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An opportunistic maintenance strategy for offshore wind turbine system considering optimal maintenance intervals of subsystems

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ABSTRACT

Operation and maintenance (O&M) costs account for a large proportion of the total costs for offshore wind energy. Performing a reasonable maintenance strategy is an effective approach to reduce O&M costs and gain more profits. In this paper, an opportunistic maintenance strategy for offshore wind turbine systems considering maintenance intervals of each subsystem is proposed to minimize the total maintenance cost. First, a Non-homogeneous Continuous-Time Markov Process based state transition model is established to study degradation process of subsystems. The influence of maintenance time schedule on the maintenance cost is studied to obtain the optimal maintenance intervals of each subsystems. Then, an opportunistic maintenance model considering economic dependencies between multiple subsystems is proposed to optimize the maintenance strategy by combining maintenance activities of individual subsystems to a grouping maintenance activity. A numerical example is used to indicate the significant effectiveness of the maintenance model. The result shows that the total maintenance cost of an offshore wind turbine system will be reduced by adopting the opportunistic maintenance strategy when compared with conventional preventive maintenance strategy.

1. Introduction

Limited fossil fuel capacity and global greenhouse gas emission have become critical issues. As one of the effective solutions for global warming and environmental pollution, the development of renewable energy is attracting significant attention from many countries. Compared with biofuel, water power, geothermal heat, and solar energy, wind energy trends to be the most widely explored renewable energy resource in the near future. Furthermore, with advantages of higher wind speed, steadier wind supply and unlimited installation space [15], offshore wind energy is showing its enormous potential especially when populations keep rising and land becomes scarcer.

Offshore wind turbines (OWT) operate in the complicated environment and suffer from the harsh marine conditions including waves, weather, winds, water currents, sea ice, and salt-fog[24], under which they face more severe risk events and degrade to break down with more probabilities. Shafiee[38] adopted a fuzzy analytic network process (FANP) approach to evaluate the most effective risk mitigation strategy for offshore wind farms. The study concluded that the improvement of maintenance activities is the most suitable solution of reducing the risks related with offshore wind farms. Feng et al.[16] and Ren et al.[36] discussed how to reduce risks and optimize reliability for complicated systems in dynamic environments, and a case study of an offshore wind farm was presented. Moreover, Lin et al.[27] proposed that the O&M cost can contribute more than 30 % of the total life-cycle cost for offshore wind farms. Once the maintenance strategy is unreasonable, a negative influence on the reliability and performance of the offshore wind farm will be caused, resulting in lower wind power output and unnecessary maintenance costs. For improving reliability of OWTs and reducing the O&M costs, it is necessary to provide an appropriate maintenance strategy for OWTs.

The existing maintenance strategies for OWTs can be generally categorized into two types, namely corrective maintenance (CM) and preventive maintenance (PM). CM, can be also called reactive maintenance, only performs after failures occur during operation time, aiming to restore or recover operation conditions[49]. PM is carried out under given intervals or based on certain criterion, like the age of turbines or schedule of operation[21]. Compared with CM, although PM has the advantages of effectively guaranteeing the system reliability and power output, but unnecessary inspection and maintenance activities for OWTs cannot be avoided[33]. Until now, CM and PM are still the major maintenance strategies in offshore wind industrial practice, but based on these two maintenance strategies, more maintenance strategies have been developed in recent years, such as condition-based maintenance (CBM) and opportunistic maintenance. Due to rapid development of continuous monitoring and inspection techniques, CBM has received increasing attention in the O&M field of offshore wind systems. Based on health states and degradation process of equipment which are reflected by recorded data from condition monitoring systems, the potential failure occurrences can be predicted, thus maintenance performance can be scheduled in advance[48]. As a maintenance strategy which depends on combining data-driven methods with condition monitoring systems installed on OWTs[2], CBM is showing its potential at aspects of reducing failure times during operation, improving reliability of systems, de-

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creasing maintenance costs[17].

Generally, maintenance activities are considered to be in conflict with production operations[8]. In fact, although preventive maintenance can slow down the equipment degradation and reduce the need for complex and expensive corrective actions, it shows a negative impact on the availability of equipment. Among preventive maintenance strategies, opportunistic maintenance is an effective method to reduce the impact of maintenance operations in multi-stage manufacturing systems[23]. McCall[30] firstly introduced the concept of opportunistic maintenance, which is an effective strategy to reduce the interference between maintenance and production operations in a multi-component manufacturing system. According to this strategy, due to the dynamic behavior of the system, preventive maintenance tasks should be performed when a suitable window of opportunity is available. Opportunity windows are defined as specific time intervals generated by favorable system conditions, where preventive maintenance tasks can be performed. By taking advantage of these opportunity windows, the coordination between production and maintenance operations can be better achieved, thereby reducing the impact of maintenance on system performance. Compared with the conventional scheduled maintenance strategy, the opportunity maintenance strategy can save more maintenance costs. The reason is that the opportunity maintenance strategy can repair multiple components in a single dispatch, so it has obvious advantages in saving fixed maintenance costs. This strategy sets the concept of maintenance opportunities, that is, a single repair activity to repair multiple equipment satisfying maintenance conditions and requirements. Under this premise, only one maintenance activity is needed, and a single fixed maintenance cost is generated to conduct the replacement and maintenance activities of multiple components. Therefore, the opportunity maintenance strategy can avoid unnecessary costs, making maintenance costs more reasonable.

The optimization of maintenance strategies for multi-unit systems is usually more complicated than single-unit systems [39]. The reason is that dependencies among units should be taken into consideration. Dependencies can be categorized into three types, economic[9], structural[37], and stochastic [32]. As a typical multi-component system which are composed of many subsystems, OWTs also have these dependencies, implying it is inevitable to consider these dependencies when optimizing maintenance strategies[12]. In an offshore wind farm, if a failure takes place on one turbine, a maintenance team will set out to perform maintenance [18]. The advantage of opportunistic maintenance is taking this opportunity to simultaneously repair other deteriorated components meeting maintenance conditions in this failed turbines or other operating ones[13]. Obviously, economic dependencies exist among these components and turbines. In comparison with sending teams to repair single components in one single maintenance activity, opportunistic maintenance policies can save a large amount of substantial cost[14]. Yildirim et al. [46] studied the game between optimal maintenance schedule driven by real-time sensor data, and cost reduction brought by opportunistic maintenance. Zhang et al. [47] proposed an opportunistic maintenance model for wind turbines, meanwhile reliability-based imperfect maintenance is taken into account. considered three types of maintenance including perfect, imperfect and two-level action to develop an opportunistic maintenance policy for wind farms. Ding and Tian [10] considered three types of maintenance including perfect, imperfect and two-level action to develop an opportunistic maintenance policy for wind farms. Abdollahzadeh et al. [1] optimized opportunistic maintenance for a wind farm under the situation that number of maintenance team is limited. Maximizing the production rates and reducing the total expected maintenance costs as low as possible are both objectives during optimization. In the literature[50], by analyzing condition monitoring data by an artificial neural network (ANN) model, life percentages of components can be predicted. Then, a dynamic opportunistic condition-based maintenance strategy is proposed for offshore wind farms considering the economic dependencies. Most of the current OM models use failure rates or failure distribution (such as Weibull distribution) to illustrate the degradation process of complicated systems. These conventional models have two discrete states, namely, functional and failure. However, the binary-state model is insufficient to describe multi-state degradation systems, which are widespread in practice.

Actually, subsystems of OWT can consecutively degrade into several operation and failure states, meaning they can be assumed as multi-state systems and operation performance decreases as working time goes on. The Markov process is a common method to analyze reliability of multi-state degraded system[28, 4].Hou et al. [19] proposed a continuous time Markov chain based sequential analytical approach to evaluate reliability of composite power system. Ye et al. [45] proposed a mixed integer nonlinear programming (MINLP) model where system failures and maintenance are considered as a continuous-time Markov chain, then the inspection and repair tasks are optimized in terms of both time and money. When paying attention to issues about reliability analysis and maintenance of wind energy, Markov process also demonstrates excellent capacity and potential. Besnard and Bertling [5] adopted a continuous time Markov chain to model the deterioration process of wind turbine blades, hence condition-based maintenance strategies could be optimized according to the degradation status. Li et al. [26] improved a Hidden-Markov model considering performance degradation in order to realize the reliability analysis of wind turbine bearing. Byon and Ding [6] adopted a Markov model to show the aging behavior of wind turbines, then studied the effect of weather, failure modes, imperfect or perfect repairs and revenue losses on maintenance effort, and chose the most cost-efficient maintenance scheduling. Huang et al. [20] presented a Markov-chain-based availability model to evaluate mean availability of OWTs, and finally found correlation between logistic activities, maintenance investment and OWT availability. According to the literature, when developing degradation models of wind turbines components, the state transition rates are usually assumed to be constant, indicating that these transition rates will not change as the time goes by. But the systems may degenerate in a continuous manner in the practical situations, so the state transition rates are continuous-time. Hence, a continuous-time Markov model should be adopted to describe how offshore wind turbine components will degrade during operation.

The study about degradation processes and maintenance strategies for OWTs are not sufficient enough according to the literature reviewed. In order to optimize maintenance strategy for OWTs, the turbine is always simplified as a system with critical components such as gearbox, generator, rotor and bearing, indicating the influences of other components or subsystems and their mutual dependencies have to be neglected to some degree. Moreover, aiming to study working states of components or subsystems, Markov models are usually adopted to describe the degradation processes. The conventional Markov models only use constant transition rates to establish the state transition processes, which is obviously not reasonable enough because the states of subsystems should be dynamic and state transition rates are time-dependent. Finally, when optimizing OM strategy for offshore wind systems, the current study usually adopted failure rates or Weibull models to determine failure events of subsystems. This assumption is not convincing enough especially for OWTs, this kind of complex multi-state degraded system.

The objective of this study is to propose an optimal OM strategy for OWT systems following the criteria of minimizing the total maintenance cost. First, the entire OWT system is separated into seven subsystems, namely drivetrain, electrical system, generator, rotor blade, rotor hub, control and yaw system, to preserve integrity of the system as much as possible. Second, in order to study deterioration of each subsystem more accurately, the Non-homogeneous Continuous-Time Markov Process (NHCTMP) model is established to illustrate degradation processes, then a recursion algorithm is used to efficiently calculate the time-dependent state distribution of the multi-state system. Using these state transition probabilities, the optimal maintenance schedule for each subsystem can be determined, thereby minimizing the expected maintenance cost per unit time. Eventually, an OM strategy is integrated and developed in OWT level considering maintenance activities of each subsystems, achieving the goal of reducing the total cost of maintenance to the lowest.

The remainder of the paper is listed as follows. Section 2 is devoted to the Non-homogeneous Continuous-Time Markov Process which can illustrate degradation processes of these subsystems. Section 3 proposes an opportunistic maintenance strategy considering economic dependence among subsystems. Section 4 makes a brief introduction of offshore wind turbine system and applied case study. In Section 5, calculation results and analysis are presented. Finally, conclusions and future works are presented in Section 6.

2. Non-homogeneous Continuous-Time Markov Process

There are several operation states corresponding to different working efficiency for subsystems of OWT. Degradation caused by harsh marine environment leads to a decrease of system condition. Markov theory can be employed to analyze degradation problem of such multi-state systems. Based on the conventional Markov theory, the concept of time change is introduced to develop Markov Process. In this paper, the subsystems of OWT have several separate states which are defined as from perfect states to ultimate failure state. The degradation process of multi-state system is modeled as a Non-homogeneous Continuous-Time Markov chain. By solving Chapman-Kolmogorov equation, the time-dependent state probability can be obtained. In terms of these state probabilities, the optimal age-based replacement time and the minimum expected cost per unit time can be determined.

2.1. State probability

If $\phi(t) \in \{0, 1, 2, \cdots, M\}$ presents the state of system at time t, and $\phi(t)$ follows the continuous time Markov process [43, 29], when $0 \le t_1 < t_2 \cdots < t_n < t_{n+1}$

$$\begin{aligned} &P\{\phi(t_{n+1}) = k_{n+1} \,|\phi(t_1) = k_1, \cdots, \phi(t_n) = k_n\} \\ &= P\{\phi(t_{n+1}) = k_{n+1}\phi(t_n) = k_n\} \end{aligned} \tag{1}$$

When $t \ge 0$, $s \ge 0$, the transfer probability is related to time t, $P_{i,j}(t, t+s)$ means the probability that the system is in state i at time t given that the system is in state j at time $(t+s)$

$$P_{i,j}(t, t+s) = P\{\phi(t+s) = j \,|\phi(t) = i\} \tag{2}$$

Based on Markov theory, when $t \ge 0$, $s \ge 0$

$$P_{i,j}(t, t+s) \ge 0 \tag{3}$$

$$\sum_{j=0}^{M} P_{i,j}(t, t+s) = 1(i, j = 0, 1, 2, \cdots, M) \tag{4}$$

The C-K equation can be derived

$$P_{i,j}(t, t+s+u) = \sum_{k=0}^{M} P_{i,k}(t, t+s)P_{k,j}(t+s, t+s+u) \tag{5}$$

Then, it can be written as

$$P(t, t+s+u) = P(t, t+s)P(t+s, t+s+u) \tag{6}$$

Suppose a finite time h, if $h > 0$

$$P_{i,j}(t, t+h) = \lambda_{i,j}(t)h + o(h) \tag{7}$$

Where $\lambda_{i,j}(t)$ is the state transfer rate from state$i$ to j at time t. Therefore, it is a continuous function related to t. The equation of C-K can be written as

$$P_{i,j}(0,t+h)=\sum_{k=0}^{M}P_{i,k}(0,t)P_{k,j}(t,t+h)= \\ P_{i,j}(0,t)P_{j,j}(t,t+h)+\sum_{k=0,k\neq j}^{M}P_{i,k}(0,t)P_{k,j}(t,t+h) \tag{8}$$

At any time t, when $h>0$

$$P_{i,j}(0,t+h)-P_{i,j}(0,t)=P_{i,j}(0,t)* \\ \left[P_{j,j}(t,t+h)-1\right]+\sum_{k=0,k\neq j}^{M}P_{i,k}(0,t)P_{k,j}(t,t+h) \tag{9}$$

As the model proposed, assuming $\phi(0)=M$ and according to $P_j(t)=P_{M,j}(0,t)$ and $P_j'(t)=P_{M,j}'(0,t)$, it can be obtained a

$$P_j'(t)=P_j(t)(-\sum_{k=0,k\neq j}^{M}\lambda_{j,k}(k))+\sum_{k=0,k\neq j}^{M}P_k(t)\lambda_{k,j}(t) \tag{10}$$

Where $P_M(0)=1$, $k\neq M$, and $P_j(t)$ is the probability that the multi-state system transfers from state M at the beginning into state j at time t. The formulation can be shown as a matrix as

$$P'(t)=P(t)A \tag{11}$$

$$P(t)=[P_M(t)P_{M-1}(t)P_{M-2}(t)\cdots P_1(t)P_0(t)] \tag{12}$$

$$P'(t)=[P_M'(t)P_{M-1}'(t)P_{M-2}'(t)\cdots P_1'(t)P_0'(t)] \tag{13}$$

$$A=\begin{bmatrix}\lambda_{M,M}(t) & \lambda_{M,M-1}(t) & \cdots & \lambda_{M,0}(t)\\ 0 & \lambda_{M-1,M-2}(t) & \cdots & \lambda_{M-1,0}(t)\\ 0 & 0 & \cdots & \lambda_{M-2,0}(t)\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \lambda_{1,0}(t)\\ 0 & 0 & \cdots & 0\end{bmatrix} \tag{14}$$

For a multi-state system with $M+1$ states, its state transfer probability based on the C-K equation can be acquired as [22]

$$P_M(t)=P\{\phi(t)=M\}=\exp\left[\int_0^t\lambda_{M,M}(s)ds\right] \\ =\exp\left[-\int_0^t\sum_{k=0}^{M-1}\lambda_{M,k}(s)ds\right] \tag{15}$$

$$P_i(t)=P\{\phi(t)=i\}=\sum_{k=i+1}^{M}\int_0^t P_k(\tau_{M+1-k}) \\ \lambda_{k,i}(\tau_{M+1-k})\exp\left[\int_{\tau_{M+1-k}}^t\lambda_{i,i}(s)ds\right]d\tau_{M+1-k} \\ =\sum_{k=i+1}^{M}\int_0^t P_k(\tau_{M+1-k})\lambda_{k,i}(\tau_{M+1-k}) \\ \exp\left[-\int_{\tau_{M+1-k}}^t\sum_{j=0}^{i-1}\lambda_{i,j}(s)ds\right]d\tau_{M+1-k} \tag{16}$$

2.2. Degradation model establishment

The Non-homogeneous Markov model is applicable to multi-state degradation systems, hence it can be applied to subsystems of OWT. By establishing the suitable degradation model, the reliability of the multi-state system can be illustrated.

2.2.1. System description

In the process of degradation, the performance rate decreases from the initial state to failure state. Multi-state system has $(n+1)$ different operating states, and gradually degraded from state 1 to n. Sudden failure will make the system transfer to state $(n+1)$ immediately. The system starts working at time 0 in the initial perfect state, and the interval between preventive maintenance is T, meaning preventive maintenance will be regularly performed at time $kT(k=1,2,3,\cdots)$. The time required for inspection is relatively short compared to the duration of maintenance, so this period is negligible.In this maintenance model, the minimum repair will be carried out when sudden failure happens. It can only restore the system to the working state before the sudden failure. Perfect preventive maintenance can repair the system to the initial operating state. Imperfect preventive maintenance can restore the system into the working state before the final failure state. After a preventive maintenance cycle, the system returns to its original state.

The diagram of the Non-homogeneous Continuous-Time Markov model is shown in Fig.1, where the parameters are defined as, S_1 is the initial perfect function state; S_i is the degradation states of the system, where $i=2,\ldots,n-1$; S_n is the ultimate failure state after gradual degradation; S_{n+1} is the state caused by sudden failure from any working state; $\lambda i,j(t)$ is the transition rate from state i to j at time t, where $i,j=1,2,\ldots,n+1$ and $i<j$

The Chapman-Kolmogorov equation of the system, which follows the Non-homogeneous Continuous-Time Markov Process, can be expressed as a matrix as

$$\left[P_1{}'(t)P_2{}'(t)\cdots P'n(t)P'n+1(t)\right]= \\ \left[P_1(t)P_2(t)\cdots P_n(t)P_{n+1}(t)\right]* \\ \begin{bmatrix}\lambda_{1,1}(t) & \lambda_{1,2}(t) & \cdots & \lambda_{1,n}(t) & \lambda_{1,n+1}(t)\\ 0 & \lambda_{2,2}(t) & \cdots & \lambda_{2,n}(t) & \lambda_{2,n+1}(t)\\ 0 & 0 & \cdots & \lambda_{3,n}(t) & \lambda_{3,n+1}(t)\\ \vdots & \vdots & \ddots & \vdots & \vdots\\ 0 & 0 & \cdots & \lambda_{n,n}(t) & \lambda_{n,n+1}(t)\\ 0 & 0 & \cdots & 0 & 0\end{bmatrix} \tag{17}$$

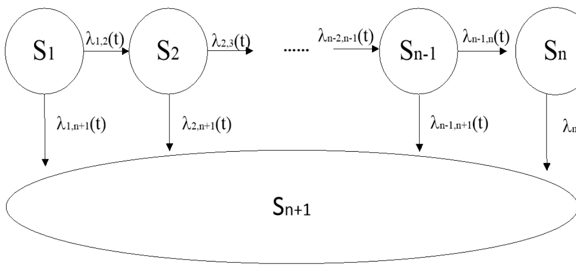


Figure 1: State transition diagram of Non-homogeneous Continuous-Time Markov Process

Where $\lambda_{i,i}(t) = -\sum_{j=i+1}^{j+1} \lambda_{i,j}(t)$,$P_j(t)$ indicates the possibility that system is in state j at time t, and $P_j'(t) = \partial P_j(t)/\partial t$. S_{n+1} is the failure state and absorption state in the model. The system will not change once it develops into S_{n+1}. According to the Markov theory, the value of $\lambda_{n+1,n+1}(t)$ is 0.

Sheu and Zhang [40] calculated the possibilities that the system is at different states at time t based on the state transition matrix

$$P_1(t) = \exp\left[\int_0^t \lambda_{1,1}(s)ds\right] \tag{18}$$

$$P_j(t) = \sum_{i=1}^{j-1} \int_0^t p_i(\tau_i)\lambda_{i,j}(\tau_i)\exp\left[\int_{\tau_i}^t \lambda_{j,j}(s)ds\right] d\tau_i \tag{19}$$

$$P_{n+1}(t) = 1 - \sum_{j=1}^{n} P_j(t) \tag{20}$$

At the initial time 0, $P_1(0) = 1$, , because the system must be in complete perfect state, and it is impossible to be in other states at the beginning. The reliability function $R(T, w)$ of the system should be selected based on the state of the system

$$R(t, w) = \Pr\{G(t) \geq w\} \tag{21}$$

$G(t)$ represents working efficiency of the system. Only when it is greater than w, the system is considered to be reliable. Hence the reliability function is the sum of possibilities of each acceptable state.The distribution function $F(t, w)$ is the sum of probabilities of all unacceptable states. $f(t, w)$ is the probability density of failure state,

$$f(t, w) = \frac{\partial F(t, w)}{\partial t} = \frac{\partial}{\partial t}\left(\sum_{j=m+1}^{n+1} P_j(t)\right) \tag{22}$$

Further the failure rate of system can be calculated as

$$r(t, w) = \frac{f(t, w)}{R(t, w)} = \frac{\frac{\partial}{\partial t}(\sum_{j=m+1}^{n+1} P_j(t))}{\sum_{j=1}^{m} P_j(t)} \tag{23}$$

2.2.2. State transition rates

The state transition rate of the system is a function following Weibull distribution,

$$\lambda_t(i, j)(t) = \beta {\alpha_{i,j}}^{\beta} t^{\beta-1} \tag{24}$$

The scale and shape parameters are related to the degeneration coefficient of the objects. The value of $\alpha_{i,j}$should meet the following requirements that with the increase of operation time, transient degradation rate should increase, and the possibility of degrading to the distant state is less than to the recent state. The scale parameter is assumed to be [22, 43]

$$\alpha_{i,j} = \frac{1}{(5-i) - 0.5 * (5-j)} \tag{25}$$

Because the state transition rates should also be related to $MTTF$, so

$$\lambda_{i,j}(t) = \lambda_t(i, j)(t) * \frac{1}{(MTTF)_{i,j}} \tag{26}$$

Based on the characteristics of Markov matrix,

$$\lambda_{i,i}(t) = -\sum_{j=i+1}^{6} \lambda_{i,j}(t) \tag{27}$$

In the state classification, state 5 is the ultimate failure state after degradation process and state 6 is the failure state after sudden failure, which cannot meet the production requirements. States from 1 to 4 are acceptable working states. Therefore, reliability function $R(t, w)$, failure function$F(t, w)$, probability density function $f(t, w)$ and failure rate function $r(t, w)$ are obtained.

2.2.3. Maintenance cost rate calculation

In the whole maintenance scheduling, the total number of preventive maintenance before the final perfect maintenance is set as N, and $\bar{P}k$ is the possibility that the first k preventive maintenance is imperfect ($N > k$). Then the probability that the k-th repair is an imperfect repair is $\bar{P}_k \big/ \bar{P}_{k-1}$. The probability that the k-th repair is perfect is [42]

$$\theta_k = 1 - \frac{\bar{P}_k}{\bar{P}_{k-1}} \tag{28}$$

In the model, u_{k-1} is the effective life of the equipment after the $(k-1)$th imperfect repair, and a_{k-1} is the service life improvement factor after each imperfect repair. With each maintenance, the service life improvement factor will gradually weaken [11], and

$$A_k = \sum_{i=1}^{k-1} \prod_{l-i}^{k-1} a_l \tag{29}$$

After kth imperfect repair, the effective age becomes $u_k = a_{k-1}u_{k-1}+T = \left(A_k+1\right)T$. The failure rate in the kth circle will be $r_k(t,w) = r(a_{k-1}u_{k-1}+s,w)$, and $0 < s < T$.

$\bar{P}_k$ is the probability that the first k preventive maintenances are imperfect preventive maintenance. The probability of each imperfect preventive maintenance is a constant value q. Hence the probability of each imperfect maintenance is q. The value of $\bar{P}_{k-1}$ decreases with the increase of k, so $\bar{P}_k$ is q^k. According to [41] , the value of service age improvement factor b_k can be obtained as $k/(5k+1)$.

The cost of perfect preventive maintenance, imperfect preventive maintenance and minimum maintenance is C_{Pm}, C_{Im} and C_{min} respectively, and the fixed cost of each maintenance is C_0, then these expenses constitute the total maintenance cost of the system. The maintenance costs of the k-th maintenance scheduling can be obtained, and maintenance cost rates can be calculated as,

$$M(T; w, \{\bar{P}_k\}) = \frac{\sum_{k=1}^{\infty}(\bar{P}_{k-1}-\bar{P}_k)}{\sum_{k=1}^{\infty}(\bar{P}_{k-1}-\bar{P}_k)kT} * C_{total} \tag{30}$$

where $r_i(t,w) = r(b_{i-1}y_{i-1}+s,w)$ and $0 < s < T$.

$$\begin{aligned} C_{total} &= (k-1)(C_{Im}+C_0)+(C_{Pm}+C_0)+ \\ &(C_{mim}+C_0)\int_0^T r_k(s,w)ds \end{aligned} \tag{31}$$

3. Opportunistic maintenance model

Based on the Non-homogeneous Continuous-Time Markov Process, the degradation processes of each subsystem have been analyzed, and the optimal maintenance intervals have been proposed. Next, multiple individual components will be studied as the whole system, and the opportunistic maintenance can be modeled to achieve the optimization.

3.1. Model description

When establishing an opportunistic maintenance model for a multi-component system, the following assumptions need to be set

(1) A multi-component system is composed of a number of mutually independent components. The number of components is set to n.

(2) When the state of the component reaches a preset reliability threshold, preventive maintenance operations can be performed on the component, so that maintenance can be performed in advance to avoid failure.

(3) If the component fails before preventive maintenance, then corrective maintenance measures need to be taken to return the component to normal working condition, and this maintenance activity will not change the failure rate of the component. When the preventive maintenance operation is completed, the equipment will enter another circle of degradation process.

(4) When entering the opportunity maintenance phase, each component under maintenance is assumed to share the same downtime and downtime loss,

Based on the above assumptions, an opportunistic maintenance model for a complex system with multiple components is established. In the process of maintenance, perfect repair and imperfect repair are mainly involved. When perfect repair is performed, the system will return to the original perfect state again, and the operation life regression factor $\alpha_i = 0$, so $n_{i,j+1}(t) = n_{i,j}(t)$. $n_{i,j}(t)$ is the failure rate function of component i before the j-th preventive maintenance. When imperfect repair is performed, the multi-component system cannot return to the original perfect state. The failure rate function of component i before and after the j-th preventive maintenance can be expressed as $n_{i,j+1}(t) = n_{i,j}(t+\alpha\times\Delta t_{i,j})$. $\Delta t_{i,j}$ represents the j-th preventive maintenance cycle of component i, Based on the previous assumptions, a certain reliability threshold is set for the component in advance. Once the component i reaches the threshold R_i, a preventive maintenance circle is taken, so

$$\int_0^{\Delta t_{i,1}} n_{i,1}(t)dt = ... = \int_0^{\Delta t_{i,j}} n_{i,j}(t)dt = N_{fi} \tag{32}$$

The meaning of $\int_0^{\Delta t_{i,j}} n_{i,j}(t)dt$ is the cumulative failure risk of component i during the j-th preventive maintenance cycle. In this case, the number of accidental failures and the number of repairs in the model are actually the same.

In the total time T, the expected repair cost of the component i is

$$EC_i = \frac{C_0 + C_{m(i)}(N_{fi}) + C_{p(i)} + C_{d(i)}\tau_{i,j}}{\Delta t_{i,j} + \tau_{i,j}} \tag{33}$$

where C_0 represents the fixed cost, $\Delta t_{i,j}$ represents the preventive maintenance time period of component i, $\tau_{i,j}$ is the time consumed for this preventive maintenance, $C_{m(i)}$ is the maintenance cost required for accidental failure, $C_{p(i)}$ and $C_{d(i)}$ are the cost of a preventive maintenance for component i and the economic loss due to equipment shutdown per unit time respectively.

3.2. Model establishment

Suppose $t_{i,j}$ is the operation time of component i at the j-th preventive maintenance, and $\Delta t_{i,j}$ the time period of preventive maintenance, then $t_{i,j}$ can be expressed as $t_{i,1} = t_{begin} + \Delta t_{i,1}$, and

$$t_{i,j} = t_{i,j-1} + \Delta t_{i,j-1} + \tau_{i,j-1}(j > 1) \tag{34}$$

t_{begin} is the start time of maintenance, and under the normal situation, the value is 0. The time of each preventive repair of the multi-component system during the whole maintenance circle can be known.

For a complex system with n components, when performing preventive maintenance on one of the components, part i will get a chance to be repaired within the maintenance duration $\tau_{k,j}$ of part k. If this opportunity is adopted, at this time the maintenance cost is

$$C_{S(i,k,j)} = C_0 + C_{D(i,k,j)} + C_{M(i,k,j)} - C_{P(i,k,j)} \quad (35)$$

where $C_{D(i,k,j)}$ represents the loss of equipment shutdown when component i and component k are being repaired at the same time, which can be calculated by

$$C_{D(i,k,j)} = C_{d(i)} \times \tau_k \quad (36)$$

$C_{M(i,k,j)}$ means if the repair opportunity is performed on component i, the avoided economic loss caused by accidental failure,

During the overall maintenance plan, the maintenance time will be constantly updated. Assume $\Delta t_{i,j}$ is the preventive maintenance time at the start time, and $\Delta t'_{i,j}$ is the updated preventive maintenance time. The total time deviation accumulated after such a long time is

$$\delta t_{i,k} = \sum_{j=1}^{M} (\Delta t_{i,j} - \Delta t'_{i,j}) M = \min\{N_i, N_i'\} \quad (37)$$

where N_i is the number of preventive maintenance in the initial scheduling, N_i' indicates the number of preventive maintenance in the plan as the update changes.

At the beginning, the component failure function $n_{i,j}(t)$ and the updated component failure function $n'_{i,j}(t)$ can be calculated, and the economic loss of component i after the opportunistic maintenance is

$$C_{P(i,k,j)} = E\overline{C}_i \times \delta t_{i,k} = E\overline{C}_i \times \sum_{j=1}^{M} (\Delta t_{i,j} - \Delta t'_{i,j}) \quad (38)$$

It can be calculated that if the opportunistic maintenance strategy is adopted for component i and component k, the maintenance cost can be reduced. If $C_{s(i,k,j)} < 0$, it means that the opportunistic repair cannot save the maintenance cost, it is not appropriate to take advanced maintenance for component i; if $C_{s(i,k,j)} > 0$, it means that the opportunistic maintenance can reduce the maintenance cost, and simultaneous repair measure should be adopted for component i and component k.

The next step is to analyze all the components in the multi-component system as a whole, calculate the maintenance cost of multiple opportunities for group maintenance, and select the most economical maintenance solution. Assuming that the maintenance timing combination of the multi-component system is set G, there will be a subset $G_1, G_2, ..., G_l$ at each maintenance time, and

$$\begin{aligned} &G_p \cap G_q = \emptyset (p \neq q) \\ &G_1 \cup G_2 \cup ... \cup G_l = G \end{aligned} \quad (39)$$

When the number of components in a multi-component system increases, the subset in the set G will increase rapidly, so that the number of maintenance grouping schemes that need to be considered is also increasing. All maintenance combinations will be calculated and the cost balance will be obtained

$$C(G_l) = \sum_{i \in G_l} C_{S(i,k,j)} (i \neq k) \quad (40)$$

The cost balance of different combinations will be compared, then the optimal opportunistic maintenance strategy is the combination with the largest cost savings.

4. Offshore wind turbine system and numerical example

The strategy will be applied on an offshore wind turbine system. On system level of OWTs, the overall system can be divided into several subsystems. Based on the fault detection and fault isolation theory, considering the detection time, error detection and missed detection, as well as fault trigger problems and system restart faults, there are various criterion for separating system. Márquez et al. [31] divided the wind turbine system into four major subsystems, namely, power train, foundation and tower, generator, electrical and electronic components, and blade system based on the logicality and integrity of fault tree method. Odgaard et al. [34] considered failures of wind turbine system level and divided the system into sensor subsystem, actuator subsystem, pitch subsystem, drive train subsystem, generator subsystem, and converter subsystem. In this paper, in order to facilitate reliability analysis and maintenance planning optimization research, the overall system is separated into multiple subsystems, mainly considering the interconnection of the various subsystems and different types of maintenance activities. The separation is based on the components function, the specificity of maintenance requirement and maintenance strategy. The OWT system is separated into seven subsystems: electrical subsystem, drive train, generator, rotor blade, rotor hub, electrical control, yaw subsystem. It is noted that this work focus on the OWT system, including blades and nacelle, therefore the tower and foundation are not considered.

The degradation process of subsystem is divided into several states, which have been described in [35]. Life cycles of subsystems have been studied, and aging components are more likely to fail due to stress-induced damage or environmentally induced ruptures. The risk of failure is expected to be different in different life cycle phases. It is assumed that the subsystems of the OWT follow the five life cycle phases: introduction, maturity, ageing, terminal, failure. The residence time between states is the value of $(MTTF)_{i,j}$.

5. Results

Due to the difference of the repair types, we can determine that the minimum maintenance cost is less than the imperfect maintenance and the perfect maintenance, which are summarized in Table 1. Model parameters in the model are listed in Table 2. These data can be referred to [25, 7].The production loss per day due to maintenance is assumed to be 7500 Euros.

5.1. Maintenance cost rate

According to the model establishment and calculation in Chapter 3, the maintenance cost rates of each subsystems can be obtained. In Fig. 2, the curves representing the cost rates are illustrated. The bottom of curves is the selection of optimal maintenance intervals. It can be concluded that the optimal maintenance intervals for electrical system, drive train, generator, rotor blade, rotor hub, electrical control, yaw system are 3.9 years, 2.7 years, 4.2 years, 3.8 years, 2.3 years, 4.1 years, and 5.7 years respectively. According to the optimal maintenance cost rate of each subsystem, the maintenance cost per unit of time will rapidly decrease within the initial period of time, and as the decline rate slows down to the lowest point of the curve, it will then increase. The lowest point of the maintenance cost curve is the optimal maintenance intervals in the maintenance strategy. The results demonstrate that in the process of formulating a maintenance strategy, the total maintenance cost will vary greatly with the maintenance interval. When the maintenance interval is too short or too long, the maintenance strategy is not economical due to excessive maintenance costs or excessive reduction in equipment reliability, resulting in high maintenance costs. From the curve in the figures, it can be seen that the maintenance cost rate varies not so much during a period of time near the lowest point, and this point is the most economical. If the maintenance interval is set in this period of time, after multiple rounds of preventive maintenance, the total maintenance and operation cost is the most cost-effective.

At the same time, it can be noted that maintenance cost rates are different for various subsystems. This is because the formulation of maintenance strategies involves many aspects, including the cost of different types of maintenance, different equipment failure rates, diverse Weibull distribution parameters, etc., which shows that different subsystems need to formulate corresponding repair plans according to their characteristics.

5.2. Maintenance schedule

Based on the degradation illustrated by Non-homogeneous Continuous-Time Markov Process, the calculation results are inputted to the opportunistic maintenance model for the OWT system. The simulation time is set to 10 years. Fig.3 shows the time of maintenance schedule. The blue bars represent the performance of opportunistic maintenance, and the red ones represent preventive maintenance. It can be found that every opportunistic maintenance must be triggered by a preventive maintenance carried out at the same time. The reason is only the preventive maintenance can bring an opportunity to conduct opportunistic maintenance on components satisfying repair requirements.

Table 1
Cost of different maintenance types[25, 7]

	Perfect repair /Euros	Imperfect repair /Euros	Minimum repair /Euros	Shutdown /days
Electrical system	12000	2000	100	3
Drive train	197000	59000	4200	7
Generator	70000	22000	3500	4
Rotor blade	90000	41000	4700	6
Rotor hub	51000	32000	3500	5
Electrical control	13000	2300	180	1
Yaw system	10500	12000	7000	2

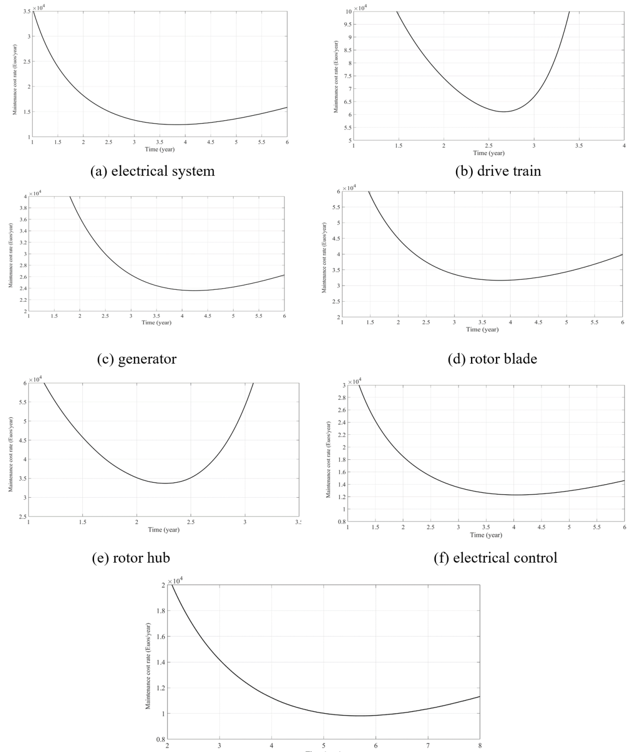
Table 2
Model parameters of each subsystem[25, 7]

	Imperfect repair probability q	Shape parameter	Shape parameter
Electrical system	0.89	2.3	3455
Drive train	0.71	10.4	7988
Generator	0.77	2	3300
Rotor blade	0.99	3	4783
Rotor hub	0.97	8.3	2581
Electrical control	0.99	2.3	4606
Yaw system	0.86	2.3	9024

In Table 3, the number of performed maintenance on each subsystem are presented. The results show that drive train and rotor system are the components which need to be checked and repaired frequently.Hence these repair activities can provide many maintenance opportunities for other components. Nearly all of the maintenance performed on electrical system, generator, and yaw system are opportunistic maintenance, indicating that the economic profits of opportunistic maintenance strategy are mainly generated from these three components. Detailed maintenance schedule times are listed in Table 4. From component 1 to 7 means electrical system, drive train, generator, rotor blade, rotor hub, electrical control, yaw system respectively.

5.3. Cost reduction

In order to illustrate the economic profits of the proposed method, a comparison analysis is presented between individual maintenance and OM. Table 5 shows that the opportunistic maintenance model can indeed reduce the overall cost



(a) electrical system (b) drive train

(c) generator (d) rotor blade

(e) rotor hub (f) electrical control

(g) yaw system

Figure 2: Maintenance cost rate of each subsystem

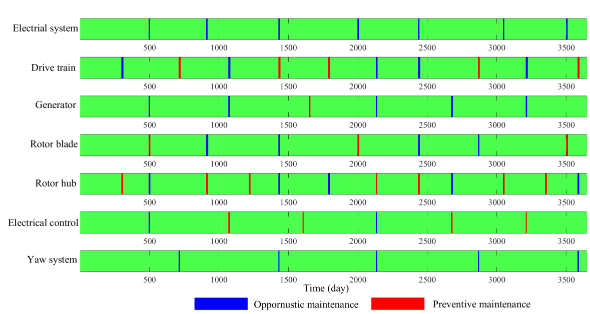


Figure 3: Schematic diagram of maintenance schedule times

by grouping various sub-components for maintenance. The maintenance cost will reduce from 1636 Euros/day to 1533 Euros/day, and percentage reduction will be 6.3%.

5.4. Comparison analysis

In this section, a comparison analysis between previous literature and current study will be performed.

Nguyen and Chou [33] proposed an approach to determine the optimal maintenance schedules for offshore wind system. By grouping maintenance activities of different component, the maintenance cost can be minimized. Xie et al. [44] developed an effective opportunistic maintenance strategy to reduce the maintenance costs of offshore wind turbines in consideration of their accessibility. Atashgar and Abdollahzadeh [3] formulated a joint redundancy and imperfect block opportunistic maintenance optimization model

Table 3
Number of performed maintenance on various components

Subsystem	Preventive maintenance	Opportunistic maintenance
Electrical system	0	7
Drive train	5	5
Generator	1	5
Rotor blade	3	4
Rotor hub	7	5
Elctrical control	4	2
Yaw system	0	5

Table 4
Maintenance schedule of each component

	Component						
Time point (days)	1	2	3	4	5	6	7
300	—	OM	—	—	PM	—	—
495	OM	—	OM	PM	OM	OM	—
711	—	PM	—	—	—	—	OM
910	OM	—	—	OM	PM	—	—
1069	—	OM	OM	—	—	PM	—
1215	—	—	—	—	PM	—	—
1429	OM	PM	—	OM	OM	—	OM
1604	—	—	—	—	—	PM	—
1649	—	—	PM	—	—	—	—
1788	—	PM	—	—	OM	—	—
1998	OM	—	—	PM	—	—	—
2130	—	OM	OM	—	PM	OM	OM
2435	OM	OM	—	OM	PM	—	—
2674	—	—	OM	—	OM	PM	—
2865	—	PM	—	OM	—	—	OM
3045	OM	—	—	—	PM	—	—
3209	—	OM	OM	—	—	PM	—
3350	—	—	—	—	PM	—	—
3501	OM	—	—	PM	—	—	—
3583	—	PM	—	—	OM	—	OM

Table 5
Strategy comparison

	Individual maintenance	Opportunistic maintenance
Daily cost (Euros)	1636	1533
Percentage reduction	——	6.3%

for wind farms, and minimizing maintenance costs is one of the objectives of the proposed model. Generally, the proposed opportunistic model in this paper can reduce the maintenance costs although the cost saving is not as significant as some literature. It can be explained by the scale effect of the numerical model. The better performance of opportunistic

Table 6
Comparison of cost savings in literature

References	Turbine conponents	Cost Savings (%)
Nguyen and Chou [33]	Rotor, generator, bearing, gearbox, electrical system, transmission cable	4.60%
This paper	Electrical system, drive train, generator, rotor blade, rotor hub, electrical control, yaw system	6.30%
Xie et al. [44]	Blade, gearbox, bearing, generator	10.20%
Atashgar and Abdollahzadeh [3]	Rotor, main bearing, gearbox, generator	10.40%

maintenance strategy can be achieved when the number of wind turbines is larger. In this paper, the proposed model is applied to an offshore wind turbines instead of a large-scale offshore wind farm. The reason is when the number of components considered increases, the number of grouping combinations will also increase exponentially, resulting in great difficulty in obtaining the optimal solution.

6. Conclusions

In this paper, we develop an opportunistic maintenance strategy for offshore wind turbines, aiming to decrease maintenance costs as far as possible during life time. As a typical multi-component system, the offshore wind turbine system can be separated into several subsystems which degrade with time going by. In order to evaluate operation states of offshore wind turbines, a Non-homogeneous Continuous-Time Markov Process (NHCTMP) is adopted to illustrate degradation processes of each subsystems. Following the Markov Process, the economic parameters during maintenance schedules are taken into account, hence the optimal maintenance intervals for each subsystems can be obtained following the objective to reduce maintenance cost. When we pay attention to the economic dependencies among subsystems, a large number of opportunities will be created during implementation of maintenance activities. Capturing these opportunities can effectively optimize maintenance strategies for offshore wind turbines.

For achieving the goal of reducing O&M costs for offshore wind energy, there are still many topics to be explored and completed in the future. The maintenance activities cannot usually carried out without any block. Weather conditions, availability of vessels or manpower, accessibility of the locations, these constraints can affect the implementation of maintenance scheduling. In addition, the maintenance strategy can also be updated from wind turbine level to wind farm level when considering these constraints, indicating the model will be more complicated but also more practical. The topics will be studied in the near future in order to apply theoretical maintenance models into realistic world.

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