Remaining life prediction of wind turbine bearing based on Wiener process

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Abstract. In order to know about the real-time operating condition and the remaining life of the wind turbine bearings in time, a method of life prediction was proposed based on Wiener process. Firstly, the relationship model of bearing temperature parameters and speed parameters of wind turbine was established by using multiple linear regression; Secondly, the established relationship model was been used to build the real-time monitoring and performance degradation model of the wind generator bearings; Thirdly, Linear Wiener process and nonlinear Wiener process were respectively used to establish the remaining life prediction model of wind turbine bearing; Finally, the feasibility and effectiveness of the method in practical application were verified by analyzing the temperature data of a wind turbine’s gearbox.

Keywords. Wind turbines; Wiener process; SCADA data; Remaining life protection; Linear regression

1. Introduction
Bearing is one of important components of wind turbine transmission units and it’s running state and remaining life directly affect the running state of wind turbine. At present, the residual life prediction of wind turbine bearings is rarely studied at home and abroad [1]. Most of the characteristic data used in related research are load data or vibration signal data [2-5], However, the acquisition of these two kinds of signals requires an additional signal acquisition system, and that will increase the cost of operation and maintenance; By using the finite element simulation analysis method [5-7], or using the modified formula which based on the standard calculation formula of bearing life [8,9], due to the insufficient consideration of the environmental impact on the bearing. It is difficult to be effectively applied to the actual operation and maintenance, establishing the prediction model based on neural network [10,11] needs to be taken a large number of training sample. Extracting these sample data is time-consuming and laborious, which is not conducive to practical work. Hu Yaogang et al. [12] proposed a real-time life prediction method based on temperature. This method ignored the hysteresis of the bearing temperature change relative to the change of speed, so it cannot be effectively applied to the actual operation and maintenance.

This paper proposes a bearing life prediction method based on Wiener process. Firstly, with time, wind speed and bearing temperature characteristic, established between bearing temperature, rotational speed and time of multiple linear relationship model. Secondly, set up a new bearing running condition monitoring programme according to the established relationship model. Thirdly, the degradation model of bearing performance is established, According to the failure principle that degradation parameters
exceed the failure threshold for the first time, a bearing life prediction model based on Wiener process was established. Finally, the method proposed in this paper is verified by taking the performance degradation data of wind turbine’s gearbox bearing in actual operation as an example.

2. The relationship model of bearing characteristic quantity and the monitoring of running condition of wind turbine

2.1 Bearing feature extraction and relationship model establishment

Bearing temperature of wind turbine is related to various factors such as speed and friction torque, the parameters directly recorded by the SCADA system are rotational speed. There is a delay in the transfer of heat from the bearing to the temperature sensor. Therefore, it is necessary to establish the relationship model among bearing temperature, speed and time. The relationship model of real time temperature, time and speed of bearing was established from SCADA data. In this paper, according to the time series data from SCADA system to extract the feature parameters \((t_0, T_0, r_0), (t_1, T_1, r_1), \ldots, (t_n, T_n, r_n)\), where, \(t_0, t_1, \ldots, t_n\) is the directly derived continuous time point in the SCADA system, The time interval is the data collection cycle. According to literature [13,14], it can be concluded that the total heat generated by the bearing of the wind turbine unit is proportional to the speed and the temperature field of the bearing is gradually decreasing from inside to outside, with a certain loss in heat transfer process in, therefore, its measured temperature value can be regarded as the result of the joint action of multiple continuous time points. Then, the actual measured temperature of the bearing can be expressed by the following function expression:

\[
T_i = a \sum_{j=0}^{n} \alpha_j r_{t_i-t_j} + T_0 + \varepsilon_i
\]

(1)

Where, \(T_i\) is bearing temperature measured at time \(t\); \(a\) is temperature rise coefficient of relative speed; \(\alpha_j\) is the weight of the temperature rise at the moment \(t - \tau - iT\) relative to the temperature rise at the moment \(t\); \(r_{t_i-t_j}\) is the rotate speed at the moment \((t - \tau - iT)\); \(\tau\) is Measurement lag time (The time of heat transfer from the bearing to the sensor part, if the time is less than one data collection cycle, it shall be calculated as one collection cycle); \(T\) is data acquisition cycle; \(T_0\) is Initial temperature; \(\varepsilon_i\) is Deviation.

The value \(\tau\) in formula (1) represents the heat conduction performance of the bearing’s own material; \(n\) is the number of acquisition time occupied by the heat generation time on the bearing at a certain time, and represents the heat transfer performance of the bearing. Value \(a\) represents the thermogenic performance of the bearing. Where, the value \(\tau\) and \(n\) can be determined by observing the time difference between each rotation speed and temperature turning point or by simulation. Other parameters can be estimated by regression method and determined by data normalization.

2.2 Real-time monitoring scheme of operation condition

Wind turbines bearing operation condition monitoring is done by monitoring the temperature of the bearing, the early warning and protection is set temperature upper limit as a general alarm, fault threshold. However, in fact, the wind speed of the wind turbine also has a certain randomness due to the randomness of the wind speed. When it does not operate at the maximum speed, a single temperature value cannot effectively monitor the running condition of the bearing in a timely manner and timely alarm the failure. In this paper, a new method of state monitoring and alarm threshold setting is proposed to make up for the above deficiencies. According to the normal operation parameters of the wind turbine, the parameters in equation (1) are determined. Then, the real-time operation parameters of the wind turbine are substituted into the established equation, it can be obtained that the temperature rise coefficient of relative speed at time \(t\) as follows:
Substitute the wind turbine's speed and temperature threshold at the maximum speed into equation (2), and the threshold \( \zeta \) of \( a_t \) can be obtained. The real-time running condition of the bearing is judged by the value of the temperature rise coefficient \( a_t \) of the relative speed at the moment \( t \): The smaller the value \( a_t \) is, the better the running condition of the bearing is; on the contrary, the larger the value \( a_t \) is, the worse the running condition of the bearing is; An alarm is issued when the value \( a_t \) is greater than the set threshold.

3. Remaining life prediction model of wind turbine bearing

3.1 Wind turbine bearing performance degradation model establishment

The characteristic parameter data were extracted from SCADA system in time series \((t_0, T_0, r_0), (t_1, T_1, r_1), \ldots, (t_n, T_n, r_n)\). Through the calculation of formula (2), it can be concluded that the trend sequence of the relative speed temperature rise coefficient of wind power bearing is \((t_0, a_{0}), (t_1, a_1), \ldots, (t_n, a_n)\). As the bearing is affected by different degrees of external adverse factors in each operation stage, the relative speed temperature rise coefficient of the bearing will fluctuate and rise with the continuous deterioration of the bearing. Therefore, according to literature [15, 16, 17], the linear Wiener process and the nonlinear Wiener process were used for modeling in this paper.

\[
a_t = (T_t - T_0) / \sqrt{\sum_{i=0}^{n} \alpha_i r_{t-i}}
\]  
(2)

Where, \( \alpha_i \) is degradation trend quantity initial value; \( \mu \) is drift parameter; \( B(t) \) is Standard Wiener process; \( \sigma \) is diffusion parameters; \( r \) is exponential of \( t \). When \( r \) is not 1, the process is nonlinear Wiener process; When \( r \) is 1, This process is a linear Wiener process.

3.2 Performance degradation parameter estimation

The trend of bearing performance degradation at each monitoring point in a certain detection cycle is \((t_0, x_0), (t_1, x_1), \ldots, (t_n, x_n)\). The drift parameters \( \mu \), diffusion parameters \( \sigma \) and values \( r \) of the degradation model of bearing performance are obtained by using the maximum likelihood estimation method. For the initial value, in order to reflect the overall performance degradation degree of the bearing in the monitoring period, the average value of the temperature rise coefficient of the relative speed within the period is taken as the initial value. According to equation (3), let’s make \( \Delta t \), then, the increment expression of temperature rise coefficient of relative speed can be expressed as:

\[
\Delta x_t = x_t - x_{t-1} = \mu \Delta t + \sigma \Delta B(t)
\]  
(3)

Where, \( \Delta x_t = x_t - x_{t-1} \); \( \sigma \Delta B(t_t) = \sigma \Delta B(t_t) - \sigma \Delta B(t_{t-1}) \). As can be seen from the Wiener process definition: \( \Delta B(t_t) \sim N(0, \Delta t) \). Thus:

\[
\Delta x_t \sim N(\mu \Delta t, \sigma^2 \Delta t)
\]  
(4)

According to the definition of the Wiener process, \( \Delta x_1, \Delta x_2, \ldots, \Delta x_n \) It satisfies the independent homology distribution, the sample likelihood function is:

\[
L(\mu, \sigma, r) = f(\Delta x_1) f(\Delta x_2) \ldots f(\Delta x_n)
\]  
(5)
According to equations (5) and (6), the logarithmic likelihood function of the sample can be obtained as follows:

\[
\ln[L(\mu, \sigma)] = -\frac{n}{2} \ln(2\pi) - \frac{1}{2} \sum_{i=1}^{n} \ln(\Delta t_i)
\]

\[-n \ln \sigma = \frac{1}{2\sigma^2} \sum_{i=1}^{n} \frac{\left(\Delta x_i - \mu \Delta t'_i\right)^2}{\Delta t_i} \]

Equation (7) take Partial differential and set it equal to 0:

\[
\frac{\partial \ln L}{\partial \mu} = \frac{1}{\sigma^2} \sum_{i=1}^{n} \frac{\Delta x_i'\left(\Delta x_i - \mu \Delta t'_i\right)}{\Delta t_i} = 0
\]

\[
\frac{\partial \ln L}{\partial \sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum_{i=1}^{n} \frac{\left(\Delta x_i - \mu \Delta t'_i\right)^2}{\Delta t_i} = 0
\]

The maximum likelihood estimation values of equations formed by solving equations (8) and (9) are:

\[
\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} \frac{\Delta x_i}{\Delta t'_i}
\]

\[
\hat{\sigma} = \left[ \frac{1}{n} \sum_{i=1}^{n} \frac{\left(\Delta x_i - \hat{\mu} \Delta t'_i\right)^2}{\Delta t_i} \right]^{\frac{1}{2}}
\]

Substituting equations (10) and (11) into equation (7), it can be obtained that the contour likelihood function (excluding the constant term) of \(r\) is:

\[
\ln[L(r)] \propto -n \ln \hat{\sigma} - \frac{1}{2\hat{\sigma}^2} \sum_{i=1}^{n} \frac{\left(\Delta x_i - \hat{\mu} \Delta t'_i\right)^2}{\Delta t_i}
\]

When the nonlinear Wiener process is applied, the estimated value \(\hat{r}\) of \(r\) can be obtained by using the one-dimensional search method; when using linear Wiener process, directly take \(\hat{r}\) is 1. Then substitute \(\hat{r}\) into equations (10) and (11) to determine \(\hat{\mu}\) and \(\hat{\sigma}\).

3.3 Estimation wind turbine bearing remaining life prediction model

It is generally believed that bearing performance failure occurs when the performance characteristic quantity exceeds the failure threshold for the first time. Therefore, it can be defined that failure occurs when the degradation parameter value \(x\) exceeds the set threshold value \(\zeta\) for the first time [17]. Remaining life \(L_t\) of wind turbine bearing refers to the time from the performance degradation amount at the current time \(t\) to the first time when the bearing exceeds the failure threshold. Namely, \(L_t\) can be expressed as:

\[
L_t = \inf \{x_s \geq \zeta \} = \{t \mid x_s \geq \zeta, x_s \leq \zeta, 0 \leq s \leq t\}
\]

According to literature [18], the probability density function of the following approximation is used:
According to the probability density function, $f(t | \mu, \zeta, r)$ can be considered as the probability that the failure threshold $\zeta$ may be reached within the minimum range near the time point $t_i$. Therefore, this paper takes the time point $t'$ corresponding to the maximum value $f(t')$ of the probability density function as the residual life $L_e$ of the bearing. The prediction process is shown in the following figure 1.

\[
f(t | \mu, \zeta, r) \geq \frac{\zeta - \mu^r (1 - r)}{\sigma \sqrt{2\pi t'}} \exp\left[-\frac{(\zeta - x_0 - \mu^r)^2}{2\sigma^2 t'}\right]
\]

\[14\]

\[15\]

In order to represent the degree of difference between the predicted results, the relative error is adopted to express:

\[e = \frac{L_e - L}{L} \times 100\%
\]

Where, $e$ is relative error of bearing life prediction; $L$ is actual residual life of the bearing. In this paper, remaining life prediction model of wind turbines bearing, can real-time prediction of residual life of wind turbines bearing. In the process of residual life prediction, the probability distribution of predicted residual life is closely related to the detected data volume $N$. Based on the literature [12], $n < 9$ can meet the requirements of statistical analysis.

4. Instance analysis

4.1 Instance specification
In order to verify the effectiveness and feasibility of the method in this paper, the gearbox bearing temperature of a 1WM wind turbine in a wind field was taken as an example for verification. Because the bearing temperature measuring point of the gearbox of this type of wind turbine set is arranged close...
to the brake (as shown in figure 2 below), the temperature value represents the common degradation characteristics of both the bearing and the brake.

![Schematic diagram of temperature sensor measuring point layout.](image)

**Figure 2.** Schematic diagram of temperature sensor measuring point layout.

As the temperature value is affected by the brake, when the rotate speed is greater than the upper limit rotate speed and remains basically constant, the temperature change is positively correlated with the wind speed; when the rotate speed does not reach the upper limit rotate speed, the wind speed is positively correlated with the rotate speed. Namely, the change of temperature is positively correlated with the wind speed. So, this article part instance using wind speed instead of the proposed speed for validation. The measuring point temperature since January 6, 2018, gear box after repair (it is generally believed to normal after the maintenance) and on July 21, 2018, beyond the threshold at 95 °C of alarm. In this paper, the temperature data and wind speed data were extracted from the maintenance in January to the alarm in July. The data acquisition interval was 8 min, as shown in figure 3.

![Monitoring data of wind speed and gear box bearing temperature.](image)

**Figure 3.** Monitoring data of wind speed and gear box bearing temperature.

As can be seen from the figure, the temperature value fluctuates with the change of wind speed, and the overall trend of temperature rises until the alarm. The instance is based on the data shown in figure 3, and the process in figure 1 is used to predict the life of this measurement point, and then comparative verification analysis is carried out.

4.2 Prediction and analysis of remaining life of gearbox bearing temperature

As described in section 1.1, \( r \) was taken as 8 min (one acquisition cycle), \( n \) was 4, and 2000 sets of data after maintenance in January were used to train formula (1) model. The values of each parameter were shown in table 1 below.
Table 1. Relational model parameters.

|   | $a$ | $a_1$ | $a_2$ |
|---|-----|-------|-------|
|   | 3.08| 0.37  | 0.25  |

Then, according to formula (2), the degenerate trend (remove outliers according to principle $3\sigma$) is obtained, as shown in figure 4.

![Figure 4. Performance degradation trend of gear box bearing.](image)

According to equation (2), the threshold of degradation coefficient $x$ is obtained according to the original temperature threshold and rated wind speed. According to the processing of the original temperature data, it can be seen that the actual degradation coefficient of the original alarm point is 3.84, which is less than the threshold and at a normal level. Therefore, it can be judged that the temperature alarm is a false alarm. The wind field maintenance personnel also confirmed this conclusion after on-site inspection. As can be seen from the comparison between Fig 3 and Fig 4, the real-time condition monitoring of the bearing of the wind turbine set with the temperature rise coefficient of the relative speed as the monitoring index can largely reduce the errors caused by the speed, and the false alarm phenomenon caused by the change of the speed can be detected to a certain extent. Although the alarm is false, it can be clearly seen from figure 4 that the degradation parameter is in a nonlinear rising state. In this paper, when the degradation parameter reaches the maximum value (8.48), it will be taken as the remaining life time for verification.

According to the time series, a total of 5 sets of arrays were extracted with each 5000 sets of Numbers as a cycle. Through the calculation of equations (11), (12) and (13), the performance parameters of each cycle of the nonlinear Wiener process and the linear Wiener process were obtained, as shown in table 2 and table 3.
Table 2. The performance parameters of nonlinear Wiener process in each period.

| Period  | $\mu$   | $\sigma$ | $r$  | $x_0$ |
|---------|---------|----------|------|-------|
| Period 1| 0.086711| 0.010592 | 0.50 | 0.43  |
| Period 2| -0.000498| 0.008945 | 1.06 | 1.16  |
| Period 3| 0.000023 | 0.010017 | 1.54 | 1.28  |
| Period 4| -0.000171| 0.017563 | 1.09 | 2.08  |
| Period 5| -1.533439| 0.017969 | 0.27 | 3.00  |

Table 3. The performance parameters of linear Wiener process in each period.

| Period  | $\mu$   | $\sigma$ | $x_0$ |
|---------|---------|----------|-------|
| Period 1| 0.001104| 0.010592 | 0.43  |
| Period 2| -0.000787| 0.008945 | 1.16  |
| Period 3| -0.000173| 0.010017 | 1.28  |
| Period 4| -0.000453| 0.017563 | 2.08  |
| Period 5| -0.001676| 0.028940 | 3.00  |

According to the parameters in table 2 and table 3, equation (14) is used to calculate the probability distribution of each period, as shown in figure 5.

Figure 5. Comparison of residual life prediction results of gearbox bearing.

The predicted results and relative errors of nonlinear Wiener process and linear Wiener process obtained in figure 5 are shown in table 4 and table 5 respectively.
Table 4. Comparisons between actual and predicted remaining life by nonlinear Wiener process.

| Period | $L_1/(\times 8 \text{ min})$ | $L/(\times 8 \text{ min})$ | Error days / (day) | $e$(%) |
|--------|-------------------------------|-----------------------------|-------------------|--------|
| Period 1 | 8129                          | 23177                       | -83.60            | -64.93 |
| Period 2 | 7542                          | 18177                       | -59.08            | -58.51 |
| Period 3 | 3670                          | 13177                       | -52.82            | -72.15 |
| Period 4 | 11425                         | 8177                        | 18.04             | 39.72  |
| Period 5 | >25000                        | 3177                        | >121.24           | >68.69 |

Table 5. Comparisons between actual and predicted remaining life by linear Wiener process.

| Period | $L_1/(\times 8 \text{ min})$ | $L/(\times 8 \text{ min})$ | Error days / (day) | $e$(%) |
|--------|-------------------------------|-----------------------------|-------------------|--------|
| Period 1 | 7150                          | 23177                       | -89.04            | -69.15 |
| Period 2 | 9114                          | 18177                       | -50.35            | -49.86 |
| Period 3 | >25000                        | 13177                       | >65.68            | >89.72 |
| Period 4 | 12060                         | 8177                        | 21.57             | 47.49  |
| Period 5 | 2862                          | 3177                        | -1.75             | -9.92  |

It can be seen from the above table 4 and table 5 that, no matter the nonlinear Wiener process or the linear Wiener process, except that the predicted results of the nonlinear Wiener process in the 5th cycle and the linear Wiener process in the 3rd cycle are deviated too much, the predicted error days and relative errors of other monitoring cycles generally show a decreasing trend as the running time goes by. Except for the 3rd and 5th cycles, the results of the other three cycles using the nonlinear Wiener process and the linear Wiener process are not too far off. Therefore, in practical applications, in order to simplify the calculation, the linear Wiener process can be used as the main method for life prediction. According to the time series, the prediction results should show a fluctuation reduction trend. When the local prediction results deviate greatly from the main trend, the nonlinear Wiener process can be used as an auxiliary to correct the local prediction results.

5. Conclusion

- The relationship model of wind power bearing temperature, speed and time is established.
- A new real-time monitoring method of bearing running state is proposed.
- The nonlinear Wiener process and linear Wiener process were used to establish the bearing degradation model and remaining life prediction model.
- The method is verified by an example, and the results are compared and analyzed.

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