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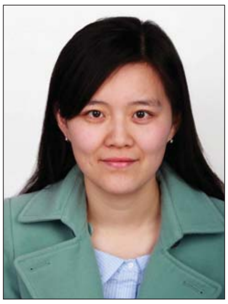

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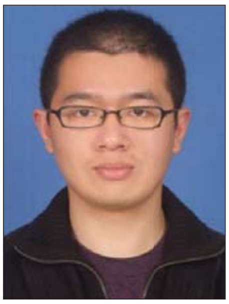

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HEAT PUMP FAULT DIAGNOSIS BASED ON GENETIC BP NEURAL NETWORK

DOI 10.15589/SMI. 20170209

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Abstract. The paper analyzes a method for fault diagnosis proposed for the heat pump DK-FXRS-17II. In order to enhance the detection of heat pump's soft faults and determine the location of the soft faults, and fix them without delay, it establishes the technique of fault diagnosis based on Genetic Algorithm and Back-Propagation neural network. The MATLAB simulation verifies the feasibility of the algorithm and can be applied to the monitoring system of heat pump.

Keywords: genetic algorithm; back-propagation network; fault diagnosis.

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Problem statement. When a fault occurs in the air source heat pump, it enters the abnormal state of operation, which leads to a decline of the system performance. Therefore, it is necessary to enhance the fault detection for heat pumps, quickly diagnose location of the soft fault, find out the cause of the fault, solve the fault in time, and reduce the probability of further failure [1].

Because of the complexity of the heat pump, it is difficult to construct its mathematical model. The emergence of Back Propagation (BP) neural network provides a solution for the fault diagnosis of this system. Neural network is more suitable for online fault diagnosis, can filter out noise and learn directly from the stored fault history. Thus, it can be widely used in the field of fault diagnosis. However, the algorithm results often fall into local minima, greatly affected by the selection of the initial weights and thresholds of the BP neural network [2].

Genetic Algorithm (GA) is a probabilistic search algorithm based on the principles of genetic mechanism and natural selection. It has many advantages, such as direct optimization of the structure objects, global parallel search, and wide application range. Therefore, this paper considers using it to optimize BP neural network in the fault diagnosis for heat pumps [3].

BASIC MATERIAL

1. Fault diagnosis based on BP neural network

BP neural network is a typical feedforward artificial network. Generally, it is composed of an input layer, a hidden layer and an output layer. The hidden layer can contain several layers [4]. Fig. 1 shows a BP neural network with three layers.

Suppose the network input vector is $P_k = (p_1, p_2, ..., p_r)$. The hidden layer output vector is $S_k = (s_1, s_2, ..., s_m)$, and the corresponding activation function is f_1. The actual output vector of the output layer is $A_k = (a_1, a_2, ..., a_n)$, the corresponding activation function is f_2. The target vector is $T_k = (t_1, t_2, ..., t_n)$.

The output of the i neuron in the hidden layer:

$$s_i = f_1(\sum_{j=1}^{r} w1_{ij} p_j + b1_i), i = 1, 2, ...m, \tag{1}$$

The output of the k neuron in the output layer:

$$a_k = f_2(\sum_{i=1}^{m} w2_{ki} s_i + b2_k), k = 1, 2, ...n, \tag{2}$$

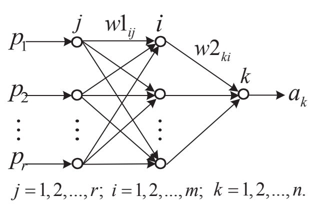


Fig. 1. BP neural network with three layers

The error function:

$$E(W,B) = \frac{1}{2}\sum_{k=1}^{n}(t_k - a_k)^2, \tag{3}$$

When the error propagates backwards, the weights in the output layer is expressed as follows:

$$\Delta w2_{ki} = -\eta \frac{\partial E}{\partial w2_{ki}} = -\eta \frac{\partial E}{\partial a_k}\frac{\partial a_k}{\partial w2_{ki}}$$

$$= \eta(t_k - a_k)\cdot f2' \cdot s_i = \eta \cdot \delta_{ki} \cdot s_i, \tag{4}$$

As part of formula 4, δ_{ki} is defined as follows:

$$\delta_{ki} = (t_k - a_k)\cdot f2' = e_k \cdot f2', \quad e_k = t_k - a_k \tag{5}$$

Similarly, the thresholds in the output layer are equal to the following:

$$\Delta b2_{ki} = -\eta \frac{\partial E}{\partial b2_{ki}} = -\eta \frac{\partial E}{\partial a_k}\frac{\partial a_k}{\partial b2_{ki}} =$$

$$= \eta(t_k - a_k)\cdot f2' = \eta \cdot \delta_{ki}, \tag{6}$$

The weights in the hidden layer:

$$\Delta w1_{ij} = -\eta \frac{\partial E}{\partial w1_{ij}} = -\eta \frac{\partial E}{\partial a_k}\frac{\partial a_k}{\partial s_i}\frac{\partial s_i}{\partial w1_{ij}} =$$

$$= \eta \sum_{k=1}^{n}(t_k - a_k)\cdot f2' \cdot w2_{ki} \cdot f1' \cdot p_j =$$

$$= \eta \cdot \delta_{ij} \cdot p_j, \tag{7}$$

Within formula 7, δ_{ij} is defined in the following way:

$$\delta_{ij} = e_i \cdot f1', \quad e_i = \sum_{k=1}^{n}\delta_{ij}\cdot w2_{ki}, \tag{8}$$

Similarly, the thresholds in the hidden layer are expressed as

$$\Delta b1_i = \eta\delta_{ij}, \tag{9}$$

Through the procedure given above, the weights and thresholds of each layer of BP neural network can be obtained [5].

The BP neural network adopts the error back propagation algorithm. Firstly, the activation of neurons spreads back layer by layer; meanwhile, training samples are used to train the network. Then, the output response of the output layer neurons is obtained. After that, in order to reduce the mean square error between the actual output and the target output, the connection weights and thresholds are corrected layer by layer, while the mean square error is transmitted backward. With the continuous improvement, the error between the actual output and the target output of the network is also getting smaller and smaller. The nonlinear image of the new sample can be obtained after the appropriate network connection value is obtained.

Fig. 2 demonstrates the structure of a fault diagnosis system based on neural network. The diagnosis process is as follows. First, in order to obtain the expected diag-

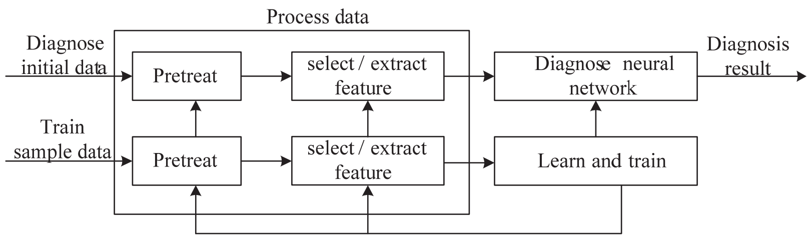


Fig. 2. Structure of a fault diagnosis system based on neural network

nosis network, this paper uses a certain number of training sample sets (symptom – fault data sets) to train the neural network. Second, the test sample set is used as the input of the current diagnosis network to train.

The specific steps of fault diagnosis based on BP neural network using MATLAB tools are as follows [6].

A. Determine the input sample data and target output of the network.

Determination of the neural network input actually implies extraction of characteristic values. In this paper, the common soft faults are simulated through the study of the heat pump DKFXRS-17II.

Table 1 presents a partial input sample data after linear normalization of the original data of a heat pump.

In Table 1, the inputs are eight characteristic values: high pressure p_1, low pressure p_2, condensing temperature p_3, evaporation temperature p_4, suction overheating temperature p_5, liquid subcooling temperature p_6, exhaust temperature p_7 and water temperature difference through condenser p_8.The outputs are fault free F1, refrigerant leakage F2, leakage of compressor vent valve F3, obstruction of liquid pipeline F4, fouling of condenser F5, and fouling of evaporator F6.

The expected output values of the five faults are shown in Fig. 3.

B. Determine and train the network structure.

Since the sample data has 8 characteristic values, the input layer has 8 nodes (n = 8). There are 6 types of faults in the sample data, thus the output layer has 6 nodes (m = 6). The number of nodes in the hidden layer is determined according to the empirical formula $h = \sqrt{n+m} + a$. There, a = 9.26 (a is the constant between 1 to 10), so h = 13. Finally, the structure of BP neural network is as follows: 8 – 13 – 6 nodes.

This paper sets the square sum of errors between the target output and the actual output equal to 0.001. The transfer function of the hidden layer is 'tansig', and the transfer function of the output layer is 'logsig'. The training function is 'traingda'. The target accuracy is 0.001, and the maximum training period is 1000. The sample data of Table 1 and the target output value of Table 2 are used to train the BP neural network. Thus, the weights $w1_{ij}$, $w2_{ki}$ and the thresholds $b1_i$, $b2_k$ of the hidden layer and the output layer will be obtained.

C. Test network and analyze results.

In order to test the fault diagnosis ability and accuracy of the network, Table 2 provides 12 sets of data. The test data in Table 2 are input for the trained BP neural network, and then the program is launched.

Table 1. Fault sample data

Types Of Fault	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8
Fault Free F1	0.4253	0.7238	0.5722	0.9253	0.3007	0.1089	0.6930	0.9846
Fault F2	0.1843	0.5543	0.1193	0.6536	0.4968	0.2600	0.8744	0.4154
Fault F3	0.1275	0.7845	0.0766	0.9601	0.1596	0.1614	0.4708	0.3359
Fault F4	0.8201	0.1381	0.8778	0.0255	0.8668	0.9347	0.9728	0.2795
Fault F5	0.6744	0.6501	0.7320	0.8152	0.3925	0.0021	0.8239	0.6462
Fault F6	0.3088	0.5967	0.3181	0.7486	0.0623	0.1146	0.7989	0.6949

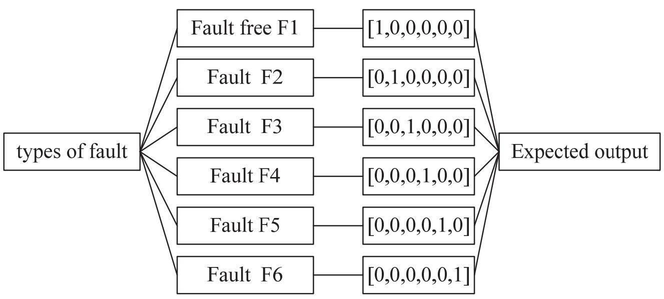


Fig. 3. The expected output values of faults

Table 2. Test data

Number	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	Fault
1	0.3984	0.6759	0.4827	0.9205	0.2968	0.1110	0.7131	1.0000	F1
2	0.5142	0.7164	0.5162	0.9368	0.2494	0.1218	0.0000	0.8462	F1
3	0.2367	0.4917	0.1635	0.6462	0.5387	0.2569	0.8521	0.4692	F2
4	0.2338	0.5948	0.1576	0.7035	0.4723	0.2682	0.8648	0.3590	F2
5	0.1646	0.7680	0.0865	0.9634	0.1526	0.1562	0.5019	0.3897	F3
6	0.1158	0.7366	0.0773	0.9579	0.1561	0.1511	0.4807	0.3744	F3
7	0.8165	0.0866	0.8347	0.0000	0.8454	1.0000	0.9635	0.3949	F4
8	0.7393	0.1584	0.8218	0.1091	0.8185	0.9517	0.9511	0.3026	F4
9	0.5827	0.7551	0.7765	0.8344	0.4439	0.0000	0.8171	0.6718	F5
10	0.6344	0.6906	0.7496	0.8532	0.3626	0.0010	0.8177	0.6564	F5
11	0.3809	0.6961	0.3520	0.7516	0.0673	0.1131	0.8062	0.6846	F6
12	0.3547	0.6538	0.3844	0.7497	0.0633	0.1023	0.8020	0.7000	F6

In this paper, the test data were trained for 100 consecutive times. Two different training effects are given in Fig. 4.

When the BP neural network is run on the test sample, upon reaching the minimum gradient, the training will end automatically without achieving the required accuracy. Fig. 4 b is one of the renderings that fall into the local minimum point.

The divergence between the above test results and the actual situation shows that the BP neural network may easily fall into the local minimum due to insufficient data sampling and the defects of the BP neural network itself. Therefore, it is necessary to employ effective methods for its improvement, so as to better diagnose faults of the heat pump.

2. Implementation of the BP neural network optimized with a genetic algorithm

The search space can be determined to train the network to converge in optimization of the initial weights and thresholds based on genetic algorithm so as to obtain the optimal solution. This method not only realizes the generalization ability of BP neural network to the full extent, but also highlights the advantages of genetic algorithm in global search, and achieves the purpose of being fast and stable [7]. Specific optimization ideas are as follows.

The first step is to real code the initial weights and thresholds of BP neural network in a certain region to generate the initial population.

The second step is to calculate the fitness of the population by using the minimum mean square error of the network as an evolutionary criterion aimed at network input sample data and target output. Then a set of weights and thresholds is obtained through the iteration number according to the evolutionary principle defined as the survival of the fittest of genetic algorithm. This set of weights and thresholds is the global search of the genetic algorithm to minimize the mean square error of the network.

The last step is to train the BP neural network with the weights and thresholds obtained by the above genetic algorithm, and test the samples [8].

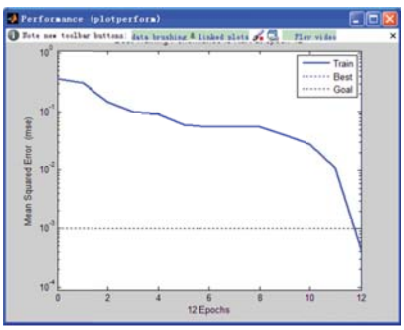
The flow chart of BP neural network optimized by genetic algorithm is shown in Fig. 5.

According to the above optimization idea, this paper uses Genetic Algorithm Toolbox to optimize the BP network in MATLAB [9] within the following framework.

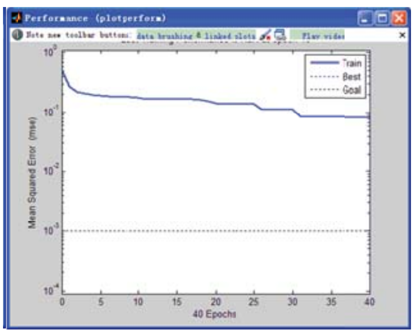
A. Initialize parameters.

The number of individuals in the initial population $G = 40$

The maximum genetic algebra $T = 100$



a)



b)

Fig. 4. Graphs for training samples:
a — convergent; *b* — trapped into local minimum

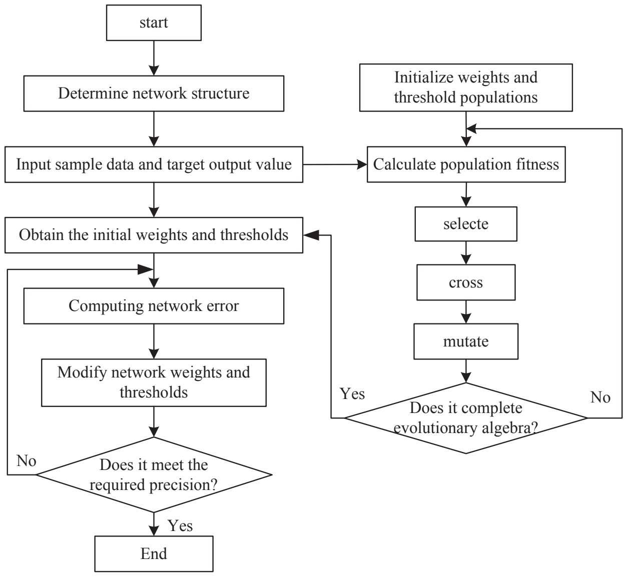


Fig. 5. Flowchart of BP neural network optimized with a genetic algorithm

The selection probability $P_{selection} = 0.9$
The crossover probability $P_{crossover} = 0.7$
The variation probability $P_{mutation} = 0.1$

B. Code and generate the initial population.

The structure of BP neural network for the heat pump unit fault diagnosis is 8 – 13 – 6 nodes. Therefore, the number of weights is $13 \times 8 + 6 \times 13 = 182$, while the number of thresholds is $13 + 6 = 19$. After adding, a total of 201 values need to be optimized. Any of the weights $w1_{ij}$, $w2_{ki}$ and the thresholds $b1_i$, $b2_k$ is coded with real numbers to construct a chain of codes $W = (w1_{11}, w1_{21}, \ldots w1_{131} \ldots w2_{11}, w2_{21}, \ldots w2_{61}, \ldots b1_1, b1_{13}, b2_1, \ldots b2_6)$. Each code chain is an individual, called a chromosome [9]. Each weight and threshold is a gene on a chromosome. There are 201 genes on each chromosome. Because the number of individuals in the initial population is 40, there are 40 chromosomes in this population. Any random gene on any chromosome of the randomly generated initial population is a random number between –1 and 1.

C. Compute the optimal solution.

The value of fitness of each individual is calculated according to the selected fitness function. Then, selection, crossover and mutation operations are performed to generate new individuals to constitute the next generation population. The mean square error of the neural network is calculated according to the expected and actual output values. If the expected value $\varepsilon_{GA} = 5.0$ is not reached, the genetic operation continues. If the condition is satisfied within 100 generations of genetic operation, the final optimal solution is obtained [11].

After 100 generations of searching, the square error sum curve and the fitness curve of chromosomes are shown in Fig. 6.

D. Decompose the obtained optimal solution into initial weights and thresholds of BP neural network.

According to the chain coding defined above, the first 104 numbers are taken as the connection weights from the input layer to the hidden layer corresponding to $w1_{11}, w1_{21} \ldots w1_{131} \ldots w1_{18}, w1_{28} \ldots w1_{138}$. The numbers 105 to 182 (78 numbers total) are used as the connection weights of the hidden layer to the output layer corresponding to $w2_{11}, w2_{21} \ldots w2_{61} \ldots w2_{113}, w2_{213} \ldots w2_{613}$. The numbers from 183 to 195 (13 numbers total) are used as the thresholds of the hidden layer corresponding to $b1_1$, $b1_2 \ldots b1_{13}$. The numbers from 196 to 201 (6 numbers total) are used as the thresholds of the output layer corresponding to $b2_1, b2_2 \ldots b2_6$.

E. Training of BP neural network with the initial weights and thresholds obtained by optimization.

The initial weights $w1_{ij}$, $w2_{ki}$ and thresholds $b1_i$, $b2_k$ obtained by optimization are brought into the BP network

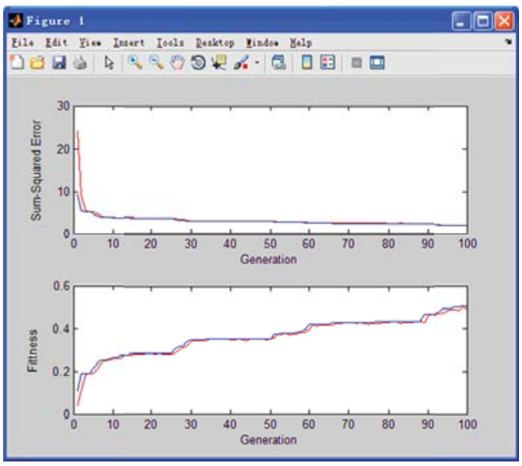


Fig. 6. Square error sum curve and fitness curve

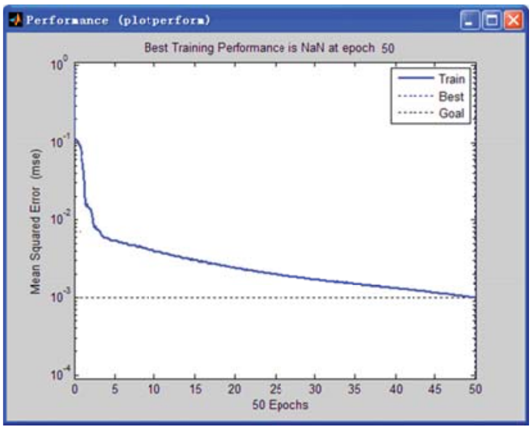


Fig. 7. Training target curve

for its training with the input of the fault sample data of Table 1. Using the trained genetic neural network, the test data in Table 2 are tested. The training target curve is shown in Fig. 7.

CONCLUSIONS

By training 100 consecutive groups (1000 times), it was possible to achieve the level of convergence equal to 100%. Compared to the convergence of BP neural network, this indicator of the neural network optimized by genetic algorithm is obviously enhanced. The feasibility of using genetic algorithm to optimize BP neural network in fault diagnosis is proved.

Статью рекомендует в печать
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