Electronic Circuits Modeling Using Artificial Neural Networks

Miona Andrejević and Vančo Litovski

Abstract - **In this paper artificial neural networks (ANN) are applied to modeling of electronic circuits. ANNs are used for application of the black-box modeling concept in the time domain. Modeling process is described, so the topology of the ANN, the testing signal used for excitation, together with the complexity of ANN are considered. The procedure is first exemplified in modeling of resistive circuits. MOS transistor, as a four-terminal device, is modeled. Then nonlinear negative resistive characteristic is modeled in order to be used as a piece-wise linear resistor in Chua's circuit. Examples of modeling nonlinear dynamic circuits are given encompassing a variety of modeling problems. A nonlinear circuit containing quartz oscillator is considered for modeling. Verification of the concept is performed by verifying the ability of the model to generalize i.e. to create acceptable responses to excitations not used during training. Implementation of these models within a behavioural simulator is exemplified. Every model is implemented in realistic surrounding in order to show its interaction, and of course, its usage and purpose.**

I. INTRODUCTION

There are two basic approaches to the modeling of electronic circuits: the physical and the black-box approach. When the physical laws undergoing the behaviour of the component are known one may create a set of expressions (usually by solving differential equations) relating the input and output terminals. 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 modeling expressions. There are, however, many difficulties in the implementation of such models [1]. Firstly, one rarely knows the physics of the component in such a detail that enables establishing the mutual dominance of all physical and technological parameters. The number of such parameters is usually so large leading to very complex models [2]. Further, in most cases it is not possible to describe the complete behaviour by one equation only having in mind different operating regimes of the component [3]. 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 behaviour is captured by measuring of input (excitation 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 modeling. In some cases polynomial interpolation is used in between two measured points [4]. In other cases the complete measurement is described by linear segments leading to piece-wise linear models [1], [5]. 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 modeled. 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 modeling simultaneously of the nonlinear and dynamic behaviour of the device. In such cases the excitation signal used activates only part of the inner properties of the devices meaning that the model generated based on one measurement may be inadequate for other excitations. In addition, the problem of parameterization arises. Namely, the model obtained by the black-box approach is useful only for one device with fixed parameters. If parameterization is preferred one should use measurements for many components being produced by variation of one or more parameters and include the parameter value into the approximation process as if it is an input signal.

Artificial neural networks were shown to be an excellent candidate for the approximant needed in the black-box modeling. The first example of application of ANN for modeling an electronic device was given in [6]. There the output characteristics of a MOS transistor are approximated by a feed-forward three layer ANN. The implementation of such model is limited by the need of existence of behavioural simulator being able to formulate circuit equations for system containing simultaneously component described by electrical equations and others described by functions (i.e. ANNs) [7, 8].

After publication of the first results in [6], ANNs were successfully applied in electronic circuits modeling several times [9]. In all these applications feed-forward networks were used meaning that only resistive properties of the devices were captured. The first attempt of modeling dynamic behaviour was described in [10]. A micro-electro-magneto-mechanical actuator was modeled but the modeling 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.

In this paper we will first describe our method of using ANNs for modeling of nonlinear resistive and dynamic

Faculty of Electronic Engineering, University of Niš, Beogradska 14, 18000 Niš, Serbia and Montenegro e-mail:miona@elfak.ni.ac.yu, vanco@elfak.ni.ac.yu

networks. Then we will exemplify the complete modeling procedure and the properties of the models generated. Finally, we will demonstrate the possibility of implementation of this procedure into a behavioural electronic simulator.

II. MODELING USING ARTIFICIAL NEURAL NETWORKS

Among the first attempts to use ANNs for modeling of dynamic nonlinear devices was the one described in [11]. Here, however, the signals were transformed so that the approximation was performed in the frequency domain. During the training process the error is minimized between the spectral characteristics of the responses of the original device and the ANN.

Here we propose a method where the approximation is performed in a natural-time domain. We start from the fact that the ANN may be used as an universal approximant [12, 13]. Following that we propose solution being able to exploit the properties of the ANNs. These solutions are related to the following: synthesis of the waveform of the excitation signal, synthesis of the topology of the ANN, getting the complexity of the ANN.

Before proceeding to the description of the solutions to the above problems we will describe the basics of feed-forward neural network used as the core approximant throughout our work. An example of a feed-forward neural network [12] is given in Fig. 1. It is a fully connected network with one hidden layer. n, n_0, and n' are the number of neurons in the input, hidden, and output layer, respectively. θ_{ji} is the threshold of the i-th neuron in the j-th layer, while $w(p, j)(q, i)$ is the weight of the connection between the j-th neuron in the p-th layer and the i-th neuron in the q-th layer. The neurons belonging to the hidden layer are activated by the following function:

$$z_i = \frac{1}{1+e^{-\lambda_1 \cdot s_i}} \tag{1}$$

For the neurons in the output layer we use:

$$y_i = \lambda_2 \cdot q_i \tag{2}$$

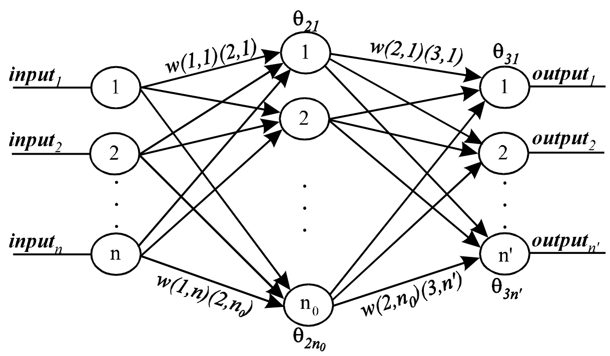


Fig. 1. Feed-forward ANN

λ_1 and λ_2 are constants, while z_i and y_i are the responses of the neurons in the hidden and the output layer, respectively. In addition:

$$s_i = \sum_{j=1}^{n} w(1, j)(2, i) \cdot x_j + \theta_{2i} \tag{3}$$

$$q_i = \sum_{j=1}^{n_0} w(2, j)(3, i) \cdot z_j + \theta_{3i} \tag{4}$$

x_j are the input signals of the corresponding neurons.

Synthesis of a signal for excitation is a fundamental issue. The signal used in modeling is supposed to activate the complete behaviour of the device to be modeled. In the same time it is supposed to be rational enough to shorten both the modeling process and the simulation time. Observing the DC characteristic, for example, it should have amplitude large enough to activate every nonlinearity. From the other side, in order to capture the dynamic properties, its spectre should be broad enough to cover the complete "pass-band" of the component. Both the amplitude and the spectre are to be taken into account when devices with inherent dynamic nonlinearities are to be modeled. Chirp signal is proposed to be used for this purpose. It is a frequency modulated sinusoidal signal. Such a signal is depicted in Fig. 2. and given by:

$$i(t) = I_0 \cdot \sin(2\pi \cdot (f_0 + k \cdot t) \cdot t) \tag{5}$$

k is calculated from the simulation time (t_{final}) and the highest frequency of interest (f_{high}):

$$k = \frac{f_{high} - f_0}{2 \cdot t_{final}} \tag{6}$$

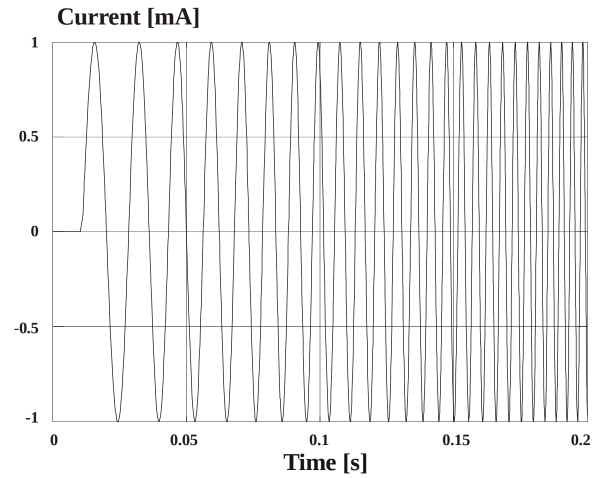


Fig. 2 Chirp signal used for excitation

Optimal network topology is never known in advance. The solution should be based on experience and knowledge related to the properties of ANNs. Topology suitable for modeling of nonlinear dynamic circuits presented in this paper is Recurrent Time-Delay Neural Network, Fig. 3 [14]. The network output, denoted by y^n, is a function of the excitation in the present and several previous time instants, and in the same time, is a function of its own values in some previous instants.

The network complexity was always accommodated to the problem complexity while recommendations [15, 16] were accepted. In this paper, all these considerations will be applied to modeling of resistive and nonlinear dynamic circuits.

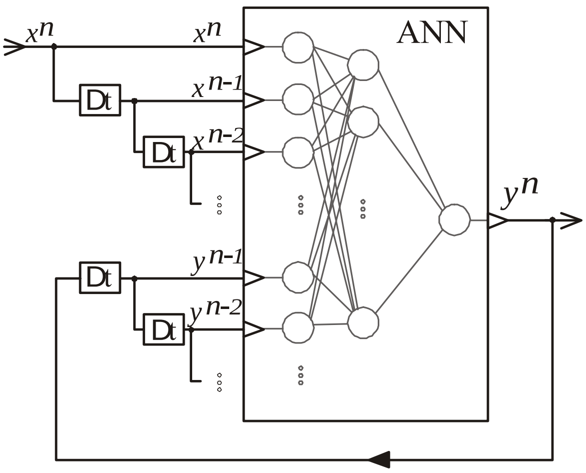


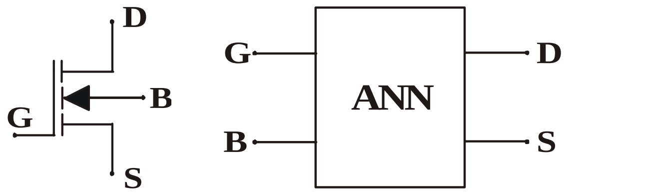
Fig. 3. Recurrent Time-Delay Neural Network

III. MODELING OF THE RESISTIVE CIRCUITS

First model of MOS transistor, “Level1” model, built in the first version of SPICE, was very simple. As technology was moving on, there were many new models developed, expected to encompass more different effects, so they were becoming more and more complex. At first, the dimensions of the transistors were directly built in the equations, considered as independent variables. The improvement was accomplished with BSIM model, where there was new dependence between parameters and dimensions. This model also had its disadvantages, so its further correction is now available in BSIM3v3 model. As technology and simulation tools are in the constant progress, it is necessary to include more and more physical effects and technological improvements in the model. This leads to permanent development of the model by adding new mathematical expressions and new parameters. So, the actual model of MOS transistor is very complex with great number of parameters. It is shown that number of parameters is doubled every ten years [17].

When we use black-box approach, we are not interested in the physics of the component, and we do not even have to know every one of its parameters. The only thing is to measure its input-output dependencies, and then make an approximation of its function using neural network, of course. Parameterization is also possible, because we can introduce different input to the neural network for every parameter, and then present corresponding data during the learning process. In that way, temperature or some other ambient parameter can be used.

In the following example, a four terminal device is modeled (Fig. 4). In this case, the drain current I_d is a function of three variables: V_{ds}, V_{gs}, V_{bs}. The corresponding neural network is a feed-forward network with one hidden layer, three inputs (current values of drain-source voltage, gate-source voltage and bulk-source voltage) and one output (current value of the drain current). Ten hidden neurons are used. It is necessary to include as many different combinations of three inputs as possible, in order to cover all operating regimes of the transistor. In this example, voltage applied to all of three inputs is changed in the range from 0 to 5V.

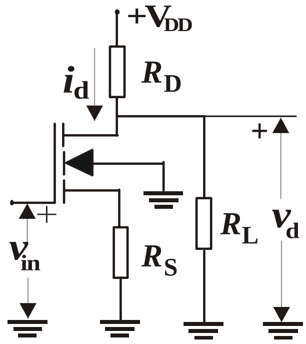


a) b)

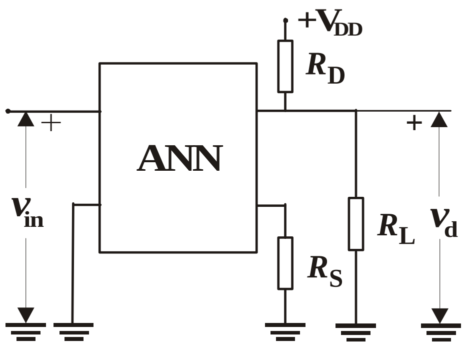
Fig. 4. a) MOS transistor as a four-terminal component, b) ANN model

Implementation of such ANN model is presented in Fig. 5. MOS transistor and its model are loaded by resistance (R_L=100kΩ). The values of resistors in drain and source are: R_D=10kΩ, R_S=1kΩ.

It is shown here that this model can be used in a complex circuit, because it can be loaded and connected to other circuit elements. Transfer characteristics are depicted in Fig 6.



a)



b)

Fig. 5. MOS transistor a), and its model b), loaded by resistor

Modeling of resistive circuits will also be presented in an example of modeling nonlinear negative resistive characteristics, and its implementation in Chua’s circuit, a standard paradigm for studying chaotic phenomena. In fact, it is one of the very few physical systems in which a formal proof of the existence of chaos has been accomplished and in which the theoretical, simulation and experimental results match precisely [18]. It is a chaotic attractor consisting of only one nonlinear element, piecewise-linear resistor. Under the action of external periodic excitation, this circuit exhibits a large variety of bifurcation sequences, including period doubling and period adding in chaos regime [18].

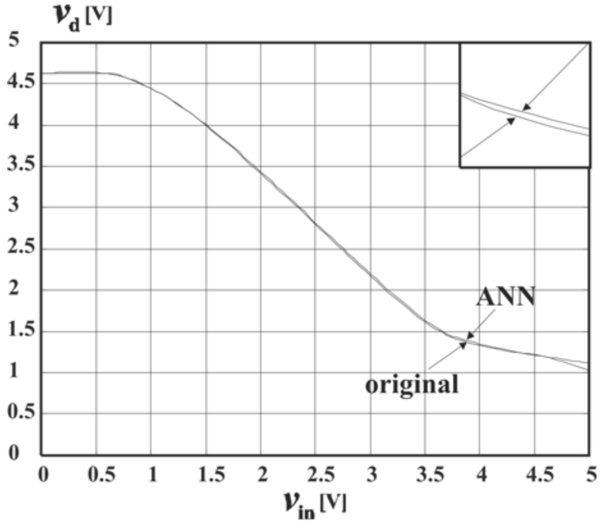
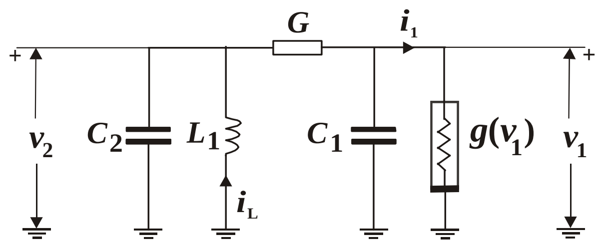


Fig. 6. Transfer characteristics of the original circuit and its model from Fig. 5

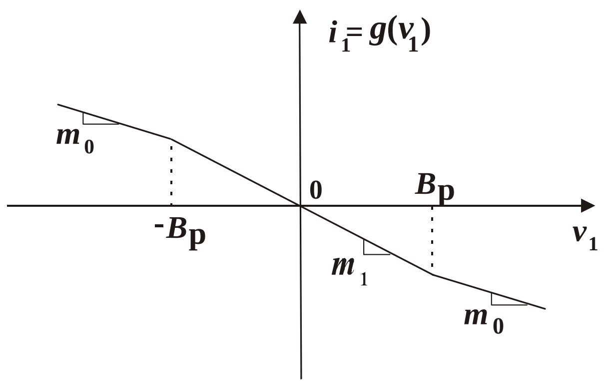
Here, an ANN is used for modeling the nonlinear resistor in the Chua's circuit. Concerning that resistance, we know the current-voltage relation, meaning that current is a function of its controlling voltage. In [19] the simulator for piecewise-linear circuit analysis was used for the modeling of this dependence. This simulator is not in a common use, and, generally, SPICE-like simulators are preferred. We will present here an ANN model for this piecewise-linear characteristic. The new model being expressed by analytical functions will not ask for PWLSPICE any more.

Circuitry given in Fig. 7a is called Chua's circuit. $g(v_1)$ is the piecewise linear function, Fig. 7b, given by:

$$g(v_1) = m_0 v_1 + 0.5(m_1 - m_0)\,|\,v_1 + B_p\,| + 0.5(m_0 - m_1)\,|\,v_1 - B_p\,| \tag{7}$$



a)



b)

Fig. 7. a) Chua's circuit, b) Constitutive relation of the nonlinear resistor

This circuit behaves like an chaotic attractor only if we specify parameter values exactly (C_1, C_2, L_1, G, m_0, m_1, B_p). Equation (7) with the specified parameters has three equilibria. Each equilibrium has one real and two complex eigenvalues. A typical trajectory in the attractor rotates around one of the two outer equilibria [20], suppose the upper one, in a counterclockwise direction with respect to the left handed coordinate system. After each rotation the trajectory gets further from the equilibrium until a certain time after which there are two possibilities: 1) the trajectory goes back to a position closer to the equilibrium and repeats a similar process, 2) the trajectory does not go back to a point close to the equilibrium but descends downward in a spiral path and "lands" on the lower part of the attractor. The point where it lands is close to the lower equilibrium and starts rotating counterclockwise around the lower hole. After this, the behaviour is similar to that in the upper part of the attractor except for the fact that it starts ascending after rotating around the lower equilibrium several times.

Theoretic interpretation of the chaotic behaviour is given in [20]. The parallel connection of C_2 and L constitutes a lossless oscillatory mechanism in the (v_2- I_L)-plane, whereas the conductance G provides interactions between the (C_2, L)-oscillatory component and the active resistor together with C_1. The active resistor is responsible for the circuit's chaotic behaviour. Since $g(v_1)$ is active, it keeps supplying power to the external circuit. The attracting nature of the chaotic trajectories is, therefore, due to the power dissipated in the passive element.

There exist many problems concerning the realization of Chua's attractor, because of the nonlinear, negative resistance shown in Figure 7b. The main problem is to realize a piecewise-linear characteristic of the resistor. In fact, in the solutions offered in the literature, there is a smooth transition of the curve near the breakpoints.

Though the characteristic is resistive, a feed-forward network with one hidden layer would fit quite well. Since current is the nonlinear function of the controlling voltage, $i_1 = g(v_1)$, a linear change of voltage is used, in order to capture behaviour of the resistance.

The actual parameters for the constitutive relation of the piecewise linear characteristic are: m_0=-5*10^{-4}, m_1=-8*10^{-4}, B_p=1. Electrical simulation of the resistor was performed first. The change of voltage was linear, as mentioned above, in the range -3V÷3V. For the example used here, one input, four hidden, and one output neuron were incorporated. The current-voltage relation of the model is shown in Fig. 8 together with the original current-voltage relation used for training. Excellent agreement of the relations was obtained.

In order to show the quality of the approximation procedure and the generalization capabilities of the ANN, the new model is implemented in a double scroll circuit with the following parameter set (Fig. 7a): C_1=0.0055μF, L_1=7.07mH, C_2=0.0495μF, G=7mS. Projections onto three different planes are presented in Fig. 9.

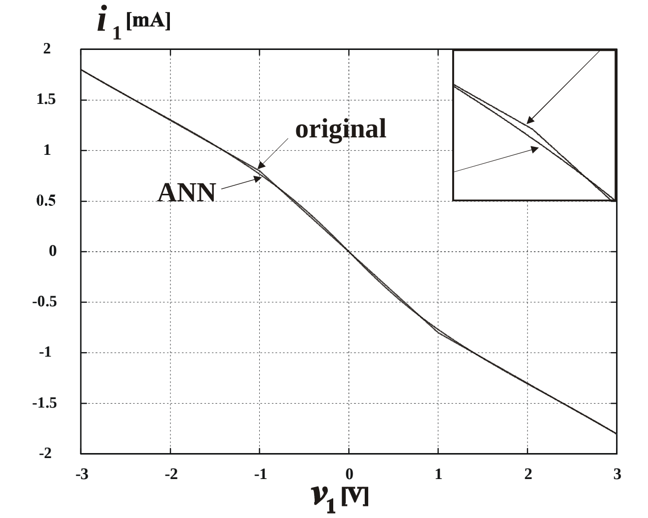
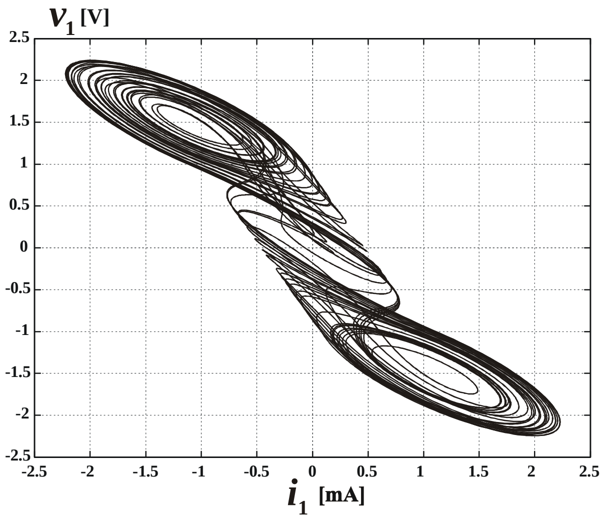
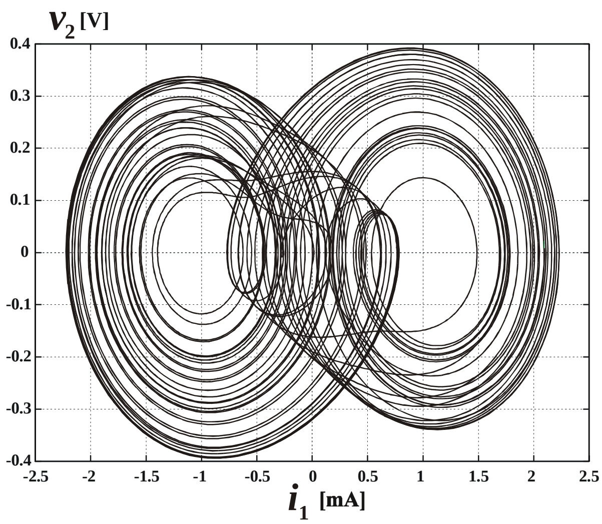


Fig. 8 Constitutive relation of the nonlinear resistor in Fig. 7 described in simulator and ANN model



a)



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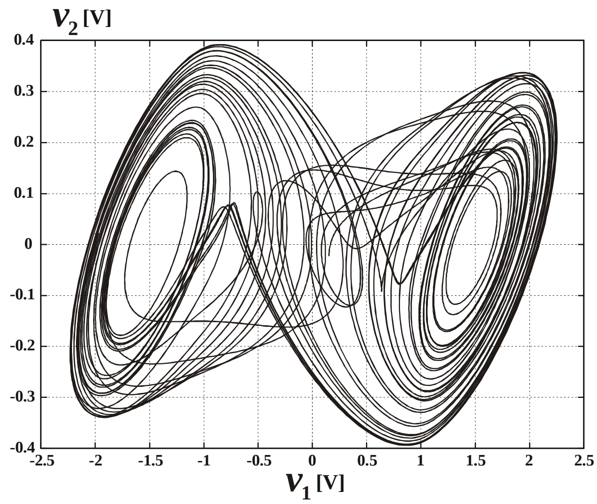


c)

Fig. 9. Double scroll attractor with ANN model performing like negative resistance. Projections onto: a) (i_1- v_1) plane, b) (i_1- v_2)-plane, c) (v_1- v_2)-plane

IV. MODELING OF NONLINEAR DYNAMIC CIRCUITS

The motivation for modeling of this kind of circuits appeared with the problem of modeling implanted hearing aids [21]. Here, however, in order to present reproducible results the nonlinear circuit, Fig. 11, containing quartz crystal, Fig. 10, will be considered for modeling. The schematic symbol for a quartz crystal is shown in Fig. 10a. The equivalent circuit for a quartz crystal near fundamental resonance is shown in Fig. 10b. 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 [22].

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 equation is:

$$f_s = \frac{1}{2\pi\sqrt{L_1 C_1}} \tag{8}$$

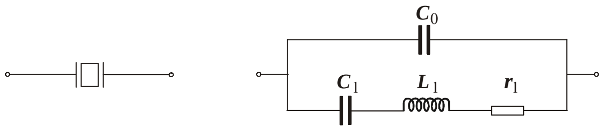
When the crystal is operating at its series resonant frequency the impedance will be at a minimum and current flow will be at a maximum.

The second resonant frequency is the anti-resonant f_a, frequency. The equation is:

$$f_a = \frac{1}{2\pi\sqrt{L_1 \cdot \dfrac{C_1 C_0}{C_1 + C_0}}} \quad (9)$$

When the crystal is operating at its anti-resonant frequency the impedance will be at a maximum and current flow will be at a minimum.

As an example of modeling of nonlinear dynamic circuits, the electronic circuit depicted in Fig. 11 will be modeled. The pair of branches containing diodes is introduced enabling the nonlinearity of the circuit to be accounted for. Values of the elements in the circuit are: C_1=0.018pF, L_1=22mH, r_1=30Ω, C_0=4.5pF, R_1=200kΩ, R_2=200kΩ, E_1=E_2=1V. Resonant frequency of the crystal oscillator is 8MHz, meaning that both f_s and f_a are close to that value.



a) b)

Fig. 10. a) Crystal equivalent circuit and b) its symbol

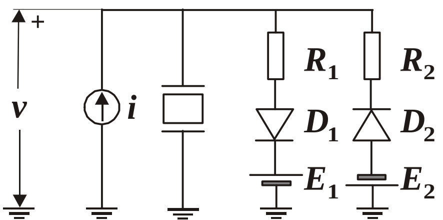


Fig. 11. Nonlinear dynamic circuit chosen for modeling

So, a chirp $i(t)$ signal is needed to cover the frequency band around 8MHz. Reccurent time delay neural network with five input, four hidden and one output neuron is used, because the structure from Fig. 11 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. 12. Series resonant frequency can be noticed first, and then, anti-resonant frequency.

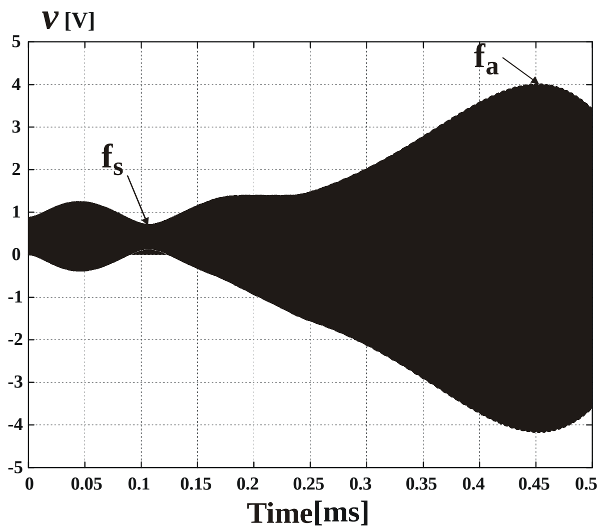


Fig. 12. Response of the circuit, Fig. 11, excited by a chirp signal

The responses of the modeled circuit and the model are shown in Fig. 13. It is obtained as an envelope of the time domain response [23].

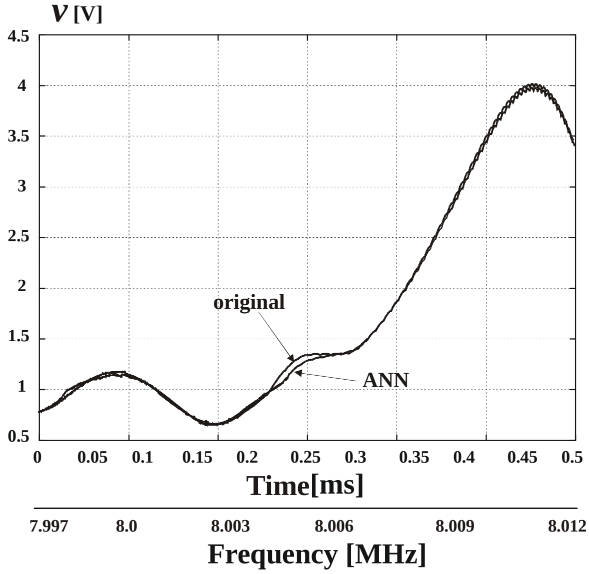


Fig. 13. Responses of the original circuit (Fig. 11) and the model (only the envelopes of the positive periods are shown)

V. CONCLUSION

Artificial neural networks are used for application of the black-box concept in the time domain for modeling of electronic circuits. The topology, the testing signal used for excitation, and the complexity of the ANN are considered. Modeling of resistive circuits is shown on two examples: MOS transistor modeling, and modeling of negative nonlinear resistance. Nonlinear dynamic circuits are also modeled and verified by getting acceptable responses to excitations not used during training. Implementation of all these models within a behavioural simulator is exemplified.

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