Research of Fault Diagnosis of Belt Conveyor Based on Fuzzy Neural Network

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Abstract: To address deficiencies in the process of fault diagnosis of belt conveyor, this study uses a BP neural network algorithm combined with fuzzy theory to provide an intelligent fault diagnosis method for belt conveyor and to establish a BP neural network fault diagnosis model with a predictive function. Matlab is used to simulate the fuzzy BP neural network fault diagnosis of the belt conveyor. Results show that the fuzzy neural network can filter out unnecessary information; save time and space; and improve the fault diagnosis recognition, classification, and fault location capabilities of belt conveyor. The proposed model has high practical value for engineering.

Keywords: Belt conveyor, BP neural network, fault diagnosis, fuzzy theory.

1. INTRODUCTION

Due to its large capacity, small transport resistance, smooth running, small damage to material in transit and other advantages, belt conveyor ranks as relatively important long-distance transport equipment for bulk materials. Running state of belt conveyor system is directly related to safety of production equipment and staff. For instance, in the event of longitudinal tear, if not found timely, great economic losses will be caused. Thus, study of belt conveyor monitoring system is very necessary.

A belt conveyor is a large, complex mechanical device. Its faults are of different kinds, and many of its parts are difficult to detect. Therefore, advanced detection methods and equipment are needed to test and analyse raw data collected by the sensor. Analysing these data will allow for accurate detection of time, fault type, fault number, and fault location, thereby providing the necessary assistance for researchers and repair staff to ensure the safe performance of the entire machine [1, 2].

Literature [3-5] are based on coal mine as the background, which focus on common fault of belt conveyor and designing PLC-based belt conveyor monitoring system; literature [6] designs C #-based belt conveyor fault diagnosis system which achieves real-time monitoring of the belt conveyor and fault diagnosis; literature [7] designs CAN bus-based belt conveyor monitoring system, which processes and analyzes test data with monitoring host to achieve on-line detection and real-time system monitoring of belt conveyor fault; literature [8] develops a LabVIEW- based centralized control system for belt conveyor; in the above belt conveyor real-time monitoring and fault diagnosis system, although it lacks effective link between subsystems, yet actually these subsystems are not independent of each other. Otherwise, true information integration and intelligent judgment cannot be realized.

Fuzzy neural network technology is developed based on neural networks and fuzzy systems: it fully considers the complementarity between neural networks and fuzzy systems; fully unites the advantages of neural network and fuzzy theory; can quickly deal with abstract information; and has a strong function of self-learning, recognition and automatic tuning, and fuzzy information processing. Fuzzy neural network technology has been successfully applied in many fields [9]. Using fuzzy neural network technology can help identify the complex fault diagnosis mode and assess the severity of fault and predict their occurrence. At present, many researchers at home and abroad have used the technology to study machine running fault prediction and diagnosis, but limited research and application have been conducted on the fault diagnosis of belt conveyor. Zhang [10] demonstrated that fuzzy neural network technology has been applied in the fault trend prediction for hydraulic press tension devices of the belt conveyor. The experiments proved that fuzzy neural network technology can predict the faults of the device quickly and accurately. In the present paper, a BP (Back Propagation) neural network algorithm is combined with fuzzy theory to provide an intelligent fault diagnosis method for belt conveyor. Subsequently, a BP neural network fault diagnosis model with a predictive function is established to improve the ability to judge and recognise faults. The BP neural network fault diagnosis model can identify the various faults of the belt conveyor, such as belt deviation, belt slipping, and longitudinal tear.

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Fig. (1). Fuzzy neural network model of fault diagnosis of the belt conveyor.

2. APPLICATION OF FUZZY NEURAL NETWORK IN FAULT DIAGNOSIS OF BELT CONVEYOR

Fuzzy neural network technology has recently become a popular research topic in the intelligence field. It has a good potential for development and has been widely used in complex systems with non-deterministic problems for which establishing an accurate mathematical model is difficult [11]. Four collection approaches of fuzzy neural networks exist, namely, a model with independent fuzzy system and neural network, a model with a fuzzy system integrated with the neural network, a model with a neural network integrated with the fuzzy systems, and a model in which the fuzzy system and neural network are completely integrated together [12, 13]. Filtering fault diagnostic data and subsequently training these filtered data by neural network is necessary because the fault diagnostic data of the belt conveyor varies. Therefore, the algorithm finally possesses the decision and predication function. This process occurs in models where the fuzzy system and neural network are independent. The output is blurred data, and the blurred data are inputted into the neural network model for data processing.

The BP neural network is an artificial neural network model that is widely used in fault diagnosis. It has a very strong nonlinear mapping ability. The BP neural network with a feedback training ability is used in fault diagnosis of belt conveyor. A fuzzy neural network model of fault diagnosis of the belt conveyor is shown in Fig. (**1**). The main idea of this model is that the relevant data of the belt conveyor are uploaded to the computer through appropriate sensors, setting a variety of integrated data through the computer as input for the training model. Then, impossible fault samples are removed through blurred samples, and the remaining samples are inputted to the BP neural network to be trained.

2.1. Acquisition and Processing of Belt Conveyor Fault Signal

Appropriate tension, speed, and other sensors are selected according to the type of signal collected. Data acquisition and signal conditioning equipment are selected according to the signal type of the sensor and the number of channels. After signal conditioning, data collected by each sensor are transferred to the data acquisition card and displayed in real time on the industrial control computer. The aforementioned devices are connected by a shielded cable and form a complete test and control system together with a software system. Thus, the test system is intelligent and equipped with a high degree of automation [14, 15].

2.1.1. Fault Signal Type of Belt Conveyor

Belt conveyor is with many points to be detected, heavy workload and high detection precision. Normally, machine halt is not allowed and random disassembling inspection is impossible, which requires us to adopt equipment with advanced technology and scientific instruments for real-time monitoring and fault diagnosis without machine halt and strip inspection. The following are concrete analyses of the belt conveyor typical faults and the corresponding sensor type, installation position, and collected data types.

1. Longitudinal Tear of the Belt

For belt conveyor, there exists widespread use of steel rope core belt to improve its tensile strength, but its longitudinal tear is strength of the rubber itself, which is particularly likely to cause longitudinal tear. Longitudinal tear accident of steel rope core belt mainly occurs in the tail loading point.

In case of tear during operation of belt conveyor, the belt is bound to be subject to a relatively large additional downward pressure which will persist for some time until the belt is pierced and then significantly decreased. So, if we want to obtain fault features for monitoring and diagnosis of longitudinal tear accident of belt, we can monitor variation trend of belt conveyor under downward pressure at the feeding position. Because of continuous motion of belt, its mechanical characteristics cannot be measured directly. But as the belt pressure is downward and pressure can be passed to roller under belt, stress of roller carrier shaft can be monitored to obtain pressure on belt. Force sensor is adopted for tear belt sensor, which needs to be installed on roller as shown in Fig. (**2**).

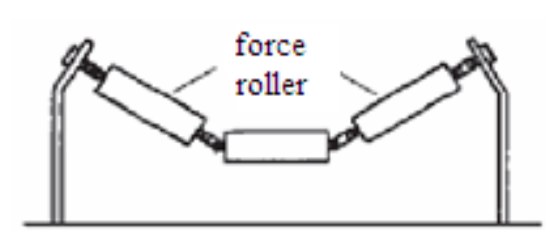

Fig. (2). Installations of sensors at loading place.

2. Belt Slippage

Due to changes in load and tension forces from the tension device, running speed of conveyor will fluctuate. In case of normal operation of driving device and belt speed decrease, it suggests belt slippage on the driving drum. Therefore, belt speed detection in the belt slippage has been an important part of operational monitoring of the belt.

In general, sensors which can determine speed signal can be applied in belt conveyor. Photoelectric speed sensor is selected herein, which is mounted below the belt, as shown in Fig. (**3**).

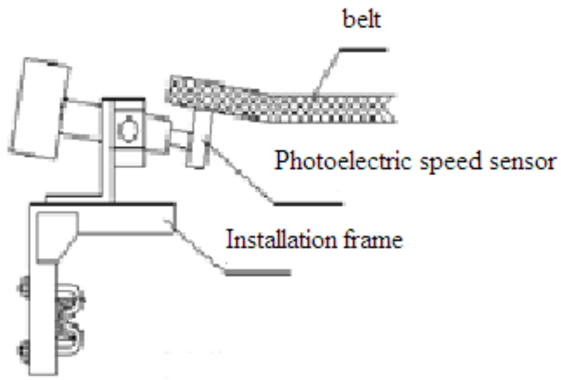

Fig. (3). The sketch map of installation.

3. Belt Deviation

The belt deviation of belt conveyor, a common fault of belt conveyor, is an important cause of partial or whole spillage of conveyor and belt edge wear. The fundamental reason for belt deviation is that the centerline of belt tension deviates from geometric centerline of conveyor.

In order to avoid accidents due to belt deviation, deviation protection device is set on conveyor and deviation switch is applied herein. In general, the head, tail of conveyor are equipped with deviation switch. Installation schematic diagram of deviation switch is shown in Fig. (**4**).

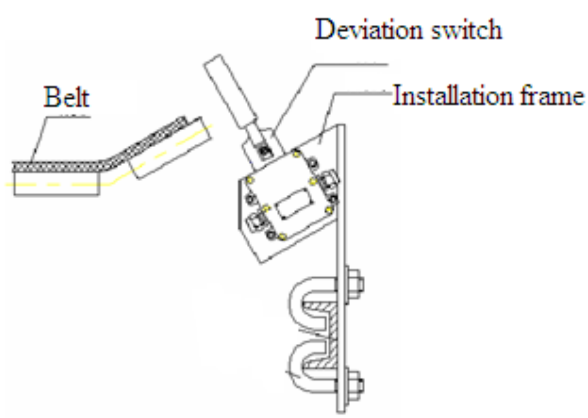

Fig. (4). Installation schematic diagram of deviation switch.

4. Belt-Breaking

Since steel rope core conveyor is commonly used for belt conveyor, strength retention rate of vulcanized joint of steel rope core belt often fails to meet requirements, plus vulnerability to injury of joint, longitudinal fracture of steel rope core belt mostly occurs in the joint. Therefore, monitoring of transverse fracture of the belt will be mainly focused on joint monitoring and diagnosis.

For monitoring of the belt joint fracture, we apply method of comparison of measured curve and calibration curve, and determine whether alarm is needed based on whether the belt joint is damaged, so as to provide early warning for joint damage and fracture. Schematic diagram of belt joint length and tension measuring is shown in Fig. (**5**).

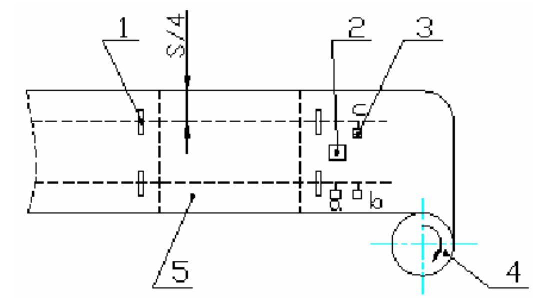

Fig. (5). Schematic diagram of belt joint length and tension measuring. 1. Magnet blocks; 2. Wireless force-measuring device; 3. Hall element; 4. Driving drum; 5. Belt.

5. Stacking

During work process, due to working conditions, material properties and other reasons, silo and feed inlet of conveyor is prone to stacking accidents with very bad consequences. Therefore, choosing a reliable stacking monitoring equipment plays a very big role in safe operation of conveyor. Structural feature and working principle of Stacking sensor are shown in Fig. (**6**) and Fig. (**7**). The core of stacking sensor is a Schmitt trigger.

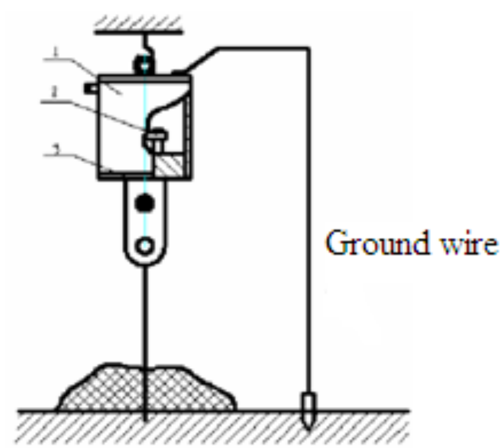

Fig. (6). Structure of bulk accumulation monitor. 1. Shell 2. Electric appliance components 3. End cover

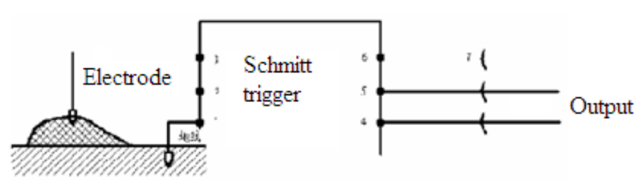

Fig. (7). Schematic diagram of bulk accumulation monitor.

Table 1. Fault characteristic signals of belt conveyor.

Fault type	Fault location	Sensor type	Installation location	Data type
Longitudinal Tear of the belt	Load point of tail	Force sensor	Loading point on roller	Voltage signal
Belt Slippage	Driving pulley	speed sensor	Below the belt	Frequency signal
Belt Deviation	Head, tail point, load point	Deviation switch	Head, tail	Switching signal
Belt-breaking	Belt joint point	Hall sensor	Belt joint area	Pulse signal
Stacking	Silo, feed inlet	Schmitt trigger	Hang above the detected material point	Voltage signal
Spillage	Concave section, Transshipment location, deviation point	Camera	Concave transshipment location	Image information

6. Spillage of Belt Conveyor

Belt conveyors are often accompanied by spillage in operation, which not only causes a waste of resources, but also causes environmental pollution in the whole transport work area. Spillage often occurs in concave section, transshipment point, and deviation position. For spillage, camera should be installed in an accident-prone segment, so as to perform most intuitive monitoring of transporting operation through industrial television.

In summary, according to fault type, fault location, fault detection equipment, installation location, type of collected data of belt conveyor are summarized, as shown in Table 1.

2.1.2. Conditioning and Acquisition of Belt Conveyor Fault Signal

Signal measured from sensor may be very weak due to a series of reasons, including a lot of noise with nonlinearity. These signals can only enter acquisition card after conditioning to become the available signals. Signal conditioning methods mainly include amplification, attenuation, isolation, multiplexing, filtering, excitation, digital signal conditioning, etc. The test system applies signal conditioning accessories of SCXI-1121 module and SCXI-1141 module for common treatment of these signals.

After comprehensive consideration of factors such as hardware investment costs, multi-channel data acquisition and association coordination of control software, three NI company's PCI-6239M series multifunction data acquisition card is chosen which can gather four types of signals of quadrature encoder, digital, frequency, and voltage.

2.2. Fuzzy Diagnosis of Belt Conveyor System Fault

A belt conveyor is an extremely complex system. Each subsystem and part can break down in the work process, and various indications of faults are often inconspicuous. The corresponding relationship between fault phenomena and their cause is also fuzzy. A fuzzy decision is applied to the analysis and diagnosis.

1) Determining the symptom set X: Fault symptom set, composed of testable information for belt conveyor system, X = {improper installation of roller, improper installation position of the head pulley and tail pulley, outer surface machining error of the pulley,……, contact surface between belt and pulley is immersed in the dust} = { X_1, X_2, X_3,……, X_{14}}.

2) Establishing fault set W: The belt conveyor system is divided into each subsystem artificially; therefore, the fault set of belt conveyor system W = {belt deviation, spillage, longitudinal tear detection, belt slippage} = {W_1, W_2, W_3, W_4}.

3) Establishing a fuzzy relation matrix R and weight set A. We assume that a single fault cause for the fuzzy evaluation set of the i-th symptom is

$$r_i = \sum \frac{r_{ij}}{g_j} \tag{1}$$

Where r_{ij} is the membership degree of i-th symptom for the j-th element of evaluation set g. The membership degree of the fuzzy evaluation set of a single fault cause is taken as a row to form fuzzy comprehensive evaluation matrix R.

$$R_i = \left\{ \begin{matrix} r_{11} & r_{12} & r_{13} & \cdots\cdots & r_{1j} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ r_{j1} & \cdots\cdots & \cdots\cdots & \cdots\cdots & r_{ij} \end{matrix} \right\} \tag{2}$$

We suppose that the weight assigned to each symptom x_j (j = 1, 2, 3,……, 14) is:

$$A_i = \sum \frac{a_{ij}}{x_j} \tag{3}$$

Where a_{ij} is the weight of the j-th symptom for the i-th element of the fault set W. The total weight matrix is:

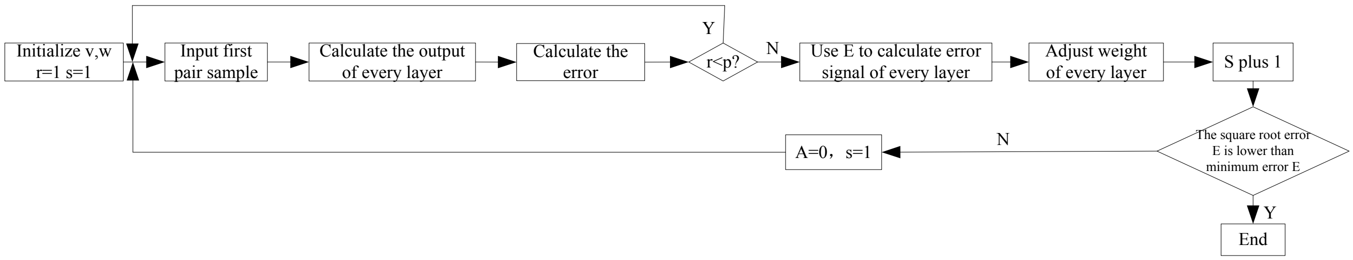

Fig. (8). The BP neural network algorithm flow chart.

$$A_i = \left\{ \begin{array}{ccccc} a_{11} & a_{12} & a_{13} & \cdots\cdots & a_{1j} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ a_{j1} & \cdots\cdots & \cdots\cdots & \cdots\cdots & a_{ij} \end{array} \right\} \quad (4)$$

4) Diagnosis description: The comprehensive evaluation results of the belt conveyor system fault set W are:

$$W = A_I \bullet R = \left\{ \begin{array}{ccccc} \omega_{11} & \omega_{12} & \omega_{13} & \cdots\cdots & \omega_{1j} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \omega_{j1} & \cdots\cdots & \cdots\cdots & \cdots\cdots & \omega_{ij} \end{array} \right\}$$

(5)

If element in the last row of W minus the corresponding element in the first row, then according to the size, such asω_{13}-ω_{11}≥ω_{23}-ω_{21}≥ω_{33}-ω_{31}≥ω_{43}-ω_{41}, the fault set by membership degree is arranged as follows: ω_1, ω_2, ω_3, ω_4; if we set a threshold value in the algorithm, $\omega_1 > \lambda > \omega_2 > \omega_3 > \omega_4$, so the most impossible fault is ω_1, the initial decision can remove ω_1, and lower operations for subsequent BP network training, improve operational efficiency.

2.3. Data Algorithm Flow Diagram of BP Neural Network

The BP algorithm, which can be designed from the derivation and data flow diagram presented in this paper, is shown in Fig. (**8**). First, two weight vectors must be initialised. For the vector values between three layers, set learning efficiency, α, β (0,1); the error can be initialised as 0 (arbitrary). An initial sample number $r = 1$, and the training time $s = 1$. Second, input the designed sample. Then, train all the output errors of the network, for calculating σ_i, σ_j. Therefore, adjust the weights w, v. If $r < P$ (the total number of training), then adjust r and s simultaneously plus one. When returning to the initial moment, if $E < \varepsilon$ (ε is the minimum error value set), the training is concluded.

2.4. Fuzzy Neural Network Flow Diagram

The main idea for this model is that the belt conveyor state signals are collected by many sensors to obtain the status features as fully as possible. The acquisition signals include the frequency signal, pulse signal, voltage signal, and so on. The original signals acquired by many sensors are pre-processed by fuzzy sets. Then, these signals can be divided into three parts by the physical meaning of each signal, respectively obtaining the smallest decision table as the input node signal for each sub-network and using sub-network identification to obtain sub-output type. Finally, we obtain the final judging result by the decision fusion. Specific operation steps and the diagnostic flow diagram are shown in Fig. (**9**).

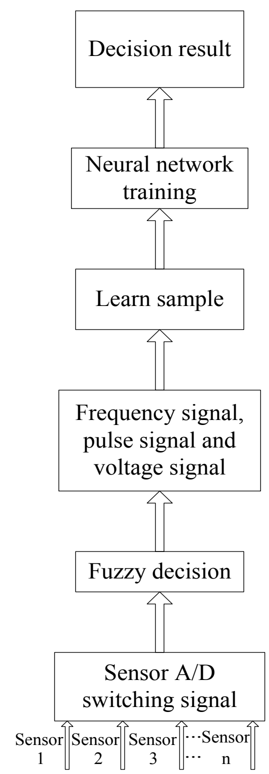

Fig. (9). Fuzzy neural network flow chart.

3. INSTANCE SIMULATION OF BELT CONVEYOR FAULT DIAGNOSIS BASED ON FUZZY NEURAL NETWORK

3.1. Establishment of Fault Diagnosis Model Based on Fuzzy Neural Network

The simulation system diagram of belt conveyor fault diagnosis is shown in Fig. (**10**). Detection signals are 15

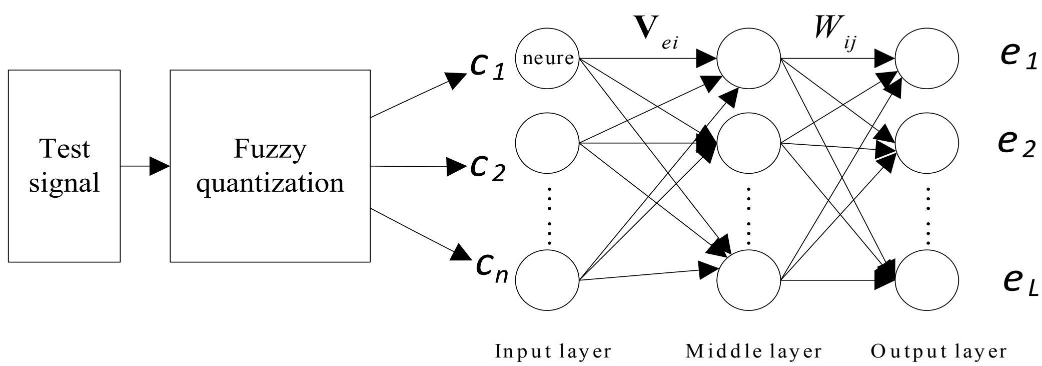

Fig. (10). The simulation system structure diagram.

Table 2. Fault reason and phenomenon of belt conveyor.

C1	Belt deviation	e1, e2, e3 e4, e5	1. improper installation of rollers; 2. improper installation location of driving pulley and driven pulley; 3. machining error of pulley surface, uneven wear; 4. location of blanking mouth is wrong; 5. improper belt tension;
C2	Spillage	e6, e7	6. serious overload of belt conveyor; 7. rubber skirt of feed channel is broken and so on;
C3	Longitudinal tear test	e8, e9,	8. deviation; 9. manufacturing accuracy;
C4	Belt slippage	e10, e11, e12 e13, e14	10. roller is broken; 11. sundries winding; 12. material hides the cause and thus prevents many rollers from rotating; 13. belt plastic deformation after a period of time; 14. contact surface between belt and driving pulley is immersed in dust.

sample signals from the belt conveyor monitoring equipment of certain departments under normal operating conditions. Fuzzy quantification often uses triangular or normal membership functions. Monitoring signals are fuzzy quantified with the triangular membership function; the pressure signal is quantified with the normal membership function, respectively, according to experience, speed, temperature, and other data.

According to the actual measurement of a manufacturer, when the speed of a belt conveyor maintains 2–3.15 m/s, the state of the complete machine is the best, which transforms the contact wheel's belt speed into an angular speed of 17. 39–27. 39 rad/s. Represented by a triangular membership function is, $b = 0$, $a = 22.39$, $c = 50$. At this moment, if the angular speed is 22.39 rad/s, the membership degree is 1 and the belt conveyor operates in the best condition. If angular speed deviates by 22.39 rad/s, it lowers the membership degree, deviating by 1. When speed is 0 or 50 rad/s, the membership degree is assumed to be 0. In such cases, the collected data can be blurred to [0, 1]; all the samples can be blurred to [0, 1] so that the data can be identified easily. In practice, a three-layer BP neural network has a wider application and can handle non-linear mapping functions.

Table **2** shows that the input layer has a total of four nodes, reflecting that the belt conveyor fault phenomena comprises spillage, belt deviation, dysfunctional rollers, and belt slippage. The output layer possesses 14 nodes, reflecting the fault reason of the belt conveyor. Currently, intermediate hidden layer nodes are selected by trial and error by using the empirical formula $m_2 = 2m_1+1$, where m_2 is the number of hidden layers and m_1 is the number of input layers. Therefore, the hidden layer initially is set as 9. However, the number of hidden layers is not unique; it is derived from experience. Thus, its value can be flexibly changed in the experiment for comparison.

3.2. Simulation of Fault Diagnosis Model Based on Fuzzy Neural Network

Data collected through fuzzy quantification possess values of [0, 1]. The function of neurons of the intermediate layer is the S-type tangent function, and the corresponding function of software is the tansig function. The function of the output layer is the S-type logarithmic function, and the corresponding function of software is the logsig function. The purpose of selecting the two functions is consistent with the sample values being [0, 1] running efficiently in the software. To achieve higher training accuracy, the training function selected is traingdx. The designed total step is 500, total error is 0. 001, learning rate is set to 0. 01, and the code is as follows:

```
threshold=[0 1; 0 1;0 1; 0 1;0 1;0 1;0 1;0 1;0 1;
0 1;0 1;0 1;0 1;0 1;0 1;];
net=newff(threshold,[9. 3],{’tansig','logsig'},'traingdx';
net. trainParam. epochs=500;
net. trainParam. goal=0. 00 1;
LP. Lr=0. 1;
```

Ten groups of fuzzy quantification input data P and expect data T for training:

P=[0. 0379 0. 0695 0. 0675 0. 1713 0. 2058 0. 0285 0. 1507 0. 0157 0. 1817 0. 2293 0. 0858 0. 0210;

0. 1746 0. 1046 0. 0737 0. 0253 0. 1193 0. 1212 0. 2146 0. 1767 0. 1962 0. 0523 0. 1937 0. 1476;

0. 2005 0. 0978 0. 1507 0. 1571 0. 1619 0. 0756 0. 0384 0. 1547 0. 1168 0. 1504 0. 1691 0. 0424;

0. 0813 0. 0833 0. 2201 0. 1071 0. 0362 0. 1261 0. 2119 0. 1648 0. 1466 0. 1395 0. 1318 0. 0113;

0. 1580 0. 1289 0. 2153 0. 0496 0. 2193 0. 0923 0. 1830 0. 1480 0. 2188 0. 0897 0. 0415 0. 1666;

0. 0684 0. 1710 0. 1059 0. 0236 0. 1249 0. 0961 0. 1332 0. 0970 0. 1027 0. 0336 0. 2202 0. 0806;

0. 1225 0. 0982 0. 0561 0. 1896 0. 1567 0. 0424 0. 1018 0. 0905 0. 0147 0. 0068 0. 0618 0. 1523;

0. 1916 0. 0993 0. 1759 0. 0411 0. 0094 0. 0595 0. 0600 0. 1879 0. 1995 0. 0974 0. 2127 0. 0889;

0. 1378 0. 0296 0. 1749 0. 0385 0. 1863 0. 0057 0. 1732 0. 0737 0. 1455 0. 0432 0. 0522 0. 1447;

0. 0778 0. 0066 0. 1706 0. 1535 0. 1724 0. 2125 0. 0534 0. 1875 0. 0823 0. 1672 0. 0865 0. 0060];

T=[1 1 1 1 1 0 0 0 0 0 0 0 0 0;0 0 0 0 0 1 1 0 0 0 0 0 0 0; 0 0 0 0 0 0 0 1 1 0 0 0 0 0; 0 0 0 0 0 0 0 0 0 1 1 1 1 1];

Fig. (**11**) shows the desired accuracy that can be achieved after the fuzzy quantification training step reaches 271. A network that has been trained needs to be tested before obtaining their accuracy. Therefore, several sets of fuzzy quantification test data need to be observed for verification of training results.

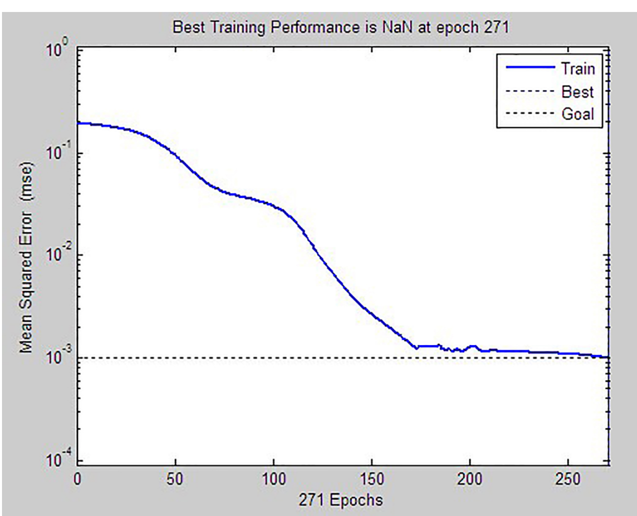

Fig. (11). Error curve after training 271 steps.

The test data to verify results are as follows:

Ptest=[0. 2161 0. 1233 0. 0326 0. 0255 0. 0950 0. 2273 0. 0569 0. 0953 0. 1274 0. 1658 0. 0803 0. 0509;

0. 0052 0. 2037 0. 0509 0. 1422 0. 2264 0. 1766 0. 0687 0. 1390 0. 1346 0. 2291 0. 2040 0. 0298;

0. 1576 0. 2069 0. 0427 0. 2162 0. 2175 0. 0781 0. 1568 0. 1729 0. 1182 0. 0822 0. 1051 0. 0717;

0. 1805 0. 1443 0. 0106 0. 0822 0. 1560 0. 1527 0. 1219 0. 1346 0. 0199 0. 2234 0. 0957 0. 1673;

0. 1623 0. 1551 0. 0416 0. 0257 0. 0453 0. 1286 0. 0786 0. 1450 0. 1158 0. 1122 0. 2134 0. 0796;

0. 1681 0. 1103 0. 1910 0. 0427 0. 2062 0. 1779 0. 0491 0. 0243 0. 0999 0. 2058 0. 2111 0. 2154;

0. 0524 0. 1438 0. 1766 0. 0237 0. 0237 0. 0724 0. 1178 0. 0905 0. 2294 0. 0325 0. 1644 0. 0296];

The running results in Matlab are as follows:

Y =

0.8846	0.0229	0.0292	0.0287	0.0092	0.0181	0.0141	0.0092
0.0106	0.0130	0.0105	0.0019	0.9631	0.0202	0.0080	0.0222
0.0190	0.0153	0.8692	0.0113	0.0077	0.0024	0.0217	0.0050
0.0115	0.0211	0.0224	0.0202	0.0191	0.0111	0.0258	0.9771

Y is obtained by Matlab; the first, third, sixth, and eighth groups are used to diagnose four faults of spillage, belt deviation, poor running of rollers, and belt slippage, respectively. Fault deviations are 0.1154, 0.1348, 0.0369, and 0.1229. The error reached the expected accuracy, which can be used as a reference for application [16].

3.3. Single BP Neural Network Simulation

Setting the input samples C = (c_1, c_2, c_3, c_4) expresses the fault phenomenon of the belt conveyor, where c_1= (1, 0, 0, 0,), expresses the belt deviation phenomenon, and c_2= (0, 1, 0, 0) expresses that the belt conveyor has a spillage phenomenon after two and so on. Output sample E = (e_1, e_2, e_3, ... e_{14}) indicates the cause of the belt conveyor fault, where E = (1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0) signifies the reasons for the belt deviation, E = (0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0) signifies the reasons for spillage of the belt conveyor, and so on. Thus, C and E form mapping relations for experimental purposes to maintain weight consistency when training the sample. Therefore, setting learning efficiency α, β to 0. 05 is an effective approach.

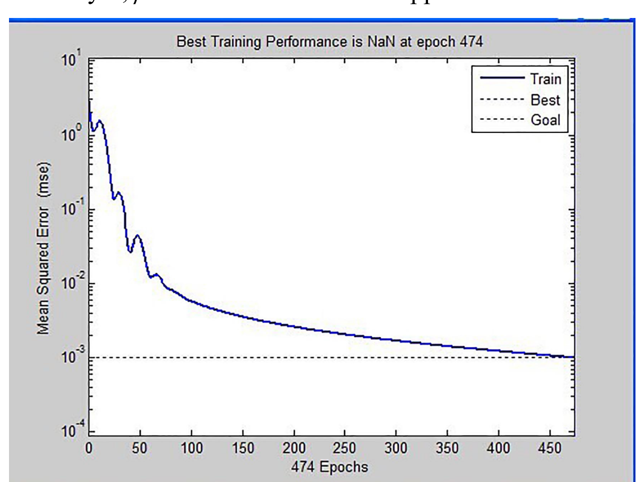

Fig. (12). Error curve after training.

Table 3. Error and diagnostic data.

Sample data number \ Sample number	A1	A2	A3	A4
e1	0. 2311	0. 2985	0. 2046	0. 0851
e2	0. 0263	0. 0776	0. 2055	0. 1222
e3	0. 0958	0. 2755	0. 3275	0. 1897
e4	0. 1429	0. 0754	0. 3184	0. 0941
e5	0. 3289	0. 1490	0. 2586	0. 3381
e6	0. 0008	0. 0013	0. 0019	0. 0015
e7	0. 0196	0. 3126	0. 3251	0. 0923
e8	0. 0697	0. 0347	0. 2143	0. 0704
e9	0. 2605	0. 3719	0. 1419	0. 0930
e10	0. 2934	0. 3108	0. 3758	0. 1757
e11	0. 2600	0. 1960	0. 3507	0. 1262
e12	0. 1817	0. 1758	0. 2212	0. 3695
e13	0. 2199	0. 1801	0. 2499	0. 1735
e14	0. 1203	0. 1243	0. 2359	0. 0760

The single BP neural network error curve after training is shown in Fig. (**12**). Training achieved the desired accuracy. Samples were inputted by using the trained sample network, and actual samples were added under the conditions of the satisfactory algorithm. Error and diagnosis data were obtained after normalizing the data provided by the company, as shown in Table **3**.

Table **3** shows that e_6 is significantly closer to the fault type setting error. Tables **2** and **3** show that the belt conveyor is seriously overloaded, thereby resulting in spillage. This result is consistent with simulation, and the training algorithm is accurate.

As shown in Figs. (**11** and **12**), the training step of the fuzzied BP neural network decreased by 203 steps compared with the single BP neural network although both are accurate. A clear improvement is observed in the real-time monitoring of faults.

CONCLUSION

1) This paper used a fuzzy neural network to identify the type of belt conveyor system faults. By contrast, the traditional fault diagnosis methods have significant limitations. First, fault samples of the belt conveyor must be fuzzied before the sample is inputted into a trained BP neural network to train the data. Results show that the fault type of the belt conveyor can be deduced based on meeting the minimum error.

2) Results show that the BP neural network fault diagnosis model with reasoning function efficiently screens useful information, whereas the single non-fuzzy BP neural network includes miscellaneous information in the training process and the information has not been screened efficiently.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

The project is supported by The National Natural Science Foundation of China 51075289; The Shanxi Natural Science Foundation of 2014011020-2; Shanxi Science and Technology Development Plan 2014 (Industrial) Project 20140321008-04; and Shanxi Province Graduate Excellent Innovation Project Fund under Grant 20133116.

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Received: December 8, 2014 Revised: December 15, 2014 Accepted: December 16, 2014