Two-stage algorithm for soft fault diagnosis in analog dynamic circuits

Abstract. The paper deals with the soft fault diagnosis in analog dynamic circuits. The two-stage algorithm for soft fault location and identification has been presented. It is based on the spectrum analysis of the circuit response to the rectangular input signal, a neural network and one of the new evolutionary techniques - gene expression programming. The first stage enables fault location using neural network. The result of the second stage is fault identification performed with formulas derived using gene expression programming. The method is illustrated with a numerical example.

Introduction

Fault diagnosis of analog circuits is an important element of the analysis, designing process and testing of electronic systems. During the last decades the problem was considered in numerous papers and books [1-11] and many methods relating to this issue have been developed. The presence of circuit nonlinearities and component tolerances causes that fault diagnosis of analog circuits is very complex [9,10] and it has not achieved the development level of the method for digital circuits.

Three major parts of analog circuit testing are fault detection, location and identification. Analog fault diagnosis techniques are classified into two groups: simulation-before-test (SBT) [6] and simulation-after-test (SAT) [8]. The methods represented the first approach are usually profitable for catastrophic diagnosis, especially for single fault cases. Algorithms of second group need more computational time after a test and can be effectively used only during the design stage.

This paper is devoted to the soft fault location and identification in analog dynamic circuits. The proposed method represents SBT approach. It is based on the spectrum analysis of the circuit response to the given input signal. It uses neural network to the fault location (1. stage) and one of new evolutionary computational procedures - gene expression programming (GEP) - (2. stage).

The base of the proposed method

The method is assigned to fault detection, location and identification in dynamic circuits. The scheme and all nominal values of CUT parameters need to be known in order to perform repeated analyses with different values of elements. In the presented method all diagnostic decisions are made on the basis of the spectrum analysis results of the circuit response to the rectangular-wave input signal. The low decreasing of harmonic value with increasing of harmonic number is an important advantage of this signal. Let \( r \) be the number of accessible for measurement points. The response signal \( y_i(t) \) at the \( i \)-th measurement point depends on the input signal \( u(t) \) as follows:

\[
y_i(t) = H_i[u(t), x], \quad i = 1, 2, \ldots, r
\]

where: \( x = [x_1, x_2, \ldots, x_k] \) is the vector of possible faulty element parameters, \( H_i \) are in general nonlinear functions of the input signal \( u(t) \) and parameters of elements \( x \).

Keywords: soft fault diagnosis, neural networks, gene expression programming.

The first stage – fault location

The aim of the first stage of the presented algorithm is fault location. It is performed with a neural network [5]. The neural classifier is based at results of spectral analysis. The first step consists of creating set \( S \) of \( \gamma \) possible faulty elements \( x_j (j = 1, 2, \ldots, n) \) and all its subsets \( S_i \) of \( k \) elements (\( k \) is the maximal number of simultaneously faulty elements). Number \( m \) of subsets \( S_i \) is equal to:

\[
m = \frac{n!}{k!(n-k)!}
\]

For each \( S_i \) output signals at all test points \( y_{j\gamma}(t), (j = 1, \ldots, m; \gamma = 1, \ldots, \gamma) \) are calculated, than spectrum analysis of them are performed and values of \( \gamma \) harmonics \( F_{\gamma}^0[y_{j\gamma}, u(t)] \) obtained \( (F_0^0) \) is the amplitude of \( \gamma \)-th harmonics. The number of \( \gamma \) is determined accordingly to measurement possibility. For each test point the results of simulations form tables. The size of each table is \( q \times r \). The number of rows \( q \) is equal to the number of different sets of possibly simultaneously faulty elements \( x_p = [x_{p1}, x_{p2}, \ldots, x_{pk}] \). If simulations are performed for \( z \) different values of each of \( v \) parameters than number of rows \( q \) is equal to \( q = z^v \). For each \( S_p \), the results of simulations form \( r \) tables as follows:

\[
F_{(i)}^{(1)}[x_p] \quad F_{(i)}^{(2)}[x_p] \quad \ldots \quad F_{(i)}^{(q)}[x_p]
\]

where \( F_{(i)}^{(j)}[x_p] \) is \( s \)-th harmonic of output signal at \( j \)-th test point calculated with \( i \)-th set of \( k \) values of parameters \( x_p \).
To improve working of neural network classifiers and evolutionary algorithm all values of harmonics are normalized in the interval \([-1, 1]\) according to (4):

\[
\delta F_i^{(l)} = \frac{F_i^{(l)} - F_{\text{nom}}^{(l)}}{F_{\text{nom}}^{(l)}}
\]

A multi layer perceptron (MLP) with sigmoid activation functions, and back-propagation learning using a Levenberg-Marquardt algorithm, has been used as the classifier. The network has as many nodes in input layer as the number of used harmonics of all test points. It is equal to product of \(p\) and \(r\). Number of output neurons is equal to the number of possible states of CUT. The network has only one hidden layer. The Matlab neural network toolbox has been used to realize the classifier.

To generate a training set for the neural network the formulas enables fault identification are obtained. In each pattern of dictionary \(S_p\) formulas as (6) are associated.

\[
x_{p,j} = f_{p,j}(\delta F_i^{(s)})
\]

where: \(x_{p,j} (j=1,...,k)\) – the actual value of faulty element \(j\), \(\delta F_i^{(s)}\) – value of the normalized \(s\)-th Fourier coefficient of signal at the \(i\)-th node. In evolutionary process are used only indispensable number of normalized harmonics. In order to maximize of accuracy of formulas (6), the selection of harmonics is performed with respect to sensitivity of harmonics to changes of parameters.

A numerical example

The analysis of the benchmark circuit [14] shown in fig.2 is presented as a numerical example.

![Fig.2. The benchmark circuit analysed in the paper](image_url)

The presented circuit is a filter with three outputs. Faults of all resistors and capacitors from the range ±50% are considered. Only the single fault case is presented in the paper because the extension of the procedure to double faults has been implemented with limited effort. The rectangular signal with the amplitude 5V is closed at input node. An output signal is acquired at the node marked as LPO. The constant term and all odd harmonics from 1-th to 11-th are used in location and identification process.

An MLP network with sigmoid activation functions, and back-propagation learning using a Levenberg-Marquardt algorithm has been used. The network has as many nodes in input layer as the number of all used harmonics of all test points. As only one measurement node is used, \(r=1\), and 7 harmonics are taken into account (together with the 0-th harmonic), \(p=7\), the number of input neurons is equal to 7.
The hidden layer consist of 15 neurons. Number of output neurons is obtained by to the number of possible states of CUT. As the faults of elements: $R_2$ and $C_1$ such as $R_3$ and $R_4$ are undistinguish the output layer consists of 8 neurons, 7 for faults and 1 for unfaulty circuit. The Matlab neural network toolbox has been used to simulate the classifier.

A set of Spice simulations are performed in order to calculate elements of 8 tables like (3), one for each faulty and one for unfaulty CUT. Each faulty case table has 7 columns and 40 rows according to 40 different faulty element values. The unfaulty case table has also 7 columns and 80 rows associated with various values of unfaulty elements from the tolerance range. Hence, the size of input pattern matrix with normalized values of harmonics (from the range [-1, 1]) is 360 x 7. Additionally, for learning process 360 vectors of 7 values, 0 or 1, are formulated. The 360 sets of input output values are divided into two groups: 160 for training and 200 for testing.

The results of location test are shown in table 1. The unfaulty circuit case is in nearly 100% correctly separated, 19 from 20 tests. All faulty circuit cases are correctly separated in below 89%. The location system works with a success rate of almost 90%.

Table 1. The results of location process

<table>
<thead>
<tr>
<th>State of CUT</th>
<th>Number of test simulations</th>
<th>Number of correctly locations</th>
<th>Number of ambiguities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault free</td>
<td>20</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td>Faulty $R_1$</td>
<td>20</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td>Faulty $R_2$</td>
<td>20</td>
<td>17</td>
<td>1</td>
</tr>
<tr>
<td>Faulty $R_3$</td>
<td>20</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>Faulty $R_4$</td>
<td>20</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td>Faulty $C_1$</td>
<td>20</td>
<td>18</td>
<td>0</td>
</tr>
<tr>
<td>Faulty $R_1$ or $C_2$</td>
<td>40</td>
<td>36</td>
<td>2</td>
</tr>
<tr>
<td>Faulty $R_1$ or $R_2$</td>
<td>40</td>
<td>35</td>
<td>1</td>
</tr>
</tbody>
</table>

The second stage of diagnostic process is identification. For each faulty element the formula for calculating an actual value is found. An evolutionary algorithm gene expression programming is used. Each gene of GEP consists of basic function and arguments. The set of basic functions consist of 8 elements: addition of two arguments (+), subtraction (-), multiplication (*), division (/), logarithm (l), exponential (e), sinus (S) and co sinus (C). The arguments are normalized changes of harmonics. For one fault cases, when the function for obtaining a value of any harmonic is monotonic, only one argument need to be used for calculating the parameter change, only one column of table like (3) need to be used. Each gene consists of 13 elements, 6 from the beginning so-called a head of gene, are basic function or arguments, 7 from the end of gene, so-called a tail are only arguments.

For the presented CUT 9 formulae are found. Let us consider the case of the faulty resistor $R_2$. The formula (8), obtained using GEP, is encoded form of the function (10), which enable us to calculate value of $R_2$. Three genes create the first line, two – the second line.

\[ SC \cdot Caaaahh + \star \cdot a^a \cdot aaaa + S \cdot a^a \cdot aaaaaa \]
\[ a\cdot E \cdot S \cdot aaaa \cdot S \cdot E \cdot a \cdot C \cdot S \cdot aaaaaaaa \]

where: symbols \( +, -, \cdot, S, C, E \) represent the basic functions, and \( \cdot a \) marks an argument (the relative change of 0-th harmonic). Each gene of (8) represents a function:

\[ SC \cdot Caaaahh \rightarrow (cos(a) \cdot a^a \cdot sin(cos(a))) \]
\[ ** \cdot S \cdot aaaa \rightarrow 0 \]
\[ ** \cdot S \cdot aaaa \rightarrow (sin(a^a) \cdot sin(a)) \]
\[ a \cdot E \cdot S \cdot aaaa \rightarrow a \cdot exp(sin(a^a)) \]

As the function connecting genes is addition the formula for the normalized change of $R_2$ is as follows:

\[ \delta R_2 = cos(a) \cdot a^a \cdot sin(cos(a)) + sin(a^a) + a \cdot exp(sin(a^a)) \]

The formula (10) is correct only for the in advance obtained range of element $R_2$. As an example, let us consider the case when the actual value of the resistor $R_2$ is 7kΩ. The measured value of 0-th harmonic is -0.4225. From the formula (10): $\delta R_2=0.27$ and $R_2=7.3$ kΩ is obtained. The relative error in this case is 5%. The accuracy of all formulas for calculating of faulty elements is in the range ±9%.

**Conclusion**

The two-stage algorithm for soft fault diagnosis in analog dynamic circuit is proposed. In order to improvement its working in double and multiple fault cases, new art of training set generation and another art of neural network need to be applied. The higher accuracy at the second stage may be achieved with changes of GEP parameters.

**REFERENCES**


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