



Test Point Selection and Multiple Soft Faults Detection in Linear Analog Circuits Based on Multiple Frequency Measurements

G.Puvaneswari

Department of Electronics and Communication Engineering, Coimbatore Institute of Technology, Coimbatore-641 014, India.

S.UmaMaheswari

Department of Electronics and Communication Engineering, Coimbatore Institute of Technology, Coimbatore-641 014, India.

ABSTRACT

A method to identify and select test points for analog circuit testing and to detect multiple soft faults in linear analog circuits using multiple frequency measurements is proposed in this paper. Modified nodal analysis (MNA) method is used to simulate the circuit under test (CUT) and to derive the circuit parameters. With the knowledge of circuit topology and the component values, the test vectors associated with each components of the CUT are derived. The group of potentially faulty components, suitable test nodes and diagnosis variables for testing are identified and selected based on the test vectors. To solve the component tolerance issue in analog circuit testing, fault detection is performed based on the diagnosis variables obtained from multiple frequency measurements for fault free and faulty conditions of the CUT. Effectiveness of the proposed method is validated through the results obtained from simulation of benchmark circuits.

KEYWORDS

analog circuit – fault diagnosis – test vector –tolerance –test node – multifrequency- modified nodal analysis

1 INTRODUCTION

Analog circuit test process involves in developing methodologies to detect the variation in component value or open and short circuits called faults which leads to variation in system performance. Analog circuit faults are classified as soft faults or parametric faults and hard or catastrophic faults. Soft or parametric faults cause variation in system performance and are hard to detect whereas hard or catastrophic faults cause complete variation in system performance. The factors such as nonlinearity of circuit components, tolerance and the number of test nodes to locate the faulty elements, limit the development of standardized methods for testing. Different methods have been proposed to detect multiple soft faults in analog circuits. In [1], test vector based method is proposed to identify parametric or soft faults in linear analog circuits. Multiple parametric faults are identified based on thresholding technique. A two-dimensional fault model is proposed in [2] to simplify the algorithms for test point selection and potential fault simulations, which are primary difficulties in fault diagnosis of analog circuits. Further to reduce the process of identification of faults location, a 3D complex space is proposed to achieve better fault detection ratio against measurement error and parametric tolerance. In [3], mathematical model based on normalization algorithm to reduce the dimension of the fault samples and to improve the accuracy and efficiency of fault diagnosis is proposed. A method to locate faulty components with lesser test points and test frequencies combined with complex field modeling is proposed in [4]. A method based on principal component analysis of pretreatment and particle swarm hybrid neural network is proposed in [5]. The method adopts hybrid algorithm to adjust the network weights and thresholds to avoid falling into the local minimum value, which uses principal component pretreatment effectively reduce the complexity of calculation. Kalman filter based method for diagnosing both parametric and catastrophic faults in analog circuits is proposed in [6] to improve the efficiency of diagnosing a fault through an iterative structure, and the Shannon entropy to mitigate the influence of component tolerance.

In [7], Neural network based fault diagnosis method is proposed. The structure and training methods of LVQ neural networks are presented and it has been proved to be a simple and effective practical method. In [8], Neural network based

parametric fault diagnosis in analog circuit using Polynomial Curve Fitting is proposed. This method aims to cover faults as small as 10% or less. A polynomial of suitable degree is fitted to the output frequency response of an analog circuit and the coefficients of the polynomial attain different values under faulty and non faulty conditions. Using these features of polynomial coefficients, a BPNN is used to detect the parametric faults. A method based on two kinds of feature vectors from frequency response data of a filter system to train least squares SVM (LS-SVM) to diagnose faults is proposed in [9]. The first is defined as the conventional frequency feature vector, which includes the center frequency and the maximum frequency response. The second is a new wavelet feature vector that is composed of the mean and standard deviation of wavelet coefficients. A method based on Mahalanobis distance, a near-optimal feature vector selection method has been proposed in [10] for diagnostics of analog circuits using the least squares SVM. In [1], test vectors associated with each component of CUT are derived and multiple parametric faults are identified by finding a fault variable corresponding to each component of CUT and estimating an average value (threshold) from the fault variables. A component is said to be faulty if its fault variable value is less than the threshold. This paper extends the approach proposed in [1] to solve tolerance issue by multiple frequency measurements.

Section 2 describes the mathematical fundamentals of the proposed method. Section 3 explains the test procedure and section 4 explains the results obtained from the simulation of benchmark circuits. Section 5 deals with the discussion on the proposed approach. Section 6 concludes.

2 MATHEMATICAL FUNDAMENTALS

Analog circuit test procedure begins with the simulation of the CUT and deriving the diagnosis variables such as node voltages and branch currents. The simulation of an electronic circuit involves formulation of the circuit equation and solving it for the unknowns. To simulate the CUT, Modified Nodal Analysis (MNA) is used as explained as in [11] & [12]. MNA for linear systems results in the system equation of the form

$$AX = Z \quad (1)$$

where A is the coefficient matrix or the circuit matrix which is formed by the conductance of the components in the CUT and the interconnections of the voltage sources, X is the unknown vector consists of circuit variables (node voltages and few branch currents which are useful for testing) and Z is the excitation matrix. The right hand side matrix (Z) consists of the values of independent current and voltage sources. The unknown vector is found by matrix inverse operation. Faults in the CUT are simulated using Fault Rubber Stamp (FRS) as explained in [13]. FRS is based on the MNA stamp of the components of a CUT. The MNA stamp of a component C_n connected between the nodes j and j' ($V_j, V_{j'}$ - respective node voltages) in the coefficient matrix is,

$$X = \begin{bmatrix} V_n \\ I_v \end{bmatrix} \tag{3}$$

$$Z = \begin{bmatrix} I \\ V \end{bmatrix} \tag{4}$$

$$\begin{matrix} V_j & V_{j'} \\ j & \begin{bmatrix} +C_n & -C_n \\ -C_n & +C_n \end{bmatrix} \\ j' & \end{matrix} \tag{5}$$

If this component is assumed to be faulty, its value changes from C_n to $C_n \pm \Delta$. This deviation causes the current through that faulty component to deviate from its nominal value. This current deviation called fault variable (ϕ) is introduced in the faulty circuit unknown matrix as an unknown branch current. To indicate the current deviation through the faulty component, the faulty component is represented as a parallel combination of its nominal value and the deviation (Δ) (fig.1). V_j and $V_{j'}$ are the node voltages at the nodes j and j' respectively. i_f is the current deviation through the faulty component.

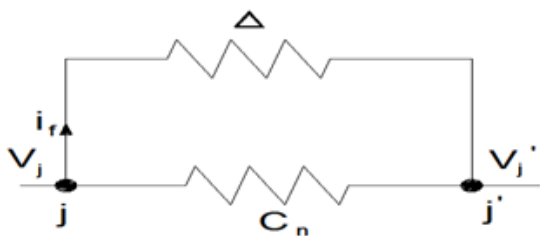


Fig.1 Faulty Component representation
The fault rubber stamp for the component C_n is

$$\begin{matrix} V_j & V_{j'} & I_f \\ j & \begin{bmatrix} +C_n & -C_n & \vdots & 1 \\ -C_n & +C_n & \vdots & -1 \\ \dots & \dots & \dots & \dots \end{bmatrix} \\ j' & \end{matrix} \tag{6}$$

The bottom row line is the faulty component equation and the right most column corresponds to the extra fault variable. As seen in (6), for each faulty component there is an additional column at the right side and row at the bottom of the coefficient matrix is introduced. The faulty system with the FRS in matrix form is,

$$\begin{bmatrix} A & c \\ r & \Delta \end{bmatrix} \begin{bmatrix} X_f \\ \phi \end{bmatrix} = \begin{bmatrix} Z \\ 0 \end{bmatrix} \tag{7}$$

where C and r are the additional column and row introduced corresponding to a faulty component. The additional column C indicates the location of the faulty component. The additional row r is the faulty component equation with its node voltages. The value of Δ depends the faulty value of the component. It can be observed that a new variable called fault variable (ϕ) is also introduced as unknown into the unknown vector matrix (X_f) of the faulty circuit. It can also be noted that this fault variable is the unknown branch current. As seen in (7), the coefficient matrix (A) of the nominal circuit is retained in forming the faulty system equation without any modification in the values of it. Thus from (7), the faulty circuit equations are written as,

$$AX_f + c\phi = Z \tag{8}$$

$$rX_f + \Delta\phi = 0 \tag{9}$$

replacing $Z = AX$ from (1),

$$AX_f + c\phi = AX \tag{10}$$

$$A(X - X_f) = c\phi \tag{11}$$

$$X - X_f = A^{-1}c\phi \tag{12}$$

$$X - X_f = T\phi \tag{13}$$

$$\phi = (X - X_f) / T \tag{14}$$

$$T = A^{-1}c \tag{15}$$

The product $A^{-1}c$ is a complex column vector and it is called test vector [13]. As C describes the location of a component in the CUT, the test vector is associated to that component and the values are independent of the faults. And it can be observed that the test vectors are associated to a specific component in the CUT and also the diagnosis variables. And it can also be observed that the test vector is sensitive to circuit component values (A is the circuit component matrix) as well as test frequencies.

3 TEST FLOW

Test procedure consists of two stages. In the first stage called pretesting stage (fig.2), the CUT is simulated with multiple frequencies and the diagnosis variables are measured for fault free condition and recorded. Test vectors corresponding to each component of CUT are generated using (15). Diagnosis variables or test nodes are selected for which the test vectors are found to be with different valued. The diagnosis variables with same test vector lead to same fault variable which limits the fault diagnosability. The potentially faulty components group or testable groups also can be detected from the test vectors. Testable components are detected by identifying the components forming ambiguity sets. Two or more circuit com-

ponents belong to same ambiguity set if a fault cannot be resolved between them. Two elements belong to same ambiguity group if and only if their test vectors are equal [13].

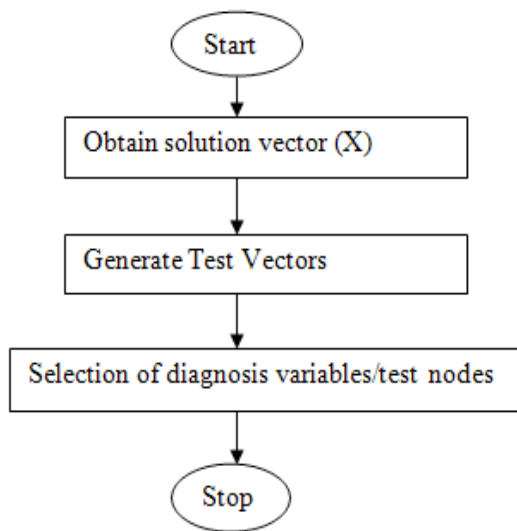


Fig.2 Pre testing stage

The second phase, called test phase begins by applying test signal with suitable magnitude and test frequencies, measuring the diagnosis variables and estimating the fault variable as in (14). To identify faulty components, the average value & relative standard deviation of fault variables associated with each components of CUT are obtained. An average value (threshold) of the relative standard deviation is found from all the columns of fault variables. A component is said to be faulty if the estimated relative standard deviation is less than the threshold. The flow diagram (figure) 3 explains this.

4 ILLUSTRATIONS

The efficiency of the proposed work is tested through benchmark circuits like Sallen key low pass filter. The operational amplifiers and the sources used are assumed to be fault free and ideal. The CUT with its nominal value is shown in fig. 4. Testing is performed at multiple frequencies with the test signal magnitude 1V. Four test frequencies are selected around the centre frequency with interval 500Hz. The centre frequency of the CUT is 1.9 KHz. Therefore the selected test frequencies are 500Hz, 1000Hz, 1500Hz, and 2000Hz. All the components are assumed to be with 5% tolerance. The magnitude of output voltage (V_o), op-amps output current (I_{opamp1} & I_{opamp2}) are used as diagnosis variables. These diagnosis variables are selected so that most of the components can be detected under faulty condition or to increase the size of the testable group. Test vectors corresponding to each node or diagnosis variable are generated at test frequencies using (15) and are shown in fig.5 & fig.6. It has been found that the test vectors associated with the components R_1 , C_1 & C_2 , R_5 & R_6 , R_7 & R_8 are with same values. Therefore the faulty conditions of these components cannot be detected. The other components of CUT form the testable group or they are treated as potentially faulty components. To identify the faulty components, a test signal of magnitude 1V is applied and testing is performed at multiple frequencies. The fault variable corresponding to each potentially faulty component is estimated using (14). The average value of each fault variable is obtained and the average value of all the fault variables is used as the threshold for locating the faulty elements. A component is classified as faulty if the relative standard deviation is less than the threshold.

Case i) For example, two faulty components R_2 & R_3 with the values 3000 Ω & 500 Ω respectively are injected and fault variables are found at all the test frequencies. The relative standard deviation each column of fault variable for the components R_2 , R_3 , R_4 , C_3 & C_4 is found to be 0.52, 0.34, 1.55, 0.97, 0.94. The threshold value estimated from these values is 0.8687. It can be noted that the values corresponding to R_2 , R_3 are lesser than the threshold obtained. Hence these two components are declared as faulty. Table 1 shows the results obtained for a fourth order Sallen key low pass filter.

Case ii) Two faulty components R_3 & R_4 with the values 2.5k Ω , 1k Ω respectively are injected and the relative standard deviation of all the fault variables is obtained as 0.752, 0.363, 0.509, 0.5735, and 0.6825. The threshold value estimated from this is 0.5683. It can be observed that the relative standard deviation of R_3 & R_4 is lesser than the threshold (0.363, 0.509). Hence these elements are said to be faulty.

Case iii) For the faulty conditions $C_3=130nF$ & $C_4=30nF$, the relative standard deviation of the fault variable of the components R_2 , R_3 , R_4 , C_3 & C_4 is obtained as 0.8738, 0.928, 1.3754, 0.5885, 0.6825. The threshold estimated from these values is 0.8375. It can be noted that the relative standard deviation of C_3 & C_4 is lesser than the threshold. Hence these components are identified as faulty.

Case iv) The components R_2 , C_4 with the values 1k Ω , 200nF are injected as faulty and the relative standard deviation is obtained as 0.7656, 1.214, 1.6, 1.2568, 0.7065. The threshold value estimated is 1.1386. It is observed that the relative standard deviation obtained for the components R_2 , C_4 is lesser than the threshold value. Hence they are declared as faulty.

Case v) Three faulty conditions with the values $R_3=2.8k\Omega$, $C_3=120nF$ & $C_4=90nF$ leads to the relative standard deviation of 1.6398, 0.8733, 1.9586, 1.2568, 0.896023 and the threshold obtained is 1.2757. The estimated relative standard deviation of the components R_3 , C_3 , C_4 is found to be lesser than the threshold. Hence they are faulty.

Case vi) Three faulty components with the values $R_2=3.2k\Omega$, $R_3=500\Omega$, $R_4=5k\Omega$ are injected and the relative standard deviation obtained is 0.2876, 0.3613, 0.4523, 0.9926, 0.8976 and the threshold value estimated is 0.5653. The relative standard deviation of the faulty variables corresponding to the components R_2 , R_3 , R_4 is found to be lesser than the threshold. Hence they are faulty.

Case vii) Three components with the values $R_3=800\Omega$, $R_4=4.8k\Omega$, $C_3=50nF$ are introduced in to the CUT and the relative standard deviation corresponding to all the components is found to be 0.8365, 0.4088, 0.523, 0.5885, 0.9158. The threshold value estimated is 0.6133. It can be observed from the above values that the relative standard deviation corresponding to the components R_3 , R_4 & C_3 is lesser than this threshold. Hence they are declared as faulty.

5 DISCUSSION

A method to detect multiple soft faults based on multiple frequency measurements and test vectors is proposed. Test vectors are generated by simulating the circuit under test using modified nodal analysis. Test nodes or the diagnosis variables and the potentially faulty components are identified from the test vector values. Test nodes or the diagnosis variables are selected so that their test vectors are different. Same value test vectors associated with the components of CUT lead to same fault variables generation and affects the fault diagnosability of the CUT. The testable group of components is also identified from the test vectors and it requires no separate approaches or algorithms. To locate the faulty components, fault variables estimated from the diagnosis variables measured at the specific nodes and at all the test frequencies.

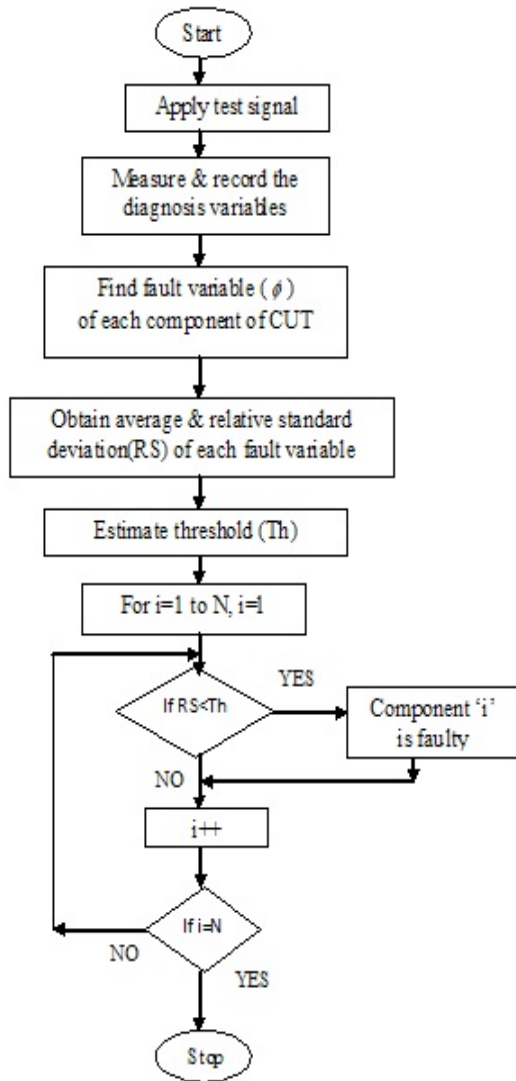


Fig. 3 Test Stage

The average and relative standard deviation of all the fault variables corresponding to the components of the CUT is estimated. The average value of the relative standard deviation of all the fault variables is estimated and used as a threshold. The components are said to be faulty, when the obtained relative standard deviation is less than the threshold. Thus the fault identification approach is very simple and requires no complex algorithms or procedures. But it is possible to detect up to three faults and it is because of the threshold used to identify the faulty conditions of the components.

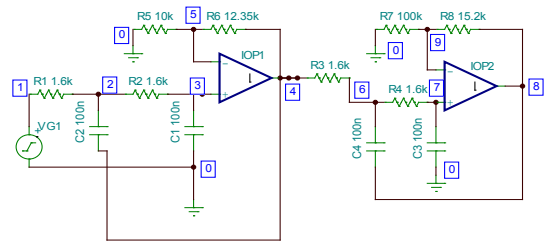


Fig.4 Fourth order Sallen Key LPF

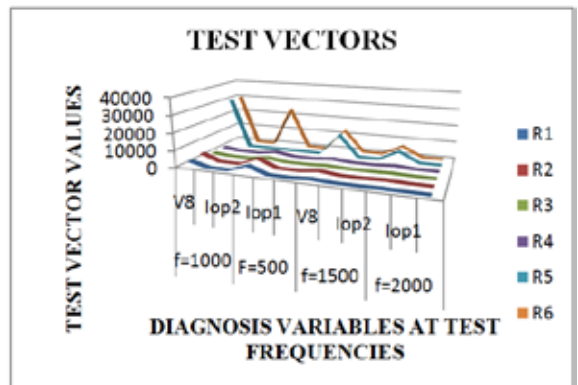


Fig .5 Test Vectors

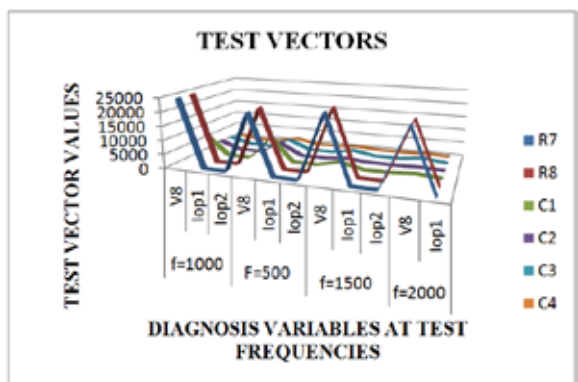


Fig. 6 Test Vectors

6 CONCLUSION

An approach to select test nodes and to detect multiple parametric faults called soft faults based on multiple frequency measurements is proposed. The test vectors and the diagnosis variables are derived by forming the circuit equations using MNA and solving it by linear system solver. A fault variable estimated from the diagnosis variables and test vectors generated are used to identify the faulty conditions of a component of the CUT. As the test vectors are derived from the circuit matrix and location of the components, the fault variables are associated with specific component. Test points or test nodes are selected from the test vector values. A simple average value based thresholding technique is used to locate or identify multiple faulty components. A component is identified as faulty if the fault variable is lesser than the threshold value. The proposed approach helps to identify the diagnosis variables or test nodes for testing and testable group from test vector values without the requirement of special approaches or algorithms.

REFERENCES

1. G.Puvaneswari, S.UmaMaheswari, "Multiple Parametric Fault Detection based on Test Vectors and Statistical Threshold", International Journal of Applied Engineering Research, 2015, Volume 10, No.8, pp.20485-20488. | 2. Hongzhi Hu, Shulin Tian, and Qing Guo, "Fault Modeling and Testing for Analog Circuits in Complex Space Based on Supply Current and Output Voltage", Journal of Applied Mathematics Volume 2015 (2015), Article ID 851837. | 3. L.Huang & C.Yao, "Data Processing method of fault samples in analog circuits", Future Communication, Information and Computer Science-Sheng(Ed.), Taylor & Francis Group, London, 2015. | 4. C. Yang, J. Yang, Z. Liu, and S. Tian, "Complex field fault modeling-based optimal frequency selection in linear analog circuit fault diagnosis," IEEE Transactions on Instrumentation and Measurement, 2014, vol. 63, no. 4, pp. 813–825. | 5. G. Huang, B. R. Han, "Analog Circuit Fault Diagnosis Based on Principal Component Analysis of Pretreatment and Particle Swarm Hybrid Neural Network", Applied Mechanics and Materials, Feb. 2014, Vols 494-495, pp. 809-812. | 6. Li X., Xie Y., Bi D., Ao Y. "Kalman filter based method for fault diagnosis of analog circuits", Metrology and Measurement Systems, 2013;20(2):307–322. | 7. Shiguan Zhou, Guojun Li, Zaifei Luo, Yan Zheng, " Analog Circuit Fault Diagnosis Based on LVQ Neural Network", Applied Mechanics and Materials, 2013,Vols.380-384, pp 828-832. | 8. Ashwani Kumar and A P Singh, " Neural Network based Fault Diagnosis in analog Electronic Circuit using Polynomial Curve Fitting", International Journal o Computer Applications 61(16):28-34, January 2013. | 9. Long B., Tian S., Wang H., "Diagnostics of filtered analog circuits with tolerance based on LS-SVM using frequency features", Journal of Electronic Testing: Theory and Applications, 2012, 28(3):291–300. | 10. Long B., Tian S., Wang H., " Feature vector selection method using Mahalanobis distance for diagnostics of analog circuits based on LS-SVM," Journal of Electronic Testing: Theory and Applications, 2012;28(5):745–755. | 11. C.-W.Ho, A.Ruehli and P.Brennan, " The modified nodal approach to network analysis", IEEE Transactions on Circuits and Systems, 1975, Vol.22, no.6, pp.504-509. | 12. Jiri Vilach and Kishore Singhal, Computer methods for circuit analysis and design, Van Nostrand Reinhold Company, 1983. | 13. Jose A. Soares Augusto and Carlos Beltran Almeida, " A Tool for Single-Fault Diagnosis in Linear Analog Circuits with Tolerance Using the T-vector Approach", Hindawi Publishing Corporation, VLSI design, 2008, pp 1-8.