Prediction of Energy Storage Capacitor Values Based on Neural Networks. (Case of a Planar Capacitor)

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Abstract. Energy storage is a very important operation in continuously operating systems, such as telecommunications systems, embedded systems and power systems. Energy storage can be performed by various means such as batteries and super capacitors. In our work, we used neural networks to determine the capacitance values C of the planar capacitors as a function of the relative permittivity εr, the distance d and the dimensioning (Width and Length) of the capacitor plates and as a function of the maximum desired charge Qmax. The results of simulation will be better and more satisfying if the databases are richer and good.

Keywords: Energy storage · Capacitor · Neural networks · Activation function · Normalized square error

1 Introduction

The methods of implementing electronic circuits with more optimal performance are based primarily on their technical characteristics and experience during the experimental or operating phases to predict future performance of the various components of the circuits in question.

New technologies bring to the design of products, methods and information that make it possible to do better than before and above all, to predict the future behavior of a material or a component. The results of these studies can be used to identify critical components and undesired failures, or to estimate failure probabilities and associated downtime.

The universal predictive aspect of neural networks and their ability to adapt to the desired behavior allow to expand their uses for system identification and control.

Artificial neural networks are one of the artificial intelligence approaches whose development is done through the methods by which man always tries to imitate nature and to reproduce his own modes of reasoning and behavior.

M. Hatti (Ed.): ICAIRES 2019, LNNS 102, pp. 442–449, 2020.
https://doi.org/10.1007/978-3-030-37207-1_47

In our study, we used gradient-retro-propagating multilayer neural networks to predict the capacitance values from appropriate parameters from a good choice of theoretical or experimental database.

2 Description of the Planar Capacitor [1–4]

A planar capacitor consists of two metal plates of surface A = La.Lo (La, Lo: are respectively the width and the length of the two plates). Between these two plates of distance d there is a dielectric of permittivity $\varepsilon = \varepsilon_0.\varepsilon_r$ (with ε_0= 8,854.10^{-12} F/m the permittivity of the vacuum and ε_r the variable relative permittivity) as shown in Fig. 1.

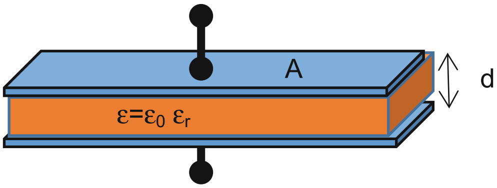

Fig. 1. Classic planar capacitor

The capacity of the capacitor is given by

$$C = \varepsilon_0.\varepsilon_r.\frac{A}{d} = \varepsilon_0.\varepsilon_r.\frac{L_a L_O}{d} \tag{1}$$

3 Energy Storage in a Capacitor [3–6]

A capacitor is an energy storage device. When we connect a battery to both plates of a capacitor, it charges. The potential difference gradually increases between the two plates and the battery has had to do more work to provide the same amount of charge due to the continuous increase in the potential difference as shown in Fig. 2.

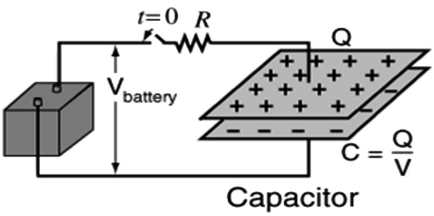

Fig. 2. The capacitor charge circuit

Storing energy on the capacitor involves doing the work to transport the charge from one capacitor plate to the other against the electrical forces. As the load accumulates in the charging process, each successive charging element requires more work to force it onto the positive plate. The sum of these constantly changing quantities requires an integral.

If a driver's capacitance is C, it is initially unloaded and the potential difference between its plates is V when connected to a battery. If q is the load on the plate at that moment, then q = CV.

We know that W = Vq, that is, the work done is equivalent to the product of potential V and load Q.

Therefore, if the battery delivers the infinitely small charge load dq to the capacitor at constant potential V, then

$$dW = Vdq = \frac{q}{C}dq \tag{2}$$

The total work done to provide a charge of Q quantity to the capacitor is given by

$$W = \int_0^Q \frac{q}{C}dq = \frac{1}{2}\frac{Q^2}{C} \tag{3}$$

Therefore, the energy stored in a capacitor is

$$E = \frac{1}{2}\frac{Q^2}{C} \tag{4}$$

By replacing Q = CV, we get

$$E = \frac{1}{2}CV^2 \tag{5}$$

So, if the capacity of a capacitor is charged to 10 F up to a potential of 10 V, the energy stored in it is 5000 J.

4 Mathematical Model of the Artificial Neural Network [4, 7–10]

Artificial neural networks are highly connected networks of elementary processors operating in parallel. Each elementary processor calculates a single output based on the information it receives. Any hierarchical network structure is obviously a network.

The mathematical model of an artificial neuron is shown in Fig. 3. A neuron essentially consists of an integrator that performs the weighted sum of its inputs. The result ***n*** of this sum is then transformed by a transfer function ***f*** which produces the output of the neuron. Following the notation presented in the previous section, the

R entries of the neurons correspond to the vector P = [P_1 P_2…… P_R] while W = [W_{11} W_{12}… W_{1R}] represents the vector of the neuron weights. The output ***n*** of the integrator is given by the following equation:

$$\boldsymbol{n} = \sum_{j=1}^{R} \boldsymbol{W}_{1,j}\boldsymbol{P}_j - \boldsymbol{b}$$

The structure of the multilayer networks consists of an input layer, a hidden layer that can consist of several sub-layers, and another output layer as shown in Fig. 3.

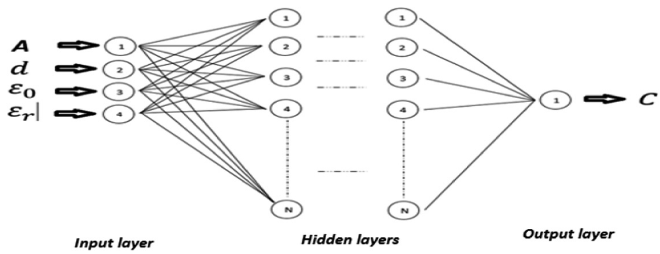

Fig. 3. Back propagation neural network

In our case we used a hidden layer of 10 neurons as shown in Fig. 4.

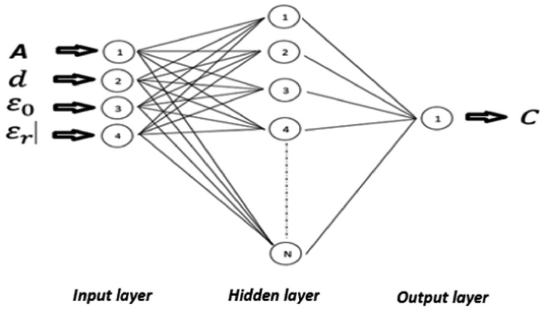

Fig. 4. Back propagation neural network of one hidden layer

The activation function chosen is the sigmoid function

$$f(\boldsymbol{x}) = \frac{1}{1 + \boldsymbol{Exp}(\boldsymbol{x})}$$

The database used is related to the different types of insulation as shown in the following Table 1:

Table 1. Permittivity and calculated capacitance of used insulators database.

Insulation	ε_r: Permittivity (pF/m)	Capacitance (pF)	Insulation	ε_r: Permittivity (pF/m)	Capacitance (pF)
Dry air	1	$26{,}562 * 10^{-12}$	Polyethylene	2,25	$59{,}76 * 10^{-12}$
Bakelite	5	$132{,}81 * 10^{-12}$	Polyprpylène	2,2	$58{,}43 * 10^{-12}$
Rubber	4	$106{,}24 * 10^{-12}$	Polystyrene	2,4	$63{,}74 * 10^{-12}$
Silicone rubber	4,2	$11{,}56 * 10^{-12}$	Polycarbonate	2,9	$77{,}02 * 10^{-12}$
Cardboard	4	$106{,}24 * 10^{-12}$	Porcelain	5	$132{,}81 * 10^{-12}$
Mica	6	$159{,}36 * 10^{-12}$	Pressboard	3	$79{,}68 * 10^{-12}$
Paper	2	$53{,}12 * 10^{-12}$	Steatite	5,8	$154{,}04 * 10^{-12}$
Baked paper	5	$132{,}81 * 10^{-12}$	Styroflex	2,5	$66{,}4 * 10^{-12}$
Paraffin	2,2	$58{,}43 * 10^{-12}$	Teflon	2,1	$55{,}77 * 10^{-12}$
PVC	5	$132{,}81 * 10^{-12}$	Glass	5	$132{,}81 * 10^{-12}$
Plexiglass	3,3	$87{,}64 * 10^{-12}$	Stratifé glass-epoxy	5	$132{,}81 * 10^{-12}$
Polyster	3,3	$87{,}64 * 10^{-12}$			

The stages of the gradient retro-propagation algorithm are:

1. Initialization of weights to random values of small quantities.
2. Selection of a learning matrix [A, d, ε_(0), ε_r] of the learning base
3. Calculation of the output s_i of each Neuron
4. Propagation of layer-by-layer outputs
5. Evaluation of the error between the output calculated by the network and the desired output (s-d).
6. Backward propagation of the error to the back of all neurons from the output to the input
   - If $\boldsymbol{i}$ is an output neuron then $\delta_i = f'(s_i)(s_i - d_i)$
   - If $\boldsymbol{i}$ is a hidden neuron then $\delta_i = f'(s_i)\sum_k (W_{ki}.s_k))$

   $\boldsymbol{k}$: neuron between the current layer and the output layer
7. Adjustment of weights by the gradient procedure

$$\boldsymbol{W_{ij}(t+1) = W_{ij}(t) + \mu.\delta_i.s_i}$$

   µ: No learning
8. As long as the error is too important, go back to step 2 (following example).
9. Save the weights and end.

5 Simulation Results

The software MATLAB realized the simulation of our algorithm based on neural networks to prevent the values of the capacities. The algorithm consists of two main parts, the learning part and the test part.

In the learning part we used a part of the database to determine the weighting coefficients (weights) by setting the iteration number by determining the mean squared error between the desired value and the calculated value of capacitance.

The variation of the mean squared error between the desired outputs and calculated by the neural network as a function of the number of iterations represented in the following figure Fig. 5.

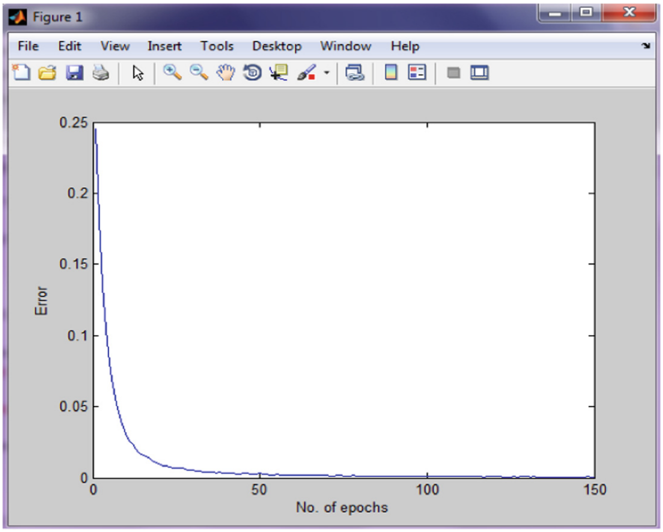

Fig. 5. Evolution curve of NSE according to the number of iterations

In the Test part, to determine the desired values, we used the weights determined by learning. Where the results are very satisfactory and show a very good convergence with a low quadratic error. The following Table 2 presents some examples of tests:

Table 2. Desired and calculated capacitance of some test insulators.

Area A [m^2]	Distance d [m]	Permittivity of the void ε_0 [pF/m]	Relative permittivity ε_r	Desired capacitance C_d[pF]	Calculated capacitance by NN C_{out} [pF]	Normalised square error
0.03	0.01	8.85	1.5	39.825	39.815	$5.021\ 10^{-4}$
0.03	0.01	8.85	2.2	58.430	58.420	$3.423\ 10^{-4}$
0.03	0.01	8.85	2.8	74.34	74.33	2.69010^{-4}
0.03	0.01	8.85	5.2	138.06	138.05	1.44910^{-4}

From these results it can be seen that the normalized quadratic error becomes rather weak, the higher the permittivity. So we can extend this study to the case study of energy storage in the capacitor based on a well-chosen database, so that we can do the predetermination stored energy following the load Q, the supply voltage V and the dimensioning of the capacitor.

6 Conclusion

What can be drawn as a conclusion is that the use of the algorithm of the gradient retro-propagation gave us good results in the field of the prediction of the computations with an acceptable convergence according to the dimensioning of the capacitors.

For this type of study, a very rich database is needed by changing the sizing parameters, permittivity and power parameters in the case of energy storage. So the learning phase is very important for this study based on neural networks by carefully choosing the weight coefficients and the activation function.

During the test, the choice to take slight variations on the permittivity parameter of the insulator or the dielectric is the final goal of the subject because in fact this variation, even if it is taken randomly, it actually represents the influence of the characteristics or external phenomena applied to the capacitor of his working environment such as temperature, humidity, pressure or even if it is variable capacitor use.

The results obtained were quite reliable and quite satisfactory in order to be able to predict a final capacitance of a capacitor deployed in a medium subjected to external stresses taking into account its geometrical parameters as well as to the construction characteristics.

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