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A novel method for Analog Circuit Faults Diagnosis Based on CSA

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***Abstract*—The paper emphasizes the way to the analog circuit fault diagnosis. The extreme learning machine(ELM) is used as classifier optimized by cuckoo search algorithm (CSA) and discussed in detail in the novel. The feasibility and effectiveness of the proposed method will be verified by the simulations of Sallen-Key low-pass filter circuit. Compared with other methods, the proposed method is more effective to identify and classify mistakes.**

Keywords—Cuckoo Search Algorithm, Extreme learning machine, Analog circuit, Fault diagnostic

I. INTRODUCTION

With development of technologies, analog circuits are becoming an important role in electrical equipment. Accordingly, analog circuit fault diagnosis has become extremely important to electronical industry [1]. And now, there are two main categories of diagnostic methods for analog circuits. [2]: simulation before test (SBT) and simulation after test (SAT). The researches of intelligent diagnosis, such as neural network (NN) [3] and support vector machine (SVM) [4], become one of the most significant matters for analog fault diagnosis 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 plan of single hidden-layer feed-forward neural networks (SLFNs), called extreme learning machine (ELM), is proposed by Huang et al. [4]-[5], who chooses the input weights at random and analyzes the output weights of SLFNs. ELM has been proved having better generalization ability than other machine learning algorithms. In the paper, the ELM will be optimized through cuckoo search algorithm to get improved for fault diagnosis. We can conclude that the algorithm classification holds high classified accuracy through the example of Sallen-Key low-pass filter circuit.

II. CSA AND ELM

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

A. Cuckoo Search Algorithm(CSA)

In nature, the way of cuckoo breeding is unusual. Some cuckoos lay their eggs in other birds' nests. It the eggs are found by other birds, they would be thrown or be abandoned [6]. The standard CAS steps can be expressed as the following three idealized rules [7]:

Basic definitions can be summarized as following [8]:

1) Number of nests that contain eggs with high quality will be transferred to the generation (elitism).

2) The number of available host nests is fixed, and a host can discover alien eggs with probability $pa \in (0,1)$ (mutation operator).

CAS simulates a random walk, a Markov chain, in which the following step lies on the transition probability from current location to the next one, to create new solutions in the first rule. Comparing with other potential approaches, Lévy finds a random walk is more efficient than regular walk or Brownian motions. CAS uses Mantegna's algorithm to produce a symmetric Lévy stable distribution.

When $pa \geq r$, outline of generating new solutions x_i^t via Lévy flights can be summed up as below [7]:

$$x_i^{t+1} = x_i^t + s \otimes Levy(\partial) \tag{1}$$

$$s = s_o \otimes (x_j^t - x_i^t) \tag{2}$$

$$Levy(\partial) = \frac{u}{|v|^{\frac{1}{\partial}}} \tag{3}$$

Where s is the amplification parameter, s_o is the scaling factor, x_i^t and x_j^t are the t -th iteration, the i -th and j -th nest, that is, two potential solutions, $\otimes$ shows entry-wise multiplications, $Levy(\partial)$ is the step length generated according to the Mantegna's algorithm, and ∂ is Lévy flights exponent.

Also, u and v are two random values from normal distribution with zero means and related variance, which is known in Eq.. (4). In this equation, G is the standard Gamma function.

$$\sigma_u = \left\{ \frac{G(1+\partial)\sin(\pi\partial/2)}{G(1+\partial/2)\partial 2^{(\partial-1)/2}} \right\}^{1/\partial}, \sigma_v = 1 \tag{4}$$

The second rule includes an optimal design to expedite convergence property of CAS. [7]. Finally, the last rule in this outline applies a probabilistic tactics to replace known solutions with new generated ones. The solutions proposed in this step are completely different from the current best solution.

When $pa < r$, the new solution is Come up with by original random walk which can be expressed as [9].

$$x_i^{t+1} = x_i^t + r \otimes H(pa-\varepsilon) \otimes (x_j^t - x_k^t) \tag{5}$$

Where, $H(u)$ is the Heaviside function, ε and r are two random numbers with a normal distribution, and the term in the second bracket corresponds to the difference of two stochastic solutions.

B. Extreme learning machine (ELM)

ELM relies on fixed-weight hidden neurons (nodes) with non-linear activation functions. The weights of the hidden neurons are planned stochastically. To achieve the original single-hidden layer feedforward network, the connection can be represented as following, when $\{(x_i, y_i)\}_{i=1}^N$ is given [10].

$$H_{ij} = g(\omega_i * x_i + b_j) \tag{6}$$

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

$$HB = y_i^T, i = 1, 2, ..., N \tag{7}$$

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

$$HB = Y \tag{8}$$

Where H, B and Y are followed:

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

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

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

$$\hat{B} = H^{\dagger} Y \tag{9}$$

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

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

The presented method will be applied in fault diagnosis of analog circuit in this section.

Although ELM can contribute to classify data, such as lessen learning samples, faster speed and so on, the connection weight, between the hidden layer and the input layer, is given randomly, which may cause the worsen of the classified accuracy. To solve the problem, the cuckoo search algorithm will be drew into the classified model to get better classified performance in this paper.

When a component fails, the amplitude frequency curve will undergo some changes. The characteristics of the fault data can be extracted from it. In Fig. 1, the schematic diagram of the combination of CSA and ELM for analog circuit fault diagnosis is given. Drive signals are considered as input to analog circuits, and fault information is treated as outputs. Then the samples are normalized, and the training data and the test data are sorted. Attention can be paid to the correlation between training samples and test samples. Therefore, principal component analysis (PCA) is needed to eliminate redundant information and reduce complexity. Through the cuckoo search algorithm, the parameters and ELM are optimized, and the sample is put into the optimal classification model by cross validation, and the classification results are obtained. The parameters ω, b and B of ELM will be optimized by cuckoo search algorithm, then the classified results could be obtained after test samples are put into optimal classified model with cross validation.

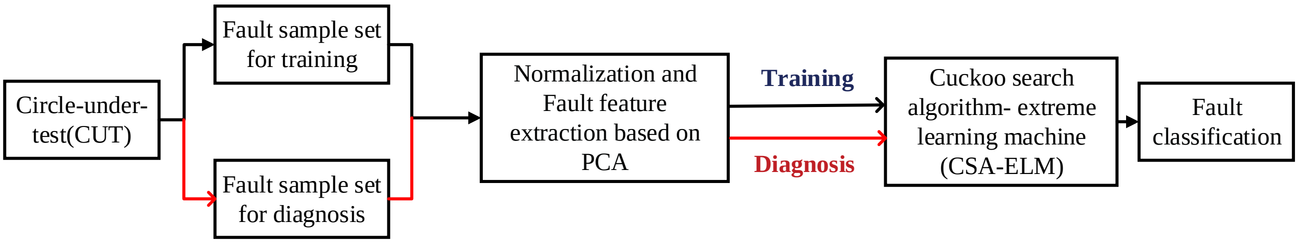

Fig. 1. CSA-ELM algorithm Schematic

Among the methods proposed in this paper, the optimization of the ELM classifier by the cuckoo searching algorithm is shown as follow:

Initialization:

Step1: Initialize parameters of the algorithm, such as the number of nest *m*, the maximum iteration n, the Lévy flights exponent ∂ and r. And generate randomly location of every nest.

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

Search process:

Step3: Define the size of nest SizePop applying the optimization object "connection weight matrix ω".

$$SizePop = l \times n_i \tag{10}$$

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

Step4: Update location of every nest using Eq:(1) and (5).

Step5: Update location of every nest according to r: if $r > pa$, it means host bird has found cuckoo's egg and remove them from its nest; Otherwise, there is no need to update location of nest.

Step6: Produce connection weights matrix between input layer and the hidden layer in ELM.

Step7: Calculate the weight matrix *B* by (8).

Step8: 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.

Step9: Calculate the mean squared error (MSE) between the classified value and the actual value.

$$RESM = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(\hat{y}_i - y_i)^2}, i = (1, 2, \cdots, k) \tag{11}$$

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

Convergence:

Step10: update the global optimal individual.

Step11:Judge whether the iteration is equal to maximum iteration and the accuracy is less-than 10^{-3} or not. If so, jump Step12.

Step12: 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

The Sallen-Key in this section is tested as a lowpass filter circuit to verify the feasibility and effectiveness.

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

The normal values for each component are shown in the table. 1. Resistors and capacitors have 5%tolerances 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 nest is 10, and the number of iteration is 100 and $\partial = 1.5$.

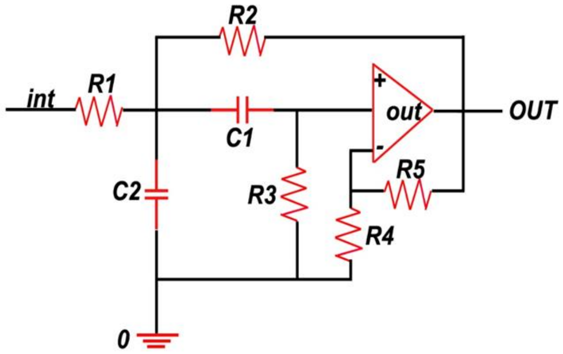

Fig.2. Sallen-Key low-pass filter.

Table 1. 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	-	-

"↑" means component failure value is higher than the normal value. Similarly, the "↓" means value is less than the standard component. All modes have 9 fault types,including a fault free style. The diagnostic Sallen-Key lowpass filter circuit, shown in Fig. 2, is simulated by circuit emulation software OrCAD10.5. This circuit is driven by 5V sinusoidal voltage signal, and the corresponding frequency and voltage value of fault characteristic can be obtained according to the amplitude frequency curve. Finally, through the Monte Carlo analysis, 20 characteristics were obtained,and 720 samples of 9 categories were used..

B. Discussion and Analysis

From the point of view of classifier's performance, satisfactory results are obtained in the iteration of high classification rate. Fig. 3 shows the classified results of the classified data and the actual data, in which only one data is incorrectly classified. Fig. 4 shows the curve of fitness function,

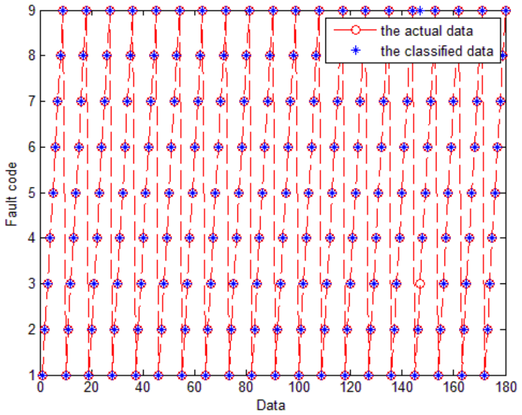

Fig.3. Curves of the actual and classified data

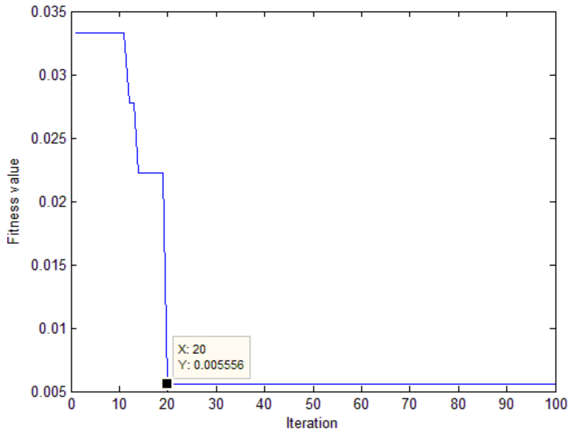

Fig.4. Curve of fitness value

Table 2. 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**								
$C_1\downarrow$		**20**							
$C_2\uparrow$			**19**						
$C_2\downarrow$				**20**					
$R_2\uparrow$					**20**				
$R_2\downarrow$						**20**			
$R_3\uparrow$							**20**		
$R_3\downarrow$								**20**	
NF			1						**20**

and it is noticeable that the fitness has decreased quickly and then comes to be stable in the twenty iterations and the fitness value is 0.005556, finally.

Table.2 shows the detailed results of our proposed method with the Sallen-Key low-pass filter to assure 8 fault kinds. Each line corresponds to a fault pattern in the table. Different grids represent classified fault data belonging to various fault types. For example, all 20 tests of $C_1\downarrow$ are correctly classified in the second row and second columns. However, 19 indicated that only 19 test data were correctly diagnosed as third lines, and the other was erroneously diagnosed as NF (normal state) in the ninth row and third column. 8 faults can be successfully diagnosed as Sallen-Key low-pass filters, with our proposed fault diagnosis method and classification accuracy of 99.4%. The classification results are in line with expectations.

A number of methods have been proposed in the past few years for the fault diagnosis of Sallen-Key low-pass filters. Now, we compare and discuss our approach with other methods. An analog fault diagnostic method based on Neural-Network (NN) was proposed in [11], 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. [12] An analog circuit fault diagnosis method based on wavelet neural network (WNN) is proposed. The genetic algorithm optimizes the structure of the wavelet neural network parameters during training. That two methods could effectively improve the performance of the analog circuit fault classifier. However, the accuracy rate of our method (99.4%) is significantly 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 [13]. 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. However, our accuracy rate is higher than its, what is more our method is simpler and concise that is easier to implement than its.

Table 3. The comparisons between proposed method and others

Algorithm	categories	Accuracy
Neural-Network [11]	9	95%
Genetic-WNN [12]	9	95%
WT-BPNN [13]	9	96.72%
WT-QNN [13]	9	98.13%
Algorithm proposed	9	99.77%

V. CONCLUSIONS

In this paper, the problem of analog circuit fault diagnosis is studied and discussed. The main contribution of this paper is to propose a method for fault classification using the cuckoo search algorithm and the extreme learning machine. The method combines the excellent classification ability of the extreme learning machine and the optimization ability of the cuckoo search algorithm. In order to improve the accuracy of fault classification, we can optimize the input weights, the output weights and the threshold by using the cuckoo searching algorithm. The Sallen-Key low pass filter is tested with analog circuits. Simulation and comparison results show that the proposed method performs better than other methods proposed in the previous literature.

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