Bearing Fault Diagnosis Based on BP Neural Network

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Abstract. Rolling bearings are essential parts, and its operation directly affects the overall condition of the equipment. Due to the complicated non-mapping relationship between the fault and the symptom issued, this paper adopts the strong non-mapping of the neural network and the ability to self-learn and adapt to the state detection and fault diagnosis of the rolling bearing. Through select the fault characteristic parameters, and the BP neural network to select normal operation and inner ring fault characteristic parameters for fault diagnosis. Experiments show that the BP neural network constructed in this paper can accurately determine whether the rolling bearing is fault based on actual data.

1. Introduction
The rolling bearing is composed of four types: inner ring, rolling element, cage and outer ring, as shown in Fig. 1. In the rotating machinery, it plays the role of transmitting load and bearing the load.

The reliability, accuracy and life of the mechanical equipment will be affected by the bearing state. Rolling bearings are under the complex stress state: stretched, compressed, bent, sheared, alternating and high stress value, the high speed and long time work, the working environment is very complicated. Bearing failures are divided into two categories based on the range of speeds. When the bearing speed is within n<1r/min, the damage form is plastic deformation caused by thermal deformation, excessive impact load, excessive working load, etc., resulting in relatively large noise and vibration during bearing operation. When the bearing speed is n>10r/min, the bearing will experience fatigue spalling, abrasion and abrasion, rust and corrosion, fracture failure, indentation, gluing, etc. The fault diagnosis of rolling bearings is an accident for discovering the potential failure of the equipment and avoiding mechanical damage. The research from abroad is mainly to apply wavelet transform, expert system, fuzzy diagnosis, neural network, .apply to the field of fault diagnosis of rolling bearings. Zhang Guoxin introduced neural network technology into the fault diagnosis of rolling bearings, and used this as an example to write a diagnostic system based on neural network technology [1]. Fu Jun applied the BP neural network method to the fault diagnosis of locomotive bearings, and developed a user interface based application using VB [2]. Since then, the bearing fault diagnosis system has begun to interface, which laid the foundation for the design of the user interface using Lab VIEW software. Chang Jiadong began to study the application method of BP neural network in the fault diagnosis of mill centering rotor bearing [3]. Xie Peifu applied wavelet analysis and BP neural network theory to the fault diagnosis system of rolling bearings, and used the characteristic parameters of the kurtosis values obtained by the signal to train and predict the neural network [4]. In this paper, the training of neural network and the number of nodes in
the layer and hidden layer are selected. The characteristic parameters include normal and inner ring fault data and diagnosis whether the bearing is fault according to the output result.

**Figure 1.** Schematic diagram of a rolling bearing.

2. **BP Neural Network**

BP Neural Network (Back Propagation) is a multi-layer feed forward network trained by error inverse propagation algorithm. As shown in Fig. 2, nodes represent neurons, which are connected by weights, the neurons in the network have n input layer and m output layer and some hidden layers in the network. There may be many neurons in each hidden layer, and the sum is greater than or equal to 1.

The working principle is as follows: the training sample enters the neural network through the neuron, and after the input layer and the hidden layer and the two transfer functions between the hidden layer and the output layer, the operation result is output through the output layer neurons, and the process is the forward propagation of the signal. Compare the output of the output layer with the expected value. If the output meets the expected requirements, stop the BP neural network. Conversely, if there is a certain difference between them, the difference is passed back to the output layer. In the BP neural network, after the adjustment of the weight and threshold of the neural network itself, the adjusted actual output value of the neural network is re-calculated until the requirement is met. This is the error back propagation adjustment process.

**Figure 2.** A schematic diagram of a vibration separator.

The learning process of the BP network is completed by the neurons in each layer. The gradient descent algorithm is used in the process to continuously adjust the weight of the neurons, so that the error can quickly converge and meet the requirements. The output error $E$ of the defined network is:

$$E = \frac{1}{2}(d-o)^2$$

(1)
The weight adjustment formula for each layer of the single hidden layer BP network output layer and hidden layer learning algorithm:

\[ \Delta w_{jk} = \eta \delta_j y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j \]

\[ \Delta v_{it} = \eta \delta_i x_i = \eta \sum_{k=1}^{l} (\delta_k w_{jk}) y_j (1 - y_j) x_i \]

Where: \( \eta \) is the proportional coefficient, reflecting the learning efficiency, its value range is (0.01, 0.8). The vector form of the single hidden layer BP network learning algorithm is:

For the output layer, set \( Y = (y_1, y_2, ..., y_l)^T \), \( \delta = (\delta_1, \delta_2, ..., \delta_l)^T \), \( \Delta w = \eta (\delta Y)^T \)

For the input layer, set \( X = (x_1, x_2, ..., x_n)^T \), \( \delta X = (\delta_1 X, \delta_2 X, ..., \delta_n X)^T \), \( \Delta v = \eta (\delta X)^T \)

3. Bearing Fault Diagnosis Based on BP Neural Network

The faults of rolling bearings are basically divided into three types: inner ring fault, outer ring fault and rolling element fault. The bearing fault diagnosis usually uses vibration data analysis. The data in this paper comes from the data of the rolling bearing test of the West Reserve University. The experiment is carried out using a 2 hp Reliance Electric motor. And the acceleration data is measured at a position close to and away from the motor bearing. Motor bearings are fault sown using electrical discharge machining (EDM). In the inner raceway, the rolling elements (i.e., the ball) and the outer raceway introduce faults from 0.007 inches in diameter to 0.040 inches in diameter, respectively. Reinstall the faulty bearing into the test motor and record the vibration data of the motor load from 0 to 3 horsepower (motor speed 1797 to 1720 RPM). In this paper, we select 5200 sets of inner ring faults and normal data of rolling bearings. Each group uses 200 time points corresponding data, so the selected input node is 200. The data screenshot is shown in Fig. 3.

![Figure 3. Part of data.](image-url)
training samples. The normal bearing output is 0. The fault bearing training sample the output is 1. The target output is shown in Fig. 4.

Figure 4. Targets output.

Using Matlab to build My Neural Network Function (Neural Network Function) brings in training samples and output targets a total of 5200 columns, as shown in Table 4.1, through the network processing to get 5200 outputs is the judgment result. The error precision is set to 0.0001. For some results that do not reach the rational target, a discriminating interval (0.1, 0.9) is taken. If the output is less than 0.1, the disc is judged as 0. If the output is greater than 0.9, the disc is judged to be 1. It is considered invalid. The obtained output is subtracted from the ideal result to obtain the absolute value, and the maximum error of the obtained result is 0.0483. The result basically conforms to the ideal output, so it can be seen that the neural network can well diagnose whether the rolling bearing has a fault. At the same time, it also has a strong ability to learn, through continuous learning and perfection to monitor the status of rolling bearings in real time.

Table 1. System output.

| 0.9975 | 0.0000 | 0.9998 | 0.9995 | 0.0153 | 0.0102 | 0.9997 | 0.9999 | 0.9998 | 0.0000 |
|-------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 0.0000 | 0.9999 | 0.9999 | 0.0000 | 0.9998 | 0.9991 | 0.9999 | 0.9999 | 0.0000 | 0.9993 |
| 0.9997 | 0.9995 | 1.0000 | 0.9987 | 1.0000 | 0.9997 | 0.0191 | 0.9995 | 1.0000 | 0.9999 |
| 0.9995 | 1.0000 | 0.9995 | 0.9995 | 0.9999 | 0.0002 | 0.9987 | 0.9997 | 0.9998 | 1.0000 |
| 0.9997 | 0.9981 | 1.0000 | 0.9996 | 0.9996 | 1.0000 | 0.0004 | 0.9992 | 1.0000 | 0.9958 |
| 0.9995 | 0.9994 | 0.9998 | 0.9999 | 0.9999 | 0.0000 | 0.9996 | 0.9994 | 0.9996 | 0.0090 |
| 0.9995 | 1.0000 | 0.0000 | 0.9990 | 0.9995 | 0.0000 | 0.9998 | 1.0000 | 0.9998 | 1.0000 |
| 0.9994 | 0.9958 | 0.0001 | 0.9992 | 0.9998 | 0.9991 | 0.9993 | 1.0000 | 0.0002 | 0.0003 |
| 0.0000 | 0.9997 | 0.9999 | 0.0000 | 1.0000 | 0.9996 | 0.0000 | 1.0000 | 1.0000 | 0.9997 |
| 0.9999 | 0.9997 | 0.9999 | 0.9998 | 1.0000 | 0.9999 | 0.9999 | 0.0002 | 0.9996 | 0.9997 |
| 0.0000 | 0.9992 | 0.0005 | 0.0016 | 0.9996 | 0.9992 | 0.9998 | 0.9995 | 0.9999 | 0.0003 |
| 0.9998 | 0.9948 | 0.0002 | 0.0008 | 0.0021 | 0.9998 | 0.9996 | 0.0002 | 0.0172 | 1.0000 |
| 0.9993 | 0.9995 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9993 | 0.9996 | 0.9996 | 1.0000 |
| 0.0001 | 0.9998 | 0.9997 | 0.9995 | 0.9991 | 0.9999 | 1.0000 | 0.9983 | 0.9995 | 1.0000 |
| 0.9995 | 0.9992 | 0.0000 | 0.9987 | 0.9998 | 0.9994 | 0.9997 | 0.9997 | 0.0000 | 0.9984 |
| 1.0000 | 0.0000 | 0.9998 | 0.9998 | 0.9997 | 0.9993 | 0.9999 | 0.9961 | 0.9996 | 0.9998 |
| 0.9999 | 1.0000 | 0.9999 | 0.9999 | 0.9998 | 0.9997 | 0.9998 | 0.0012 | 1.0000 | 0.9940 |
| 0.9995 | 0.0004 | 0.9998 | 0.9994 | 1.0000 | 0.9997 | 1.0000 | 0.9994 | 0.9999 | 1.0000 |
| 0.9997 | 0.9977 | 0.0001 | 0.0043 | 0.0008 | 0.9999 | 0.9994 | 0.0000 | 0.0012 | 1.0000 |
| 0.9999 | 0.0000 | 0.9998 | 0.9999 | 0.0000 | 0.9999 | 0.9995 | 1.0000 | 0.9996 | 0.0005 |

4. Conclusion
Rolling bearings will experience fatigue spalling, abrasion and abrasion, rust erosion, fracture failure, indentation, gluing, etc. in the harsh working environment. The BP neural network learning ability will be used to analyze the parameter data of 5200 train bearings. The error is affordable. Within the scope, the BP neural network learning algorithm can perform state detection and fault prediction on the state of the bearing.

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