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Condition based maintenance optimization for wind power generation systems under continuous monitoring

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ABSTRACT

By utilizing condition monitoring information collected from wind turbine components, condition based maintenance (CBM) strategy can be used to reduce the operation and maintenance costs of wind power generation systems. The existing CBM methods for wind power generation systems deal with wind turbine components separately, that is, maintenance decisions are made on individual components, rather than the whole system. However, a wind farm generally consists of multiple wind turbines, and each wind turbine has multiple components including main bearing, gearbox, generator, etc. There are economic dependencies among wind turbines and their components. That is, once a maintenance team is sent to the wind farm, it may be more economical to take the opportunity to maintain multiple turbines, and when a turbine is stopped for maintenance, it may be more cost-effective to simultaneously replace multiple components which show relatively high risks. In this paper, we develop an optimal CBM solution to the above-mentioned issues. The proposed maintenance policy is defined by two failure probability threshold values at the wind turbine level. Based on the condition monitoring and prognostics information, the failure probability values at the component and the turbine levels can be calculated, and the optimal CBM decisions can be made accordingly. A simulation method is developed to evaluate the cost of the CBM policy. A numerical example is provided to illustrate the proposed CBM approach. A comparative study based on commonly used constant-interval maintenance policy demonstrates the advantage of the proposed CBM approach in reducing the maintenance cost.
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1. Introduction

Maintenance management for wind power generation systems aims at reducing the overall maintenance cost and improving the availability of the systems. Since the operation and maintenance costs represent a substantial portion of the total life cycle costs of wind power generation systems [1], reliability and maintenance management of wind turbines have drawn increasing interests for the reduction of these costs [2–5]. The existing maintenance methods for wind energy systems can be classified into corrective maintenance, preventive maintenance (PM) and condition based maintenance (CBM) [6]. PM can be further divided into time-based and usage-based maintenance depending on the trigger mechanism. In time-based maintenance, the maintenance activities are routinely carried out based on the predetermined time interval or the age of the components. If the wind turbine lifetime is measured by usages such as the amount of energy produced, the maintenance action is triggered once the system has generated a specified amount of electricity. In many studies, though, the usage-based maintenance can be treated as a special case of the time-based maintenance in which the time is measured by the usage. Two challenging issues are always involved in PM: under-maintenance and over-maintenance. The former occurs when the system performance is not appropriately monitored, resulting in unexpected failures. For the over-maintenance, we tend to schedule excessive maintenance activities to prevent the unexpected down events, resulting in the waste of resources.

CBM is an advanced maintenance strategy that is based on performance and/or parameter monitoring and subsequent actions [7]. Maintenance decision is reached based on condition monitoring data, such as vibration data, acoustic emission data, oil analysis data and power voltage and current data, which are collected from wind turbine components [8,9]. In Refs. [10–12], Fourier transforms are used as a major signal processing technique for monitoring the wind turbine health conditions, which turns out to be very promising in

Abbreviations: PM, preventive maintenance; CBM, condition based maintenance; ANN, artificial neural network.

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Nomenclature

P_t	Life percentage obtained using artificial neural network (ANN);
μ_p	Mean of the ANN life percentage prediction error;
σ_p	Standard deviation of the ANN life percentage prediction error;
T_p	The predicted failure time;
N	The number of wind turbines in a wind farm;
M	The number of critical components considered in a wind turbine;
Pr	Failure probability;
$Pr_{n,m}$	The failure probability of component m in wind turbine n;
Pr_n	The failure probability of wind turbine n;
t	The age of a general component at the current inspection point;
L	The maintenance lead time;
d_1	Level 1 failure probability threshold value;
d_2	Level 2 failure probability threshold value;
C_E	The total expected maintenance cost per unit time;
$\mu_{p,m}$	Mean value of the ANN life percentage prediction error for component m;
$\sigma_{p,m}$	Standard deviation of the ANN life percentage prediction error for component m;
α_m	Weibull distribution scale parameter for component m;
β_m	Weibull distribution shape parameter for component m;
T_{Max}	The maximum simulation time;
T_I	The inspection interval;
$c_{f,m}$	The failure replacement cost for component m;
$c_{p,m}$	The variable preventive replacement cost for component m;
$c_{p,T}$	The fixed cost of maintaining a wind turbine;
c_{Farm}	The fixed cost of sending a maintenance team to the wind farm;
C_T	The total maintenance cost;
t_{ABS}	The current time in the simulation;
$TL_{n,m}$	The real failure time for component m in turbine n;
$t_{n,m}$	The current age of component m in turbine n;
$TP_{n,m}$	The predicted failure time for component m in turbine n using ANN;
$IF_{n,m}$	Indicating whether a failure replacement being performed on component m in turbine n;
$IP_{n,m}$	Indicating whether a preventive replacement being performed on component m in turbine n;
IT_n	Indicating whether a preventive replacement being performed on turbine n;
I_{Farm}	Indicating whether a maintenance team being sent to the wind farm;
t_{CI}	The maintenance interval in the constant-interval maintenance policy;
$C^{CI}_{p,m}$	The total cost of a failure replacement for component m in the constant-interval maintenance policy;
$C^{CI}_{f,m}$	The total cost of a preventive replacement for component m in the constant-interval maintenance policy;
$H_m\ (t_{CI})$	The expected number of failures for component m in interval $(0,t_{CI})$.

dealing with stationary degradation signals. In reality, signals from wind turbines are often non-stationary as large wind turbines often operate at variable speeds. The wavelet transform seems more appropriate in handling non-stationary signals [13]. In Ref. [14], a life cycle cost approach is adopted to evaluate the financial benefit using condition monitoring system, a tool for implementing CBM policy. In Ref. [15] a multi-state Markov decision process is used to estimate the wind turbine degradation process based on which the optimal maintenance scheme is devised.

By leveraging condition monitoring information, CBM is expected to reduce the operation and maintenance costs of wind power generation systems. Existing CBM methods for wind power generation systems deal with wind turbine components separately, that is, maintenance decisions are made on individual components, rather than the whole system [16]. However, wind farms are often located in remote areas or off-shore sites. Each wind farm consists of multiple wind turbines, and each wind turbine has multiple components including main bearing, gearbox, generator, shafts, etc. Obviously, there are economic dependencies among wind turbines and their components. That is, once a maintenance team is sent to the wind farm, it may be more economical to take the opportunity to maintain multiple turbines. If a turbine is stopped for maintenance, it may be more economical to replace or repair multiple components which have shown high risks of failures.

In this paper, a CBM policy is developed to address the abovementioned issues. The proposed policy is defined by two failure probability thresholds at the wind turbine level. Based on the condition monitoring information, decisions can be made on whether a maintenance team should be sent to the wind farm, which turbines should be maintained and which components should be maintained. A simulation method will be presented for evaluating the cost of the proposed CBM policy. Numerical examples will be used to illustrate the proposed approach, and comparisons to commonly used PM policies will be provided to demonstrate the advantage of the proposed CBM approach.

2. Component health condition prognostics

The objective of health condition prognostics is to predict the equipment future health conditions as well as the remaining useful life. At each inspection point, the condition monitoring measurements are collected, and the health condition prognostics methods can be used to estimate the failure time value or the remaining useful life. Some prognostics methods are also capable of estimating the associated prediction uncertainties. The health condition prediction methods can be divided into model-based methods and data-driven methods. The model-based methods, also known as the physics-of-failure methods, perform reliability prognostics using equipment physical models and damage propagation models. Model-based prognostics methods have been reported for analyzing component reliability such as bearings (Marble et al. [17]) and gearboxes (Kacprzynski et al. [18], Li and Lee [19]). The key limitation of the model-based methods is that for some components or systems, authentic physics-of-failure models are very difficult to build because equipment damage propagation processes and dynamic responses are very complex. Data-driven methods directly utilize the collected condition monitoring data for health condition prediction, and do not require physics-of-failure models. Examples of the data-driven methods include the proportional hazards model developed by Banjevic et al. [20], the Bayesian prognostics methods [21], and the ANN based prognostics methods [22,23].

Outputs of the prognostics methods are the predicted failure time and the associated uncertainty. That is, at a certain inspection point, the predicted failure time distribution can be obtained for the component being monitored. Among various data-driven methods, ANN based methods have been shown very effective and flexible for prognosing component health condition. In this work, we use the ANN prediction approach developed in Ref. [23]. The ANN model used in this approach is shown in Fig. 1, which is a feed forward neural network model with one input layer, two hidden layers and one output layer. The inputs of the ANN are the component age values and the condition monitoring measurements at the current and previous inspection points. The number of condition monitoring measurements used in the ANN model depends on the specific problem. In the example of the ANN model shown in Fig. 1, there are two condition monitoring measurements. Specifically, t_i is the age of the component at the current inspection point i, and t_{i-1} is the age at the previous inspection point $i-1$. z_i^1 and z_{i-1}^1 are values of measurement 1 at the current and previous inspection points, and z_i^2 and z_{i-1}^2 are values of measurement 2 at the current and previous inspection points. The output of the ANN model is the life percentage at current inspection time, denoted by P_i. For example, if the failure time of a component is 850 days and the age of the component at the current inspection point is 500 days, the life percentage value would be $P_i = 500/850 \times 100\% = 58.82\%$.

The ANN model utilizes failure histories as well as suspension histories. A failure history of a unit refers to the period from the beginning of the component life to the end of its life, a failure, and the inspection data collected during this period. In a suspension history, though, the unit is taken out of service before the failure occurs. Once trained, the ANN prediction model can be used to predict the remaining life based on the component age and the condition monitoring measurements. As mentioned above, the output of the ANN model is life percentage, based on which the predicted failure time can be calculated. For example, at a certain inspection point, if the age of the component is 400 days and the life percentage predicted using ANN is 80%, the predicted failure time would be 400/80% = 500 days.

To obtain the predicted failure time distribution, reference [25] developed a method to calculate the standard deviation of the predicted failure time. The basic idea is that the ANN life percentage prediction errors can be obtained during the ANN training and testing processes, based on which the mean, μ_p, and standard deviation, σ_p, of the ANN life percentage prediction error can be estimated. These values can be used to build the predicted failure time distribution at a certain inspection point. Suppose the component age is t and the ANN life percentage output is P_t, then the predicted failure time will be $t/(P_t - \mu_p)$, and the standard deviation of the predicted failure time will be $\sigma_p \cdot t/(P_t - \mu_p)$. That is, the predicted failure time T_p at the current inspection point follows the normal distribution as [25]:

$$T_p \sim N\left(t\Big/\left(P_t - \mu_p\right),\ \sigma_p \cdot t\Big/\left(P_t - \mu_p\right)\right) \tag{1}$$

It is assumed that the ANN life percentage prediction errors follow normal distribution, and due to this assumption, the predicted failure time at a certain inspection point also follows normal distribution. It is also assumed in Ref. [25] that the standard deviation of the ANN life percentage prediction errors is constant and does not change over time.

3. The proposed CBM approach for wind power generation systems

In this section, a CBM policy for wind power generation systems is proposed, and a simulation method for the cost evaluation of the proposed CBM policy is developed. Without loss of generality, suppose there are N wind turbines in the wind farm, and each turbine has M critical components. In this work, it is assumed that all the wind turbines under consideration are identical. We also assume that the degradation process of one wind turbine component does not affect those of other components and other wind turbines.

3.1. Failure probability estimation at the component and turbine levels

At the turbine component level, condition monitoring data, such as vibration data and acoustic emission data, can be collected, and failure time distribution can be predicted for each component using the prognostics methods presented in Section 2. It is assumed that the predicted failure time follows the normal distribution, as discussed in Section 2. The failure probabilities for the wind turbine components, which will be defined later, can be calculated based on the predicted failure time distributions. Therefore the CBM decisions will be made based on the failure probabilities. The failure probability for a general component is defined as follows [25]:

$$\Pr = \frac{\displaystyle\int_t^{t+L} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-t_p}{\sigma}\right)^2} dx}{\displaystyle\int_t^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-t_p}{\sigma}\right)^2} dx} \tag{2}$$

where, L is the maintenance lead time, which is defined as the interval between the time maintenance decision is made and the time when the maintenance is performed. Notice that t is the age of the component at the current inspection point, t_p is the predicted failure time using ANN, and σ is the standard deviation of the predicted failure time distribution. The failure probability for component m in turbine n is denoted by $\Pr_{n,m}$. Based on the discussions in Section 2, we can obtain the following relationships:

$$t_p = t\Big/\left(P_t - \mu_p\right), \sigma = \sigma_p \cdot t\Big/\left(P_t - \mu_p\right). \tag{3}$$

The lead time, L, consists of the time required to assemble the maintenance team, order the spare parts, prepare the repair equipment, and travel to the wind farm, etc. Thus, the maintenance decisions made at the current inspection point can affect the wind turbines only when the lead time has passed, and we have no influence on the failures during the lead time. So, it is reasonable to decide an optimal maintenance based on the probabilities of failures occurring during the lead time in order to reduce the failure risks. To reasonably simplify the problem, we assume L is the same for all maintenance actions in this study.

If the critical turbine components are considered, the wind turbine can be treated as a series system connected by rotor, main bearing, gearbox, generator, etc. That is, a failure of any component will lead to the system malfunction. Thus, the failure probability for wind turbine n during the lead time L can be expressed as follows:

$$\Pr_n = 1 - \prod_{m=1}^{M} \left(1 - \Pr_{n,m}\right) \tag{4}$$

3.2. The proposed CBM policy

For the purpose of simplifying the descriptions, we use replacement to refer to a maintenance action, such as the replacement of the main bearing, or the replacement of a faulty gear within the gearbox. Suppose wind turbine components are continuously monitored. Maintenance decisions are made based on the failure probabilities of the components and the wind turbines, which can be calculated based on the component health condition data and prognostics information.

The proposed CBM policy for the wind power generation systems is summarized as follows:

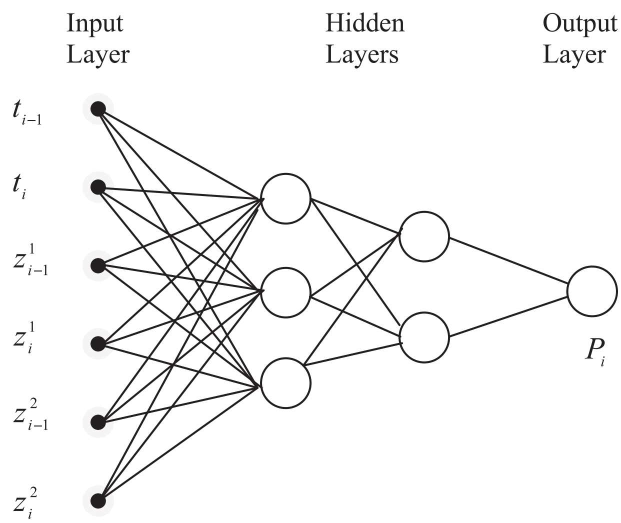

Fig. 1. Structure of the ANN model for component health condition prediction [23].

(1) Perform failure replacement if a component fails. The maintenance equipment and replacement parts will be scheduled, and the maintenance team will be sent to the wind farm.
(2) Send a maintenance team to the wind farm and perform preventive replacements if any wind turbine in the wind farm is determined to be maintained.
(3) Perform preventive replacements on components in wind turbine n if $Pr_n > d_1$, where Pr_n is the failure probability of the wind turbine n, and d_1 is the pre-specified level 1 failure probability threshold value.
(4) If turbine n is to be performed preventive replacement on, perform preventive replacement on its components in order to bring the turbine failure probability below d_2, and d_2 is called the level 2 failure probability threshold.

As can be seen, once the two failure probability threshold values, d_1 and d_2, are specified, the CBM policy is determined.

3.3. CBM optimization model and solution method

Based on the above CBM policy, the CBM optimization model can be simply formulated as follows:

$$\begin{aligned} &\min\ C_E(d_1, d_2) \\ &\text{s.t.} \\ &\quad 0 < d_2 < d_1 < 1 \end{aligned} \tag{5}$$

where C_E is the total expected maintenance cost per unit time under a certain CBM policy defined by the two failure probability threshold values d_1 and d_2. These thresholds take real values between 0 and 1, and $d_2 < d_1$. The objective of the CBM optimization is to find the optimal d_1 and d_2 such that the total maintenance cost is minimized.

Before performing the search of the optimization, we need to calculate the cost value C_E given two failure probability threshold values d_1 and d_2. Due to the complexity of the problem, it is very difficult to develop a numerical algorithm to evaluate the cost of the CBM policy for the wind power generation systems. In this paper, we present a simulation method for the cost evaluation. The flow chart for the procedure of the simulation method is presented in Fig. 2, and detailed explanations of the procedure are given in the following paragraphs.

3.3.1. Step 1

Building the ANN prediction model. For each type of wind turbine component, determine the lifetime distribution based on the available failure and suspension data. Weibull distributions are assumed to be appropriate for components lifetime, and the distribution parameters α_m and β_m can be estimated for each component m. For each type of component, based on the available failure and suspension histories, an ANN prediction model can be trained, and the mean and standard deviation of the ANN life percentage prediction error, denoted by $\mu_{p,m}$ and $\sigma_{p,m}$, can be calculated.

3.3.2. Step 2

Simulation initialization. As mentioned earlier, suppose there are N wind turbines in the wind farm, and M critical components are considered for each turbine. Specify the maximum simulation time T_{Max}, and the inspection interval T_{I}. T_{I} can be set to be a small value, say 1 day, so that we can approximately achieve continuous monitoring. Or we can set T_{I} to be a larger value, say 10 days, to improve the computation efficiency, yet still obtain an accurate result. For each component m, specify the cost values, including the failure replacement cost $c_{f,m}$ and the variable preventive replacement cost $c_{p,m}$. The fixed cost of maintaining a certain wind turbine, $c_{p,T}$, and the fixed cost of sending a maintenance team to the wind farm, c_{Farm}, also need to be specified. The total replacement cost is set to be $C_{\mathrm{T}} = 0$, and will be updated during the simulation. Set $t_{\mathrm{ABS}} = 0$, and generate the real failure times for each component in each turbine. That is, for component m in turbine n, generate a real failure time $TL_{n,m}$ by sampling the Weibull distribution for component m with parameters α_m and β_m. Thus, at time 0, the age values for all the components are 0, that is, $t_{n,m} = 0$ for all n and m.

3.3.3. Step 3

Component health condition prognostics and failure probability calculation. At a certain inspection point when the time $t_{ABS} > 0$, the age of component m in turbine n is represented by $t_{n,m}$, and its real failure time is known at this point, which is $TL_{n,m}$. For each component, generate the predicted failure time, $TP_{n,m}$, by sampling the normal distribution $N(TL_{n,m},\ \sigma_p \cdot TL_{n,m})$. Based on the discussion in Section 2, the predicted failure time distribution can be obtained as $N(TP_{n,m},\ \sigma_p \cdot TP_{n,m})$. Now, based on Equation (2), the current failure probability during the lead time for the component is:

$$\Pr_{n,m} = \frac{\displaystyle\int_{t_{n,m}}^{t_{n,m}+L} \frac{1}{\sigma_p TP_{n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - TP_{n,m}}{\sigma_p TP_{n,m}}\right)^2} dx}{\displaystyle\int_{t_{n,m}}^{\infty} \frac{1}{\sigma_p TP_{n,m}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - TP_{n,m}}{\sigma_p TP_{n,m}}\right)^2} dx} \tag{6}$$

Finally, the failure probability for each turbine can be calculated using Equation (4) based on the failure probabilities of its components.

3.3.4. Step 4

CBM decision making and cost update. At the current inspection point t_{ABS}, the CBM decisions can be made according to the CBM policy, described in Section 3.2, based on the failure probabilities of the turbines and their components:

(1) If $t_{n,m} \geq TL_{n,m}$, it implies that a component failure occurred. A failure replacement needs to be performed on the component, and the failure replacement cost is incurred. The change in the total cost due to failure replacements is:

$$\Delta C_{T,F} = \sum_{n=1}^{N} \sum_{m=1}^{M} IF_{n,m} c_{f,m}. \tag{7}$$

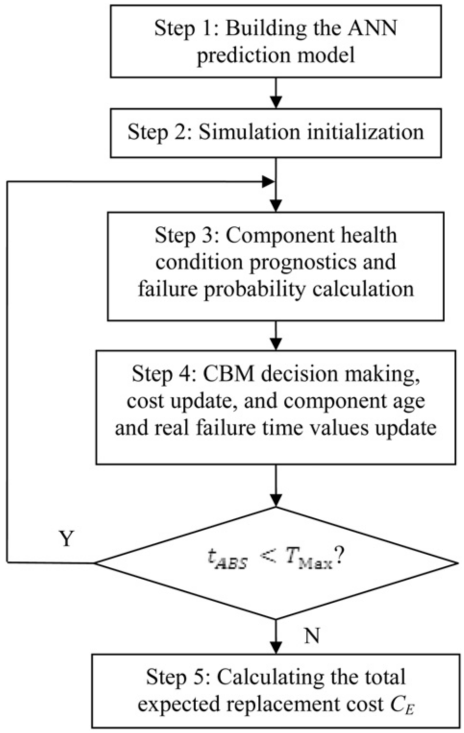

Fig. 2. Flow chart for the proposed simulation method for cost evaluation.

where $IF_{n,m} = 1$ if a failure replacement is to be performed on the component, and it equals 0 otherwise.

(2) For wind turbine n, if $Pr_n > d_1$, perform preventive replacements on its components with higher failure probabilities until the turbine failure probability is lower than level 2 threshold value d_2. If preventive replacement is performed on component m, the preventive replacement costs are incurred. Thus, the change in the total cost due to preventive replacements is:

$$\Delta C_{T,P} = \sum_{n=1}^{N}\left(\sum_{m=1}^{M} IP_{n,m}c_{p,m} + IT_n c_{p,T}\right). \tag{8}$$

where $IP_{n,m} = 1$ if a preventive replacement is to be performed on the component, and it equals 0 otherwise. $IT_n = 1$ if preventive replacements are performed on components in turbine n, but no failure replacements are performed on the turbine, and it equals 0 otherwise.

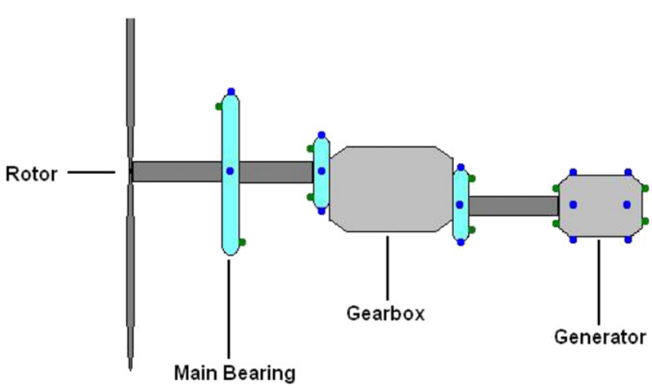

Fig. 3. Key wind turbine components considered in the example [26].

Table 1
Weibull failure time distribution parameters for major components.

Component	Scale parameter α (days)	Shape parameter β
Rotor	3000	3.0
Main bearing	3750	2.0
Gearbox	2400	3.0
Generator	3300	2

(3) If a failure replacement or preventive replacement is to be performed on any component in the wind farm, the fixed cost of sending a maintenance team to the wind farm, c_{Farm}, will be incurred:

$$\Delta C_{T,\text{Farm}} = I_{\text{Farm}}c_{\text{Farm}}. \tag{9}$$

where $I_{Farm} = 1$ if c_{Farm} is incurred, and otherwise it equals 0. Thus, the change in the total replacement cost at the current inspection point is:

$$\Delta C_T = \Delta C_{T,F} + \Delta C_{T,P} + \Delta C_{T,\text{Farm}} \tag{10}$$

(4) At the current inspection point, if any replacement is to be performed, the time will be moved to the point when the maintenance lead time has passed, i.e.,

$$t_{ABS} = t_{ABS} + L. \tag{11}$$

Otherwise, we will move the next inspection point:

$$t_{ABS} = t_{ABS} + T_I. \tag{12}$$

At the new inspection point, if a failure replacement or preventive replacement has been decided to be performed on component m in turbine n, generate a new real failure time $TL_{n,m}$ by sampling the Weibull distribution for component m with parameters α_m and β_m. If the current time t_{ABS} has not exceeded the maximum simulation time T_{Max}, repeat Step 3 and Step 4.

3.3.5. Step 5

Total replacement cost calculation. When the maximum simulation time is reached, that is, $t_{ABS} = T_{\text{Max}}$, the simulation process is completed. The total replacement cost for the wind farm can be calculated as:

$$C_E = \frac{C_T}{T_{\text{Max}}}. \tag{13}$$

And the total replacement cost for each turbine is:

$$C_{ET} = \frac{C_T}{N \cdot T_{\text{Max}}}. \tag{14}$$

It should be noted that the cost measure of the maintenance policy is cost per unit of time, that is, \$/day or \$/year. This cost

Table 2
Failure replacement and preventive maintenance costs for major components.

Component	Failure replacement cost (\$1000)	Variable preventive maintenance cost (\$1000)	Fixed preventive maintenance cost (\$1000)	Fixed cost to the wind farm (\$1000)
Rotor	112	28		
Main bearing	60	15	25	50
Gearbox	152	38		
Generator	100	25		

Table 3
ANN life percentage prediction error standard deviation values for major components.

Component	Standard deviation
Rotor	0.12
Main bearing	0.10
Gearbox	0.12
Generator	0.10

measure corresponds to annual cost in engineering economics. If we are interested in other discounting related measures, such as the net present value (NPV), for a certain period of time, they can be calculated based on the annual value [24].

4. An example

4.1. Maintenance optimization using the proposed CBM approach

In this section, an example is used to demonstrate the proposed CBM approach for wind power generation systems. Consider a group of 5 wind turbines, produced and maintained by a certain manufacturer, in a wind farm at a remote site. To simplify our discussion, in this example, we study 4 key components in each wind turbine: the rotor (including the blades), the main bearing, the gearbox and the generator, as shown in Fig. 3 [26].

Assume the Weibull distributions are appropriate to describe the component failure times, and the Weibull parameters are given in Table 1. The component lifetime distribution parameters are specified based on the data given in Ref. [27] and [28]. The cost data are given in Table 2, including the failure replacement costs for the components, the fixed and variable preventive replacement costs and the cost of sending a maintenance team to the wind farm. The cost data are specified based on the cost related data given in Ref. [1] and [29]. The ANN prediction method is used to predict the failure time distributions of the wind turbine components, and suppose the standard deviations of the ANN life percentage prediction errors are 0.12, 0.10, 0.10, and 0.12, respectively, as shown in Table 3. The standard deviation values are selected by referring to that estimated using the bearing degradation data in Ref [25] and [30]. The maintenance lead time is assumed to be 30 days, and the inspection interval is set at 10 days.

The total maintenance cost can be evaluated using the proposed simulation method presented in Section 3.3. The cost versus failure

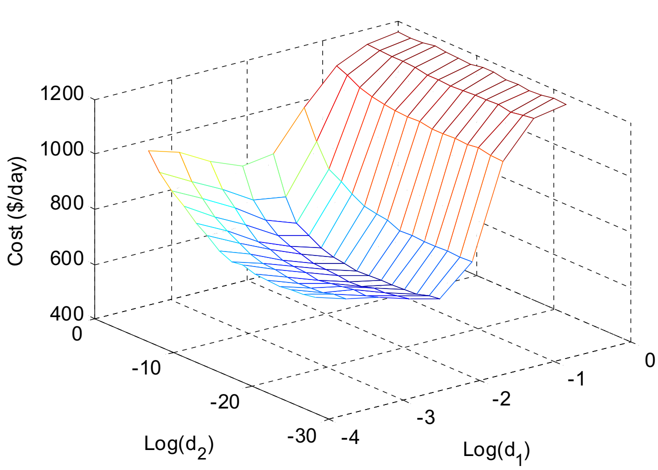

Fig. 4. Cost versus failure probability threshold values in the logarithm scale.

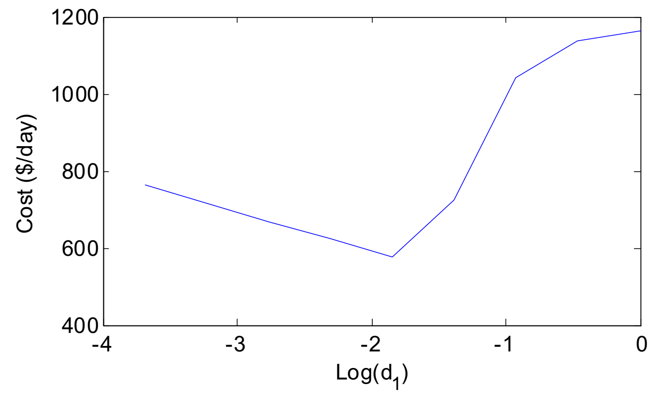

Fig. 5. Cost versus threshold d_1 in the logarithm scale ($d_2 = 3.4145 \times 10^{-6}$).

probability threshold values plot is given in Fig. 4, where the failure probability threshold values are given in the logarithm scale. It is found that the total maintenance cost is affected by the two failure probability threshold values, and the optimal CBM policy exists which corresponds to the lowest cost. Optimization is performed, and the optimal CBM policy with respect to the lowest total maintenance cost can be obtained. The obtained optimal threshold failure probability values are: $d_1 = 0.1585$, $d^2 = 3.4145 \times 10^{-6}$, and the optimal expected maintenance cost per unit of time is 577.08 $/day. Fig. 5 shows the cost versus d_1 plot while d_2 is kept at 3.4145×10^{-6}, and the cost versus d_2 plot while d_1 is kept at 0.1585 is presented in Fig. 6. These two figures can more clearly show the change in the maintenance cost with respect to one of the failure probability threshold value around the optimal point.

4.2. Comparative study with the time-based maintenance policies

There are mainly two types of time-based maintenance policies: the constant-interval maintenance policy and the age-based maintenance policy. The former is also called block replacement policy. Under constant-interval maintenance, if a component fails, a failure replacement will be performed right away. Preventive replacements will be performed on components at constant intervals, say every 3 months. In age-based maintenance, a failure replacement will also be performed right away if a component fails, and a preventive replacement is performed once the age of the component reaches a pre-specified age value. The age of the component is reset to 0 once a replacement is performed. For the wind power generation systems, there are significant fixed maintenance costs on the wind farm level and on the wind turbine level. Thus, the age-based maintenance policy is not suitable for the wind

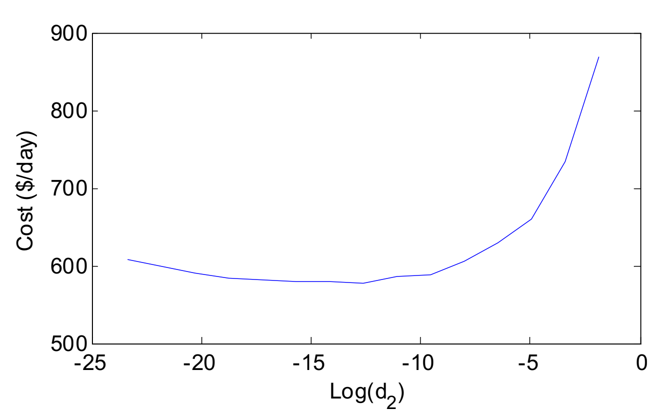

Fig. 6. Cost versus threshold d_2 in the logarithm scale ($d_1 = 0.1585$).

Table 4
Cost data for the constant-interval maintenance policy.

Component	Failure replacement cost ($1000)	Preventive replacement cost ($1000)
Rotor	162	36.75
Main bearing	110	23.75
Gearbox	202	46.75
Generator	150	33.75

power generation systems because these fixed maintenance costs will be incurred whenever a preventive replacement is performed on a component when the preventive replacement age is reached. Currently, the constant-interval maintenance policy is the maintenance policy that is adopted the most in wind power industry [1]. So, we only investigate the constant-interval maintenance policy in this comparative study.

In the constant-interval maintenance policy, t_{CI} is used to denote the maintenance interval. The objective of the maintenance optimization is to find the optimal t_{CI} value to minimize the expected maintenance cost. Based on the discussion of the constant-interval maintenance policy in Ref. [6], we can extend the method in Ref. [6] and use the following equation to calculate the total expected maintenance cost:

$$C(t_{CI}) = N \cdot \frac{\sum_{m=1}^{M} \left(C_{p,m}^{CI} + C_{f,m}^{CI} H_m(t_{CI}) \right)}{t_{CI}} \qquad (15)$$

where $C_{p,m}^{CI}$ is the total cost of a failure replacement for component m, and $C_{f,m}^{CI}$ is the total cost of a preventive replacement for component m. $H_m(t_{CI})$ denotes the expected number of failures for component m in interval $(0, t_{CI})$, which can be evaluated using a recursive procedure [6].

To ensure a fair comparison, for the constant-interval maintenance policy, we use the same lifetime distributions for the components, as given in Table 1. We also try to use the same cost data in Table 2. Since the fixed cost on the farm level, c_{Farm}, is incurred whenever a failure replacement is performed, the failure replacement cost in Equation (15) is equal to c_{Farm} plus the failure replacement cost in Table 2, as shown in Table 4. As to the preventive replacement cost, the turbine level fixed cost in Table 2 is shared by all the turbine components, and the wind farm level fixed cost is shared by all the components in the wind farm. That is, the preventive replacement cost for component m can be calculated as:

$$C_{f,m}^{CI} = c_{p,m} + c_{p,T}/M + c_{\mathrm{Farm}}/NM. \qquad (16)$$

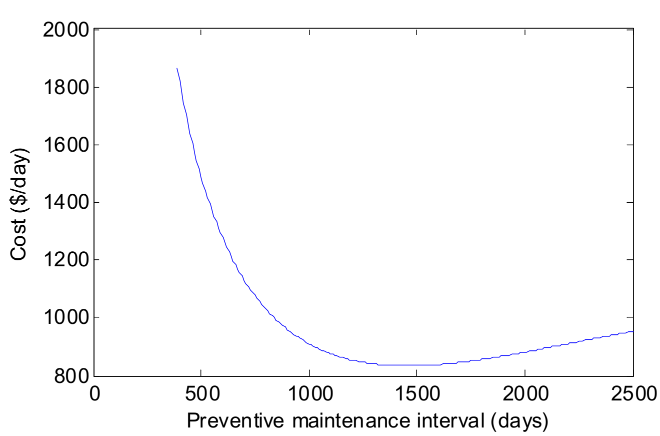

Fig. 7. Cost plot for the constant-interval based preventive maintenance policy.

The calculated preventive replacement cost data using Equation (16) are also shown in Table 4.

Using Equation (15), the expected maintenance cost $C(t_{CI})$ can be calculated. The plot of the cost versus the preventive maintenance interval t_{CI} is shown in Fig. 7. As can be seen, an optimal preventive maintenance interval with respect to the lowest cost exists. The optimal constant-interval maintenance policy can be found using a simple optimization procedure. The optimal preventive replacement interval is found to be 1460 days, and the corresponding optimal maintenance cost is 833.41 $/day. As presented in Section 4.1, using the proposed CBM approach, the optimal expected maintenance cost is 577.08 $/day. Thus, a cost saving of 44.42% can be achieved using the proposed CBM approach. The comparative study demonstrates that the proposed CBM approach is more cost-effective comparing to the widely used constant-interval maintenance policy.

5. Conclusions

In this paper, we proposed an optimal CBM policy to address the maintenance of wind farms where multiple wind turbine generators are installed. The proposed maintenance policy is defined by two failure probability thresholds at the wind turbine level. Leveraging the condition monitoring data, prognostics tools are devised to predict the distribution of component failure times. Given the failure probabilities for components and the system, optimal CBM decisions can be made on: 1) the maintenance schedule; 2) target wind turbines to be maintained; and 3) key components to be inspected and fixed. A simulation method has been developed to evaluate the cost of the proposed CBM policy. Numerical examples and comparative studies are presented to illustrate and examine the effectiveness of the proposed approach. Our future efforts will concentrate on systems where dependent failures are involved or wind farms employing heterogeneous turbines.

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