Applications of Artificial Neural Networks in Electronics

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***Abstract*—In this paper we will give short overview of different applications of artificial neural networks in electronics. Artificial neural networks are shown to be universal approximators, so they were successfully used in applications in modelling of electronic circuits, as well as in fault diagnosis and classification.**

***Index Terms*— artificial neural networks, diagnosis, modelling, simulation.**

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I. Introduction

Artificial neural networks (ANNs) were shown to be an excellent candidate for the approximant needed in the black-box modelling. Also, they are universal approximators so they can be used in the best way both to capture the mapping, and to search through the dictionary, thereby to perform diagnosis.

We will give in this paper an overview of numerous applications of ANNs both in modelling in diagnosis. There are also many more applications of artificial neural networks that we performed, but they cannot be presented here. We will abstract only the ones we consider most important.

We will start from the first example of application of ANNs in modelling, when characteristics of MOS transistor were modelled and implemented in behavioral simulator. Then, a micro-electro-magneto-mechanical actuator was modelled but the modelling was in fact quasi-dynamic. The motivation for modeling of non-linear dynamic networks appeared with the problem of modeling implanted hearing aids, so this example is followed by different instances of modelling nonlinear dynamic circuits. Modelling of the A/D and D/A interfaces in mixed-mode simulation is one of the most published examples.

Another aspect of our application of artificial neural network is defects diagnosis. Here, we started from analogue electronic circuits, which are difficult to be diagnosed due to huge number of possible faults, and inherent nonlinearity of these circuits. This concept is also shown in a complex system that can be decomposed in order to simplify the process of diagnosis. This is followed by few examples where ANNs are used to capture mappings in different fault dictionaries.

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II. Application of ANNs in Modelling

There are two basic approaches to the modelling of electronic components: the physical and the black-box approach. When the physical laws undergoing the component's behavior are known one may create a set of expressions (usually by solving differential equations) relating the terminals excitations and responses. The obtained current-voltage relations are referred to as *physical model* of the component. Main advantage of this concept may be devoted to the existence of physical meaning of the coefficients arising in the modelling expressions. There are, however, many difficulties in the implementation of such models [1]. Firstly, one rarely knows the physics of the components in such a detail that enables to establish the mutual dominance of all physical and technological parameters. Further, in most cases it is not possible to describe the complete behavior by one equation only having in mind different working regimes of the component [2]. The equations describing parts of the model, frequently become incompatible leading to non-analytical overall approximating function.

When no full knowledge of the physics of the device is available one uses the so-called black-box approach. The behavior is captured by measurements of input (signal) and output (response) quantities. After that an approximation procedure is performed over the set of measured data in order to get an analytical expression convenient for equation formulation in the circuit-simulation process. The question of the choice of adequate approximant is crucial for this type of modelling. In some cases polynomial interpolation is used in between two measured points [3]. In other cases the complete measurement is described by linear segments leading to piece-wise linear models [1], [4]. To our knowledge there is no general receipt for the choice of an analytical function for this approximation. Main advantage of the black-box approach is related to the fact that one doesn't need to have full knowledge on the physics of the device being modelled. In general there are no limitations about the choice of the approximants, most frequently, the main restriction is that they need to be analytical function. From the other side, main problem encountered during use of this approach is modelling simultaneously of the non-linear and dynamic behavior of the device.

Artificial Neural Networks (ANN) were shown to be an excellent candidate for the approximant needed in the black-box modelling. The first example of application of an ANN for modelling an electronic device was given in [5]. Fig. 1. contains reproduction of the first modelling results. There the output characteristics of a MOS transistor are approximated by a feed-forward three layer ANN. The implementation of such model was limited by the need of existence of behavioral simulator being able to formulate circuit equations for system containing simultaneously component described by electrical equations and others described by functions (i.e. ANNs) [6, 7].

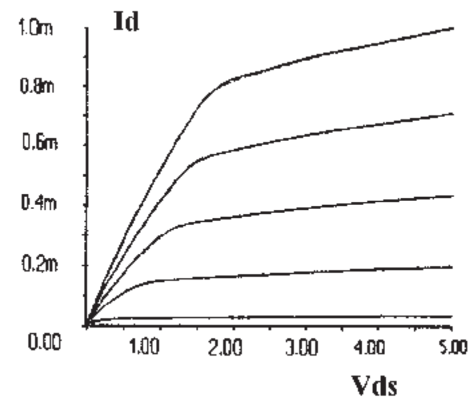
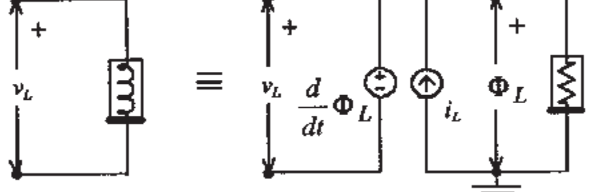


Fig. 1. MOS transistor characteristics and approximation

After publication of the first results in [5], ANNs were successfully applied in electronic modelling several times [8]. In all these applications feed-forward networks were used meaning that only resistive properties of the devices were captured. The first attempt of modelling dynamic behavior was described in [9]. A micro-electro-magneto-mechanical actuator was modelled but the modelling was in fact quasi-dynamic. Namely, by its virtue it was possible to separate the resistive and the dynamic part of the model. The ANN was applied for the resistive part but strongly connected to the rest of the model. This is illustrated in Fig. 2. Fig. 2a represents the electrical schematic of the model of a non-linear magnet, while Fig. 2.b represents the characteristics of the non-linear-inductor both original and approximated. Note the magnet has a moving armature hence the dependence of the characteristics on the displacement x. These drawings were taken from [9] without changes so one should note that Φ and Ψ stand for the same variable: the magnetic flux.



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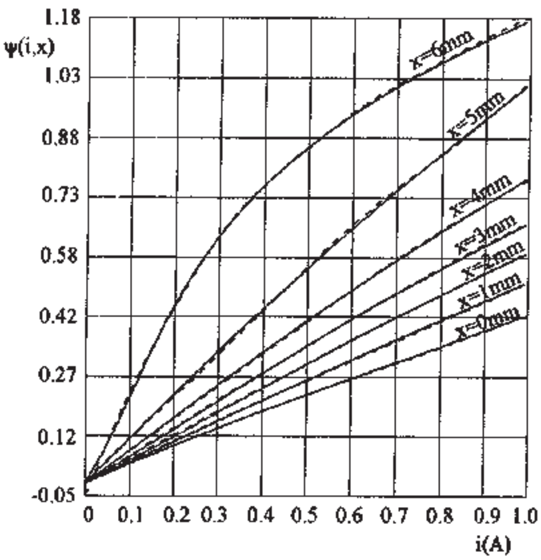


b)

Fig. 2. Modelling of an electro-magnet with moving armature

ANNs are then used for modelling of non-linear dynamic networks. The motivation for modeling of this kind of circuits appeared with the problem of modeling implanted hearing aids [10], [11]. Here, however, in order to present reproducible results the nonlinear circuit, Fig. 3, containing quartz crystal, Fig. 4, will be considered for modeling. The schematic symbol for a quartz crystal is shown in Fig. 4a. The equivalent circuit for a quartz crystal near fundamental resonance is shown in Fig. 4b. The equivalent circuit is an electrical representation of the quartz crystal's mechanical and electrical behavior. The components C_1, L_1, r_1, are called the motional arm that represents the mechanical behavior of the crystal element. C_0 represents the electrical behavior of the crystal element and holder [12].

C_1 is motional arm capacitance representing the elasticity of the quartz, the area of the electrodes on the face, thickness and shape of the quartz wafer. Values range in femtofarads.

L_1 is motional arm inductance representing the vibrating mechanical mass of the quartz in motion. Low frequency crystals have thicker and larger quartz wafers and range in a few Henrys. High frequency crystals have thinner and smaller quartz wafers and range in few millihenrys.

r_1 represents the real resistive losses within the crystal.

C_0 is shunt capacitance representing the sum of capacitance due to the electrodes of the crystal plate plus stray capacitances due to the crystal holder and enclosure.

Crystal has two resonant frequencies characterized by a zero phase shift. The first is the series resonant, f_s frequency. The second resonant frequency is the anti-resonant f_a, frequency.

As an example of modeling of nonlinear dynamic circuits [13], [14] the electronic circuit depicted in Fig. 3. will be modeled. The pair of branches containing diodes is introduced enabling the nonlinearity of the circuit to be accounted for. Resonant frequency of the crystal oscillator is 8MHz, meaning that both f_s and f_a are close to that value. So, a chirp $i(t)$ signal is needed to cover the frequency band around 8MHz. Recurrent time delay neural network with five input, four hidden and one output neuron is used, because the structure from Fig. 3. is highly nonlinear.

The response of this circuit excited by a chirp signal with the change of frequency from 7.997÷8.03MHz is given in Fig. 5. Series resonant frequency can be noticed first, and then, anti-resonant frequency.

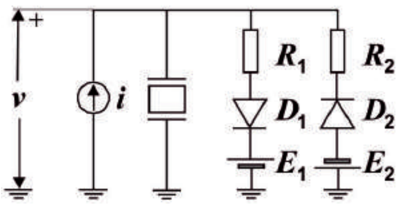
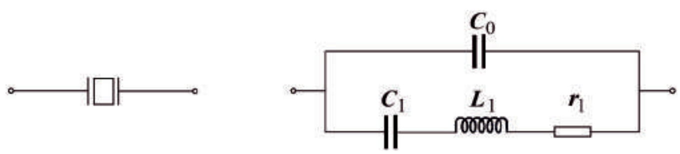


Fig. 3. Nonlinear dynamic circuit chosen for modeling



a) b)

Fig. 4. a) Crystal equivalent circuit and b) its symbol

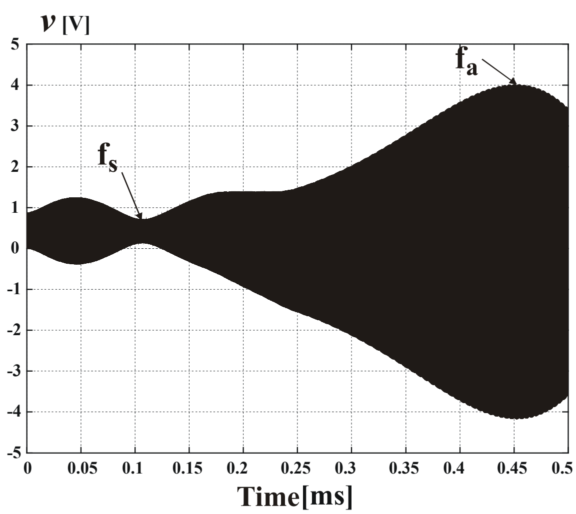


Fig. 5. Response of the circuit, Fig. 4, excited by a chirp signal

The responses of the modeled circuit and the model are shown in Fig. 6. It is obtained as an envelope of the time domain response [15].

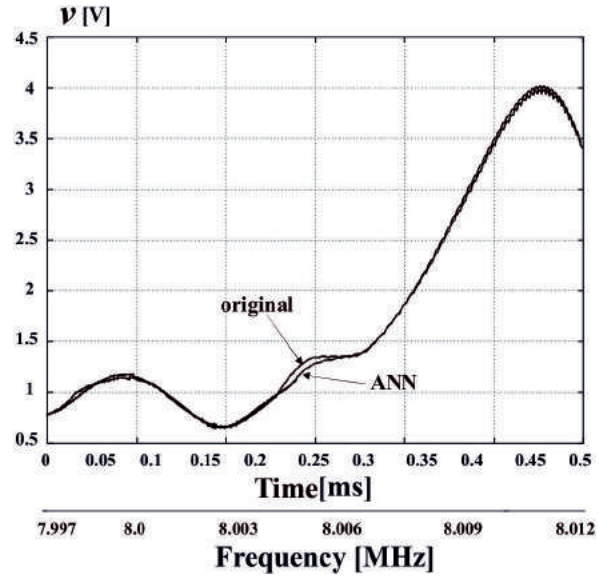


Fig. 6. Responses of the original circuit (Fig. 4) and the model (only the envelopes of the positive periods are shown)

The next example of ANNs implementation for behavioral modelling of nonlinear dynamic circuits is modelling of the A/D and D/A interfaces in mixed-mode simulation. We will here present only modelling of D/A interface. Modelling of A/D interface is explained in detail in [16], [17].

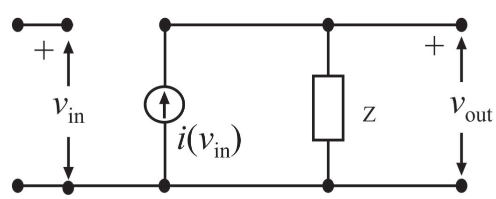
For modelling of the D/A interface [16], [17], [18] the output circuit of the digital part is represented by a circuit that is supposed to drive an analog load. Note that mixed-mode simulation is considered. This means that an event scheduler is active, marking the controlling input of the digital circuit. The event scheduler does not allow for two inputs to be active simultaneously because that is considered as a hazard. Hence, modelling the output of an inverter is general enough for verification of the modelling procedure.

The topology of the new model is depicted in Fig. 7a. In the figure, v_{in} stands for a controlling ramp-shaped voltage-waveform:

$$i(v_{in}) = I_{max}\left[1-\tanh(v_{in} - v_T)\right] \tag{1}$$

and Z is a recurrent time-delay neural network approximating the function:

$$v_{out} = Z(i)\,. \tag{2}$$



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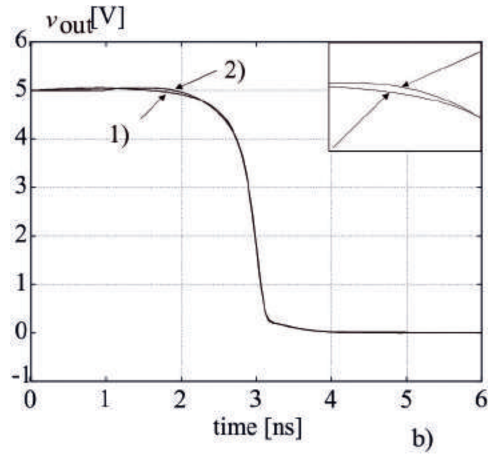


Fig.7. a) Circuit representation of the model and b) responses: 1) unloaded CMOS inverter (considered as digital output) and 2) of the new model.

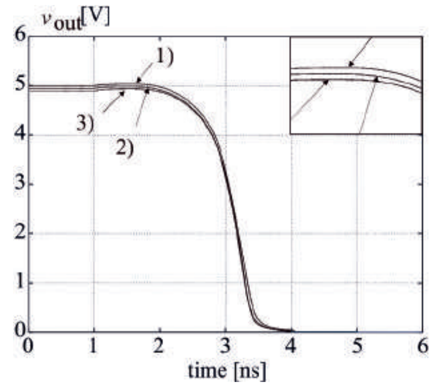
Here, I_{max} is the maximum supply current during the transition in the inverter, and v_T is (usually) equal to V_{DD} /2, V_{DD} being the supply voltage. Obviously, the ANN model of Z has one input (current) and one output (voltage) terminal. The network is trained using input-output pairs [$i(t)$, $v_{out}(t)$], where $i(t)$ is calculated from (1) while $v_{out}(t)$ is obtained from simulation by the *Alecsis* simulator of the circuit to be modelled (here an inverter). Note that we need the electrical schematic of the digital part during the modelling phase.

First results are shown in Fig. 7b. Here output waveforms of the original inverter and the model are shown to illustrate the quality of the approximation procedure. Unloaded circuits are simulated. The ANN has five input units, three hidden units, and one output unit.

The following three examples are intended to check the modelling procedure based on situations not present during training. The first trace (marked 1)) in Fig. 8a is the output voltage of an inverter being loaded by an inverter, all modelled by regular transistor models, i.e., obtained by regular circuit simulation. The second one (marked 2)) represents the response of the same circuit with the ANN model used for the driving part and circuit model for the loading. This situation was not encountered in the training process. Excellent agreement was obtained, especially in the steepest part of the response that defines both the gain and the delay of the loaded inverter.

Further, Fig. 8b gives a similar comparison the loading element here being a transmission line modelled by a π-RC network. Finally, a TTL load (diode), Fig. 9, was used to demonstrate the success of the ANN model in the case of a 'large' non-linear dynamic load. Note the average value of the output voltage is less than 0.5 V while the difference is still smaller than 10 mV. Once again, the ANN model was developed using an unloaded inverter.

Our next usage of artificial neural networks in modelling is producing a small signal linear dynamic model of the solar cell that may be used for characterization of the interface and in the whole PV system in the frequency domain [19]. This idea is based on the experience that the output voltage and the output current of a PV panel are not pure DC constant due to the inevitable connection to a converter (or inverter) which is working as a switching system, so we came to a conclusion that interest exists for the behavior of the solar cell at the frequencies of the harmonics of the converters switching frequency which is subject of change according to the maximum-power-point tracking.



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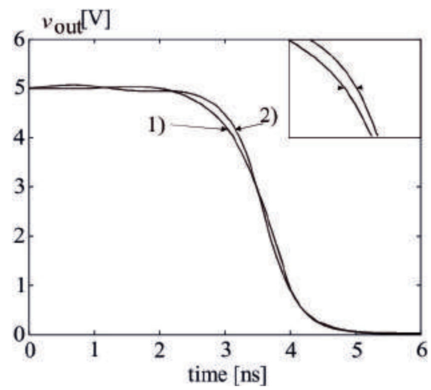

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Fig. 8. a) Responses of 1) inverter loaded by inverter, 2) a model loaded by inverter, and 3) an ANN (modelling the output) loaded by an ANN modelling the input of an inverter. b) Responses of 1) an inverter loaded by RC ð -network and 2) a model loaded by RC ð -network.

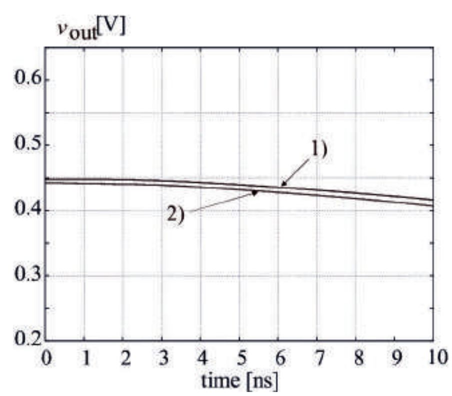

Fig. 9. Responses of a) inverter loaded by a diode and b) ANN model loaded by a diode.

To extract the small signal model the usual one-diode large signal dynamic model is used with known parameter values. The modeling process is conceived to be performed in two steps. In the first one, for a given cell, measurements are performed in order to produce the element values and proper parameters for the one-diode nonlinear model. In the second step the nonlinear model obtained so far is exploited for generation of the linear one. The element values versus photocurrent and cell-voltage dependences are captured by feed-forward artificial neural networks, one per element. The ANNs serves as a mapping algorithm capturing the "look-up" tables with the dependences of the model elements on the illumination and cell voltage. Verification of the model is performed by comparisons of the small signal frequency domain responses of the original nonlinear dynamic model and of the new linear RC model. We expect implementation of these results to find place not only in modeling for energy conversion applications but also for modeling devices that are capturing light as signal carrying information.

III. Application of ANNs in Diagnosis

Whenever we think about why something does not behave, as it should, we are starting the process of diagnosis. Diagnosis is therefore a common activity in our everyday lives [20]. Every system is liable to faults or failures. In the 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 and location of a fault manifested by some observed behaviour. This is often considered to be a two-stage process: first the fact that fault has occurred must be recognized – this is referred to as *fault detection*. Secondly, the nature and location should be determined such that appropriate remedial action may be initiated.

The general structure of a diagnostic system is shown in Fig. 10. Signals $u(t)$ and $y(t)$ are input and output to the system, respectively. Faults and disturbances (here measurement errors) also influence the system under test, here denoted as the "Process", but there is no information about the values of these errors. The task of the diagnostic system is to generate a diagnostic statement $\boldsymbol{S}$, which contains information about fault modes that can explain the behaviour of the Process. Note that the diagnostic system is assumed to be passive i.e. it cannot affect the Process itself.

The whole diagnostic system can be divided into smaller parts referred here to as tests. These tests are also diagnostic systems, DS_i. It is assumed that each of them generates diagnostic statement S_i. The purpose of the decision logic (voting system) is then to combine this information in order to form the diagnostic statement S.

Analogue electronic circuits are known to be difficult to test and diagnose. Apart from the huge number of possible faults, this difficulty is a consequence of the inherent nonlinearity of these circuits. Even linear circuits (having linear input-output signal interdependence) exhibit nonlinear relations between circuit parameters and the output response. There are no linear active networks. Active networks are nonlinear with nonlinear reactive elements. They may be linearized and thought of as such in situations where signal and parameter changes are small in comparison to nominal values. When large parameter changes or even catastrophic faults occur (affecting the DC state), however, one must distinguish between linear and analogue circuits.

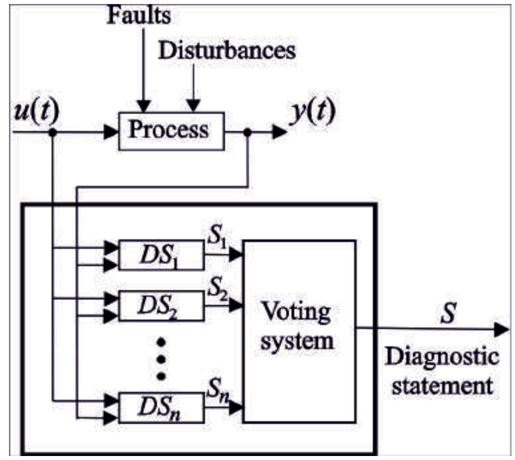

Fig. 10. A general diagnostic system

Here we describe the results of applying feed-forward ANNs to the diagnosis of non-linear dynamic electronic circuits with no restriction on the number and type of faults. This method is based on fault dictionary creation and using an ANN for data compression by memorizing the table representing the fault dictionary. Only DC and small signal sinusoidal excitations are applied, so preserving the usual measurement procedure for generating the data given in a component's and/or a circuit's data-sheets. The ANN so created is, consequently, used for diagnosis by applying to it the signals obtained by measuring the faulty network. This process may be considered as looking-up a fault in the fault dictionary. The ANN finds the most probable *fault code* that corresponds to the measured signals.

The network used for this diagnostic example is a feed-forward neural network structured in three layers. It has only one hidden layer, which has been proved sufficient for this kind of problem [21]. The neurons in the hidden layer are activated by a sigmoidal function, while the neurons in the output layer are activated by a linear function. The learning algorithm used for training this network is a version of the steepest-descent minimization algorithm [22].

In order to describe the way in which the fault dictionary was created, the circuit in Fig. 11. is used as an application example [23]. This is a CMOS operational amplifier consisting of seven transistors. To our knowledge this example belongs to the category of the most complex ones reported, both from the number of circuit elements point of view and the number of faults inserted. Three (nonlinear) capacitors are associated with every transistor totalling the number of nonlinear circuit elements to 28 but, for the sake of simplicity, are not shown in the figure. In order to emphasize the method as such, while not offering a full solution of the diagnostic problem for this circuit, having in mind abundance of possible faults, a reduced set of faults was considered. To this end only single transistor faults are sought. That, of course will not affect the generality of the ideas implemented in the next.

Ten faults per transistor, six catastrophic and four parametric were added to the dictionary. As shown in the figure (using T_7 as an example) there exist three open-circuit faults (OC) and three short-circuit faults (SC) per transistor. In addition, two faulty values for every channel length (±20%), and two for every channel width (±20%) were introduced, totalling 10 faults per transistor.

The DC output values were first obtained by simulation. In addition, the frequency response of the circuit (the non-inverting input terminal was excited by a signal of amplitude 1mV) was obtained by simulation over a fixed frequency range in order to extract two response parameters: the nominal gain (A_m) and the 3-dB cut-off frequency ($f_{3\ \mathrm{dB}\ m}$). Note that, for the DC supply current point of view, the fault effects of most open faults at sources and drains in series connected transistors may have equivalent signatures.

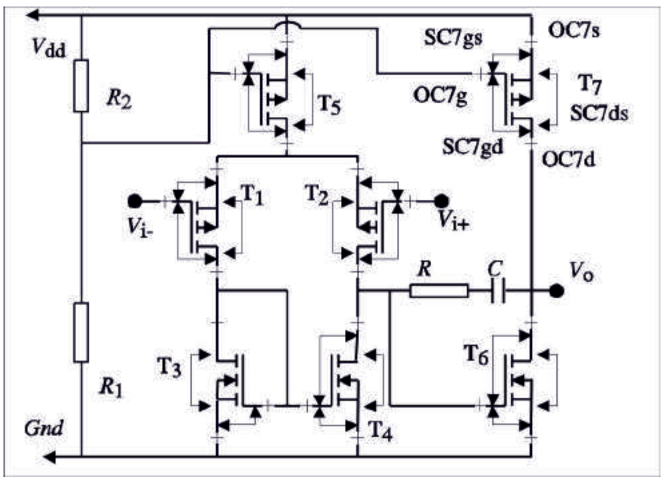

Fig. 11. The operational amplifier circuit. SC = short circuit, OC=open circuit

There are several important issues that need to be considered in this diagnosis process. The fault coding is one of them. In fact, some defects exhibit very similar effects. So, input data can have very close numerical values, and if the output values (defect codes) were also similar, the network could not always be trained successfully. Thus, faults are coded randomly, so that faults with similar effects are unlikely to have similar codes. This approach is proven to be good, because the way of coding influences the training time, and also, the training error.

Another issue is existing of the *ambiguity groups* or the groups of equivalent faults. Here, we can say that an ambiguity group consists of a set of *faults* that propagate identical signatures to the output, making the faults detectable and the circuit testable, but no distinction between the individual faults is possible making them un-diagnosable. In this example, we formed 10 ambiguity groups, so only one representative of each ambiguity group is included in the fault dictionary. We found that the complete fault dictionary in this case had 55 elements.

With three pieces of data for each fault, the neural network input structure was restricted to three input terminals. The ANN diagnoses the fault by outputting the fault-code (m) as a signal level, so we needed only one output neuron. The number of hidden neurons, n, was found by trial and error after several iterations starting with an estimation based on that in [24]. The goal was to find the optimum n leading to a satisfactory classification even with noisy excitations. Using too many neurons would increase the training time, but using too few would starve the network of the resources needed to solve the problem. In practice, 30 hidden neurons were used. After successful training, no mistakes were observed for all 55 faults.

The generalization property of the network was verified by supplying noisy data to its inputs. Thirty samples were examined. For each sample, one input is incremented by +5% or -5%, representing noise generated during the measurement process. The ANN response was considered to be correct (i.e. acceptable) when its value was in the range [(m-0.5), (m+0.5)]. All faults were diagnosed, though few of them with some difficulties.

Next application of feed-forward artificial neural networks to the diagnosis of mixed-mode electronic circuit is in a more complex system that can be decomposed in order to simplify the process of diagnosis [25]. Actually, in order to tackle the circuit complexity and to reduce the number of test points, we implemented hierarchical approach to the diagnosis generation with two levels of decision: the system level and the circuit level. For every level, using the simulation-before-test (SBT) approach, fault dictionary was created first, containing data relating the fault code and the circuit response for a given input signal. ANNs were used to model the fault dictionaries. During the learning phase, the ANNs were considered as an approximation algorithm to capture the mapping enclosed within the fault dictionary. Later on, in the diagnostic phase, the ANNs were used as an algorithm for mapping the measured data into fault code what is equivalent to searching the fault dictionary performed by some other diagnostic procedures. At the topmost level, the fault dictionary was split into parts simplifying the implementation of the concept. A voting system was created at the topmost level in order to distinguish which ANN's output is to be accepted as the final diagnostic statement. The approach was tested on an example of an analog-to-digital converter, and only one test point was used i.e. the digital output. Full diversity of faults was considered in both digital (stuck-at and delay faults) and analog (parametric and catastrophic faults) part of the diagnosed system. Special attention was paid to the

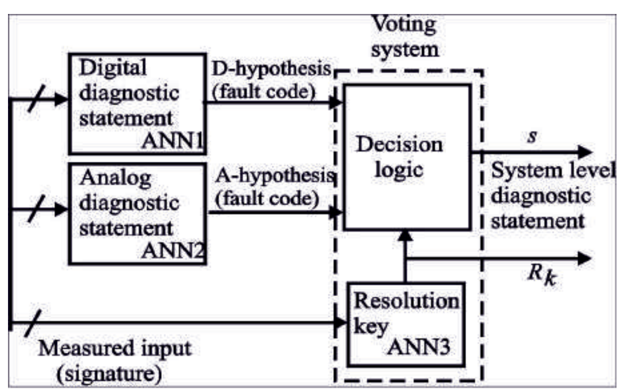

Fig. 12. The ANN based hierarchical diagnostic system

faults related to the A/D and D/A interfaces within the circuit. The example is given in Fig. 12, where a mixed-mode circuit is diagnosed.

ANN1 diagnoses defects in the digital part of the system, while *ANN2* diagnoses defects in the analog part of the system. *ANN3* gets the measured signature as an input as *ANN1* and *ANN2* do. It gets trained so that its output code takes values from the set {-1, 0, 1}. We refer to these values as to resolution key. Namely, if the defect comes from the digital part, the output code is set to 1, while if it comes from the analog, the output code is set to -1. In the special cases when ambiguity arises, that is when one has the same signature coming from faults belonging to the digital and analog part, we assign 0 to the output of *ANN3.* Generally, one can introduce as many levels of diagnosis as necessary.

The implementation of ANNs for diagnostic purposes was also performed in [26] and [27] in the same way as that described in [23], [25]. An artificial neural network (ANN) was used to capture the fault dictionary and perform the diagnosis.

Namely, oscillation-based diagnosis (OBD) was used for the first time as a systematic method for diagnosis of analog filter cells. The method was implemented on a second order Sallen and Key notch cell [28]. A minimum number of test points and, accordingly, measurements were used: just the response at the output terminal. The measured output signal was processed in order to obtain the following parameters: frequency of the first harmonic and four consecutive harmonics. This is clearly simpler than versions of oscillation-based *testing* that also require monitoring of the supply current. Single soft and catastrophic faults were considered in detail, while some double soft faults were also shown to be detectable.

For every passive element within the RC circuit, a short- or open-circuit is considered as a catastrophic fault. We found that in six out of twelve faulty cases the circuit oscillated. In all cases the fault effect is distinct from the fault-free, because the oscillation frequency is not the same as that of the fault-free circuit, or there is no oscillation. In general, therefore, we can state that by implementing OBT we got almost perfect fault coverage of catastrophic faults. We also calculated the frequency change relative to the oscillating frequency, given as a percentage.

When considering parametric (soft) defects, we decided that parametric defects were seen when the element value within the RC-circuit was changed by 20% compared to its nominal value. Both positive and negative changes are taken into account. By inspection of the obtained results, we noticed that in only two cases there was no difference between the behavior of the fault-free and the faulty circuit. In four cases, the change in the frequency value was relatively low (less than 5%) so making the decision difficult. Here again we may conclude that the fault coverage is almost perfect.

The possible number of double parametric defects is much larger than in the case of the single faults. Therefore, a reduced set of pairs of soft faults was considered. We may observe that in all cases, the faulty circuit exhibits a new value for oscillation frequency. In five cases the change in the frequency value is small.

The complete fault dictionary was memorized as parameters (weights and thresholds) of artificial neural network. Diagnosis was performed by running the neural network after measurement (here simulation) of the faulty circuit. Noise was added to the signals obtained by simulation in order to check for the robustness of the method. It was shown that OBD may be successfully used for diagnosis of the notch cell, which in our experience, is among the most difficult circuits to handle. In order to enable manipulation with an extremely large amount of data we now intend to implement a hierarchical approach, as was done for testing purposes in [25].

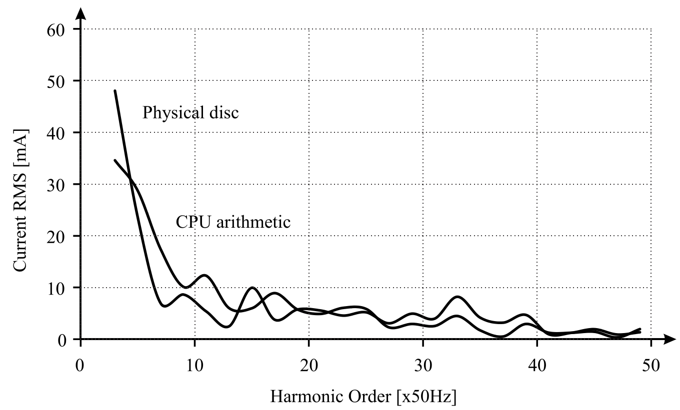

Fig. 13. Odd harmonics measured from supply current, running different benchmark tests. The first harmonic is omitted for convenience

One more example of using artificial neural networks in diagnosis is given in the next. The method we proposed [29] is based on measurement of the supply current and analysis of its harmonic content. Namely, we suppose that different activities happening within a computer map themselves into the supply current waveform in a different way and consequently may be recognized by analysis of the harmonic content. To demonstrate the method we selected a set of software packages with the goal to develop a tool that will recognize every one of them when running within the computer. For each of them we measured the supply current and computed the harmonics generated by one personal computer (DELL Optiplex 980, Intel Core i7 CPU @ 2.8GHz, 4GB RAM, 500GB HDD) under different working conditions i.e. by different benchmark tests running.

Approximately 50 harmonics were observed in a sample (200 ms, 10000 samples) of a grid current. Fig. 13. illustrates two (out of eight) different states of the workstation. Since even-harmonics have incomparably smaller values than the odd ones, only the DC, the main, and the odd harmonics are presented.

We showed in [29], [30] how one can establish, by measurement of the supply current taken from the electricity distribution grid, which software, one out of a previously given list, is running within the computer. For that purpose artificial neural networks were used to perform the classification i.e. recognition of the state of the computer. The method was proven to be good.

IV. Conclusion

In this paper we presented numerous examples where we proved that artificial neural networks could be used in many different applications in electronics. We applied them successfully in modelling of electronic circuits, as well as in fault diagnosis and classification.

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