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Fault Diagnosis of Wind Turbine Vibration Based on Wavelet Transform and Neural Network

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Abstract. *To improve poor performance of wavelet transform which can not effectively distinguish signal change caused by wind turbine fault from normal process dynamics, and in order to overcome the difficulties caused by the lack of fault samples. A method for wind turbine vibration fault diagnosis based on wavelet transform and neural network is proposed in this paper. Firstly, the possible fault of wind turbine is detected by wavelet transform. Secondly, neural network is utilized to estimate the value of vibration signal. Furthermore, it only needs the samples of the system under normal situation while training the neural network. Finally, according to the residual of estimate value and real value to complete diagnosis. Simulation experiments have shown that this method of wind turbine vibration fault diagnosis is more feasible and more effective than those of the existing ones, and accurate rate of fault diagnosis reaches 90%.*
Keywords: Wind turbines, Wavelet transform, Neural network, Fault diagnosis

1. Introduction.

The fault diagnosis of wind turbine is crucial to wind generating systems. Vibration fault of wind turbine generator not only decreases generating efficiency but also affects its safe operation, which will lead to loss of property and threaten personal security. Under this background, a variety of condition monitoring and fault diagnosis methods have been developed for avoiding serious damages at present. However most of the methods are not suitable for achieving high accuracy, so how to use the limited information of wind turbine to improve the fault diagnosis rate becomes a hot topic.

In wind turbine condition monitoring, vibration analysis is a common and available way, especially in the rotating parts. But the wind turbine working environment is strict and poor, which makes the vibration signals have non-stationary and non-Gaussian characteristics. Besides fault characteristics distribution in different frequency bands, which increases the difficulty of fault diagnosis [1]. In recent decades, some approaches have been proposed to solve these problems. For example, a method to extract the fault point location based on the principle of wavelet singularity detection was proposed in [2]. Using ART2 neural network and C-average clustering algorithm for detecting fault classification was explored in [3]. The particle swarm optimization to optimize fuzzy neural network model was presented in [4]. The method for wind turbine fault diagnosis based on artificial neural network and expert system hybrid model was developed in [5]. The fault diagnosis scheme of genetic algorithm to optimize the BP neural network was designed in [6].

But, these methods listed above have their own limitations. Wavelet transform can effectively detect the fault, however, when the fault signal is close to the normal signal dynamics, the wavelet transform can not distinguish whether the wind turbine is damaged or not. In this case it may increase false-positive rate. On the other hand, the neural network algorithm needs the samples of all the fault information to train the neural network. It is unpractical to get so many fault samples.

In this work, we propose a method for wind turbine fault diagnosis based on wavelet transform and neural network hybrid model, which use the federal vibration signal of wind turbines which belong to the same area to accomplish fault diagnosis. So it is more suitable for practical condition. This method has better effectiveness as well as higher accuracy, which provides a reliable method for wind turbines fault diagnosis. Main contributions of our work are briefly introduced as follows:

(1) The samples of same area wind turbine under normal situation are used to train the neural network.

(2) The wind turbine which is possibly wrong is detected by wavelet transform.

(3) Neural network is used to estimate the wind turbine vibration signal.

(4) Residual of real value and estimated value of the wind turbine vibration signal is used to decide the diagnosis result.

The remainder of this paper is organized as follows. In section 2, we briefly describe the preliminaries theory of our scheme. In section 3, we introduce procedures of our algorithm in detail. In section 4, the simulation performance analysis is presented. Finally, in section 5, we summarize our main works.

2. The Preliminaries Theory.

2.1. Wavelet transform.

Wavelet transform is a kind of algorithms whose window size (the window area) is fixed, but its shape is variable. In other words, it is a time-frequency local analysis method whose time window and frequency window can change. Signal singularity, which can depend on the comprehensive information under different scales to reflect the mutation or instantaneous characteristics of the signal [7]. The basic equation of wavelet transform is defined as follows:

$$WT_x\left(a,\tau\right) = \frac{1}{\sqrt{a}} \int x(t)\Psi^*(\frac{t-\tau}{a})\mathrm{d}t = \langle x(t), \Psi_{a,\tau}(t)\rangle \tag{1}$$

Where $\alpha(\alpha > 0)$ is scale factor and τ is shift factor. With the increase of the scale factor α, the resolution in time domain decrease, and the resolution in frequency domain increase. And the other way round, the resolution in time domain increase, and the resolution in frequency domain decrease with the decrease of the scale factor α. So, wavelet transform could change the resolution of the time-frequency domain. $WT_x(a,\tau)$ stands for the wavelet coefficients. $\Psi(t)$ denotes the wavelet basis function, $\Psi^*(t)$ is conjugate function of wavelet basis function. Actually, wavelet basis function requires to satisfy.

$$\sum_{-\infty}^{+\infty} \Psi(t)\mathrm{d}t = 0 \tag{2}$$

A smooth function $\theta(t)$ needs to be satisfied two prerequisites:

$$\begin{cases} \int\limits_{-\infty}^{+\infty} \theta(t)\mathrm{d}t = 1 \\ \lim\limits_{|t|\to+\infty} \theta(t) = 0 \end{cases} \tag{3}$$

Suppose, $\Psi^{(1)}(t)$ is the first differential of $\theta(t)$, so it must satisfy

$$\int_{-\infty}^{+\infty} \Psi^{(1)}(t)\mathrm{d}t = 0 \tag{4}$$

Then $\Psi^{(1)}(t)$ can be regard as wavelet basis function. According to the convolution expression of wavelet transform, we can get the wavelet transform of the signal $x(t)$ while the scale factor is α and the shift factor is τ, which means that the computational formula can be presented as follows:

$$W_a^{(1)}x(t) = x * (a\frac{\mathrm{d}\theta_a}{\mathrm{d}t})(t) = a\frac{\mathrm{d}}{\mathrm{d}t}(x * \theta_a)(t) \tag{5}$$

Thus, the wavelet transform modulus maxima have close affiliation with the singular points of signals. We can select a suitable wavelet basis function to decompose the signal, and then use the singular points of signal to find the break points. But due to unfavorable factors caused by poor working conditions or strenuous vibration of equipment for the wind turbines, the diagnosis result is easy to misjudgment just rely on wavelet transform. So further determine needs to be executed by the following method.

2.2. **BP neural network.** The BP neural network is a kind of learning process of error back propagation algorithm, which includes both information dissemination and error back propagation. Generally neural network includes: input layer, hidden layer and output layer. Using the gradient descent method to adjust the network weight and threshold in terms of the training samples, which can simulate the function relationship between the input and output, in order to get the minimum square sum of error of the network [8]. In this work, we select three layers structure of neural network as the foundation, and the output layer needs only one neuron node, so the neural network structural model is shown in Fig.1.

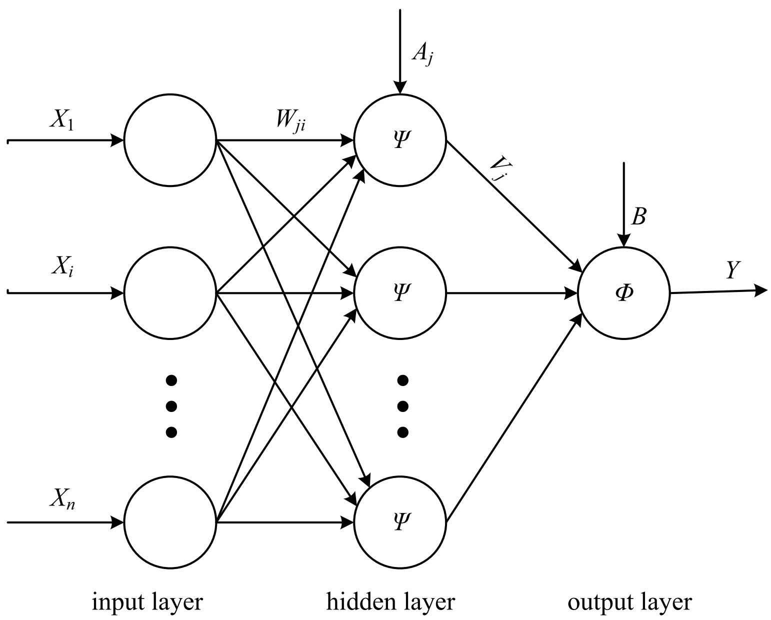

FIGURE 1. BP neural network model

Where X_i $(i = 1, 2, 3 \ldots n)$ is the ith neuron node of input layer; W_{ji} denotes the weight between the jth neuron node of hidden layer and the ith neuron node of input layer; A_j stands for threshold of the jth neuron node of hidden layer; $\Psi(x)$ is activation function of hidden layer; V_j is the weight between neuron node of output layer and the jth neuron node of hidden layer; B denotes the threshold of the output layer; $\Phi(x)$ stands for activation function of output layer; Y is the neuron node of output layer.

Assuming there are n wind turbines in the same area. Taking vibration signal of the ith wind turbine under normal situation as output value, then the vibration signals of the rest of the $n-1$ wind turbines under normal situation are regarded as input values while training neural network, so that we can build the neural network of the ith wind turbine. In this way, we can get neural networks of all the wind turbines which belong to the same area. The possible broken wind turbine (suppose its number is x) has been detected by wavelet transform. At the same time, we put the vibration signals of the rest of wind turbines into the neural network whose number is x. So that we can get the vibration signal estimated value Y of wind turbine whose number is x under normal situation. Finally, we can judge the wind turbine is broken or not from the residual of estimate value Y and real value y.

3. **Procedures of Algorithm.** The flow chart of diagnosis method is shown in Fig.2.

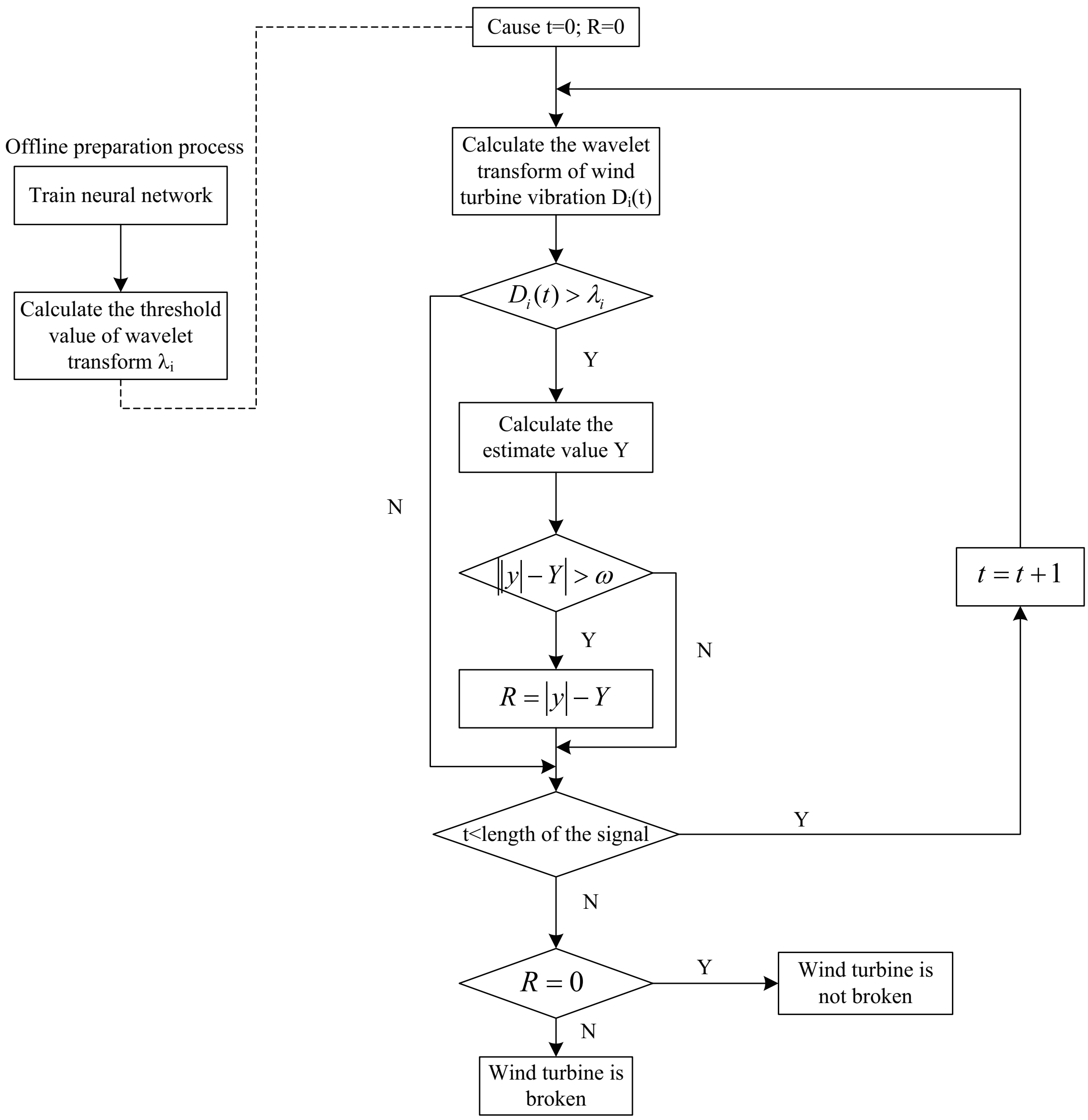

FIGURE 2. The flow chart of diagnosis method

Overall segmentation scheme is described as follows:

Step 1: Vibration signal under normal situation of wind turbine i ($i = 1, 2, \cdots, n$) act as output value, on the other side, vibration signals under normal situation of the other wind turbines play the part of input values while training the neural network. It is emphasized that these wind turbines must belong to the same area.

Step 2: Cause time $t = 0$; residual signal $R = 0$.

Step 3: Calculate the wavelet transform of all wind turbine vibration signals, so that we can extract singular points in signals. Then we can estimate possible broken wind turbine (suppose its number is x) on the basis of signal singularity preliminary.

Step 4: At the same time, vibration signals of the rest $n - 1$ wind turbines input the xth neural network, hence we can get the estimate value Y of vibration signal from the output of the xth neural network.

Step 5: Estimated value Y compares with real value y: if $||y| - Y| > \omega$, then execute step6; else $||y| - Y| \leq \omega$, then execute step7. Where ω is the threshold, which is depend on the characteristics of different processes.

Step 6: Cause $R = |y| - Y$.

Step 7: If $t <$ the length of the signal, then adds t with 1, return step3; if $t \geq$ the length of the signal, then executes step8.

Step 8: $R = 0$, wind turbine x is not down; $R \neq 0$, wind turbine x is broken.

4. **Simulation Performance Analysis.** We have used MATLAB version 12.0 to simulate the proposed method and compared it to other algorithms such as wavelet transform and BP neural network.

4.1. **Simulation setup and parameters.** According to the German engineers association issued "VDI3834 wind power standard" [9] and national energy bureau issued the "guidelines for the wind turbine vibration condition monitoring" [10]. Acceleration sensor should be preferentially chosen to monitor vibration condition in high temperature or strong magnetic field environment. So that acceleration sensor is the optimal choice to monitor roll bearing and gearbox of wind turbine. An acceptable measurement should be in vertical radial, radial and axial, witch needs 20% of the minimum load. In experiment, we select GW50-750 wind turbines which belong to the same region of Buerjin wind farm as experimental subject. Acceleration sensor is used to measure gear box intermediate level acceleration relays on the standard, sampling every millisecond while system is working. As for the noise of the collected datas, it is eliminated by means of the soft threshold wavelet de-noising. Normalization is the last step about data processing. Part of the normal samples and fault samples are exhibited in Table 1 and Table 2 respectively.

Table 1. Part of the normal samples

m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}	m_{15}	m_{16}	m_{17}
0.15	0.22	0.23	0.15	0.17	0.17	0.07	0.05	0.14	0.10	0.13	0.16	0.28	0.24	0.33	0.98	0.15
0.12	0.23	0.25	0.23	0.20	0.09	0.00	0.06	0.11	0.26	0.22	0.14	0.29	0.35	0.35	0.97	0.21
0.13	0.26	0.21	0.23	0.16	0.24	0.04	0.04	0.22	0.17	0.17	0.18	0.31	0.32	0.29	0.96	0.26
0.17	0.27	0.25	0.20	0.25	0.11	0.06	0.10	0.24	0.20	0.20	0.09	0.21	0.27	0.39	1.00	0.25
0.20	0.18	0.17	0.19	0.21	0.11	0.09	0.07	0.15	0.19	0.24	0.23	0.33	0.17	0.41	0.87	0.11

Table 2. Part of the fault samples

m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}	m_{15}	m_{16}	m_{17}
0.62	0.22	0.61	0.34	0.69	0.47	0.60	0.63	0.57	0.64	0.47	0.15	0.28	0.56	0.25	0.44	0.48
0.42	0.62	0.69	0.01	0.66	0.47	1.00	0.42	0.00	0.20	0.66	0.59	0.32	0.36	0.67	0.54	0.41
0.26	0.20	0.00	0.69	0.65	0.68	0.62	0.66	0.55	0.57	0.69	0.49	0.62	0.17	0.33	0.33	0.37
0.56	0.20	0.57	0.09	0.33	0.64	0.59	0.44	0.54	0.20	0.13	0.28	0.37	0.16	0.02	0.28	0.41
0.55	0.20	0.11	0.43	0.40	0.72	0.90	0.29	0.23	0.06	0.14	0.37	0.14	0.67	0.14	0.23	0.65

Where m_1 is vertical acceleration of gearbox, m_2 is horizontal acceleration of gearbox, m_3 stands for axial acceleration of gearbox, m_4 is vertical acceleration of ring gear, m_5 denotes horizontal acceleration of ring gear, m_6 is vertical acceleration of low speed shaft, m_7 stands for horizontal acceleration of low speed shaft, m_8 is vertical acceleration of main bearing, m_9 is horizontal acceleration of main bearing, m_{10} stands for axial acceleration of main bearing, m_{11} denotes vertical acceleration of high speed shaft, m_{12} is horizontal acceleration of high speed shaft, m_{13} is vertical acceleration of generator drive end, m_{14} is horizontal acceleration of generator drive end, m_{15} denotes axial acceleration of generator drive end, m_{16} stands for vertical acceleration of generator non-drive end, m_{17} is horizontal acceleration of generator non-drive end.

4.2. **Simulation result.** We acquire 5500 datas and introduce fault at the 5000th data point. Fig.3 shows the Time-domain waveform of gear box intermediate level acceleration. It can be seen that the waveform is complicated, so achieve the exact diagnosis result is difficult. Then wavelet transform takes advantage of the wavelet toolbox of MATLAB, "db4" is the wavelet basis function, decomposition layers are 4. So the transform result is shown in Fig.4. However, the detail coefficients after wavelet transform can only preliminary judge whether wind turbines malfunctioned or not because of signal fluctuation, there are singularities in the datas where we don not introduce fault, such as the 1700th data is shown in Fig.4. Wavelet transform cannot effectively distinguish signal change caused by wind turbine fault from normal process dynamics. It is too hasty to draw a conclusion only according to wavelet transform. Therefore we need to neural network for further diagnosis.

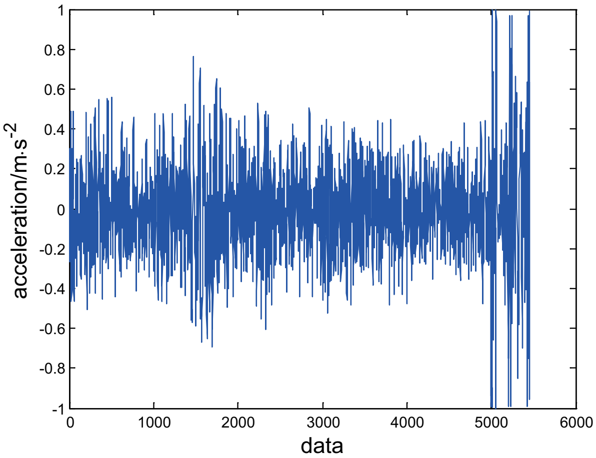

Figure 3. Time-domain waveform of gear box intermediate level acceleration

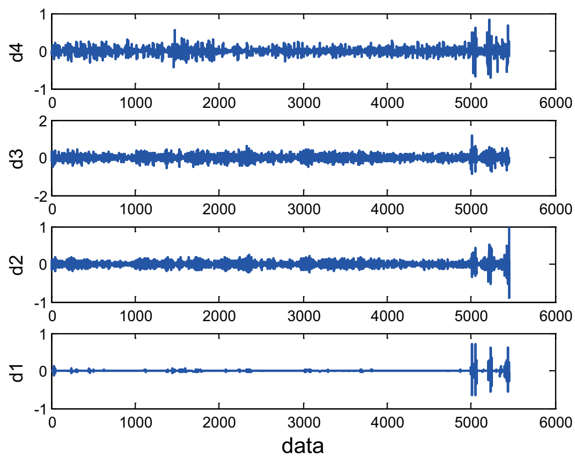

Figure 4. The result of wavelet transform

BP neural network makes use of the neural network toolbox of MATLAB. In this work, the BP neural network input layer has 10 nodes, output layer has 1 node, and hidden layer has 10 nodes. Functions of hidden layer and output layer respectively are "tansig" and "purelin". So the waveform of residual signal is shown in Fig.5.

It can be found that the residual signal at the 5000th data point suddenly appeared numerical value, however as of the 5000th data point, the value of the residual signal has been 0 from the Fig.5. That is to say, wind turbine is not faulty until at the 5000th data point. Obviously the singularity of the signal at other data points in Fig.4 may be caused by process dynamics which is susceptible to external environment. Thus it can be seen that residual signal is superior to wavelet transform, especially in severe environment.

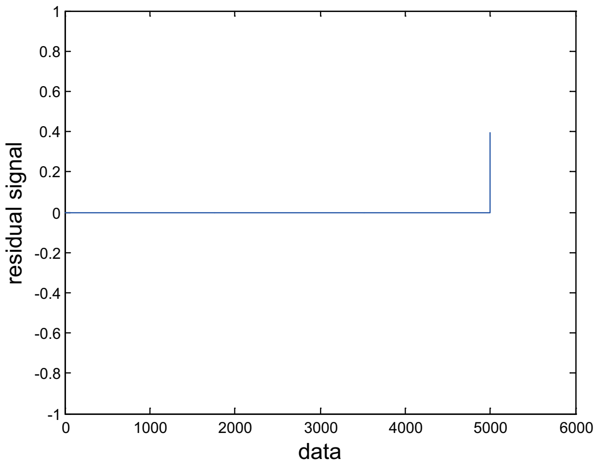

Figure 5. Time-domain waveform of residual signal

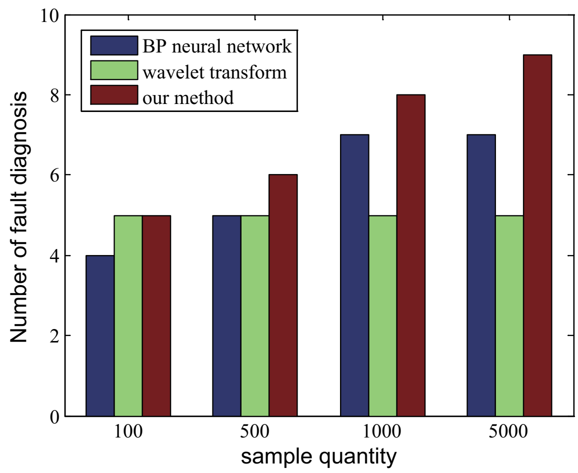

Figure 6. Number of fault diagnosis contrast of three kinds of methods

Accuracy of fault diagnosis is one of the most important performance indexes in fault diagnosis schemes. In order to further verify the accuracy, experiments are carried out by choosing 100groups, 500 groups, 1000 groups, 5000 groups sample data, and importing 10 fault points into every group. Number of fault diagnosis contrast of BP neural network, wavelet transform and our method is shown in Fig.6. It can be seen that there is not major difference in three kinds of methods when groups are 100 and 500. However the proposed method performs much better than the other methods when groups are 1000 and 5000, and the data size is larger, the superiority is better. Moreover accurate rate of fault diagnosis reaches 90%.

5. **Conclusions.** In this paper, we have proposed a new method for wind turbine fault diagnosis based on wavelet transform and neural network hybrid model. By making better use of the samples of the system under normal situation while training the neural network, then wind turbines which may be down is found by wavelet transform. In order to improve the diagnosis accuracy, we use BP neural network to estimate the normal value of the wind turbine which may be down. Finally, according to the residual of estimate value and real value to complete diagnosis. Simulation results show that the method can achieve higher accuracy rate, especially in harsh environment. And data size is lager, the accuracy is better by comparison.

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