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The Faults Diagnostic Analysis for Analog Circuit Faults Based on Firefly Algorithm and Extreme Learning Machine

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***Abstract*—In this paper, a novel method for analog circuit fault diagnosis based on extreme learning machine (ELM) as classifier which is optimized firefly algorithm (FA) is proposed. The feasibility and effectiveness of the proposed method are verified by the simulations of Sallen-Key low-pass filter circuit. The results show that the proposed method is effective to identify and classify faults by comparisons to other methods, which indicate feasibility and practicability of our proposed method.**

***Index Terms*—firefly algorithm, extreme learning machine, analog circuit, fault diagnostic**

I. Introduction

Under the conditions of increased complexity and integration for large-scale integrated circuit, analog circuit fault diagnosis has become utmost importance to electronical industry [1]-[2]. And now, diagnostic methods for analog circuits are mainly classified into two categories [3]: Simulation Before Test (SBT) and simulation after test (SAT). The research of intelligent diagnosis, such as neural network (NN) [4] and support vector machine (SVM) [5], becomes one of the focus issues for analog fault diagnosis among to SBT. These technologies can be classified as the intelligent fault dictionary method, which use machine learning to get an intelligent fault dictionary. However, fault dictionary method can only diagnose circuit fault in known fault types. Meanwhile, it needs a large number of independent data, which may lead to weak scalability.

A new learning scheme of single hidden-layer feed-forward neural networks (SLFNs), called extreme learning machine (ELM), is proposed by Huang et al.[5]-[6], which randomly chooses the input weights and analytically determines the output weights of SLFNs. ELM has been proved having better generalization ability than other machine learning algorithms. In this paper, the ELM will be optimized via firefly algorithm to get improved classification performance for fault diagnosis. The example of Sallen-Key low-pass filter circuit shows that the algorithm classification holds high classified accuracy.

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II. FA and ELM

In this section, the basic involved theory will be introduced briefly.

A. Firefly Algorithm(FA)

In natural environment, fireflies use flash signals to attract each other. Based on this behavior, a metaheuristic algorithm was proposed by Xin-She Yang [7]. All the fireflies are considered unisexual and their attraction is directly proportional to the brightness. Therefore, firefly will be more attracted toward the firefly with higher brightness and moves in that direction.

Basic definitions can be summed up as following [8].

Definition 1: The intensity of firefly:

$$I = I_o \times e^{-\gamma r_{ij}} \tag{1}$$

where I_o is the biggest brightness of firefly. γ is light intensity absorbed coefficient that is constant. r_{ij} is distance of the firefly i and the firefly j.

Definition 2: The attractiveness of firefly is:

$$\beta = \beta_o \times e^{-\gamma r^2_{ij}} \tag{2}$$

β_o is the biggest attractiveness in the light source ($r = 0$).

Definition 3: The movement of a firefly i attracted to another more attractive (brighter) firefly j is determined by:

$$x_i(t+1) = x_i(t) + \beta(x_j(t) - x_i(t)) + \alpha(rand - \frac{1}{2}) \tag{3}$$

where α is the vector of random number taken from Gaussian distribution belonging to (0, 1).

The basic steps of the FA can be summarized as the following:

Step 1: Initialize parameters of the firefly algorithm, including the dimension of the problem, the number of

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fireflies, the maximum number of iterations, the values of α , β_o and γ are chosen.

Step 3: Random initialize fireflies' locations. Calculate the fitness function value as the original light intensity of a firefly.

Step 3: Calculate the light intensity and the attractiveness of each firefly by (1) and (2).

Step4: Update the state space location by (3), random interfere firefly in the best location.

Step 5: Recalculate the light intensity of each firefly in new location by (1).

Step 6: If the results meet its requirements, break to step 7; else, the number of iterations plus one, go to step 4.

Step 7: Output the global optimal location and the optimal individual values.

B. References Extreme Learning Machine (ELM)

ELM relies on fixed-weight hidden neurons (nodes) with non-linear activation functions. The weights of the hidden neurons are assigned randomly. For the traditional single-hidden layer feedforward network, the relation can be represented as following, when $\{(x_i, y_i)\}_{i=1}^{N}$ is given [9].

$$H_{ij} = g(\omega_i * x_i + b_j) \tag{4}$$

where x_i , y_i L and $g(x)$ is input data, corresponding targets, hidden nodes and activation function, respectively. If the outputs of the SLFN can approximate these N training data with zero errors, we have the following compact formulation:

$$HB = y_i^T , i = 1, 2, ..., N \tag{5}$$

Hidden layer activation function $g(x)$ is simplified expression as following:

$$HB = Y \tag{6}$$

where H , B and Y are followed:

$$H = \begin{bmatrix} g(\omega_1, b_1, x_1) g(\omega_2, b_2, x_1) \ldots g(\omega_N, b_N, x_1) \\ \vdots \\ g(\omega_1, b_1, x_N) g(\omega_2, b_2, x_N) \ldots g(\omega_N, b_N, x_N) \end{bmatrix}_{N \times N}$$

$$B = \begin{bmatrix} B_1^T \\ \vdots \\ B_N^T \end{bmatrix}_{N \times m} \qquad Y = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix}_{N \times m}$$

Hence a simple form of the solution is given explicitly, which can minimize the training errors as well as the norm of the output weights:

$$\hat{B} = H^{\dagger} Y \tag{7}$$

where $H^{\dagger}$ is the Moore–Penrose generalized inverse of matrix H .

III. Fault Diagnosis of Analog Circuit Based on FA-ELM

In this section, the proposed method will be described for fault diagnosis of analog circuit.

Although ELM has many advantages to classify data, such as lesser learning samples, faster speed and so on, the connection weight, between the hidden layer and the input layer, is given randomly, which may lead classified accuracy to be worse. To solve the problem, the firefly algorithm will be drew into the classified model to get better classified performance in this paper.

The amplitude-frequency curve will have certain changes when one component is in a fault. The features of fault data can be extracted using it. In Fig. 1, the algorithm schematic of FA combined with ELM is given for analog circuit fault diagnosis. Drive signal is regarded as input of analog circuit and fault information is regarded as output of that. Then samples will be normalized, and training data and testing data will be sorted. Note that the training and testing samples may have certain correlations, so principal component analysis (PCA) is necessary to eliminate redundancy information and reduce complexity. The parameters ω , b and $\boldsymbol{B}$ of ELM will be optimized by firefly algorithm, then the classified results could be obtained after test samples are put into optimal classified model with cross validation.

The processes of ELM classifier optimized by firefly algorithm in our proposed method is as followed:

Initialization:

Step1: Initialize parameters of the algorithm, such as the number of firefly m, the maximum iteration n , the random parameter α , the initialized attractiveness β_o , the light absorption coefficient. And generate randomly location of every firefly.

Step2: Construct ELM classified model and set the neuron number and the search space in the hidden layer.

Search process:

Step3: Define the size of firefly Size Pop using the optimization object "connection weight matrix ω ".

$$SizePop = l \times n_i \tag{8}$$

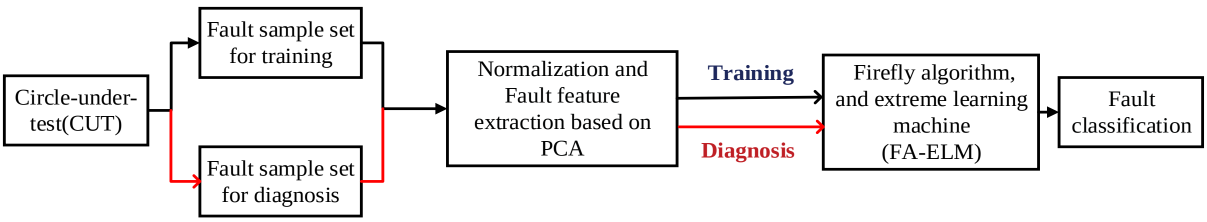

Figure 3. FA-ELM algorithm Schematic

where n_i and l are the neuro number of input layer and hidden layer, respectively.

Step4: Update location of every firefly:

$$x_i^{k+1} = x_i^k + \beta(x_j^k - x_i^k) + \alpha(rand - \frac{1}{2}) \tag{9}$$

Step5: Calculate the attractiveness β of every firefly by (10) and (11). And generate connection weights matrix between input layer and the hidden layer in ELM.

$$I_i = I_o e^{-\gamma r_{ij}} \tag{10}$$

$$\beta = \beta_o e^{-\gamma r^2{}_{ij}} \tag{11}$$

Step6: Calculate the weight matrix B by (4).

Step7: Calculate output training samples $\hat{y}_i$ by ω 、 b and β , $i = 1,2,\cdots,n$, where n is the number of output training samples.

Step8: Calculate the mean squared error (MSE) between the classified value and the actual value.

$$RESM = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(\hat{y}_i - y_i)^2}, i = (1,2,\cdots,k) \tag{12}$$

where k , y_i and $\hat{y}_i$ is the number of samples, the actual value and the classified value, respectively.

Convergence:

Step 9: update the global optimal individual.

Step10:Judge whether the iteration is equal to maximum iteration and the accuracy is less-than 10^{-3} or not. If so, jump Step11.

Step11: Judge whether l is less than the maximum value of searching range in the hidden layer neurons. If so, the iteration is initialized as l . And back to Step3.

Classification:

Step13: Calculate the B_{best} by (4). And construct the classified model by ω_{best} 、 b_{best} and B_{best} .

Step14: Classify the analog circuit faults with the trained ELM classifier.

IV .The Simulation and Results

In this section, the Sallen-Key low-pass filter circuit will be tested to verify the feasibility and effectiveness.

A. The Circuit under Test (CUT) and Parameters Settings

The normal value of every component is shown in Table I. And resistors and capacitors have 5% tolerance, respectively. Every normal value is: $C_1 = 5nF$, $C_2 = 5nF$ $R_1 = 1k\Omega$, $R_2 = 3k\Omega$, $R_3 = 2k\Omega$, $R_4 = R_5 = 4k\Omega$. Here, we assume resistors and capacitors in this interval $[50\%X, 95\%X) \cup (105\%X, 150\%X]$ (X is the normal value). Then faults can be classified to 8 fault models: $C_1\uparrow$, $C_1\downarrow$, $C_2\uparrow$, $C_2\downarrow$, $R_2\uparrow$, $R_2\downarrow$, $R_3\uparrow$, $R_3\downarrow$. Parameters of diagnostic classification method are defined as following: the number of hidden layer is 6 in ELM, the size of the firefly is 100, and the number of iteration is 200 and $\alpha = 0.5$, $\gamma = 1$.

where the meaning of '↑'is that value of component in fault comes to larger than normal value. Likewise, the '↓' is that value of components in fault comes to smaller than standard. And all patterns have 9 kinds of fault styles, including trouble-free style. The diagnosis Sallen-Key low-pass filter circuit, as shown in Fig. 4, is simulated by a circuit simulation software OrCAD10.5. The circuit is driven using sinusoidal voltage signal of 5V, and the corresponding frequency-voltage value of fault feature could be got according to the output amplitude-frequency curve. Finally, 20 features, 720 samples of 9 categories could be got by Monte Carlo Analysis.

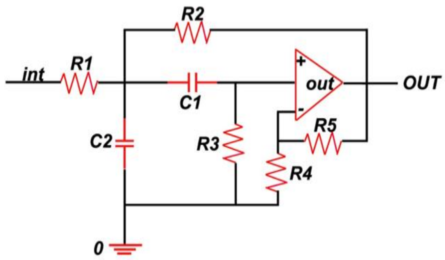

Figure 4. Sallen-Key low-pass filter.

TABLE I. Definition of Faults Type

Fault code	Fault class	Normal	Faulty value
1	$C_1\uparrow$	$5nF$	$7.5nF$
2	$C_1\downarrow$	$5nF$	$2.5nF$
3	$C_2\uparrow$	$5nF$	$7.5nF$
4	$C_2\downarrow$	$5nF$	$2.5nF$
5	$R_2\uparrow$	$3k\Omega$	$4.5k\Omega$
6	$R_2\downarrow$	$3k\Omega$	$1.5k\Omega$
7	$R_3\uparrow$	$2k\Omega$	$3k\Omega$
8	$R_3\downarrow$	$2k\Omega$	$1k\Omega$
9	NF	-	-

B. Discussion and Analysis

From the point of view of classifier's performance, the desirable results have been obtained in a few iterations with high classification rates. Fig. 5 shows the classified results of classified data and actual data, which only three data couldn't classified correctly. Fig. 6 shows the fitness function curve, and it is noticeable that the fitness has decreased quickly and then comes to be stable in the sixth iteration. Table II shows the detailed results of our proposed method to diagnose 8 fault styles with Sallen-Key low-pass filter. Every row corresponds to one fault style in this table. Different grid indicates the classified fault data belonging to various fault styles. For instance, All 20 test data of $C_1\downarrow$ was correctly classified in the second row and second column. However, 18 indicates that only 18 test data has been diagnosed correctly in the third row and another two is incorrectly diagnosed to NF (normal state) in the ninth row and third column.

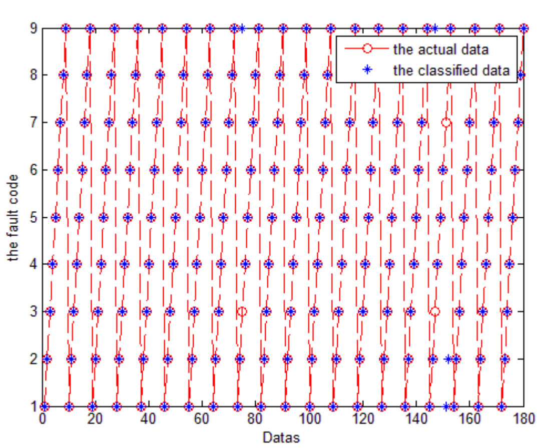

Figure 5.Curves of the actual and classified data

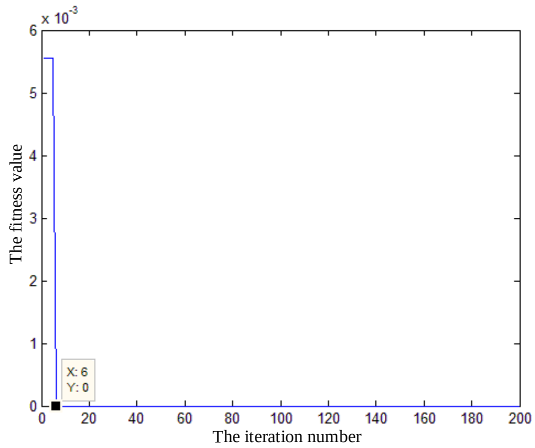

Figure 6. Curve of evolution

TABLE II. FAULT DIAGNOSIS OF SALLEN-KEY LOW-PASS FILTER CIRCUIT

Categories	$C_1\uparrow$	$C_1\downarrow$	$C_2\uparrow$	$C_2\downarrow$	$R_2\uparrow$	$R_2\downarrow$	$R_3\uparrow$	$R_3\downarrow$	*NF*
$C_1\uparrow$	**20**						1		
$C_1\downarrow$		**20**						1	
$C_2\uparrow$			**18**						
$C_2\downarrow$				**20**					
$R_2\uparrow$					**20**				
$R_2\downarrow$						**20**			
$R_3\uparrow$							**19**		
$R_3\downarrow$								**19**	
NF			2						**20**

There are many methods that have been proposed for fault diagnosis for Sallen-Key low-pass filter in the last few years. Now, we make comparison and discussion between our proposed method and others. An analog fault diagnostic method based on Neural-Network (NN) was proposed in [10], which used a data acquisition board to excite a circuit with an impulse and sample its output to collect training data for the neural network. Ref. [11] proposed analog fault diagnostic method based on wavelet neural networks (WNN) for actual circuits. And genetic algorithm was presented to optimize the structure and the parameters of WNN in the training process. That two methods could effectively improve the performance of the analog circuit fault classifier. However, the accuracy rate (97.775%) of our method is obviously higher than their accuracy rate (95%). A method for fault diagnosis in analog circuits using S-transform (ST) as a preprocessor and a quantum neural network (QNN) as a classifier is proposed in [12]. In this paper, the proposed ST method with the conventional wavelet transformation (WT) as a preprocessor to extract fault feature vectors with different NN classifiers for 9 test categories of Sallen-key. Although the classified accuracy is similar to our proposed method, our method is simpler and concise that is easier to implement than neural network.

TABLE III. THE COMPARISONS BETWEEN PROPOSED METHOD AND OTHERS

Algorithm	categories	Accuracy
Neural-Network[9]	9	95%
Genetic-WNN [10]	9	95%
WT-BPNN [11]	9	96.72%
WT-QNN [11]	9	98.13%
Algorithm proposed	9	97.77%

V. CONCLUSIONS

The fault diagnosis of analog circuit is focused to study in this paper. The main contribution is that a method of fault classification using firefly algorithm and extreme learning machine, is presented in our study. The proposed method takes advantages of excellent classification capacity of extreme learning machine. The input weight, output weight and threshold value would be optimized via firefly algorithm in order to improve the fault classification accuracy. The Sallen-Key low-pass filter has been simulated as the circuit under test. The simulation and comparison results show that this method has better performances and is indeed more effective and reliable than other methods proposed in past literatures.

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