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Analog Circuit Fault Detection using Soft Computing Techniques

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***Abstract*— A new method for detecting faults in analog circuits is proposed. In the proposed method, the fault present in the circuit is detected using system parameters such as location of poles and values of magnitude and phase. The CUT is simulated under various faulty conditions and based on that a fault dictionary is created. Fault classification is done using Fuzzy Inference System (FIS). The CUT used is sallen-key band pass filter.**

Keywords : Poles. Magnitude And Phase. Fault Dictionary. Fuzzy Inference System. Sallen-Key Filter.

I. INTRODUCTION

Parametric Fault detection and identification has been an active research topic in recent years and gained a wide attention in the field of analog circuit testing . Detection of faults depends on the response of faulty circuits being suf iciently different from the fault-free response. The definition of sufficiency might be arbitrary thresholds of around 10% from the original values. Analog circuit fault diagnosis has been addressed by two methods: simulate-before-test (SBT) and simulate-after-test (SAT).SBT is based on the use of fault dictionary, which contains responses from simulations of the circuit for different predefined faults. SAT uses measurements to compute parameters of the circuits solving a set of fault diagnosis equations. All computations occur after measurements are acquired. Faults in analog circuits are categorized as catastrophic and parametric faults. Catastrophic faults are due to open and short circuits, caused by sudden and large variations of components. The parametric faults are reported to the circuit functionality. Thus, the value of parameters deviates continuously with time or with environmental conditions to an unacceptable value. Analog fault diagnosis usually consists of three stages which respectively address three important problems in the analog testing and diagnosis:

Fault detection – during that we have to find out if the circuit under test is faulty or not;

Fault location – which has as purpose to identify where the faulty parameters are;

Parameter evaluation – to tell how much the parameter deviations from nominal values are.

The analog circuit faults can be broadly classified into catastrophic fault and parameter fault. The catastrophic fault would change the circuit network, and then the transfer fu nction of the CUT is also changed according to the circuit network. There by it is not appropriate to diagnose hard fault using parameter identification method. Some of the soft faults also can't be diagnosed. For example for two series resistances, if the parameter value of one resistance become larger and the other become smaller or vice versa the total parameter value of the two resistors remain unchanged, so the output also remains constant. Therefore parameters are grouped into several modules for the CUT.

In recent years, the number and variety of applications of fuzzy logic have increased significantly. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. In this paper a new method to diagnose component level parametric faults is attempted . Two different signatures are used to detect the parametric faults present in the CUT. Both single fault and double faults are attempted in this project.The structure of this paper is presented as follows: section 2 outlines the fault diagnosis framework of the proposed method. Section 3 deals with the proposed method. section 4 discusses the results and discussion of the proposed method. Section 65concludes the proposed fault diagnosis method.

II. FAULT DIAGNOSIS FRAME WORK

The basic idea is to derive the transfer function of the filter. Once the transfer function is derived the signature values are extracted from the fault free condition of the CUT. Then faults are injected in the CUT and the signature values are extracted.

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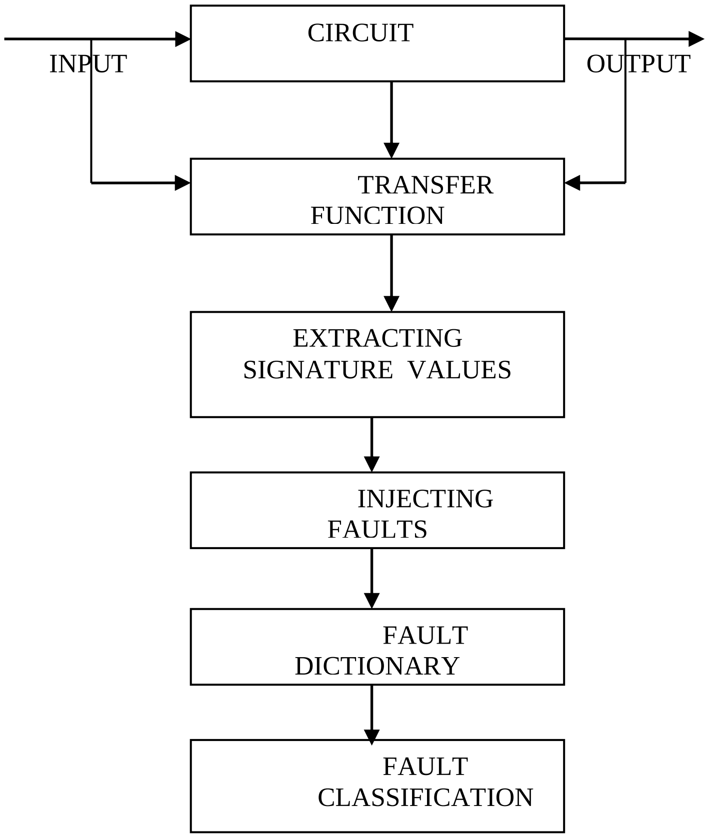


Fig 1: flowchart of the proposed method

III. FAULT DIAGNOSIS

A. SALLEN-KEY BAND PASS FILTER

The CUT used is sallen-key band pass filter. The first step is to derive the transfer function of the CUT. The transfer function of the CUT is given by

$$G(s) = \frac{SA_0G_1C_1}{S^2C_1C_2+S(G_3C_1+G_3C_2+G_1C_1+C_1G_2(1-A0))+G_3(G_1+G_2)} \quad = \quad [1S]$$

Where A0 = 1+ (R5/R4)

$G1 = (R1)^{-1}$; $G2 = (R2)^{-1}$; $G3 = (R3)^{-1}$

Once the transfer function of the circuit is derived, the next step is to simulate the circuit under fault free condition to obtain the corresponding pole location. Each component present in the circuit is varied from ± 10% to ± 50%.After injecting the fault in the circuit components, the CUT is simulated under various fault conditions and the corresponding pole location is obtained.

For single fault, only one component value is changed at a time. For double fault two components values are changed at a time. Based on the result a fault dictionary is created which consists of both single and double faults. Fault index is assigned to each fault present in the fault dictionary.

B. FAULT CLASSIFICATION

Fault classification is done using fuzzy inference system (FIS). The value of pole is a complex number hence it have a real and an imaginary part.

C. CONSTRUCTION OF FIS

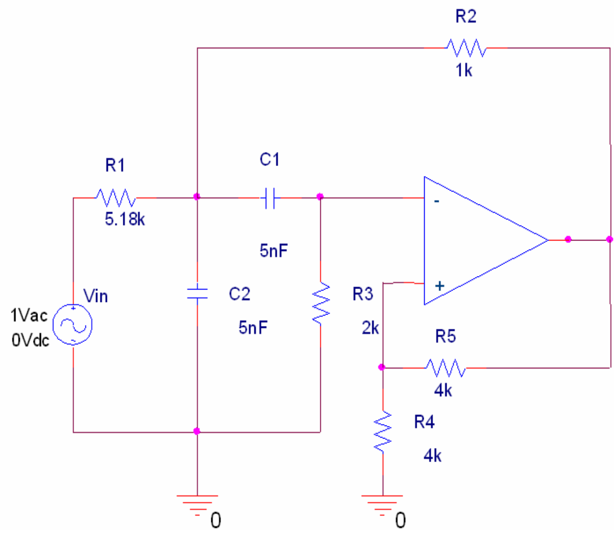
The FIS is designed to accept two inputs, real and imaginary part of the pole location. 'AND' operator is used to construct the rules for the FIS. Let us consider a fault case.

if (input1 is membership function1) and/or (input2 is membership function2) and/or �. then ($output_n$ is output membership $function_n$).

Consider a sample test case for a fault with input value of real part [-0.2639] which is entered using triangular member ship function as [-0.27 -0.26 -0.25] and for the imaginary part [1.3288] using triangular membership function it is defined as [1.31 1.32 1.33] and the output is defined as [8.9 9 9.1]. The Centroid of Area (COA) defuzzifier produces the output value 9.02 which is equal to the fault index 9.
Similarly for other faults, input membership function and output membership function are determined from the extracted feature and fault number respectively.

D.VALIDATION

Inject any one of the faults present in the fault dictionary for example fault Index 9 is injected by increasing C2 by 30%.The CUT is simulated with the above injected fault and the corresponding locations of poles are obtained. The real part and imaginary part of the pole are found to be -0.2639 and 1.3288.The FIS produced output of 9.02 which is equal to fault index 9.



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E. Fault Dictionary

The fault dictionary is created after injecting the faults to the components. This fault dictionary consists of values of poles, where the pole value consists of real and imaginary part and fault index is assigned to each fault.

The step size for each fault is 10%. The fault range is varied between -50% to +50% which is shown in the table 1. A selected set of faults are tabulated in the sample fault dictionary. After creating fault dictionary, fault classification is done with the help of Fuzzy Inference System(FIS).

Table 1:Sample fault dictionary

FAULT CONDITION	REAL	IMAGINARY	FAULT INDEX
Fault free	0.1931	1.5326	1
C2-50%	0.1139	2.1816	2
C2-40%	0.0116	1.9942	3
C2-40%	-0.0615	1.8452	4
C2-30%	-0.1163	1.7231	5
C2-10%	-0.1589	1.6205	6
C2+10%	-0.2210	1.4561	7
C2+20%	-0.2442	1.3888	8
C2+30%	-0.2639	1.3288	9
C2+40%	-0.2808	1.2750	10
C2+50%	-0.2954	1.2262	11
C1-50%	-0.6931	2.0171	12
C1-40%	-0.5264	0.1.9235	13
C1-30%	-0.4073	1.8008	14
C1-20%	-0.3181	1.6975	15
C1-10%	-0.2486	1.6092	16
C1+10%	-0.1476	1.4654	17
C1+20%	-0.1097	1.4058	18
C1+30%	-0.0777	1.3526	19
C1+40%	-0.0502	1.3045	20
C1+50%	-0.0264	1.2610	21
R1R2-50%	-1.192	1.834	22
R1R2+10%	-0.472	1.822	23
R1R2+30%	-0.583	1.672	24
C1C2-30%	-0.0321	1.481	25

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F.FUZZY INFERENCE SYSTEM

In fuzzy inference system, as the pole values consists of both real and imaginary part two input variables are used one for real and other for imaginary part which is shown in Fig 3.

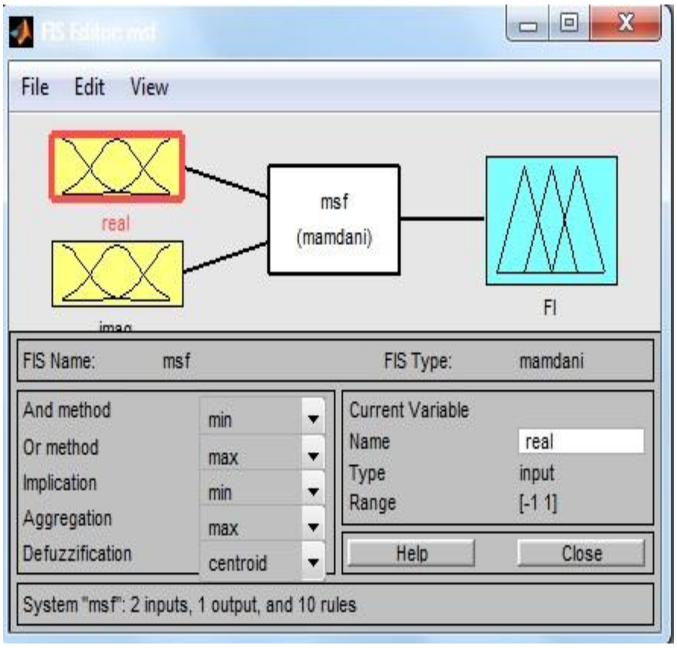

Fig 3:FIS editor

The input values are entered in the form of triangular membership function. Fig 4 shows the membership function editor.

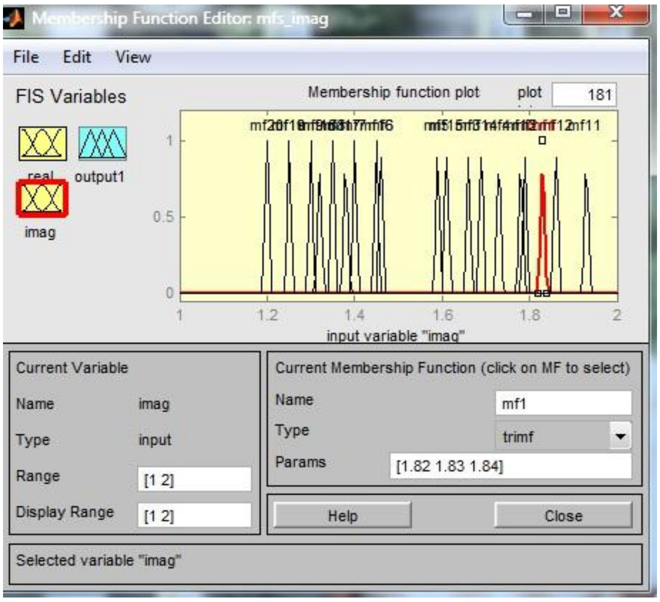

Fig 4: Membership function editor

Rules are constructed using rule editor, here 'AND' operator is used to construct the rules because pole has a two variable input. Fig 5 shows the Rule editor.

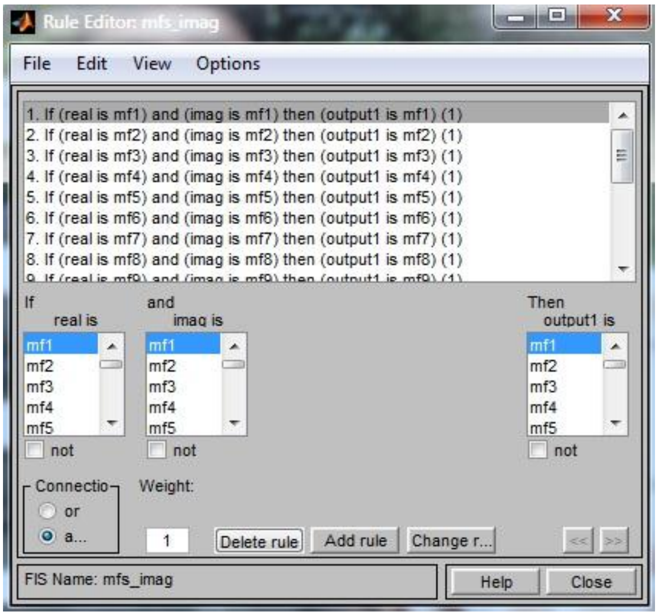

Fig 5: Rule editor

Once the rules are constructed, Validation is done through rule viewer. Taking any one of the fault from the fault from the fault dictionary and entering its real and imaginary value in respective fields, the fault classification is validated. Fig 6 shows the rule viewer.

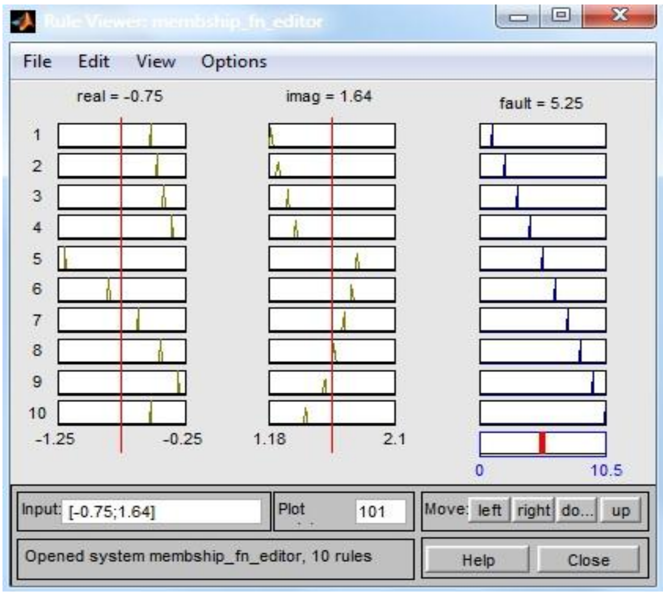

Fig 6: Rule viewer.

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G.MAGNITUDE AND PHASE VALUE

The signature used to detect the faults is phase and magnitude value of the CUT. The CUT is simulated under various fault and fault free conditions and the corresponding value of phase and magnitude is obtained. Depending on the results a fault dictionary is created and faults are classified using FIS. All the remaining operations are carried out in a same way similarly in fault classification.

IV.RESULTS AND DISCUSSION

In this project two different signatures are used to detect the faults present in the CUT. Table 1 shows the fault dictionary, which is created using the location of poles which consists of real and imaginary parts. Fig 3 shows the FIS editor where it uses two input variables such as real and imaginary. Fig 4 shows the membership function of imaginary part and its values. Fig 5 shows the construction of rules, here 'AND' operator is used to construct the rules. Fig 6 shows the rule viewer, once the rules are constructed validation is done through rule viewer. Table 2shows the fault dictionary created using magnitude and phase value.

V.CONCLUSION

In this project two different signatures are used to detect the faults present in the CUT. The first signature used is location of poles which have a complex value and for each fault the values of both real and imaginary part varies, so the fault classification is done effectively using FIS. Where as while using magnitude and phase value as a signature for some faults the phase value remains constant but the value of the magnitude changes constantly. In FIS, using AND as an operator for rules construction it doesn't have any effect on the output.

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FAULT CONDITION	MAGNITUDE	PHASE	FAULT INDEX
FF	0.536	74.434	0
R1-30	0.6699	70.430	1
R1-10	0.5750	73.289	2
R1+10	0.5029	75.436	3
R1+40	0.4225	77.802	4
R2-10	0.477	84.181	5
R2+10	0.579	64.752	6
R2+30	0.615	47.485	7
R3-10	0.438	69.775	8
R3+10	0.650	80.089	9
R4-10	0.583	83.257	10
R4+10	0.492	67.719	11
R4+20	0.453	62.569	12
R4+50	0.369	52.782	13
R5-40	0.338	49.44	14
R5-30	0.385	54.57	15
R5-20	0.436	60.44	16
R5+10	0.579	82.353	17
C1C2-20	0.3484	79.96	18
C1C2-10	0.4306	77.56	19
C1C2+10	0.6793	70.14	20

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