About Fault Diagnosis of Multiport Analog Electronic Circuits Based on Transformations in Multidimensional Spaces

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ABSTRACT

Some new methods of fault diagnosis of electronic linear multiports based on bilinear transformation in multidimensional spaces are presented. They are extensions of the input-output methods 3D, 4D and 6D previously elaborated by authors [1][2] for diagnosis of twoport electronic circuits. The methods can be applied in a diagnosis of linear electronic circuits with the aid of different technologies: conventional measurement systems, testing buses and neural networks. They can be utilised in practice for localisation and identification of single, double and triple faults. Examples illustrating the methods and the neural network application are included.

Keywords: bilinear transformation, fault localisation and identification.

1. INTRODUCTION

In testing and fault diagnosis of analog and mixed signal electronic circuits new testing and diagnostic methods are needed. Some possibilities of synthesis and development of such methods are offered by bilinear transformation. In our previous works [1] [2] input-output methods (3D, 4D, 6D methods), limited to twoports, based on measurement of independent circuit functions and mapping of loci in multidimensional spaces of these functions were presented.

In this paper, we propose extension of the previous twoport methods on diagnosis of multiports, in particular to electronic circuits with some measurement access to internal nodes.

2. IDEA OF NEW INPUT-OUTPUT METHODS

The new input-output methods 3D, 4D, 6D are related to the bilinear transformation method (named by us 2D), proposed by Martens and Dyke for single fault diagnosis [3]. The 2D method bases on the bilinear form of circuit function, which maps changes of circuit component parameters p_i into family of p_i-loci on a complex plane, as shown in Fig. 1. These loci can be used for localisation and identification of parametric (soft) faults via measurements of the real and the imaginary part of a single circuit function. It was difficult to implement this method in practice, because in many cases p_i-loci are situated too close each other or superimpose one another (e.g. C_2, R_2 loci in Fig. 1).

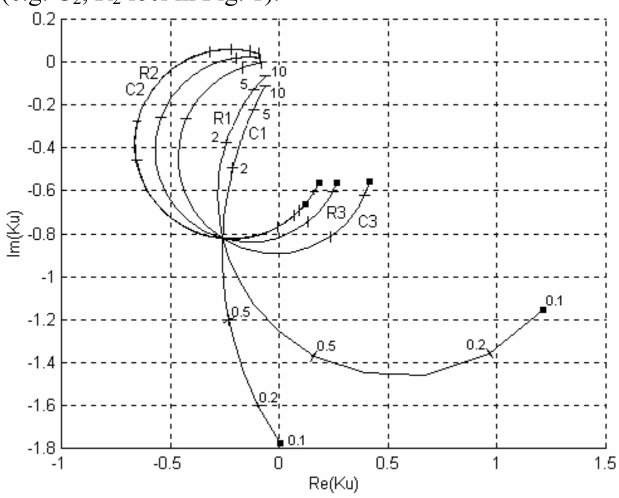

Fig 1. The family of p_i-loci for the 3-Order Low-Pass Butterworth Filter for the 2D method and function K_u at f_{opt}=830Hz

Authors proposed an idea of transferring of p_i-loci family from a plane to multidimensional spaces and developed the new class of input-output (twoport) methods named 3D, 4D and 6D. In multidimensional spaces distances between p_i-loci are significantly longer. It implies better fault resolution. The new methods give also possibility of diagnosis of double and triple faults.

Starting point of the input-output methods 3D, 4D, 6D is measurement, using the same frequency f_{opt}, of two or three independent input-output circuit functions $F^1(\cdot)$, $F^2(\cdot)$ and $F^3(\cdot)$ of p_i circuit parameter for single, p_i and p_j for double or p_i, p_l and p_m parameters for triple fault diagnosis.

The input-output methods will be presented on example of the 3D method for single fault diagnosis case. This method bases on transformation

$$T_i(p_i) = \mathrm{Re}(F_i^1(p_i))\mathbf{i} + \mathrm{Im}(F_i^1(p_i))\mathbf{j} + \left|(F_i^2(p_i))\right|\mathbf{k} \quad (1)$$

where: **i**, **j**, **k** – are versors, $|\cdot|$ – absolute value, which maps changes of p_i-values into p_i-loci in three-dimensional (3D) space.

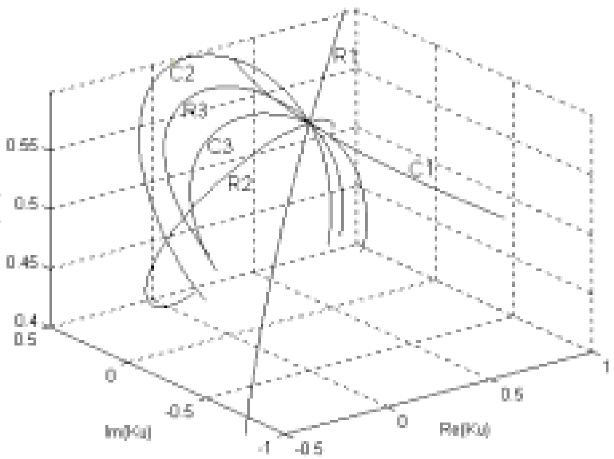

Fig 2. The family of p_i-loci for the 3D method basing on K_u and Y_{in} functions

Family of p_i-loci obtained from transformation Eq. (1) is shown in Fig. 2. As the second function in Eq. (1) we chose input admittance Y_{in}. It is seen that and distances between p_i-loci are evidently longer. R_2 and C_2-loci are separated. It is an advantage of the 3D method, which implies better its fault resolution as well as its robustness on component tolerances and measurement errors.

For the 4D and 6D methods, distances between p_i-loci are much longer in comparison with 3D. In [4] distances between R_2 and C_2-loci taken in the same radius from nominal point for 2D, 4D and 6D methods were calculated. For analysis we chose independent circuits functions: transfer function K_u, input admittance function Y_{in} and current to voltage transfer function K_{iu}. The distance between these loci taken in radius 0.07 from nominal point for 4D method increases above 14.3 times and for 6D method above 19.6 times in comparison with the 2D method. These values are coefficients of improvement of fault localisation resolution [4]. It is an advantage of these methods, which implies better properties than the 3D method.

The input-output methods can be also used to diagnosis of two or three faults.

For localisation and identification of double faults in the 3D method is used following transformation:

$$T_{ij}(p_i, p_l) = \mathrm{Re}(F_{il}^1(p_i, p_l))\mathbf{i} + \mathrm{Im}(F_{il}^1(p_i, p_l))\mathbf{j} + \left|(F_{il}^2(p_i, p_l))\right|\mathbf{k} \quad (2)$$

This transformation Eq. (2) maps changes of a pair p_i and p_l-parameters into $p_i\, p_l$-surface in three-dimensional (3D) space. In this case we obtain a family of $p_i\, p_l$-surfaces in the space, which enables localisation and identification of double faults.

The example of two surfaces in three-dimensional space is shown in Fig. 3. Each surface represents a pair of faulty components (e.g. R_2 and C_2). A belongings of a measuring point to adequate p_i p-surface localises the double faults. A lattice in p_i and p_l-values can scale the surface. It enables identification of both faults.

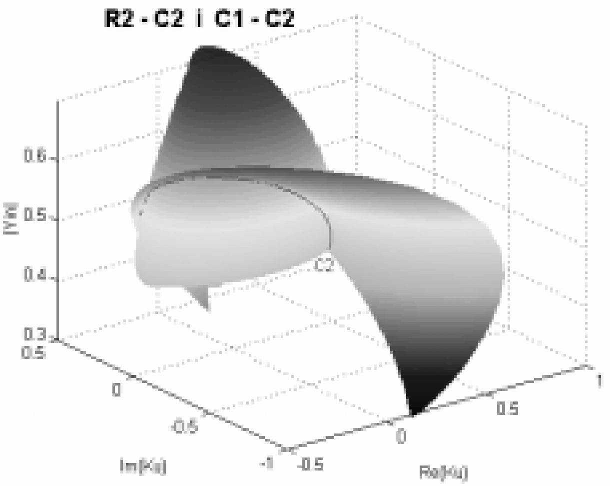

Fig 3. The R2-C2 and C1-C2 surfaces for the 3D method basing on K_u and Y_{in} functions

The disadvantage of input-output methods is limitation to fault diagnosis of two port circuits, with moderate number of elements (order 10). In practice, particularly in diagnostic with the aid of mixed signal testing bus the IEEE 1149.4, it is needed to methods enabling diagnosis of more complicated multiport circuits. So, our task is extending the two port, input-output methods on diagnosis of multiport circuits.

3. EXTENSION OF INPUT-OUTPUT METHODS ON MULTIPORT DIAGNOSIS

For single fault diagnosis we propose a new transformation T_i^n, which maps changes of p_i-values into p_i-loci in multidimensional spaces:

$$T_i^n(p_i) = \sum_{j=1}^{n}\left(\mathrm{Re}(F_i^j(p_i)\mathbf{k}^{2j-1} + \mathrm{Im}(F_i^j(p_i)\mathbf{k}^{2j}\right) \quad (3)$$

where: F_i^j are the independent input-output or accessible node circuit functions of p_i-parameter , j- number of the function, **k** – versor, j=1,2,..,n, n – number of circuit functions.

It is possible to extend this approach into diagnosis of double faults by changing Eq. (3) into the new form:

$$T_{il}^n(p_i, p_l) = \sum_{j=1}^{n}\left(\mathrm{Re}(F_{il}^j(p_i, p_l)\mathbf{k}^{2j-1} + \mathrm{Im}(F_{il}^j(p_i, p_l)\mathbf{k}^{2j}\right) \quad (4)$$

where: F_{il}^j are the functions of p_i and p_l parameters ($i \neq l$) and ($2 \leq n$).

The transformation Eq. (4) maps changes of a pair p_i and p_l-values into $p_i\, p_l$-surface in multidimensional spaces. In this case we obtain a family of $p_i\, p_l$-surfaces in the spaces, due to which it is possible to localise and to identify double faults.

For triple fault diagnosis can be used modified transformation with 3 parameter dependent circuit functions:

$$T^n_{ilm}(p_i, p_l, p_m) = \sum_{j=1}^{n} (\operatorname{Re}(F^j_{ilm}(p_i, p_l, p_m)\mathbf{k}^{2j-1} + \operatorname{Im}(F^j_{ilm}(p_i, p_l, p_m)\mathbf{k}^{2j} \quad (5)$$

where: F^j_{ilm} - the functions of p_i, p_l and p_m parameters ($i \neq l \neq m$) and ($3 \leq n$).

The transformation Eq. (5) maps changes of p_i, p_l and p_m-values into $p_i\, p_l\, p_m$ -solid in multidimensional spaces. In this case we obtain a family of $p_i\, p_l\, p_m$ -solids in the space. Belongings of measuring point to adequate $p_i\, p_l\, p_m$ -solid localises the triple faults. The three-dimensional lattice scaled in p_i, p_l and p_m-values enables identification of triple faults.

It is possible to generalise Eq. (3), (4) and (5) on multiple fault diagnosis:

$$T^n_{i_1 i_2 .. i_k}(p_{i_1}, p_{i_2},.., p_{i_k}) = \sum_{j=1}^{n} (\operatorname{Re}(F^j_{i_1 i_2 .. i_k}(p_{i_1}, p_{i_2},.., p_{i_k})\mathbf{k}^{2j-1} + \operatorname{Im}(F^j_{i_1 i_2 .. i_k}(p_{i_1}, p_{i_2},.., p_{i_k})\mathbf{k}^{2j}) \quad (6)$$

where p_{i_1}, p_{i_2},.., p_{i_k} – circuit parameters, k – number of faults ($k \leq 2n-1$ and $k \leq N$).

4. METHODOLOGY OF FAULT DIAGNOSIS

The fault diagnosis consists of two steps. In the first pre-testing step the measuring frequency is determined. It bases on an algorithm of determination of optimal measuring frequency. In the next testing step the faulty element (elements) is (are) localised and identified using algorithm of fault identification.

For fault diagnosis we assume soft faults closed from 0.1 to 10 $p_{i\ nom}$, where $p_{i\ nom}$ is the nominal value of p_i parameter, i=1,2,..,N, N – number of DUT parameters.

4.1. The algorithm of determination of optimal measuring frequency

A significant pre-testing problem is the determination of the optimal frequency ensuring the best conditions for measurements and detection of faults. For single fault case, for which one circuit function is utilised, the pre-testing algorithm was presented in [1]. Here we present the extension of this algorithm for measuring more circuit functions.

Steps of the algorithm for measuring frequency optimisation:

1. The variables' initiation: setting of start frequency f_{start}, step frequency f_{step} and number of steps Γ.
2. For next frequency $f_\gamma = f_{step} \cdot \gamma + f_{start}$, where γ= 1,2,..,Γ execution of following steps:
   a. Calculation of coordinates of nominal point: ($x^1{}_{nom}$,$x^2{}_{nom}$,..,$x^{2j}{}_{nom}$), where $x^{2j-1}_{nom} = \operatorname{Re}(F_i^j(p_{i\,nom}))$, $x^{2j}_{nom} = \operatorname{Im}(F_i^j(p_{i\,nom}))$.
   b. Calculation of coordinates of p_i-loci ends for all elements ($x^1{}_i$,$x^2{}_i$,..,$x^{2j}{}_i$), ($x^1{}_{i+N}$,$x^2{}_{i+N}$,..,$x^{2j}{}_{i+N}$): $x_i^{2j-1} = \operatorname{Re}(F_i^j(0.1 \cdot p_{i\,nom}))$, $x_i^{2j} = \operatorname{Im}(F_i^j(0.1 \cdot p_{i\,nom}))$, $x_{i+N}^{2j-1} = \operatorname{Re}(F_i^j(10 \cdot p_{i\,nom}))$, $x_{i+N}^{2j} = \operatorname{Im}(F_i^j(10 \cdot p_{i\,nom}))$.
   c. Computation of distances between all p_i-loci ends and the nominal point d_i^j, d_{i+N}^j: $d_i^j = \sqrt{\left(x_i^{2j-1} - x_{i\,nom}^{2j-1}\right)^2 + \left(x_i^{2j} - x_{i\,nom}^{2j}\right)^2}$, $d_{i+N}^j = \sqrt{\left(x_{i+N}^{2j-1} - x_{i\,nom}^{2j-1}\right)^2 + \left(x_{i+N}^{2j} - x_{i\,nom}^{2j}\right)^2}$.
   d. Normalisation of all distances: $d_i^j = d_i^j / \max_i\{d_i^j\}$, From this step we assume i=1,2,..,2N.
   e. Determination of the coefficient of optimally placed p_i-loci $\alpha_\gamma^j = \alpha^j(\gamma)$, where γ is the number of the consecutive:

$$\alpha_\gamma^j = \frac{\sum_{i=1}^{2N}(d_i^j - d_{mean}^j)^2}{d_{mean}^j} \quad (7)$$

where $d_{mean}^j = \frac{1}{2N}\sum_{i=1}^{2N} d_i^j$.

3. Sum of α^j coefficients $\alpha = \sum_{j=1}^{n} \alpha^j$ and finding minimum value $\alpha_{\min} = \min_\gamma\{\alpha_\gamma\}$.
4. Designation of γ_{min} from α_{min} and finding optimum $f_{opt} = f_{step} \cdot \gamma_{\min} + f_{start}$. Additional, in this step for f_{opt} are determined maximum values of all coordinates $x^1{}_{max}$, .. , $x^{2j}{}_{max}$, which will be needed to the diagnosis algorithm.

4.2. The single fault localisation and identification algorithm

Starting point of the fault localisation and identification is measurement, with the same frequency f_{opt} of two, three or more independent circuit functions $F^1(\cdot)$, $F^2(\cdot)$, .. $F^j(\cdot)$, which can be expressed as functions depended on p_i circuit parameter. Next we have to utilise the following algorithm.

The algorithm enables localisation as well as identification of single faults. It searches all p_i-loci and finds a locus lying nearest to measurement point. Simultaneously, it also finds p_{iM}-value with minimum distance to measurement point. In the algorithm, the following steps can be distinguished.

1. Taking the measurement data: measurement frequency f_{opt}, results of measurements of real and imaginary part of all circuit functions (denoted F_{mes}). In this step we introduce the data describing the circuit under test (CUT): N – number of elements, $p_{i\,nom}$ - nominal values, and analytical description of

circuit functions $F^j(p_i)$, which are used to real time computing (generating) chosen points representing p_i-loci.
2. Checking the distance between the nominal point and the measurement point. If the distance is less then assumed value ε, the circuit is qualified as fault free and algorithm is stopped. Otherwise, go to next step.
3. Determination of minimum distances between the measurement point and each p_i-locus as well as p_{iM}-values corresponding the minimum distances.
4. Finding a p_i-locus nearest to the measurement point. Its index locates the faulty element, and p_{iM}-value identifies soft fault: $\Delta p_i = p_{i0} - p_{iM}$.

The procedure of the step 3 is repeated NM times, where: M – number of iteration steps. For m=1 (m=1,2,..,M) the algorithm calculates L_1 points representing p_i-locus. For next values of index m the L_m points are generated around the previously determined minimum distance point p_{im}, with the adequately smaller step. We assumed $L_1=L_2=..=L_M=L$. It gives ML calculations in process of determination of minimum distances between measurement point and each p_i-locus. The numerical complexity is moderate and it does not stand in the way in practical applications of the methods.

4.3. The multiply fault localisation and identification algorithm

It is possible to extend the previously algorithm on multiple fault diagnosis by its generalisation. In this case circuit functions can be expressed as functions depended on p_{i_1}, p_{i_2},.., p_{i_k} circuit parameters, where k – number of faults ($k \le 2n-1$ and $k \le N$).

The modified algorithm searches all $p_{i_1}p_{i_2}..p_{i_k}$-hypersolids in $2n$–dimensional space and finds a hypersolid lying nearest to the measurement point. Simultaneously it also finds $p_{iM_1}p_{iM_2}..p_{iM_k}$-values with minimum distance to the measurement point. Steps of the algorithm:
1. Taking the measurement data: optimised frequency f_{opt}, measurements of real and imaginary of circuit functions F_{mes}. In this step we introduce the data describing CUT: N – number of elements, k –number of faults, nominal values of all components, and analytical description of circuit functions $F^j(p_{i_1}, p_{i_2},.., p_{i_k})$.
2. Checking the distance between the nominal point and the measurement point. If the distance is less then assumed value ε, the circuit is qualified as fault free and algorithm is stopped. Otherwise, go to next step.
3. Searching a minimum distance $d_{i_1 i_2..i_k M}$ between the measurement point and $p_{i_1}p_{i_2}..p_{i_k}$- hypersolids. The idea of searching minimum distance for k=2 is shown in Fig. 4. This distance is determined in iterating way, where m – index of iterating step (m=1,2,..,M). Around point with minimum distance $d_{i_1 i_2..i_k m}$ are generated nodes of the lattice representing $p_{i_1}p_{i_2}..p_{i_k}$-hypersolids ($p_{i_1}p_{i_2}$-surface) with smaller node distances in successive steps of iteration m.
4. Repeating the step 3 for all hypersolids. The number of step repetitions is equal to number of k combinations from N elements C^N_k.
5. Determination of a minimum value d_{min} of the set of $d_{i_1 i_2..i_k M}$ values. It indicates a $p_{i_1}p_{i_2}..p_{i_k}$- hypersolids lying nearest the measurement point. Indexes of this hypersolid locate the faulty elements, and $p_{iM_1}p_{iM_2}..p_{iM_k}$-values corresponding to the minimum distance identifying faults.

We generate L^k points representing the $p_{i_1}p_{i_2}..p_{i_k}$-hypersolid. It gives ML^k calculations of distances between the measurement point and each $p_{i_1}p_{i_2}..p_{i_k}$- hypersolid. In this case, the number of all calculations of distances is equal to $ML^k C^N_k$.

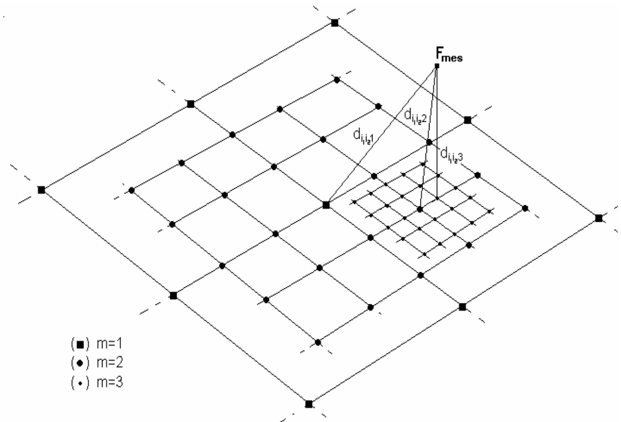

Fig. 4. Idea of searching minimum distance between measuring point F_{mes} and $p_{i_1}p_{i_2}$- surface

The algorithm of multiply fault identification needs r times more calculations than the algorithm for single fault, where r:

$$r = \frac{L^{k-1} C^N_k}{N}. \tag{8}$$

It is seen, that numerical complexity of the algorithm exponentially depends on a number of faults k and linearly depends on the number of numerically generated points representing $p_{i_1}p_{i_2}..p_{i_k}$-hypersolid as well as the number of CUT components. To make the algorithm faster, with retaining the given resolution, we may reduce the number of generated points L, while appropriately increasing the number of iteration steps M.

For example, if we decrease the number of surface points L four times, we can increase M to M+1. In this case we speed up the algorithm about 4^k times. However, the number of points L can not be too few. Generally speaking, the number of computed points of $p_{i_1}p_{i_2}..p_{i_k}$-hypersolid can't be too small, because it may cause divergence of the algorithm.

5. EXPERIMENTAL VERIFICATION

The 4D method was experimentally verified and compared with 2D one on example the 3-Order Low-Pass Butterworth Filter [4], in a system based on transmittance analyser HP4192A. Measurements of K_u ([dB] and [°]) were made at f_{opt}=830Hz (2D/K_u method) and measurements of Y_{in} ([mS] and [°]) at f_{opt}=675Hz (2D/Y_{in} method). For the 4D method these functions were measured at f_{opt}=735Hz. We fixed, that measurements were carried out for i-th element with following its values: 0,1, 0,2, 0,3, 0,4, 0,5, 0,6, 0,7, 0,8, 0,9, 1, 1,1, 1,3, 1,5, 2, 3, 4, 5, 6, 7, 8, 9, 10 $p_{i\,nom}$.

In this paper we presents a few results of diagnosis only R_2 resistor. For all elements these results are included in [4].

Localisation and identification of single faults were made by the 2D/K_u, 2D/Y_{in} and the 4D methods based on measuring data presented in [4]. We assumed accuracy of fault identification on level 1% (m=3). Results of fault diagnostics are shown in table 1.

Table 1. Relative errors of fault identification for R_2 resistor

$p_i/p_{i\,nom}$	$\delta_{2D\,(Ku)}$	$\delta_{2D\,(Yin)}$	δ_{4D}
0.6	1,80	5,21	1,96
0.7	1,55	5,02	1,68
0.8	1.47	C1	1.71
0.9	1.42	3.43	1.63
1.1	C2	2.65	1.43
1.3	C2	C1	1.21
1.5	1.38	1.57	1.18
2	C2	1.03	1.08
3	C2	0.46	1.18
4	C2	0.22	1.30

Table 1 includes relative errors in [%] of fault identification of R_2 and R_3 resistors. They were defined:

$$\delta = \frac{p_{i\,ident} - p_{i\,real}}{p_{i\,ident}} \cdot 100\% \qquad (9)$$

where $p_{i\,ident}$ – identified value of p_i by diagnosis algorithm, $p_{i\,real}$ – real value of p_i.

When the algorithm localises a false fault of the resistor R_2, it is written localised element. This way enables simultaneously to pass correctness of fault localisation and accuracy of fault identification.

It is seen (table 1), that 2D/K_u and 2D/Y_{in} methods perform localisation errors. But the 4D method does not make any error. It follows that 4D method has better localisation resolution and identification correctness in comparison with the 2D method, as well as higher robustness on element tolerances and measurement errors [4].

6. IMPLEMENTATION THE 4D METHOD IN A NEURAL NETWORK

The 4D method was also implemented and investigated in a neural network, 3-lyers perceptron type on example the 3-Order Low-Pass Butterworth Filter. For this method, after thirty experiments, it was found the best architecture of neural network consisting of: 4 neurones in the input layer, 25 neurones in first hidden layer, 10 neurones in second hidden layer and 3 neurones in the output layer (Fig. 5).

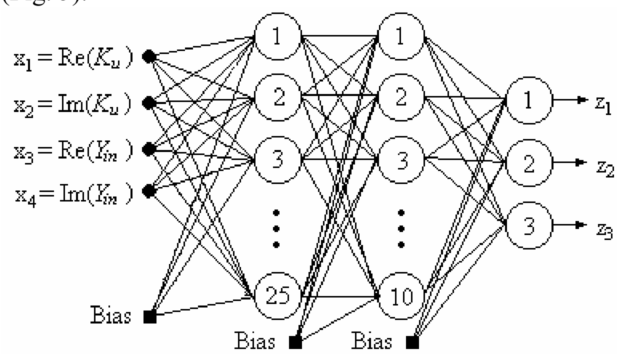

Fig. 5. The neural network for the 4D method

Results are much better in comparison with the 2D/K_u and 2D/Y_{in} methods. These methods were implemented in neural network consisting of 2 neurones in input layer, 20 neurones in first hidden layer, 15 neurones in second hidden layer and 3 neurones in the output layer. For the 4D method the fault covering is equal 98% and training time 65 min., for 2D/K_u method it is equal 61% (2h 5min) and for the 2D/Y_{in} method is equal 87.5% (14h 42min). It is seen, that training time for the 4D method is at last 2 times shorter in comparison with 2D one. Advantage of 4D method is evident. For instance, the process of training neural network via the 4D method is shown in Fig. 6. It is seen that the training process is fast convergent.

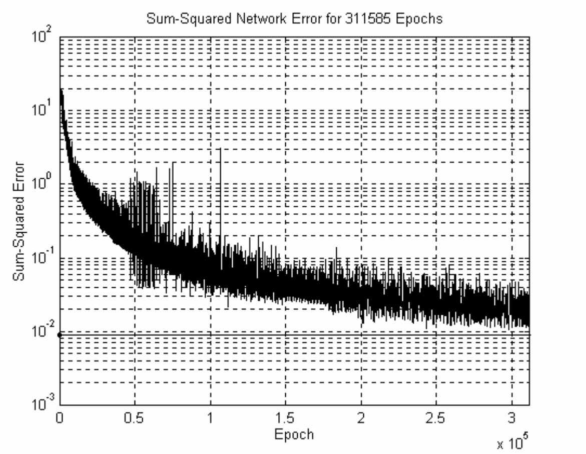

Fig. 6. The process of training neural network via the 4D method

Applying the 4D method to neural networks improves training set (increasing information about DUT). Its results are the better faults covering as well as shorter training time.

7. CONCLUSIONS

Presented multiport methods based on the proposed transformations in 3D, 4D and 6D spaces of circuit functions give longer distances between p_i-loci and enable a significant increase of fault localisation resolution. Increasing the distances between p_i-loci implies also more robustness to measurement errors and component tolerances.

The methods are useful for diagnosis on the level of localisation and identification of single, double, triple, and for multiports, multiple faults.

The methods can be applied in practice for fault diagnosis of analog electronic circuits and parametrical identification of other objects modelled by electrical circuits. Perspective field of application of these methods is testing and diagnosis of electronic circuits with the aid of mixed signal testing bus IEEE 1149.4. They can be implemented in conventional testing systems as well as in artificial neural networks.

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