# Failure Diagnosis System of Continuous Miner Walking System Base on HOFNN

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*Abstract*— In order to diagnose quickly and effectively fault state, reduce failure rate, save maintenance time of a continuous miner walking system and improve the reliability and productivity, enhance performances of a continuous miner, the GA-PSO hybrid optimization method of fuzzy neural network(ie HOFNN) is used in fault diagnosis of a walking system in the paper, a intelligent fault diagnosis expert system of a continuous miner walking system is designed by means of taking VC 6.0 as the programming platform, using SQL SERVER 2000 as database, embedding MATLAB7.1 in the internal. The system is simple in manmachine interface and good in man-machine conversation, capable of analyzing accurately and judging properly failures of a continuous miner walking system.

Keywords— Continuous miner; walking system; fuzzy neural network; fault diagnosis; GA-PSO; HOFNN

# I. INTRODUCTION

Because of poor working conditions [1, 2], complex loads [3-11] of a continuous miner, there are high demands for its reliability. A walking system is an important part of a continuous miner, if it fails, the whole continuous miner will stop working, which affect seriously woke and productivity of the machine [12, 13]. Therefore, study of a fault diagnosis for a continuous miner walking system is very important. A GA-PSO hybrid optimization method of BP neural network (abbreviated as HOFNN) is put forward in the paper, a fault diagnosis system of a continuous miner walking system is researched and established, which lay the foundation for determining sites and causes of the system failures [14-17], giving diagnosis in expert level for a continuous miner.

## II. ESTABLISHING MODEL

According to fault symptom numbers and fault numbers of the system, a 3-layer BP neural network optimized hybrid with genetic algorithm (GA) and particle swarm optimization (PSO) is formed; the net input values from input layer to hidden layer of the neural network are

$$n_{1j} = \sum_{i=1}^{n} \omega_{ij} X_i - \theta_{1j} \tag{1}$$

Where,  $\overline{\sigma}_{ij}$ ,  $\theta_{1j}$  are weights and thresholds from input layer to output layer;  $X_i$  are fault values input training sample.

Bring net input values  $n_{1j}$  into the sigmoid function, the values of the hidden layer are

$$y_i = \frac{1}{1 + e^{-\lambda n_{ij}}}, \quad (i = 1.2...j)$$
 (2)

Where,  $\lambda$  is a speed factor of sigmoid function.

The relation between net values  $n_{2k}$  and weights  $V_{ik}$  as well as threshold  $\theta_{2k}$  is

$$n_{2k} = \sum_{i=1}^{m} v_{ik} y_i - \theta_{2k}$$
(3)

These output values are

$$p_i = \frac{1}{1 + e^{-\lambda n_{2k}}}$$
,  $(i = 1.2...k)$  (4)

Let output values of the training sample be  $Y_i$ , by selflearning cycle training of the BP neural network, the network output error is

$$E = \frac{1}{2} \sum_{i=1}^{k} (Y_i - o_i)^2$$
(5)

A knowledge base of a continuous miner walking system is set up by adjusting weights  $v_{ik}$  and threshold  $\theta_{2k}$  from the hidden layer to output layer, weights  $\overline{\sigma}_{ij}$  and threshold  $\theta_{1j}$ from the input layer to output layer by gradient algorithm.

## III. HYBRID OPTIMIZATING

Because of fast convergence rate, short training time, high precision and small error of the BP neural network optimization of the GA [18], the method is used in the paper, the specific process is followed:

A. Initializing swarm. Taking population size m = 60, by generating randomly weights  $\omega_{ij}$  (10×10 random matrix) and thresholds  $\theta_{1j}$  (10×1 random matrix) from input layer to output layer, weights  $v_{ik}$  (10×14 random matrix) and thresholds  $\theta_{2k}$  (1×14 random matrix) from the hidden layer to output layer, there is  $n = \{\omega_{ij}, \theta_{1j}, v_{ik}, \theta_{2k}\}$ .

B. Striking fitness value. Striking fitness value of particle at new location

$$f = \frac{1}{2} \sum_{i=1}^{k} (Y_i - o_i)^2$$
(6)

C. Renewing minimum. Renewing individual and global minimum values according to particle fitness.

D. Renewing speeds and positions. Take learning factors  $c_1$  and  $c_2$  as 2, weighted coefficient as 1, let  $N_i$ ,  $x_i$  and  $N_{i+1}$ ,  $x_{i+1}$  be respectively a current speed, location and a new speed, location, there are

$$N_{i+1} = c_0 N_i + c_1 [P_i - x_i] + c_2 [G_i - x_i], \quad (i = 1.2...m)$$
(7)

$$x_{i+1} = x_i + N_{i+1} \tag{8}$$

E. Determining initial population. Taking half of larger fitness population as the initial population of genetic algorithm (GA), binary code, operations of selection, crossover and mutation genetic are repeatedly down, it jumps out the circulation once meeting a required accuracy, becomes a new particle population. The other half of the smaller fitness populations is as the next new particle generation.

F. Substituting. Bring the new particle swarm into formula (2), repeating loop until to m eet precision and jumping out the loop, taking  $\omega_{ij}$ ,  $\theta_{1j}$ ,  $v_{ik}$  and  $\theta_{2k}$  as the initial values of the BP neural network, the self-learning cycle training is carried on, a knowledge base of a continuous miner walking system is established.

# IV. ESTABLISHING EXPERT SYSTEM

## A. Main System Interface

Because MATLAB has a powerful computing power and graphics capabilities, and can easily do wavelet transform by using its wavelet toolbox functions, a continuous miner walking system fault diagnosis system is established by means of VC + +6.0 and MATLAB7.1 mixed programming, the main system interface is shown in Figure 1.

#### B. Database Management System

Figure 2a and 2b are fault diagnosis expert system databases for neural network 1 and 2 of a continuous miner walking system. Database form consists of SQL SERVER 2000. The table is database objects that contains all the data in the database, uses primarily to store the information needed to input the sample table, output sample table, a failure phenomenon table, a failure reason table, a weight table from the input layer to hidden layer, weight tables from the hidden layer to the output layer and a historical fault table. Each column (field) in tables is corresponding to the corresponding data in the database.

The connection of VC + +6.0 and SQL SERVER 2000 is through this latest ADO database access technology. Because of simple and flexible, a List Control controls provided by VC + +6.0 is used to connect to the database in the paper.

# C. Fault Diagnosis Program

Signals at key points (locations) in the continuous miner walking system are picked up with corresponding sensors, they are connected to a A/D converter of a microcontroller via MUX after pre-treatment to collect these data, then these analogy signals are transformed into digital signals, and transmitted these data into the expert system through a serial port of the system, the working state and the damage extent of the continuous miner walking system are analysed by the failure diagnosis expert system.





Fig.1 Interface of expert systems

You can enter the neural network fault diagnosis interface after clicking on "Neural Network Fault Diagnosis" button on the main interface of the expert system, obtain processed signal characteristic values (in the from of channel data graph) when clicking on "Connection Data" after selecting sub-neural network, enter a neural network knowledge base as clicking on "Start Diagnostics", the possibility of failure (in the form of graphs that the probability of failure) is calculated. Numerical results are translated into Chinese characters (ie, fault reasons) by membership of fuzzy theory when licking on the "Explanation". Diagnosis results are stored in diagnosis fault history table once you click "Save Data" button.

#### V. CONCLUSIONS

A GA-PSO hybrid optimization fuzzy neural network method is applied to fault diagnosis in this paper, a intelligent continuous miner fault diagnosis expert system of a continuous miner is established by taking VC++6.0 as a programming platform and using SQL SERVER 2000 as database and embedding MATLAB7.1 in the internal. The system interface is simple, human-computer interaction function is good, and it can accurately diagnose failures, save maintenance time of a walking system and improve the work reliability and increase productivity of a continuous miner.

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Table of fault reason

Add

Table of sample output

Add

Table of sample input

Add

XM10

0

0

0.89

XY21

0.91

0.81

0

Category

system fault reason

system fault reason

system fault reason

XM11

0

0

0

0 71

XY22

0.87

0.97

0

Π

Reason

1 th

XM8

0.95

0

0

Î

XY19

0

0

0

Î

Link

Link

Link

right track chain scission or off

right tensioning device failure

XM9

0.93

XY20

0

0

0

n

0

lubrication in right gearbox lack

(b)

•

XW19

-1.2021

1.0652

-0.6592

-0.9489

-0.6097

1.2654

-0.7046

Link

Reason

Link

•

Link

XW20

-1.2884

0.7526

-0.7314

1.0779

-0.9055

0.9727

-0.8611

Add

Table of knowledge base from hidden layer to input layer

XW22

0.2554

0.9966

1.6359

2.0987

-0.3504

-1.0351

-1.0260

XW21

-0.1106

0.6044

-1.9158

1.6956

0.1123

0.5374

-0.7653

Add

Table of fault history

Category

Add

Symbol -

1

XI^

0

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×-

0.

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0. 0

n F

0

XY19 XY20

XY21

Remove

Remove

Remove

XM12

0

0

0

XY23

0.87

0.85

0

n

Fig.2 Management interface of neural network database

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XW2

-0.65

0.80

0.60

0.47

-0.56

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Remove

XW23

-0.6511

0.9966

1.6359

2.0987

-0.3504

1.0260

-0.3228

Remove

Remove

Fault Occurrence







(b) Fig.3 Interface of signal processing

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