

# Application of Multi-frequency Test and Neural Network to Fault Diagnosis in Analog Circuits

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## ABSTRACT

In this paper, the multi-frequency test and neural networks (NNs) are applied to fault diagnosis in analog circuits. The reason is that multi-frequency test can maximize differences between the failure and the normal circuit's response, and NNs can solve complex classification problems. Firstly, using sensitivity analysis, the multi-frequency test vectors of the circuit under test(CUT) are generated. Then, selecting waveform amplitude, fault features of test points in CUT are extracted and fused. Last, NNs are used to classify the features for the faulty components detected and located. The experimental result shows that this approach is effective and practical for fault diagnosis in the analog circuits.

**Keywords:** multi-frequency, neural networks, sensitivity analysis, fault diagnosis

## 1 INTRODUCTION

Analog circuit fault diagnosis has been a challenging research topic. The nature of the signal in the objective world determines the universality and irreplaceable of analog circuits. The algorithms and theoretical research have not a breakthrough in analog circuit fault diagnosis and test vector generation[1], which is determined by analog circuits own characteristics, namely: the continuous signals in the input and output ports, the complex fault models, the component tolerances, the nonlinear feedback[2]. The neural network has many advantages, such as nonlinear mapping, learning reasoning, etc., which is suitable for analog circuits fault diagnosis. So it has the prospects for development in analog circuits.

In recent years, many researchers have made significant progress in the two aspects of fault feature extraction and neural network's application in analog circuits. In feature extraction[3-5], many methods, such as principal component analysis, wavelet transform and information fusion, are used to extract the fault characteristics of linear and nonlinear analog circuit for fault diagnosis. In the neural network's application[6-8], many kinds of neural networks, such as multi-layer perceptron network, radial basis function network and wavelet neural network, are used for fault classification and identification in analog

circuits. However, in the above literatures, the work about the test stimuli(test vectors generation) is not popular. And there are many shortages, such as the randomness and the lack of theoretical guidance for the test stimuli generation. This provides development opportunities for the application of multi-frequency test. So the research of the multi-frequency test vector generation in analog circuits has a positive meaning.

Multi-frequency test is to stimulate the circuit under test(CUT) with sinusoidal signals of different frequencies. By observing the output signal amplitude of the pre-selected test node in analog circuits, the output response between the normal circuit and the fault circuit is different. This method can reduce and simplify the difficulty of the classification and identification of faults in analog circuits.

A single failure probability is 70 to 80 percent of the total number of failures in electronic devices. And some multi-faults are often linked with different single failure, which can be used as a single-fault handling. For exposition convenience, the single-fault test of analog circuits is considered in this paper. Firstly, sensitivity analysis is used to guide multi-frequency test vector generation and select the optimal test stimulus, which makes the circuit status differences are significant. Then the neural network is used to detect and locate the fault components in analog circuits. The experimental results show that this method is very effective and highly practical for fault diagnosis of analog circuits.

## 2 MULTI-FREQUENCY TEST

The fault diagnosis equations of the components in the circuit under test are composed of the selected test points' network transfer functions. As the following equation (1) shown.

$$H_l^{(k)}(s) = \frac{N_l(p, s)}{D(p, s)} = \frac{\sum_{i=0}^n a_i^{(k)}(p) s^i}{s^m + \sum_{j=0}^{m-1} b_j^{(k)}(p) s^j}; l = 1, 2, \dots, K \quad (1)$$

Where  $P = [p_1, p_2, \dots, p_r]^T$  are the potential faults,  $K$  is the number of test nodes, and coefficients of  $a_i^{(k)}$  and  $b_j^{(k)}$  are the functions of components in CUT.

Multi-frequency test vector is a set of different test frequencies, which can get the significant differences between the fault circuit and the normal circuit output. The sensitivity analysis is an effective method of fault diagnosis in analog circuits[9-10]. And the sensitivity analysis can be used to select the multi-frequency test frequencies and obtain the best multi-frequency test vectors, which makes the normal circuit's nodes output  $y(t)$  and fault circuit's nodes output  $y'(t)$  significantly different.

Sensitivity analysis has two types: differential sensitivity, which is for soft fault of the components; incremental sensitivity, which applies to components of the hard fault. Differential sensitivity equation is as (2) shown.

$$S_{p_i}^{H_i^{(k)}}(f) = \frac{x}{H_i^{(k)}} \frac{\partial H_i^{(k)}}{\partial p_i} = \frac{x}{H_i^{(k)}} \frac{\partial}{\partial p_i} \left( \frac{N(f, p_i)}{D(f, p_i)} \right) \quad (2)$$

In the industrial, on the one hand, by the test efficiency and test cost constraints, only less actual test frequencies are used to test; on the other hand, the components of soft fault diagnosis has been the difficulty of the study. Therefore, in this paper the differential sensitivity are used to generate multi-frequency test vectors, as shown in the following steps:

Step1: According to the equation (2), the sensitivity equation of each test node is calculated;

Step2: Each graph of the sensitivity equation in optimal test nodes is drawn;

Step3: Calculating the frequency of extreme points in each sensitivity graph, the necessary multi-frequency test vector is obtained.

### 3 EXPERIMENTS AND ILLUSTRATION

The CUT is Band Pass State Variable Filter(BPSVF), as Figure 1 shown. Each component has a tolerance of 5%.

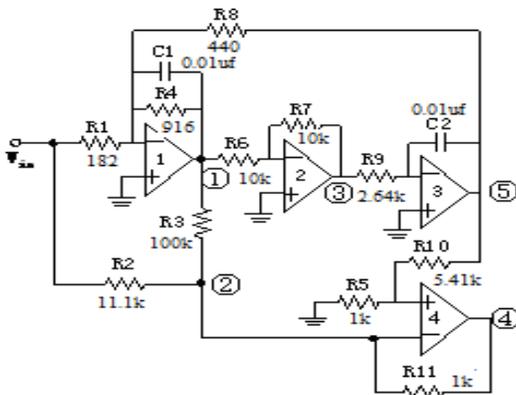


Figure 1: A Band Pass State Variable Filter

### 3.1 Multi-Frequency Test Vector Generation

After testability analysis for BPSVF, the optimal nodes-①③④⑤ are obtained. The components for diagnosed are {G2,G5,G6,C1,C2}.The steps of multi-frequency test vector generation are as following:

Step1:According to the equation (2),  $S_{p_i}^{H_i^{(1)}}$ ,  $S_{p_i}^{H_i^{(3)}}$ ,  $S_{p_i}^{H_i^{(4)}}$  and  $S_{p_i}^{H_i^{(5)}}$  are calculated respectively through MATLAB;

Step2: Sensitivity graphs(SGs) of the chosen nodes are drawn, as Figure 2-3 shown;

Step3: The frequency values, where located in peaks/troughs of SGs, are obtained. (Table 1)

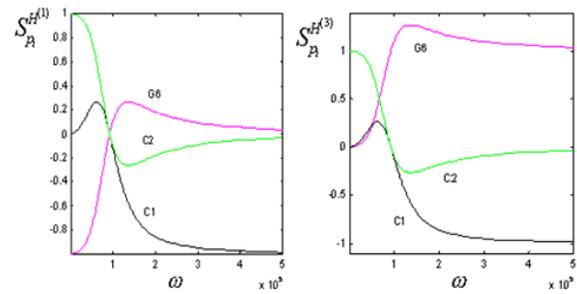


Figure 2: SGs of ①③

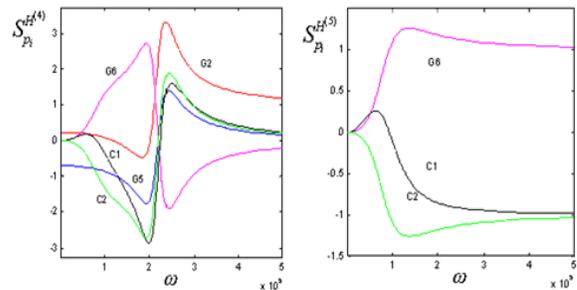


Figure 3: SGs of ④⑤

Nodes Com.	①	③	④	⑤
G2	-	-	1.8/2.4	-
G5	-	-	1.9/2.4	-
G6	1.3	1.3	1.9/ 2.5	1.3
C1	0.6	0.6	2.0/ 2.5	0.6
C2	1.3	1.3	2.0/ 2.5	1.3

Table 1: Test Nodes and Multi-Frequency Vector

According to Table 1, the obtained multi-frequency test vectors are  $\omega = \{1.3, 0.6, 1.8, 1.9, 2.0\}$ (rad/s) . In actual testing, multi-frequency test vectors are compressed to further reduce the cost and time required for testing. The analysis shows that  $\omega = 1.8$ rad/s, all kinds of fault components in Table 1 could be detected and identified.

### 3.2 Fault Components Diagnosed

In order to verify test vectors on the effect of the fault components diagnosis, the sinusoidal stimuli signal is  $V_{in} = \sin(1.85E5*t)$ . We assume that the components of  $R_i(i=2,5,6)$  have soft faults within the  $\pm 40\%$  normal value, and  $C_j(j=1,2)$  within the  $\pm 50\%$ . So faults can be classified into two simple fault modes:  $R_i \uparrow$  and  $R_i \downarrow$ ,  $C_j \uparrow$  and  $C_j \downarrow$ . Where  $\downarrow$  and  $\uparrow$  stand for low and high. A total of 10 kinds of failure modes are diagnosed.

The Peaks and troughs value in the output waveform from the test nodes are extracted, namely  $V_{mH}$  and  $V_{mL}(m=1,3,4,5)$  are as fault features. The fault feature information of the four test nodes ①③④⑤ are fused. And the formation of 8-dimensional fault feature vectors is  $F_{ij} = \{V_{1H}^{ij}, V_{1L}^{ij}, V_{3H}^{ij}, V_{3L}^{ij}, V_{4H}^{ij}, V_{4L}^{ij}, V_{5H}^{ij}, V_{5L}^{ij}\}$ , where:  $i=1,2,\dots,10; j=1,2, \dots,30$ .

BP NN input and output sequences are constituted by the fault feature vectors and failure modes respectively. Two patterns, ie. train patterns and test patterns, are constructed. For each failure mode, the Monte-Carlo analysis is 30 times, which are divided by 20 training patterns and 10 testing patterns.

BP NN is used to diagnose the faults of the CUT. To improve the NN training speed, the heuristic improvement algorithm, which means momentum correction, is adopted in BP NN. The training patterns are input to BP NN, and the mean square error(MSE) is set to 0.015. After several adjustments, BP NN's parameters are as following: network structure 8-8-15-10, learning rate 0.25 and momentum factor 0.8. The pre-set MSE is achieved after 4,390 times train for BP NN.

In order to test the fault diagnosis capability of the trained BP NN, the NN is tested with the training patterns and the testing patterns (Table 2).

Fault Components	Training Patterns			Testing Patterns		
	Total	Correct	Correct	Total	Correct	Correct
	Num	Num	Rate (%)	Num	Num	Rate (%)
R2↓	20	20	100	10	10	100
R2↑	20	20	100	10	10	100
R5↓	20	16	80	10	6	60
R5↑	20	20	100	10	10	100
R6↓	20	20	100	10	10	100
R6↑	20	20	100	10	10	100
C1↓	20	20	100	10	10	100
C1↑	20	20	100	10	10	100
C2↓	20	20	100	10	9	90
C2↑	20	15	75	10	8	80

Table 2: Results of BP NN for fault diagnosis

From Table 2, the average correct of training and testing mode is 94%. The fault diagnosis accuracy is high. It provides that the selected test vector is effective for the fault diagnosis in analog circuits.

## 4 SUMMARY

In this paper, a multi-frequency test and neural network fault diagnosis method is presented, which is described in detail from the test vectors generation to the test response analysis. Using sensitivity analysis, the test frequencies are selected. And using BP NN, the features of each node's response are fused for fault diagnosis. The simulation results show that the method is effective and has some references for large-scale analog circuit testing.

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