Neural Network Based Algorithm of Soft Fault Diagnosis in Analog Electronic Circuits

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Summary

This paper addresses the fault diagnosis in analog electronic circuits based on neural network. Iterative algorithm of solving the system of diagnostic equations, using integral sensitivity matrix is also proposed in this paper. To obtain the system of diagnostic equations, the integral sensitivity matrix is used. The integral sensitivity matrix is constructed based on a result of the comparisons of signals measured at the nodes of circuit under test (CUT) and appropriate signals of circuit with nominal parameter values. The response of the circuit with nominal values of parameters is recorded and trained using a feed forward neural network. The proposed method has capability to detect single and multiple faulty components, also it is applicable to a wide class of electronic devices and can be integrated into modern computerized diagnostic tools.

Key words:
Neural Network, Fault detection, Sensitive Matrix.

1. Introduction

Testing and diagnosis of electronic devices are fundamental topics in the development and maintenance of reliable and safe complex systems. While fault diagnosis in digital electronic circuits has been developed to the point of automation, the development of an effective automated diagnosis tool for analog devices mostly relies on the engineers experience [1]. A survey of the research conducted in this area [2,3,4,5] indicates that there are two major types of fault model: either catastrophic or parametric. Catastrophic failures such as short circuit or open loop lead to the change of circuit topology and complete failure of device. Parametric fault mechanism is one which leads to the difference of the actual circuit parameters from their nominal values. Parameter deviations depend on the intrinsic nature of the production process of the devices and their relative aging effects. Such situations which do not change circuit topology are commonly defined as "soft" or parametric faults and may lead to an unpredictable and incorrect operation of the system. Among number of papers dealing with parametric faults, recently, distinguished papers considering the application of neural network for fault diagnostic were published [6,7,8,9,10,11]. Here we consider the neural network approach for solving the system of diagnostic equations, which are constructed on the basis of integral sensitivity matrix, presented in the authors paper [12].

Neural network approach is robust by its nature, easily overcomes problems associated with the presence of noise in measurements of node voltages or local minima if such an issue arises. Neural network approach works much faster if implemented on specialized neuro-chip.

2. Theoretical Consideration

For completeness we briefly present the methodology for generating diagnosis equations, which has been suggested in [12]. This methodology is based on sensitivity of the circuit nodes voltages with respect to its parameters and the differences between node voltages of the circuit with nominal values of parameters and appropriate node voltages of circuit under test.

It is assumed that the topology of the circuit is known and vector of node voltages of circuit with nominal parameter values can be found from equation

$$C\dot{V} + GV = J \quad (1)$$

Where **C**= capacitive matrix, **G** – conductance matrix, **V** – vector of node voltages, $\dot{V}$ - Vector of node voltage derivatives, **J** – vector of currents.

Let's denote by $\mathbf{P}_{[k,1]}$ the vector of nominal parameters, where **k** is the number of parameters. Number of nodes is made-up from accessible nodes $\mathbf{n}_{acc}$, partially accessible nodes $\mathbf{n}_{pacc}$, and inaccessible nodes $\mathbf{n}_{iacc}$

$$\mathbf{n} = \mathbf{n}_{acc} + \mathbf{n}_{pacc} + \mathbf{n}_{iacc} \quad (2)$$

Application of excitation to each accessible node and sampling response signal on $\mathbf{n}_t$ intervals for every $(\mathbf{n}_{acc} + \mathbf{n}_{pacc})$ yields m test equations

$$\mathbf{m} = \mathbf{n}_t \bullet \mathbf{n}_{iacc} + (\mathbf{n}_{acc} + \mathbf{n}_{pacc}), \quad (3)$$

which can be written in vector-matrix form as in [5]

$$\mathbf{W}_{[m,k]} \cdot \delta\mathbf{P}_{[k,1]} = \Delta\mathbf{U}_{[m,1]} \quad (4)$$

Where $\mathbf{W}_{[m,k]}$ Matrix of integral sensitivity of **(mxk)** dimension with elements $\mathbf{W}_{ij}$, which is the sensitivity of

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voltage in node **j** with respect to deviation of **i** components;
$\Delta \mathbf{U}_{[m,1]}$ vector of differences between appropriate integral node voltages of circuits with nominal $\mathbf{U}_{[m,1]}$ parameters and circuit under test $\mathbf{U}^*_{[m,1]}$; $\delta \mathbf{P}_{[k,1]}$ vector of relative changes of parameters .
Components of equation (4) are calculated as follows:

$$Wij = \frac{h}{2}\sum_{k=1}^{N}[\partial\, vj(tk)/\partial Pi + \partial\, vj(tk-1)/\partial Pi\,]\ Pi \quad \textbf{(5)}$$

$$\Delta U[m,1] = U_{[m,1]} - U \times [m,1] \quad \textbf{(6)}$$

$$U_j = \frac{h}{2}\sum_{k=1}^{N}[\,vj(tk) + vj(tk-1)\,], \quad j = \overline{1,m} \quad \textbf{(7)}$$

$$\delta P_{[k-1]} = [\Delta P1/P1, \Delta P2/P2, ...\Delta Pk/Pk]^T \quad \textbf{(8)}$$

In formula (5), (6), (7), and (8)
$\mathbf{V_j\ (t_k)}$ is a voltage of **j** node in $\mathbf{t_k}$ moment of time;
N is a number of time points in the selected interval of numerical integration;
h size of step in numerical integration;
$\mathbf{P_i}$ normal value of **i** parameter;
$\Delta\ \mathbf{P_i}$ deviation of **i** parameter from its nominal value;
T symbol of transposition.

Procedure of diagnosis consists of solving equation (4) with respect to $\delta \mathbf{P}_{[k,1]}$ and consequent comparison of each parameter deviation with its given tolerance

$$\Delta\ Pi/Pi \quad \le TOL\,(p_i), \quad i = \overline{1,k} \quad \textbf{(9)}$$

where TOL $(\mathbf{p_i})$ is a tolerance of component **i**. Components for which inequality does not hold are considered faulty.

3. Neural-Based Solution of Diagnosis Equations

In general, for solving system of linear identification equation (4) where **m>k,** it is necessary to find such value $\delta\partial\mathbf{P}^*$for which

$$\textbf{Min}_{\delta P}\ \|\Delta U - W\delta P\| = \|\Delta U - W\,\delta P^*\| \quad \textbf{(10)}$$

Where $\|\cdot\|$ - denote the Euclidian distance between appropriate vectors.
Application of necessary condition of finding minimum of equation (10) yields system of **k** linear equations

$$M_{w1w1}\delta P_1 + M_{w2w1}\delta P_2 + \bullet\bullet\bullet\bullet + M_{wk\,w1}\delta P_k = M_{Y1} \quad \textbf{(11a)}$$

$$M_{w1w2}\,\delta P_1 + M_{w2w2}\,\delta P_2 + \bullet\bullet\bullet\bullet + M_{wkw2}\,\delta P_k = M_Y \quad \textbf{(11b)}$$

$$M_{w1wk}\,\delta P_1 + M_{w2wk}\,\delta P_2 + ... + M_{wkwk}\,\delta P_k = M_{Yk} \quad \textbf{(11c)}$$

where

$$M_{wn\,wl} = \sum_{i=1}^{m} W_{i,n}\ W_{i,l}\ , L = \overline{1,k}\,, n = \overline{1,k} \quad \textbf{(12)}$$

$$M_{Yl} = \sum_{i=1}^{m} Ui\ Wi\,, L = \overline{1,k} \quad \textbf{(13)}$$

Neural network approach as dynamic system designed for solving linear equations (11) requires determination of network attributes, which can be detailed as the following [15]:
1. Input vector of neural network is a vector $\delta \mathbf{P}_{[k,1]}$ to be determined at the initial moment. This vector is equal to zero i.e. $\delta \mathbf{p}_{(0)} = \delta \mathbf{Po}$.
2. Output signal of neural network is a vector $\mathbf{Z}_{[k,i]}$ with the number of components equal to the number of equations in (11). Desirable output signal equals to zero. So, solution of system of linear equation (11) can be interpreted as finding under given matrix $\mathbf{M_w} = \|\ \mathbf{M_{wi\ wj}}\ \|$ such input vector which convert output vector **Z** to zero vector : $\mathbf{Z} = \check{\mathbf{z}} = [\mathbf{0}]$.
3. Structure of neural network which transform input signal to output signal adequately to the solution of (11), can be represented as

$$\mathbf{Z} = [f(h_1), f(h_2), ...f(_{hk})]^T = f(M_w\delta P - M_Y) \quad \textbf{(14)}$$

Where

$$f(_{hk}) = \left\{\begin{matrix} 0, -G \quad hk < G\,; \\ \#0,\ h \notin\,]-G, G\,[; \end{matrix}\right\} \quad \textbf{(15)}$$

and

$$M_y = [M_{Y1}, M_{Y2}...............M_{Yk}\,]^T \quad \textbf{(16)}$$

The value of **G** is selected in accordance with the required accuracy of calculation. This is the structure of a single layer neural network with the matrix of weight coefficients $\mathbf{M_w}$ and bias vector $\mathbf{M_y}$. The structure of this network is shown on Fig.1.

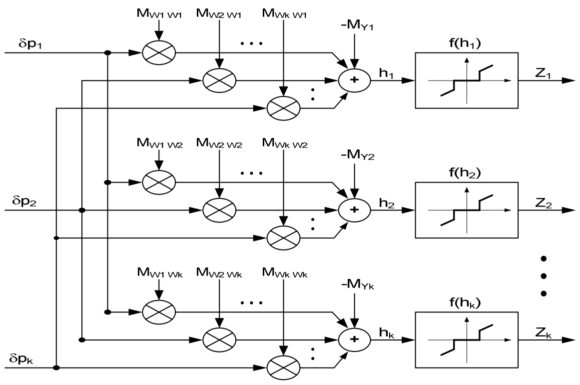

Fig1. Structure of single layer neural network with weighted coefficients **Mw** and bias vector – $\mathbf{M_Y}$.

4. An activation function is selected to be uniform for each **i**.

$$\mathbf{f(h_i)} = \begin{Bmatrix} 0, & -G < hk < G; \\ hi, & hi \notin [-G, G]; \end{Bmatrix}, \mathbf{i} = \overline{1,k} \qquad \mathbf{(17)}$$

5. Error signal for the convenience of differentiation is determined as difference between received and desired output signals, taking into account that ž **= [0],** yields

$$\mathbf{e = z - \check{z} = Z} \qquad \mathbf{(18)}$$

6. Criterion of optimization is a function of error determined as

$$F(\delta P) = e^T e = \sum_{i=1}^{k} e^2 i \qquad \mathbf{(19)}$$

Solution consists of finding such input signals **δp** , which provides

$$\mathbf{F(\delta p) = \min \delta p} \qquad \mathbf{(20)}$$

Combing (14), (18), and (19) yields

$$\mathbf{F(\delta p) = \sum (f(M_w\, \delta(p - M_Y))^2} \qquad \mathbf{(21)}$$

Adjusting of input signal is conducted by iteration method

$$\mathbf{\delta P(q+1) = \delta P(q) - H \quad \partial F/\partial(\delta P) \,\big|\, \delta_{P=\delta P(q)}} \qquad \mathbf{(22)}$$

where **q** –number of iterations, **H** – amplification coefficient. Differentiation of (21) and taking into account (17) yields

$$\partial F/\partial(\delta P) = 2\sum_{i}^{k} Z_i M_w W_n, \; n = \overline{1,k} \qquad \mathbf{(23a)}$$

or in vector –matrix form

$$\partial F/\partial(\delta P) = 2 \overset{T}{\underset{w}{M}} Z \qquad \mathbf{(23b)}$$

Then

$$\partial P(q+1) = \partial P(q) - 2H^T \overset{T}{\underset{w}{M}} Z(q). \qquad \mathbf{(23c)}$$

The value of correction is calculated for each iteration according to equation (22)

The Neural network approach for solving the system of diagnostic equations is described by expressions

$$\mathbf{\delta(P(0)) = \delta P_o} \qquad \mathbf{(24a)}$$

$$\mathbf{Z(q) = f(M_w\, \delta P - M_Y)} \qquad \mathbf{(24b)}$$

$$\mathbf{\delta P(q+1) = \delta P(q) - 2H} \overset{T}{\underset{w}{M}} \cdot \mathbf{Z(q)} \qquad \mathbf{(24c)}$$

The structure of neural network approach as a feedback system is depicted on Fig2.

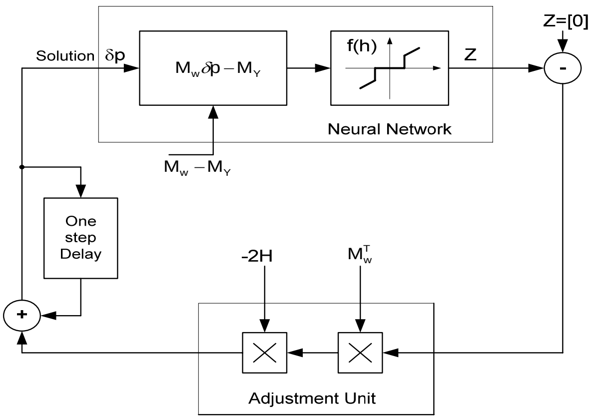

Fig2.Neural network approach structure as a feedback system.

3. Experimental Consideration

To present the developed algorithm, the circuit shown in Fig.3 was chosen as the CUT, where points 1, 2 are accessible nodes, point 3 is partly accessible node and 4, 5 are inaccessible nodes. Vector of nominal values of parameter P^4,vector of CUT (real parameter P^+) and result of solving diagnostic equations δP are given in table 1. Diagnostic decision is made by the application of equation (9) with

$$\delta Pi \leq TOL(Pi), \qquad i = 1,6,$$

where TOL (Pi) given tolerance of parameter Pi

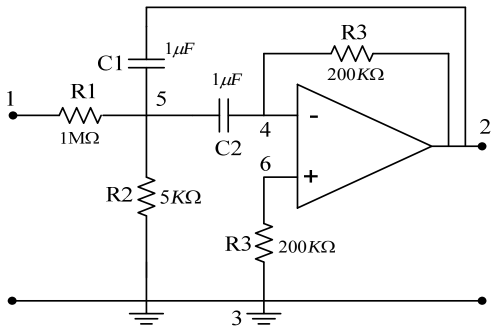

Fig.3.Circuit Under Test.

Fig. 4 shows responses of real (faulty) circuit and model of fault free circuit (with nominal values of parameter) before identification.

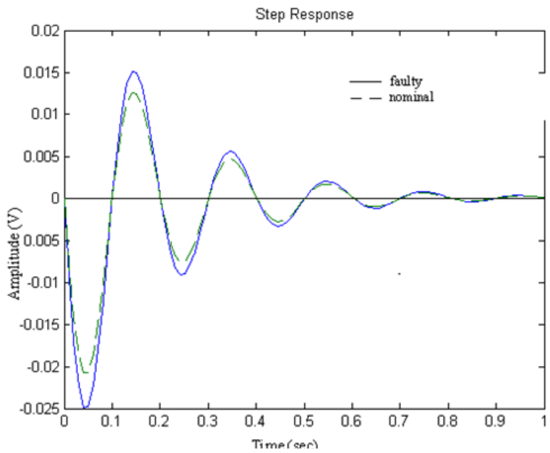

Fig.4.Response of real (faulty) circuit (solid line) and a model of nominal (fault free) circuit (dashed line),
Excitation –node 1 ,measurements –node 2.Source of excitation – unit step function.

Fig.5. shows response of real circuit and model of circuit after parameter identification.

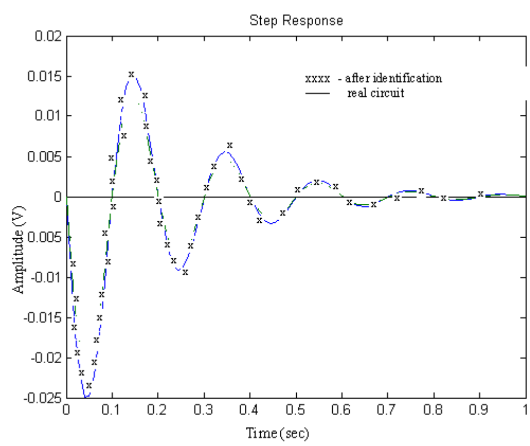

Fig.5. Response of real (faulty) circuit (solid line) and a model of circuit received as a result of identification ("x").
Excitation – node 1, measurements- node 2 ,source of excitation- unit step function.

Table1. hVector of nominal values, faulty and identified parameters of circuit under test.

Vector	R_1 *(MΩ)*	R_2 *(KΩ)*	R_3 *(MΩ)*	R_4 *(MΩ)*	C_1 *(μF)*	C_2 *(μf)*
P^n	1	5	0.2	0.2	1	1
P^f	0.85	5.2	0.215	0.2	0,8	1
$P^f - P^n / P^n$	0.15	0.04	0.0075	0	- 0.2	0
δP	0.02	0.009	0.0014	0	- 0.03	0.01

4. Conclusion

A neural network based algorithm for solving the system of diagnostic equations has been presented. According to expression (24) to solve equation (11) proposed algorithm requires **4Q N^2** arithmetic operations: **2QN^2** additions and **2QN^2** multiplication, where **Q** – number of iteration and **N** order system of linear equations. As a comparison application of direct method such as Gauss method requires approximately **(1/3)** N^3 additions, **(1/3)** N^3 multiplications and **(1/2) N (N+1)** divisions [14]. Hence, provided that **Q < 1/6** N neural network based approach is more effective.

Another well known Jacobi and Gauss-Seidel method requires **2N^2** multiplication **2N^2** addition and **N** divisions, which is equivalent to neural-based algorithm, but requires symmetries of matrix **Mw,** which limit the range of its applicability for solving diagnostic equation. In addition to the mentioned improvements, the methodology can be easily and effectively implemented as an automatic tool for the circuit diagnostic.

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References

[1]. Liu RW, " Testing and Diagnosis of Analog Circuit and Systems". New York: Van Nosland, 1991.

[2]. Spence H, "Automatic Analog Fault Simulation "AUTOTESTCON Conference, PP 17-22, 1996.

[3]. Chatterjee A, "Concurrent Error Detection and Fault Tolerance in Linear Analog Circuit using continuous Checksums", IEEE Trans.VLSI Systems Vol.1 no2 pp 138-150, 1993.

[4]. Hamdi NB and Kaminska B, " Multiple Fault Testing in Analog Circuits Proc. 7th Int,1 Cont.VLSI Design IEEE Computer Society Press,Los Alamitos,California, pp. 61- 66, 1994.

[5]. Mismar D., Soukosov E., Algadi B., " Transmission Zeros Based Fault Testing of Analog Circuits", Jordan Journal of Applied Science, vol. 2, pp. 62-70, 2003.

[6]. R.Spina and S.Upadhyays, "Linear Circuit Fault Diagnosis using Neuro-Morphic Analyzers", IEEE Trans. Circuits Syst.II, vol 44, pp.188-196, Mar.1997.

[7]. Y.Maiden B.W.Jervis, P. Fouillat and S.Lesage," Using Artificial Neural Networks or Lagrange Interpolation to characterize the fault in an Analog Circuit: an Experiment Study," IEEE Trans Instrum.Meas., vol. 48, pp 932-938, Oct.1999.

[8]. M. Catelani and M.Gori, "On the application of several Neural Network to Fault Diagnosis of Electronic Analog Circuits," Measurement, vol.17, pp.73-80, 1996.

[9]. Y. Deng and Y. He." On the Artificial Neural Networks to Fault Diagnosis in Analog Circuits with Tolerance," in 5th Int. Conf. on Signal Processing, WCCC- ICSP, 2000, pp. 1639-1642.

[10]. Y.Maiden, B.W.Jervis ,P. Fouillat and S.Lesage," Diagnosis of Multi-faults in Analogue circuit using Multilayer Perception," in Proc.IEE Circuits devices Syst.,vol.144.pp149-154,1997.

[11]. M.Catelani and A. Fort," Fault Diagnosis of Electronic Analog Circuits using a radial basis Function Network Classifier," Measurement, vol 28, pp 147-155,2000.

[12]. Alqadi B., Mismar D., Sukusov E, "Fault Diagnostic of Dynamic Analog Circuit" Jordan Journal of Applied Science, Vol.3 (5), pp 1-13, 2001

[13]. Hagen S., "Neural Networks": A Comprehensive Foundation, 2nd edition Prentice Hall, 1988

[14]. E. Sali , D. Meyers, " An Introduction to Numerical Analysis " Cambridge university Press, 2003, 444p.