A Fault Diagnosis System for Main Fan in Coal Mine Based on BP Neural Network

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Abstract. By analysing the three-layer structure of BP neural network and the fault characteristics of main fan in coal mine, the BP network structure of fault diagnosis is constructed, and the learning model and algorithm of BP network are designed. The experimental simulation shows that the accuracy of the fault diagnosis of the main fan of the coal mine is improved.

1. Introduction
Fan is widely used in coal mine, chemical industry and other industries, shouldering the arduous task of uninterrupted ventilation, usually operating in a harsh environment, once a fault occurs, it will cause huge losses. Main fan is one of the most critical large-scale equipment in coal mining roadway [1,2,3]. Whether it can maintain safe and stable operation will directly affect the safety production of the whole coal mine enterprise. Usually, large and medium fans have strong vibration, big noise and easy to break down. Therefore, to carry out condition monitoring and fault diagnosis of fans and ensure the safe and reliable operation of fans can achieve great economic and social benefits.

Fault diagnosis can be carried out according to the change of the running state of the main fan in coal mine, which is reflected in the dynamic information with time, such as voltage, current, power, vibration, noise, pressure, temperature and humidity. The parameters related to vibration, such as amplitude, vibration frequency, phase, rotational speed, axis track, axial displacement, axis displacement, etc. These characteristic parameters representing the state of the fan are abstracted as fault feature vectors [2-4]. At present, BP neural network is mostly used in fan fault diagnosis, but there are some shortcomings, such as the network structure is difficult to determine, the network structure is complex, the local optimal solution can only be obtained, not necessarily the global optimal solution, easy to fall into the local minimum value and slow convergence speed, which lead to low stability of the system and low fault identification rate [1,4-12].

This paper abstracts the fault parameters of the main fan in coal mine, improves the BP network learning model and training algorithm, and diagnoses the fault of the main fan in coal mine by constructing an expert system, which improves the recognition rate and accuracy.

2. Model of BP Neural Network and Learning Algorithm
The error backward propagation neural network model, i.e. the BP neural network model [1], is the currently most widely used type of neural network model.
2.1. Model of BP Neural Network

Generally a BP neural network is consisted of an input layer, a hidden layer and an output layer. The network input layer is

\[ O_j^{(p)} = X_j, j=1, 2, \ldots, m; p=1 \]  

(1)

Where \( j \) is the number of input variables, \( X \) is composed of input fault feature vectors; \( p \) is the number of layers of BP neural network, \( p = 1, 2, \ldots, b \).

The network hiding layer is:

\[ a_i^{(p)}(k) = \sum_{j=1}^{q(p)-1} \sigma_{ij}^{(p)} O_j^{(p-1)}(k), \quad i = 1, 2, \ldots, q(p), p=2, \ldots, b-1 \]  

(2)

\[ O_i^{(p)}(k) = f\left(a_i^{(p)}(k)\right) \]  

(3)

Where \( \sigma_{ij}^{(p)} \) is hidden layer weighting coefficient; \( q(p) \) is the number of neuron of layer \( P \); \( f(x) \) is excitation function.

The network output layer is

\[ a_i^{(b)}(k) = \sum_{j=0}^{q(b)-1} \sigma_{ij}^{(b)} O_j^{(b-1)}(k), \quad i = 1, 2, \ldots, n \]  

(4)

\[ y_i = O_i^{(b)}(k) = f\left(a_i^{(b)}(k)\right) \]  

(5)

Where \( \sigma_{ij}^{(b)} \) is the output layer weighting coefficient; \( g(x) \) is the output layer neuron excitation function.

The performance index can be taken as

\[ E(x) = \frac{1}{2}(y(k) - y(k))^2 \]  

(6)

The weighting coefficient of the network is corrected by the steepest descent method.

2.2. Learning Algorithm for BP Neural Network

The learning algorithm for BP neural network is the development and application of simple Delta(\( \delta \)) learning rule. The aim of the Delta(\( \delta \)) learning rule is to minimize the square of the difference of the expected output and the actual output.

\[ E = (D_i - O_i)^2 \]  

(7)

\[ \Delta E = -(D_i - O_i)f'(wx)x_j \]  

(8)

\[ \Delta \omega_{ij} = C(D_i - O_i)f''(wx)x_j \]  

(9)

Where \( C (C>0) \) is the learning rate, \( D_i \) is the expected output, \( X \) is the input signal, \( X_j \) is the input of neuron \( i \), \( O_i \) is the output of neuron \( i \), \( w \) is the weight, and the weight of neuron \( i \), \( W_i = (p_{i1}, p_{i2}, \ldots, p_{in}) \).

If each layer of the BP network has \( N \) processing units, action function is the sigmoid function as shown in formula(4), and the training set contains \( M \) sample pattern pairs \((x_k, y_k)\), the input sum (activation function) of unit \( J \) will be \( a_{pj} \) and the output be \( O_{pj} \) for the training sample \( p (p = 1, 2, \ldots, M) \).
\[ a_{pj} = \sum_{i=1}^{N} w_{ji} O_{pi} \]  
(10)

\[ O_{pj} = f(a_{pj}) = \frac{1}{1 + \exp(-a_{pj})} \]  
(11)

Assuming that the initial weight and threshold of the network can be set freely, there must be an error between the expected output and the network output, no matter which input pattern is adopted. Let the network error be

\[ E = \sum_{p} E_{p} \]  
(12)

\[ E_{p} = \frac{1}{2} \sum_{j} (D_{pi} - O_{pi})^{2} \]  
(13)

Where \( D_{pj} \) represents the expected output of output unit \( J \) to input pattern \( p \).

Due to

\[ \frac{\partial E_{p}}{\partial w_{ji}} = \frac{\partial E_{p}}{\partial a_{pj}} \cdot \frac{\partial a_{pj}}{\partial w_{ji}} = \frac{\partial E_{p}}{\partial a_{pj}} \cdot O_{pi} = -\delta_{pj} \cdot O_{pi} \]  
(14)

the variable of weight \( w_{ji} \) will be

\[ \Delta_{p} w_{ji} \propto -\frac{\partial E_{p}}{\partial w_{ji}} \]  
(15)

\[ w_{ji} = \eta \delta_{pj} \cdot O_{pi}, \eta > 0 \]  
(16)

As there are different calculation methods for the error of the output layer unit and the hidden layer unit, the weight correction formula for BP algorithm, in the learning process of the BP network, will be

\[ w_{ji}(t + 1) = w_{ji}(t) + \eta \delta_{pj} \cdot O_{pi} \]  
(17)

Where \( \delta_{pj} = \{ f'(a_{pj})(D_{pj} - O_{pj}) \} \sum_{k} \delta_{pk}w_{kj} \), \( k \) is the upper layer unit connected to the output of unit \( j \).

For output units: \( O_{pj} \) is the output of the output layer unit, \( (D_{pj} - O_{pj}) \) is the error of the output unit \( j \). \( f'(a_{pj}) \) error is decreased as per ratio. When the value of the activation function \( a_{pj} \) is zero, the S-Type curve rises the fastest; when the maximum value of derivative \( f'(a_{pj}) \) is taken, the error correction becomes the largest.

For hidden units: \( O_{pj} \) is the output of the hidden layer unit. The error correction \( O_{pj} \) of the hidden layer unit is, by weighted summation of all upper layer unit error correction \( j \) connected to unit \( j \) output, obtained as per ratio decreasing in line with \( f'(a_{pj}) \).

In consideration of the convergence of the learning process, the learning factor \( \eta \) should be as small as possible in principle. If \( \eta \) is too large, the weight change will be drastic for every each time, which may result in vibration. Therefore, the weight correction formula (17) needs to add a correction value.

\[ w_{ji}(t + 1) = w_{ji}(t) + \eta \delta_{pj} \cdot O_{pi} + \alpha (w_{ji}(t) - w_{ji}(t - 1)) \]  
(18)
Where $\alpha$ is the potential constant factor.

The correction of weight is completed layer by layer during the backward propagation of the error. The output layer error shall firstly correct the connection weight for each output layer unit, and then the BP algorithm weight correction formula calculates the error of the inter-connected hidden layer units as well as the connection weight of the hidden layer unit. Until the entire network weight is updated again, the network experiences a learning cycle.

3. Design of the Structure of BP Neural Network and Learning Algorithm

3.1. Construction of BP Neural Network

The number of input nodes for the BP neural network must at the fewest be equal to the number of measurement points, yet some more node inputs may also be defined, with data originated from appropriate filtering of the measurement data.

According to the fault feature vectors, the type of fault pattern is related to the output node of the BP neural network. Type one is a no-fault state, and the other is a fault condition (the selectable number of output nodes of the two types of fault is $N + 1$).

When the output node is "0", it means that fault does not occur; when it is "1", it means that the fault occurs. Because the output value is within $[0, 1]$, an appropriate decision-making function could be adopted to determine whether a fault has occurred or not. If the maximum value of the output node is adopted to represent the decision-making for the type of fault, but this decision-making can not conduct multiple fault detection, the reliability of the classification can also not be evaluated. As multi-faults always occur simultaneously with rotary machines of main fans in coal mine whenever there is a fault, it is very important to improve the diagnostic ability of BP neural network.

The Multi-fault BP neural network can be decomposed into a number of integration of BP subnetworks, with three-layer BP neural network structure as shown in Figure 1, where in each BP subnetwork only outputs one node, corresponding to a type of faults. The structures of BP subnetwork are very simple. Training is very fast and will not affect each other among the subnetworks. In case there occurs new fault, by adding a new BP subnetwork, the original subnetwork will not be affected. The network learning ability is therefore greatly enhanced.

![Figure 1. Integrated structure of BP neural network](image)

The BP neural subnetwork selects nine feature vectors, such as the relative energy ratio of the vibration signal of the coal mine main fan bearing in each frequency segment, etc., as the basis to classify typical faults (single fault pattern), and the cause of the fault as the output, to form a three-layer BP neural network, with input feature vectors being obtained after preprocessing of the collected sample data.

BP Subneural Network uses the spectrum energy of the vibration signal as input, with the number of input layer units as 9, corresponding to the 9 frequency feature vectors, and the number of output layer units as 9, corresponding to the 9 typical faults. 9 samples are used for the network training. The number of hidden layer neuron selects 10, and the three layer BP neural network is adopted. BP Subneural Network uses the vibration direction and oil temperature change at the bearing as input, with the number of input layer units as 6, the output layer units as 6 and the hidden layer neuron as 6.
3.2. Improvement of BP Neural Network Algorithm

Since the basic algorithm for BP neural network uses the gradient descent search finding algorithm, it appears inevitable that the convergence speed for network learning is slow and is easy to fall into the problem of local minimum\[3, 9\]. According to the generalized Delta rule, the correction of weight has been improved in this paper with an additional potential momentum item. The weight is as formula:

\[
\begin{align*}
    w_{ji}(t + 1) &= w_{ji}(t) + \eta \delta_{pj} \cdot O_{pi} + \alpha (w_{ji}(t) - w_{ji}(t - \delta)) \\
    \text{where } \alpha &= \text{potential constant factor}, \text{which determines the impact of the weight change of the previous learning on the current weight update.}
\end{align*}
\]

Learning rate calculation:

\[
\eta = 2 \sqrt{\frac{1}{n_H + 1}}
\]

Where \( n_H \) is the node of the hidden layer.

The improved algorithm in this paper is as follows (where \( \alpha \) is the potential constant factor):

- While \( E(t) - E(t-1) > 0.05 E(t-1) \), the network converges rapidly and all the values remain unchanged.
- While \( E(t) - E(t-1) < 0 \), the network diverges, then the learning rate and potential factor could be adjusted as: \( \eta = \eta / 2, \alpha = 0 \);
- While \( 0 < E(t) - E(t-1) < 0.05 E(t-1) \), the network converges slowly, at this time, if \( \eta > 0.90 \), \( \eta \) remains unchanged; if not, \( \eta = 1.1 \eta \), \( \alpha \) shall remain unchanged.

The index that BP neural network quantitatively reflects learning performance is the mean square error (MSE):

\[
E_{mse} = \frac{1}{mn} \sum_{p=1}^{m} \sum_{j=1}^{n} (D_{pj} - y_{pj})^2
\]

Where \( m \) is the number of pattern pairs in the training set, \( n \) is the number of neural network output layer units. In general, when the value of MSE of the BP neural network is less than 0.1, it means that the learning of a given training set has met the requirements and that its upper limit can be set according to specific condition.

3.3. Integration of BP Neural Networks

The basic idea of integrated neural networks is to increase the diagnosis rate to the utmost by using various BP sub neural networks to diagnose faults from different sides through effective combination of signals, i.e., data fusion.
As shown in Figure 2 for local diagnosis, the inputs of this network can be either different types of signals or different feature factors of the same signal. They reflect the faults of electromechanical devices from different sides. The BP integrated neural network integrated system for overall diagnosis is as shown in Figure 3. Let Y be the output of the decision integration network. The purpose of integrating neural networks is to design BPNNi(i=1,2,...m), so that Y obtained by final fusion has less uncertainty.

3.4. Fusion for Decision-making

The decision-making of each BP sub network reflects the state of the device from different aspects. After reorganization, they are favourable to reduce the uncertainties amongst decisions, hence to increase the diagnosis rate and to function as group consultation. The fusion decision-making network accepts the diagnosis conclusion of BP subneural network and conducts the decision-making fusion treatment. Let the fault vector formed by the subneural network BPNN be:

\[ P_i = [P_{i1}, P_{i2}, ..., P_{in}] \]  \hspace{1cm} (22)

and its confidence weight vector for each type of fault be

\[ R_i = [r_{i1}, r_{i2}, ..., r_{in}] \]  \hspace{1cm} (23)

the parallel combination of subnetworks will be

\[ N_m = [BPNN_1, BPNN_2, ..., BPNN_m] \]  \hspace{1cm} (24)

a fault matrix P and a confidence weight matrix R is therefore formed.

\[
P = \begin{bmatrix}
P_{11} & P_{12} & \cdots & P_{1m} \\
P_{21} & P_{22} & \cdots & P_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
P_{m1} & P_{m2} & \cdots & P_{mm}
\end{bmatrix} \quad \text{and} \quad
R = \begin{bmatrix}
r_{11} & r_{12} & \cdots & r_{1c} \\
r_{21} & r_{22} & \cdots & r_{2c} \\
\vdots & \vdots & \ddots & \vdots \\
r_{m1} & r_{m2} & \cdots & r_{mc}
\end{bmatrix}
\]  \hspace{1cm} (25)

The fusion output is

\[ Y = PR \]  \hspace{1cm} (26)

where the probability of occurrence of no. r fault is

\[ P_i = P_{i1}r_{1i} + P_{i2}r_{2i} + \cdots + P_{in}r_{ni} \]  \hspace{1cm} (27)

\[ \sum_{j=1}^{m} r_{ij} = 1 \]

where the weight coefficient r indicates the degree of contribution of each subneural network to the fault.

4. Experiments for Training and Judging of the System

The experimental simulation is carried out by using traindx functions of the neural network toolbox in the Matlab. The initial weight of BP network is a random number of [-1,1]; the minimum expected error of noise-free training is set at 0.0001; the minimum expected error of noise training is set at 0.01; the maximum number of cycles is 2000; the learning rate is 0.01; and the momentum factor alpha is 0.93. The collected standard training samples for BP neural network in this paper are shown in Table 1, and the standard output results of the corresponding faults are shown in Tables 2.
Table 1. Standard training samples for BP sub-neural network

| Common fault          | Vibration frequency (f) for rotation frequency |
|-----------------------|-----------------------------------------------|
|                       | 0.01-0.39f | 0.04-0.49f | 0.50 f | 0.51-0.99f | 1 f | 2 f | 3-5 f | Odd no. f | >5 f |
| Rotor imbalance       | 0.00       | 0.00       | 0.00   | 0.00       | 0.90 | 0.06 | 0.05   | 0.00      | 0.00 |
| Rotor misalignment    | 0.00       | 0.00       | 0.00   | 0.00       | 0.40 | 0.50 | 0.09   | 0.00      | 0.00 |
| Oil film vortex       | 0.12       | 0.81       | 0.00   | 0.12       | 0.00 | 0.00 | 0.00   | 0.00      | 0.00 |
| Bearings tile loose   | 0.00       | 0.80       | 0.10   | 0.00       | 0.00 | 0.00 | 0.00   | 0.12      | 0.00 |
| Bearing seat loose    | 0.88       | 0.00       | 0.00   | 0.00       | 0.00 | 0.00 | 0.00   | 0.12      | 0.00 |
| bearing damage        | 0.00       | 0.00       | 0.12   | 0.92       | 0.00 | 0.00 | 0.00   | 0.00      | 0.00 |
| Connector damage      | 0.12       | 0.17       | 0.12   | 0.00       | 0.24 | 0.31 | 0.13   | 0.00      | 0.00 |
| Rotor axial friction  | 0.12       | 0.06       | 0.06   | 0.12       | 0.33 | 0.12 | 0.12   | 0.12      | 0.12 |
| Uneq bearing stiffness| 0.00       | 0.00       | 0.00   | 0.00       | 0.83 | 0.23 | 0.00   | 0.00      | 0.00 |

It can be seen that the number of iterations decreases significantly between 0.01 and 1 as learning rate increases. Table 3 shows the impact of different learning rate on learning speed in a living examples. After network learning, the learning results curves of the network as shown in figure 4.

Table 2. Standard output results of BP sub-neural network

| S.No. of fault | 01 col value | 02 col value | 03 col value | 04 col value | 05 col value | 06 col value | 07 col value | 08 col value | 09 col value |
|----------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| 1              | 1            | 0            | 0            | 0            | 0            | 0            | 0            | 0            | 0            |
| 2              | 0            | 1            | 0            | 0            | 0            | 0            | 0            | 0            | 0            |
| 3              | 0            | 0            | 1            | 0            | 0            | 0            | 0            | 0            | 0            |
| 4              | 0            | 0            | 0            | 1            | 0            | 0            | 0            | 0            | 0            |
| 5              | 0            | 0            | 0            | 0            | 1            | 0            | 0            | 0            | 0            |
| 6              | 0            | 0            | 0            | 0            | 0            | 1            | 0            | 0            | 0            |
| 7              | 0            | 0            | 0            | 0            | 0            | 0            | 1            | 0            | 0            |
| 8              | 0            | 0            | 0            | 0            | 0            | 0            | 0            | 1            | 0            |
| 9              | 0            | 0            | 0            | 0            | 0            | 0            | 0            | 0            | 1            |

Table 3. Impact of learning rate on learning speed

| Learning rate | 0.01 | 0.05 | 0.1 | 0.2 | 0.5 | 1   | 1.5 | 2  | 3  | 4  | 5  |
|---------------|------|------|-----|-----|-----|-----|-----|----|----|----|----|
| No. of iterations | 210  | 175  | 160 | 140 | 130 | 120 | 135 | 140| 330| 400*| 500*|
5. Conclusion
In this paper, an improved BP neural network based on momentum method and adaptive learning rate is proposed, which reduces the number and time of network training, improves the learning efficiency and effectively restrains the network from falling into local minimum. The test results show that the diagnosis efficiency of the fault diagnosis system is greatly improved, stable and high recognition rate, and the fault diagnosis accuracy of the main fan in coal mine is strong.

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