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ANN APPLICATION IN ELECTRONIC CIRCUITS DIAGNOSIS

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Abstract - *In this paper artificial neural networks (ANNs) are applied to diagnosis of soft and catastrophic defects in a nonlinear analog circuit. In fact, today the technical diagnosis is great challenge for design engineers because the diagnostic problem is generally underdeterminate. The diagnosis methods are based mostly on proprietary knowledge and personal experience, although they are built into integrated diagnostic equipment. ANN approach is proposed here as an alternative to existing solutions, based on the fact that ANNs are expected to encompass all phases of the diagnostic process. The approach is demonstrated on the example of an integrated operational amplifier, and the generalization property is shown by supplying noisy data to ANN's inputs during diagnosis.*

1. INTRODUCTION

Every complex system is liable to faults or failures. In most general terms a fault is any change in a system that prevents it from operating in the proper manner. We define diagnosis as the task of identifying the cause of a fault that is manifested by some observed behavior. Then some method of determining what fault has occurred is required. This is most often considered to be a two-stage process: firstly the fact that fault has occurred must be recognized – what is referred to as fault detection. Secondly, the nature should be determined such that appropriate remedial action may be initiated.

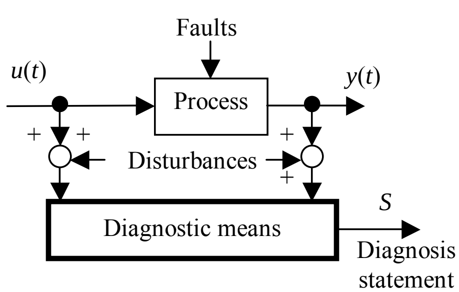

Fig. 1. *A general diagnosis system*

The general structure of application of a diagnostic system is shown in Fig. 1. Inputs to the diagnostic system are the signals u(t) and y(t). Except the control signals the system under test, here denoted as “process”, is affected by faults and disturbances (here measurement errors) not known to the diagnostic system. The task of the diagnosis system is to generate a diagnosis statement S, which contains information about fault modes that can explain the behavior of the process. Note that the diagnosis system is assumed passive i.e. it can by no means affect the Process.

In this paper we will show that ANN may be trained for modeling the look-up table. Then, the ANN running with the given vector of stimuli may be viewed as search of the look-up table. The ANN response, if the network properly trained, will immediately find the fault. In addition, uncertain (to some extent) input data will lead to correct fault isolation thanks to the generalization property of the ANN.

2. CONCEPTS OF DIAGNOSIS

Besides the human expert that is usually performing the diagnostic project, one needs tools that will help, and what is most desired, will perform diagnosis automatically. Such tools are a great challenge to design engineers that pertains to the fact that generally the diagnostic problem is under determinate. In addition, it is a deductive process with one set of data creating, in general, unlimited number of hypotheses among which one should try to find the solution. This is why permanent attention of the research community is attracted by this problem [1].

Thanks to the advent of computation intelligence in the last decades new concepts were applied based on: Production rule based artificial intelligence, such as [2], Artificial neural networks, such as [3], and Fuzzy-neural networks, such as [4], trying to create a system that contains properties that we consider as “intelligent behaviour”. Here the ANN approach was selected. The reason will be discussed later on.

In order to get the idea on why and how the ANNs are applied to analog electronic circuit diagnosis, the very diagnostic concept will be described first. It is about collaboration of design, test, and field engineers and about mutual distribution of responsibilities aiming long life cycle of the electronic product containing the analog subsystem considered here. We consider that field engineers are expected to react after functional failure of the system. In order to diagnose such system they are to be supplied with: testing equipment, list of specific measurements to be done (including set of signals and test points), and diagnostic software to process the measurement data. Similar set of data and tools are expected to be given to the test engineer in a production foundry in order to create a picture of the production yield and create feedback to process engineers. We believe design engineers are the most familiar with the product and capable to synthesize test and diagnostic signals and procedures should prescribe all these. This means the so-called concept of simulation before test is to be applied to create fault dictionaries containing exhaustive list of faults and corresponding responses. The fault dictionary is in fact a

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table representing the mapping from the fault list into a list of faulty (or possibly, fault-free) responses. In that way the diagnostic process becomes a search through the fault dictionary. We claim here that ANNs, being universal approximators [5], are the best way to perform this search and consequently to perform diagnosis.

Analog electronic circuits are known to be difficult to test and diagnose. Apart from the huge number of possible faults, this is a consequence of the inherent nonlinearity of these circuits. Even linear circuits (having linear input-output signal interdependence) exhibit nonlinear relation between circuit parameters and output response. There are no linear active networks. They may be linearized and sought as such for situations where signal and parameter changes are small in comparison to nominal values. For defects, however, where large changes of the parameters or catastrophic faults are present in the circuit (affecting the DC regime), circuit theoretical approaches face sever limitations. Accordingly, the circuit theoretical concepts that are proposed encompass limited subclasses of circuits (linear passive or linear active), limited types of faults (mostly parametric), and signals (DC or sinusoidal) [1], [6], [7], [8]. When nonlinear circuits were to be diagnosed small amplitudes of the parameter increments were allowed in [9]. Large parametric fault diagnosis was described in [10] where piecewise linear models were implemented for the DC analysis, and separate considerations were given for diagnosis of faults in the dynamic part of the network based on large change sensitivity computations.

A specific aspect related to diagnosis is the number and location of the test points. To simplify, we can say that measurements on the primary inputs and outputs are preferred. This is not only related to their automatic accessibility but also to the nature of the diagnostic reasoning. Namely, one looks for function when is to diagnose something, and the function is seen at the output. Of course, to compensate for the small number of test points one should perform more measurements applying different types of signals so extracting complete information about the system behavior.

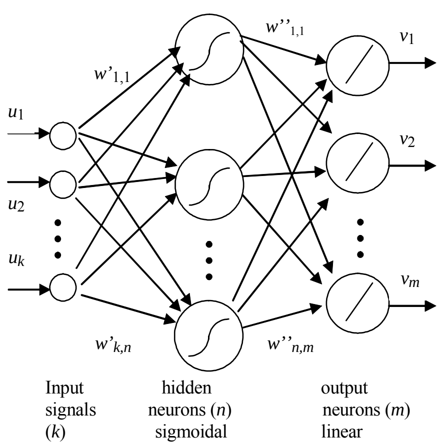

Fig. 2. *A fully connected feed-forward neural network*

ANNs were already applied to diagnosis [11], [12], [13], [14], [15]. These were however applications concerning linear analog circuits. Here we describe preliminary results of application of a feed-forward ANNs for diagnosis of nonlinear dynamic electronic circuit with no restriction to the number and type of faults. It is based on fault dictionary creation and application of ANN as both the system for data compression that memorizes the table representing the fault dictionary, and as the mapping machine that looks-up the table to find the most probable fault-code.

The feed-forward neural network is structured in layers. The most frequently used structure of a feed-forward ANN is shown in Fig. 2. It has k input signals, one hidden layer of n neurons with sigmoidal transfer function, and one output layer of m linear-transfer-function neurons. Arrows mark the signal transfer between neurons. The value denoted for some arrows is to express the fact that the output signal of a neuron from the previous layer is multiplied by a constant, here referred to as weight, $w_{i,j}$, before exciting the neuron of the next layer. The network is fully connected if all $w_{i,j}$ are nonzero. Prime and second are used to distinguish weights affecting different layers.

3. APPLICATION EXAMPLE

A CMOS operational amplifier consisting of seven transistors, shown in Fig. 3, is used as an application example. Only transistor faults were considered - ten faults per transistor, six catastrophic and four parametric. As shown in the figure (around TR7) there are three open-circuited faults (denoted as OC), and three short-circuited faults (SC) per transistor. In addition, two faulty values for every channel length (±20%), and for every channel width (±20%), were introduced. By inspection of the circuit one obtains a set of 70 faults.

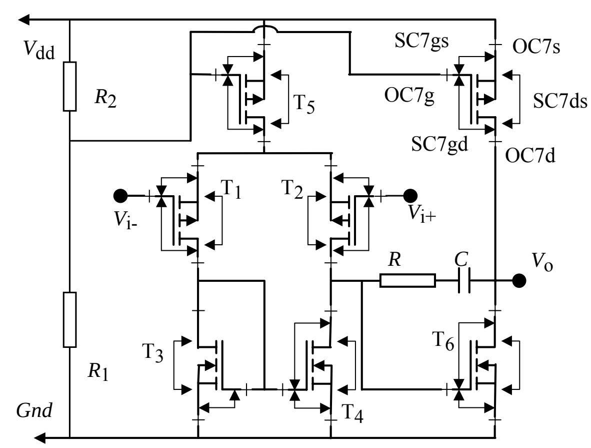

Fig. 3. *The operational amplifier circuit. SC=short circuit, OC=open circuit*

Only one test point is allowed, the primary output where we measure V_o. The DC output value ($V_{oDC\,j}$) was obtained by simulation first. Here j=0,1,2,…,69 stands for the fault code, where j=0 denotes the fault-free circuit. Faults are coded randomly, in order to avoid that similar fault effects have close values of the codes. In addition, the frequency response of the circuit (non-inverting input terminal was excitated by the signal of amplitude 1mA) was obtained by simulation over a fixed frequency range in order to extract two response parameters: the nominal gain (A_j) and the 3-dB cut-off frequency ($f_{3\ \mathrm{dB}j}$). Note that because of the nonlinearity of the circuit, every fault is expected to change the linearized-circuit version that is used for frequency domain performance extraction. We need to create fault models to be implemented into the original circuit in order to generate the linearized version. It is done according to [16] and [17] and will be not discussed here. Finally, the fault dictionary created here has three columns containing the set of circuit performances: $\{V_{oDCj}, A_j, f_{3\ \mathrm{dB}j}\}$. Part of the fault dictionary is depicted in Table 1. Fault SC3gd is undistinguishable because of the existing connection between the gate and drain of T3. This reduced the fault dictionary to 69 elements.

Table 1. *Part of the Fault Dictionary for the Circuit of Fig. 3*

Type	Code (j)	A_j	$f_{3\ \mathrm{dB}\ j}$ [MHz]	$V_{oDC\ j}$ [V]
FF	0	419	0.01527	0.127
1W+	44	0.055	1.848	3.3
1W-	14	0.012	3.043	0.052
1 L+	37	0.0053	6.791	0.0497
1L-	30	0.0416	4.058	3.3
OC1G	49	0.047	501.187	0.127
OC2G	18	0.32	19000	0.127
OC3G	47	0.049	544.042	0.093
OC4G	19	0.318	21000	0.064
SC1DG	6	0.042	320.440	0.0458
SC2DG	21	0.83	12300	3.3
SC5DG	11	0.211	24000	0.022

The fault dictionary is further reduced by processing the ambiguity groups that exist in this structure. According to [18] "an ambiguity group is, essentially, a group of components where, in case of fault, it is not possible to uniquely identify the faulty one". Here we would say that an ambiguity group consists of a set of *faults* that propagate identical fault effect to the output, so being testable, while no distinction among them is possible making them not diagnosable. Table 2 represents all ambiguity groups discovered after simulation. Only one representative of a group was included into the fault dictionary. The faults italized in the Table 2 represent physically the same connection in the circuit, so the effect must be the same. After some simple calculation one may find that the complete fault dictionary in this case will have 70-1-24+10=55 elements.

Having three data for every fault, the neural network input structure is restricted to k=3. We expect the ANN to diagnose the fault in a way it outputs the fault-code (j), so we need only one output neuron. The number of hidden neurons is found by trial and error after several iterations starting with an estimation based on [19]. The goal was to find the minimum n that still leads to satisfactory classification even under noisy excitation. Of course, no mistakes were observed for all 55 faults. The software for neural network training was used [20].

The generalization property of the network is verified by supplying noisy data to its inputs. This is presented in Table 3, 30 samples are examined. For each sample, one input (bolded in the table) is changed for ±5%, representing noise generated during the measurement process. The responses of the network are given in the last column of the table. We can notice that faults can be distinguished in that situation also.

Table 2. *Ambiguity Groups*

Ambiguity group	Faults included	A	F_3 [MHz]	V_o [V]
1	OC1D	0.31	20000	0.0179
	OC1S			
2	OC3D	0.041	365.8	3.3
	OC3S			
3	OC4D	0.303	20000	0.0458
	OC4S			
	SC4GS			
	SC3GS			
	SC3DS			
4	OC5D	0.056	507.298	3.3
	OC5S			
5	OC6D	0.063	0.039	3.3
	OC6S			
6	OC7D	$A\to\infty$	Undeter-minable	0
	OC7S			
7	SC1GS	0.055	515.993	3.3
	SC2GS			
8	*SC5GS*	0.109	0.036	0
	SC7GS			
9	*SC4DS*	A=0	Undeter-minable	3.3
	SC6GS			
	SC7DS			
10	3L+	0.05	2.37	3.3
	4W+			

Table 3. *Inputs with Noise and ANN Responses*

Code	A_j	$f_{3\ \mathrm{dB}\ j}$ [MHz]	$V_{oDC\ j}$ [V]	ANN response
0	419	**0.0145**	0.127	-0.02128
1	129.6	**0.0248**	0.079	1.09057
2	0.109	0.036	**-0.05**	2.01405
3	6028	**0.001575**	0.1712	2.93868
5	4453	**0.002415**	1.0255	5.03203
6	**0.0441**	320.44	0.0458	6.03224
9	1000	1000	-0.05	9.0707
10	**0.043**	365.8	3.3	10.0278
12	1000	1000	**3.39**	12.1771
13	5770	**0.00171**	0.2146	13.2376
16	8220	**0.00197**	0.4876	16.031
18	0.32	1000	**0.133**	17.8458
20	0	1000	**3.46**	20.4409
21	0.83	1000	**3.46**	20.6497
25	**0.0588**	507.298	3.3	25.0605
26	11.739	**0.114**	0.127	26.0098
27	0.071	312.071	**3.46**	27.0091
34	5809	**0.00169**	0.1811	33.7541
35	209	0.0237	**0.115**	35.47
36	**0.05**	1000	0.8824	36.3514
37	**0.00556**	6.791	0.0497	37.2652
43	**0.004**	17.191	0.0509	43.0008
46	**0.0523**	515.993	3.3	45.99
47	**0.0514**	544.042	0.093	47.0133
49	**0.04935**	501.19	0.127	49.042
50	6030	**0.001425**	0.2466	49.9284
52	0.005	133.757	**3.46**	52.0044
53	119.4	**0.0258**	0.0843	53.0205
54	0.041	**428**	3.3	53.5346
55	0.688	0.57	0.0186	54.8614

4. CONCLUSION

ANN approach is applied here to diagnosis of a nonlinear dynamic electronic circuits. Both the catastrophic and soft defects were diagnosed in this example. The generalization property of the ANN was verified by supplying noisy data to its input terminals. Accordingly, we may conclude that ANNs are convenient and powerful means for diagnosis, and, what is important, realisable as a hardware that may be as fast as necessary to follow the changes of the system's response in real time. Also, more complex systems may be considered and larger fault dictionaries may be sought.

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Sadržaj – U radu je prikazana primena veštačkih neuronskih mreža na dijagnozu mekih i katastrofalnih defekata u nelinearnom analognom kolu. Zapravo, danas je tehnička dijagnostika veliki izazov za projektante, pa je dijagnostički problem teško definisati. Zato su metodi dijagnostike bazirani na sopstvenom znanju i ličnom iskustvu. Ovde je prikazan pristup, zasnovan na veštačkim neuronskim mrežama, koji predstavlja alternativu postojećim rešenjima jer se očekuje da neuronska mreža obuhvati sve faze procesa dijagnoze. Pristup je pokazan na primeru integrisanog operacionog pojačavača, a svojstvo generalizacije prikazano je dovođenjem signala sa šumom na ulaze neuronske mreže radi dijagnoze.

PRIMENA VEŠTAČKIH NEURONSKIH MREŽA U DIJAGNOSTICI ELEKTRONSKIH KOLA

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