A review of bearing fault diagnosis for wind turbines

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Abstract. Bearings are the core components of the wind turbine's mechanical transmission system, but the bearings of wind turbines are prone to wear and failure during vibration, and it is often difficult to determine the fault-bearing status and fault location. Therefore, the monitoring and fault diagnosis of wind turbine bearing status are very necessary. This paper introduces the types of bearings of wind turbines and common faults of bearings, analyzes from the aspects of bearing vibration data and supervisory control and data acquisition (SCADA) systems, summarizes the existing fault diagnosis methods and systems of wind turbine bearings, and points out the basics of these methods thought. Finally, the research focus of future bearing fault diagnosis is elaborated.

1. Introduction

At present, wind energy has become a new type of energy that various countries in the world are competing to develop. My country's wind resource development has reached an unprecedented high-speed growth stage. With the expansion of the scale of wind power generation, mechanical transmission failures of wind turbines are gradually exposed, especially in the bearings of the transmission system. After long-term operation, the bearings are prone to wear and damage. If there is a problem with the bearing, it will cause noise and abnormal noise, and it will cause the collapse of the transmission system, which will seriously affect the operation of the wind turbine. Due to the constraints of high-altitude, low-speed and heavy-load working conditions of wind turbines, the bearings are not easy to observe and disassemble, which brings great difficulties to the operation and maintenance of wind power equipment, and increases the maintenance cost of the unit. The maintenance cost of the unit is increased [1]. Therefore, real-time condition monitoring and fault diagnosis of wind turbine bearing are of great significance to ensure the safe and reliable operation of wind turbine and the economy of wind farm.

This paper classifies the bearings of wind turbines, introduces the common causes of bearing faults, then introduces the bearing diagnosis method of bearing wind turbines based on vibration data analysis and the bearing fault diagnosis system based on SCADA system, and finally summarizes the full text and points out the wind turbine Research direction of bearing fault diagnosis.

2. Wind turbine bearing classification and common faults

Wind turbine bearings can be roughly divided into 4 categories: pitch bearings, yaw bearings, transmission system bearings (main shaft and gearbox bearings) and generator bearings. The role of the pitch system is to change the aerodynamic torque obtained by the wind turbine by adjusting the
blade pitch and changing the angle of attack of the blades when the wind speed is too high or too low, so as to keep the power output stable. The yaw system has two main functions: one is to make the wind wheel track the wind direction; the other is that due to yaw, when the cables drawn out of the cabin are tangled, the cables are automatically unwound. Spindle bearings are used to hold the hub and blades, which can transmit torque to the gearbox. The gearbox is the transmission component that connects the main shaft of the unit and the generator. Its main function is to convert the low-speed operation input of the main shaft into the output required by the medium-speed or high-speed generator. It is one of the important components of the wind turbine [2].

Bearings are generally divided into 4 parts: outer ring, cage, rolling element (ball) and inner ring. The interior of the bearing is filled with grease, so dustproof devices will be installed at both ends of the cage to prevent foreign objects from weakening the various effects of grease. The characteristic frequency of each part of the bearing is determined by its size, and the calculation formula is as follows:

**Inner circle characteristic frequency:**
\[
BPFI = (n/2)[1 + (d / D) \cos \varphi]
\]

**Outer circle characteristic frequency:**
\[
BPFO = (n/2)[1 - (d / D) \cos \varphi]
\]

**Rolling element characteristic frequency:**
\[
BSF = \frac{D}{2d} \left[1 - \left(\frac{d}{D} \cos \varphi\right)^2\right]
\]

**Cage characteristic frequency:**
\[
FTF = \frac{1 - (d / D) \cos \varphi}{2}
\]

Where: \(d\) is the diameter of rolling element; \(D\) is the average diameter of rolling bearing (diameter at the center of rolling element); \(\varphi\) is the contact angle in radial direction; \(n\) is the number of rolling elements.

If a fault occurs in different parts of the rolling bearing, its frequency spectrum and waveform characteristics are different, the degree of fault is different, and its waveform amplitude is also different. The common bearing faults of wind turbine include fatigue fault, wear fault, notch or dent fault and corrosion fault. The common fault characteristics and causes of wind turbine bearing are summarized as follows:

The characteristic of fatigue failure is the shedding or peeling of the rolling element or the surface of the raceway. The reason is that the manufacturing process of the supporting devices such as shafts and cages is low, so their accuracy cannot be guaranteed. Long-term axial load conditions that are too high will cause great performance. Impact. Abrasion failures can cause color changes due to sliding wear between tiny gaps and long-term use in harsh environments. Overload, improper installation and foreign particles can cause notch or dent failure of the bearing. Ingress of water, moisture, or corrosive substances into the bearing will cause the bearing to rust, which is characterized by gray-black stripes between the raceways, and rust spots on the raceway and the bearing and its surface. The electrochemical corrosion is characterized by dark brown or gray-black grooves on the raceways and rollers, which is caused by the current passing through the rotating bearings [3].

3. **Fault diagnosis of fan bearings based on vibration analysis**

Vibration analysis is one of the most common and effective methods. In order to ensure the efficient and reliable operation of the bearing within the effective time and under special working conditions, the bearing is diagnosed by analyzing the vibration data of the bearing. When a bearing fails, it often shows abnormal vibration and increased noise. It is necessary to analyze the vibration signal and determine the operating state through effective processing methods. Bearing fault diagnosis is mainly divided into data collection, data transmission, fault feature extraction, and fault classification.
diagnosis. It can be seen from Figure 1 that in the original time domain waveform of the vibration signal in the normal state, the outer ring fault, the inner ring fault and the rolling body fault, the outer ring fault and the inner ring fault have more obvious periodic characteristics, the normal state and rolling the time-domain waveform of body failure has no obvious characteristics.

Figure 1. The time-domain waveform of the vibration signal of the rolling bearing has four states: (a) normal state; (b) outer ring failure; (c) inner ring failure; (d) rolling element failure.

Vibration data analysis mainly includes time domain, frequency domain, time frequency domain and other analysis methods. Time-domain signal characteristics mainly include dimensional parameters such as peak value and mean value, dimensionless parameters such as kurtosis and impulse factor, and probability distribution characteristics. Time domain analysis can determine the development trend of bearing failure. In order to accurately determine the location of the fault and the degree of the fault, frequency domain analysis of the vibration data is required. In the frequency domain analysis of bearing faults, the frequency spectrum of the vibration signal intuitively expresses the frequency components in the signal and the energy magnitude of each frequency component. Fast Fourier Transform (FFT) plays a very important role in the field of fault analysis. It is transformed into an intuitive and regular spectrum chart through a messy time-domain waveform diagram [4]. The time-frequency analysis method combines the two together and describes the relationship between the signal frequency and time. Common time-frequency analysis methods include short-time Fourier transform, wavelet transform, empirical mode decomposition, and variational mode decomposition etc.

When the fan bearing is working in a harsh environment, useful fault signals are often easily submerged by noise sources and mechanical interference sources in the vibration signal, thereby seriously affecting the accuracy of fault diagnosis. For the extraction of weak fault features, literature [5] proposed a rolling bearing feature extraction method based on modified variational mode decomposition and Teager energy operator (MVMD-TEO), which has high efficiency and feasibility. Reference [6] proposes an improved empirical mode decomposition (EMD) method based on multi-objective optimization. This method is used to extract the fault characteristics of rolling bearings with inner and outer ring faults, which has better decomposition capabilities and more faults. Feature information. Reference [7] proposed a periodic pulse harmonic noise ratio (ACFHRN) index of autocorrelation function based on SVD-Teager energy operator (TEO) method. This method can effectively detect the initial fault characteristics of rolling bearings, and the ratio is based on the method of kurtosis and RMS index has better performance. Reference [8] proposed a new frequency-shifted multi-scale noise-tuned stochastic resonance (SR) method, which uses noise to enhance the characteristics of weak signals. This method can realize the feature enhancement and extraction of weak signals at any frequency. Wind turbine generators an example of bearing fault diagnosis verifies the effectiveness of this method.

After the bearing fault signal is effectively extracted, it is necessary to diagnose and classify the bearing fault signal. For the diagnosis of bearing fault signals. Reference [9] studied a fault diagnosis
method based on wavelet transform to analyze the early defect characteristics of the bearing, and then use the health index algorithm to fuse the extracted features to represent the defect status of the bearing. Reference [10] proposed a multi-masking empirical mode decomposition (MMEMD) and fuzzy c-means (FCM) cluster wind turbine bearing fault diagnosis method (FCM-MMEMD), which overcomes the modal mixing defects in empirical mode decomposition (EMD). A new MMEMD method is proposed. It has the advantages of simple implementation and strong ability to suppress modal mixing. Reference [11] proposed an improved adaptive variational mode decomposition (AVMD) method, which improves the accuracy of variational mode decomposition (VMD). Reference [12] proposed a fault diagnosis method based on random subspace identification (SSI) and multi-core support vector machine (MSVM). This method can successfully identify the fault type of bearings, which is better than K-means clustering and fuzzy-means clustering. And the traditional support vector machine method has higher diagnostic accuracy. Reference [13] proposed adaptive local iterative filtering (ALIF) and singular value decomposition (SVD) methods for fault diagnosis of rolling bearings of wind turbines. ALIF is a new signal decomposition method. It uses an iterative filtering strategy combined with adaptive and data-driven filter length selection to achieve decomposition.

4. Analysis of fault diagnosis system of fan bearing based on SCADA

The SCADA system has the functions of remote real-time monitoring, control and diagnosis of wind turbines. It can optimize the operation of wind farms, and can be operated through process commands, which greatly reduces the time for on-site inspection and maintenance management of operation and maintenance personnel. The wind turbine is a complex nonlinear system, which is composed of multiple components, and each component is coupled and interacts with each other. If one of the components is abnormal, it may cause the whole machine to malfunction. The SCADA system can collect the running state data of wind turbine through various sensors on the wind turbine. Generally, a data is recorded from several seconds to 10 minutes, and the operation parameters are sent to the central database. By using the existing temperature data, power and electrical signal data of wind turbine SCADA system, the fault diagnosis of wind turbine bearing is realized [14].

![Figure 2. RE value of normal state.](image1)

![Figure 3. RE value of fault state.](image2)

Bearing fault diagnosis method based on SCADA system, more research has been conducted in the field of bearing fault diagnosis. Reference [15] proposes a method for early warning of main bearing failure of wind turbines based on data acquisition and monitoring control (SCADA) system. By extracting the characteristic variables of the main bearing. Establish the early warning model of main bearing failure. In reference [16], the extreme gradient boosting (xgboost) algorithm is proposed to the fault of main bearing of wind turbine. Firstly, feature analysis is carried out on SCADA data of main bearing of wind turbine, and the correlation between feature and fault is found, and the importance of each feature is evaluated. Then, xgboost algorithm is used to build the fault prediction model of main bearing. Finally, according to the measured data collected by SCADA system, the model is trained and
tested, and the main parameters of xgboost model are adjusted to improve the prediction accuracy. Reference [17] proposed a deep learning method based on layer-by-layer coding network of SCADA condition monitoring data of wind turbine generator main bearings for the long-term dynamic balance relationship among wind turbine SCADA variables. The exponentially weighted moving average (EWMA) threshold was used to detect heavy. The trend of the structural error is used as the basis for the decision to determine the failure of the main bearing of the wind turbine. In the fault detection of the main bearing, the established LWE model is used to calculate the reconstruction error (RE) of the input and output of the new data set, which is used as the detection quantity of the main bearing state trend, and the main bearing is realized by analyzing the trend of the RE Fault detection and abnormal state identification. When the change of RE crosses the alarm threshold and there is a continuous rise, it is determined that the main bearing is faulty, an alarm signal is issued, and then a fault shutdown occurs, thereby achieving early fault detection and early warning, as shown in Figure 2 and 3.

5. Summary and future research priorities
The vibration signal of the wind turbine bearing has nonlinear and non-stationary characteristics, and when the fan bearing works in a harsh environment, the useful fault signal is often submerged under strong background noise, which seriously affects the accuracy of fault diagnosis. Vibration monitoring is the trend of wind power bearing monitoring. However, as wind power load and wind instability affect the effectiveness of traditional time and frequency domain analysis methods, new non-stationary signal processing methods need to be introduced. At present, the overall utilization level of SCADA data is still low, and there are few researches on fault diagnosis of specific components of the fan, and there are problems of low efficiency and poor accuracy of monitoring data. Most condition monitoring and fault diagnosis technologies are based on vibration signal analysis. However, with the continuous development of multi-sensor fusion, data drive, artificial intelligence in recent years, and the establishment of big data wind power remote fault diagnosis and analysis platform. For the future research on bearing fault diagnosis, it is necessary to develop some intelligent methods and different combination technologies of data collection, such as grease, endoscopy and acoustic emission analysis. The extracted signal features of different types, scales and sources are fused to realize multi-source, multi-time scale and multi parameter information fusion fault diagnosis The group carries out intelligent on-line condition monitoring, realizes remote fault diagnosis of hierarchical distributed network, and ensures the safe and stable operation of wind turbines.

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