation of failure events in the simulation, and then make the outputs different.

TABLE I

DIFFERENT FAILURE DISTRIBUTION UNDER THE SAME FAILURE RATE

Component	Failure distribution	Parameter	MTTF (days)	Failure rate (per year)
Generator	Weibull distribution	3300,2	2924	0.125
	Weibull distribution	3274,3		
	Uniform distribution	1462,4386		
	Gaussian distribution	2924,500		
	Exponential distribution	2924		

C. Uncertain maintenance quality

A perfect maintenance action can completely recover the system to a perfect state, and an imperfect maintenance procedure can recover the component to a state between the initial perfect state and current operation state. A large number of studies of wind energy maintenance assumed the imperfect maintenance recovers the age/reliability of component with a fixed and certain value. Quality of imperfect maintenance is closely related to many factors including technician expertise, maintenance methods and tools, environment conditions, and so on [20]. For instance, human factors, which is defined as physical and psychological capabilities of the individual, like training, education and experience, has a straightforward and significant influence on the performance of maintenance activities [21]. In this work, we only discuss the possible stochastic behaviours of maintenance quality which are caused by these factors, instead of deeply investigating how the factors affect maintenance quality.

If the age of component i in turbine k is A_{ik}^{m} in mth inspection, and then it is performed on an imperfect maintenance with the maintenance quality θ which means the age of the component can be reduced to a percentage of θ. The component age is updated to $A_{ik}^{m}\theta$ after the conduction of maintenance. When the value of θ is 0, it means this is a perfect maintenance because the age is reduced to 0 and the component is restored to a perfect state. When the value of θ is 1, it means this maintenance action doesn't improve the component state at all. It is usually difficult to specify accurately the maintenance quality in practice. Even if the same maintenance action is carried out on one component several times, the final maintenance quality is difficult to be guaranteed the constant. It is more practical to model the maintenance quality as a random value represented by an appropriate probability distribution. The value of quality of imperfect maintenance θ is between 0 and 1. In probability theory and statistics, the beta distribution is a family of continuous probability distributions defined on the interval [0, 1]. The distribution is parameterized by two shape parameters, denoted by α and β. The random value of θ is assumed to follow a beta distribution [22]. The probability density function which is defined on the support [0,1] is:

$$f(\theta)=\frac{1}{Beta(\alpha,\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1} \tag{3}$$

where α and β are two positive shape parameters, and $Beta(\alpha,\beta)=\int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt$.

The expected value μ_θ is:

$$\mu_\theta=\frac{1}{1+\frac{\beta}{\alpha}} \tag{4}$$

The standard deviation σ_θ is:

$$\sigma_\theta=\left(\frac{\alpha\beta}{(\alpha+\beta)^2(1+\alpha+\beta)}\right)^{\frac{1}{2}} \tag{5}$$

The values of μ_θ and σ_θ can specify the quality of imperfect maintenance. The value of μ_θ represents the expected maintenance quality, and the value of σ_θ characterises the uncertainty of the maintenance quality. As shown in Fig.1, when the expected maintenance quality is of the same value 0.7, the value σ_θ can change the instability of the maintenance quality. As the increase of σ_θ, the maintenance quality disperses in a larger range due to more influence from external factors, e,g,. maintenance techniques, environment factors.

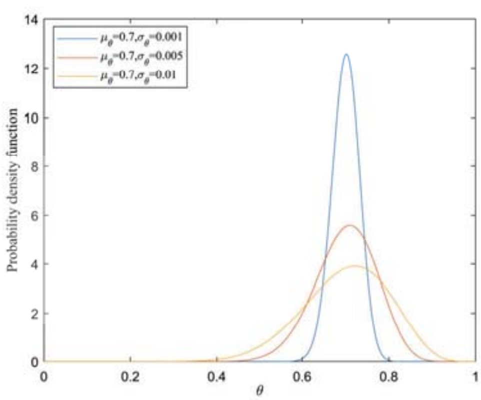

Fig. 1. Probability density function of uncertain maintenance quality

The maintenance quality improves with the amount of the budget invested and the time spent during conduction of maintenance activities [23]. In other words, the money and time spent during maintenance is related to the maintenance quality. Therefore, we assume the stochastic maintenance quality means the consumed repair cost and time also vary correspondingly. It should be clarified that the existence of uncertain maintenance quality induces a difference between the actual maintenance quality and the improvement we expect, and the repair cost and time are considered to be the same once the actual maintenance quality is the same.

If the actual maintenance quality is θ, the corresponding repair cost C_θ is :

$$C_\theta=C_r(1-\theta)^{f_\mathrm{c}} \tag{6}$$

where C_r denotes the replacement cost and f_c determines the exact relationship between maintenance quality and corresponding repair cost [24].

Similarly, the repair time for imperfect maintenance T_θ is:

$$T_\theta=T_r(1-\theta)^{f_\mathrm{t}} \tag{7}$$

where T_r denotes the repair time for replacement; f_t determines the exact relationship between maintenance quality and corresponding repair time. The values of f_c and f_t are assumed to be certain and fixed in this subsection. For example, if the value of f_c is 2 and maintenance quality is 0.7, then we can obtain $C_\theta=(0.3)^2C_r$, which is a common method to estimate repair cost in many studies [25].

D. Uncertain repair cost and time

Generally, the money and time spent on maintenance are positively related to maintenance quality. However, the specific relationship is not explicit enough so far. On the one hand, the cost and time of different types of maintenance can be collected in wind energy industry, but the quality and quantity of these historical maintenance record is still not sufficient enough to explore the explicit relationship and make accurate estimation [26]. On the other hand, similar to uncertain maintenance quality, the maintenance cost and time is affected by many factors such as the maintenance method. In addition, some studies mentioned the existence of different inherent characteristics among components, such as age, may result in the varying maintenance cost and time [27]. Instead of specifying a deterministic values (constants that are known in advance), it is more reasonable to represent the repair cost and time in a probabilistic approach [28].

Equation (6) and (7) can estimate repair cost and time according to maintenance quality. Instead of certain values, f_c and f_t can be represented by a probability distribution. In this study, they are assumed to follow a Gaussian distribution $N(\mu_r,{\sigma_r}^2)$. Fig. 2 illustrates the relationship between cost ratio R_c, time ratio R_t and maintenance quality θ, where $R_c=\frac{C_\theta}{C_r}$, $R_t=\frac{T_\theta}{T_r}$, $\mu_r=2$, and σ_r increases from 0 to 0.5. By introducing the probability distribution to replace the fixed f_c and f_t, the uncertainty of repair cost and time can be modelled. In the paper, we keep the value of μ_r constant (equal to 2), as it is commonly set as 2 in many studies of wind energy maintenance [15]. The change of σ_r can help us model the uncertainty in different degree.

III. Simulation Module

In this section, maintenance cost and lost production during the lifetime of offshore wind farm is evaluated based on a

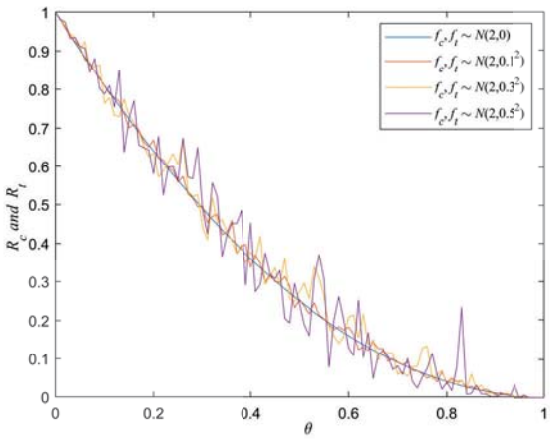

Fig. 2. Cost ratio and time ratio versus maintenance quality under different uncertainty

simulation-based maintenance model developed earlier [29]. As shown in Fig.3, the model includes the following maintenance opportunities:

- Failure-based opportunity. When the component fails due to degradation, the maintenance opportunity will be triggered
- Incident-based opportunity. If a critical incident occurs causing component failure, the maintenance opportunity will appear.
- Age-based opportunity. No component fails, but a certain number of components reach the specific age threshold, the maintenance opportunity will arrive.

The component states are classified into four cases: failed, aged, mature, and young. For the failed component, it should be completely replaced. The total cost of failure replacement is $M_{\text{total}}^{\text{CR}}$. If the component age reaches the maximum age threshold, it should be replaced preventively. The cost spent on preventive replacement is $M_{\text{total}}^{\text{PR}}$. The mature components between maximum and minimum age thresholds are performed major repair on. The total cost for major repair is $M_{\text{total}}^{\text{MR}}$. There is no maintenance needed for young components. In addition, fixed cost $M_{\text{total}}^{\text{f}}$ is used to prepare a maintenance cycle. Transportation cost $M_{\text{total}}^{\text{TR}}$ represents the money for transportation in the offshore wind site. If the lifetime of offshore wind farm is S years which N cycles of maintenance are carried out during the lifetime, then the annual maintenance cost C_{annual} is calculated as follows:

$$\begin{aligned} &C_{\text{annual}}(A^{\min}, A^{\max}, \zeta) = \frac{1}{S}\sum_{n=1}^{N}\big(M_{\text{total}}^{\text{f}} + \\ &M_{\text{total}}^{\text{TR}} + M_{\text{total}}^{\text{PR}} + M_{\text{total}}^{\text{CR}} + M_{\text{total}}^{\text{MR}}\big) \\ &\text{s.t.} \quad 0 < A^{\min} < A^{\max} < 1 \end{aligned} \tag{8}$$

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

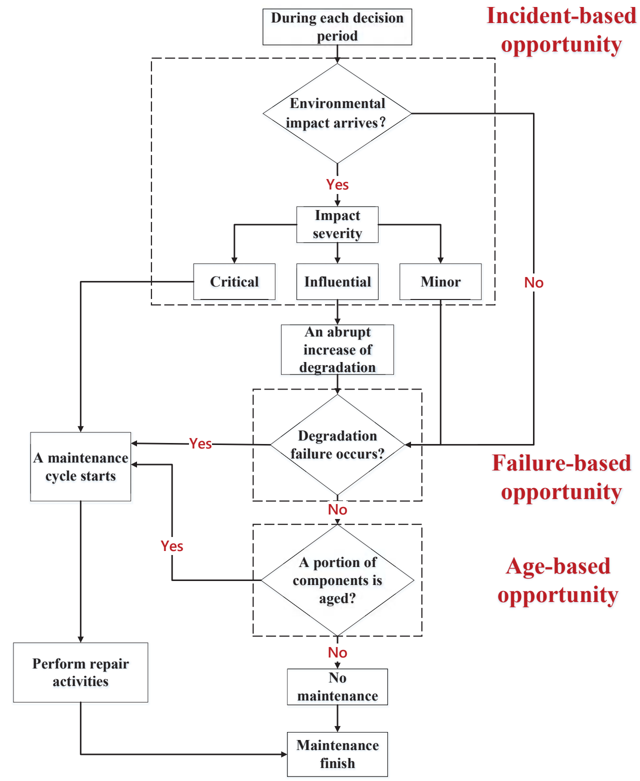

Fig. 3. The flow chart of the developed opportunistic maintenance model

the proposed model. The variable, ζ, can determine how many aged components can trigger the age-based opportunity. More details can be found in the [29].

In addition to maintenance cost, availability and lost production are the expected outputs of the model as well. The downtime of the turbine results from two aspects: turbine failure and maintenance execution. During these periods of time, the turbine can not produce power. The number of offshore wind turbine is K. The total downtime of turbine k during its lifetime is denoted by D_k^{d}, the total repair time is D_k^{r}, and the operational time is D_k^{w}. The availability of the offshore wind farm A_{farm} can be calculated as:

$$A_{\text{farm}} = \frac{\sum_{k=1}^{K} D_k^{\text{w}}}{\sum_{k=1}^{K}\left(D_k^{\text{d}} + D_k^{\text{r}} + D_k^{\text{w}}\right)} \tag{9}$$

The lost power (P_{loss}) is modelled based on the daily average wind speed during downtime and repair time. Every wind turbine design has a cut-in wind speed (v_{in}), a cut-out wind speed (v_{out}), and a rated wind speed (v_{rated}). When the wind speed reaches cut-in speed, the blades begin to rotate and electricity is produced. As the speed reaches the rated wind speed, the turbine can produce power in the rated power (P_{rated}). If the wind speed is higher than cut-out speed, then it may risk damage from further operation. In such a overspeeding situation, brake mechanism is needed to shut down the turbine before it reaches the danger zone. The relationship between wind speed (v) and power generation (P_{ge}) is [30]:

$$P_{\text{ge}} = \begin{cases} 0 & 0 \leq v < v_{\text{in}} \\ P_{\text{rated}}(a + bv + cv^2) & v_{\text{in}} \leq v < v_{\text{rated}} \\ P_{\text{rated}} & v_{\text{rated}} \leq v < v_{\text{out}} \\ 0 & v_{\text{out}} \leq v \end{cases} \tag{10}$$

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

$$a = \frac{v_{\text{in}}}{(v_{\text{in}} - v_{\text{rated}})^2}[(v_{\text{in}} + v_{\text{rated}}) - 4v_{\text{rated}}\left(\frac{v_{\text{in}} + v_{\text{rated}}}{2v_{\text{rated}}}\right)^3] \tag{11}$$

$$b = \frac{1}{(v_{\text{in}} - v_{\text{rated}})^2}[4(v_{\text{in}} + v_{\text{rated}})\left(\frac{v_{\text{in}} + v_{\text{rated}}}{2v_{\text{rated}}}\right)^3 - (3v_{\text{in}} + v_{\text{rated}})] \tag{12}$$

$$c = \frac{1}{(v_{\text{in}} - v_{\text{rated}})^2}\left[2 - 4\left(\frac{v_{\text{in}} + v_{\text{rated}}}{2v_{\text{rated}}}\right)^3\right] \tag{13}$$

IV. Case study and results

The proposed method is applied in an offshore wind farm, designed for a 20-year lifetime, located in the North Sea (Fig. 4). The location is about 30 km away from the Netherlands shore. The scale of the farm is 50 turbines, and each 5-MW turbine is composed of five critical components (gearbox, generator, rotor blade, main bearing and pitch system). The total capacity of the farm is 250 MW. The technical specification of the turbine is shown in Table II.

Fig. 4. Geographical localization of the offshore wind farm in the North Sea

In order to investigate the influence of different types of uncertainty on the outputs of the proposed maintenance model, it is necessary to derive a set of results as the benchmark. Deterministic parameters shown in Table III and Table IV are set as the input parameters. Further, fixed cost is 50 k€, transportation cost is 10 k€. Maintenance improvements of two levels are 0.5 and 0.7 respectively, indicating the maintenance quality will be more significant for older components. The repair time for failure replacement and preventive replacement is 70 hours and 50 hours respectively. The model assumes a work shift of 8 hours each day. The above deterministic parameters are derived and estimated from studies [5], [31], [32].

TABLE II
Technical specification of the 5-MW turbine

Rating	5 MW
Rotor configuration	3 blades
Drivetrain	High speed, multiple-stage gearbox
Rotor diameter	126 m
Hub height	90 m
Cut-in speed	3 m/s
Rated speed	12 m/s
Cut-out speed	25 m/s

TABLE III
Failure distribution of five critical components

Component	Weibull distribution	
	Shape parameter	Scale parameter
Rotor&blade	3	3000
Bearing	2	3750
Gearbox	3	2400
Generator	2	3300
Pitch system	3	1858

By using Monte Carlo method, the simulation module is run in the following base scenario: $A^{\max} = 0.9$, $A^{\min} = 0.5$, ζ=1.2% for 500 times, the average values of the outputs including annual maintenance cost C_{annual}, availability A_{farm}, and total lost production $P_{\text{farm}}^{\text{lost}}$ are regarded as the benchmark results listed in Table V.

We need to make a comparison under the same uncertainty level with the purpose of exploring which uncertainty is more influential for the model output. We introduce the mean absolute percentage error (MAPE) denoted by $\bar{U}$ to represent uncertainty level:

TABLE IV
Cost parameters of five critical components

Component	Failure replacement (k€)	Preventive replacement (k€)
Rotor&blade	215	55
Bearing	60	15
Gearbox	260	65
Generator	90	25
Pitch system	44	10

TABLE V
Benchmark results

	Cost (k€)	Availability (%)	Production loss (MWh)
Benchmark	1100	99.12	219140

$$\bar{U} = \frac{100}{X}\sum_{x=1}^{X}\frac{|V_\mathrm{f} - V_\mathrm{u}|}{V_\mathrm{f}} \tag{14}$$

where V_f and V_u is the expected fixed value and produced uncertain value of input parameter correspondingly; X is sample size. Different uncertainty levels are calculated by varying parameters in the uncertainty module. In this paper, the influence of different types of uncertainties is compared under three uncertainty levels: 5%, 10%, and 15%. The comparison is shown in Table VII. The MAPE of benchmark equals 0. We use U1, U2, U3, and U4 respectively represent four types of uncertainty as shown in Table VI.

TABLE VI
NOMENCLATURE OF DIFFERENT TYPES OF UNCERTAINTY

Uncertainty type	Nomenclature
deviation of predicted and real failure times	U1
stochastic attributes of time to failure	U2
uncertain maintenance quality	U3
uncertain repair cost and time	U4

TABLE VII
COMPARISON OF DIFFERENT TYPES OF UNCERTAINTY UNDER THREE UNCERTAINTY LEVELS

MAPE (%)	Uncertainty type	Cost (k€)	Availability (%)	Production loss (MWh)
0	-	1100	99.12	219140
5	U1	1135	99.09	227060
	U2	1127	99.11	221200
	U3	1108	99.10	223060
	U4	1103	99.12	219380
10	U1	1296	99.00	248480
	U2	1161	99.09	227150
	U3	1136	99.08	229180
	U4	1110	99.10	223020
15	U1	2485	98.19	451970
	U2	1222	99.06	235260
	U3	1176	99.05	236460
	U4	1114	99.10	224870

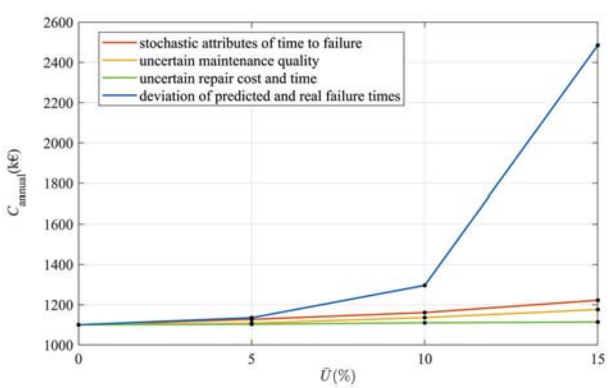

Fig. 5. Uncertainty level versus annual maintenance cost

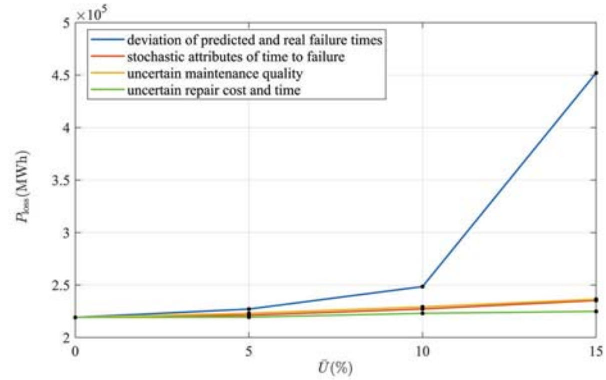

Fig. 6. Uncertainty level versus lost production

Fig. 5 and 6 illustrates the three uncertainty levels versus annual maintenance cost and lost production. When $\bar{U}$ is 5%, the model outputs considering four types of uncertainty are all close to the benchmark results, because the degree of the uncertainty is still relatively small. With the increase of $\bar{U}$, the effect of U1 becomes particularly obvious when compared to U2, U3, and U4. When $\bar{U}$ is as large as 15%, the output considering U1 is more than twice than the benchmark. Such a large deviation between failure and real times causes two results: (1)A large number of component lifetimes are underestimated, hence they are not repaired in a timely manner. Many turbines may break down due to the underestimation, then more maintenance cycles are triggered, and a large amount of maintenance cost and lost production are induced due to the turbine failure. (2)A large number of component lifetimes are overestimated. Preventive repair and replacement is conducted in a premature way, resulting in more maintenance cycles and much unnecessary cost. These two reasons can explain why the influence of U1 is so large. Compared to U1, the effect of U2, U3, and U4 is relatively small, but it doesn't mean they don't deserve our concern. The influence of U2 and U3 is close. When $\bar{U}$ is 15%, the deviation caused by U2 and U3 in the economic aspect is about 11.1% and 6.9%, and the deviation is 7.4% and 7.9% respectively in the aspect of loss production. U2 is more influential than U3 in terms of maintenance cost, and it is reversed when in terms of lost production. Compared to others, U4 is the least prominent. The deviation of maintenance cost and production loss is 1.3% and 2.6% respectively when $\bar{U}$ is 15%. It may be explained by the fact that this paper mainly focuses on the uncertain cost and time for major repair, which only is a portion of total maintenance cost and repair time.

The effect of each type of uncertainty is discussed respectively below. In every inspection point, we can predict the failure time of component $\widetilde{F}_{ik}$. Then, maintenance decisions are made based on the predicted failure time. The deviation between predicted and real failure time naturally result in the timing of maintenance decisions that are not ideal. As introduced in the uncertainty module, parameters $\mu_a, \mu_b, \delta_a, \delta_b$ are used to describe the degree of deviation. Four cases are selected to make the comparison: $\mu_a = \delta_a = 0.01$, $\mu_b = \delta_b = 0.1$ (case 1-1); $\mu_a = \delta_a = 0.02$, $\mu_b = \delta_b = 0.1$ (case 1-2); $\mu_a = \delta_a = 0.01$, $\mu_b = \delta_b = 0.2$ (case 1-3); $\mu_a = \delta_a = 0.02$, $\mu_b = \delta_b = 0.2$ (case 1-4). The comparison is shown in Table VIII. It is found that as accuracy of prediction decreases (average prediction error grows), the deviation between outputs and benchmark increase at a growing rate. We use $\hat{E}$ to denote the deviation percentage between outputs and benchmark results. The simulation is run in more cases to roughly demonstrate the relationship between $\hat{E}$ and $\overline{e}$, as shown in Fig.7 where we use an exponential distribution to fit. When average prediction error $\overline{e}$ is 10%, the deviation of maintenance cost and production is about 16% and 12% respectively. If we set the acceptable value of $\hat{E}$ for both cost and production is 20%, it indicates the average prediction error should be no more than 10.5%. In recent years, some studies have shown that their methods can improve the average prediction error as good as about 10% [33], which provides a powerful tool for making the maintenance decisions more accurate and effective.

TABLE VIII
COMPARISON CONSIDERING DEVIATION BETWEEN PREDICTED AND REAL FAILURE TIME

	Cost (k€)	Availability (%)	Production loss (MWh)	Average prediction error(%)
Case 1-1	1165	99.07	229730	7.0
Case 1-2	1228	99.04	237800	8.2
Case 1-3	1623	98.79	301960	12.8
Case 1-4	2041	98.51	372580	14.0

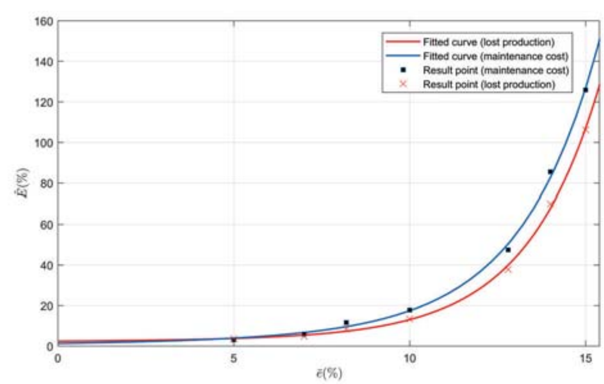

Fig. 7. Average prediction error versus output error

When investigating the influence of different failure distributions and parameters, the simulations are run under different cases listed as: Weibull distribution, shape parameter is 3 (case 2-1); Weibull distribution, shape parameter is 2 (case 2-2); Weibull distribution, shape parameter is 2.5 (case 2-3); Weibull distribution, shape parameter is 3.5 (case 2-4); Exponential distribution (case 2-5); Uniform distribution (case 2-6); Gaussian distribution, standard deviation is 300 (case 2-7); Gaussian distribution, standard deviation is 500 (case 2-8); Gaussian distribution, standard deviation is 700 (case 2-9).

The results of the different cases are listed in Table IX. When we use Weibull distribution to model component failure and compare it with the benchmark, the deviation of maintenance cost varies from -7.5% to +12.4% and the deviation of lost production is from -8.5% to +9.5%. Further, as the increase of shape parameter (from 2 to 3.5), the outputs, maintenance cost and lost production, will both decrease. When Exponential distribution is adopted, we can find there is a large difference in the result (maintenance cost: +78%, lost production: +71.8%). When using Gaussian distribution and Uniform distribution, the outputs are both lower than benchmark, and the scale of the difference is much less than Exponential distribution. Based on the results, it is found that:

(1) The selection of failure time modelling has an obvious influence on the outcome of maintenance model. Although Weibull distribution is commonly used in wind industry, the uncertainty of Weibull distribution parameters still significantly affect the results.

(2) When failure times of components are modelled by using the distribution where failure times tend to stay within a narrow range around MTTF, the outputs of the model are lower. It can explain the lower results when using the Weibull distribution with higher shape parameter and the Gaussian distribution with less standard deviation to model component failure times.

TABLE IX
MODEL OUTPUTS UNDER DIFFERENT FAILURE DISTRIBUTIONS AND PARAMETERS

Case	Cost (k€)	Availability(%)	Production loss(MWh)
2-1	1056	99.17	207030
2-2	1236	99.03	240010
2-3	1129	99.11	221910
2-4	1017	99.20	201060
2-5	1958	98.49	376520
2-6	989	99.22	194480
2-7	905	99.27	179720
2-8	948	99.24	188250
2-9	1019	99.18	204750

In (5), a larger standard deviation means the actual maintenance quality is more unstable. Three cases are conducted to study the influence of uncertain maintenance quality: standard deviation is 0.001 (case 3-1); standard deviation is 0.005 (case 3-2); standard deviation is 0.01 (case 3-3). The results of different cases are listed in Table X. As the increase of uncertainty of maintenance quality, the results also grow in a roughly linear trend.

Repair cost and time are modelled as a random value by randomizing f_{c} and f_{t} in (6) and (7). Three cases are presented in Table XI: $\sigma_r = 0.1$ (case 4-1); $\sigma_r = 0.3$ (case 4-2); $\sigma_r = 0.5$ (case 4-3). The results are shown in Table XI.

TABLE X
MODEL OUTPUTS UNDER UNCERTAIN MAINTENANCE QUALITIES

Case	Cost (k€)	Availability(%)	Production loss(MWh)
3-1	1112	99.10	223700
3-2	1158	99.06	233760
3-3	1213	99.02	244800

TABLE XI
MODEL OUTPUTS UNDER UNCERTAIN REPAIR COST AND TIME

Case	Cost (k€)	Availability(%)	Production loss(MWh)
4-1	1108	99.11	218100
4-2	1127	99.08	229410
4-3	1181	99.02	242170

V. CONCLUSIONS

Most of the O&M models for wind energy commonly assume the input parameters are certain and known in advance. However, such an assumption may bring a negative influence on the investment estimation and decisions-making for offshore wind farm owners, because the model output is largely misestimated due to the existence of the uncertainty. In order to assist the owners to make a realistic estimate and provide valuable suggestions for the project management, it is necessary to identify the potential uncertainty which affects the O&M model outcome, and then quantify the extent of influence. We make the conclusions and provide the suggestions as follows:

(1) The most influential uncertainty is resulted from the deviation between failure and real failure times, followed by stochastic attributes of time to failure and uncertain maintenance quality. Uncertain repair cost and time cause the least difference compared to benchmark results, which can almost be neglected.

(2) Considering the deviation of predicted and real failure times, the increase of the RUL prediction error results in an exponential increase of deviation between the probabilistic model output and benchmark results. If a more accurate O&M estimation is expected, offshore wind farm owners should pay high attention to condition monitoring and RUL prediction technology. If we set the acceptable deviation as 20%, the average prediction error should be no more than about 10.5%.

(3) Considering the stochastic attributes of TTF, the failure distribution and parameters have an obvious influence on the outputs of the maintenance model, especially when adopting Exponential distribution. When we use the distribution with the shape where failure times are more concentrated around MTTF, the model outputs are less. It can be explained by the different characteristics of the failure distribution. If a more accurate failure database can be developed or the failure information can be updated during the full lifetime, the deviation resulted from stochastic attributes time to failure may be eliminated to some extent.

(4) The uncertain maintenance quality, cost, and time may be caused by some factors such as environment conditions, human factors, and inherent characteristics among components when conducting maintenance activities on offshore wind turbines. The total consumed costs and time will be reduced if maintenance activities can be carried out in a more stable manner through enhancing technician training, improving maintenance methods, etc. Furthermore, if the quantity and quality of maintenance data can be ensured and improved, a more explicit relationship between maintenance activities and corresponding consumption can be clarified and then input in the O&M model. An unambiguous input can assist the offshore wind industry to estimate the O&M results more accurately and reliably.

There are still limitations in the model. The data and parameters input in the model are derived from the existing literature. If more real data can be obtained in the future, the model output will be more realistic. Furthermore, the model mainly focuses on the maintenance decisions regardless maintenance logistics organization, and potential uncertainties exiting in maintenance logistics organization are not clarified and studied. It is assumed that 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. The accessibility to the location of the farm will not be affected by any negative factor. These assumptions make the output of model (especially availability and lost production)higher than the practical case where failed turbines can only be repaired in scheduled maintenance activities. Maintenance logistics organization is significant in the O&M process for offshore wind farms, and the potential uncertainties deserve our attention and effort. Further, in the long lifetime of offshore wind farm, the investment, such as material cost, is assumed to stay constant and doesn't change due to the change of policy, the development of technology, etc. The cost for hiring vessels, technicians, and other logistics related cost are not considered in the model. The authors will gradually take these factors into account in the future work.

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