Intelligent Diagnosis Technology of Wind Turbine Drive System based on Neural Network

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Abstract—The seriousness of air pollution appears to be the importance of wind energy as a non-polluting energy source. Today, the use of wind power has become a trend for new countries to develop new energy sources. Wind turbines are the key equipment for converting wind energy into electrical energy, the quality of the state directly affects the efficiency of wind power generation. Therefore, how to effectively diagnose the wind turbine drive system is the guarantee of wind power generation. This paper establishes a fault diagnosis method for wind turbine drive based on vibration characteristics, by wavelet packet decomposition of vibration signals. The feature extraction is carried out and back propagation neural network is used for classification research. Finally, the simulation results show that the recognition rate is over 90%, which verify effectiveness of the proposed method.

Keywords—trouble shooting, wind turbine, vibration characteristic, back propagation neural network.

1. Introduction

AS a non-polluting renewable energy source, wind energy has become one of the areas in which the world is competing for development. With the increasing number and capacity of wind turbines, wind power has formed a new type of industry. However, wind turbines are prone to failure under severe conditions such as variable load, large temperature difference, and unstable wind speed. Especially the transmission components such as the main shaft and gear box are prone to failure under the action of alternating load, resulting in long-term shutdown of the unit and overhaul. Difficulties and high maintenance costs seriously damage the economic benefits of wind power generation. Therefore, it is of great significance to carry out monitoring and diagnosis research on wind turbine drive system and develop networked monitoring and diagnosis system for wind turbine drive system to prevent and reduce wind turbine faults, ensure normal and stable operation of wind turbines, and improve economic benefits.

With the increasing number and capacity of operating wind turbines, the potential problems and faults of wind turbines are also increasing. The state monitoring and fault diagnosis of wind turbines are gradually receiving attention from the industry. Because wind turbines are often installed in remote areas such as mountains, wilderness, beaches, islands, etc., tens of meters or even hundreds of meters from the ground, and long-term work in the harsh environment of wind speed instability, variable load, large temperature difference, low pressure, etc., the service life of the unit is greatly affected. Especially, transmission components such as the main shaft and gear box of the wind turbine are prone to failure under the action of alternating load [1-4], causing the unit to stop. According to the fault data of Swedish, Danish and German research institutes, the wind turbine faults mainly include electrical control system faults, mechanical transmission system faults, hydraulic system faults, yaw system faults and switch control system faults.

Due to the complicated structure of the wind turbine transmission system and the long-term working under severe working conditions, it is easy to cause different types of failures of the transmission components such as blades, generators, gear boxes and bearings. Only by monitoring, it is sometimes difficult to capture the signs and signs of the failure of the unit's transmission system, causing the maintenance personnel to misjudge the cause of the failure, resulting in an over-maintenance of the undamaged parts and insufficient maintenance of the faulty parts. Group accidents reduce the reliability and stability of wind turbines. Therefore, domestic and foreign scholars have carried out a large number of researches on fault diagnosis methods, and their research results have been widely used in wind turbine fault diagnosis. These methods are mainly divided into two types: signal processing based methods and knowledge based methods.

In the research of fault diagnosis methods for wind turbines based on signal processing, Tang B et al. [5] proposed a wind turbine fault diagnosis method. The use of Continuous Wavelet Transform (CWT) to filter unwanted noise in the original vibration signal, and the use of Automatic Term Window (ATW) functions to suppress cross terms in Wigner-Ville Distribution (WVD), which may be due to moisture absorption, fatigue, gusts or lightning strikes on the wind turbine. Damaged faults are analyzed and diagnosed. Liu et al. [6] proposed a new wind turbine fault diagnosis method based on Local Mean Decomposition (LMD) technology.

Vibration analysis is a commonly used and useful technique in wind turbine condition monitoring and fault diagnosis. However, the relatively slow speed of wind turbine components sets limits in early fault diagnosis using vibration monitoring methods. Traditional time-frequency analysis techniques have some drawbacks that make them unsuitable for nonlinear, non-Gaussian signal analysis. LMD is a new iterative method for demodulating amplitude and frequency modulated signals, which is suitable for obtaining instantaneous frequencies in wind turbine condition monitoring and fault diagnosis. The experimental analysis of the vibration signal of the wind turbine proves the effectiveness and effectiveness of the method. In recent years, with the use of wind energy equipment, the detection results of wind energy equipment failures are also increasing [7-10].

Although the above method provides new ideas and ways for fault diagnosis of wind turbines, the accuracy and completeness of diagnosis affect the application of the results. In order to more accurately identify the faults of the wind turbine drive system, it is necessary to find a new method. Since the occurrence and development of any fault will inevitably go through a time process, sometimes the seemingly accidental fault must have its inherent regularity. Even if it is a sudden fault, there is a period of gestation and development, so the vibration characteristics are used to mechanical failure. Diagnosis is an effective method. At present, there are many methods for fault diagnosis of mechanical equipment based on vibration detection. The representative classification is divided into three categories: mathematical model based methods [10-12], data analyses based methods [13-15] and knowledge-based methods [16].

It can be seen from the research experience of predecessors that the mechanical fault diagnosis method based on vibration detection is widely used in the fault diagnosis of rotating equipment or its components, and all have received good diagnostic results. Introducing this method into the automatic fault diagnosis of the wind turbine drive system is a feasible method to improve the accuracy of the diagnosis results. In this paper, the wavelet packet decomposition of the vibration signal of the wind turbine drive system is analyzed, and the frequency characteristics are analyzed. It is found that the frequency energy distribution is the same for different parts, the middle and low frequency energy accounts for the majority, and the extracted features are back propagation (BP) nerve. The network classification results show that the detection accuracy of three fault samples, rolling element fault, inner ring fault and outer ring fault, is 97%, 92% and 99% respectively.

2. Method

2.1. System Framework

Firstly, vibration signals of collected key components are preprocessed, and the singular value decomposition and noise reduction method are applied to improve the signal-to-noise ratio of the vibration signal. Then, time-frequency analysis of the denoised signal is performed based on the wavelet packet energy entropy to extract the characteristic parameters and extract the extracted parameters. The characteristic parameter is set as the input of BP network to realize the automatic diagnosis of the failure. The detailed method is shown in the system flow diagram of Figure 1:

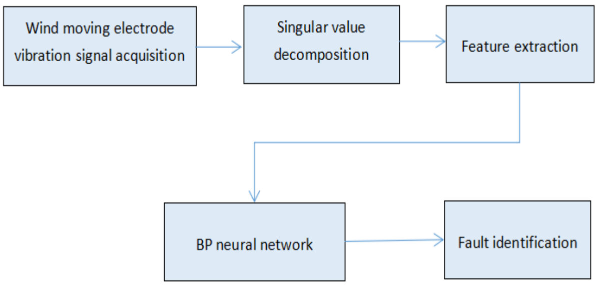

Fig. 1. The framework of analysis process

The vibration signal acquisition system hardware includes sensors, data acquisition instruments, notebook computers, connecting cables, etc., among which the vibration data acquisition instrument adopts BENTLY 8-channel vibration signal acquisition instrument, vibration signal acquisition system.

2.2. Singular Value Decomposition

Due to the large number of vibration sources and the interference of noise, the key information contained in the acquired signal is easily masked. Therefore, the signal should be denoised before taking the signal characteristics. Signal noise reduction is a key step in signal processing and troubleshooting. In engineering practice, there are many different noise reduction techniques that can be applied. Wavelet noise reduction, time domain averaging, frequency domain feature extraction, and adaptive filtering are commonly used. But these methods have their own limitations. When the wind turbine drive system fails, shock signals appear in the vibration signal. These shock signals are coupled with noise and other vibration signals. It is difficult to extract the noise by the general noise reduction method. To this end, this paper proposes a vibration signal denoising method by singular value decomposition to filter the collected noisy signals. Assuming the collected noisy vibration signal is X, the phase space reconstruction theory is used to embed the elements of $X = [x(1), x(2), \dots, x(n)]$ into the m*n dimensional space to obtain a Hankel matrix. According to singular value decomposition principle, given any m*n-dimensional matrix A, singular value decomposition can be expressed as Equation (1):

$$\mathrm{A} = U \sum V^t = U \begin{bmatrix} \sum r & 0 \\ 0 & 0 \end{bmatrix} V^T \tag{1}$$

In the Equation (1), U and V are orthogonal matrices of m*n and n*m, respectively, $\sum r = diag(\lambda_1, \lambda_2, \dots, \lambda_r)$ and $\lambda_1 > \lambda_2 > \cdots > \lambda_r, r = \mathrm{rank(A)}$.

The energy information of the signal, the noise intensity information, etc. are all included in singular spectrum. Furthermore, separation of the useful signal and disturbance can be realized by applying the singular spectrum. The set signal X is composed of two parts: no noise and noise. The noise-free signal should be smooth, and the noise signal is Gaussian. Therefore, the singular value of the signal X is also composed of two parts. Noise-free singular values and singular values of noise, then the singular value of the entire noise will be evenly offset from the original size $\lambda_i^2 = \overline{\lambda^2} + \lambda_{noise}^2, i = 1,2,3, \dots, n_{min}$.

At this point, the trajectory matrix of signal X can be expressed as Equation (2):

$$\mathrm{A} = [U_1 U_2] \begin{bmatrix} 1 & 0 \\ 0 & \sum r \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} \tag{2}$$

In the Equation (2), it can be seen that by decomposing singular value of trajectory matrix, A can be divided into two parts. As long as the noise interference part is removed, the part of effective signal can be obtained.

The basic steps of noise reduction for singular value decomposition are as follows:

Firstly, phase space reconstruction is performed on the original signal. The reconstructed matrix line number is half or one tenth of the original signal length. Then, the obtained Hankel matrix is subjected to singular value decomposition, and the singularity corresponding to each step of the singular spectrum is obtained. The entropy increment determines the order at which the singular entropy increment begins to decrease and tends to be stationary as the signal denoising order.

The matrix is reconstructed by using the previously obtained noise reduction order as the effective order of the singular spectrum. The first row element of the reconstructed matrix is the noise reduction signal.

2.3. Wavelet Packet Energy Entropy Characteristics

As a signal processing method, wavelet packet analysis is extended from wavelet analysis, which can perform more detailed reconstruction and processing analysis of signals. The advantage of wavelet packet analysis is that it further decomposes and reconstructs the approximate signal in the wavelet transform, and then analyses high-frequency part of the signal. Because the processing of the signal by orthogonal wavelet transform will only further analyze the low-frequency part, and cannot continue to decompose the high-frequency part, the wavelet transform can well represent the low-frequency information, but it is not very good. Ground decomposition and representation of high frequency signals containing a large amount of detail information.

The vibration signal of wind turbine drive system is a typical non-stationary signal containing a lot of detailed information. It can be processed in a more detailed way by using wavelet packet transform, and this decomposition does not have redundancy, even no omissions, which is a better time-frequency localized analysis. To be more specific, by decomposing and reconstructing signals at diverse scales, wavelet packet analysis not only obtains distribution information of original signal in different frequency bands, but also captures the time points at which signals are abrupt.

The wavelet packet decomposition essentially performs multi-layer bisection on high frequency and low frequency sub-section which are divided by original signal. In this paper, noise-reduced signal S is decomposed by wavelet packet. From the decomposition relationship, wavelet packet divides the signal into eight frequency bands, and decomposition of high-frequency part is more detailed. So the noise-reduced signal can be fully utilized. Wavelet packet analysis disintegrates non-stationary signal into a family of basic functions that are stretched by wavelet function. The information is complete and is very suitable for the decomposition of the vibration signal.

After 3-layer decomposition of the signal, the wavelet energy S_{3j} of the E_{3j} sub-channel signal can be expressed as Equation (3):

$$E_{3j} = \int \left| S_{3j}(t) \right|^2 dt = \sum_{k=1}^{n} \left| x_{jk} \right|^2 \tag{3}$$

In the Equation (3), formula $x_{jk} (j = 0,1, \dots, 7; k = 1,2, \dots, n)$ represents the discrete point amplitude of the reconstructed signal S_{3j}.

The magnitude of the energy entropy represents how much energy is ordered in the observed signal. When defining the number of wavelet packet decomposition layers as i, the energy sum of the signals is E_i, can be expressed as Equation (4):

$$E_i = \sum_{j=0}^{N} E_{ij} \tag{4}$$

Depending on the law of energy conservation, the total energy of signal is equal to the sum of signal energies of sub-bands, can be expressed as Equation (5):

$$E_s = E_i = \sum_{j=1}^{N} E_{ij} \tag{5}$$

The great uncertainty of the variable means high entropy, and the greater the amount of information needs to make it clear. For spectrum analysis, different frequency segments reflect various characteristic information. Therefore, specific information entropy based on characteristics of frequency distribution is applied to reflect fault. Entropy is identified as Equation (6):

$$H(x) = E\left[\log_2 \frac{1}{P(x_i)}\right] = -\sum P(x_i)\log_2 P(x_i) \qquad (6)$$

where, $P(x_i)$ is output probability function and the x represents random variable, defined as a symbol set, which is the set of all possible outputs.

In frequency domain, vibration signals of segments present the component of mechanical structure. Frequency segments of wind turbine can be divided into low-frequency 10-1000Hz, mid-frequency 1000-2000Hz and high-frequency 2000-10000. In this paper, frequency domain is tessellated up with eight segments. After decomposition, the mutation phenomenon is reduced.

2.4. BP Neural Network

BP has a simple structure to implement characteristics. More importantly, its excellent pattern recognition ability has also been widely applied in mechanical diagnosis. The learning process of BP neural network consists of two parts: the forward propagation of signal and the back of error.

From input layer, the error is generated by the result of forward propagation and the expected, which is allocated to the nodes of each layer through back propagation for weight modification until the error is under an accredited level or a predetermined learning time.

Distinctive faults produce specific vibration signals. Fault classification based on neural network trains weights to extract features of fault signals.

3. Data Sources

3.1. Vibration Signal

The vibration signal acquisition system hardware includes sensors, data acquisition instruments, notebook computers, connecting cables, etc. The vibration data acquisition instrument adopts NEGO 8-channel vibration signal acquisition instrument, and the vibration signal acquisition system is shown in Figure 2.

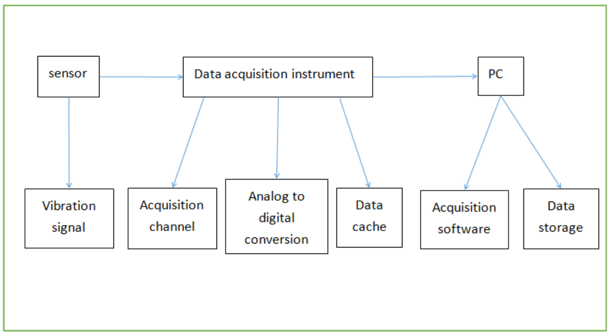

Fig. 2. Vibration signal acquisition system structure

The signal is the carrier of the fault information, and the measuring point is the window for obtaining the fault information. The merits of the measuring point arrangement will determine whether the collected signal is typical and representative, and the rationality of the measuring point selection is the basis of the subsequent signal analysis and processing. For the collection of the wind turbine signal, the selection of measuring points must be in accordance with the international standard VDI3834, and the following principles shall be met:

1) The measuring point should try to select the most abundant part of the vibration information;
2) Pick up as many working conditions as possible with as few points as possible and maintain sensitivity to the measured parameters;
3) The position of the measuring point should be close to the tested part to prevent attenuation, distortion and transmission obstruction;
4) Selecting the position of the measuring point should consider the convenience of sensor assembly and disassembly.

As the experimental object, Hansen EH80421-BN gearbox of 2MW wind turbine, primary structure includes main shaft, planetary-stage gear and two parallel gears. The geometrics of the planet gear system and parallel gears used in gearbox are showed in Table 1.

Tab. 1. Geometrics of the planet gears (High Shaft Speed is 26.67Hz)

Parameter	Sun gear	Planet gear	Ring gear	Carrier	Low-speed big gear	Mid-speed small gear	Mid-speed big gear	High-speed small gear
Number of teeth	18	34	87	-	70	16	84	19
RPM	82.72	50.47	-	14.18	82.72	361.91	361.91	1600
Hz	1.38	0.84	-	0.24	1.38	6.03	6.03	26.67
Meshing frequency	20.562	20.562	20.562	20.562	96.508	96.508	506.668	506.668

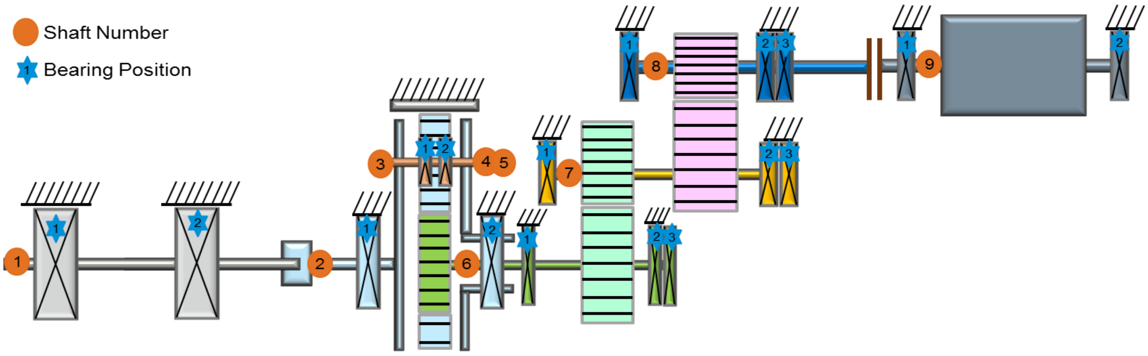

Fig. 3. Diagram of gearbox

Vibration sensor is 8071LF-01-010 MEAS, whose parameter description is introduced in Table 2. The data acquisition process is as follows: acceleration of vibration signal collected by sensors is converted into electrical signal. Then the data are transmitted to server by digital signals. Figure 3 shows the positions of nine vibration sensors and diagram of gearbox structure. Actual field installation is displayed in Figure 4.

Finally, a small amount of vibration data shown as Table 3, which are collected from horizontal direction of high-speed shaft of the Hansen.

Fig. 4. Sensor installation

Tab. 3. Vibration data

NO.1	NO.2	NO.3	NO.4	NO.5	NO.6	NO.7	NO.8	NO.9
0.0957	-0.006	-1.7048	-1.2262	4.4563	-1.0468	70.972	-14.326	-11.395
0.0239	0.0179	1.1066	-0.2094	-0.5683	1.3459	-49.8569	-10.3781	-5.2937
-0.1316	0.0179	3.4993	0.2094	-0.8075	2.3029	77.1929	-11.2156	-18.8122
-0.0718	0.0179	5.3536	0.6281	-0.9272	5.1741	-80.0043	13.4288	28.2034
-0.1794	0.0419	6.9686	-0.2094	-2.1235	6.7891	43.5762	-10.6772	-5.6526
-0.0957	0.1137	6.5499	-0.2094	-2.4226	-1.8842	-46.9259	-2.3029	33.5868
-0.1316	0.1974	3.7983	-1.3459	-0.6281	4.3965	36.8169	-14.326	40.047
-0.1196	0.2811	0.8075	-2.5422	-3.0207	-0.6281	-55.6591	-16.3598	10.7968
-0.1555	0.317	-1.1066	-2.9011	0.7477	-3.0805	-23.2386	-0.4486	24.1359
-0.1436	0.3051	-2.4226	-2.602	1.2262	-6.3106	-39.0899	7.3873	-3.4394

3.2. Noise Reduction

To improve signal-to-noise ratio, denoising is necessary processing. In this paper, signal is decomposed into effective signal corresponding with larger singular value and noise corresponding with the smaller by SVD. The noise is eliminated by setting zero to the latter. When noise is tiny, the singular value displays obvious step distribution. Singular value decomposition order and the separation order are significant to the denoising results.

Figure 5 shows gearbox vibration signals which are raw state and denoising effect.

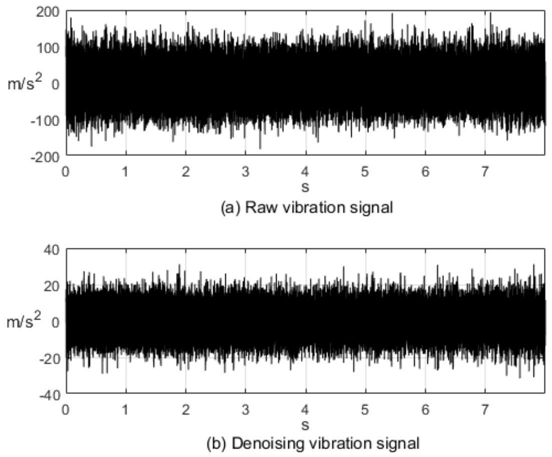

Fig. 5. Noise Reduction

3.3. BP Neural Network Layers of Neurons

Regardless of the rotor or bearing fault identification, the selected feature indicators are 8 Shannon entropy and 6 time domain indicators as input vectors, so the input node of BP neural network should be 14. For the output layer, this paper will identify the three working conditions of the rotor and the four working conditions of the bearing respectively. Therefore, output nodes of the network are set to 3 and 4 respectively. The determination of hidden layer neurons is determined according to the following three Equation (7), Equation (8) and Equation (9):

$$m < \sqrt{n + l} + \alpha \tag{7}$$

$$m = log_2 n \tag{8}$$

$$m < n - 1 \tag{9}$$

In the Equation (7), Equation (8) and Equation (9), m and n represent the node number of hidden layer and input layer, and l is used to represent the number of output layer nodes. Normally, α is a constant between 1 and 10. The eigenvector training samples are input into BP neural network for training. Furthermore, global error is 0.01 and the maximum number of training set is 1000.

Shannon entropy represents the information of eight frequency segments. That is to say, the entropy of low frequency domain expresses conditions of main shaft and planetary-stage gear. Likewise, the feature of parallel gears reflects in mid segment.

There are six indicators in time domain. First, effective value represents whole vibration energy. Further, the margin indicator increases obviously with vibration augment. For description of impact, kurtosis and pulse index are calculated. On the other hand, peak value indicates surface roughness of bearing. In particular, the waveform indicator is the root mean square value divided by the absolute average.

4. Results

4.1. Gearbox Bearing Vibration Signal

The gearbox bearing data set contains various aspects of bearing mechanical status information, including different bearing fault locations, fault levels, fault bearing positions and different workloads. Therefore, the data set can be used at multiple angles and different classifications. Experiments are tested to verify effectiveness of the proposed method.

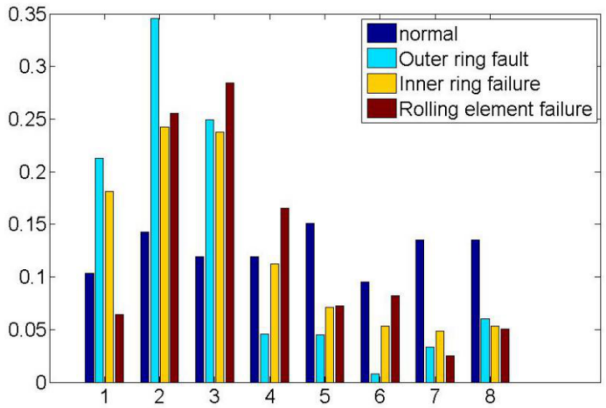

Fig. 6. Energy distribution of components obtained by decomposition of different bearing signals

The three-layer decomposition of the wavelet divides the frequency of the signal into 8 parts according to the low to high average. Figure 6 shows the energy distribution of the 8 types of signals after different wavelet decomposition. After the wavelet packet decomposition, the normal non-fault is presented in the figure. If the fault occurs, the frequency distribution is not uniform. There are three types of faults, rolling element, inner and outer ring fault, which are frequently occurring in the three wind turbine drive systems. The fault energy distribution has great similarity, and it is basically concentrated in the low frequency range. The low frequency 2, 3 and 4 frequency segments have the highest distribution evaluation rate, and the lowest rolling fault is compared with the other two faults. The frequency segment energy distribution is lower than the other two faults.

Under healthy conditions, vibration frequency domain of bearing indicates mechanical structure in wind turbine gearbox. The information in each segments, for smooth running turbine, is homogeneous. Otherwise, entropy of high frequency comes from higher harmonic of vibration.

Bearing failure accompanied by 1X or other bearing failure frequency sideband. The failure of inner and outer ring precedes rolling body and cage. The retainer fracture results in appearance of Rolling Element Defect Frequency (BSF) and Cage Defect Frequency (FTF) of retainer fault frequency. When rolling body fails, several times of BSF will be generated. Furthermore, inner and outer ring faults produce their fault characteristic frequency.

In normal condition, expectation is 4.514 and variance is 0.0002705. Obviously, Shannon entropy distribution of bearing vibration signal is relatively uniform. Table 4 illustrates variances and expectations of four entropy distributions.

Tab. 4. Vibration signal entropy analysis

Case	Expectation	Variance
Normal	4.514	0.0002705
Outer ring fault	2.819	0.0138
Inner ring fault	3.192	0.0069
Rolling element failure	3.510	0.0088

While fault occurs, a lot of fault characteristic information appear in low frequency band, which results in the decrease of higher-frequency proportion. It can be noticed that the variance of outer ring reaches 0.0138, and the proportion is highly attenuated in region 6. Correspondingly, the Shannon entropy of inner ring fault is dominant in band 2 and 3. However, the expectation caused by rolling body fault is 3.510.

4.2. Fault Identification Results

In order to verify the proposed method, fifty Hanse gearboxes of wind turbines with different degree of bearing wear were tested. The tests were operated with MATLAB code on a PC with fourth-generation i7 CPU and 16GB of RAM.

The generators driven by wind turbines run at about 1600 rpm with 2 MW. To obtain detailed condition of bearing wear, signals were sampled constantly. Stuck on bearing bracket, accelerometer collected vibration signals with 16384 Hz sampling frequency. The collected gearbox vibration signals were stored on server by the on-line condition monitoring systems. Particularly, output shaft frequency was 26.67 Hz.

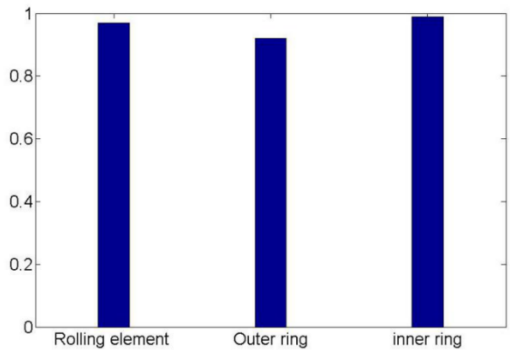

Fig. 7. The accuracies of fault detection for three parts

Figure 7 shows the accuracies of fault detection for three parts, which are 97%, 92% and 99% respectively. To verify the correctness of fault detection, bearings of gearbox are disassembled as shown in figure 8. The results prove that the method can well identify the bearing fault of wind turbine.

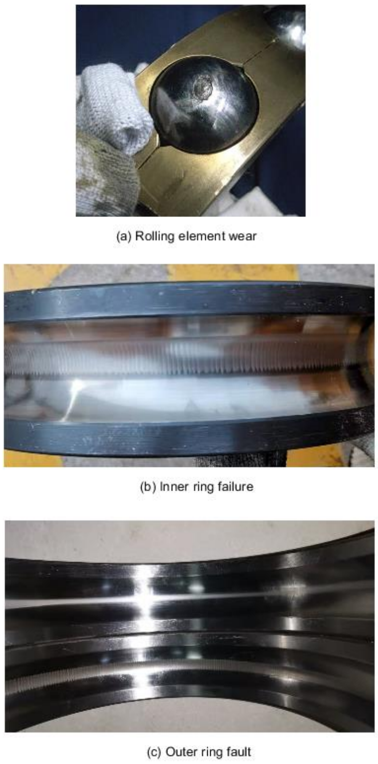

Fig. 8. Bearing fault verification

5. Conclusions

The vibration signal generated by the wind turbine drive system during operation contains important equipment status information. This paper selects vibration signal of wind turbine drive system as the research object, and extracts the fault characteristics to realize fault diagnosis of wind turbine drive system. In this paper, combined with characteristics of vibration signal, frequency distribution of different faults is solved by wavelet packet decomposition method, and then the feature extraction is carried out. Then fault types are realized by BP neural network. The experimental results prove the method is more accurate than single-variable diagnosis. The fault diagnosis of the unit drive system provides new ideas and ways.

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