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Fault Diagnosis of Coal Equipment Based on Dynamic Fuzzy Neural Network and BP Neural Network

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Abstract

In Coal Mechanical & electrical equipment fault detection process, due to the large number of hardware devices, prone to voltage instability, indirectly affecting the fault signal is not stable, sample data space dimension, diagnosis the disadvantages of poor real-time. Using dynamic fuzzy self-learning theory and BP neural network combination method for fault diagnosis are proposed in this paper, first of all, through the dynamic fuzzy self-learning method of fault data, then the rapid diagnosis and classification using BP neural network. Simulation results show that the proposed algorithm can effectively improve the accuracy of fault diagnosis, which can improve the ability of diagnosis and decision making.

Keywords: *Coal Mine Equipment; Dynamic Fuzzy; BP; Neural Network*

1. Introduction

With the development of the world economy, the exploitation of resources is more and more relying on large machinery and equipment to complete, coal resources as a nonrenewable resource, mining and utilization is highly valued by people. In the process of mining, large equipment plays an important role, but the equipment is susceptible to wear from the outside and their own equipment, resulting in failure of equipment [1]. Literature [2-3] propose analysis method in the application of condition monitoring of electrical equipment is required for acquiring information, condition monitoring task and can be used, then for the detection of primary equipment and secondary equipment and circuit state of the meticulous research, and make an evaluation function of networking technology in the condition based maintenance. Literature [4] points out that the current fault sensor control is mainly distributed in the lower of the scale body, through the sensor output signal, but it is easy to deviate from the center. Literature [5] points out that a kind of digital sensor can realize the uninterrupted work and can obtain the fault signal in a short time, but the disadvantage is that the price is expensive. Literature [6] presents a fault detection method of large coal electromechanical equipment based on K means clustering algorithm. K means clustering method is used to classify and deal with the collected signal, and the fault signal of mechanical and electrical equipment is extracted. Positioning and processing the fault signal, so as to realize the fault detection of large coal mechanical and electrical equipment. The experimental results show that the improved algorithm can effectively improve the accuracy of the detection of coal mechanical and electrical equipment, and has achieved satisfactory results. Energy operator algorithm is combined with peak energy and resonance demodulation fault analysis method, and to mine water pump as an example, on time domain vibration signal envelope, demodulation draw the waveform of frequency that the peak energy of the vibration signal spectrum and spectral characteristics of frequency and fault about can be used to predict the coal mine electrical and mechanical equipment fault state and type, prevention and repair of mine

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electromechanical equipment health management scheme is proposed in literature [7]. Literature [8] proposes a based on expert system and artificial neural network fault diagnosis of mechanical equipment system, the system first of all be able to accurate positioning of mechanical equipment fault. Secondly, through the expert system can fault proposed solutions, provide a reference for the maintenance personnel and the system has the function of real-time monitoring on the working state of the equipment, to guarantee coal mine machinery and equipment safety normal operation to provide protection. Literature [9] proposes a quantum neural network fault diagnosis algorithm. In quantum phase sliding door and controlled not gate for basic computing unit to construct 3-layer quantum neural network fault diagnosis model, and the gradient descent method is used as the learning algorithm of the model, the scraper conveyor deceleration for multiple fault diagnosis. Preliminary research results show that the proposed quantum neural network fault diagnosis technology is feasible, and it is helpful to improve the fault diagnosis rate of rotating machinery and electrical equipment in coal mine.

On the basis of the above research, according to the characteristics of coal equipment voltage signal of the fault, the were sampled and then using fuzzy dynamic learning method to diagnose, find the effective data, and then combined with the BP neural network classification of the fault, so as to improve the equipment fault diagnosis effect. Simulation experiments prove that the algorithm has some validity.

2. Coal Equipment Fault Sampling

Equipment in the mining process of the output signal is mainly voltage signal, when the device is unable to connect between the signal collector and ECU, the voltage signal will be beyond the normal range and thus cause failure. Suppose the number of nodes in the network sensor in coal equipment is J, each node in the signal acquisition process runs n times, the data length of each node is n. Then the data collection network data can be expressed as

Write a data node as a vector form, such as a formula (1)

$$\mathrm{X} = F(\mathrm{X}_D)$$
$$= (x_{11}, \ldots, x_{1n}, x_{12}, \ldots, x_{n2}, x_{1J}, \ldots, x_{nJ})^T = (x(1), x(2), \ldots x(N))^T \tag{1}$$

Among them, $\boldsymbol{X} \in R^N$, $N = J \times n$. Using the discrete cosine transform to the voltage signal using sparse transform.

$$\boldsymbol{X} = \boldsymbol{\Psi s} = \sum_{i=1}^{N} \psi_i s_i = \sum_{k=1}^{K} \psi_k s_k, \quad s_k \neq 0 \tag{2}$$

Among them, Ψ is the $N \times N$ dimensional DCT transformation matrix, and the N dimension sparse coefficient vector s_k contains K ($K << N$)nonzero elements. The measurement matrix is used to measure the data. The measurement matrix generated by the node j ($j \in 1,2, \ldots, J$)is Φ_j, and the dimension of the matrix is $m \times n$ ($m << n$).

The measurement process of the network data can be represented by the following matrix vector:

$$\boldsymbol{Y} = \boldsymbol{\Theta X} = \boldsymbol{\Phi \Psi s}$$

$$\mathbf{\Phi}=\begin{pmatrix} \Phi_1 & 0 & \cdots & 0 \\ 0 & \Phi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Phi_J \end{pmatrix} \in R^{M\times N} \tag{3}$$

Among them, $\boldsymbol{Y}\in R^{M}$, $M=J\times m$, Measurement matrix.

In order to better determine the data in the equipment fault node, the fault node vector is reconstructed by the known measurement value Y and matrix. However, the sparse representation of the fault nodes in the coal equipment may be limited by the signal itself, the network signal is not stable and other factors, cannot be accurate to find the fault point of the equipment. This paper presents a new fault diagnosis method for this problem.

3. Fault Detection and Diagnosis Based on Dynamic Fuzzy and BP Neural Network

3.1. Energy Self-Learning Based on Dynamic Fuzzy Function

The sensor fault of coal equipment is random, it is a kind of typical nonlinear structure, and the dynamic fuzzy function can be very good to find the dead node in the fault of equipment sensor. Dynamic fuzzy basis functions are constructed as follows:

$$F_n(x)=\frac{\prod_{i=1}^{n}T_i(x)}{\sum_{i=1\ldots n}\prod_{i=1}^{n}T_i(x)}=\frac{ruq\left[\sum_{i=1,j=1}^{n}(\frac{x_i-\overline{x_j}}{\varpi_{ij}})^2\right]}{\sum_{i=1,j=1\ldots n}ruq\left[-\sum_{i=1,j=1}^{n}(\frac{x_i-\overline{x_j}}{\varpi_{ij}})^2\right]} \tag{4}$$

Assuming the sensor energy of the faulty node is w_i , the input formula (4) is obtained and the corresponding improved node energy is as follows:

$$Y=\sum_{i=1}^{k}F_i(x)*w_i \tag{5}$$

In the formula (5), where k represents the number of sensor nodes. By constructing the dynamic function in the fuzzy function as follows:

$$Y=\sum_{i=1}^{N}\frac{u_i}{y_i} \quad x_i\in T(x) \tag{6}$$

In the formula (6), x_i is the fuzzy variable value of the first i sample, and the $T(x)$ represents the reference fuzzy variable set. Where u_i is set to 0-1 between the real number, $\frac{u_i}{y_i}$ said the two ratio; the meaning of the standard setting is when x_i reached $T(x)$, the possibility of y_i is u_i . Set Mamdani with $T^{'}$ implication, through inference $T^{'}=(\alpha_1 u_1\cdots\cdots\alpha_n u_n)$. Using formula (7) on the $T^{'}$ for self-learning to get $T^{''}$, which is far greater than the accuracy of $T^{'}$.

$$T^{''}=\frac{\sum_{i=1}^{N}Y_i\alpha_i u_i}{\sum_{i=1}^{N}\alpha_i u_i} \tag{7}$$

First equipment failure node data collection, calculation of the value of the dynamic fuzzy function, then by formula (7) each data node fault precise values, judge the fault node energy loss and quickly.

3.2. BP Neural Network

BP neural network is a one-way transmission network, which is usually composed of input layer, hidden layer and output layer. It will forward the signal transmission and reverse transmission. The weights are adjusted by back-propagation learning rule Delta. In the forward pass, the input and output of each layer are calculated by the formula (8) to the output layer. When the output layer is not expected to be the output of the inverse propagation, according to the desired error between the actual output and the adjustment of the weights and thresholds. Adjustment formula of weight value, see formula (9).

$$W_i = \sum_j w_{ij} x_j + \theta_i$$
$$y_i = f(W_i) \tag{8}$$

In the formula (8), W_i is the first i layer node's activation value, θ_i is the threshold, x_j is the input signal, w_{ij} is the first i node and the connection weight coefficient of the first j node, y_i is the output value of node i.

$$w_{ij}(t+1) = w_{ij}(t) + \frac{\partial E}{\partial w_{ij}} \tag{9}$$

In the formula (9), the error of the expected output and the actual output of the neural network

3.3. Description of Algorithm

Specific steps are as follows:

Initialization: the residual $\boldsymbol{r_0} = \boldsymbol{Y}$, the number of iterations of $t=1$, the support set potential iteration step size $size \neq 0$, the support set potential $L = size$, the segment number $stage = 1$, the index value set $\Lambda_0 = \phi,\ \Omega_0 = \phi$.

(1) The correlation coefficient between each column and the residual of the recovery matrix is calculated, and the $2L$ correlation coefficient of the maximum amplitude is calculated.

$u_t = \{u_i | u_i = |\langle r, \Theta_i \rangle|\}\ \ i = 1,2,..N,\ \Omega_{t_0} = (u_t, 2L)$

(2) Update index value set, the formula (5)

(3) Estimated sparse coefficient vector

(4) Update residual: $\boldsymbol{r_t} = \boldsymbol{y} - \boldsymbol{\Theta}_{\Lambda_t} \hat{\boldsymbol{s}}$

(5) The introduction of formula (8) and formula (9), to determine the termination conditions of the algorithm: $\|\hat{\mathbf{s}}_{\mathbf{t-1}} \times y_i - \hat{\mathbf{s}}_{\mathbf{t}}\|_2 < \varepsilon$. If satisfied, stop algorithm, output $\hat{\mathbf{x}} = \mathbf{\Psi}\hat{\mathbf{s}} \times w_{ij}$; if not satisfied, turn to step (6).

(6) Continue with this subsection iteration: $t = t+1$, turn to step (1).

Final solution： $\hat{\mathbf{x}} = \mathbf{\Psi}\hat{\mathbf{s}} \times w$

Therefore, the final solution is the optimal solution for the fault diagnosis.

4. Experiment Simulation and Analysis

In order to better validate the algorithm's effectiveness. First of all, the original coal equipment fault samples of 200 data as a sample, n = 50 data divided into 4 groups of data, in which a set of data used for training, the remaining three groups data for testing. Then the dynamic fuzzy function is used to classify the fault samples, and 1 BP neural network classifiers are designed to verify the function of the dynamic fuzzy function self-learning. Comparison of the diagnostic results of BP neural network classifier in the two groups is shown in Table 1. Three sets of data in the equipment failure are selected as shown in Table 2. After the dynamic fuzzy function is processed by the self-learning method, the actual output data of the BP neural network classifier is obtained as shown in Table 4.

Table 1. Comparison of Detection Results

Input layer	Hide layer	Output layer	Training times	Recognition rate
20	20	10	200	42/50
9	20	5	100	40/50

Table 2. Choose Three Groups of Fault Data

Group 1	Group 2	Group 3
0.35	0.38	0.42
0.37	0.34	0.28
0.38	0.42	0.48
0.41	0.57	0.88
0.93	0.88	0.91
0.86	0.51	0.76
0.78	0.57	0.66
0.40	0.38	0.45
0.49	0.35	0.32
0.39	0.37	0.49
0.45	0.31	0.37
0.37	0.41	0.45

Table 3. Fault Data after Treatment of Dynamic Fuzzy Function

Group 1	Group 2	Group 3
0.3218	0.3568	0.3211
-0.2118	0.0758	0.1848
0.2108	0.2555	-0.6081
0.0725	0.0472	-0.0046
-0.0686	0.0156	0.1913
-0.1273	-0.3423	-0.3551
-0.2789	0.0041	-0.2991
0.0374	-0.0629	-0.0605

Table 4. Actual Output Data of BO Neutral Network Classifier

Group	Start fault	Rocker fault	End fault	Gas power fault
Group 1	0.5233	0.1875	0.0458	0.0704
Group 2	0.4815	0.0751	0.0885	0.0483
Group 3	0.6625	0.0287	0.0913	0.0472

From Table 1-4 found using dynamic fuzzy function to deal with the fault sample data, the neural network input layer from 20 reduced to eight, training times greatly reduced to 100 times obviously CPU time was significantly shorter, and keep the fault recognition rate unchanged. The recognition accuracy is greatly improved, and the accuracy of diagnosis is improved, and the diagnosis speed is improved, and the classification of the fault samples of the coal mine equipment is an effective method.

In order to further illustrate the superiority of this algorithm, the algorithm of this paper and the reference [7], literature [8] detection algorithm in the detection error rate, detection failure rate and detection time is 3 aspects of the comparison. The results are shown in Figure 1-3.

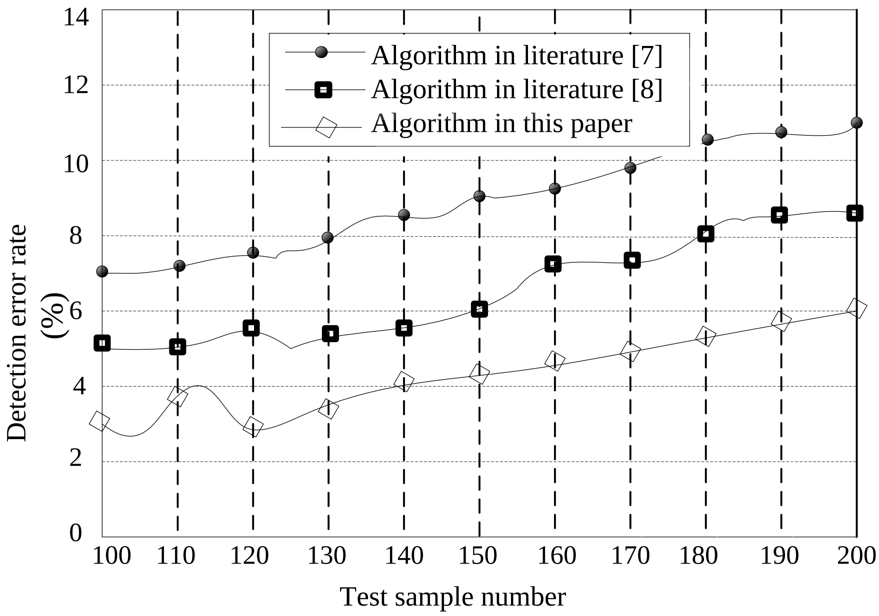

Figure 1. Comparison of Three Algorithms' Detection

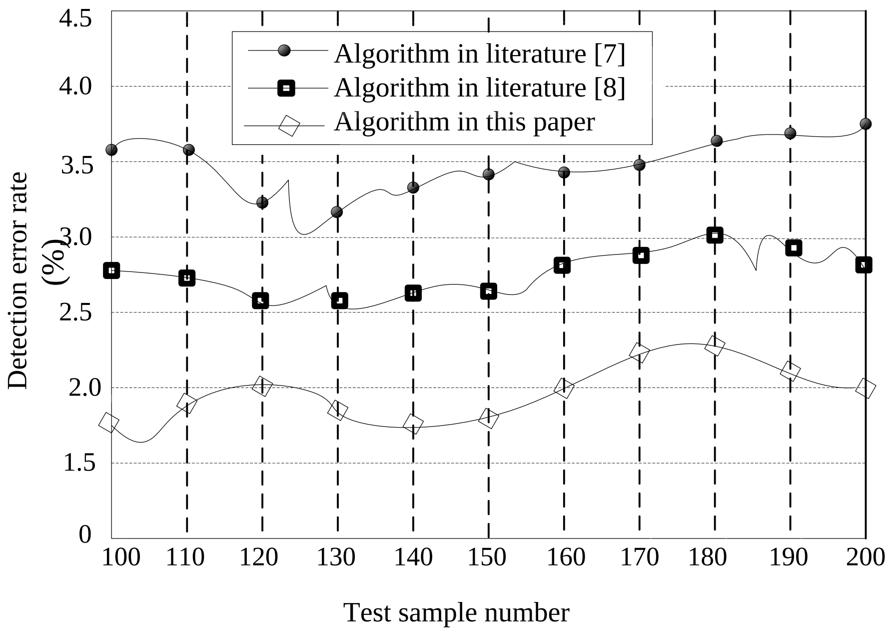

Figure 2. Comparison of Three Algorithms' Detection Failure Rate

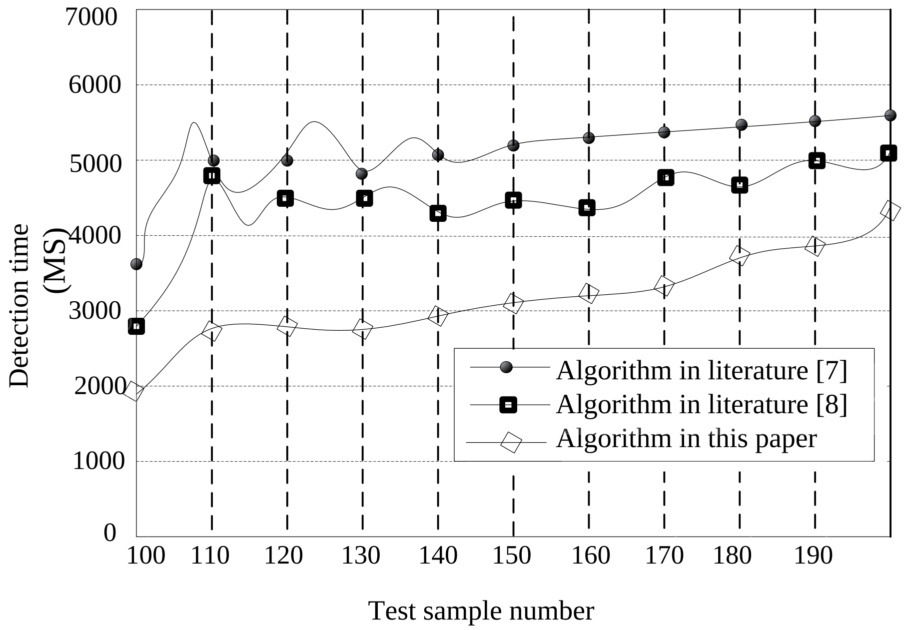

Figure 3. Comparison of Three Algorithms' Time Consumption

It can be seen from the above three Figure that the algorithm in this paper is superior to the other 2 algorithms in detecting the error of the algorithm, which improves the precision of detection to a certain extent; At the same time, the detection failure rate is low and the other 2 algorithms, which can improve the performance of the algorithm; In the time consuming comparison, the fluctuation range of the algorithm is the least, which shows that the algorithm is more stable than the other 2 algorithms, the algorithm has a certain advantage.

5. Conclusion

According to the fault detection of coal mine equipment, this paper presents a method based on dynamic fuzzy function and BP neural network. First, the input data of the fault samples are collected by using the dynamic fuzzy function to collect the data, and then the results Are classified according to the BP neural network. The simulation results show that the algorithm can effectively improve the accuracy of fault diagnosis in coal mine equipment.

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