International Journal of Applied Mathematics in Control Engineering 1 (2018) 9-14

Contents lists available at YXpublications

International Journal of Applied Mathematics in Control Engineering

Journal homepage: http://www.ijamce.com

Fault Diagnosis of Analog Circuit based on Extreme Learning Machine

Wenxia Du[a], Xiuping Zhao[a], Hailian Du[a, *], Feng Lv[a]

[a] College of Vocational and Technical, Hebei Normal University, No. 20 Road East, 2nd Ring south, YuHua District, Shijiazhuang, Heibei, China

ARTICLE INFO

Article history:
Received 12 April 2017
Accepted 15 July 2017
Available online 25 December 2017

Keywords:
Weighted extreme learning machine
Extreme learning machine
Fault diagnosis
Analog circuit

ABSTRACT

In electronic system, analog circuits are more likely to get wrong, it is very significant to research the fault diagnosis of analog circuits in the theory and practice. Extreme learning machine (ELM) has quick learning speed and good generalization performance, which randomly chooses the input weights and analytically determines the output weights. Weighted extreme learning machine (WELM) could improve the accuracy of analog circuit fault diagnosis for imbalance samples. ELM and WELM are applied to fault diagnosis of analog filter circuit in this paper. The simulation results of examples show that the fault diagnosis methods based on ELM have good diagnosis effect and feasibility and can diagnose the faults in analog circuits correctly.

1. Introduction

Through years of research and development, the fault diagnosis of analog circuit has preliminarily laid the foundation of fault diagnosis theory. General diagnosis method for analog circuits, basically depends on the analog circuit diagnosis equation or optimization model. But there are some shortcomings such as large amount of calculation, lack of flexibility, and even there is no way to get a diagnostic equation. With the development of artificial intelligence methods, some problems have been improved to some extent. It needn't establish the fault model of the analog circuit, and the fault features could be extracted by the input data easily, then the faults could be diagnosed by fault features. As a result, many intelligent methods are applied in fault diagnosis. AminianF and AminanM used wavelet transform and principal component analysis to extract feature, and used the neural network to diagnose the fault[1-2]. Catelani M used radial basis neural network and fuzzy rules to study the soft faults of analog circuits[3], Cannas B studied analog fault diagnosis based on neural network using testability analysis[4-5]. . Based on the theory of one-dimensional neural network, D zhao put forward the concept and theory of multi-dimensional neural networks, which is applied in the field of analog circuit fault diagnosis[6-7] However, the following defects are commonly found in the diagnosis process: slowly convergence rate, the local optimal, low accuracy of fault diagnosis. Compared with the traditional neural network, Extreme Learning Machine (ELM), which is proposed by G.B.Huang is not easy to fall into local optimal, with good generalization performance nd fast learning speed, which is suitable for solving classification and fitting problems[8]. Extreme learning machine is constantly improved for multi-categoties classification and regression based on optimization method[9-11]. L Zhang proposes a learning algorithm which is based on the differential evolution extreme learning machine (DE-ELM) for parameter optimization of ELM[12-13]. Xiong J presents a novel fault diagnosis method for analog circuits using ensemble empirical mode decomposition, relative entropy, and extreme learning machine[14-16]. But the unbalance sample data in practice problems affects the accuracy of fault diagnosis. Weighted extreme learning machine (WELM) could solve the problems to a certain extent and greatly improve the accuracy of analog circuit fault diagnosis[17]. In the paper, WELM is combined with the fault diagnosis theory to diagnose fault of analog circuit.

2. Extreme learning machine(ELM)

2.1 Extreme learning machine

Extreme learning machine (ELM) is a typical single hidden layer feed-forward networks whose structure is shown in Fig.1.

In Fig.1, the input layer contains n neuron nodes, which are corresponding to n input variables; the hidden layer contains K neuron nodes, w is the connection weight matrix between the input layer and the hidden layer,

$$w=\left\{w_{jt}\right\}\ (j=1,2,\cdots,K;t=1,2,\cdots,n) \tag{1}$$

* Corresponding author.
E-mail addresses: duhailian@126.com (H. Du)

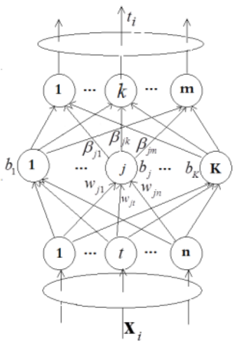

Fig.1 ELM architecture

where w_{jt} is the connection weight value linking the jth neuron node of hidden layer with the tth neuron node of input layer, and b_j is the threshold of the jth hidden layer neurons node. The output layer contains m neuron nodes. β is the connection weight between the hidden layer and output layer ,

$$\beta=\{\beta_{jk}\}\ (j=1,2,\cdots,K;\ k=1,2,\cdots,m) \tag{2}$$

where β_{jk} is the connection weight value between the jth hidden layer neurons node and the Kth neuron node of input layer.

Assume there are N samples, and each of them contains n attributes, the network input and expectations output are indicated as the following,

$$\mathbf{x}_i=\begin{bmatrix}x_{i1} & x_{i2} & \cdots & x_{in}\end{bmatrix}^T \tag{3}$$

$$\mathbf{y}_i=\begin{bmatrix}y_{i1} & y_{i2} & \cdots & y_{im}\end{bmatrix}^T\ (i=1,2,\cdots,N) \tag{4}$$

The activation function of the hidden neurons node can choose Sigmoid , RBF and so on. The actual output of the network is formulated as:

$$T=[t_1 \quad t_2 \quad \cdots \quad t_i \cdots \quad t_N] \tag{5}$$

$$t_i=\begin{bmatrix}t_{i1}\\ t_{i2}\\ \vdots \\ t_{im}\end{bmatrix}=\begin{bmatrix}\sum_{j=1}^{K}\beta_{j1}g(w_jx_i+b_j)\\ \sum_{j=1}^{K}\beta_{j2}g(w_jx_i+b_j)\\ \vdots \\ \sum_{j=1}^{K}\beta_{jm}g(w_jx_i+b_j)\end{bmatrix}\quad (i=1,2,\cdots,N) \tag{6}$$

where $w_j=[w_{j1},w_{j2},\cdots,w_{jn}]$, The training example is approached with zero error by ELM defined in the above, that is

$$\sum_{i}^{N}\|t_i-y_i\|=0 \tag{7}$$

The above can be written into the matrix form:

$$Y^T=H\beta \tag{8}$$

$$H=\begin{bmatrix}g(w_1x_1+b_1) & \cdots & g(w_Kx_1+b_K)\\ \vdots & & \vdots \\ g(w_1x_N+b_1) & \cdots & g(w_Kx_N+b_K)\end{bmatrix}_{N\times K} \tag{9}$$

$$\beta=\begin{bmatrix}\beta_{11} & \beta_{12} & \cdots & \beta_{1m}\\ \beta_{21} & \beta_{22} & \cdots & \beta_{2m}\\ \vdots & \vdots & & \vdots \\ \beta_{K1} & \beta_{K2} & \cdots & \beta_{Km}\end{bmatrix}$$

$$Y=\begin{bmatrix}y_1 & y_2 & \cdots & y_N\end{bmatrix}_{m\times N}=\begin{bmatrix}y_{11} & \cdots & y_{1N}\\ \vdots & & \vdots \\ y_{m1} & \cdots & y_{mN}\end{bmatrix} \tag{10}$$

where H represents the output matrix of the hidden layer. When the activation function is infinitely differentiable, the connection weight and the threshold of the hidden layer can be chosen randomly. These parameters remain the same in the training process. The connection weight value between the hidden layer and output layer could be obtained by solving the equation set

$$H\hat{\beta}-Y^T=0 \tag{11}$$

The least-squares solution is shown below,

$$\hat{\beta}=H^+Y^T \tag{12}$$

H^+ is generalized inverse matrix of H. When H^TH is nonsingular matrix[15],

$$H^+=\left(H^TH\right)^{-1}H^T \tag{13}$$

In ELM, The hidden layer parameters are assigned randomly , the weight of the output layer is be gotten by least-squares method, so ELM has the advantage of the strong generalization ability and fast training speed and so on.

The steps of learning machine algorithm can be summarized as follows,

Step1: Ascertain the number of the neurons nodes of the hidden layer, then set randomly the connection weight of the input layer and the hidden layer and the threshold of the hidden layer neurons node.

Step 2: Choose an activation function, calculate the output matrix of the hidden layer neurons node.

Step 3: Calculate the output weight.

2.2 Weighted extreme learning machine

Although ELM has strong generalization ability and fast training speed, its classification performance tends to decrease significantly when the distribution of sample data is unbalanced. H.L. Yu analyzes the reasons why the imbalance distribution of the sample is harmful to the performance of the extreme learning machine. To deal with data with imbalanced distribution [15]. Zong proposed the weighted ELM which could be generalized to cost sensitive learning, by assigning different weights for each example according to users' needs[16]. The objective function WELM is

$$\begin{cases} Minimize L=\frac{1}{2}\|\beta\|^2+\lambda\frac{1}{2}\sum_{i=1}^{N}(W_{ii}\|\varepsilon_i\|^2)\\ Subject\ to: h(x_i)\beta=t_i-\varepsilon_i\end{cases} \tag{14}$$

Where W is a diagonal matrix with the size of N×N, W_{ii} is the corresponding weight of the ith training sample. If minority sample is given greater weight than majority sample, penalty of training error will be increased, and the misclassification probability will be reduced. λ is the penalty factor to regulate the balance between generalization and accuracy of network. There are usually two kinds of weighting schemes, one is the automatic weighting scheme, and the calculation formula is as follows:

$$W_1=1/count(t_i) \tag{15}$$

Where W_1 represents the first weighting method, $count(t_i)$ means that the number of the sample which output set is t_i in the training.

The training samples are divided into minority class and majority class according the number of training samples in the second weighted scheme. It follows the idea of assigning weights by 0.618:1 for minority class and majority class. Its calculation formula is as follows:

$$W_2 = \begin{cases} 0.618/count(t_i), & t_i \text{ is majority class} \\ 1/count(t_i), & t_i \text{ is minority class} \end{cases} \quad (16)$$

It can be seen from the above formula that the classification precision of minority class is improved by reducing the classification precision of majority class in the second weighted schemes.

Therefore, the weighted schemes has to be selected according to the characteristics of the training samples to ensure the accuracy of the diagnosis.

The formula to calculate the output weight of the hidden layer is as follows:

$$\hat{\beta} = H^+Y = H^T(\frac{I}{\lambda} + WHH^T)^{-1}Y \quad (N \le K) \quad (17)$$

$$\hat{\beta} = H^+Y = (\frac{I}{\lambda} + H^TWH)^{-1}H^TWY \quad (N \ge K)$$

The corresponding output function is:

$$f(x) = \begin{cases} h(x)H^T(\frac{I}{\lambda} + WHH^T)^{-1}Y & (N \le K) \\ h(x)(\frac{I}{\lambda} + H^TWH)^{-1}H^TWY & (N \ge K) \end{cases} \quad (18)$$

The algorithm of WELM can be summarized as follows:

Step1： Set the number of hidden layer node K and penalty factor λ , set randomly the connection weight of the input layer and the hidden layer and the threshold of the hidden layer neurons node.

Step2: Calculate the hidden layer output matrix H;

Step3: Select the appropriate weighted scheme to calculate the sample weighted matrix W;

Step4: Calculate the connection weight of hidden layer output layer $\hat{\beta}$;

Step5: Calculate network output.

3. Fault diagnosis of analog filter circuit

3.1 Fault sample data of filter circuit

Sallen Key filter[17] is regarded as the example of analog circuit for fault diagnosis. The circuit schematic diagram is shown in Fig.2, where the input signal of filter is sine function. The tolerance of capacitances and resistances is -5%~+5%and -10%~+10% respectively.

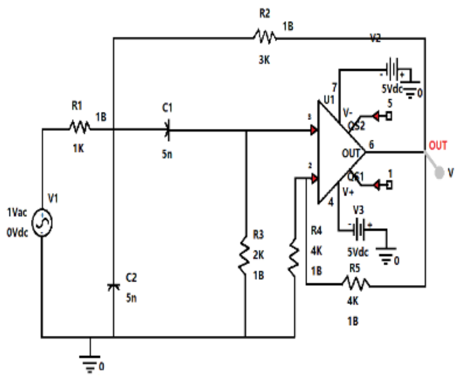

Fig. 2 schematic diagram of filter circuit

The fault of capacitances and resistances such as C_1, C_2, R_2, R_3 have great effect on filter circuit by sensitivity analysis. It is easy to measure and extract the corresponding fault characteristic.

To improve reliability of the data, in the frequency range of 1 ~ 100kHz, the node voltage of four components which is under the frequency of 2kHz, 9kHz, 18kHz, 35kHz,48kHz and 86kHz are randomly chosen as the sample data. It is shown in tab.1.

The data in Table 1 is divided into training set and test set, serial number 1 is the fault of capacitance C_1, serial number 2 is the fault of capacitance C_2, serial number 3 is the fault of resistance R_2, serial number 4 is the fault of resistance R_3. The number of all kinds of the sample is shown in Tab.2.

Tab.1 Part sample data

Fault type	2kHz	9kHz	18kHz	35kHz	48kHz	86kHz
1	0.07	0.67	0.99	0.87	0.70	0.52
1	0.12	0.99	1.28	0.98	0.78	0.57
1	0.10	0.85	1.36	0.75	0.75	0.60
1	0.09	0.80	0.87	0.89	0.64	0.51
1	0.09	0.68	0.92	0.84	0.68	0.60
2	1.014	1.143	1.231	1.309	1.489	1.555
2	1.062	1.127	1.238	1.331	1.408	1.545
2	1.027	1.166	1.281	1.391	1.41	1.508
…	…	…	…	…	…	…
2	1.028	1.149	1.276	1.359	1.428	1.572
2	1.052	1.169	1.288	1.364	1.469	1.568
3	13.4	14.97	15.75	16.27	17.99	18.94
3	13.38	14.03	15.1	16.25	17.2	18.61
…	…	…	…	…	…	…
4	21.31	22.14	24.98	27.85	28.06	29.91
4	20.36	23.54	24.11	27.69	28.14	28.16

Tab.2 The number of all kinds of samples

Fault number	fault type	training sample set	test Sample set
1	C_1	5	5
2	C_2	10	5
3	R_2	10	5
4	$\boldsymbol{R_3}$	8	6

3.2 Fault diagnosis of filter circuit based on ELM

Using the input and output data of the training set sample, an extreme learning machine fault classification model can be established. The specific steps are as follows:

(1) Determine input matrix of the training set and test set.

In table 1, each sample contains 6 features corresponding to the input voltage of 6 different frequency, that is, each sample has 6 properties. The training set input matrix can be expressed as $X = [x_{i1}, x_{i1}, \cdots, x_{i6}]\ (i = 1, 2, \cdots 33)$; The test set input matrix can be expressed as $X = [x_{i1}, x_{i1}, \cdots, x_{i6}]\ (i = 34, 35, \cdots 54)$.

(2) Determine network structure and parameters of extreme learning machine

Determine network structure and parameters of extreme learning machine, which means that the input layer, hidden layer, output layer node number of ELM are determined according to the characteristics of the sample and the type of fault. Each sample in table 1 has 6 properties, The 54 samples contain four types of fault in table 2. Corresponding to the sample properties and fault types, the ELM input layer includes 6 neuron nodes and the output layer includes 4 neuron nodes, if the number of hidden layer neurons is 120, the ELM network structure is (6-120-4). The parameter setting of the extreme learning machine include the input layer and the hidden layer connection weight matrix w_i , hidden layer neuron threshold matrix b , set w_i is the random number from -1 to 1, and its dimension is 120×6, b is the random number from 0 to 1, and its dimension is 120×1.

(3) Establish output matrix of training set and test set.

For the convenience of training, testing and fault diagnosis, the fault type of the filter circuit is represented by 0 and 1 , the desired output matrix of training set and a test set are composed of codes 0 and 1, which represent the fault type of the filter circuit ; Each column of the desired matrix corresponds to the neuron node of output layer of the extreme learning machine. If the fault type of the jth $(j=1,2,\cdots,54)$ sample is i $(i=1,2,3,4)$, then the elements in the ith row and jth column of the desired output matrix are 1, and the other elements in the jth column are 0, That means, in the expected output matrix, the row and column which element 1 is in indicate the fault type and the sample number respectively, the corresponding relationship between the fault type and the output node ELM of are shown in Tab.3.

Tab.3 Relationships of fault types and output of neurons

serial number	fault type	expected output 1	…	5	6	…	15	16	…	25	26	…	54
1	C_1	1	…	1	0	…	0	0	…	0	0	…	0
2	C_2	0	…	0	1	…	1	0	…	0	0	…	0
3	R_2	0	…	0	0	…	0	1	…	1	1	…	0
4	R_3	0	…	0	0	…	0	0	…	0	0	…	1

The 33 columns data corresponding to the training set input matrix are selected from table 3 to form expectation output matrix of the training set, its dimension is 4×33, the remaining 21 columns in table 3 constitute the expectation output matrix of test set, and its dimension is 4×21.

(4) Calculate the output matrix H of the hidden layer neuron

The activation function $g(\cdot)$ adopts the sigmoid function,

$$g(w_i x+b_i)=\frac{1}{1+e^{(-w_i x+b_i)}} \tag{19}$$

The output matrix of the hidden layer neuron $H_{N\times K}$ can be obtained by substituting each row of the normalized input matrix of training set into the sigmoid activation function.

(5) Calculate the output weight

Substitute the expected output matrix H of the training set and the hidden layer neuron into equation (12), and the estimated value of the output weight matrix $\hat{\beta}$ can be obtained. The ELM classifier model for fault diagnosis is the following,

$$Y^T=H\hat{\beta}$$

(6) Test the classification accuracy using the trained ELM

The sample under test is substituted into the base classifier model, the fault type of the sample can be determined according to which low the maximum value of the sample output is. The diagnostic results of the training set and test set are shown in Fig.3 and Fig. 4.

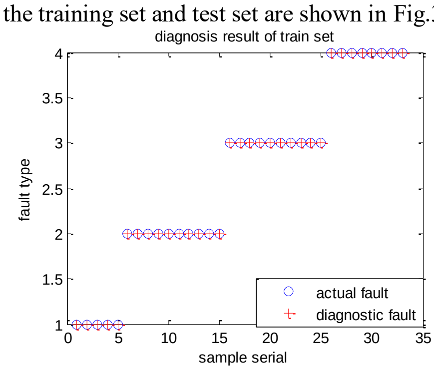

Fig.3 Diagnosis result of train test based on ELM

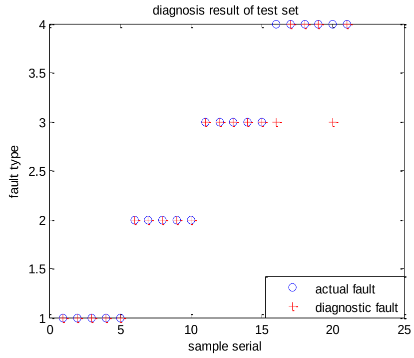

Fig.4 Diagnosis result of test set based on ELM

Fig. 3 shows that all 33 samples of the training set are correctly classified, it can be seen from Fig.4 that the 16th and 20th sample in the test concentration are misclassified, 19 samples are correctly classified, and the overall classification accuracy of the test set is 90.47% (19/21).

3.2 Fault diagnosis of filter circuit based on WELM

WELM is an improved algorithm based on ELM to deal with the imbalance data. WELM can be performed as long as the weighted matrix W and penalty factor λ the parameters are determined. The main steps are as follows,

(1) Determine the weighted matrix of each sample

For Sallen Key filter analog, using the data in Tab.1 and Tab.3, the weighted matrix for fault types of train set is assigned by formula (15).

$$W=\begin{bmatrix}0.2 & 0 & 0 & 0\\ 0 & 0.1 & 0 & 0\\ 0 & 0 & 0.1 & 0\\ 0 & 0 & 0 & 0.125\end{bmatrix}$$

(2) Calculate output matrix H

According the step 4 of ELM algorithm calculate the output matrix H of the hidden layer neuron.

(3) Select penalty factor λ

The punishment factors λ is searched in the range of [30-3030]. The data was divided into 100 groups in sequence, each group is an minimal interval. The average classification of train set and test set is obtained in different interval. The results are shown in the Fig.5. The average accuracy of the 80th groups reaches 93 percent, and then it is leveling off after that. The 84th interval is selected as more accurate range of the punishment factors λ. λ is in the range of (252-282). λ is selected 260 by trial and error.

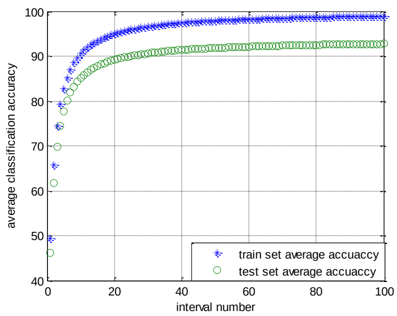

Fig 5 Average classification accuracy of different interval

(4) Output weight of the hidden layer

Because the number of hidden layer nodes is more than the samples, the output weight of the hidden layer is calculated by the first equation in (17)

That is,

$$\hat{\beta} = H^{+}Y = H^{T}(\frac{I}{\lambda} + WHH^{T})^{-1}Y$$

Finally network output could be obtained, the diagnosis result based on WELM is shown in Fig.6 and Fig.7.

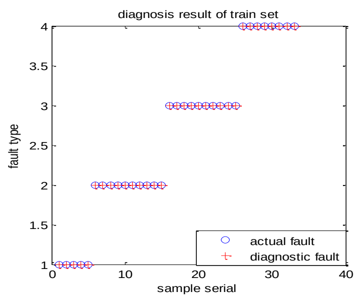

Fig.6 Diagnosis result of train test based on WELM

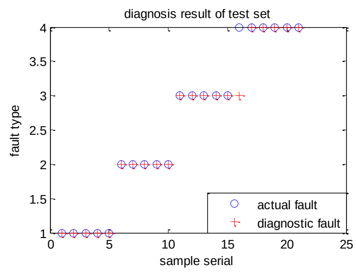

Fig.7 Diagnosis result of test set based on WELM

Fig.6 shows that all 33 samples of the training set are correctly classified, it can be seen from Fig.7 that the 16th sample in the test set are misclassified, 20 samples are correctly classified, and the overall classification accuracy of the test set is 95.238% (20/21).

The comparison of diagnosis result of different algorithm is shown in Tab.4.

Tab.4 Comparison of diagnosis result

Algorithm	total number of samples	Accuracy of training set (%)	Accuracy of test set (%)
ELM	54	100%	90.4762%
WELM	54	100%	95.2380%

It can been seen from Tab.4 that the two algorithms have the same accuracy for training set ,but for the test set WELM has the higher classification accuracy then ELM.

4. Summary

The Sallen Key analog filter circuit is diagnosed based on ELM and WELM. There are quick learning speed and good generalization performance in the two methods. For imbalance samples, weighted extreme learning machine has improved the accuracy of analog circuit fault diagnosis to some extent. ELM and WELM are applied to fault diagnosis of analog filter circuit in this paper. The simulation results of examples show that the two algorithms have the same accuracy for training set, but for the test set WELM has the higher classification accuracy then ELM.

Acknowledgements

This work has been partly supported by National Natural Science Foundation (NO. 61673160), Hebei Education Department Program (ZD2016053, Z2011141, Z2015097), Major Foundation of Hebei Normal University (L2013Z06), Hebei Province Science and Technology Department Program (15212115).

References

[1] Aminian F, Aminian M, Collins H W J. Analog fault diagnosis of actual circuits using neural networks[J]. Instrumentation & Measurement IEEE Transactions on, 2002, 51(3):544-550.

[2] Aminian M, Aminian F. A Modular Fault-Diagnostic System for Analog Electronic Circuits Using Neural Networks With Wavelet Transform as a Preprocessor[J]. IEEE Transactions on Instrumentation & Measurement, 2007, 56(5):1546-1554.

[3] Catelani M, Fort A. Soft fault detection and isolation in analog circuits: some results and a comparison between a fuzzy approach and radial basis function networks[J]. IEEE Transactions on Instrumentation & Measurement, 2002, 51(2):196-202.

[4] Cannas B, Fanni A, Manetti S, et al. Neural network-based analog fault diagnosis using testability analysis[J]. Neural Computing & Applications, 2004, 13(4):288-298.

[5] Yuan L, He Y, Huang J, et al. A New Neural-Network-Based Fault Diagnosis Approach for Analog Circuits by Using Kurtosis and Entropy as a Preprocessor [J]. IEEE Transactions on Instrumentation & Measurement, 2010, 59(3):586-595.

[6] Li X, Zhang Y, Wang S, et al. Analog circuits fault diagnosis by GA-RBF neural network and virtual instruments[C]// International Symposium on Instrumentation & Measurement, Sensor Network and Automation. IEEE, 2012:1-5.

[7] Zhao D, Xing J, Wang Z. Multi-dimensional neural network and its application in fault diagnosis of analog circuits[C]// International Conference on Materials Engineering, Manufacturing Technology and Control. 2016.

[8] Huang G B, Zhu Q Y, Siew C K. Extreme learning machine: a new learning scheme of feedforward neural networks[J]. Proc.int.joint Conf.neural Netw, 2004, 2:985-990 vol.2.

[9] H. J. Rong, G. B. Huang, Y.-S. Ong. Extreme Learning Machine for Multi-Categoties Classification Applications. In: International Joint Comference on Neural Networks (IJCNN), 2008, 1709-1713

[10] G. -B. Huang, X. Ding, H.Zhou. Optimization method based on extreme learning machine for classification. Neurocomputing,2010:1-8

[11] Huang G B, Zhou H, Ding X, et al. Extreme learning machine for regression and multiclass classification [J]. IEEE Transactions on System, Man and Cybernetics, Part B: Cybernetics, 2012, 42: 513-529

[12] Huang G, Huang G B, Song S, et al. Trends in Extreme Learning Machine: A Review, Neural Networks [J]. 2015, 61: 32-48.

[13] Zhang L, Qin Q, Shang Y, et al. Application of DE-ELM in analog circuit fault diagnosis[C]// Prognostics and System Health Management Conference. IEEE, 2017:1-6.
[14] Xiong J, Tian S, Yang C. Fault Diagnosis for Analog Circuits by Using EEMD, Relative Entropy, and ELM[J]. Computational Intelligence & Neuroscience, 2016, 2016(1):7657054.
[15] YU Hualong ，QI Yunsong ，YANG Xibei，Study of Class Imbalance Fuzzy Weighted Extreme Learning Machine Algorithm. Journal of Frontiers of Computer Science and Technology. 2017, 11(4):619-632.
[16] Zong W, Huang G B, Chen Y. Weighted extreme learning machine for imbalance learning [J]. Neurocomputing, 2013, 101: 229-242.
[17] Zhang C, He G, Liang S. PCA-Based Analog Fault Detection by Combining Features of Time Domain and Spectrum[C]// International Workshop on Intelligent Systems and Applications. IEEE, 2009:1-4.

Du Wenxia obtained her master degree and doctor degree of control theory and control engineering major from the institute of electrical engineering of YanShan University in 2001 and 2012 respectively. She is currently working in Hebei Normal University. Her main research interests are in area of neural network control and predictive control of nonlinear system, the fault diagnosis based on data driven is her new research direction in recent years.

Zhao Xiuping obtained her master degree of Mechanical Manufacturing and Automation from the institute of Manufacture of SiChuan University in 2001. She is currently working in Hebei Normal University. Her main research interests are in area of integration of mechanics and electrics, Mechanical Manufacturing and Automation.

Du Hailian obtained her master degree control science and control engineering major from the Department of Automation of North China Electric Power University in 2006. She is currently working in Hebei Normal University. Her main research interests are in area of neural network control and information fusion, the fault diagnosis based on data driven is her new research direction in recent years.

Lv Feng obtained her bachelor's degree from electrical automation major of Hebei Electromechanical College in 1982. She obtained her Master’s degree from test measurement technology and instrument major of YanShan University in 2006. She is currently working in Hebei Normal University as professor and master supervisor. Her main research interests are in area of industrial intelligent control, information processing, fault detection and diagnosis technology and so on.