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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 enable us 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*

***Streszczenie.** Tematem pracy jest diagnostyka uszkodzeń parametrycznych w analogowych układach dynamicznych. Przedstawiony jest dwustopniowy algorytm lokalizacji oraz identyfikacji uszkodzeń parametrycznych bazujący na analizie widmowej odpowiedzi układu na prostokątny sygnał wejściowy. Pierwszy stopień realizuje lokalizację uszkodzenia wykorzystując sieć neuronową. Wynikiem drugiego jest identyfikacja, którą umożliwiają zależności wyznaczone przez ewolucyjny algorytm programowania wyrażeń genetycznych. (**Dwustopniowy algorytm lokalizacji oraz identyfikacji uszkodzeń parametrycznych w analogowych układach dynamicznych**)*

Keywords: soft fault diagnosis, neural networks, gene expression programming.
Słowa kluczowe: diagnostyka uszkodzeń parametrycznych, sieci neuronowe, metoda programowania wyrażeń genetycznych.

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 group: 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:

$$y_i(t) = H_i[u(t), \mathbf{x}] \qquad i = 1, 2, \ldots, r \tag{1}$$

where: $\mathbf{x}=[x_1,x_2,\ldots x_n]$ 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 $\mathbf{x}$.

When one or more element values $x_j,(j=1,2\ldots n)$ are not equal to their nominal values, $y_i(t)$ are changed. The knowledge about changes of the amplitude spectrum of CUT with nominal values and a faulty circuit, in particular relative differences of Fourier coefficients, enable us to make diagnostic decisions. The results of before test simulations form the training sets for neural network learning and for determine formulas enabled faults identification.

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 $\mathbf{S}$ of n possible faulty elements x_j $(j=1,2\ldots n)$ and all its subsets $\mathbf{S}_p$ ($p=1\ldots m$) of k elements (k is the maximal number of simultaneously faulty elements). Number m of subsets $\mathbf{S}_p$ is equal to:

$$m = \binom{n}{k} = \frac{n!}{(n-k)!k!} \tag{2}$$

For each $\mathbf{S}_p$ output signals at all test points $y_{p,j}(t)$, $(p=1\ldots m;\ j=1\ldots r)$ are calculated, than spectrum analysis of them are performed and values of γ harmonics $F^{(s)}[y_{p,j}(t)]$, $(s=1,2\ldots\gamma)$ obtained ($F^{(s)}$ is the amplitude of s-th harmonics). The number of γ is determined accordingly to measurement possibility. For each test point the results of simulations form tables. The size of each table is q x γ. The number of rows q is equal to the number of different sets of possibly simultaneously faulty elements $\mathbf{x_p}=[x_{p,1},\ldots x_{p,k}]$. If simulations are performed for z different values of each of k parameters than number of rows q is equal to $q=z^k$. For each $\mathbf{S}_p$ the results of simulations form r tables as follows:

$$F_{(j)}^{(1)}\left(\mathbf{x}_\mathbf{p}^{(i)}\right),\ F_{(j)}^{(2)}\left(\mathbf{x}_\mathbf{p}^{(i)}\right),\ \ldots\ F_{(j)}^{(\gamma)}\left(\mathbf{x}_\mathbf{p}^{(i)}\right) \tag{3}$$
$$i = 1,2,\ldots,q \qquad j = 1,2,\ldots,r$$

where $F_{(j)}^{(s)}\left(\mathbf{x}_\mathbf{p}^{(i)}\right)$ is s-th harmonic of output signal at j-th test point calculated with i-th set of k values of parameters $\mathbf{x_p}$.

To improve working of neural network classifiers and evolutionary algorithm all values of harmonics are normalized in the interval [-1, 1] according to (4):

$$\delta F^{(i)} = \frac{F^{(i)} - F_{nom}^{(i)}}{F_{nom}^{(i)}} \tag{4}$$

A multi layer perceptron (MLP) with sigmoid activation functions, and back-propagation learning using a Levemberg-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 γ 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 measurements at all r test points are used. As the number of simulations for each p is equal to $q=z^k$ and d for the unfaulty CUT, total number of simulations is equal to $b = p$ x $q + d$. Hence, the input pattern matrix has b rows. The number of columns c is equal to the number of all used features. It is product of γ (the number of used in diagnostic process harmonics) and r (the number of measurement nodes): $c = \gamma$ x r. Hence, the input matrix for learning purpose is as follows:

$$\begin{gathered}\delta F_i^{1,1},\ldots,\delta F_i^{1,\gamma},\delta F_i^{2,1},\ldots,\delta F_i^{2,\gamma},\ldots,\delta F_i^{r,1},\ldots,\delta F_i^{r,\gamma} \\ i = 1,2,\ldots,c\end{gathered} \tag{5}$$

Each input training matrix is associated with the 0 -1 output vector. Its elements are expected values of the n output neurons.

When the training process of the network has been ended, the diagnosis process can be performed. The normalized values of γ harmonics, as (5), measured at the r nodes create the input vector. The states of output neurons determine the result of location process.

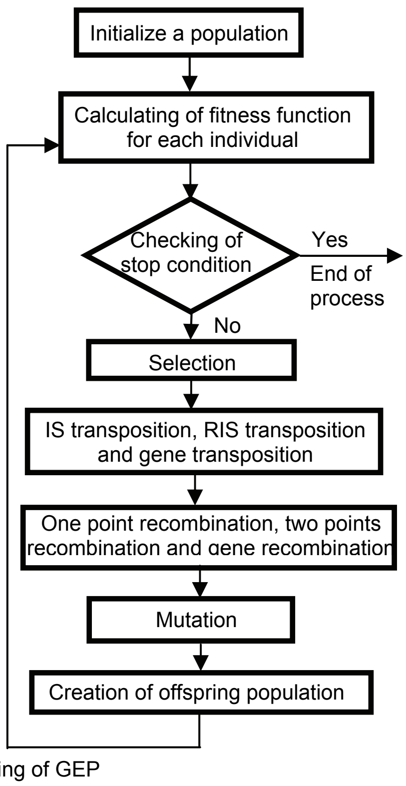

Fig.1. Working of GEP

The second stage – fault identification

The goal of the second stage of the method is fault identification. To this end the fault dictionary is constructed. Each pattern in the dictionary is associated with a subset $\mathbf{S}_p$. The formulas enables fault identification are obtained. In this process the new evolutionary methods, invented by Candida Ferreira in the end of the past century, *gene expression programming* (GEP) is applied [12].

GEP (fig.1) enable us to determine a formula for calculation of a variable *β* as a function of variables α_i (i=1,2...k), using training sets. The obtained by GEP formulas are solutions of approximation problem. GEP creates *expression trees,* which are made of functions belonging to set of *base functions*. In an example below 8 functions create the set of base functions: addition, substraction, multiplication, division, logarithm, exponential function, sinus and cosinus.

The result of evolutionary process are formulas for calculating actual values of faulty elements [13]. For each $\mathbf{S}_p$ k formulas are obtained. Each formula is valid for determined at location stage p and is designed for calculating only one parameter $x_{p,j}$ (j=1,2..k).

Hence, the number of formulas is equal to m x k. With each pattern of dictionary k formulas as (6) are associated.

$$\begin{gathered}x_{p,j} = f_{p,j}\left(\delta F_{(i)}^{(s)}\right) \\ j = 1,2,\ldots,k \quad s = 1,2,\ldots,v \quad i = 1,2,\ldots,r\end{gathered} \tag{6}$$

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.

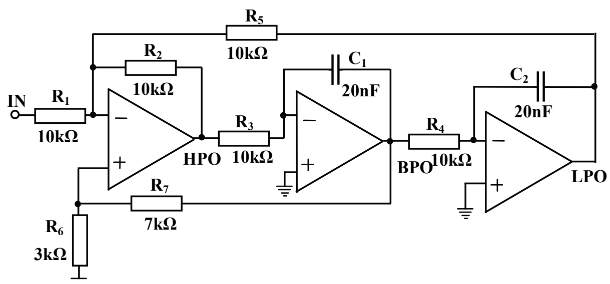

Fig.2. The benchmark circuit analysed in the paper

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 Levemberg-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), γ=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_4 and C_2 such as R_6 and R_7 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

State of CUT	Number of test simulations	Number of correctly locations	Number of ambiguities
Fault free	20	19	0
Faulty R_1	20	19	0
Faulty R_2	20	17	1
Faulty R_3	20	16	0
Faulty R_5	20	19	0
Faulty C_1	20	18	0
Faulty R_4 or C_2	40	36	2
Faulty R_6 or R_7	40	35	1

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 function (E), sinus (S) and cosinus (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 likes (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 formulas are found. Let us consider the case of the faulty resistor R_5. The formula (8), obtained using GEP, is encoded form of the function (10), which enable us to calculate value of R_5. Three genes create the first line, two – the second line.

(8)
--SC*Caaaaaaa**S-a*aaaaaaa+SS-a*aaaaaaa
-aE-S*aaaaaaaSEaCS-aaaaaaa

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

--SC*Caaaaaaa → $\cos(a)-a^2-\sin(\cos(a))$
**S-a*aaaaaaa → 0
+SS-a*aaaaaaa → $\sin(a^2-a)+\sin(a)$
-aE-S*aaaaaaa → $a-\exp(\sin(a-a^2))$

(9) SEaCS-aaaaaaa → $\sin(\exp(a))$

As the function connecting genes is addition the formula for the normalized change of R_5 is as follows:

$$\delta R_5 = \cos(a)-a^2-\sin(\cos(a))+\sin(a^2-a)+\sin(a)+ a-\exp(\sin(a-a^2))+\sin(\exp(a)) \tag{10}$$

The formula (10) is correct only for the in advance obtained range of element R_5. As an example, let us consider the case when the actual value of the resistor R_5 is 7kΩ. The measured value of 0-th harmonic is -0.4225. From the formula (10): δR_5=-0.27 and R_5=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 other art of neural network need to be applied. The higher accuracy at the second stage may be achieved with changes of GEP parameters.

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