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Research on fault diagnosis of TBM main bearing based on improved BP neural network

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Abstract—**Main bearing that plays the role of supporting and making the cutter to rotate and tunnel is the core part of TBM. Because of the harsh working conditions and complex changeful construction, the axial and radial load and environmental factors such as temperature of TBM main bearing are changing to make the fault of main bearing presenting randomness, and then the not easy identified fault may be produced. The traditional neural network model can not dynamic consider the cause of the reasons, parts and types, BP neural network fault diagnosis model based on fault reasons—signs matrix is presented in this paper. Firstly, the faults are screened through the fault reasons—symptom matrix, and the neural network structure is designed according to the screening result, then, the fault type is identified by way of model training. According to TBM main bearing fault symptoms data provided by a heavy enterprises practical engineering and MATLAB simulation validation, the feasibility and superiority of this model method are proved.**

Keywords-TBM; BP neural network; fault diagnosis; signs matrix; MATLAB

I. INTRODUCTION

TBM is the main construction machinery of the underground tunneling construction, it can prevent soft foundation excavation face collapse and keep excavation face stable, at the same time, it can also finished the tunnel excavation and lining operations securely in machine[1-2]. At present, TBM is used widely in the large tunnel projects of city subway, river tunnel, and sea-crossing tunnel and so on. Because of the harsh working conditions and complex construction, the TBM fault rate is higher. Now, troubleshooting means still mainly rely on artificial maintenance, and timely fault repaired rate is low. The experiences show that a skilled technicians who to eliminate fault, need the time of total time of 70% to 90% to determine the fault reasons and parts, while only about 10%-30% for clearing the faults.

Main bearing that plays the role of supporting and making the cutter to rotate and tunnel is the core part of TBM[3]. In the Shiziyang tunnel engineering right line of China railway 12th bureau Guangshengang special passenger line, when the TBM was propelling, because of the bad lubrication and severe wear making the TBM appearing the abnormal vibration, the TBM was often at half stop condition, and the average working time was 2-5 hours. The construction progress was influenced seriously. Therefore, the significance is very great to ensure the security of TBM main bearing.

II. ESTABLISHMENT OF THE FAILURE REASONS — SYMPTOM MATRIX

A. *Main Bearing Fault Diagnosis Model Based on Boolean Function*

Assume that the fault symptoms of a common system are $S_1, S_2, \cdots, S_n$, and the reasons of the malfunction are $R_1, R_2, \cdots, R_m$. Fault diagnosis means that it infers one or a few possible failure causing reasons in the collection basing on a few signs in the collection of the observed fault symptoms. Therefore, we define a Boolean function $E(S_1, S_2, \cdots, S_n; R_1, R_2, \cdots, R_m)$, which is used to describe which combinations of fault symptoms appearing in which causes of the malfunctions; Define Boolean function $G(S_1, S_2, \cdots, S_n)$ to indicate the sign of a combination of the cause of the malfunction, namely the fault symptoms detected by the sensor.

Then define the Boolean function $C(R_1, R_2, \cdots, R_m)$, which is used to show that which combinations of the causes of the malfunctions can match with the existing sign combinations, namely the fault diagnosis which is looking for. The whole process of the fault diagnosis can be described the process of looking for the function $G(\bullet)$ in Formula (1):

$$C(\bullet) = G(\bullet) \bullet E(\bullet) \tag{1}$$

Failure causes and symptoms are binary Boolean relations, so Boolean Relation matrix is used to represent the function $E(\bullet)$ in the actual diagnosis, namely the failure reasons — symptom matrix.

Function $G(\bullet)$ is the fault symptoms collected through sensors and other detection means, which can be represented by Boolean vectors. So with the knowing of $G(\bullet)$ and $G(\bullet)$, we can get the diagnostic results $G(\bullet)$ through equation (1), $G(\bullet)$ is also a Boolean vector.

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B. Establishment of Failure Reasons —Symptom Matrix

The binary Boolean relation matrix between systems' failure causes and symptoms is used to describe Boolean function $E(S_1, S_2, \cdots, S_n; R_1, R_2, \cdots, R_m)$ in this paper.

An ordinary system, for example, the relationship matrix between failure causes and symptoms is:

$$\begin{bmatrix} I_{1,1} & I_{1,2} & \cdots & I_{1,j} & \cdots & I_{1,m} \\ I_{2,1} & I_{2,2} & \cdots & I_{2,j} & \cdots & I_{2,m} \\ & & & & & \\ I_{i,1} & I_{i,2} & \cdots & I_{i,j} & \cdots & I_{i,m} \\ & & & & & \\ I_{n,1} & I_{n,2} & \cdots & I_{n,j} & \cdots & I_{n,m} \end{bmatrix}$$

In the formula: R_j is the fault type of number j; S_i is the sign type of number i; m is the type number of the possible cause of the malfunctions; n is the type number of the detected signs.

$I_{i,j}$ is the possible state of sign S_i, when a fault R_j occurs, and

$$I_{i,j} = \begin{cases} 1, & (S_i \textit{ may be caused by fault } R_j) \\ 0, & (S_i \textit{ may not be caused by fault } R_j) \end{cases}$$

At the same time, Let $s_j = (I_{1,j},\ I_{2,j}, \cdots, I_{n,j})$ is the sign vector produced by fault R_j; $r_i = (I_{i,1},\ I_{i,2}, \cdots, I_{i,m})$ is the fault vectors may exist when symptom S_i occurs; $s^{'} = (I_1^{'},\ I_2^{'}, \cdots, I_n{'})$ is the observation vector, If we can observe sign S_i, the value of $I_i^{'}$ is 1, and 0 otherwise; $r^{'} = (I_1,\ I_2, \cdots, I_m)$ is the result vector, when I_j is 1, there may be a fault, on the contrary, there is no fault; s_j $(j = 1, 2, \cdots, m)$ is the matrix's column vector, namely the vertical rules of a matrix. When $I_{i,j}$ is 1, it means the sign type S_i may occur when the fault type R_j occurs; And the sign type S_i may not occur when $I_{i,j}$ is 0. r_i $(i = 1, 2, \cdots, n)$ is the Matrix's row vector, namely the horizontal rules of a matrix. When $I_{i,j}$ is 1, it means the sign S_i may be caused by failure R_j, otherwise, it isn't caused by failure R_j.

We collect the system's Fault signal (Fault symptoms), and then Make the assignment of each sign type whit 1 or 0, to determine the function $G(\bullet)$.

The results of the observation signs Depicted by $G(\bullet)$ is called the observation vector, which is represented by $s^{'}$, and $s^{'} = (I_1^{'},\ I_2^{'}, \cdots, I_n{'})$. If the sign S_i can be observed, the value of $I_i^{'}$ is 1 and 0, otherwise. Then we get an observation vector $s^{'}$, namely we assign a value to the function $G(\bullet)$, we can get a result vector According to equation (1), which is represented by $r^{'}$, $r^{'} = (I_1,\ I_2, \cdots, I_m)$. When I_j is 1, that may be a problem, and there is no fault on the contrary. This method is the theoretical model of the matrix screening method.

III. BP NEURAL NETWORK MODEL OF THE MAIN BEARING

BP network is a multilayer feed forward neural network, and it is composed of input layer, hidden layer and output layer. Figure 1 shows the structure of the BP network, Neural network learning uses BP algorithm, The learning process are composed of prior to the calculation process and the error back-propagation process, In the prior to the calculation process, the input information calculates layer by layer from the input layer to the hidden layer, and transmit to the output layer, the state of each layer's neuron only affect the status of the next layer's neurons. If the output layer can not get the desired output, it transfers to the error back-propagation process, and the error signal returns along the original connection path, then makes the network system error minimization by modifying the value of every layer's neuron. Finally, the actual outputs of the network are approaching to their corresponding desired output.

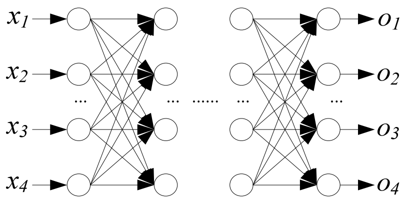

Figure 1. BP network model

To make the algorithm implementation process clearly, we can use the flow chart 2 to represent. The specific steps are as follows:

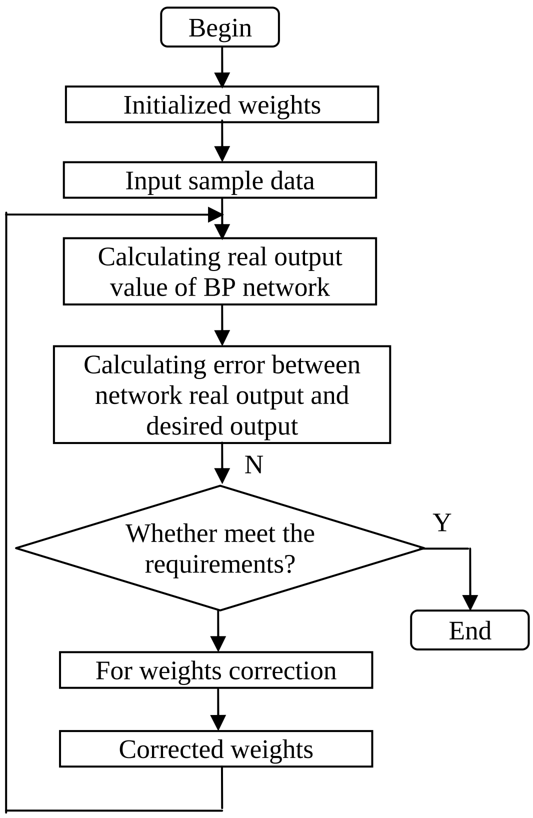

Figure 2. Flow chart of BP algorithm

- Initialize the weights W and the threshold θ, namely assign the weights W_{ij} Connecting input layer units and the hidden layer, the weights connecting the hidden layer and output layer, the threshold of hidden layer θ_j and the unit threshold of output layer θ_k with a smaller value between 0 and l.
- Provide a learning sample pair (Input and expected output values), give the input vector $X_i = (x_1, x_2, \ldots x_n)$ and the expected output vector $\hat{Y}_i = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_m)$, which corresponds with the input one, import value x_i to input and output layer node, and calculate forward one by one:

$$x'_j = f(\sum_{i=0}^{n} w_{ij} x_i - \theta_j) \qquad (j = 1,2,\ldots,n) \tag{2}$$

$$y_k = f(\sum_{k=1}^{n} v_{jk} x'_j - \theta_k) \qquad (j = 1,2,\ldots,n) \tag{3}$$

- Calculate the error { δ_k } between the output value { y_k } of the output node and the expected value { $\hat{y}_k$ }.

$$\delta_k = y_k (1 - y_k)(\hat{y}_k - y_k)$$

- Allocate error to the hidden layer nodes Reversely, namely use the connect right{ V_{jk} }、the generalization error of the output layer{ δ_k }、output of the hidden layer { x'_j }to calculate the error{ δ_J } of hidden layer's every unit:

$$\delta_j = x'_j (1 - x'_j) \sum_{k=1}^{n} v_{jk} \delta_k \tag{4}$$

- Use the generalization error { δ_k } of the output layer unit and the output { x'_j } of hidden layer's each unit to correct the output layer's weights { V_{jk} } and thresholds { θ_k }:

The weights correction of output layer and hidden layer:

$$v_{jk}(t+1) = v_{jk}(t) + \eta \delta_k x'_j \tag{5}$$

The threshold correction of output layer:

$$\theta_k(t+1) = \theta_k(t) + \eta \delta_k \tag{6}$$

- Use the generalization error { δ_j } of hidden layer and input { x_i } of input layer's each unit to correct the connection weight { W_{ij} } and threshold { θ_j }:

Correction of connection weights between the input layer and hidden layer:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j x_i \tag{7}$$

The threshold correction of the hidden layer:

$$\theta_j(t+1) = \theta_j + \eta \delta_j \tag{8}$$

- Repeat steps two select different training samples, implement the above iterative process constantly, until meet the requirements, makes the error is small enough or zero, stop learning.

IV. REALIZATION OF THE FAULT DIAGNOSIS FOR MAIN BEARING

There are three steps in the process of TBM fault diagnosis. Firstly, collect different vibration signal by the data acquisition card. Then, eliminate the noise of vibration signal by wavelet, and pick up the Eigen value. Finally, determine the fault type and remove the faults by fault diagnosis.

Applying TRFDS based on BP neural network to diagnose faults includes the following steps:

1) Using vibration data about main bearing from TBM produced by one Heavy equipment company in Shenyang, we can establish the faults cause—symptoms matrix. Due to the limited space, it can only take the 6*6 sub matrix. The values of fault symptoms function $G(\bullet)$ by the data collecting are $s' = (1\ \ 0\ \ 1\ \ 0\ \ 0\ \ 0)$. Then by formula (1):

$$r' = C(\bullet) = G(\bullet) \bullet E(\bullet) = (1\ \ 0\ \ 1\ \ 0\ \ 0\ \ 0)\begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} = (1\ \ 1\ \ 1\ \ 0\ \ 1\ \ 1)$$

Then we can know that, $r' = (1\ \ 1\ \ 1\ \ 0\ \ 1\ \ 1)$ shows when the value of the function $G(\bullet)$ is $s' = (1\ \ 0\ \ 1\ \ 0\ \ 0\ \ 0)$, the possible fault types are in the table 1.

2) To design neural network structure. According to the faults cause—symptoms matrix, we can determine the node number of input and output layer in neural network. If the vibration signal was divided into N layers, the input layer node number is N; if there are M kinds of equipment fault, the output layer node number is M; the hidden layer node number is chosen by experience. And the transfer function is single polarity S function. According to successful experience of neural networks in fault diagnosis, we can determine the following two preliminary conclusions:

a) Most problems of the fault pattern recognition could be resolved by the three-layer network.

b) There is the approximate relationship between the neurons number of hidden layer and the input layer in three-layer network $N_2 = 2N_1 + 1$.

3) Training the neural network. The extracted eigenvector is input neural network as training samples, and it assume that there are M kinds of equipment fault, then the output of the network is $\hat{Y}_i = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_m)$, if the equipment is in j state, the output of the network is $\hat{y}_j = 1$, and the rest is 0, finally the output of network is $(0, 0, 0, ..., 1, ..., 0)$. Using sample data to train the network until the simulation error is less than the target error, and save the network weights and bias after training.

TABLE I. THE VIBRATE FAULTS CAUSE—SYMPTOMS MATRIX OF MAIN BEARING OF TBM

Fault symptoms	Fault causes					
	Unbalance	Touch grinding	Not centring	Rotor damaged	Surge	Bearing pedestal loosened
Vibration value whether stable	1	1	1	0	1	1
Vibration value whether mutations	0	0	0	0	0	1
Axial vibration whether obvious	0	0	0	0	1	0
cutter pressure fluctuations	1	0	0	1	1	0
Vibration value with the oil temperature changes	0	1	0	0	0	0
Vibration value with engine speed change	0	0	0	1	1	1

4) Identifying the fault type. The eigenvector of vibration signals are put into neural network and trained BP neural network is used to solve the problems, then to identify the fault type according to the output of network.

The six typical faults, including unbalance, touch grinding, rotor damaged, surge, bearing pedestal loosened, are the neural network output; six spectrum peak energy value of frequency spectrum from vibration signal spectrums are used as characteristic variable to form the training samples. Shown as table 2 and table 3.

TABLE II. MAPPING TABLE OF OUTPUT NODES AND FAULT TYPES

Output nodes	1	2	3	4	5	6
Fault types	unbalance	touch grinding	not centring	rotor damaged	surge	bearing pedestal loosened

TABLE III. MAPPING TABLE OF INPUT NODES AND FREQUENCY RANGE

Input nodes	1	2	3	4	5	6
Frequency range	0-0.5f	0.5-0.99f	1f	2f	3-5f	High frequency range

To avoid network saturation, the value of spectrum peak energy value cannot be used as input vector directly, so the data must be normalized before network training. Each input is normalized as following:

$$\overline{E} = \frac{E}{\sum_{i=1}^{n}|E_i|} \qquad i = 1, 2, ..., 6$$

In this way, the input values of network are all among [0, 1].

The membership degree vector of faults is obtained by membership function through measured data. For example, like the fuzzy relation of the 'large vibration' and 'fault severity', according to the experience, the fault is obvious when vibration is small. So it is appropriate to use Half Causy distribute function in fault diagnosis, the mathematic representation is:

$$\mu(x) = \begin{cases} 0 & (0 \le x \le a) \\ \dfrac{k(x-a)^2}{1+k(x-a)^2} & (a \le x \le \infty) \end{cases} \tag{9}$$

In the problems we researched, $a=0$, that is effective for positive region. The formula (9) can be simplified as follows:

$$\mu(x) = \frac{kx^2}{1+kx^2} = \frac{x^2}{1/k + x^2}$$

In the formula, the influence of k to $\mu(x)$ can be obtained by formula (10): when k is the maximum, that is $k=1$, the influence of k to $\mu(x)$ is very small; but k is too small, the influence of k to $\mu(x)$ is still very small. They all do not reflect the membership degree, so k depends on the value of x .

$$k = \frac{1}{\left(\sum_{i=1}^{n} \frac{x_i}{n}\right)} \tag{10}$$

In the formula, n is the number of not equal to 0.

TABLE IV. TRAINING SAMPLE AND TARGET OUTPUT

Input sample						Expected output					
0. 00	0. 90	0. 05	0. 05	0. 00	0. 00	1	0	0	0	0	0
0. 10	0. 10	0. 10	0. 20	0. 10	0. 30	0	1	0	0	0	0
0. 00	0. 10	0. 70	0. 10	0. 10	0. 00	0	0	1	0	0	0
0. 60	0. 06	0. 16	0. 18	0. 00	0. 00	0	0	0	1	0	0
0. 20	0. 10	0. 60	0. 05	0. 05	0. 00	0	0	0	0	1	0
0. 90	0. 00	0. 00	0. 00	0. 10	0. 00	0	0	0	0	0	1

It chose the three layer network, 6 input units, 13 middle layers, and 6 output units. Besides, the error coefficient is set as 0.0001. Simulation result of the MATLAB is displayed as the figure 3; the actual output is displayed as table 5.

After the wavelet neural network has finished the study for the input and output sample, we can use it to the fault diagnosis on the bearings. Assume that a new vibration signal $[0.00, 0.15, 0.65, 0.10, 0.10, 0.00]$ which is put into neural network as Eigenvectors, then we can get the results [-0.0315, 0.1574, 0.6221, 0.0329, 0.2245, -0.0626] by nonlinear mapping in neural network. From the output results, it is obvious that the maximum is 0.6221, which correspond the third fault type. So the fault signal is in line with the type of not centring fault.

TABLE V. ACTUAL OUTPUT OF TRAINING SAMPLE

Actual output					
1. 007145	0. 008596	−0. 00033	0. 03914	−0. 04347	−0. 00267
0. 002015	0. 997113	0. 030207	0. 039964	−0. 06028	0. 064406
−0. 00694	−0. 00297	1. 002852	−0. 00296	0. 000423	0. 009778
0. 008455	0. 012074	−0. 01246	1. 002135	0. 001375	−0. 01221
−0. 02881	−0. 02597	0. 003585	−0. 04818	1. 062456	0. 032021
0. 025081	0. 021992	0. 001093	0. 057425	−0. 06466	0. 971879

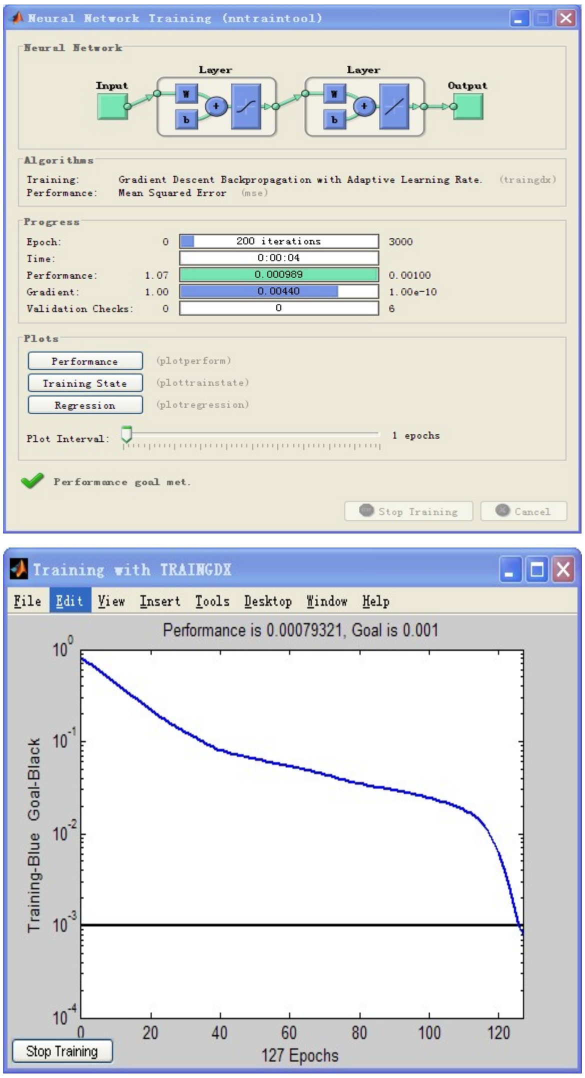

Figure 3. Simulation result of the MATLAB

V. CONCLUSIONS

Real-time fault diagnosis of TBM main bearing can improve the efficiency of the project construction, and ensure the construction period. This paper put forward BP neural network fault diagnosis model based on the fault reasons—symptom matrix. Through practical engineering data validation and MATLAB simulation, it confirmed that this fault diagnosis model of TBM main bearing is more feasible and advantaged than the common BP neural network model.

1) The fault reason of TBM main bearing is dynamic changing, so the scope of the fault types can be further narrowing through the fault reasons—symptom matrix screening, and make the BP neural network to lock the fault type rapidly in the training process. Then the problem that the traditional algorithm can't dynamic diagnosis main bearing fault is solved.

2) The training process of neural networks can be real-time tested by MATLAB simulation, to ensure that the training results are accurate feasible.

3) The algorithm has shorten the fault diagnosis time and improved the working efficiency of TBM.

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