Review of noise reduction methods of vibration signal for wind turbine bearings fault analysis

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Abstract. Considering that the vibration signals of wind turbines are interfered with by low-frequency noise and background noise at the same time, it is difficult to extract the characteristic frequencies of early weak faults. The research on wind turbine bearing vibration noise reduction method to found that the potential failure symptom as early as possible for reducing the failure rate and reduce the operation maintenance cost reduction and to strengthen the reliable operation of the wind turbine is of great significance. Based on the analysis and summary of vibration signal characteristics of wind turbine bearing, the fault signal analysis, and noise reduction method of wind turbine bearing is introduced in detail.

1. Introduction
As a clean and renewable new energy, wind power generation has been developing rapidly in recent years. According to the data statistics of the China Wind Energy Association by the end of June 2015, China’s total installed capacity of wind power grid-connected grid has reached 126GW. As the installed capacity of wind power generation increases year by year, the failure problem of wind power units becomes more and more prominent [1~3]. Bearing as a key component of wind turbines is one of the parts with the longest downtime due to its complex load and special working environment. With the rapid development of China’s wind power industry and the grid-connected operation of large-scale wind power generation, the study on how to apply the wind turbine bearing state monitoring technology to reduce the wind turbine bearing failure frequency and operation and maintenance cost and improve its generating capacity has aroused wide attention. Among them, accurately and comprehensively extracting characteristic signals and weak signs of bearing fault is the key to state monitoring and fault diagnosis. As the wind turbine bearing affected by the operating speed, the vibration signal in its condition monitoring is easily interfered with by various noises which makes it difficult to extract its characteristic frequency which directly affects the early detection and service life of the condition monitoring system. Therefore, it is of great practical significance for improving the accuracy of wind turbine condition monitoring to study the effective extraction of vibration signal fault frequency of wind turbine bearing and the earlier and more effective extraction of fault characteristics. Therefore, this paper studies the noise and vibration signal reduction method of wind turbine bearing, to timely find the bearing fault and take effective measures to avoid possible major accidents and enhance the operating reliability of wind turbines [4].
2. Analysis of vibration signal of wind turbine bearing

Aiming at the problem that wind turbine vibration signals are affected by background white noise and short-time interference noise at the same time which makes it difficult to extract early weak fault characteristics, this paper summarizes the existing research results and analyzes and summarizes the noise fault characteristics extraction and noise characteristic dimension reduction of wind motor bearing vibration signals.

2.1. Feature extraction of wind turbine bearing fault vibration signal

In the process of acquisition and transmission, vibration signals are vulnerable to low-frequency local vibration interference and high-frequency electromagnetic interference of wind turbine which will generate transient energy changes characterized by non-stationary and non-periodic vibration signals representing wind turbine operation. How to extract vibration signal characteristics efficiently is the key to correctly identify wind turbine fault types [5]. In the literature [6], presented an ensemble mode decomposition with adaptive noise (CEEMDAN) and a sample entropy extraction method for extracting vibration signal features. After adopting the complete ensemble mode decomposition with adaptive noise algorithm and wavelet threshold noise reduction, each Mode component is obtained by calculating a unique residual signal and the reconstruction error is almost 0. Also, combining with wavelet threshold noise reduction and noise reduction generated during vibration signal acquisition which can effectively decompose the energy mutation in the process of mechanical action into the component characteristics of high-frequency intrinsic mode function (IMF). Vibration signals processed by ensemble mode decomposition with adaptive Noise were decomposed into a series of transient frequencies ranging from high to low intrinsic mode function (IMF) components. The distribution of noise components of the original vibration signal in different modes is different, and the high-frequency intrinsic mode function (IMF) component can be used to remove the noise interference caused by the low-frequency local vibration.

2.2. Feature dimension reduction

In the complex working environment, the sensors pick up signals are often mixed signals generated by different source signals. At the same time, related to the structure of fault vibration signals are often contaminated by noise interference, especially the early fault signal is often very weak and low signal-to-noise ratio and the sensor is higher. The characteristic dimension of the vibration of the collected information after the noise reduction of vibration signal feature extraction affected by a large, high false alarm rate. It is necessary to reduce the characteristic dimension of the vibration signal. At present, the dimensionality reduction methods can be divided into linear and nonlinear dimensionality reduction methods. Principal components analysis (PCA) is a commonly used linear dimension reduction method. It is effective in data reduction and feature extraction for stationary and linear problems, but poor in bearing data with typical nonlinear and non-stationary distributions. And manifold learning as a kind of typical nonlinear dimension reduction method can reveal the regularity of high-dimensional data. Which thought is one of the few independent variables in the high-dimensional space work together to form a manifold, it can effectively expand the space of manifold or digging the inner main variables and can realize the characteristics of high dimensional data compression [7]. In the literature [8], put forward a kind of based on blind source separation and manifold learning algorithm of wind turbines bearing fault feature extraction methods, through vibration signal blind source separation of source signals and extract its parameter to constitute a source signal parameter matrix. As the source signal with noise parameter matrix dimension is higher, so the dimensional reduction of high-dimensional data signals with noise, thus the failure of many because of the noise drown in the high-dimensional data state information extracted effectively.

3. Analysis of bearing vibration signal

Vibration analysis is a common method for health monitoring and fault diagnosis of rotating machinery. When a rotating machine is working in a bad environment which useful fault signals are
often submerged in strong background noise, thus seriously affecting the accuracy of fault diagnosis. To extract useful signals from complex original signals, many scholars extract information from weak fault signals from the Angle of noise reduction of vibration signals. When the wind turbine works in a specific environment, the wind turbine is affected by the random and uncertain wind speed and variable speed and constant frequency control. Therefore, the interference of strong noise will affect the extraction of feature frequency, which directly affects the effectiveness of early detection and life cycle management of the status monitoring system. Many scholars have conducted extensive research on the noise reduction method of extracting bearing vibration signals. Although the individual correlation denoising method can remove short-term interference noise (non-stationary signal and white noise). But in the strong background noise environment, when the signal is processed separately by the correlation denoising method for the weak signal, the spectrum after denoising may be distorted. In recent years correlation analysis and spectral analysis have been widely used in signal denoising. In the literature [9], put forward a kind of denoising algorithm based on the maximum modulus of the wavelet window is proposed based on relevant denoising and maximum modulus denoising. However, the algorithm has some disadvantages such as large computation and slow convergence rate. In the literature [10], a wavelet coefficient correlation denoising algorithm combining correlation analysis and wavelet theory is proposed. In the calculation of the correlation coefficient, the deviation of wavelet coefficients of different scales will affect the accuracy of the algorithm. Considering the characteristics of empirical mode decomposition, the noise signal can be decomposed into the natural mode functions and intrinsic mode functions at different frequencies [11], and then the vibration signal can be reconstructed. The fault characteristics can be expressed by denoising combined with the empirical mode decomposition algorithm. In the literature [12], a signal denoising method based on empirical mode decomposition (EMD) is proposed. But the denoising ability of the above method is relatively simple, most of them can only remove the background white noise and can not deal with the short-term interference noise. In the literature [13], a vibration detection method based on local mean decomposition (LMD) is improved. Because of its ability to analyze amplitude and frequency modulation signals, LMD is particularly suitable for describing the noise generated by time-varying control loop oscillations. Compared with empirical mode decomposition (EMD), the improved LMD performs better in noise processing in the following aspects: (1) single/multiple oscillations in the output of the extraction process, (2) robustness to noise, and (3) ability to deal with non-stationary trends. Besides, the improved LMD can accurately represent the time-varying oscillations without distortion and frequency leakage even in the short time series. However, LMD affects the accuracy of fault feature extraction when dealing with strong background noise. In the literature [14], the wavelet packet denoising algorithm is adopted to process signals. To effectively suppress impulse noise, wavelet packet contraction denoising operation minimizes signal distortion and greatly preserves partial discharge waveform.

In 2014 by Dragomiretskiy etc. [15] put forward a new method of adaptive signal processing variational mode decomposition, the method in the process of removing the noise component for decomposition by the iterative search for the optimal solution of the variational model to determine the center frequency and bandwidth of each component, which can adaptively realize signal frequency domain decomposition and effective separation of each component. However, in terms of strong noise background or early fault diagnosis, the single variational mode decomposition method has certain limitations and it is difficult to accurately extract fault characteristic information. Gu Jiaoxiao et al. [16] proposed an adaptive stochastic resonance noise reduction and variational modal decomposition method based on a quantum particle swarm optimization algorithm to extract vibration signals of wind turbine bearing. Firstly, according to the original vibration signal characteristics, the quantum particle swarm optimization algorithm is used to optimize the stochastic resonance parameters adaptively. Secondly, the original signal is denoised by stochastic resonance (SR) with the optimal stochastic resonance noise reduction parameter value, to weaken the influence of noise interference and impact components on the result and enhance the amplitude of the vibration signal. The noise reduction and extraction of vibration signals are realized by using the variational mode method.
4. Wind turbine noise reduction method

Under the interference of strong background noise, the above noise reduction methods have some limitations in the extraction of bearing early fault characteristics. In 2018 by Hong-shan Zhao et al. [17] proposed a bearing fault diagnosis method based on maximum correlated kurtosis deconvolution (MCKD) and variational mode decomposition (VMD) to solve the problem that bearing fault signals are difficult to extract, due to strong noise interference. Firstly, the noise reduction of the bearing vibration signal is carried out by the MCKD algorithm, then the signal after noise reduction is decomposed by VMD, and the sensitive intrinsic mode function (IMF) is screened out by the murkiness index for state monitoring and fault diagnosis. The purpose of the maximum correlated kurtosis deconvolution (MCKD) algorithm is to enhance the correlation kurtosis of the original signal through deconvolution by highlighting the continuous pulse with strong interference noise. This feature of the algorithm is very suitable for noise reduction processing of bearing early fault signal. This method can effectively reduce the feature extraction of bearing vibration signals caused by interference and high noise. Compared with the pure variational mode decomposition method, this method overcomes the influence of disturbance impact and impact components on fault information identification. The strong background noise mixed in the bearing fault signal is effectively eliminated. After MCKD noise reduction, the impact pulse signal reflecting the fault information is highlighted. It can be seen that the main frequency component in the envelope spectrum is the inner ring fault characteristic frequency and its double frequency, and there is almost no other frequency component with obvious amplitude.

The variational modal decomposition algorithm is a new non-recursive variational mode signal decomposition method, which can decompose complex input signals into a set of discrete modal components. In the process of obtaining decomposed components, this method determines the frequency center and bandwidth of each component by iteratively searching for the optimal solution of the variational model. Compared with EMD and LMD, this method can better realize the frequency domain division of signals and the effective separation of each component adaptively. Therefore, the specific calculation process of the VMD algorithm is explained as follows [18]:

1) Perform Hilbert transformation for each modal function $\mu_k$ to obtain its analytic signal.

$$\left[ \delta(t) + \frac{j}{\pi t} \right] \times \mu_k(t)$$  \hspace{1cm} (1)

2) The estimated center frequency $e^{-j\omega t}$ of $\mu_k$ is mixed and its spectrum is modulated to the corresponding base frequency band:

$$\left[ \delta(t) + \frac{j}{\pi t} \right] \times \mu_k(t) \times e^{-j\omega t}$$  \hspace{1cm} (2)

3) In Formula (2), the square $L^2$ norm of the demodulation signal gradient is calculated and the bandwidth of each modal signal is estimated. The variation problem is constructed as follows:

$$\min_{\{\mu_k\}, \{w_k\}} \left\{ \sum_k \left[ \frac{1}{t} \left( \delta(t) + \frac{j}{\pi t} \right) \times \mu_k(t) \times e^{-j\omega t} \right]^2 \right\}$$

s.t. $\sum_k \mu_k = f$

Where, $\{\mu_k\}$ is $k$ variational modal components, $\{\mu_k\} = \{\mu_1, ..., \mu_k\}$; $\{w_k\}$ is the central frequency of each component, $\{w_k\} = \{w_1, ..., w_k\}$; $k$ is number of variational modal components; $t$
is time; $\delta(t)$ is the partial derivative of $t$; $j = \sqrt{-1}$ is the delta function; $w$ is the cycle frequency; $f$ is the input signal.

Then, to transform the constrained variational problem into an unconstrained problem, a second penalty factor $a$ is introduced to ensure the accuracy of signal reconstruction and convergence under noise conditions. The Lagrange multiplicative operator $l$ is introduced to ensure the constraint conditions are strict. At last, the alternating direction method of multiplication operator (ADMM) is used to solve the extended Lagrangian expression.

The vibration signals of wind turbine bearing in the working state are usually non-stationary and weak signals which are often submerged in strong background noise, making it difficult to detect and extract feature information. Adopts wind turbine experimental apparatus were tested, the measured vibration signals of rolling bearings for roller bearing inner ring vibration signal of time domain and frequency domain waveform as shown in figure 1a and figure 1b. You can see through the waveform has an obvious vibration signal of noise interference and impact and abundant spectral components, not directly for fault information [19]. So the original vibration signal with noise is decomposed by variational mode.

![Figure 1. Spectrum of bearing vibration signal](image-url)
The fault signal of the inner ring of the rolling bearing was decomposed into 6 modes respectively and VMD was used for reduction and denoising. The time-domain and frequency-domain waveforms of the decomposition results are shown in Figures 2a and 2b. It can be seen from the IMF decomposition diagram that noise interference and impact components are effectively removed from the modal components so that the characteristic frequency fault characteristics of the denoised bearing inner ring are obvious [21]. The IMF center frequencies obtained by the warp-mode decomposition are independent of each other, and the modal components are effectively separated with prominent advantages, to achieve the purpose of dimension reduction and denoising. Moreover, VMD has a good effect on the feature decomposition of each part containing noise and high frequency, especially the part with similar high frequency, which can be distinguished obviously.

5. Conclusion

Because of the development demand for noise reduction technology for wind turbine bearing vibration signals, this paper summarizes the noise characteristic dimension reduction and noise reduction method of vibration signal of the wind turbines. Given the existing problems in the noise reduction process of vibration signals of wind turbines, the following research points and trends are proposed:

1) Wind turbines operate in a harsh environment and are subject to great interference. Therefore, sensors with high signal-to-noise ratio and high precision need to be developed and fault tolerance analysis of sensors also needs to be carried out.

2) It can be seen from the current research status that the existing vibration signal noise reduction methods have their advantages and disadvantages. How to make use of the advantages of various noise reduction processing methods to carry out statistical classification of all kinds of early weak fault information extracted from different types and scales and to realize multi-source and multi-parameter fault diagnosis technology of noise-containing vibration signal information fusion will be one of the future research directions.

3) The intelligent condition monitoring technology is the key to realize the wind turbine on-line monitoring. The intelligent condition monitoring will be an important research direction of the wind turbine condition monitoring and fault diagnosis.

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