Research on wind turbine system reliability modeling and preventive maintenance policy considering performance degradation and shock

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Abstract. With the development of the wind turbine industry, the operation and maintenance of wind turbines has gradually become one of the main concerns of the wind turbine industry. In view of the wind turbine system's vulnerability to external environment, this paper considers the performance degradation and external shocks of the unit to establish a reliability model and develop preventive maintenance policy. First, Markov chain is used for degradation modeling, and unit is divided into different health states; Homogeneous Poisson process is used for shock modeling, assuming that the shock is cumulative. The impact of shocks on unit degradation was described as the unit in different states had different state transition matrices, and then establish the state reliability. According to the state probability of the unit, formulate the corresponding preventive maintenance policy. Finally, a generator in a wind turbine system is taken as an example, the influence of external shocks on unit performance degradation is explained. Meanwhile, the preventive maintenance strategy proposed in this paper is compared with the maintenance policy with fixed maintenance threshold, and the advantages of the reliability model and maintenance strategy proposed in this paper are illustrated.

1. Introduction
With the increasing development of the world economy and society, various countries pay more and more attention to the protection of the environment. Therefore, the development and utilization of renewable energy has drawn many countries’ attention. Wind power generation is one of the more economical renewable energy sources nowadays. According to the Energy Research Institute of the National Development and Reform Commission, China's installed wind power capacity will reach 2 400 GW by 2050, accounting for 33.8% of the total domestic installed capacity [1]. To develop wind power and other clean energy is an inevitable choice to realize China's sustainable development strategy. Wind turbines use wind energy as power source, and the working environment is especially harsh. Therefore, in addition to the performance of the unit itself will decline, external environmental factors. The failure of the unit will bring huge economic losses to the wind farm. In addition to it, stable operation of power system also has obvious negative impact. With the development of sensor technology, real-time data about wind speed, vibration, pressure and other health status of wind power system can be obtained through sensors installed on wind power machine, so as to realize state maintenance or preventive maintenance based on equipment reliability.
2. Literature review

Some researchers use Control charts of residuals to improve the productivity [2]. Reliability is also the main quality index of modern products. In relevant literature, degradation caused by internal factors is generally called performance degradation process. Degradation process caused by external factors is called shock process [3]. From the perspective of reliability analysis, degradation models are usually divided into three: performance degradation model, shock model and degeneration-shock model.

The failure caused by performance degradation is also called soft failure. Since the 1970s, domestic and foreign studies on performance degradation have been started. Gertsbackh and Kordonskiy first proposed to use performance degradation data to conduct reliability research [4]. At present, the commonly used models mainly include continuous models and discrete models. Li Yaping use Hidden Markov Model to assess Degradation [5]. However, the degradation process of equipment includes natural degradation process and the degradation caused by external shocks. Therefore, shock model has become an important research branch in reliability research. The failure due to external shocks is also called hard failure. There have been many literatures dedicated to the study of shock models, such as Esary [6], Chen [7], Li and Kong [8], Mallor [9], Bai [10], etc. Gut et al. described the shock process [11]. These models do not consider the performance degradation process of the equipment itself, but believe that if the product is not shocked, the equipment can continue to operate normally.

In recent years, a large number of scholars have begun to concentrate on the research of systems where shock and degradation exist simultaneously. Most domestic and foreign researchers use Poisson process to establish shock models to describe the different types of shock processes. Among them, some models assume that the degradation process and the random shock process are independent of each other [12-14]. However, this assumption does not reflect the reality accurately. In recent years, more and more scholars have begun to study the independent relationship between the degradation and the shock process. Cha and Finkelstein proposed a degradation model based on the random shock process, and pointed out that shock will have two types of effects on the degradation process: causing the system to fail immediately, and shortening the actual use time of the system [15]. Subsequently, according to the internal performance level of the system and the external shock damage level, Chen Tong et al. adopted three different types of preventive maintenance, and replaced them when the system failed [16]. Wang and Pham proposed a hybrid model of multiple degradation and random shock by Copula function [17]. Peng et al. proposed a degradation and shock model combining cumulative shock model and extreme shock model and a new maintenance strategy was proposed [18].

Now, many scholars have studied the reliability and maintenance strategies of wind turbine systems. Yin Peiting proposed a dynamic state opportunity maintenance policy based on the average effective maintenance cost based on the condition monitoring data to extract the degradation characteristics of each unit component [19]. Su Chun et al. established a state maintenance optimization model based on the semi-Markov decision process, and considered the influence of wind speed, spare parts logistics, downtime loss and other factors [20]. From the perspective of maintenance, Besnard, F, et al. divided the state of wind turbines into five states according to the impact of maintenance requirements and costs when the state of the equipment reached different degrees of degradation [21]. However, these factors have not taken into account the fact that wind turbines are vulnerable to external shocks. Tao Hongyu et al. used non-stationary gamma process and non-homogeneous Poisson process to model the degradation process of wind turbine components with two degradation paths, and introduced degradation influence factors and shock influence factors [22]. The state preventive maintenance strategy of the wind power system has been established. Eunshin Byon et al. used a partially observable Markov model to consider the influence of seasonal weather factors on the maintenance cost of wind turbines, but believed that external environmental conditions had no obvious relationship with the degradation or failure of wind turbines [23]. Brede Hagen is proposed to consider the weather of the multivariate markov chain model based on time [24].

According to the literature, many scholars have considered the impact of shocks on performance degradation, including degradation increment and degradation rate caused by shocks. In most literature, the system state is assumed to be two states: "normal" and "failure". But in practice, many systems are
different from these two extreme states. Therefore, this article uses Markov chain describe performance degradation of the system, and divides the state of the system according to the vibration data of the state detection. The clear state classification can more intuitively reflect the health status of the unit, which is conducive to simplifying maintenance decisions. At the same time, it is found that most researches on preventive maintenance strategies for wind turbine systems are based on the reliability of the system to set preventive maintenance thresholds. This paper considers the preventive maintenance thresholds based on system status.

Therefore, based on the research of Li J [11], considering the influence of random shocks on unit performance degradation, this paper constructs a Markov chain describe performance degradation model and a Poisson process shock model to obtain a state transition probability matrix related to the system state and the probability vector of the system state. According to the state probability of the system, the preventive maintenance policy is determined. Finally, compared with other related studies, the advantages of the model constructed in this paper are illustrated.

3. Reliability analysis with degradation and shocks

3.1. Degradation modelling

This paper uses Markov chains to model the health status of the wind power system. The state of the system is represented by Markov chain, \( S = \{s_1, s_2, \ldots, s_n\} \), Where \( s_1 \) represents the new state of the system, \( s_a \) represents the failure state of the system, \( \{s_2, \ldots, s_{n-1}\} \) indicates that the system is in degraded states. The failure can be reached by the natural degradation of the system performance, or it can be caused by the external shocks of the system. The one-step transition probability of the system state is \( p_{ij} = P(S_{i+1} = s_j | S_i = s_i) \). The one-step transition matrix is \( P \cdot \pi \) is the initial state probability vector of the system, \( \pi(t) = [\pi(t)_{s_1}, \pi(t)_{s_2}, \ldots, \pi(t)_{s_n}] \). Suppose that the state can only be transferred to the next adjacent state shock modeling.

Shocks are often random, so the Poisson process is used to count random shocks. This paper assumes that random shocks follow homogeneous Poisson processes, which can be expressed as:

\[
P = (N(t) = \theta) = \frac{(\lambda t)^\theta}{\theta!} e^{-\lambda t}
\]

\( \theta \) denotes the total number of shocks at time \( t \), \( \lambda \) denotes the intensity of shocks.

According to the shock size, shock can be divided into fatal shock and non-fatal shock. When the shock magnitude exceeds a certain threshold \( D_0 \), the system can directly fail, which is called fatal shock; although non-fatal shock will not cause direct system failure, it will have an impact on the state transition of the system, and accelerate the degradation of the system. Suppose the impact of the shock damage to the system is cumulative. The magnitude of the \( i \)-th shock is denote by \( W_i \), and it is assumed to follow the standard normal distribution:

\[
(1) \quad P(W_i \geq D_i, i = 1,2,\ldots,n) \text{, failure of the system will be caused, and the probability is}
\]

\[
P(W_i \geq D_i) = 1 - F_i(t) = 1 - \Phi(D_i - \mu_{W_i})/\sigma_{W_i}
\]

\( \Phi \) denotes the standard normal distribution function.

(2) When \( W_i < D_i, i = 1,2,\ldots,n \), the system will not failure, but the shock will have an impact on the state of the system. The damage of each non-fatal shock to the system follows an exponential distribution:

\[
(3) \quad G(W_i) = 1 - e^{-\mu_{W_i} t}, i = 1,2,\ldots,n
\]

Then the probability distribution of damage to the system caused by the cumulative shock is

\[
(4) \quad P(W_1 + W_2 + \cdots + W_n \leq x) = G(x)
\]

\( G(x) \) denoted by \( m \) times Stieltjes convolution of \( G(x) \).
3.2. State reliability

External shocks will have a certain influence on the degradation of the system. Therefore, based on the Markov chain model constructed by Li J [5], this paper considers the impact of external shocks on the state transition of system degradation. The performance degradation function related to the magnitude of shock damage is expressed as:

$$\hat{S}(t_j) = \left[ (1 + \bar{G}(x))F(t_j) \right] - y_d^*$$  (5)

Where $y_d^*$ is the performance degradation threshold, $y_d^*$ is the threshold that is allowed to run.

Therefore, this paper takes the probability value in the fixed state transition probability matrix as the basis and takes it as the initial value of each state transition probability in the time sequence state transition probability matrix considered in this paper. The time sequence state transition probability matrix when the unit is in $S_i$ can be expressed as:

$$P_{S_i}(t_j) = \begin{bmatrix} 1 - p_{12}(t_j) & p_{12}(t_j) & 0 & 0 \\ 0 & 1 - \frac{p_{23}}{2} & p_{23} & 0 \\ 0 & 0 & 1 - \frac{p_{34}}{2} & p_{34} \\ 0 & 0 & 0 & p_{44} \end{bmatrix}$$

$$p_{12}(t_j) = \hat{S}(t_j), (d \leq j \leq u_1), \hat{S}(u_1) = \frac{p_{23}}{2}$$  (6)

where $t_d$ is the beginning moment of the unit in $S_i$, $t_{u_1}$ is the end moment of the unit in $S_i$. When the unit is at $t_{u_1}$, the probability that the unit in $S_2$ begins to be greater than $S_i$. At this time, the unit can be considered to have started to enter $S_2$. The state transition probability of $S_i$ is maintained at the value at the end of $S_i$, $p_{12}(t_j) = p_{12}(t_{u_1}), (j \geq u_1 - 1)$. The transition probability of $S_i$ begins to change with time. Therefore, the transition probability matrix of the state of the unit in $S_2$ can be expressed as:

$$P_{S_2}(t_j) = \begin{bmatrix} 1 - p_{12}(t_{u_1}) & p_{12}(t_{u_1}) & 0 & 0 \\ 0 & 1 - \frac{p_{23}}{2} & p_{23} & 0 \\ 0 & 0 & 1 - \frac{p_{34}}{2} & p_{34} \\ 0 & 0 & 0 & p_{44} \end{bmatrix}$$

$$p_{23}(t_j) = \hat{S}(t_j), (u_1 \leq j \leq u_2), \hat{S}(u_2) = \frac{p_{34}}{2}$$  (7)

where $t_{u_1}$ is the beginning moment of the unit in $S_2$, $t_{u_2}$ is the end moment of the unit in $S_2$. When the unit is at $t_{u_2}$, the probability that the unit in $S_3$ begins to be greater than $S_2$. At this time, the unit can be considered to have started to enter $S_3$. The state transition probability of $S_2$ is maintained at the value at the end of $S_2$, $p_{23}(t_j) = p_{23}(t_{u_2}), (j \geq u_2 - 1)$.

Similarly, the state transition probability when the component is in $S_3$ and $S_4$ also follows the above calculation methods, and the time sequence state transition probability matrix of $S_3$ and $S_4$ is obtained as:

$$P_{S_3}(t_j) = \begin{bmatrix} 1 - p_{12}(t_{u_2}) & p_{12}(t_{u_2}) & 0 & 0 \\ 0 & 1 - \frac{p_{23}}{2} & p_{23}(t_{u_2}) & 0 \\ 0 & 0 & 1 - \frac{p_{34}}{2} & p_{34}(t_{u_2}) \\ 0 & 0 & 0 & p_{44}(t_{u_2}) \end{bmatrix}$$

$$p_{34}(t_j) = \hat{S}(t_j), (u_2 \leq j \leq u_3), \hat{S}(u_3) = \frac{p_{44}}{2}$$  (8)
\[
P_{s_k}(t_j) = \begin{bmatrix}
1 - p_{12}(t_{n-1}) & p_{12}(t_{n-1}) & 0 & 0 \\
0 & 1 - p_{23}(t_{n-1}) & p_{23}(t_{n-1}) & 0 \\
0 & 0 & 1 - p_{34}(t_{n-1}) & p_{34}(t_{n-1}) \\
0 & 0 & 0 & p_{ss}(t_j)
\end{bmatrix}
p_{ss}(t_j) = 1(\text{for } j = 1, 2, \ldots, n)
\]

Since \( S_4 \) is the last state, the state can only be transferred to the state itself, so \( p_{ss}(t_j) = 1 \).

According to the known health state data of the unit, the probability of the unit in different operating states at different times is calculated:
\[
\pi(t_j) = \pi(t_j_{n-1}) \cdot P(t_{n-1}) = \pi(t_j_{n-1}) \cdot P(t_{n-1}) \cdot P(t_{n-2}) \cdot \cdots \cdot P(t_1)
\]

According to the above description, the failure of the unit may be caused by the performance degradation of the unit, or the unit may have suffered a fatal shock which causes the sudden failure of the unit. When the unit is in a state of failure, it can no longer work normally. This failure is caused by performance degradation. Therefore, the probability of the unit in a failure state is regarded as the probability of the unit not operating normally, and this probability is used to describe the soft reliability of the unit:
\[
R_s(t_j) = 1 - \pi(t_j_{n-1})
\]

The hard reliability of the unit is taken as the probability that the unit can still operate normally after being shocked. Thus, the reliability of the unit can be described as:
\[
R(t_j) = R_s(t_j) \times R_p(t_j)
\]

4. **Maintenance policy**

Wind turbines are generally located in places with rich wind resources but harsh external environment, which are more susceptible to the influence of external environment. In this paper, the shock damage and performance degradation of the wind turbines are considered comprehensively. Based on this, the preventive maintenance policy of the unit is formulated.

When the unit is down due to performance degradation or external environmental shock, it should be immediately repaired. Corrective maintenance refers to the maintenance behaviour of the unit after the failure, and the unit is ‘as new as new’ after the maintenance. Therefore, the failure maintenance cost is:
\[
C_e = C_{e1} + C_{e2}
\]

Where \( C_{e1} \) is the cost of corrective maintenance, \( C_{e2} \) is the fixed cost of corrective maintenance, \( C_{e1} \) is the downtime loss of corrective maintenance.

If the unit is repaired after failure, the unit has been seriously damaged and the required maintenance cost is relatively high. This paper proposes a preventive maintenance policy. It is assumed that the unit will be ‘as good as new’ after the preventive maintenance. The specific maintenance strategy is as follows: according to the state transition probability of the unit, when the probability of the unit in \( S_4 \) is greater than the probability of the unit in \( S_1, S_2 \) and \( S_3 \), preventive maintenance of the unit shall be carried out. Therefore, the preventive maintenance cost is:
\[
C_p = C_{p1} + C_{p2}
\]

Where \( C_{p1} \) is the cost of preventive maintenance, \( C_{p2} \) is the fixed cost of preventive maintenance.

Preventive maintenance at \( t \) will restore the unit to a new state, and the risk of failure will be greatly reduced. If preventive maintenance is not carried out, the probability that the unit is in \( S_4 \) will increase. Once the failure occurs, the cost of corrective maintenance is much higher than the cost of preventive maintenance, which directly increases the operation and management cost of the wind farm, thus
reducing the profit of the wind farm. Therefore, the total cost model of preventive maintenance is as follows:

\[ C(t) = C_p \times R(t) + C_v(t) = C_p \times R(t) + C_v \times (1 - R(t)) \]  

(15)

5. Numerical examples

In this paper, for the key component of wind turbine generator, according to the data in the Reference [25], the generator enters the degradation period from the 307-th day. The vibration data of the generator starting from the 307 day is selected for degradation performance analysis. According to the vibration data, the generator performance degradation was fitted, and the states were discrete into four states: normal \((S_1)\), abnormal \((S_2)\), severe degradation \((S_3)\) and failure \((S_4)\). The initial state probability vector is \(\pi(t_0) = [0.95, 0.02, 0.02, 0.01]\). The performance degradation threshold of the generator is 1.8 mm/s, and the allowable operation threshold is 10 mm/s. Since it is difficult to obtain data about external random shocks to wind power systems, relevant parameters of random shocks subject to homogeneous Poisson process are assumed as follows in this paper: \(\lambda = 2.5 \times 10^4, D_0 = 1.5 [26]\), \(\mu = 9, W_i \sim N(\mu_w, \sigma_w^2), \mu_w = 1.2, \sigma_w = 0.2\). The fixed cost of corrective maintenance is ¥1.0324 million/unit, and the downtime loss is ¥68900/unit; the fixed cost of preventive maintenance is ¥688200/unit, and the downtime loss is ¥13780/unit.

Assuming that the generator suffered non-fatal shock during this period of time for one time \((m = 1)\), the state transition probability matrix considering random shocks and performance degradation can be calculated according to Equations (6) to (10). Due to the consideration of random shocks, compared to the case where random shocks are not considered, the time point at which the probability of a component in a failure state exceeds the probability of the other three states is advanced. Therefore, preventive maintenance at this time can effectively prevent the subsequent system from failure.

![Figure 1. Reliability of the generator when it suffers from shocks.](image)

The curves of reliability change are shown in Figure 1. For \(m = 1\), we consider that a fixed preventive maintenance threshold is set as 0.5. Then, as can be seen from the figure, the reliability is greater than 0.5 when the probability of the unit being in a failure state \((S_4)\) exceeds the other three state probabilities. According to this preventive maintenance policy, no maintenance operation is required. However, at this time, the components are already in a state of failure, and the probability of failure increases, which may increase the maintenance cost of the unit. Based on the above analysis results, the reliability assessment of random shock and performance degradation and the preventive maintenance policy are more consistent with the performance degradation of wind turbine generators.

As can be seen from Figure 1, the state reliability of the generator with shock considered is lower than that without shock considered. And with the increase of the number of external shocks suffered
by the generator, the reliability becomes lower and lower. This is because after the generator suffers from a shock, the units will be damaged, then the reliability of the generator is reduced.

According to Equation (15) above, the change curve of the total maintenance cost of the generator is calculated as follows:

![Figure 2. Total maintenance cost of the generator when it suffers from shocks.](image)

We can find in the Figure 2 that with the increasing number of shocks, the greater the total cost of maintenance. This is because the generator of the wind turbine has been repeatedly subjected to external shocks, such as typhoon, rain and snow weather, the degree of damage of the unit increases, the number of maintenance, maintenance time, maintenance materials, etc. will increase. In addition, in combination with Figures 1 and 2, we can see that the preventive maintenance policy proposed in this paper has certain advantages, because the unit suffers a shock, that is $m = 1$, the probability of the system being in a failure state at 850-th day is higher than the other three, and the maintenance cost at this time is lower than the maintenance cost when the reliability reaches 0.5.

6. Conclusions
In this paper, we consider the impact of shocks on performance degradation with markov degradation model. Then the paper analyzes the correlation between performance degradation and random shocks of wind turbine system with two degradation paths, and constructs the time sequential state transition matrix, state probability vector and unit state reliability. Combined with the state probability of the unit and the two failure modes, the preventive maintenance policy of the wind turbine system is formulated. Through the analysis of the calculation example, it can be seen that according to the different environment of the system, the number of random shocks is different, and the establishment of the reliability model based on the state is of great significance to reduce the safety accidents caused by the underestimation of the degree of system degradation, and ensure the safe operation of the system. In addition, this paper also compares the proposed reliability model with the reliability without shocks, and compares the maintenance cost with shocks and that without shocks to illustrate the advantages of the proposed model.

Acknowledgements
This research is supported by National Natural Science Foundation of China (No. 71701098, 72001138), Humanities and Social Sciences Youth Fund of Chinese Ministry of Education (No. 17YJC630070), Natural Science Foundation of Jiangsu Province (No. BK20160940).

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