Study on Fault Diagnosis of Mining Tape Conveyor Based on MPGA-BP

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Abstract. In order to detect the malfunction of the mine tape transporter drive device timely, a fault diagnosis model of mine tape transporter based on multiple group genetic neural networks is established by combining multiple swarm genetic algorithms with BP neural network algorithm. The simulation results show that the algorithm can effectively solve the problems such as the easy fall of BP neural network into local minimum value and too many training times, which leads to too slow convergence. The fault diagnosis model has strong global search ability, high training precision and fast convergence speed, and can supplement and perfect the protection system of mine tape conveyor.

1. Introduction

Belt Conveyor is the main equipment in coal mine production, it bears the indispensable responsibility of horizontal transportation or tilt lifting materials in coal mine, and has the unique advantages of long distance, large capacity, continuous transportation and so on [1]. However, because the tape transporter is full of many uncertain factors in the operation process, the fault of the tape transporter happens from time to time, which directly affects the safety production of the coal mine to a great extent [2]. In recent years, domestic and foreign scholars have put forward various of tape transport fault diagnosis models, such as mathematical model method, fuzzy neural network, expert diagnosis method, general BP neural network and so on. Because BP neural network [3] has the problem of easy to fall into local minimum, too much training times lead to too slow convergence speed, so, this paper uses immigration operator to strengthen the inter-population connection on the basis of standard genetic algorithm, and introduces multiple populations to optimize the search at the same time. A diagnostic model combining multi-population algorithm (MPGA) with BP Neural network is proposed, and the rationality and validity of the model are verified by simulation analysis.

2. Common Faults of Mine Belt Conveyor

Mining belt transporter is composed of drive device, conveyor belt, tensioning device, roller and rack, etc., so the common faults are skidding, running deviation, break zone, driving device failure and so on. Therefore, the "Coal Mine safety regulations" clearly put forward the mining belt transporter eight protection functions [4] (skid fault protection, coal heap fault protection, running offset fault protection, temperature protection, longitudinal tear protection, smoke protection, tensioning force drop protection device, emergency stop protection) and indicators. However, the vibration signal and
the frequency component of the vibration signal in normal operation will be very different when the driving device of the mine tape conveyor fails, and the vibration signal can be used to reflect the running state of the belt conveyor drive device.

The belt transporter drive device is composed of electric motor, coupler, reducer and control device \cite{5} and so on. The tape conveyor under the mine has been in a high-duty working state. So, it will cause the motor, reducer, hydraulic coupler going wrong, and even cause secondary failures, so that the tape conveyor shutdown, production can not be carried out. The main faults of the driving device are motor fault, hydraulic coupler fault, reducer fault and so on.

1) Motor failure. After a long period of high-load operation, the motor in operation will appear overcurrent, excessive speed, heating and abnormal vibration and other phenomena. Heavy loads, high or low voltages and other factors will cause temperature rising. And the abnormal vibration is mostly caused by the bad dynamic balance of the internal rotor of the motor and the loosening of the mounting fastener.

2) Hydraulic coupler failure. In the belt conveyor, the hydraulic coupler mainly solves the problem of power balance and reducing the dynamic load of the conveyor at startup. However, the defects of gears and bearings and the loosening of fasteners will cause abnormal vibration, and the abnormality of hydraulic coupler cooler will lead to the occurrence of overheating of hydraulic coupler.

3) Reducer failure. In the long running state of the reducer, the gear will appear wear, pitting, tooth root fracture and other phenomena occur. These phenomena can cause abnormal vibration of the reducer. If these problems are not detected and addressed in a timely manner, the reducer will be completely damaged. Failure of the drive device will bring huge economic losses and safety risks to the underground.

When the drive device of the tape transporter break down, the vibration signal collected is non-stationary signal and nonlinear signal, so the empirical modal decomposition (EMD) \cite{6} algorithm is used to smooth the non-stationary signal, and the modal of the signal is separated according to the time scale. The sum of the IMF components corresponding to a residual component and different frequencies is eventually decomposed. In this paper, the analysis of vibration signal in the drive device of tape transporter is achieved for the purpose of fault diagnosis of motor, hydraulic coupler and reducer.

3. Multi-population genetic neural network

The multi-group genetic neural Network algorithm combines multiple swarm genetic algorithms (MPGA) with BP neural networks. Choosing a variety of group genetic algorithm (MPGA) one side is to optimize the initial weights and thresholds of BP neural network, improve the easy to fall into the local minimum value, too many training times lead to slow convergence speed, enhance the global search ability. On the other hand, multi-group genetic algorithm can optimize the standard genetic algorithm, which inhibits the problem of immature convergence to a great extent. Therefore, multi-group Genetic Neural Network (MPGA-BP) has the advantages of BP neural network and genetic algorithm, and can improve the deficiency of genetic algorithm and BP neural network.

Compared with the standard genetic algorithm SGA, the multi-population genetic algorithm PGA has the following advantages \cite{7}.

1) Break through the structure of genetic evolution of the single group of SGA, use multiple populations to optimize at the same time, to achieve different search purposes;

2) Through the migration operator to achieve the contact of various populations, so as to achieve the synergistic evolution of multiple groups, the comprehensive evolution of multiple populations to obtain the optimal solution;

3) The optimal individuals in each evolutionary generation of various groups are preserved by artificial selection operators, and as the basis for judging the convergence of the algorithm.

Although BP neural network algorithm has simple structure, good manipulility, self-learning ability, widely used in fault diagnosis and fault prediction, but the algorithm is easy to fall into the local minimum value, can not ensure that the disadvantage of convergence global minimum has a great
impact on the effect of the algorithm. Combining multiple swarm genetic algorithms with BP neural network algorithm, the MPGA algorithm is used to optimize BP neural network, and the ideal effect can be achieved.

4. Establishment of BP neural network model based on multi-genetic algorithm

BP neural network based on multi-group genetic algorithm is mainly determined by BP neural network structure, using multiple swarm genetic algorithm to optimize BP neural network and training and diagnosis of the whole model. The topology of BP neural network needs to be determined according to the specific number of input and output parameters of realistic samples. Then the optimization parameters of the genetic algorithm for BP Neural network are determined, and the encoding length of the individual population is finally determined.

4.1. The creation of BP neural network

In this paper, BP neural network adopts three-layer structure, \( s_i = \sqrt{i_i + x_i + a} \). \( s_i \) is the number of hidden layer nodes, \( i_i \) is the number of input layer neurons, \( x_i \) is the output layer node, and \( a \) is the constant between 1--10. The weight value is \( q_i = i_i s_i + x_i s_i \), the number of thresholds is \( z_i = x_i + s_i \), so it is necessary to use a variety of group genetic algorithms to optimize the weight and threshold of BP neural network, \( c_i = q_i + z_i \). Random generation of \( m \) initialization population \( W = (w_1, w_2, \cdots, w_m) \).

In the formula, the size of \( m \) is related to the threshold and the weight value.

4.2. Fitness calculation

The initialization weights and thresholds of the generation BP neural network, first use the sample training network, and then use the test sample test network, get the test error \( e = \sum | o_{sc} - o_{sj} | \). Among them, \( o_{sc} \) is the network output value of the test sample after the input sample, and \( o_{sj} \) is the actual output value of the network. The fitness calculation function is \( f = 1 / e \).

4.3. Selection

To ensure evolution, efforts should be made to select the best individuals for fitness (choice of operation). The selection operation used in this paper is the proportional selection method (or the roulette method can also be used), and the probability of the next generation being selected is \( P_i = f_i / \sum_{j=1}^{p} f_j, \quad i = 1, 2, 3, \cdots, p \).

4.4. Crossover

Crossover is a very important step in genetic algorithm, through the parent feature crossover to obtain a new generation of individuals, the role of crossover is to exchange information. Arithmetic crossover is performed with the crossover probability to determine the individual position of the selection. The crossover probability is usually set between 0.5 and 1.0, which directly affects the quality of the system optimization.

4.5. Variations

The main function of variation is to prevent the algorithm from being caught in the local minimum value, and to mutate the mutation operation with the mutation probability pm. In this paper, uniform variation is used, usually mutation probability pm and crossover probability PC will be set according to experience to fixed value mutation probability is usually set between 0.001 and 0.1. This value over the General Assembly disrupts the original chromosome population structure, genetic algorithm loss of effect.
4.6. Multi-population genetic algorithm
The immature convergence phenomenon in standard genetic algorithm (GA) can not be ignored, and various group genetic algorithms [8] are used to make the whole evolutionary process perfect with the number of population. Multiple swarm genetic algorithms can improve the global convergence ability of standard genetic algorithm (GA), and the algorithm flow is as follows.

1) Setting i=0, randomly produce the initial population $P(0)$, the population size is $N$.
2) Determining the population whether is eligible, and output the objective function and optimal solution of the optimal individual if the conditions are met, otherwise turn to 3).
3) To selecting, intersecting, mutating operation, the production of intermediate population $P(i)$, its scale and $P(i)$ the same.
4) Determining the current population whether meets the requirements of expanding the population size, if it meet the requirements, it will be involved $P(i)$ randomly, expanding its population size until to meet the setting requirements, and obtaining the next generation of population $P(k+1)$ and return to 2). Otherwise, turn to 5).
5) Eliminating undesirable individuals and reducing the size of the population, getting $P(k+1)$, return to 2).

4.7. Fusion
The initial weights and threshold values of BP neural network are optimized by multiple swarm genetic algorithms, and then trained and studied by BP Neural network, which can not only overcome the shortcoming that BP network is easy to fall into local minimum value, but also make full use of the nonlinear approximation ability of neural network, realize complementary advantages, avoid their own defects and get better results. The algorithm flow of multiple swarm genetic neural networks is shown in the following figure.

Figure 1. Multi-group genetic neural Network flow
5. Fault Diagnosis Simulation

Taking the drive device of tape transporter as the research object, the fault diagnosis is carried out by combining BP Neural Network and various group genetic algorithms. Input normal, motor fault, hydraulic coupler fault, reducer fault 4 state of vibration signal spectrum map characteristic frequency band, using EMD decomposition to extract the eigenvectors of vibration signal, through normalized processing as the input of BP neural network.

In different working conditions, 80 sets of data of belt conveyor drive device in 4 typical states were collected, and the data in each state were 20 groups. After data processing, 76 groups were used as training samples and 4 groups as test samples. In this neural network model, the input layer has 10 nodes, corresponding to 10 frequency eigenvalues, the output layer has 4 nodes, respectively (1,0,0,0), (0,1,0,0), (0,0,1,0), (0,0,0,1) corresponds to the driving device normal, motor failure, hydraulic coupler failure, Reducer fault four kinds of States; the number of hidden layer nodes after training, it is found that when the number of implicit layer nodes is 10 o'clock, the training convergence time is shortest and the error is the best. So the structure of BP neural network is determined to be 10-10-4, so there are 140 (=1010+104) Weights, 14 (=10+4) thresholds, so the number of optimization parameters is 154 (=140+14). Among them, the transfer function of implicit layer neurons adopts s-type tangent function Tansig (), and the transfer function of output layer neurons adopts s-type logarithmic function Logsig ().

Through the training of the data, the actual output of BP neural network diagnostic samples is shown in table 1, the average absolute error of the test sample is 0.1225, and the partial error reaches 0.281. The data is trained by multiple groups of genetic neural networks, with a training frequency of 1000, the target of training is 0.0001, the number of population is set to 10, the generation gap set to 0.9, the diagnosis of the test sample is shown in table 2, and the average absolute error of the test sample is 0.01975.

| Diagnostic results            | Y1     | Y2     | Y3     | Y4     | Target value | Absolute error value |
|-------------------------------|--------|--------|--------|--------|--------------|----------------------|
| Normal                        | 0.926  | 0.003  | 0.012  | 0.031  | 1000         | 0.074                |
| Motor faults                  | 0.013  | 0.971  | 0.281  | 0.009  | 0100         | 0.281                |
| Hydraulic coupler fault       | 0.019  | 0.042  | 0.901  | 0.015  | 0010         | 0.099                |
| Reducer fault                 | 0.007  | 0.026  | 0.025  | 0.964  | 0001         | 0.036                |

| Diagnostic results            | Y1     | Y2     | Y3     | Y4     | Target value | Absolute error value |
|-------------------------------|--------|--------|--------|--------|--------------|----------------------|
| Normal                        | 0.991  | 0.003  | 0.009  | 0.012  | 1000         | 0.012                |
| Motor faults                  | 0.003  | 0.994  | 0.019  | 0.004  | 0100         | 0.019                |
| Hydraulic coupler fault       | 0.011  | 0.021  | 0.981  | 0.006  | 0010         | 0.021                |
| Reducer fault                 | 0.004  | 0.012  | 0.003  | 0.981  | 0001         | 0.019                |

BP Network training error curve and multi-group genetic neural Network training error curve are shown in Figure 2 and Figure 3.
From the simulation results, the diagnosis results based on the diagnosis model of multiple swarm genetic neural networks are closer to the expected output results, the output of non-fault points is closer to 0, the output of the fault point is closer to 1, and the fault recognition performance is very good. As can be clearly known from figures 2 and 3, the number of training sessions based on multiple group genetic neural network diagnostic models is less than that of BP neural networks, and the convergence speed is improved. And the fault diagnosis output error of multi-group genetic algorithm is lower than that of BP neural network, which shows that the training precision of multiple group genetic algorithm is high, the convergence speed is relatively fast, and the requirement of fault diagnosis is satisfied.

6. Conclusion
In this paper, a variety of swarm genetic algorithms are used to optimize the weights and thresholds of BP neural networks for fault diagnosis of tape conveyor drives. Through comparison, it can be found that the combination of multi-group genetic algorithm and BP neural network can improve the speed and accuracy of diagnosis, and can greatly avoid the problem that BP neural network is easy to fall into the local minimum value, can improve the protection mechanism of mining tape transporter, and can be better applied to the fault diagnosis of mining tape transporter.

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