Research on life prediction technology of wind turbine gearbox based on virtual simulation

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Abstract. As the core component of wind turbine energy conversion, the gearbox has been operating under variable frequency and variable load condition for a long time. The repair time is long after its fault, which leads to a large loss of power generation. This paper proposes a gearbox life prediction method. By collecting the design and manufacturing process parameters of gearbox, the gearbox virtual simulation model is established, the gearbox observable damage can be predicted accurately by inputting the actual operation load. According to the results, the maintenance and repair time of the gearbox can be arranged scientifically, which can effectively avoid the occurrence of serious faults, greatly reduce the gearbox replacement rate and unscheduled downtime, the economic benefits are obvious. After field application, the accuracy of this method can be 93.5%, which has a good prospect of application.

1. Introduction
After the wind turbine is put into operation, the initial operation and maintenance cost accounts for about 10% to 15% of the total cost. After a long period of wear and aging, the operation and maintenance cost of the wind turbine accounts for about 20% to 35% of the total cost. It can be seen that as the operating time of the wind turbine increases, the fatigue failure rate will increase, and the operation and maintenance costs will increase exponentially.

In order to reduce the operating cost and downtime of wind turbines, the reliability of wind turbines needs to be improved to improve working performance. There are two ways to improve reliability: optimizing the structure of wind turbines; rationally arranging maintenance plans. From the operator's perspective, it is mainly to improve reliability by arranging reasonable operation and maintenance plans. By studying the life prediction methods of large components of wind turbines and establishing component life prediction models to predict the short-term, mid-term and long-term life warnings of large components, firstly, the management level and maintenance level of wind turbines in the wind farm can be improved, and secondly, the company's spare parts can be improved Management, and finally through life warning can optimize supplier selection and asset allocation management.

A wind turbine gearbox is an energy conversion device for wind power generation. The gearbox is composed of gears, shafts and bearings. Due to the large changes in load and working under high-speed and heavy loads, the operating state is more complicated and it is prone to failure. With the increase in operating time, the failure rate of gearboxes continues to rise. Once the gearbox fails, it needs to be repaired and replaced under the tower, resulting in very long downtime and great economic losses. Therefore, it is possible to accurately predict the life of each part of the gearbox, that is, when the damage occurs, which will provide an accurate reference for on-site operation and maintenance decisions. At the same time, taking maintenance measures in advance can also extend the life of the gearbox. The popularization and application of this technology, can effectively reduce the
unplanned downtime of wind turbines, realize the operation and maintenance mode of wind farm equipment condition maintenance, and provide strong technical support for realizing the construction of smart wind farms with few people and no one in the wind power industry.

2. Theoretical research

In recent years, there are mainly two technical routes for the prediction of gearbox life: statistical models and physical models. In terms of statistical models, Zhao Hongshan [1] proposed a mathematical statistical model based on time series, which used historical inspection and maintenance data to evaluate and predict the remaining life of gearbox bearings, and achieved good algorithm simulation verification results, but did not fully consider wind turbines. In actual load conditions, the accuracy of life prediction cannot be guaranteed. At the same time, this method puts forward higher requirements on the frequency and precision of regular maintenance and inspection. Zhang [2] proposed a method for gearbox degradation state recognition and residual life prediction based on mixed Gaussian output Bayesian belief network model. In the experimental environment, this method determines the degradation state of the gearbox by calculating the probability value of the feature vector to be identified, and verifies with the experimental data of the whole life of the gearbox. Good results are obtained without considering the influence of the gearbox on the actual prediction results under the actual operation condition. Lin Guoyu [3] established the relationship between the degeneration state of the gearbox and the characteristic value through the state space model according to the characteristic value of the gearbox vibration signal to describe the nonlinear dynamic change of the gearbox. When a new signal is acquired, the accurate model state is estimated by the extended Kalman filter (EKF), and the EM algorithm (Experience Maximization, EM) estimates the parameters of the state space model. According to the model status and model parameters, the time when the characteristic value reaches the fault threshold is predicted, so as to estimate the remaining life of the gearbox. Sun Lei [4] [5] successively proposed a method for predicting the remaining life of equipment based on particle filter (PF) theory, Bayesian estimation method and Kalman filter theory. Comprehensive consideration of the amount of wear and the characteristic value of vibration enables the model to more accurately reflect the wear process of the gearbox and achieves good results. However, the full working condition parameters and physical model aspects of the gearbox operation are still not considered. Wu Jianwei [6] used Romax software to build a rigid-flexible coupling transmission system model for a 2.5MW power split gearbox, which is more in line with the actual situation, and the calculated fatigue life calculation is more accurate. However, under the separate action of a single working condition and an actual load spectrum, the life prediction results of gearbox components vary greatly. Wang Wannan [7] based on the Adaptive Neural Network Based Fuzzy Interference System (ANFIS) proposed by J-S.R. Jang, using the self-learning mechanism of neural network to compensate the original deficiencies of the fuzzy control system, and establish a Adaptive learning fuzzy neural network for processing fuzzy information, adding memory units to all nodes in the fuzzy processing layer, so that the information is continuously stored, strengthening the correlation between the information, reducing the deviation between the predicted value and the actual value, and further improving the accuracy of the model. Through experiments The sample data test has achieved good results. An Zongwen [8] used the probability weighting method and the linear Miner cumulative damage law to give the relationship between fatigue life and stress, and the random stress caused by random load was used as the basis for calculating the fatigue life.

This paper collects gearbox design and manufacturing parameters, establishes a gearbox load model, combines material friction and lubrication parameters, analyzes the gearbox load distribution, and establishes load models for gears, shafts, and bearings. Collecting wind turbine operating conditions parameters to establish the actual operating load model of the wind turbine, fusing the physical model and statistical model, and accurately predicting the occurrence time of visible damage to each component of the gearbox. Its composition structure is shown in Fig 1.
3. **Life prediction method of gearbox virtual simulation**

A high-precision three-dimensional model of the wind turbine gearbox was established, and a load model was established based on the historical SCADA data of the unit and the wind resource information of the wind farm. Combining information from materials science, tribology, multi-body dynamics, digital science, etc., a digital model is established and the material degradation performance prediction is accurately realized. Importing the SCADA data of the wind farm into the model can realize the life prediction of the shafts, bearings, gears and other components of the gearbox. Revise the forecast results through the historical maintenance records of the wind farm to improve accuracy. The model does not need to add any sensors, and can predict the earliest time of damage with high accuracy.

### 3.1. Collecting parameters

1. **Basic information**
   - (1) Wind farm information: wind farm name, commissioning time, geographical location;
   - (2) Unit information: unit model, manufacturer, unit capacity, latitude and longitude;
   - (3) Gearbox information: gearbox model, supplier
   - (4) Maintenance information: fault information and maintenance records of the spindle and gearbox.

2. **Design information**
   - (1) Gearbox: system drawing, SN number, BOM table;
   - (2) Spindle: system drawing, supplier, SN number, BOM table.

3. **Operation and maintenance information**
   - (1) At least 2 years of SCADA ten-minute data;
   - (2) Oil information: oil supplier, oil characteristic information;
   - (3) Wind farm feasibility study report;
   - (4) Wind turbine maintenance and repair report;
   - (5) Samples of failed bearings and gears (if any);
   - (6) Details of the main replacement parts.

### 3.2. Establishing wind turbine load model

The gearbox body is a typical linear steady system, and the dynamic model is established by the frequency response function matrix method. The transfer function of the box is

\[ H(\omega) = \frac{X(\omega)}{F(\omega)} \]  

In formula (1), \( F(\omega) \) is the Fourier transform of the excitation force, and \( X(\omega) \) is the Fourier transform corresponding to vibration. The dynamic model of the cabinet subsystem is...
In formula (2), $F_1(\omega), F_2(\omega), F_3(\omega), F_4(\omega)$ are the Fourier transform of the box excitation of the shafts at the bearing seat; $\{X(\omega)\}$ are the Fourier transform of the vibration acceleration response of the box [9]. The equivalent load calculation formula is as follows:

$$L_N = \sum_{i=1}^{n} \frac{L_{i,N}}{N}$$

In formula (3), $L_N$ represents the equivalent load of N cycles, $L_i$ represents the load range of the i-th level, and $n_i$ represents the number of rain cycles within the i-th level load range. N is generally $1 \times 10^3$; the value of $m$ is related to the material of the wheel box components, and the value is usually between 3-12. The aerodynamic load acting on the wind wheel is calculated by the following formula:

$$P_H = \frac{1}{2} \rho C_{FB} V_r^2$$

In formula (4), $C_{FB} = 8/9$, $\rho$ is the air density, $V_r$ is the rated wind speed. The load acting on the tower is:

$$F_{MH} = P_H A$$

In formula (5), $A$ is the sweeping area of the wind wheel. The wind turbine yaw load is divided into starting load and uniform load:

$$\begin{align*}
F_{XT} &= -Zm_u e_M \Omega^2 \\
M_{YT} &= -ZI_B \Omega \dot{\Omega}
\end{align*}$$

In formula (6), $Z$ is the number of blades, $I_B$ is the moment of inertia of the blades relative to the rotor axis, $e_M$ is the distance from the center of mass of the total mass to the tower, $m_u$ is the total mass of the generator and the wind wheel, $\Omega$ is the yaw angular velocity, and $\dot{\Omega}$ is the yaw angle acceleration.

Use wind turbine SCADA data, wind shear, and turbulence intensity to establish a wind turbine load model to predict the load (force and moment) on the main shaft of the wind turbine under various working conditions as shown in Fig 2.

3.3. Gearbox modeling based on Modelica

Full-scale modeling and component modeling of the gearbox will take into account the forces and moments on the main shaft, box deflection, and gear, bearing, and shaft geometry. By analyzing the load and force analysis on the gearbox system and various components, the gear and bearing
components with the greatest weight that cause the gearbox failure are obtained. The bearing prediction model is shown in Fig. 3.

![Fig. 3 Bearing Model](image)

### 3.4. Building a Predictive Model

Carry out fatigue life simulation based on material science for important weight components. Each gear and bearing will be individually modeled according to the influence of its lubrication at the gear/bearing contact point, surface accuracy, material quality, cumulative damage, fracture mechanics, etc. The output of this step will include Weibull fatigue life distribution of each component, crack initiation location, and component damage location. The establishment of the prediction model is divided into 6 steps as shown in Fig. 4:

1. Carry out load analysis on large parts to determine the contact stress concentration area;
2. Carry out micro-materials modeling for the materials in the stress concentration area, and calculate the development trend of fatigue damage through the digital model;
3. According to the surface machining accuracy (roughness) and lubrication characteristics of the parts, construct a model and conduct micro-stress analysis;
4. Using the stress data at the grid nodes in the microstructure model, calculate the number of cycles of crack initiation and propagation;
5. Calculate the simulation results of the overall fatigue life;
6. Using probabilistic methods to simulate differences in working conditions, material microstructures,
surface processing quality, etc, perform multiple fatigue life simulation calculations to form fatigue life distribution.

![Fig. 4 Prediction model building process](image)

### 3.5. Output of Prediction Results

For most mechanical parts, the occurrence of damage is a probabilistic process that starts with microscopic defects inside the material. When damage begins, the damage starts below the surface inside the material, which is invisible through direct observation or sensor signals. Visible damage refers to the key transmission components of wind turbine gearbox gears, shafts, bearings, etc., which have developed cracks on the surface and subsurface to a certain extent. The damage that can be observed through endoscope or other means, and the development trend of loss is shown in Figure 5.
For the key components of the gearbox as the reference object, the SCADA data cut-off time is used as the predicted time reference point, and the model output is the time difference between the occurrence time of the visibility damage and the reference point. For example, the cut-off point of the provided operating data is December 31, 2019. The output result is 5 months, which means that the visible damage of the component will occur in May 2020. Combining the fatigue life prediction of the important parts of the gearbox and the analysis of SCADA data, the visible damage occurrence time of each part of the gearbox is obtained.

**Fig. 5 Damage development trend**

For the practical application, input wind turbine load data in the life prediction model, and output the time when the wind turbine visibility damage occurred. The prediction result is verified with the actual situation, and the accuracy of the prediction result is an important guarantee for the field promotion and application of this technology.

**4. Practical application**

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**4.1. Verification method**

The forecast result time error window period is 6 months before and after the reference time point. If the forecast result matches the forecast result through on-site endoscopy during the window period, the forecast is considered successful; if it does not match, the forecast is considered failed, as shown in Fig 7 below.

**Fig. 6 Prediction results**

**Fig. 7 Predict the time of occurrence of damage**
According to various conditions of the verification results, a prediction accuracy evaluation model is given:

- \( TP = \text{True Positive} = \text{Predict the visible damage, and find the damage in the window period (success)}; \)
- \( FP = \text{False Positive} = \text{Predict visible damage, no damage is found in the window period (failure)}; \)
- \( FN = \text{False Negative} = \text{predict no visible damage, damage is found in the window period (failure)}; \)
- \( TN = \text{True Negative} = \text{No visible damage is predicted, and no damage is found during the window period (success)}; \)

4.2. Validation results

The life prediction technology application test was carried out for 336 units of wind farms, of which 42 units were predicted to be damaged and 294 units were normal units. After endoscopic inspection and confirmation, of 42 units predicted to be damaged, 37 units had damage prediction success \( TP=37 \), 5 units have no damage prediction failure \( FP=5 \); of the 294 units predicted to be normal, 277 units are in a normal state and successfully predicted \( TN=277 \), 17 units have damage, and fail to predict \( FN=17 \).

\[
\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = 93.5\%;
\]
\[
\text{False alarm rate} = \frac{FP}{FP+TN} = 1.8\%;
\]
\[
\text{The false negative rate} = \frac{FN}{FN+TP} = 31.5\%.
\]

5. Conclusion

The gearbox life prediction technology based on virtual simulation uses gearbox design parameters, manufacturing material information, and assembly process information without any additional sensors to establish a dynamic load simulation physical model of the gearbox. Based on at least 2 years of SCADA ten-minute data, fault alarm data, operation and maintenance records (replacement records, vibration monitoring records, oil monitoring records), a data statistics and physical fusion model was established to predict the occurrence time of visibility damage.

(1) Compared with the traditional vibration monitoring and oil monitoring technology, this technology does not need to add any sensors. It only needs to collect relevant basic information and operating parameters, which can reduce hardware investment costs and greatly improve the cost-effectiveness of gearbox condition monitoring methods.

(2) Compared with the statistical prediction model, it can find the abnormal state of the equipment in the early stage. By taking maintenance measures, it can prolong the service life of the components, avoid the expansion of faults, and effectively reduce the operation and maintenance costs.

The technology has high prediction accuracy and low false alarm rate through field application demonstration, can enhance the enthusiasm of field users, and has a good prospect of popularization and application.

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