ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 2, Issue 2, March 2013

Study of Electronic Circuit Fault Detection & Diagnosis Using Signal Processing

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Abstract: Circuit fault diagnosis is an important area of electronic manufacturing industries. It is desired to design and develop the system which detects and diagnoses the fault that appears in the system by analyzing various circuit parameters in real time. It is proposed to analyze various parameters of circuit under test using signal processing. From these parameters it is possible to understand and analyze the deviation in performance of the system.

Keywords: **Real Time, signal processing, CUT, transforms, Surgeno fuzzy.**

I. INTRODUCTION

Whenever we think about why something does not behave as it should, we are starting the process of diagnosis. Diagnosis is therefore a common activity in our everyday lives (Benjamins & Jansweijer, 1990). Every complex system is liable to faults or failures. In the most general terms, a fault is every change in a system that prevents it from operating in the proper manner. We define diagnosis as the task of identifying the cause and location of a fault manifested by some observed behavior. This is often considered to be a two-stage process: first the fact that fault has occurred must be recognized – this is referred to as *fault detection*. That is, in general, achieved by testing. Secondly, the nature and location should be determined such that appropriate remedial action may be initiated. A system which includes the capacity of detecting, isolating, identifying or classifying faults is called a *fault diagnosis* system. In the past years most efforts concentrated on fault detection and diagnosis was overlooked, also because tools were not yet powerful enough to deal with real cases. The increased power of fault simulators, testability analyzers, and ATPGs is making diagnosis a challenging field for research both in industry and academia.

II. PROCESS

In this work, a fuzzy classifier is implemented in order to process circuit input–output measurements. The assumption of accessibility is obviously satisfied; in fact, the CUT input represents the controllable node used to inject stimuli while the output represents the observable node used to measure the CUT response (voltage/current) [2]. Each signature is obtained by injecting predefined stimuli into the input of the circuit under test and by measuring the corresponding responses at the CUT output. Sinusoidal waves with fixed amplitude and different test frequencies have been chosen as stimuli. Since each signature is a collection of samples of the CUT transfer function, the harmonic analysis has been considered. A number of samples and frequencies are identified by performing a sensitivity analysis of the circuit. In the following, we consider that a CUT signature is given, where is the -th sample of the CUT transfer function magnitude. A first-order Sugeno fuzzy system [25] is considered.

1) The considered fuzzy rule is IF is AND is AND is THEN is where denotes the -th membership function of the -th fuzzy rule and are vectors belonging to . is the number of considered fault classes, i.e., the number of the fuzzy system outputs. Sugeno's fuzzy systems are characterized by a crisp output; the first-order Sugeno system has singleton outputs of the linear dependence of each rule on the input variables, the first-order Sugeno system finds a natural application as a supervisor in the control of nonlinear systems based on multiple linear controllers, where the dynamic behavior of the controlled systems is influenced by the input magnitude. In this application, a first-order Sugeno system allows the output of the classifier to be influenced by the larger fault signature components.

2) The membership functions, , are Gaussian functions (1) where is the membership function position and is a scaling factor that defines the membership function width. 3) As it can be seen from part (1), sub-expressions concerning different input variables are combined by fuzzy AND operators (T-norm), realized by the arithmetic product. In this case, the IF part of each fuzzy rule can be described by an -dimensional Gaussian (2) where and is the Gaussian center position vector in the input space. As it will be shown later, we assume the scaling factors to be equal, .It must be noted that, with the above assumptions, a Sugeno 0th order fuzzy system is equivalent to the RBF network [26]. A critical point in the implementation of a fuzzy classifier is the definition of the

ISSN: 2319-5967
ISO 9001:2008 Certified
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membership functions. A straightforward method is the grid partition of the input space. Nevertheless, this simple method is inefficient especially when the dimension of the input space is high (the number of fuzzy rules is where is the number of concerned with each input variable), or when the input data are not uniformly distributed in the input space but clustered in small regions. For these reasons, we prefer a scatter partition of the input space based on the fault dictionary data distribution. The partition can be obtained by means of the modified version of the growing cell structure algorithm, proposed by Fritzke in [27], [28]. This algorithm is particularly effective since it defines the fuzzy rules with a supervised scheme by taking into account the classifier output error, but it is characterized by a high computational burden. In order to maintain the algorithm accuracy but reduce its complexity, we suggest a modified version. The modified algorithm is divided into two steps. First, the IF parts of the fuzzy rules are defined for each class separately in an unsupervised manner by taking into account only geometrical criteria. In this way, the computational burden is reduced approximately by a factor of (is the number of fault classes considered for the CUT). In the second step, the IF position is up-dated on the basis of the classifier output error evaluated with the data contained in the fault dictionary. This step, which is highly expensive in terms of computational complexity, is used only to perfect the fuzzy rules in order to reduce the classification error. In this last phase, the weights of the THEN part, , and , are determined in a supervised manner. In more detail, by starting from a set of training data, the algorithm builds a cell structure in the input space formed by a number of cells connected by edges, which defines both the position and the width of the fuzzy rule IF parts. In the following, the position of a cell is indicated by and corresponds to the IF position in the input space, while the parameter that describes the IF width is given by the average of a subset of edge lengths.

III. EXPERIMENTAL SECTION

In this section, we compare the performance of the two classification approaches described in the previous sections. Results have been obtained by taking into account both zero mean white additive noise superimposed to the circuit output response and the component tolerance effects. To this aim, we assume that each non faulty component of the circuit under test is a random variable uniformly distributed in the tolerance range. In order to construct the fault dictionary and compensate for the component tolerance effects, multiple signatures are generated for each potential fault of the CUT.

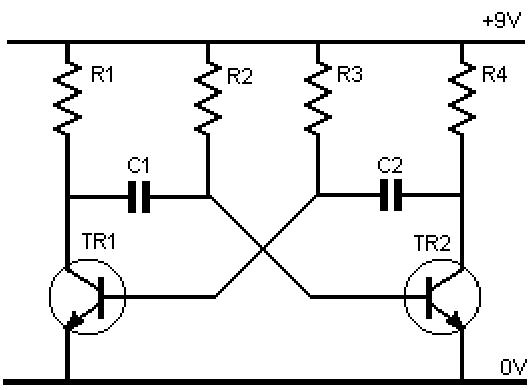

Fig 1. Circuit under test (CUT), a stable multivibrator

The signatures are obtained by injecting in the controllable node (input) a set of stimuli consisting of sine waves with constant amplitude and different test frequencies selected from the frequency range of the CUT. For each stimulus, the corresponding voltage amplitude is measured at the output test point, and, hence, samples of the frequency transfer function magnitude are obtained. In this work, two major categories of data pre-processing were applied to circuit signatures contained in the fault dictionary before using them to train the classifiers: normalization and compression. Normalization, which is commonly employed in conjunction with classifiers, prevents the subsequent pattern recognition algorithms from being biased by signature components with intrinsic larger response magnitudes. Here, data compression is achieved by means of the principal component analysis (PCA) [30]. In order to test the proposed technique, the astable multivibrator of Fig. 1(a) was considered. The nominal values and tolerance for each component of the filter are summarized in Table I. For this CUT, single faults at the component level have been taken into account while a sensitivity analysis led to the selection of eight test frequencies and were considered to be potentially faulty elements. Faults affecting the resistors and form an ambiguity class and can be grouped in a single class called "gain fault."

IV. COMPONENT VALUES AND TOLERANCE

Ranges for the component of the circuit shown in fig.

COMPONENT	NOMINAL VALUE	TOLERANCE
R1	1KΩ	±10
R2	1KΩ	±10
R3	1KΩ	±10
R4	1KΩ	±10
C1	0.1µF	±5
C2	0.1µF	±5

The gain fault can be detected by a simple dc measurement, and it is not included in the results reported hereafter. To obtain more accurate results each fault of a component is represented by two different fault classes: a class for component values larger than the nominal one and the other for component values smaller than the nominal. So, eight fault classes plus one class for the operating fault-free condition are obtained in this case. To form the fault dictionary, the faulty component values have been extracted from the uniform distribution defined in the intervals and , where is the tolerance range and the nominal value of the circuit element. The input dimension was reduced by PCA from eight to three. This reduction allows the designer to consider the grid partition method (otherwise, it could not have been applied for computational complexity reasons). For the filter of Fig. 1(a), a white additive noise is superimposed to the circuit output and a SNR of 30 dB was considered. In Fig. 1(b), the projections of the IF part centers, obtained with the growing cell structure algorithm are shown together with the projections of the vectors contained in the fault dictionary.
The projection plane shows the two first principal components of the fault dictionary data. It can be seen that where data of different classes are closer and the situation is more confused, the growing structure has a higher density of cells corresponding to a large number of fuzzy rules. In Fig. 2, the plot of classification error versus the number of fuzzy rules is given. The unsupervised phase of the training algorithm was stopped when the growing cell structure reached a given complexity. Then, the supervised algorithm was used to reduce the error and stopped when the error gradient reached a predefined threshold. Table II reports the results concerning the filter in Fig. 1(a), obtained with 900 training vectors and 1800 test vectors. It can be seen that results obtained with the three methods, fuzzy with grid partitioning, FGP, fuzzy with scatter partition (growing cell structure), FSP, and RBF networks are very similar, but the second method provides better results. It is important to observe that the complexity of the classifiers is similar. In fact, the RBF has 63 hidden nodes, and the scatter partition fuzzy classifier has 74 fuzzy rules. The same fault diagnosis technique was then applied to a more complex circuit (see Fig. 3). In this case, we considered faults at the subsystem level. The circuit is composed of four Fig. 2. Classification error as a function of number of fuzzy rules (9 fault classes).

V. CONCLUSION

An automatic diagnosis technique based on a fuzzy classifier was presented and applied to fault location in analog electronic circuits, considering single faults both at the component and subsystem level. The fuzzy rules are defined by processing a data set contained in the fault dictionary, applying an efficient algorithm based on a growing cell structure. The algorithm is divided in two phases so that the computational burden is reduced, but the advantages of a supervised scheme are preserved. It is shown that, under the assumed hypotheses, the structure of the fuzzy classifier is analogous to that of a radial basis function network. Hence, the performances of the two methods are similar. Results obtained by applying a first-order Sugeno fuzzy system are justified by the efficiency of the classifier training method and the large number of degrees of freedom.

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ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
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