Sensors & Transducers, Vol. 180, Issue 10, October 2014, pp. 190-197

Sensors & Transducers

Wire Finishing Mill Rolling Bearing Fault Diagnosis Based on Feature Extraction and BP Neural Network

[1] Hong-Yu LIU, [1] Ze-Ning XU, [2] Jun-Jie XI
[1] School of Mechanical Engineering and Automation,
University of Science and Technology Liaoning, Anshan, Liaoning Province, 114051, China
[2] School of Mechatronics Engineering, Zhengzhou Institute of Aeronautical Industry Management,
Zhengzhou, Henan Province, 450015, China
E-mail: lhy_12@126.com

Received: 16 July 2014 /Accepted: 30 September 2014 /Published: 31 October 2014

Abstract: Rolling bearing is main part of rotary machine. It is frail section of rotary machine. Its running status affects entire mechanical equipment system performance directly. Vibration acceleration signals of the third finishing mill of Anshan Steel and Iron Group wire plant were collected in this paper. Fourier analysis, power spectrum analysis and wavelet transform were made on collected signals. Frequency domain feature extraction and wavelet transform feature extraction were made on collected signals. BP neural network fault diagnosis model was adopted. Frequency domain feature values and wavelet transform feature values were treated as neural network input values. Various typical fault models were treated as neural network output values. Corresponding relations between feature vector and fault omen were utilized. BP neural network model of typical wire plant finishing mill rolling bearing fault was constructed by training many groups sample data. After inputting sample needed to be diagnosed, wire plant finishing mill rolling bearing fault can be diagnosed. This research has important practical significance on enhancing rolling bearing fault diagnosis precision, repairing rolling bearing duly, decreasing stop time, enhancing equipment running efficiency and enhancing economic benefits. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Feature extraction, BP neural network, Wire finishing mill, Rolling bearing fault diagnosis, Wavelet transform.

1. Introduction

With the development of wire finishing rolling technology, finishing mill develops toward the direction of large, continuous and automated. After finishing mill drive system arising faults, entire production line will stop. It will cause huge economic loss. The ratio of rolling bearing fault is big in finishing mill drive system faults. The ratio of rolling bearing fault causing Anshan Steel and Iron Group wire plant stop is big in entire equipment faults.

The abnormal work of rolling bearing can cause many rotary machine faults. So, rolling bearing loss plays a decisive role in the normal work of entire equipment. After rolling bearing loss, equipment vibrations were caused. Massive noises were caused. Machine equipment paralysis was caused [1]. Rolling bearing is the commonest part in machine field. Its application is very universal. It is the easiest worn part. Relevant statistical data show that thirty percent existing machine faults were caused by rolling bearing faults. So, relevant fault analysis diagnosis on rolling bearing is an important research task in equipment fault diagnosis all the time [2]. Rolling bearing is main part in rotary machine. It is feeble section in rotary machine. Its outstanding feature is big life discreteness. The life difference is big within a batch rolling bearings with same material, processing technique and equipment. Rolling bearing running status affects entire mechanical equipment system performance directly. Suitable quantities rolling bearings were all equipped with modern industrial equipment. Generally speaking, rolling bearing is the most accurate part in machine. Many rolling bearings in industry field lose efficacy because of abrasion. So, detecting rolling bearing early symptom and estimating fault severity extent are very important [3].

The method of combining feature extraction and BP neural network was adopted on Anshan Steel and Iron Group wire plant finishing mill rolling bearing fault diagnosis.

2. Frequency Domain Feature Extraction and Wavelet Transform Feature Extraction of Rolling Bearing

2.1. Finishing Mill Vibration Signal Collection

Various anomalies and losses were caused during rolling bearing work. Most faults will aggravate rolling bearing vibration. So, vibration signal becomes main information on rolling bearing fault diagnosis. There are many methods on rolling bearing fault diagnosis currently. Vibration diagnosis method was discussed in this paper mainly.

The influences on rolling bearing vibration information caused by different fault type are different. So, rolling bearing fault status can be obtained by detecting vibration information [4]. In the periodical detection of Anshan Steel and Iron Group wire plant, vibration acceleration signals of the third finishing mill drive device were regarded as research object. Acceleration sensors were adopted on collecting relative vibration acceleration signals. Sampling frequency is 1280 Hz. Anshan Steel Iron and Steel Group wire plant finishing mills is shown as Fig. 1. Collection channel is shown as Fig. 2. The third finishing mill drive device is shown as Fig. 3.

Fig. 1. Anshan Steel and Iron Group wire plant finishing mills.

Fig. 2. Collection channel.

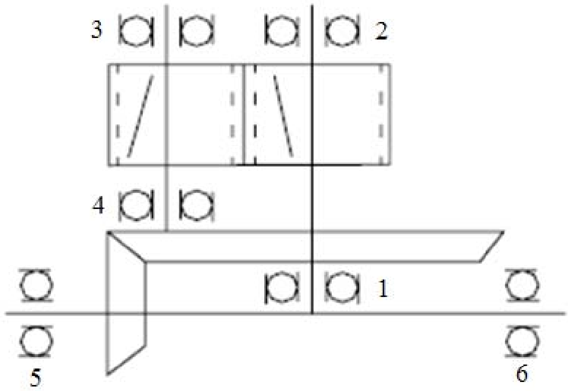

Fig. 3. The third finishing mill drive device.

Four kinds of fault feature frequencies of six running rolling bearings in the third finishing mill drive device is shown as Table 1. Four kinds of faults of six rolling bearings are inner ring roller path fault, outer ring roller path fault, rolling element fault and retainer fault separately. Axis rotation frequency of rolling bearing 1 and rolling bearing 2 is 78.0 Hz. Axis rotation frequency of rolling bearing 3 and rolling bearing 4 is 30.9 Hz. Axis rotation frequency of rolling bearing 5 and rolling bearing 6 is 26.6 Hz.

Table 1. Four kinds of fault feature frequencies of six running rolling bearings.

Rolling number	Inner ring roller path fault (Hz)	Outer ring roller path fault (Hz)	Rolling element fault (Hz)	Retainer fault (Hz)
1	313.2	242.2	238.7	13.5
2	158.0	107.4	115.8	10.7
3	201.5	137.9	121.7	12.6
4	226.1	144.2	132.9	12.4
5	795.9	608.5	574.8	33.9
6	863.6	695.9	623.4	34.8

2.2. Frequency Domain Analysis Frequency Domain Feature Extraction of Finishing Mill Vibration Signal

Collected vibration acceleration signals of the third finishing mill drive device is shown as Fig. 4. Fourier analysis and power spectrum analysis were made on relative signals. Fourier analysis of collected vibration acceleration signals is shown as Fig. 5. Power spectrum analysis of collected vibration acceleration signals is shown as Fig. 6. Relative frequency spectrum feature values on feature frequency were extracted.

Frequency spectrum feature value on feature frequency of Fourier analysis is shown as Fig. 7. Frequency spectrum feature value on feature frequency of power spectrum analysis is shown as Fig. 8.

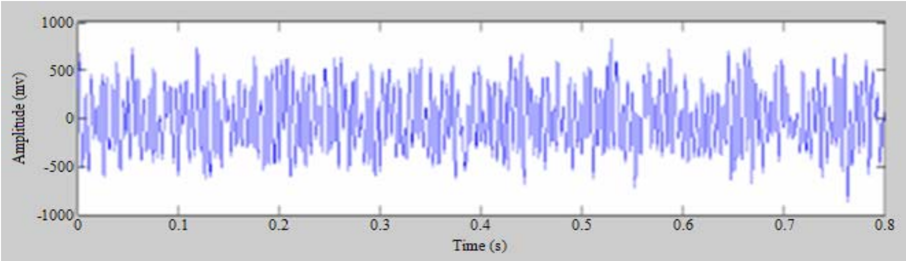

Fig. 4. Collected vibration acceleration signals of the third finishing mill drive device.

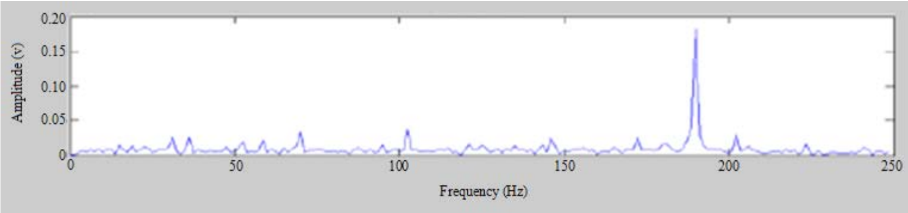

Fig. 5. Fourier analysis of collected vibration acceleration signals.

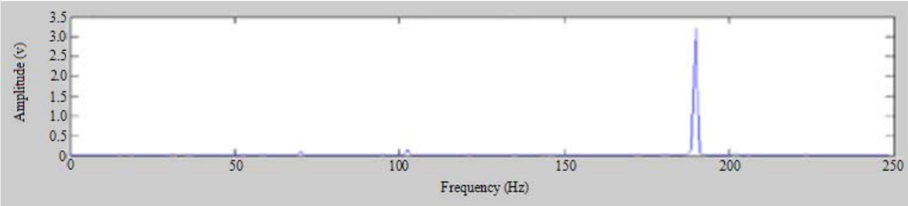

Fig. 6. Power spectrum analysis of collected vibration acceleration signals.

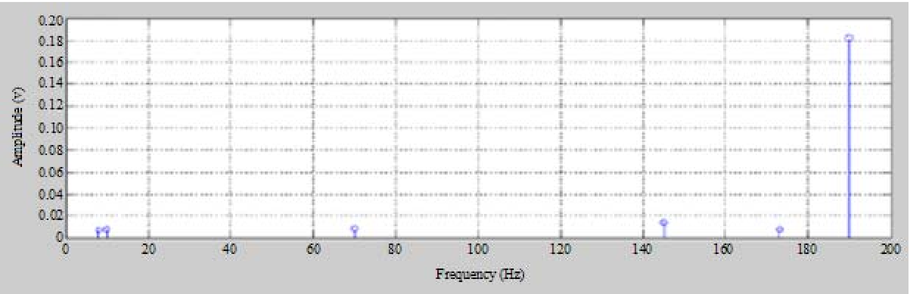

Fig. 7. Frequency spectrum feature value on feature frequency of Fourier analysis.

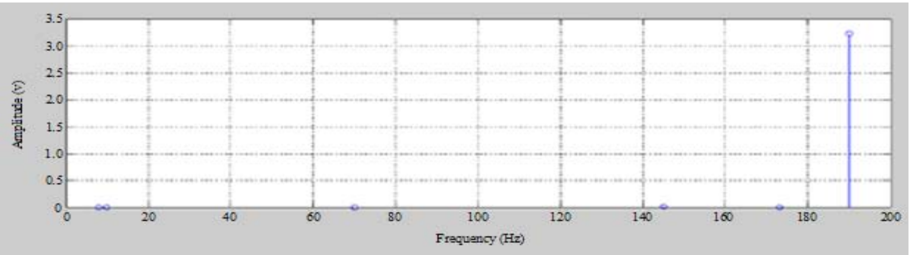

Fig. 8. Frequency spectrum feature value on feature frequency of power spectrum analysis.

Fig. 7 and Fig. 8 show that the most typical frequency of vibration signal is 190 Hz. The feature value related to the most typical frequency is maximal. Above frequency relates and approaches rolling bearing 3 inner ring roller path fault 201.5 Hz in Table 1. So, the fault type related to vibration signal was judged as rolling bearing 3 inner ring roller path fault. The feature values extracted from Fourier analysis and power spectrum analysis were treated as input that is training sample data of BP neural network model.

2.3. Wavelet Transform and Relative Feature Extraction of Finishing Mill Vibration Signal

At present wavelet analysis method is the most effective method on rolling bearing status monitoring and fault diagnosis. It has good localization feature on time domain and frequency domain. It can peel and resolve vibration signal at different extent. Different scale detail signals and outline information can be obtained. It benefits to distinguish fault features and relative interference signals [5]. Wavelet transform as a time and frequency analysis method has multiresolution feature. It has the capability of representing local signal feature on time domain and frequency domain. It has been described as math microscope [6]. It is the development and continuation of Fourier transformation thought method. It has good time and frequency analysis feature. It suits nonstationary signal treatment especially. Wavelet transform provides good technical support for feature extraction of rolling bearing fault diagnosis.

After signal orthogonality wavelet transform, every layer coefficient corresponds to some section frequency component of original signal. The sum of every layer high frequency coefficient energy and N layers low frequency coefficient energy is equal to original signal energy. Original signal energy is unchanged with wavelet decomposition from start to finish. When system fault occurrence, relative change of energy space distribution will take place between fault system output signal and normal system output signal. Energy change of respective output signal frequency component represents damage extent of some mechanical equipment components. Based on this point, rolling bearing faults were diagnosed by utilizing respective frequency component energy change.

Wavelet transform was made on the collected vibration signals of the third finishing mill drive device. Five layers wavelet decomposition were made on relative vibration signals. Six wavelet decomposition coefficients were obtained. They are a5, d5, d4, d3, d2 and d1 respectively. Six wavelet decomposition coefficients and relative frequency ranges are shown as Table 2. Restructuring graph of respective layer wavelet decomposition coefficients is shown as Fig. 9. Vibration signal energy distribution graph of respective layer wavelet decomposition coefficients is shown as Fig. 10.

Fig. 10 shows that within relative frequency range of wavelet decomposition coefficient d2 vibration signal energy amplitude is maximal. It can be checked from Table 2 that relative frequency range of wavelet decomposition coefficient d2 is from 160 Hz to 320 Hz. Above frequency relates and approaches rolling bearing 3 inner ring roller path fault 201.5 Hz in Table 1. So, the fault type related to vibration signal was judged as rolling bearing 3 inner ring roller path fault. The feature values extracted from wavelet transform were treated as input that is training sample data of BP Neural Network model.

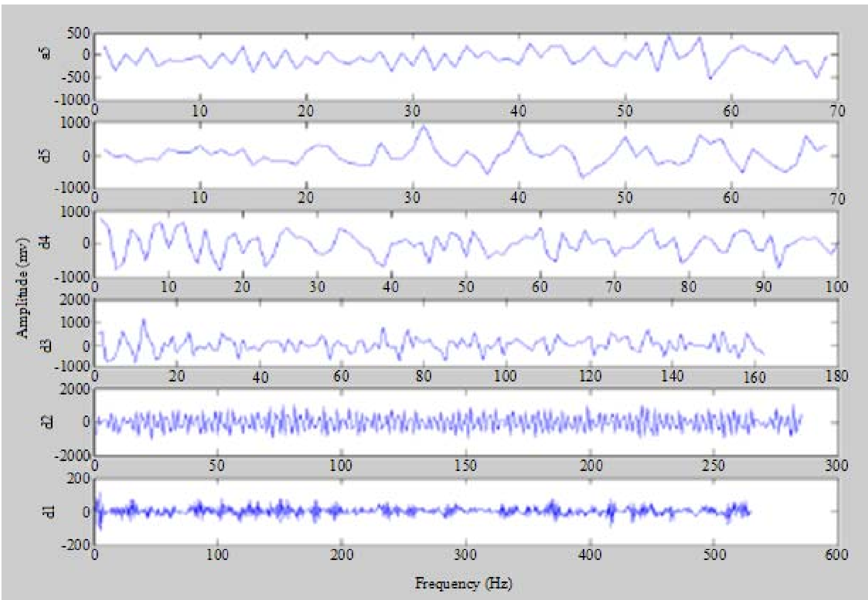

Fig. 9. Restructuring graph of respective layer wavelet decomposition coefficients.

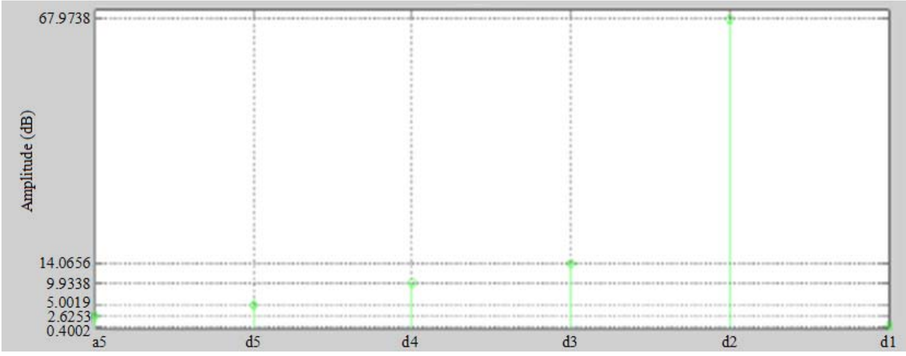

Fig. 10. Vibration signal energy distribution graph of respective layer wavelet decomposition coefficients.

Table 2. Six wavelet decomposition coefficients and relative frequency ranges.

Wavelet decomposition coefficients	Frequency ranges (Hz)
a5	0-20
d5	20-40
d4	40-80
d3	80-160
d2	160-320
d1	320-640

According to diagnosis results of Fig. 5, Fig. 6 and Fig. 10, rolling bearing 3 was checked by spot maintainer. Rolling bearing 3 is shown as Fig. 11. Actual condition is that inner ring roller path of rolling bearing 3 was worn badly. Rolling bearing 3 with bad inner ring roller path abrasion is shown as Fig. 12.

Fig. 11. Rolling bearing 3.

Fig. 12. Rolling bearing 3 with bad inner ring roller path abrasion.

3. The Construction and Application of BP Neural Network Model of Rolling Bearing

Neural network is a very large scale continuation time power system with high nonlinearity. It has the features of nonlinear mapping, quickly parallel distribution processing, autonomic organization, autonomic study and robustness. It was applied on nonlinear control and fault diagnosis. Artificial neural network was abbreviated named as neural network. It is a hot interdiscipline developed in recent years. Applying neural network technology to solve various practical problems was concerned highly and widely. It has the functions of complicated multimodal treatment, association, supposition and memory. It is suit for fault diagnosis system specially. Neural network is a kind of intelligent method with the advantages of strong nonlinear mapping, autonomic study, autonomic organization and autonomic adaptability. It is suit for fault diagnosis rolling bearing specially [7]. Neural network is a new intelligent information calculation treatment system. It can imitate human brain information, associate, remember and obtain entire information from partial information. Although system was disturbed in some extent with big feature information change, neural network can also distinguish and dispose information with optimized work status. It has important significance on on-line real time monitoring and diagnosis of system. It can train satisfied sample requirement decision region under the conditions of big data, incomplete data and noise data.

Multilevel perceptron network with BP algorithm was abbreviated named as BP neural network. It is a kind of artificial neural network with the broadest application. It has important application on various subject areas. BP algorithm applied by multilevel perceptron neural network is a kind of study algorithm wit instructor [8]. The study process of BP algorithm contains forward propagation and backward propagation. In forward propagation process, after hidden layer neures treatment, input model was transferred from input layer to output layer. Every layer neures status only affects next layer neures status. If expected output can not be obtained, propagation was transferred to backward propagation. Error signals were transferred from output layer to input layer simultaneously. Connection weight values and threshold values were adjusted during backward propagation. It can decrease system error continuously so as to satisfy precision requirement. This algorithm is to calculate error function minimal value. Weight values were changed along negative error function gradient direction and converged minimal point by repeatedly training multiple samples with fastest descent method.

3.1. Structure Determination of BP Neural Network

Three layer BP neural networks were adopted in this paper. M input points are x_1, x_2, …, x_M respectively. L input points are y_1, y_2, …, y_L respectively. Hidden network layer contains q units. BP neural network topology structure is shown as Fig. 13.

Fourier analysis, power spectrum analysis and wavelet transform can reflect signal frequency feature accurately. Incompact combination type was adopted in this paper to realize the combination of Fourier analysis, power spectrum analysis, wavelet transform and BP neural network. Fourier analysis, power spectrum analysis and wavelet transform were treated as proposed treatment means of BP neural network. Fourier analysis, power spectrum analysis and wavelet transform provide input feature vectors for BP neural network.

Every weight value change produced by cycle training was decided by study efficiency. Big study efficiency can cause system instability. Small study efficiency can cause long training time and slow convergence. So, in general condition, small study efficiency was selected so as to ensure system stability. The study efficiency selections range is between 0.01 and 0.8. Several different study efficiencies were selected in advance in order to train in the network design process of this paper. Best study efficiency was selected by comparing the system errors from all training. Study efficiency selections and system errors are shown as Table 3.

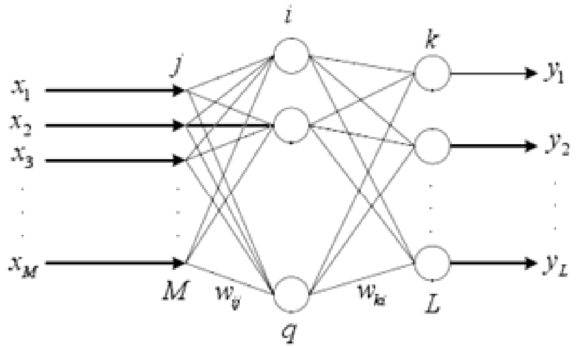

Fig. 13. BP neural network topology structure.

Table 3 shows that system error is the smallest with relative study efficiency 0.01. So, study efficiency was selected as 0.01 in this paper. Sigmoid function with abbreviated name S type function was selected as transfer function in this paper according to BP neural network requirement and requisite output purpose. The initial weight value was intercalated within 0 and 1.

Table 3. Study efficiency selections and system errors.

Serial number	Input layer node number	Hidden layer node number	Output layer node number	Study efficiencies	Study step length	System errors
1	4	4	4	0.01	5000	4.59×10^{-6}
2	4	4	4	0.03	5000	4.45×10^{-4}
3	4	4	4	0.05	5000	4.28×10^{-5}
4	4	4	4	0.07	5000	1.93×10^{-4}
5	4	4	4	0.09	5000	2.18×10^{-4}
6	4	4	4	0.1	5000	5.38×10^{-4}
7	4	4	4	0.3	5000	1.95×10^{-5}
8	4	4	4	0.5	5000	2.5×10^{-4}

Relative process knowledge was saved in trained BP neural network. Study can be made in trained BP neural network from quantitative fault information direct. BP neural network can be trained by various object status information. Current tested information can be distinguished by trained BP neural network so as to ascertain fault.

Too many BP neural network input nodes can cause too large BP neural network structure. More noise information will be inputted unavoidably. Too less BP neural network input nodes can not ensure necessary network information quantity. So, the network input node selection is important task of BP neural network mode construction. In this paper, four kinds of rolling bearing fault models are inner ring roller path fault, rolling element fault, retainer fault and outer ring roller path fault separately. Relative ideal output vectors are Y_1, Y_2, Y_3 and Y_4. They are treated as BP neural network model output vectors. Four kinds of rolling bearing fault models and relative ideal output vectors are shown as Table 4.

Table 4. Four kinds of rolling bearing fault models and relative ideal output vectors.

Fault model	Ideal output vector
Inner ring roller path fault	Y_1=[0 0 0 1]
Rolling element fault	Y_2=[0 0 1 0]
Retainer fault	Y_3=[0 1 0 0]
Outer ring roller path fault	Y_4=[1 0 0 0]

3.2. Rolling Bearing Fault Diagnosis Based on BP Neural Network

During finishing mill rolling bearing fault diagnosis process, the fault feature values extracted by frequency domain analysis and wavelet transform analysis were treated as input vectors of BP neural network that is training sample data in this paper. The input layer unit number of BP neural network adopted in this paper is 4. Four input vectors are corresponding with four units. They are inner ring roller path fault feature value X_1, rolling element fault feature value X_2, retainer fault feature value X_3 and outer ring roller path fault feature value X_4 separately. The output layer unit number of BP neural network adopted in this paper is 4. Four output vectors are corresponding with four units. They are inner ring roller path fault Y_1, rolling element fault Y_2, retainer fault Y_3 and outer ring roller path fault Y_4 separately. The hidden layer unit number of BP neural network adopted in this paper is 4. Training sample data under four kinds of rolling bearing fault models are shown as Table 5.

Before BP neural network training, standardization treatments were made on original data. Treated data were applied as BP neural network input sample. System error was stipulated as 0.001. Study efficiency was stipulated as 0.01. Training number was stipulated as 5000.

Initial weight value and threshold value were produced by uniform distribution random algorithm program. The treatment can satisfy precision requirement. Trained BP neural network model was saved to diagnose finishing mill fault. Standardization treatments were made on training sample data of Table 5. Relative treated data are shown as Table 6.

After standardization treatments, relative training sample data were inputted into trained BP neural network model. The output vectors of training sample data after standardization treatments and ideal output vectors are shown as Table 7.

Table 5. Training sample data under four kinds of rolling bearing fault models.

Fault model	Training sample serial number	Training sample data			
		X_1	X_2	X_3	X_4
Inner ring roller path fault	1	5.2104	7.0904	9.0185	98.2035
Rolling element fault	2	5.6845	8.3625	15.8705	70.2541
Retainer fault	3	4.5681	15.5002	8.9560	67.2540
Outer ring roller path fault	4	12.7410	8.0021	9.68452	69.3251

Table 6. Training sample data under four kinds of rolling bearing fault models after standardization treatments.

Fault model	Training sample serial number	Training sample data after standardization treatments			
		X_1	X_2	X_3	X_4
Inner ring roller path fault	1	0.0786	0.1366	0	1.0000
Rolling element fault	2	0	0.1513	1.0000	0.1084
Retainer fault	3	0.0090	1.0000	0	0.1054
Outer ring roller path fault	4	1.0000	0.0969	0	0.0669

Table 7. The output vectors of training sample data after standardization treatments and ideal output vectors.

Training sample serial number	Training sample output vectors	Ideal output vectors
1	Y_1=[-0.0001 0.0000 0.0005 0.9993]	Y_1=[0 0 0 1]
2	Y_2=[0.0003 -0.0000 1.0003 0.0046]	Y_2=[0 0 1 0]
3	Y_3=[0.0003 1.0000 0.0000 0.0037]	Y_3=[0 1 0 0]
4	Y_4=[1.0000 -0.0000 -0.0004 -0.0001]	Y_4=[1 0 0 0]

Frequency domain analysis and wavelet analysis were made on practical test vibration signals of finishing mill rolling bearing under rolling element fault. Relative fault feature values were extracted and inputted into BP neural network model. Relative output result is [0.0051 0.1980 1.0024 0.0089] . It is very close to relative training sample output vector that is [0.0003 -0.0000 1.0003 0.0046]. It shows that the method of combining feature extraction and BP neural network has high fault recognition precision on rolling bearing fault diagnosis.

4. Conclusions

Vibration acceleration signals of the third finishing mill of Anshan Steel and Iron Group wire plant were collected in this paper. Fourier analysis, power spectrum analysis and wavelet transform were made on collected signals. Frequency domain feature extraction and wavelet transform feature extraction were made on collected signals. BP neural network fault diagnosis model was adopted. Frequency domain feature values and wavelet transform feature values were treated as neural network input values. Various typical fault models were treated as neural network output values. Corresponding relations between feature vector and fault omen were utilized. BP neural network model of typical wire plant finishing mill rolling bearing fault was constructed by training many groups sample data. After inputting sample needed to be diagnosed, wire plant finishing mill rolling bearing fault can be diagnosed. Relative experiment was made. The outputted vector errors under various typical rolling bearing faults are small between diagnosis outputted results and ideal outputted results. It shows that the BP neural network model of typical wire plant finishing mill rolling bearing fault has high identification precision on rolling bearing fault. The model can satisfy the fault diagnosis requirement of Anshan Steel and Iron Group wire plant finishing mill rolling bearing.

Acknowledgements

This work was supported by the Science and Technology Tackle Key Problem Plan Major Project of Henan Province (No. 102102210389) and the Science and Technology Tackle Key Problem Plan Project of Henan Province (No. 082102230047).

References

[1]. W. L. Hu, Rolling bearing fault diagnosis based on wavelet analysis, *East China Science & Technology*, Vol. 29, Issue 11, 2013, pp. 369.

[2]. Q. Gu, C. Z. Chen, H. Zhou, Research on new rolling bearing fault diagnosis method, *Machinery Design & Manufacture*, Vol. 51, Issue 9, 2013, pp. 117-119.

[3]. C. S. Gou, Y. Zhang, Application of modern diagnosis technology on rolling bearing fault diagnosis, *Chongqing Steel and Iron Motorized Energy*, Vol. 26, Issue 3, 2013, pp. 35-40.

[4]. J. Huang, Y. H. Wang, Research on rolling bearing fault model and vibration test technology, *Quality and Reliability*, Vol. 24, Issue 2, 2012, pp. 30-32.

[5]. C. S. Gou, Y. Zhang, Fault diagnosis of rolling bearing based on wavelet analysis, *Mechanical Engineer*, Vol. 24, Issue 2, 2012, pp. 30-32.

[6]. T. Peng, X. Ma, Application of wavelet neural network on rolling element bearings fault diagnosis, *Computer Engineering and Applications*, Vol. 46, Issue 4, 2010, pp. 213-215.

[7]. Y. B. Hu, S. Y. Li, L. B. Hu, Fault diagnosis of rolling bearing based on neural network, *Machinery Design & Manufacture*, Vol. 50, Issue 2, 2012, pp. 187-189.

[8]. Z. F. Zhang, L. M. Xia, Intelligent method of fault diagnosis of rolling bearing based on neural network, *Information Technology*, Vol. 32, Issue 8, 2008, pp. 53-55.