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SOFT FAULT DIAGNOSIS IN ANALOG LINEAR CIRCUIT BY ARX MODELLING

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Abstract – In this paper a soft fault diagnosis technique of analog linear circuits is presented. A Simulation-Before-Test (SBT) approach is used, where the fault dictionary is designed by circuit signatures obtained using ARX model identification.

Keywords: soft fault diagnosis, neural classifier, ARX models.

1. INTRODUCTION

The development of automated fault location techniques in electronic analog circuits is still an open research field. Many problems are encountered due, for instance, to the continuous nature of soft fault mechanism and to the presence of different sources of noise.

The Simulation-Before-Test (SBT) [1] approach has provided good results in many applications. In order to use this approach, a "fault dictionary" has to be built up by collecting a set of circuit signatures. A signature consists of some parameters or functions, which summarize relevant information about the circuit's behaviour. The signature is extracted from the circuit response during a simulation phase (before the diagnosis phase), by injecting a set of predefined test stimuli under a particular fault condition, and it is stored in the fault dictionary. In this way it is possible to build a signature collection, describing both the fault conditions and the fault free condition.

The test phase is performed in a following step by comparing the signature measured from the circuit under test (CUT) and the signatures contained in the dictionary. Classification thus achieves the fault detection and isolation. Neural classifiers trained by the fault dictionary seem particularly promising solutions for this purpose [1-3].

In this context, the selection of an efficient method to obtain the circuit fault signature is of the utmost importance. It is important above all to achieve a representative fault dictionary, using as the circuit's signature a compact set of parameters.

In this paper the analog linear circuits are represented in the discrete time domain by autoregressive models with exogenous input (ARX). The set of model parameters is used as circuit signature, and collected in the fault dictionary. In this way, a very compact and complete description of the circuit's behaviour is achieved and used for subsequent fault classification.

The classification is performed using a Radial Basis Function (RBF) neural network [4], suggested by previous studies [5,6]. The purpose is to diagnose the circuit component parametric faults, which in literature are also known as soft faults. Their principal characteristic is that if they occur, the circuit may continue to work without showing evident operational deficiencies (which would instead become manifest in case of a short circuit or an open circuit, for instance). Nevertheless, it is important to diagnose these soft faults, above all in application fields critical in relation to security. Moreover, a soft fault may be a warning preceding a more serious fault and, in these terms, it needs a continuous and automatic monitoring system.

2. METHODOLOGY

The analog linear circuits are represented in the discrete time domain by an autoregressive model with exogenous input (ARX). Such an approach permits the use of an already established and efficient methodology for estimating the parameters of the model. Nevertheless, much more flexible models such as ARMAX, NARX or NARMAX can be used to supply a parametric description of the fault behaviour of the CUT (circuit under test).

For the considered ARX model, the input-output relationship can be represented in the discrete time-domain by the following equation:

$$V_{out}(t) = \sum_{i=1}^{p} a(i) V_{out}(t - iT) + \sum_{i=1}^{m} b(i) V_{in}(t - iT) + e(t); \qquad (1)$$

In equation (1) the coefficients *a(i)* determine the system poles in the z-domain. While $b(i)$ determines the system zeroes, T is the sampling period, p is the number of poles and m-1 is the number of zeroes, finally $e(t)$ represents a white noise.

To estimate the model coefficients from measured data an identification procedure must be used, in particular in this work a wide band test input signal (white noise or frequency sweep) is injected. A least mean square estimate is performed, by considering measured input and output sample sequences.

The vector of the estimated parameters is used to describe the CUT's behaviour and to perform the diagnosis.

2.1. Fault Dictionary Construction

As stated before, the soft fault location is obtained by comparing the CUT signature (from measurements) with the set of signature examples contained in the fault dictionary. Due to the continuous nature of the soft fault mechanism and the presence of different sources of noise, a complete "fault dictionary" containing all feasible fault examples cannot be generated. The problem is solved by sampling the fault space and considering an "intelligent" diagnosis system, able to generalise from a finite set of fault examples. The simulation phase can be split in the following steps:

- A set of soft faults (circuit parameter deviations) leading to an unwanted behaviour of the output response is injected in the circuit.
- The transfer function of the faulty circuit is evaluated in the s-domain.
- The circuit transfer function is transformed in z-domain using a Zero Order Hold (ZOH).
- The ARX model parameters are obtained and used as a signature.

In this phase, in order to develop an effective classification of possible circuit faults, the problems due to non-ideal automatic measurement's system have to be considered as well as the noise, the finite sampling frequency etc.

2.2. Neural Classifier

For the sake of completeness, we also present the used classifier. It has been chosen as suggested in an earlier study [6] and is composed of a Radial Basis Function Neural Network. The three-layered neural network has Gaussian radial basis activation units in the hidden layer and linear outputs. The input layer receives the CUT's actual signature (three parameters for the band-pass universal filter of figure 1) and classifies it as faulty or faulty free by indicating, in the case of fault, the faulty unit. In the output layer, a "winner takes all" philosophy, has been considered. The network is trained in three separate steps by data contained in the fault dictionary:

- The centers of the hidden node activation functions are placed on the centroids of fault dictionary data clusters. The clustering algorithm used in this work is Fuzzy C-means.
- The width of the activation function is set by a p-nearest neighbour heuristic.
- The weights of the output linear nodes is found in a supervised way by least square method.

Once the network is trained, it can be used for diagnosing subsequent circuits belonging to the same CUT family.

3. EXPERIMENTAL RESULTS

The technique has been verified using both simulations (for diagnosis validation) and experimental data, taken from sample circuits. The effect on parameter estimation of an additive noise superimposed to measured input and output signals was evaluated too.

Moreover, the robustness of the technique with respect to the selection of the measurement system parameters such as the sampling frequency (the same both for the input-output measured signal and for the transfer function transformation from continuous to discrete time domain during the simulation phase), the width of signal observation window, the constructive tolerance of components, etc., was investigated.

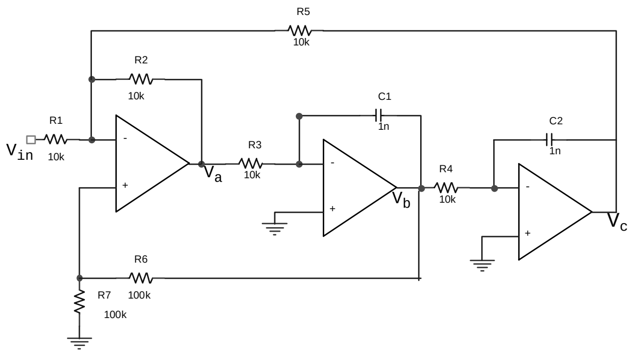

Figure 1: A Biquad filter. The nominal values are in the appropriate units.

The circuit considered for the diagnosis is a Biquad (universal filter) as shown in figure 1, designed to have a cut-off frequency of 15.9 kHz; its components' values are listed in table 1.

Component	Nominal Value	Tolerance
C1	1 nF	1%
C2	1 nF	1%
R1	10 kΩ	1%
R2	10 kΩ	1%
R3	10 kΩ	1%
R4	10 kΩ	1%
R5	10 kΩ	1%
R6	100 kΩ	1%
R7	100 kΩ	1%

Table 1: Biquad filter parameters.

The diagnosis phase is carried out by considering the hypothesis of single parametric (soft) fault, that is, all component values are kept within their constructive tolerances, except one, which deviates from its nominal value and takes a value outside the tolerance range. This approach requires the ambiguity group isolation, i.e. the identification of those components whose deviations from nominal value affect the signature in the same manner. Within every ambiguity group it is impossible to determine the parameter responsible for the fault. In a filter group R-C, for instance, it is impossible to understand, from the signature, if the fault must be ascribed to the resistor or the capacitor. For the device examined (figure 1), six ambiguity groups are obtained. One further group represents the fault free circuit operation (fault free circuit). Here the seven considered fault classes (taking into account the ambiguity groups) are listed:

Class 1: C1 or R3 faulty;

Class 2: C2 or R4 faulty;
Class 3: R1 faulty;
Class 4: R2 faulty;
Class 5: R5 faulty;
Class 6: R6 or R7 faulty;
Class 7: no faulty components (fault free circuit).

Considering the band-pass output node (V_b), the transfer function is:

$$H(s) = \frac{V_b}{V_{in}}(s) = \frac{K\,s}{\frac{s^2}{\omega_0^2} + \frac{2\xi\,s}{\omega_0} + 1}, \qquad (2)$$

where K, ξ, ω_0 are the filter coefficients connected with the circuit parameters.

The input signal, used both during the simulations and the measurements, is a sine sweep from 1 kHz and 50 kHz. Its amplitude is 4 Volt peak-to-peak, in order to assure the maximum SNR for proper signature generation. The sample frequency is 500 kHz.

The signature is obtained from input-output signal measurements by applying the ARX model identification algorithm. The ARX model found has two poles and one zero (placed in z=1). The signature is thus consisting in three parameters, i.e. we have three coefficients for each CUT's signature. They are b_0, a_1, a_0 as shown in (3).

$$H(z) = \frac{(z-1)b_0}{z^2 + a_1 z + a_0}. \qquad (3)$$

The neural classifier is trained by means of the data obtained by simulating of the CUT. A fault free circuit behaviour is simulated by considering the value of every component uniformly distributed within the range [0,99Xn 1,01Xn], where Xn represents the parameter nominal value (with reference to table 1).

On the other hand, the faulty conditions are simulated by varying the value of the fault element in the range [0,70Xn 0,99Xn) and (1,01Xn 1,30Xn]. A uniform distribution was taken into account, for its conservative properties. The values of the other fault-free components are uniformly distributed within the range of their constructive tolerances.

In figure 2, the fault signatures collected in the fault dictionary are presented, with each marker corresponding to a different faulty condition.

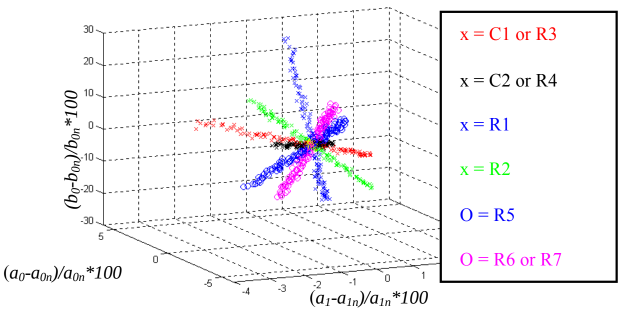

Figure 2: Relative variations of the ARX parameters with respect to the parameter nominal values (in percentages), for the band-pass filter shown in figure 1, with a sampling frequency of 500 kHz.

The choice of the signal sampling frequency is of the utmost importance to build an efficient classifier. There are two different requirements: on the one hand it is recommended to use the maximum sampling frequency to obtain the best signal reconstruction; on the other hand, the circuit signatures get closer in the parameter space when the sampling frequency increases. As a consequence, the diagnosis and isolation problems become very difficult issues to solve. This is demonstrated in figure 3, where the signatures collected in the fault dictionary, obtained using a sampling frequency of 1 MHz, are shown.

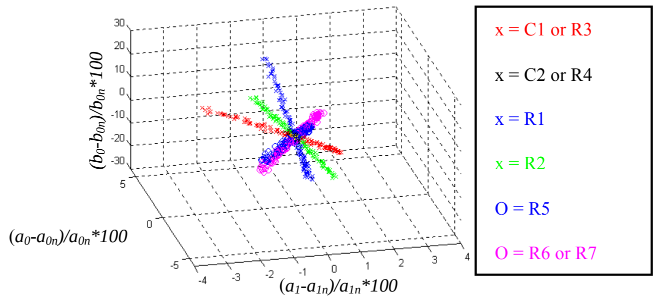

Figure 3: Relative variations of the ARX parameters with respect to the parameter nominal values (percentage), for the band-pass filter shown in figure 1, with a sampling frequency of 1 MHz.

In figure 3 it can be seen that the fault discrimination becomes a harder task when the sampling frequency gets higher, this can be observed in particular when observing the fault class given by faults of capacitance C2 or of the resistance R4.

Therefore, for the input-output signals and for the conversion continue-to-discrete time domain, a sampling frequency obtained as a trade-off between time resolution and feature significance was used. The diagnosis method for the device in figure 1 is then verified by means of the simulation.

Figure 4 shows the classification errors during both the training and the test phases, as a function of the number of the hidden layer nodes, with a sampling frequency of 500 kHz.

The test set is obtained by simulation with the same algorithm used for the training data set generation. Both sets consist of 120 examples per class.

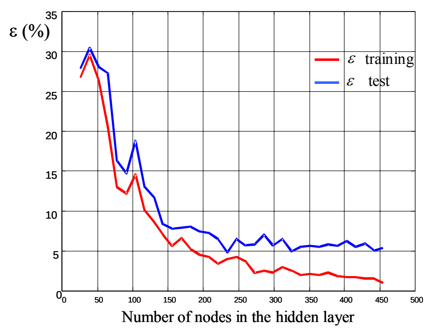

Figure 4: Simulated classification error of the training and test phases, as function of the number of the hidden layer nodes.

These results indicate that the classification error on the test set is approximately 5% when the sampling frequency is 500 kHz.

In figure 5 the test error committed on a test set consisting of 120 examples of signatures per class is shown, when the number of hidden layer nodes is 455 (35 for each fault class). The errors related to positive deviations and negative deviations of the faulty parameters are represented separately for each considered fault class. A further class (the 13^{th}) represents the classification error for the fault-free circuit .

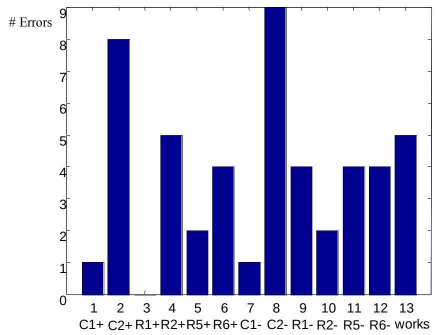

Figure 5: Test errors obtained on 60 signature examples, listed for the 13 faulty groups.

It is evident that the maximum classification error is due to the classification of fault of the capacitance C2 (and the resistance R4, which is a member of the same ambiguity group). The main reason of this difficulty is a low sensitivity of the signature with respect to a fault of the circuit components R4-C2.

4. MEASUREMENTS

In order to verify the method effectiveness, signatures are extracted from the measurements of the input-output signals performed on “a set of faulty Biquad circuits”. Faulty circuits are obtained by replacing the electrical components with others of different, well-known value.

In order to obtain a correct fault diagnosis, it is necessary to make a calibration of the automatic measurement system, in particular with respect to the noise introduced during the signal acquisition phase. We obtained good results by modelling the noise as a white additive process, with a Signal to Noise Ratio of 47 dB for the acquired input signal and of 44 dB for output one.

Figure 6 presents the measured fault signatures (the markers are squares), superimposed to those collected in the fault dictionary and already represented in figure 2.

Figure 7 presents the classification obtained with the experimental data set.

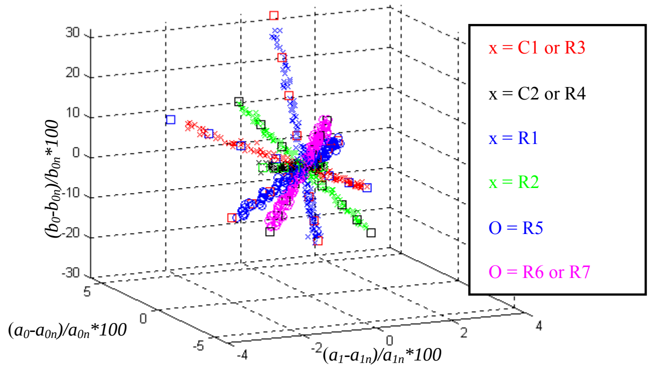

Figure 6: The signatures obtained from measurements (the markers are squares) and the signatures from the fault dictionary.

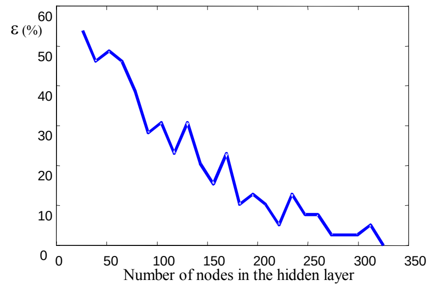

Figure 7: Percentage error committed by the classifier on a data set formed from the measurements, as function of the number of hidden layer nodes.

This error is zero when the number of the nodes in the hidden layer of the Radial Basis Function Network is 325, that is 25 nodes for each class. This experimental results are in agreement with the results obtained from the simulations. In fact experimental data seems to yield better classifier performance, but it must be note that these latter are obtained by injecting soft faults caused by deviations of the faulty parameters larger than 9% of the component nominal value. On the other hand in the simulated data set also more critical situations were comprised, since the minimum considered deviation, corresponding to a faulty condition, equals 1% of nominal value.

5. CONCLUSIONS

A technique for soft fault identification is presented. The fault location is performed by comparing the CUT signature with the examples contained in the fault dictionary. A neural classifier performs this comparison. The CUT’s signature is obtained by a model identification procedure (ARX). In this way the behaviour of the circuit is completely represented by a small set of data (the model parameters), and a large amount of information is provided to the classifier in a low dimension space. This allows obtaining better performance of the classifier, also in terms of computational complexity.

Using a different classifier or an other clustering algorithm, it may be possible to solve the problem of estimating the fault entity.

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