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The evolution of streamers with the effect of the distances covered and the nature of the insulating materials study by ANN

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***Abstract*— The streamer appears on a static photograph as a narrow luminous filament. The light emission coming mainly from the photons created at the head of the streamer, the filamentary aspect results from the integration of this light over time. The streamer moves approximately in the direction of the applied field. However, due to the random nature of the photoionization mechanisms, the photoelectrons are produced not only at the head of the streamer in the direction of the maximum field, but also in a radial direction with respect to its advancement. The streamer can then present a tortuosity or even give rise to several secondary branches, if photoelectrons produced simultaneously in opposite directions create avalanches of comparable sizes.**

In fact, the speed of propagation of the streamer and that of the electrons are not linked to each other since the progress of the streamer results rather from the efficiency of the electronic multiplication process within an avalanche than from the velocity of the electrons themselves.

This model allows evaluating the speed of streamers as a function of distances covered and the nature of the insulating materials. Indeed, a database was created from a laboratory model, to train different neuronal methods for predicting the evolution of streamers on the polymers surface which presents an interesting tool for estimating the propagation phenomena.

Keywords ; Organic Insulators, Pre disruptive phenomena, Streamers, Artificial Neural Networks, Learning process, Neural Networks Feedforward, Radial basis Function Networks.

I. INTRODUCTION

Formation of a streamer is due to the photo-ionization mechanism occurring within the primary avalanche. The electrons accelerated by the electric field excited by collisions of neutral molecules, which return to their ground state with emission of a photons. What explains that the head of the avalanche is home of a significant release of photons that are absorbed by the surrounding gas.

The resulting field is then weaker than and acquires a radial component [1], between the two charge clouds.

If the streamer thus formed goes towards the cathode it is said to be positive. Otherwise, corresponding to very high voltages and large inter-electrode distances, we speak of a negative streamer.

Thus, the process of transformation of the primary avalanche into a streamer is fundamental in the breakdown.

The predominant mechanism is then photo-ionization which is carried out by energetic photons produced in the avalanche by excited atoms [2].

If we now consider a converging field created in a negative tip-plane interval, we also observe the development of a streamer starting from the tip.

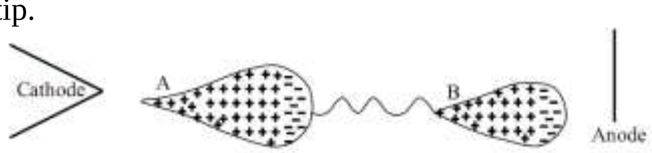

Figure 1.1 Schematic representation of the development of a negative streamer.

An avalanche forms from the cathode and develops in a rapidly decreasing applied field. The space charge thus created locally modifies the electric field. The increase both at the head and at the tail of the avalanche, in A, creates a positive streamer called "retrograde streamer", then develops towards the cathode at the same time as a photon creates in B a secondary avalanche developing under the effect of the space charge field of the primary avalanche [3]. A retrograde streamer, similar to the one that has already formed in A, is created at the tail of the secondary avalanche and spreads towards the head of the primary avalanche [4], [1] .

The negative streamer propagating from the cathode, the positive ions created by the successive avalanches extract electrons from the cathode which neutralize the positive ions and give the streamer an excess of negative charges [5]. It follows on the one hand that the propagation of the negative streamer depends much more on the lines of force of the applied field, and presents less ramifications than the positive streamer, on the other hand that the development of the secondary avalanches is reduced by the decrease fast electric field [6]. The last phenomenon explains that the tension necessary for the development of the streamers and for obtaining the discharge between the electrodes are greater in negative polarity than in positive polarity [1].

II. NEURAL NETWORKS

2.1.Principles and Definitions

An artificial neural network is a computation model whose design is inspired very schematically the operation of real neurons [7]. A neural network consists of a very large number of small identical processing units called artificial neurons.

Each of these neurons is also very complex. Essentially, this is living tissue and chemistry. Specialists of biological neurons are just beginning to understand some of their internal mechanisms. It is generally believed that their various neuronal functions, including memory, are stored at the connections (synapses) between neurons. It is this kind of theories that inspired most architectures of neural networks.

Learning is then either to establish new connections, or at modifying the existing [8].

The origin of neural networks comes from the attempt to model the biological neuron by Warren Mc Culloch and Walter Pitts [9].

They suppose that the nerve impulse is the result of a simple calculation made by each neuron, and that thought was born due to the collective effect of a network of interconnected neurons [10].

2.2.Learning Process

That to say the weight connecting the neuron to its input. At time, a change of weight can be simply expressed as follows: [11]

$$\Delta w_{i,j}(t) = w_{i,j}(t+1) - w_{i,j}(t) \qquad (1)$$

and, therefore,

$$w_{i,j}(t+1) = w_{i,j}(t) + \Delta w_{i,j}(t) \qquad (2)$$

With $w_{i,j}(t+1)$ and $w_{i,j}(t)$ representing respectively the values of the new and old weight $w_{i,j}$.

A set of clear rules for carrying out such a process of adaptation of the weights [12] is called learning algorithm of the network [8].

2.3.Multilayer Perceptron

These are best known neural networks. A perceptron is an artificial neural network feedforward type, i.e., direct propagation. There is a three-layer perceptron. The first is the input (it is not considered neural layer by some authors because it is linear and only distributes the input variables). The second is called hidden layer (or intermediate layer) and is the heart of the neural network. Its activation functions are sigmoid type. The third, consisting here of a single neuron is the output layer. Its activation function is the linear bounded [9]. Its learning is supervised type, by correcting errors. In this case only, the error signal is "feeds back" to the inputs to update the weights of neurons [8] .This is the error back-propagation method.

Neural networks Feedforward (NNF) [13] and neural networks based on radial basis function (RBFN) are a class of models widely used in nonlinear system identification [14], [15]. Justification for this is that these networks with one hidden layer can approximate any continuous function having a finite number of discontinuities [16], [17]. A net boost for RBFN neural networks has been observed in recent years because they offer major advantages over commonly used to NNF [18]. These benefits include the complexity of the model and not a lighter load during learning [19]. Neural networks RBFN (Radial Basis Function Network) have been developed by Moody and Darken [20]. They have proven successful in several areas since they can approach several types of functions [21].

The network is a network feedforward RBFN composed of three layers: an input layer, a hidden layer and output layer. The activation function in the hidden layer is a radial function. The activation function most commonly used is the Gaussian function [22].

The input layer is used as a distributor of inputs to the hidden layer. Unlike NNF, the values of entries in the input layer are routed directly to the hidden layer without being multiplied by the weight values.

The unit of the hidden layer measures the distance between the input vector and the center of the radial function, and produces an output value depending on the distance. The center of the radial function is called the reference vector [23].

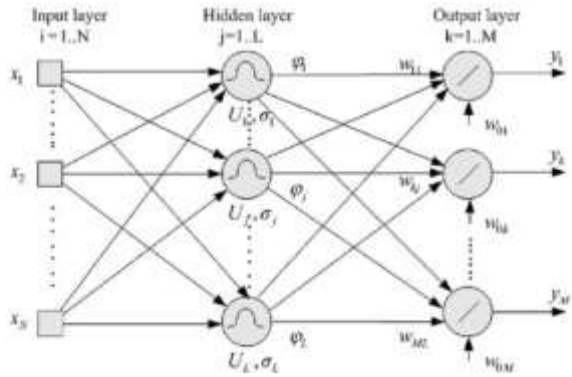

Figure 2.1 Architecture of a network based on radial functions.

III. THE ANN ALGORITHM: (NEURAL NETWORKS ALGORITHM)

The algorithms of artificial neural networks (ANN) have been successfully applied in very many applications in many fields. In the field of high voltage, ANNs were also first applied effectively for partial discharges [24]. This model can be used to estimate the output variables from the data input variables. Its tries to simulate the reasoning process of human intelligence and therefore be used instead of mathematical functions [10].

In this work, the important learning data were brought from experimental studies carried out on the propagation of streamers on the surface of insulators [25]. A certain approach using ANN as a function estimator has been used to effectively model the propagation speed of streamers V as a function of several parameters which are mainly:

- The nature of the polymer, represented by T.
- The distances D traversed by the streamer, which also represents the length of the polymer [26].

This study tries to show the efficiency of ANN as an estimator of functions in studies of the propagation of streamers [24]. The modeling of the propagation speed of the streamer as a function of the length of the insulator D and the type of material T by the neural networks as an estimated function, with the help of experimental data obtained, in the form [26] :

$$V = f(T, D) \qquad (3)$$

Each learning model includes 2 input parameters T and D, and an output parameter which is the corresponding values of V [18] . The neural network model has 2 input nodes and 1 output node [24].

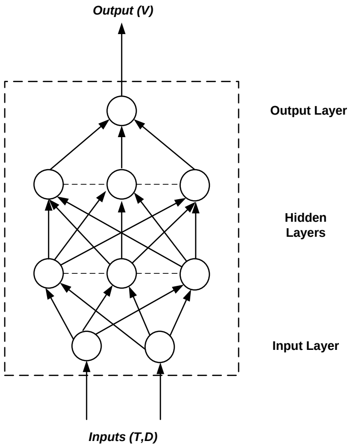

Figure 3.1 Architecture Overview of V, T, D Neural Network (V: Speeds, T: Type of material, D: Distances)

Once the neural network is trained by the training data, the network is tested by the test data in italics in the table [26].

The collection of experimental data was obtained from the experimental curve taken from the article [25].

The shape of the curve of the speeds measured as a function of the distances covered is given as follows [26]:

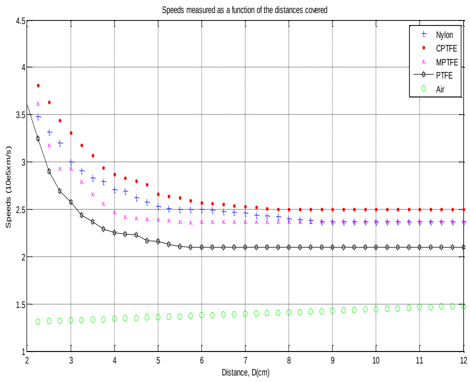

Figure 3.2 Speeds measured as a function of the distances covered.

Table 3.1 Database: Propagation speeds according to the distances covered (for example Nylon)

MATERIALS (T)	**DISTANCE (cm)**	**V (10^5x m/s)**	**DISTANCE (cm)**	**V (10^5x m/s)**
Nylon (1)	2	3,63	7,25	2,44
	2,25	***3,48***	7,5	2,43
	2,5	3,32	***7,75***	***2,42***
	2,75	3,2	8	2,4
	3	3	8,25	2,39
	3,25	2,91	8,5	2,38
h=11.1 g/m³	***3,5***	***2,83***	8,75	2,37
	3,75	2,79	***9***	***2,37***
	4	2,71	9,25	2,37
	4,25	2,69	9,5	2,37
	4,5	2,62	9,75	2,37
	4,75	***2,58***	10	2,37
	5	2,53	10,25	2,37
	5,25	2,51	10,5	2,37
RH=62%	5,5	2,5	***10,75***	***2,37***
	5,75	2,5	11	2,37
	6	2,5	11,25	2,37
	6,25	***2,49***	11,5	2,37
	6,5	2,48	***11,75***	***2,37***
	6,75	2,47	12	2,37
	7	2,46		

The ANN may have three types of layers, the layer of inputs, one or more hidden layers and the layer of the outputs. [10]. The root mean square error learning RMSE is given by:

$$RMSE = \frac{1}{NP.N_k} \sum_{p=1}^{NP} \sum_{k=1}^{N_k} \left(t_{pk} - O_{pk}\right)^2 \qquad (4)$$

The accuracy of learning is measured by the RMSE whose expression was given by equation (4), and test accuracy is measured by the percentage of the mean absolute error (MAE %), given by:

$$\%\, MAE = \frac{\sum \left[|t_k - O_k| / t_k \right]}{n} \times 100 \qquad (5)$$

Where:

t_k is the experimental result corresponding to the given test input to the output neuron k,

O_k is the output determined for the output neuron k corresponding to the data test input, and n is the number of input test data.

The input-output data are normalized before the network training to ensure good convergence and accuracy during the training process [24]. We tried nine different schemes to standardize training models input-output. The details of these schemes normalization are discussed. These different schemes for the normalization using the minimum and maximum values of the data vector components of output and also the average value and standard variance (standard deviation) SD input-output variables are presented in the following table [6] :

Table 3.2 Input-output variables

Number of schemes	**Input**	**Output**
1	Max	Max
2	Max	Max Min
3	Max	Mean & SD
4	Max Min	Max
5	Max Min	Max Min
6	Max Min	Mean & SD
7	Mean & SD	Max
8	Mean & SD	Max Min
9	Mean & SD	Mean & SD

IV. Results and Discussion

The network consists of three hidden layers and an output layer.

4.1.Choice of scheme and number of neurons:

We start with a single neuron in the first layer, do all the calculations for the second scheme, and then apply the number of neurons from the 1st, 2nd, and 3rd layers to the other schemes. We do the same thing with two neurons in the first layer, then with three and four neurons. We obtain the following summary table:

Table 4.1 Choice of scheme and number of neurons for 03 hidden layers for the logsig function

	Logsig function, scheme 2, number of layers 3		
	Number of iterations	**RMSE**	**MAE**
1st layer : 1 neuron **2nd layer: 10 neurons** **3rd layer: 13 neurons**	**2000**	**0.0049**	**0.2109**
1st layer: 2 neurons **2nd layer: 9 neurons** **3rd layer: 16 neurons**	2000	0.0042	0.2243
1st layer: 3 neurons **2nd layer: 10 neurons** **3rd layer: 3 neurons**	1000	0.0060	0.2626
1st layer: 4 neurons **2nd layer: 9 neurons** **3rd layer: 4 neurons**	1000	0.0051	0.2269

The best result was obtained for 01 neuron in the 1st hidden layer, 10 neurons in the 2nd hidden layer and the 13 neurons in the 3rd hidden layer. The number of iterations is now 2000 iterations.

4.2.Effect of the number of iterations:

Table 4.2. Effect of number of iterations for 03 hidden layers for logsig function

Logsig function, scheme 2, number of layers 3,		
1st layer : 1 neuron	**2nd layer: 10 neurons**	**3rd layer: 13 neurons**
Number of iterations	**RMSE**	**MAE**
500	0.0166	0.3855
1000	0.0065	0.3339
2000	**0.0049**	**0.2109**
3000	0.0044	0.6630
4000	0.0043	0.5880
5000	0.0040	0.5914
10000	0.0038	0.5668

The best result is obtained for 2000 iterations, for the case of a neuron in the 1st hidden layer.

The training of the neural network is represented by the following figure:

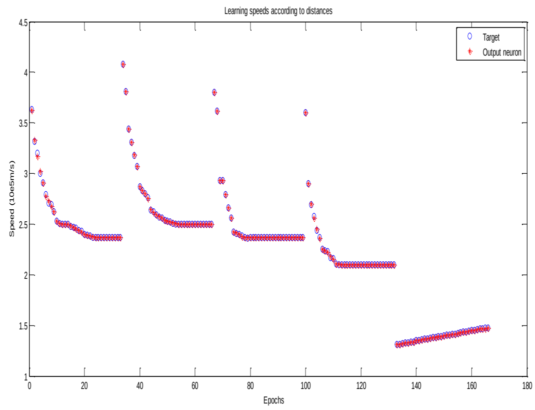

Figure 4.1 Neural network training

The neural network test is that of figure 4.2.

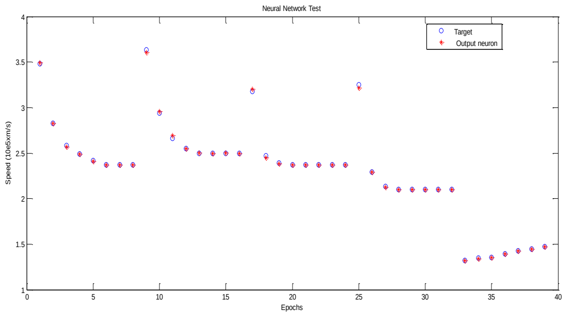

Figure 4.2 Neural Network Test

The number of iterations used is given by the following figure:

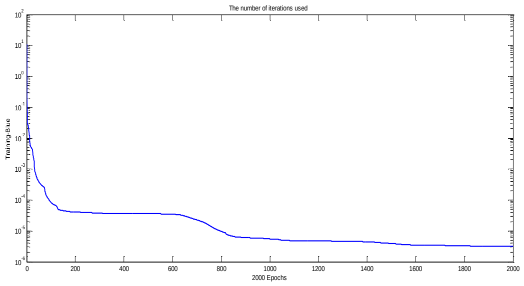

Figure 4.3. Number of iterations used in the neural network

The comparative curves of the experimental speeds (measured) and those simulated according to the distances crossed by the streamer, and this for different insulators as well as for the air for 03 hidden layers are given by the following figure :

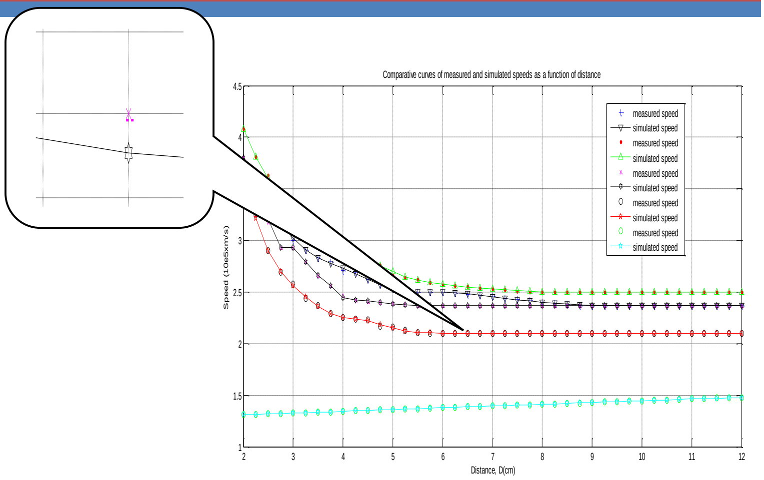

Figure 4.4. Comparative curves of measured and simulated streamer speeds as a function of distances traversed for 03 hidden layers.

The curves are identical, but with a difference that can be seen by enlarging the PTFE curves for example.

4.3.Effect of change of activation function on RMSE and MAE for 03 hidden layers :

4.3.1. Choice of arrangement and number of neurons:

The lowest RMSE was obtained for the tansig function (Table 4.3), while the lowest

MAE was obtained for the logsig function (Table 4.1), and this for 3 hidden layers.

4.3.2. Choice of arrangement and number of neurons:

The smallest RMSE was obtained for the tansig function (Table 4.4), for 10000 iterations, while the minimum MAE is obtained for the logsig function (Table 4.2).

Table 4.3. Effect of number of iterations for 03 hidden layers for tansig function

Tansig function, scheme 6, number of layers 3		
1st layer: 2 neurons	**2nd layer: 9 neurons**	**3rd layer: 16 neurons**
Number of iterations	**RMSE**	**MAE**
500	0.0093	0.4876
1000	0.0041	0.7766
2000	0.0028	1.1984
3000	9.1906e-004	1.7797
4000	7.5156e-004	1.5821
5000	5.6913e-004	1.9167
10000	**4.2342e-004**	**1.3809**

4.3.3. Comparison between Feedforward networks and Radial basis Networks:

Table 4.4. Summary table between Feedforward and RBF networks for different learning and activation functions

	Feedforward Network (Trainlm)		**Radial basis Network (Newrb)**
	logsig	**tansig**	
	RMSE	**RMSE**	**RMSE**
01 layer	0.0037	0.0042	
02 layers	0.0086	0.0113	0.0148
03 layers	0.0038	**4.2342e-004**	

The best RMSE was obtained for the Feedforward network, for the Trainlm learning function, the tansig activation function, and for 03 hidden layers.

This error can be represented as a function of the number of neurons and the number of iterations as follows:

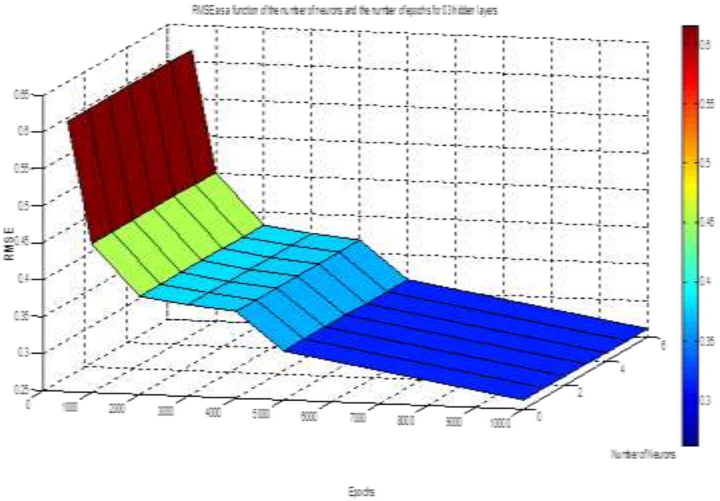

Figure 4.5. RMSE depending on number of neurons and number of iterations for 03 hidden layers for tansig function.

This method can lead us to predict the behavior of streamers, depending on the distances crossed, and this for different types of insulating materials.

V. CONCLUSION

In this model of streamer propagation speeds as a function of the distances covered, the best error result of the test was also obtained for the Feedforward neural network, for the Trainlm learning function, for arrangement N°02 , for the logsigmoid activation function, for only 2000 iterations and for 03 hidden layers.

For the learning error or RMSE, the lowest error was obtained for always the Feedforward neural network, for the Trainlm learning function, for the arrangement No. 06, for the tansigmoid activation function and for 10000 iterations and for 03 hidden layers.

Regarding the learning error for the RBF network, the number of iterations is lower (200 iterations), which gives us a greater time advantage, but does not affect the learning error which remains higher.

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