Modelling Circuits using Artificial Neural Network

R Srihari
Department of Electrical Engineering
Indian Institute of Technology, Kharagpur
E-mail: rsrihari95@gmail.com

Abstract

In this paper, the application of Artificial Neural Network to emulate the black-box behaviour of electrical/electronic elements in simulations is considered. The paper considers the advantages and disadvantages of the black-box model over the traditional physics based implementation used in popular simulation software. The structure of the ANN used for the same, the process of modelling through experimentation/simulation and application in further simulations are discussed in detail. The whole process is further exemplified in the modelling of a low pass filter using ANN in the frequency domain. This paper also explores the opportunities and possibilities arising out of ANN based modelling of electrical/electronic circuits in future simulation applications.

1. Introduction

Simulation software the likes of PSPICE try to simulate the characteristics of an element in electrical or electronic circuits based on a set of relations that are derived from the physics of the elements used (usually solving various differential equations). The rules are hardcoded into the model and developers update the model as and when more parameters are identified lending further complexity to the circuit. When circuits are modelled thus in simulation software, it's termed as *physical model*. A physical model has the fundamental advantage of clearly specifying the underlying physics of relations between the various parameters. But this approach basically runs into the following problems:

1) The physics of numerous elements are not known in enough detail to establish the mutual dominance of all physical and technological parameters.
2) One equation alone cannot quite often describe the behaviour in different operating regions.

The second approach involves a black-box model which describes the input output relations without any description whatsoever of the underlying physics of the elements used. This kind of a model is achieved by first exciting the circuit and capturing the output responses at various operating points. The collected data is further used to approximate the behaviour of the circuit over all operating points including the ones at which the circuit was not initially excited. The approximation can be polynomial interpolation between known points or a piece wise description of characteristics in intervals captured by the initial excitation. The advantage of this model is that developing this model does not requires full knowledge of physics.

The main challenge in black-box modelling is simultaneously capturing the nonlinear and dynamic behaviour of the device. A certain excitation might only activate few inner properties of the device and would not mirror the behaviour at other excitation points. Also, the black-box fails to account for variation of parameters of the device which were kept constant throughout while modelling the devices. To include the effects of variation of parameters, we should vary the parameter while modelling by treating the parameters of the device as inputs just like the parameters of the excitation signal.

Artificial Neural Networks were found extremely well suited for this purpose. The first example of using ANN to model an electronic device was described in [1]. The characteristics of a MOS transistor was modelled using a feed forward 3 layer neural network. But the first time ANN was used for modelling a dynamic circuit was described in [2]. In the current paper,we consider the modelling of a dynamic circuit (the low pass filter) by exemplifying the process of modelling and properties of the model generated.

2. Modelling using Artificial Neural Network

The modelling is based on the fact that Artificial Neural Networks are universal approximators. To achieve a good solution we need to propose solutions to these problems - what are the signal(s) we are going to use for the purpose of excitation and what is the topology of the network to be used.

Before proceeding to answer these questions, let’s consider the working of a feed forward neural network. One such network is illustrated in the diagram below [3].

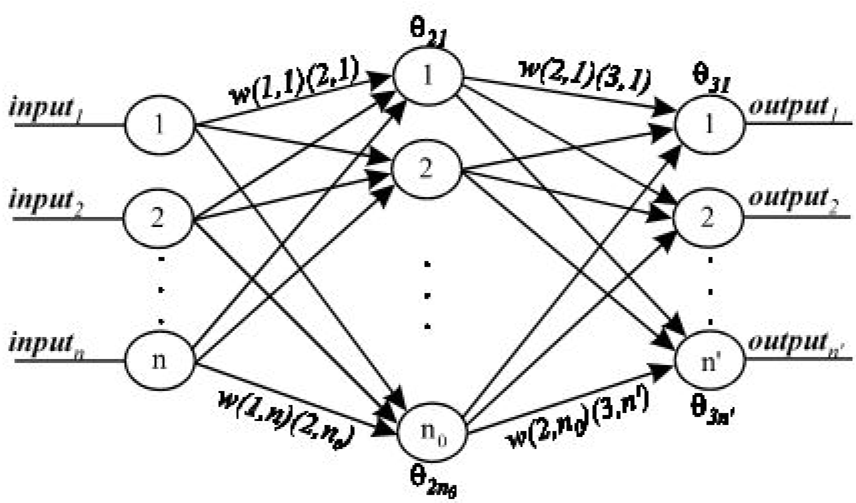

Figure 1. Feed forward neural network

There are n, n_0 and n’ number of neurons in the input, hidden and output layers of this sample network. w(i,j)(k, l) describes the weight from neuron-j in layer-i to neuron-l in layer-k. The input layer neurons and the output layer neurons are linearly activated while the hidden layer neurons are activated by a sigmoid function. The output of the hidden layer is given thus, where s_i is the input to the sigmoid function in the hidden layer.

$$z_i = \frac{1}{1+e^{-\lambda_1 s_i}} \qquad (1)$$

The output of the output layer is linearly activated and hence given by the following expression.

$$y_i = \lambda_2 q_i \qquad (2)$$

The input to the sigmoid function in the hidden layer is expressed as below.

$$s_i = \sum w(1, j)(2, i). x_j + \theta_{2i} \qquad (3)$$

Equivalent expression is used to compute the output of output layer before it is linearly scaled. These expression together describe the feed forward mechanism of an artificial neural network.

Synthesis of a signal for excitation is a crucial step as it determines the training data for the neural network. A chirp signal is identified as a suitable candidate as it ensures that the excitation signal amplitude varies over a substantial range that activates all non-linearities in the signal. In order to capture the dynamic properties of the circuit, the frequency spectre should be broad enough to cover the at least the entire pass band. A chirp signal is basically a frequency modulated sinusoidal.

$$i(t) = I_0 \cdot sin(2\pi \cdot (f_0 + k \cdot t) \cdot t) \qquad (4)$$

The parameter k can be calculated depending upon the simulation time by ensuring that in that time, the highest frequency of interest is achieved.

The topology used for the circuit cannot be predetermined and is usually arrived at by repeated trial and error. For modelling a low pass filter, a feed forward network was used and the number of neurons in the input and output layers were one each (based on the number of inputs and outputs) while an optimal number of neurons was decided by trial for the hidden layer.

3. Modelling a Nonlinear Dynamic Circuit

A low pass filter diminishes or rejects frequencies above a certain cut-off from a signal and allows only the required frequencies to pass through. A straightforward implementation is an RC circuit fed by signal whose output is obtained across the capacitor.

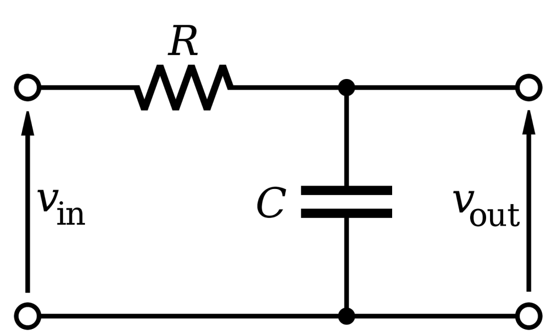

Figure 2. Low pass filter

The low pass filter can be translated into a physical model without much effort because the underlying physics is rudimentary and could easily be hardcoded. A more complex circuit could be used for the exercise too, but in the absence of lab equipments, a low pass filter was chosen as it could easily be simulated using the physical model to generate training values for the ANN. For the physical model, we use the following relation.

$$V_{out} = \frac{1}{\sqrt{1+(RC\omega)^2}} x\, V_{in} \qquad (5)$$

Table 1. Parameter Values

Serial Number	Parameter	Value
1	Resistance (R)	$47k\Omega$
2	Capacitance (C)	$47nF$
3	Peak Voltage (V_p)	$10\ V$
4	Frequency	$0 - 10000\ Hz$

The low pass filter was excited by keeping the value of R and C fixed, by a signal of constant peak value as the frequency of the input signal kept changing. The (range of) values used for the same has been recorded in the table above. Samples were taken at fifty different points during the excitation as the frequency was varied and the output values were recorded in a table. The plot of output Vc from the physical model is show here.

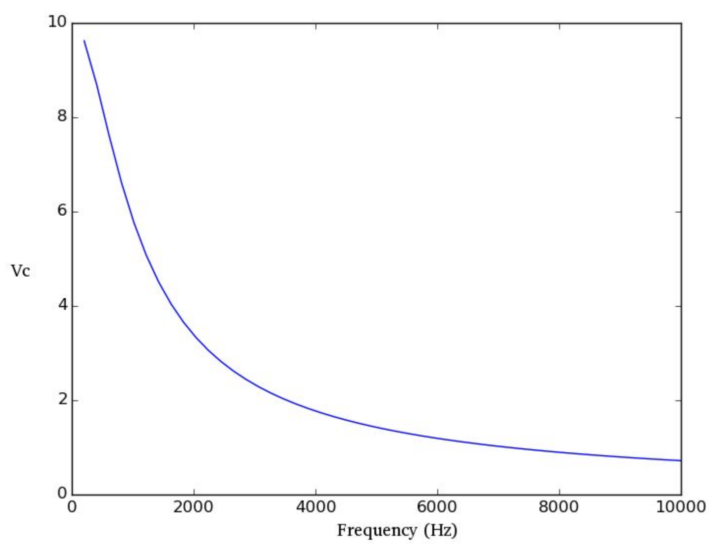

Figure 3. Output from the physical model

The ANN was found to give reasonably low error when the number of neurons in hidden layer was fixed at 50. The activation function for the input and output layer was linear, while for the hidden layer, sigmoid activation was used. Using the semantics of PyBrain library, the neural network can be described thus: *[<BiasUnit 'bias'>, <LinearLayer 'in'>, <SigmoidLayer 'hidden0'>, <LinearLayer 'out'>]*. Using an ANN, any function can be accurately mapped with any desired accuracy with only one hidden layer in between and certain number of neurons in the hidden layer. The weight values of the neurons were adjusted by the application of the backpropagation algorithm. The following table compares the values of output voltage achieved using the physical model to the one using the black-box model implemented using ANN.

Table 2. Comparing the output of the physical model to the black-box model for different inputs

Serial Number	Physical Model (Vout/10)	Black-box model (Vout/10)	Serial Number	Physical Model (Vout/10)	Black-box model (Vout/10)
1	1.0	0.7879684034	26	0.1398275747	0.1330083581
2	0.9621461754	0.7483929105	27	0.1345488613	0.1226213372
3	0.8700797143	0.7093013632	28	0.1296509189	0.1133593581
4	0.7620262671	0.6711986132	29	0.1250943081	0.1051973654
5	0.6617228503	0.6341265323	30	0.1208448126	0.09810909548
6	0.5767879246	0.59812393	31	0.1168726089	0.09206723041
7	0.5071226205	0.5632264205	32	0.113151588	0.08704354817
8	0.450310168	0.5294663165	33	0.1096587986	0.08300906699
9	0.4037321456	0.4968725501	34	0.1063739865	0.07993418401
10	0.3651736318	0.4654706178	35	0.1032792119	0.07778880768
11	0.3329006509	0.4352825528	36	0.1003585301	0.07654248363
12	0.3055900401	0.4063269206	37	0.09759772288	0.07616451377
13	0.2822369931	0.3786188374	38	0.094984072	0.07662406845
14	0.2620751366	0.3521700113	39	0.09250616756	0.07789029154
15	0.2445149705	0.3269888031	40	0.09015374461	0.07993239847
16	0.2290983904	0.303080305	41	0.08791754365	0.08271976722
17	0.2154655535	0.2804464374	42	0.08578919091	0.08622202222
18	0.2033307709	0.2590860593	43	0.08376109535	0.09040911142
19	0.1924648824	0.238995092	44	0.08182635959	0.09525137656
20	0.1826822694	0.2201666542	45	0.0799787027	0.1007196168
21	0.1738311966	0.2025912062	46	0.07821239306	0.1067851461
22	0.1657865578	0.1862567013	47	0.07652218978	0.1134198438
23	0.1584443734	0.1711487434	48	0.07490329144	0.1205962003
24	0.1517175747	0.1572507485	49	0.07335129108	0.1282873559
25	0.1455327448	0.1445441088	50	0.07186213664	0.1364671347

The same data was plotted to compare the modelling accuracy of the neural network to the actual signal output. As visible, in only a few iterations, very good accuracy was obtained.

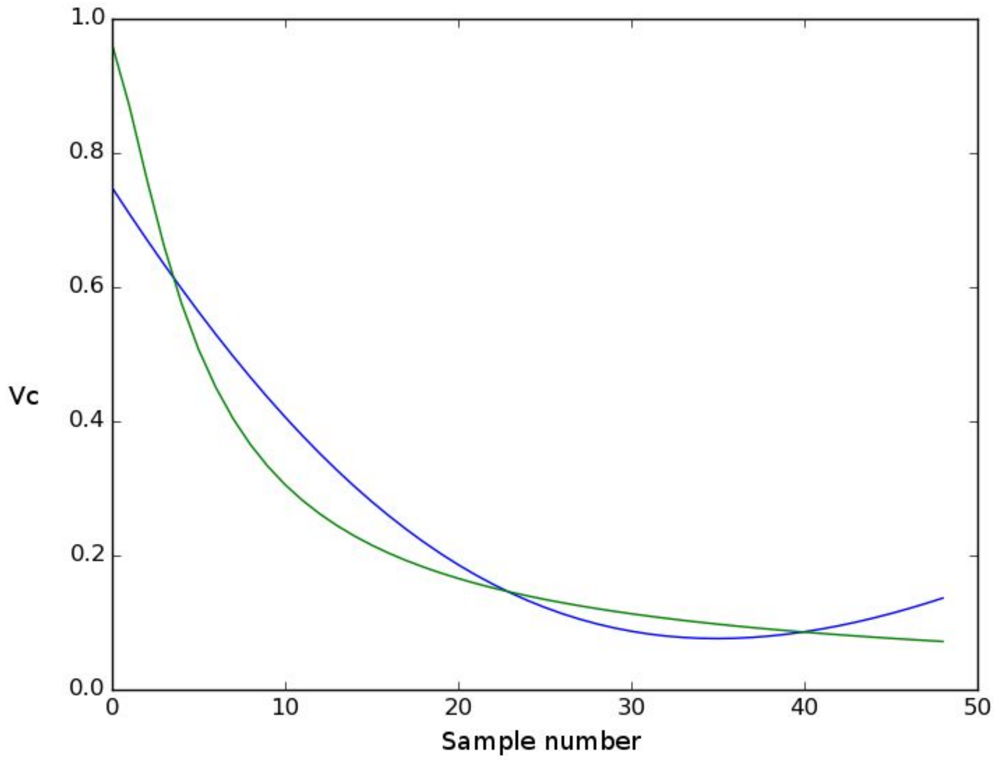

Figure 4. Plot of the above table. Green : Physical model. Blue : Black-box model

4. Extending the Black-box Model

The idea used in the above section can be extended to include the variation in parameters too. For example, if the value of capacitance used in the above example is variable, the output signal also changes with capacitance. In that case, apart from the magnitude of the output sinusoidal, the phase also varies with variation in capacitance. To accommodate for these, the value of capacitance would also be given as an input to the neural network and instead of just one output (the magnitude), the neural network would now produce two outputs (magnitude and phase). The structure would be described with 2 input neurons (frequency and capacitance) and 2 output neurons (phase and magnitude).

5. Opportunities and Summary

The ANN provides an efficient and accurate method to model complex elements in electrical systems. This would allow us to use these complex devices, whose physics is tough to hardcode into a physical model, in simulations. On the other hand, by establishing the characteristics of a device using a black-box model, it allows us to work back to the physics of the device. In this paper, we considered how black-box modelling can be a substitute to physical modelling. The advantages and disadvantages were considered before we described in detail the modelling process used in developing a black-box model. Further, the example of a low pass filter being modelled in it’s frequency domain was described with relevant data. It was shown that in a few hundred iterations, the error in the black-box model was drastically reduced. The ANN based black-box model would suffice as substitutes for physical models in electrical/electronic simulation software.

References

[1] Litovski, V.B., et all., “MOS transistor modeling using neural networks”, Electronic Letters, Vol. 28, No. 18, 1992, pp. 1766-1768.
[2] Litovski, V., Mrčarica, Ž., Ilić, T., "Simulation of nonlinear magnetic circuits modeled using artificial neural network", Simulation Practice and Theory, Elsevier, No. 5, 1997, pp. 553-570.
[3] Litovski, V., Andrejević, M., : Electronic circuits modeling using artificial neural networks, Journal of Automation Control, 2003, vol. 13(1) 31-37