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Optimization of periodic maintenance for wind turbines based on stochastic degradation model

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Abstract: The degradation process of wind turbines is greatly affected by external factors. Wind turbine maintenance costs are high. The regular maintenance of wind turbines can easily lead to over and insufficient maintenance. To solve the above problems, a stochastic degradation model (SDE, stochastic differential equation) is proposed to simulate the change of the state of the wind turbine. First, the average degradation trend is obtained by analyzing the properties of the stochastic degradation model. Then the average degradation model is used to describe the predictive degradation model. Then analyze the change trend between the actual degradation state and the predicted state of the wind turbine. Secondly, according to the update process theory, the effect of maintenance on the state of wind turbines is comprehensively analyzed to obtain the availability. Then based on the average degradation process, the optimal maintenance period of the wind turbine is obtained. The optimal maintenance time of wind turbines is obtained by optimizing the maintenance cycle through availability constraints. Finally, an onshore wind turbine is used as an example to verification. Based on the historical fault data of wind turbines, the optimized maintenance decision is obtained by analyzing the reliability and maintenance cost of wind turbines under periodic and non-equal cycle conditions. The research results show that maintenance based on this model can effectively improve the performance of wind turbines and reduce maintenance costs.

Key words: availability, maintenance optimization, stochastic differential equation, update process, wind turbine

1. Introduction

With the development of environmental protection and economy, the demand of new energy industry is increasing rapidly, which leads to the large increase in wind power installed capacity [1]. China has invested heavily in the construction of wind turbines. The conditions required for the operation of a wind turbine make its performance extremely susceptible to external uncertainties. The above situation leads to low availability of wind turbines and reduces the stability and reliability of wind turbines [2].

Therefore, we need to study how to reduce wind turbine maintenance costs and improve the reliability of wind turbine operation. At present, the main maintenance methods of wind turbines are corrective maintenance and preventive maintenance. Preventive maintenance can be divided into two types: time-based maintenance (TBM) and condition-based maintenance (CBM) [3]. According to the maintenance cost statistics of wind turbines, the maintenance cost per kilowatt hour of onshore wind farms accounts for 20%–25% of the production cost [4]. Therefore, a reasonable maintenance plan is essential to reduce maintenance costs and ensure the reliability of wind turbines.

In condition maintenance, the status changes are mainly reflected by equipment monitoring data. In order to realize the safe and stable operation of the wind turbine pitch system, Liu analyzed the monitoring data of each component of the pitch system, and proposed a method of identifying abnormal operation status of the pitch system based on the distance between multiple characteristic parameters. In this way, the abnormal state can be identified more timelier and accurately [5]. Besnard uses online monitoring information and the Markov process to evaluate the operation and maintenance cost of the equipment per unit time through the Monte Carlo algorithm, and finally obtains the optimal maintenance strategy of the wind turbine blade [6]. Liu used the Markov state transition equation to predict the state of the wind turbine. Then, considering factors such as maintenance cost, weather and electricity price loss during the stocking period, the discount cost during the operating life is calculated, and a maintenance strategy optimization model based on the semi-Markov decision process is established. Taking the lowest discount cost as the optimization goal, obtain the optimized maintenance method and inspection time interval of wind turbines [7]. The Markov process is also discussed in [8]. Zhao uses the Weibull proportional intensity models to describe the state of wind turbines. Then the state threshold value corresponding to the optimal maintenance period is obtained with the minimum maintenance cost, and then the state threshold value is used as the basis for the state maintenance time [9].

In time-based maintenance, exponential models are widely used. Based on the reliability theory and Markov process, and assuming that the failure distribution and maintenance distribution of each component of the wind turbine generator are subject to an exponential distribution, Li obtains the availability of the wind turbine generator. The average interval between preventive maintenance are calculated by the maximum availability [10]. Fu uses the Weibull model to describe the performance changes of wind turbines. The service age regression factor is used to describe the impact of maintenance on the evolution of component reliability. By considering weather factors, the maintenance cost is minimized to find the optimal repair time [11].

Aiming at the inaccurate state estimation of the state maintenance, Zhigang used two methods to predict the health state of the wind turbine. Analyze the reliability of wind turbines based on physical models. Combining the collected monitoring data is based on the ANN model to predict the failure time distribution. The purpose of CBM optimization is to find the best probability threshold, so as to minimize the total maintenance cost [12]. Yildirim proposed the use of a data-driven stochastic model to obtain the dynamic remaining life distribution (RLDS) of the equipment, and timely update the remaining life based on real-time monitoring data. A dynamic cost expression is obtained based on the remaining life, so as to improve and timely balance the cost of preventive maintenance and the cost of unexpected failures [13]. Elwany proposed two stochastic models, namely a linear degradation model and an exponential degradation model. Then revise the RLD in real time based on the real-time monitoring data. Finally, the best replacement time is obtained with the minimum maintenance cost. The analysis shows that the exponential degradation model is more applicable where cumulative damage increases the rate of degradation [14]. The use of stochastic processes to describe the randomness of equipment degradation has been discussed, for example, in [15–18].

According to the above literature, condition-based maintenance mainly relies on equipment monitoring data to achieve the purpose of accurately predicting equipment failure. Condition-based maintenance (CBM) models include both the exponential model and stochastic model. The main features of CBM models are to reflect the uncertainty of wind turbine performance degradation. The exponential model is generally used in time-based maintenance (TBM), and the degradation factor is used to describe the degradation process of wind turbines. The two maintenance strategies reflect the applicability of wind turbine maintenance. Condition-based maintenance (CBM) relies on monitoring data, but a lot of fault information on wind turbine equipment is not observable. The investment of monitoring equipment is high, and the data acquisition also has some errors. It is uncertain whether wind turbine degradation maintenance can completely eliminate the randomness of fault and ensure the economy of maintenance. At present, the actual maintenance of wind turbines is mainly periodic maintenance, and the relationship between condition-based maintenance and periodic maintenance is not clear. Therefore, this paper proposes a stochastic degradation model to describe the wind turbine decommissioning process, and analyzes the internal relationship between periodic maintenance and condition-based maintenance. Finally, the optimal maintenance time is determined with the reliability and economy of wind turbines as the optimization objectives.

2. The establishment of stochastic degradation modelled on wind turbines

2.1. Analysis on degradation principle of wind turbines

Wind turbines are composed of different components, and their performance is affected by many factors of uncertainty. Therefore, the degradation state of wind turbines has certain volatility and randomness when it changes with the operating time. The degradation process of wind turbines can be composed of both natural degradation and random external disturbances. The natural degradation process conforms to the exponential model, and the external random interference is described by Brownian motion. Therefore, a stochastic degradation model of wind turbines is proposed.

The natural degradation rate λ of the random degradation model is a constant value. Brownian motion description is used at random interference [19]. Brownian motion is represented by $B(t)$.

The repair process of wind turbines can be described by the update process [20]. During the update process, the life cycle of wind turbine equipment is random. Repairs are completed instantly, and the equipment is as good as new. Such periodic repeated maintenance constitutes an update process. The mathematical expression of the update process is: for $t \geq 0, i = 1, 2, \ldots, F_T(t)$ represents the potential distribution of the update process; $F_T(t) = Pr(T_i \leq t)$; T represents the expectation of the equipment life cycle; T_i represents the i-th cycle of the equipment; $Pr(t)$ refers to the life of the equipment at the time t distribution density; update function refers to the average number of updates within the t time; $V_N(t)$ refers to the number of equipment updates within the t time. According to the update function $W(t) = E[V_N(t)]$, the following expression can be derived:

$$W(t) = F_T(t) + \int_0^t W(t-\tau)\,\mathrm{d}F_T(\tau). \tag{1}$$

2.2. Obtaining the stochastic degradation model of wind turbines

2.2.1. Conditions for modeling:

1. $x(t)$ represents the actual state value of the wind turbine. The wind turbine is a series system, and any maintenance of its components is considered as a fault state. When the equipment is running to the scheduled maintenance time, it will be repaired no matter whether it is faulty or not.
2. The equipment is repaired immediately after the failure. The maintenance is completed instantaneously. After the maintenance, the equipment status shows that the equipment is as good as new.
3. The vessels, personnel and spare parts required for wind turbine maintenance are sufficient, that is, the impact of maintenance resources on maintenance is not considered.
4. The maintenance will not affect the inherent degradation rate of the wind turbine unit. The inherent degradation rate of the equipment is determined by the property of the equipment, and the external environment will only affect the degradation process in a life cycle.
5. Similar components have the same probability behavior.

2.2.2. Mathematical expression of stochastic degradation model

Based on the above assumptions, a wind turbine degradation model is established:

$$\mathrm{d}x(t) = \lambda x(t)\,\mathrm{d}t + \sigma x(t)\,\mathrm{d}B(t), \tag{2}$$

where λ is the natural degradation rate of wind turbines; σ is the state fluctuation rate of wind turbines; $B(t)$ is one-dimensional Brownian motion. It is used to indicate that the state of the wind turbine is randomly disturbed by the outside world.

Due to the non-differentiable characteristic of Brownian motion everywhere, it can be seen that $\mathrm{d}B(t)$ is only a recording symbol. $\mathrm{d}B(t)$ can be expressed as: If η follows $N\ (0,1)$, then $\Delta B(t) = \eta\sqrt{\Delta t}$, which is $\mathrm{d}B(t) = \eta\sqrt{\mathrm{d}}t$.

The process of solving the stochastic differential equation by the It $\hat{o}$ principle is as follows [17]:

$$\int_0^t \frac{\mathrm{d}(x(t))}{x(t)} = \lambda t + \sigma B(t),$$

$$\mathrm{d}\ln(x(t)) = \frac{1}{x(t)}\mathrm{d}(x(t)) + \frac{1}{2}\left(-\frac{1}{x(t)^2}\right)(\mathrm{d}x(t))^2 = \frac{\mathrm{d}(x(t))}{x(t)} - \frac{1}{2}\sigma^2\,\mathrm{d}t,$$

$$\ln\frac{x(t)}{x(0)} = \left(\lambda - \frac{1}{2}\sigma^2\right)t + \sigma B(t),$$

$$x(t) = x(0)e^{\left(\lambda - \frac{1}{2}\sigma^2\right)t + \sigma B(t)}, \tag{3}$$

where $x(0)$ is the state at the beginning of the cycle of the wind turbine.

2.2.3. Stochastic degradation model parameters

In order to obtain the parameter values of the random degradation model of the wind turbine, the historical fault data on the wind turbine is selected for analysis. The failure probability of the generator unit is used to describe the change of the state of the wind generator unit over time. First select the interval $[0, T]$. Take Δt as the sampling length. This way, the value of $S_{n\Delta t}$ $(0 \le n \le N, T = N\Delta t)$ can be obtained. According to the nature of the random degradation process, $(\ln S_{n\Delta t}/S_{(n-1)\Delta t})$ $(0 \le n \le N)$ obeys the distribution $N((\lambda - \sigma^2/2)\Delta t, \sigma^2\Delta t)$. The formula for obtaining model parameters can be obtained as follows:

$$\begin{cases} \lambda - \dfrac{1}{2}\sigma^2 = \dfrac{\sum\limits_{i=1}^{N} \ln \dfrac{S_{i\Delta t}}{S_{(i-1)\Delta t}}}{\sum\limits_{i=1}^{N} \Delta t} = \dfrac{\ln \dfrac{S_T}{S_0}}{T} \\ \sigma^2 = \dfrac{1}{\Delta t(N-1)} \sum\limits_{i=1}^{N} \left(\ln \dfrac{S_{i\Delta t}}{S_{(i-1)\Delta t}} - \dfrac{1}{N} \ln \dfrac{S_T}{S_0} \right)^2 \end{cases}. \tag{4}$$

3. Analysis of stochastic degradation models on wind turbines

It can be seen from the stochastic degradation model of wind turbines that the state trajectory of wind turbines is a probability space. The degradation trajectory of the wind turbine will be different to each life cycle, so the failure of the wind turbine is also a random event. In order to analyze the degradation laws of wind turbines, it is necessary to study the overall degradation trend.

Theorem 1 The expectation of the average expression of the degradation process of the wind turbine is an exponential distribution, where $x(t)$ and λ are the same as expression (2).

$$E[x(t)] = E[x(0)] \exp(\lambda t).$$

Proof: Let

$$Y(t) = \exp(\sigma B(t)).$$

It can be obtained through the Itô principle:

$$\mathrm{d}Y(t) = \sigma e^{\sigma B(t)} \,\mathrm{d}B(t) + \frac{1}{2}\sigma^2 e^{\sigma B(t)} \,\mathrm{d}t.$$

According to the principle of Itô integration:

$$E\left[\int_0^t e^{\sigma B(s)} \,\mathrm{d}B(s)\right] = 0.$$

Therefore:

$$E[Y(t)] = E[Y(0)] + \frac{1}{2}\sigma^2 \int_0^t E[Y(s)\,\mathrm{d}s].$$

Derived by differentiation:

$$\frac{\mathrm{d}}{\mathrm{d}t} E\left[Y(t)\right] = \frac{1}{2}\sigma^2 E\left[Y(t)\right], \quad E[Y(0)] = 1.$$

Therefore:

$$E[Y(t)] = e^{\frac{1}{2}\sigma^2 t},$$
$$E[x(t)] = E[x(0)]e^{\lambda t}.$$

It can be concluded from the above principles that it is feasible to use exponential models to analyze preventive maintenance time for most of the cased described in the literature. The average degradation rate of wind turbines is fixed, so it exists on the optimal maintenance cycle. Therefore, periodic maintenance is in line with the law of degradation of wind turbines. However, the occurrence of a wind turbine failure is a random event. Therefore, it is necessary to analyze the relationship between the actual degradation state and the predicted state.

Assume that the predicted degradation rate of the wind turbine is λ, when the wind turbine uses only one state $\psi(t)$ to represent its changing process. The state of the wind turbine can be obtained according to the state transition Equation [21]:

$$\psi(t) = \psi(0)\exp(\lambda t), \tag{5}$$

where $\psi(0) = 1$ indicates that the state of the wind turbine at the initial moment is as good as in new wind turbines. λ is the same as expression (2).

The actual state value of the wind turbine and the predicted state is converted into the state at the initial time, which is expressed by $\omega(t)$, $\omega(t) = x(t)/\psi(t)$. When $\omega(t) = 1$, it means that the prediction is consistent with the actual state.

Theorem 2 $\omega(t)$ is a local martingale of $B(t)$, $t > 0$

$$\omega(t) = \exp\left(-\frac{1}{2}\sigma^2 t + \sigma B(t)\right).$$

Proof: suppose that the initial state of the wind turbine is as good as in new wind turbines. For any n, any $t > s > s_1 >, \ldots, > s_n$. According to the independent incremental nature of Brownian motion:

$$\frac{\omega(t)}{\omega(s)} = \exp\left(-\frac{1}{2}\sigma^2(t-s) + \sigma(B(t) - B(s))\right)$$

and $(B(s), B(s_1), \ldots, B(s_n))$ are independent of each other. Because $\omega(t)$ is a function of $B(s)$, it can be obtained by conditional expectation.

$$\begin{aligned}
E\left[\omega(t)|B(s), B(s_1), \ldots B(s_n)\right] &= \omega(s)E\left[\frac{\omega(t)}{\omega(s)}|B(s), B(s_1), \ldots B(s_n)\right] = \\
&= \omega(s)E\left[e^{-\frac{1}{2}\sigma^2(t-s)+\sigma(B(t)-B(s))}|B(s), B(s_1), \ldots, B(s_n)\right] = \\
&= \omega(s)E\left[e^{-\frac{1}{2}\sigma^2(t-s)+\sigma(B(t)-B(s))}\right] = \omega(s).
\end{aligned}$$

It follows that $\omega(s)$ is a local martingale process of $B(t)$.

The single degradation process of wind turbines is a local martingale relative to the average degradation process. The local martingale in the operation time of wind turbines is reflected on its operation time that is limited, there is no infinite operation time. That is to say, although the degradation trajectory of wind turbines is different in each cycle, the overall trajectory is an exponential degradation trajectory with long-term operation probability. Additionally, at any moment, the actual state of the wind turbine is tending to the predicted value and reach the predicted value of a limited time.

With the increase in operating time, the specific change trend of the actual state values and the predicted value of the wind turbine is analyzed as follows.

$\zeta(t) = \zeta(\omega(t) < 1)$ represents the probability that the actual state of the wind turbine at the time t is lower than the predicted value.

$$\zeta(t) = \zeta\left(-\frac{1}{2}\sigma^2 t + \sigma B(t) < 0\right).$$

According to the nature of Brownian motion:

$$-\frac{1}{2}\sigma^2 t + \sigma B(t) \sim N\left(-\frac{1}{2}\sigma^2 t \sigma^2 t\right).$$

Therefore:

$$\zeta(t) = \Phi\left(\frac{1}{2}\sigma\sqrt{t}\right). \tag{6}$$

From Formula (6), we can see that when $t = 0$, $\zeta(0) = 0.5$. As the running time increases, the value gradually increases. It shows that the trend of the wind turbine at the initial moment is the same as the trend of good and bad. As the running time increases, its actual state is lower than the predicted value. Therefore, the maintenance cycles need to be adjusted reasonably to the maintenance process.

According to the above analysis, the maintenance of wind turbines should be based on periodic maintenance. Then, according to the actual state change, the maintenance time is reasonably adjusted with availability constraints, so as to realize the cycle maintenance strategy optimization. In other words, condition-based maintenance is actually the optimization of maintenance cycles.

4. Availability analysis

The availability of wind turbines is represented by $A(t)$. The availability refers to the probability that the wind turbine is in good operating condition at times t. Its mathematical expression is $A(t) = P[x(t) = 1)]$, where $x(t)$ refers to the state value of the wind turbine at times t [20]. The main purpose of analyzing the availability is to maximize the life cycle of wind turbines.

Wind turbine maintenance is an update process, and its availability expression is as follows:

$$A(t) = \int_0^\infty Pr\left[x(t) = 1 | T = u\right] \mathrm{d}F_T(u). \tag{7}$$

Therefore, the availability of the wind turbine is:

$$A(t) = x(t). \tag{8}$$

The availability in Formula (8) represents the change process of the availability in the normal operation state of the wind turbine. After joining the maintenance plan, the availability will change. The wind turbine sets a maintenance plan for the new life cycle. If the wind turbine is repaired to T_c, the availability of the wind turbine is expressed as $A_{\text{rep}}(t)$. There are two situations in which actual maintenance affects the availability. The specific calculation and analysis are as follows:

1. There was no failure of the wind turbine before the scheduled maintenance the time T_c. At this time, the wind turbines have completed periodic maintenance. The probability of occurrences of the current situation is expressed as follows:

$$P_1 = x\left(T_c\right). \tag{9}$$

   Under the above-mentioned conditions, the availability change of the wind turbine is equivalent to the backward delay of the availability of the wind turbine by T_c time. Availability is expressed as follows:

$$\begin{cases} A_{\text{rep1}}(t) = 1 & 0 < t < T_c \\ A_{\text{rep1}}(t) = A(t - T_c) & T_c < t \end{cases}. \tag{10}$$

2. When the wind turbine has failed before the scheduled maintenance time T_c. This means that the planned maintenance of the wind turbine has become a fault repair. The probability of occurrences of the current situation is expressed as:

$$P_2 = 1 - x\left(T_c\right). \tag{11}$$

   Under the above-mentioned circumstances, the availability of wind turbines will change due to the random maintenance time. The current availability changes satisfy the updated theory. If the wind turbine has been repaired at times T_c, the availability expression can be derived according to Equation (1) as follows:

$$A_{\text{rep2}}(t) = 1 - F(t) + \int\limits_0^t A(t-\tau)\,\mathrm{d}F_{\text{first}}(\tau), \tag{12}$$

   where $F_{\text{first}}(t)$ is the first life cycles distribution function of the equipment. $F(t)$ is the life distribution function of wind turbines at times t. $F(t)$ satisfies the reliability principle, and the expression is as follows:

$$F(t) = 1 - x(t). \tag{13}$$

According to the Itô formula:

$$\mathrm{d}F(t) = -x(0)x(t)(\lambda\,\mathrm{d}t + \sigma\,\mathrm{d}B(t)), \tag{14}$$

where λ and σ are the same as in Formula (2).

When the wind turbine is scheduled for maintenance at T_c, the current availability expression is as follows:

$$A\left(t, T_c\right) = P_1 A_{\text{rep1}}(t) + P_2 A_{\text{rep2}}(t). \tag{15}$$

5. Maintenance cost of wind turbines

5.1. Periodic maintenances cost

When the maintenance cost per unit time of the wind turbine is the smallest, the maintenance time can be used as the optimal maintenance period. The expression of the maintenance cost $C(T)$ is as follows:

$$C(T) = \frac{\text{Expected cost in one cycle}}{\text{Cycle expectation}} . \tag{16}$$

Assuming that the maintenance period of the wind turbine is Z, there are two situations in which the maintenance period is calculated. Different maintenance methods are adopted for wind turbines when they have failed before and when they have not failed. The time of maintenance of the wind turbine is the time of update. Set the wind turbine maintenance times as T. The wind turbine maintenance cycle expression is as follows:

$$Z = \begin{cases} T & x > T \\ x & x < T \end{cases} . \tag{17}$$

Analyze (17), the expectation of the maintenance cycle is as follows:

$$E(Z) = E(Z|x > T)P(x > T) + E(Z|x < T) \cdot P(x < T) = T \int_{T}^{+\infty} f(x)\mathrm{d}x + \int_{0}^{T} x f(x)\mathrm{d}x. \tag{18}$$

Using the method of partial integration for Equation (18), we can get

$$E(Z) = T(1 - F(T)) + TF(T) - \int_{0}^{T} F(x)\mathrm{d}x = T - \int_{0}^{T} F(x)\mathrm{d}x = \int_{0}^{T} (1 - F(x))\mathrm{d}x = \int_{0}^{T} R(x)\mathrm{d}x.$$

The maintenance cycle expectations are expressed as:

$$E(Z) = \int_{0}^{T} R(x)\mathrm{d}x. \tag{19}$$

The preventive maintenance cost of the wind turbine is C_p, and the corrective maintenance cost is C_f. C_0 is the sum of the fixed maintenance cost and downtime loss of the wind turbine. C_e is the average economic loss of power generation during the overhaul of the wind turbine. The total cost of the preventive maintenance is $C_{pr} = C_p + C_0 + C_e$, the total cost of the maintenance after failure is $C_{fr} = C_f + C_0 + C_e$. The expression of maintenance cost per unit time is:

$$C(T) = \frac{C_{fr}F(T) + C_{pr}R(T)}{\int_{0}^{T} R(x)\mathrm{d}x}. \tag{20}$$

The minimum maintenance cost can be obtained by calculating $C(T)$. The expression of the sum of the preventive maintenance costs of wind turbines is as follows:

$$C_{\text{sum}} = C\,(T) \cdot T_L, \tag{21}$$

where C_{sum} is the total maintenance cost; T_L is the running time.

5.2. Optimization of maintenance cost based on stochastic degradation model

The maintenance based on the stochastic degradation model is to simulate the actual state of the wind turbine to obtain the actual maintenance time. Calculate the availability Formula (15) to obtain the maintenance time for the constraint conditions. Then find the actual maintenance times f of the wind turbine in the T_L time. The maintenance cost during the T_L operation time is expressed as follows:

$$C_{\text{sum}} = (C_p + C_0 + C_e) f, \tag{22}$$

where f is the number of repairs, and the others are the same as Formula (21).

6. Example analysis

The current maintenance theory is applicable not only to a single wind turbine, but also to multiple wind turbines forming a cluster. When the availability of wind turbines meets 0.98, for a single wind turbine: assuming that it has experienced 100 life cycles of operation, it means that after the completion of condition based maintenance, there are a total of 2 times of corrective maintenance; similarly, for a cluster with 100 wind turbines: if the same condition based maintenance time is used in a life cycle, there are 2 wind turbines that require corrective maintenance. This paper selects a wind turbine for simulation. Select the failure data on the four components of the wind turbine.

Table 1. Historical faults data onto each component

Serial number	**Time/day**			
	Main shaft	**Main bearing**	**Gearbox**	**Generator**
1	315	29	329	55
2	410	129	378	411
3	305	139	815	424
4	739	406	934	789
5	424	500	1043	881
6	492	714	1585	1003
7	529	178	1649	1080
8	698	212	1676	1977
9	936	309	1699	2219
10	1233	726	1714	2289

The parameters of the random degradation model of wind turbines are obtained by Formula (4). The new parameters of the stochastic degradation mode are: $\lambda = -0.0010847$, $\sigma = 0.012675$. Set $x(0) = 1$. Then carry out a statistical analysis of maintenance costs of wind turbines that are: $C_p = 7360$ yuan, $C_f = 57538$ yuan, $C_0 = 45\,000$ yuan, $C_e = 30\,000$ yuan.

6.1. Simulation of wind turbine state prediction changes

The wind turbine state fluctuation rate σ has been calculated. The value of $\zeta(t)$ can be calculated by Formula (6). The change curve of $\zeta(t)$ is expressed as follows (Fig. 1):

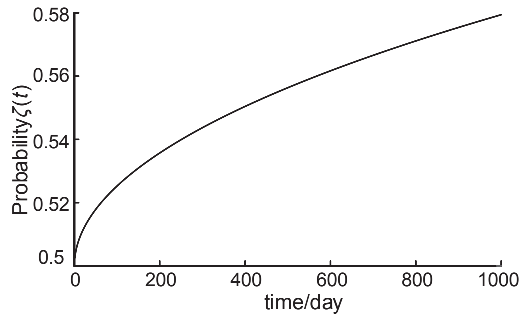

Fig. 1. The trend of the state of the wind turbine is lower than the predicted value

It can be seen from Figure 1 that as the running time increases, the probability that the actual state of the wind turbine is lower than the predicted value gradually increases. After more than 200 days, the increasing trend tends to be flat, indicating that the probability of failure of the later period becomes larger. It means that it is easier for corrective maintenance. The preventive maintenance of wind turbines should be carried out in time.

6.2. Periodic maintenance cost analysis

Based on the predicted degradation process of the wind turbine, the reliability of the wind turbine $R(t) = \psi(t)$ can be obtained by using Formula (5) and the reliability principle. Then, through Formula (20), the calculation result of the maintenance cost per unit time can be obtained when the maintenance cycle changes (Fig. 2).

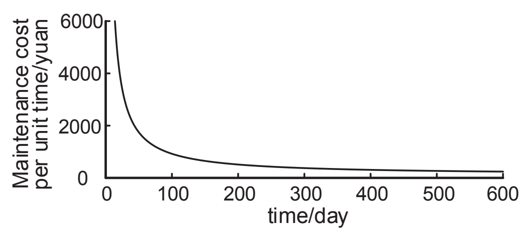

Fig. 2. Changes in maintenance costs per unit time

The analysis of the curve change in Figure 2 shows that when the maintenance period is greater than 300 days, the curve tends to be flat. This shows that when the maintenance times exceed the optimal maintenance cycle, increasing the maintenance cycle will reduce the contribution to reducing the maintenance cost of the wind turbine. The curve fails to reflect the increase in the probability of wind turbine failure due to excessive maintenance cycles. Due to the excessive maintenance cycle, more fault repairs will be required, resulting in more maintenance costs. Therefore, it is necessary to choose a reasonable maintenance cycle to avoid an excessive maintenance cycle causing insufficient maintenance.

The calculation of periodic maintenance costs for wind turbines selects the maintenance times as 150, 300, 450, and 600 days, respectively. The total maintenance cost of wind turbines in 10 years is calculated by Formula (21). It is expressed as follows (Tab. 2):

Table 2. Periodic maintenance costs

Maintenance cycle (days)	Maintenance cost (yuan)
150	2 370 200
300	1 372 561
450	1 042 929
600	880 270

6.3. Simulation of wind turbine availability

The availability change of a wind turbine is to simulate the actual change of the state of the wind turbine. Therefore, the selection of the maintenance time is also based on the periodical maintenance time. The maintenance time of selected wind turbines is $T_c = 150$, 300, 450, 600 days. The actual change curve of wind turbine availability can be obtained by Formula (15). The curve can be obtained by the Matlab simulation as follows (Fig. 3).

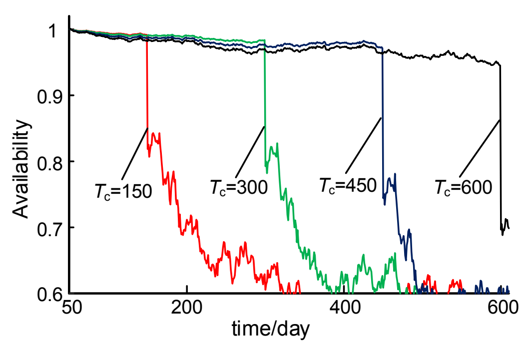

Fig. 3. Availability changes after wind turbine maintenance

From the analysis of the trend of the availability curve in Figure 3, it can be seen that the availability of wind turbines decreases as the maintenance time increases. This shows that the reliability of wind turbines begins to decrease as the maintenance time increases. Therefore, in order to ensure the reliability of the units, a reasonable maintenance time needs to be selected. The maintenance time cannot exceed the reliability limit of the wind turbine. When the maintenance time is less than 100 days, it can be concluded from the availability curve that the maintenance time is too small to reduce the contribution to the availability of the wind turbine. Too little maintenance time for wind turbines will lead to excessive maintenance and waste of resources.

6.4. Analysis of maintenance optimization

The degradation of wind turbines is a random process. Therefore, according to the analysis of availability curve changes, the actual availability of wind turbines after joining the planned maintenance time should not be lower than 0.98 [2]. At this time, the current time can be used as the actual maintenance time to ensure the reliability of the wind turbine.

Select the maintenance time as 150, 300, 450, 600 days. The availability of wind turbines can be obtained by Formula (15). Then obtain the actual maintenance time based on availability constraints. The actual maintenance time of wind turbines in 10 years is obtained through periodic changes in availability. The total maintenance cost of wind turbines in 10 years can be obtained by Formula (22). Wind turbine maintenance time combination and maintenance costs are as follows (Tab. 3):

Table 3. Maintenance optimization cost based on stochastic degradation model

maintenance time (day)	**Actual maintenance time (days)**	**Total maintenance cost (yuan)**
150	150, 150, 94, 150, 150, 150, 150, 150, 150, 150, 150, 125, 117, 150, 150, 150, 83, 150, 150, 150, 150, 150, 150, 150, 150, 150	2 141 360
300	276, 300, 85, 300, 300, 225, 300, 300, 205, 222, 300, 114, 83, 242, 173, 300	1 317 760
450	222, 450, 73, 398, 450, 233, 450, 450, 190, 316, 444, 107	988 320
600	193, 62, 397, 331, 434, 241, 221, 226, 72, 105, 392, 599, 558	1 070 680

It can be seen from Table 2 that as the maintenance cycle increases, the maintenance cost gradually decreases. It can be seen from Figure 1 that the greater the maintenance cycle, the higher the failure rate. It can be seen from Figure 2 that a reasonable maintenance cycle needs to be selected as the maintenance basis.

It can be seen from Table 3 that as the maintenance time increases, the maintenance cost gradually decreases and then increases. When the maintenance time exceeds 300 days, the time difference between the actual maintenance time and the maintenance time also increases. This shows that when the maintenance time is short, the performance of the wind turbine is stable, and as the maintenance time increases, the unstableness of the wind turbine increases.

It can be concluded from Table 2 and Table 3 that, when the maintenance cycle is less than 300 days, the cost of taking periodic maintenance is significantly higher than the maintenance cost based on the stochastic degradation model; When the maintenance period is higher than 300 days, the periodic maintenance obviously can-not meet the target of the stable performance of wind turbines. Moreover, the periodic maintenance cost does not fully reflect the cost of the corrective maintenance; When the maintenance cycle is 300 days, there is no significant difference between the periodic maintenance and the maintenance optimization cost based on the stochastic degradation model, which shows that the selection of an appropriate maintenance cycle is in line with the degradation law of wind turbines, and the average degradation of wind turbines conforms to the law of the exponential function. Therefore, the maintenance of wind turbines should be based on the periodic maintenance. The maintenance time should be optimized in conjunction with the changes in its actual state. This can effectively reduce economic losses and ensure the reliability of wind turbines. In the actual arrangement, the actual maintenance time can be reasonably and dynamically arranged according to the current weather conditions and equipment operation conditions.

The periodic maintenance optimization cost and actual maintenance time based on the stochastic degradation model are more practical than the periodic maintenance. When the maintenance period is 300 days, the optimized periodic maintenance shows its superiority in the number of maintenance arrangements and the flexibility of maintenance time. The current wind turbine maintenance is based on the analysis of a single generator set as a whole. The optimized periodic maintenance can ensure that the availability of the complete wind turbine is not less than 0.98.

7. Conclusion

1. In this paper, a stochastic differential equation model is established to describe the state change process of wind turbines, and the Brownian motion is used to describe the fluctuation process of wind turbine states affected by external disturbance. The model has higher state fitting and better dynamic and accuracy than the traditional monotone degradation model. Therefore, modeling the degradation process of different components and establishing the comprehensive preventive maintenance strategy of wind turbines based on the random degradation model is the future research direction.
2. By analyzing the dynamic changes of wind turbine availability in the maintenance process, dynamic maintenance strategies are adopted to better improve the reliability of wind turbines and reduce the maintenance cost. Through the simulation example, it is verified that the traditional periodic maintenance is feasible, and the essence of condition-based maintenance is cycling based maintenance, and then cycle-based maintenance optimization.

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