Fault Diagnosis of Large-Scale Railway Maintenance Equipment Based on GA-RBF Neural Network

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Abstract. At present, the large-scale railway maintenance equipment adopts a diesel engine as the main power plant. Therefore the diesel engine in the event of failure, will seriously affect the large-scale railway maintenance equipment of the normal work. Exploring advanced diesel engine condition monitoring and fault diagnosis technology and looking for practical and effective diesel engine fault diagnosis method, which has already become a research subject widely concerned by many experts at home and abroad. In this paper, genetic algorithm (GA) is used to optimize the parameters of radial basis function (RBF) neural network for diesel engine fault diagnosis, experimental results show the validity of this prediction method, and the accuracy of the proposed algorithm was verified by comparative.

Keywords: Large-scale railway maintenance equipment · Fault diagnosis · RBF neural network optimized by genetic

1 Introduction

Diesel engine's structure is complex, and there are many parts. The relationship between each subsystem is complex, so the fault diagnosis is complex. Typically, a source of the problem may lead to a failure, it may lead to multiple failures. Of course, a fault may be caused by a fault source or multiple fault sources. Therefore, we need to find fault diagnosis method which can scientifically and accurately collect the fault information.

With the continuous development of fault diagnosis, A novel fault detection and diagnostic method of diesel engine by combining rule-based algorithm and Bayesian networks (BNs) or Back Propagation neural networks (BPNNs) is proposed [1]. Wang presents a Bayesian network-based approach for fault isolation

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in the presence of the uncertainties [2]. Wang presents an adaptive fuzzy PID control method for the diesel engine speed control system that is accompanied by the uncertainty and time variability. [3] dedicated to the optimization of the runner dimensions determined by the numerical calculation [4]. Wang puts forward a bat algorithm based on improved optimization engine fuel system fault diagnosis model of extreme learning machine [5]. However, the neural network still has some disadvantages, such as slow convergence speed, local minimum value, lack of explicit expression between levels, and difficult to determine the network structure, which limits the application and development of neural network in diesel engine fault diagnosis. Based on RBF network, this paper uses genetic algorithm to optimize its network parameters, which makes RBF neural network algorithm have strong global search ability.

Finally, with Germany DEUTZ F12L413F type V-cylinder diesel engine simulation, the fault diagnosis experiments show that the effectiveness of the prediction method, and the accuracy of the algorithm is verified by comparison.

2 Diesel Typical Failure Modes and Failure Characteristics

When the diesel engine is working, it is possible to produce a wide variety of failures, the data was provided by the UK diesel Engineers and user downtime reports Press Association analysis of the results [6]. Injection equipment and fuel supply system fault(27.00%), Water leakage(17.30%), Valve and valve seat failure(11.90%), Bearing fault(7.00%), Piston component failure(6.60%), Leakage and lubrication system failure(5.20%), Turbo system failure(4.40%), Gears and drives fault(3.90%), Governor gear fault(3.90%), Fuel leak(3.50%), Other rupture(2.50%), Other faults(2.50%), Pedestal failure(0.90%), Crankshaft fault(0.20%), Air leakage(3.20%).

Through the analysis of above, it can be seen due to the interaction between diesel engine subsystems, complex relationships, and therefore presents a complex diversity of diesel engine fault, the fault of the main characteristics of the diesel engine: the failure of complexity; fault correlation and relativity; the coexistence of multiple faults.

3 RBF Neural Network

3.1 RBF Network and RBF Element Model

RBF element model having R-dimensional inputs shown in Fig. 1. In Fig. 1, $||dist||$ module represents obtaining input vector and weight vector distance. This model uses a Gaussian function as shown in Fig. 2 *radbas* as a radial basis function neural transfer function [7], which n is a distance between the input vector p and the weight vector w and then multiplied by the threshold b. Gaussian function as shown in Fig. 2 is a typical radial basis function, the expression is:

$$f(x) = e^{-x^2} \tag{1}$$

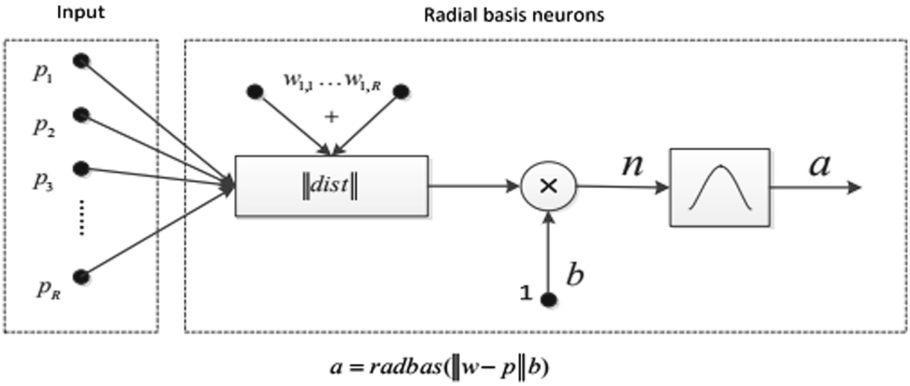

Fig. 1. Radial base function artificial neural.

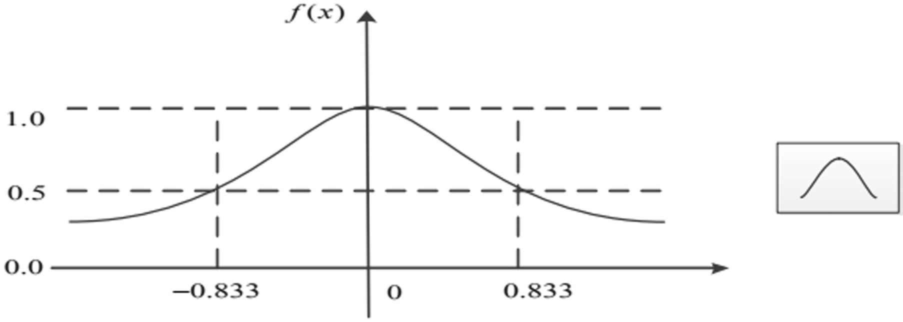

Fig. 2. Gaussian curve.

Center and width are two important parameters radial basis function neurons. Right neurons value vector w radial basis function determines the center, when the input vector p and w coincide, the output of radial basis function neurons reaches a maximum when the input vector p farther distance w, neuron output smaller. Neurons threshold F determines the width of the radial basis function, b is larger, the input vector p while away from the w, the amplitude attenuation function will be.

3.2 RBF Neural Network Model

A typical radial basis function network comprises two layers [8], hidden layer and output layer. Figure 3 shows a radial basis function network diagram, network input dimension for R, number of neurons in the hidden layer is s^1, the output number is s^2, the hidden layer neurons using Gaussian function as a transfer function, output the transfer function layer is a linear function, a_i^1 represents the hidden layer output vectors of the i -th element of a_i^1, W_i^1 is the weight vector i -th hidden layer neurons, which j -th row of hidden layer neurons weights matrix W^1.

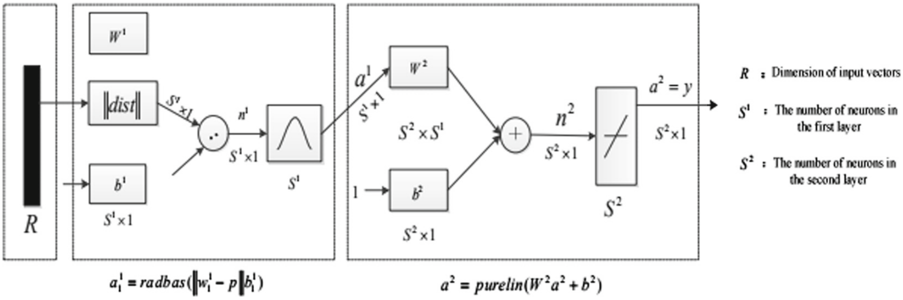

Fig. 3. Radial basis function network structure.

3.3 RBF Network Learning

In Gaussian network as an example, the network to learn three parameters, namely the weight of each RBF center and variance and an output unit. The choice of the first two parameters in two ways [9].

(1) According to the experience of the election center, M centers should be representative. Density of sample points where the center also more appropriate, if the data itself is uniformly distributed, uniform distribution of the centers, the distance between the centers of each set is d, optional variance $\sigma = d/\sqrt{2M}$.
(2) By clustering the sample clustered into M Class, the center is at the center of RBF, the most commonly used is K-means clustering, selforganizing method can also be used in the future to discuss.

If the RBF network classifier seen Parzen window or bit density function method recovery, Fukunagen noted that the usual clustering method given center and a variance is not representative, he proposed the reduction of Parzen algorithm that from N samples, choose r as a standard center should make Kullback distance between two distributions $p_r(X)$ and $p_N(X)$ minimum,

$$K = \int \ln\left[\frac{p_r(X)}{p_N(X)}\right] p_r(X)\, dX = E \times \ln\left[\frac{p_r(X)}{p_N(X)}\right] \tag{2}$$

wherein, $p_r(X)$ and $p_N(X)$, respectively, by r points or N points of the estimated density function.

After the center and variance RBF function is selected, the output unit weights are available directly calculated from the least squares method. The most common situation is that the above three parameters are used to supervised learning approach to training, such as the use of error correction based on the gradient descent algorithm, an objective function is defined as:

$$E = \frac{1}{2}\sum_{j=1}^{N} e_j^2 \tag{3}$$

where: N is the number of samples; M is a selected number of hidden units. $e_j = d - F^*(x_j) = d_j - \sum_{i=1}^{m} \omega_i G(\|x_j - t_j\| c_i)$ has three parameters to be learning, $\omega_i, t_j, \sum_i^{-1} \square$, and (with the transformation matrix C_j related).

Given directly below its learning rule (N is the number of iterations).

(1) The weight of the output unit:

$$\begin{aligned} \frac{\partial E(n)}{\partial \omega_i(n)} &= \sum_{j=1}^{N} e_j(n) G(\|x_j - t_j\| c_i) \\ \omega_i(n+1) &= \omega_i(n) - \eta_1 \frac{\partial E(n)}{\partial \omega_i(n)}, i = 1, 2, \ldots, m. \end{aligned} \tag{4}$$

(2) The center of the hidden unit t_i:

$$\begin{aligned} &\frac{\partial E(n)}{\partial \partial_i(n)} = 2\omega_i(n) \\ &\sum_{j=1}^{N} e_j(n) G\left(\|x_j - t_i(n)\| c_i \sum^{-1}(n) \left[x_i - t_i(n)\right] \right) \\ &t_i(n+1) = t_i(n) - \eta_2 \frac{\partial E(n)}{\partial t_i(n)}, i = 1, 2, \ldots, m. \end{aligned} \tag{5}$$

(3) Function Width:

$$\begin{aligned} \frac{\partial E(n)}{\partial \sum_i^{-1} n} &= -\omega_i(n) G'(\|x_j - t_j(n)\| c_i) Q_{ji}(n) \\ Q_{ji}(n) &= \left[x_j - t_j(n)\right]^T \\ \sum_i^{-1}(n+1) &= \sum_i^{-1}(n) - \eta_3 \frac{\partial E(n)}{\partial \sum_i^{-1} n} \end{aligned} \tag{6}$$

In the formula: $e_j(n)$ is the error of the j-th sample time n; $G'(\cdot)$ is derivative of Gaussian function $G(\cdot)$.

4 Fault Diagnosis Method Based on Genetic Algorithm Optimization of RBFNN

4.1 RBFNN Optimized by Genetic Algorithm

Using RBF Neural networks to solve practical problems and generally including three stages [10]:

(1) First creates a RBF Neural network on research issues, and the number of nodes, each layer of the network structure, processing units and hidden connections between base design function;
(2) Combined with the research questions, selecting an appropriate method to determine the topology of the network structure and connection weights between the nodes;
(3) Target performance that can be measured to evaluate the training network. In order to achieve the desired results, you can repeat the process.

Currently, there is a learning algorithm of RBF neural network some shortcomings: clustering methods exist must be pre-specified number of categories, and select number of categories would affect the performance of clustering; supervised learning algorithm is affected by the initial value of the set, and it is difficult to achieve global optimization; some methods and regression-related although to some extent can better solve the problem of the hidden layer number and the value of the centers, but the regression coefficients of selected parameters and width, you need to try or cross-validation, therefore, some limitations exist in the actual application process.

4.2 Fault Diagnosis of Diesel Engines Based on Genetic Algorithm Optimization of RBFNN

Combined with the above, the establishment of an experimental model of vibration signal acquisition and pressure signal analysis system based on the detection system shown in Fig. 4 Working principle of the piezoelectric vibration sensor signal acquisition, while the point sensor signal collection point dead stop after processing the charge amplifier into DASP data acquisition system, and then through the computer signal analysis system data processing, fault diagnosis of diesel engines [11].

In order to improve the reliability of diagnosis, should reflect as much as possible to extract fault feature info extracted dynamic index signal timedomain waveform as the characteristic parameter.

We mainly on the following 5 kinds of diesel engine fault diagnosis: more oil f_1, fuel supply advance angle nights f_2, supply advance angle early f_3, the oil valve wear f_4, injector needle stuck f_5.

The 5 kinds of common faults of diesel engine fault, there is a certain degree of representativeness. Vibration Fault sample collected data and pressure fault sample data shown in Table 1 and Table 2. We use the formula: $x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$, the above data is normalized, but the results are omitted.

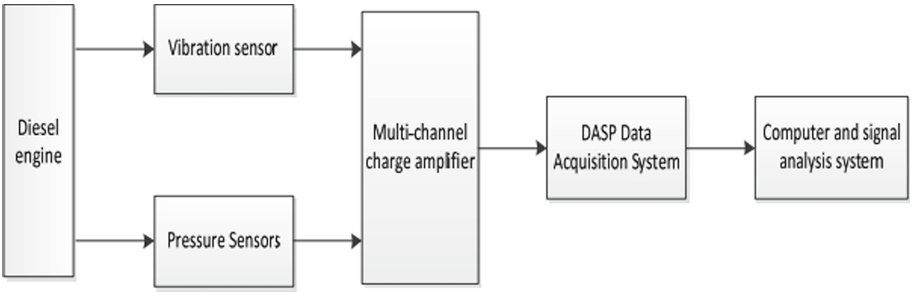

Fig. 4. The working principle diagram of the diesel engine signal detection system.

4.3 RBF Network Training Results

RBF network with the substance of troubleshooting is to conduct sample learning and pattern recognition. RBF network in the creation process, can automatically increase the number of neurons in the hidden layer unit until MSE meeting the objectives set up, so the process of creating a network that is network training process.

Setting training network error precision $goal = 0.00001$, after several tests, will be extended to the constant $spread = 0.9$, will each increase the number of hidden layer neurons is set to 1, the maximum is set to 40 the number of

Table 1. Pressure fault sample data

Fault types		Sample data							
		x_p	$\mu_{\|x\|}$	ψ_x	x_r	K	I	G	L
f_1	1	6.9323	10.0512	1.5023	0.3128	44.2460	105.8000	7.8742	10.4347
	2	6.9234	10.0635	1.5078	0.3089	44.3450	105.6000	7.8734	10.4456
	3	6.9345	10.0546	1.5067	0.3123	44.2340	105.9000	7.8656	10.4235
f_2	1	3.7209	12.6345	2.1245	0.3482	63.1502	100.0000	4.5352	7.9300
	2	3.7322	12.6234	1.1380	0.3545	61.1345	101.1000	4.5245	7.9289
	3	3.7255	12.6123	1.1325	0.3493	63.5678	100.8000	4.5453	7.9168
f_3	1	3.9520	14.3550	1.5330	0.3265	61.1076	94.1000	4.5010	6.5479
	2	3.9450	14.3443	1.5439	0.3267	63.9999	94.0000	4.4956	6.5372
	3	3.9534	14.3654	1.5346	0.3124	64.1234	94.2000	4.5012	6.5234
f_4	1	2.9580	8.0384	1.5854	0.3937	30.9800	43.1000	3.5345	5.3542
	2	2.9577	8.0478	1.5860	0.3910	30.9756	43.4000	3.5678	5.3467
	3	2.9430	8.0345	1.5862	0.4000	30.9876	43.5000	3.5467	15.3098
f_5	1	4.4000	22.9567	2.9856	0.2090	248.3011	276.0000	5.3567	12.0712
	2	4.3450	21.9870	3.1089	0.2089	249.0000	278.0000	5.3876	12.0876
	3	4.4900	23.0000	2.9767	0.2100	248.9000	279.0000	5.3767	12.1123

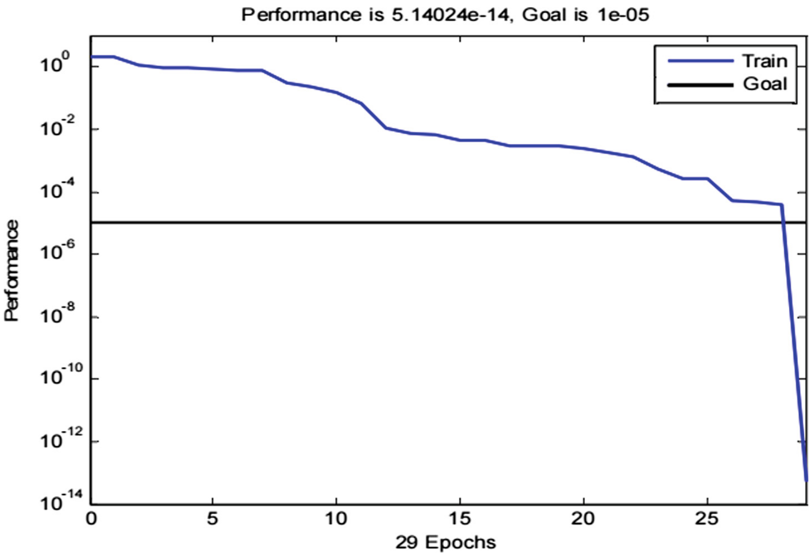

Fig. 5. The training results of RBFNN.

Table 2. Vibration fault sample data

Fault types		Sample data							
		x_p	$\mu_{\|x\|}$	ψ_x	x_r	K	I	G	L
f_1	1	6.9323	10.0512	1.5023	0.3128	44.2460	105.8000	7.8742	10.4347
	2	6.9234	10.0635	1.5078	0.3089	44.3450	105.6000	7.8734	10.4456
	3	6.9345	10.0546	1.5067	0.3123	44.2340	105.9000	7.8656	10.4235
f_2	1	3.7209	12.6345	2.1245	0.3482	63.1502	100.0000	4.5352	7.9300
	2	3.7322	12.6234	1.1380	0.3545	61.1345	101.1000	4.5245	7.9289
	3	3.7255	12.6123	1.1325	0.3493	63.5678	100.8000	4.5453	7.9168
f_3	1	3.9520	14.3550	1.5330	0.3265	61.1076	94.1000	4.5010	6.5479
	2	3.9450	14.3443	1.5439	0.3267	63.9999	94.0000	4.4956	6.5372
	3	3.9534	14.3654	1.5346	0.3124	64.1234	94.2000	4.5012	6.5234
f_4	1	2.9580	8.0384	1.5854	0.3937	30.9800	43.1000	3.5345	5.3542
	2	2.9577	8.0478	1.5860	0.3910	30.9756	43.4000	3.5678	5.3467
	3	2.9430	8.0345	1.5862	0.4000	30.9876	43.5000	3.5467	15.3098
f_5	1	4.4000	22.9567	2.9856	0.2090	248.3011	276.0000	5.3567	12.0712
	2	4.3450	21.9870	3.1089	0.2089	249.0000	278.0000	5.3876	12.0876
	3	4.4900	23.0000	2.9767	0.2100	248.9000	279.0000	5.3767	12.1123

neurons. As can be seen from Fig. 5, when training to 13 steps, error precision to meet the requirements. The corresponding input samples, RBF neural network output mode, the failed node close to 1, the non-faulty nodes close to 0.

Table 3. Vibration testing data

Fault types	Sample data							
	x_p	$\mu_{\|x\|}$	ψ_x	x_r	K	I	G	L
f_1	0.1042	0.0188	0.0063	0.0000	0.0410	1.0000	0.1472	0.1906
f_2	0.0985	0.0181	0.0057	0.0000	0.0410	1.0000	0.1196	0.1613
f_3	0.0791	0.0160	0.0049	0.0000	0.0379	1.0000	0.0975	0.1371
f_4	0.1539	0.0184	0.0056	0.0397	0.0000	1.0000	0.1817	0.2313
f_5	0.1384	0.0218	0.0041	0.0000	0.0611	1.0000	0.1551	0.1859

4.4 Network Training Results of Genetic Algorithm Optimization

Control lead using binary code, parameter uses a decimal encoding genes. Accuracy of approximation error objective function indicated by

$$MSE = \frac{1}{2}\sum_{k}^{N}(\text{yout}(k) - \text{ymout}(k))^2 \tag{7}$$

where N is the number of samples, *yout* expected output values, ymout of actual output values for RBF Neural network. Choosing roulette method is used to choose. Cross way uses the word cross. In mutation, with some probability negate the control gene; the uniform variation method for parameter real-value variation of the gene. Identify hidden nodes of RBF nerve number, hidden layer node centers, base width and linear output power value, taking the maximum number of optimization as 150 generations, hidden layer node number is 5. Training results are shown in Fig. 6.

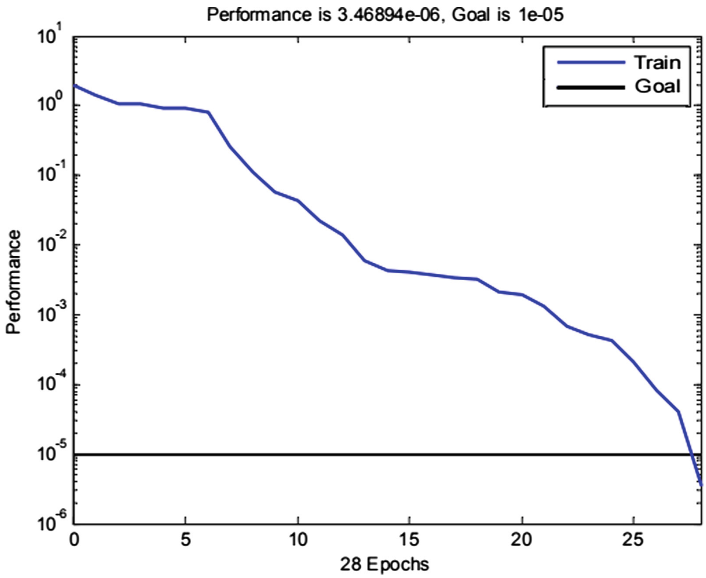

Fig. 6. The training results of genetic RBFNN.

4.5 System Test

To test network troubleshooting capabilities and accuracy of network simulation follows. The vibration test data and the pressure test data (Table 3, Table 4) into which the neural network has been trained, the training results as shown in Table 5.

Table 4. The results of fault diagnosis by different neural network

Types of neural network	Fault types	Actual output				
RBF neural network	f_1	1.0097	−0.0043	−0.0012	−0.0036	−0.0006
	f_2	−0.0325	1.0147	0.0025	0.0060	0.0094
	f_3	−0.0204	0.0394	0.9732	0.0093	−0.0015
	f_4	0.0097	−0.0010	−0.0040	0.9972	−0.0020
	f_5	0.1488	−0.0529	−0.0486	−0.0390	0.9917
GA-RBF neural network	f_1	0.9984	−0.0001	0.0002	0.0012	0.0003
	f_2	−0.0170	1.0060	0.0034	−0.0020	0.0097
	f_3	−0.0187	0.0190	0.9734	−0.0067	−0.0044
	f_4	−0.0022	0.0052	−0.0041	1.0026	−0.0015
	f_5	0.0442	0.0026	−0.0510	0.0112	0.9931

Table 5. Pressure testing data

Fault types	Sample data							
	x_p	$\mu_{\|x\|}$	ψ_x	x_r	K	I	G	L
f_1	0.0602	0.0930	0.0114	0.0000	0.4196	1.0000	0.0715	0.0960
f_2	0.0323	0.1230	0.0179	0.0000	0.6312	1.0000	0.0420	0.0760
f_3	0.0364	0.1499	0.0129	0.0000	0.6908	1.0000	0.0445	0.0664
f_4	0.0622	0.1694	0.0280	0.0000	0.7278	1.0000	0.0735	0.1163
f_5	0.0152	0.0821	0.0100	0.0000	0.8863	1.0000	0.0186	0.0429

5 Conclusions

The genetic algorithm is a global parallel and capable of random search method for optimizing the function to be substantially unrestricted, do not meet the conditions of continuous or differentiable, just solution to meet the requirements under the Solution Function self- restraint, with global convergence and robustness can be. Thus, genetic algorithms to optimize the RBF neural network, RBFneural algorithm can make a powerful global search capability.

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