The streamers dynamics study by an intelligent system based on Neural Networks

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Abstract—The formation and propagation of streamers is an important precursor to determine the characteristics of electrical breakdown of many HV electrode configurations. Understanding of the study of the interaction between the polymer surface and the development process of the streamer is of major importance when we want to improve internal and external performance insulation systems. In this context, a numerical tool using neural networks is developed. This model allows evaluating the speed of streamers as a function of the amplitude of voltage initiation and the nature of the insulating materials. For this, a database was created to train the neural model from a laboratory model. This investigation builds a database for predicting the propagation of streamers on the polymers surface by different neuronal methods and this presents an interesting tool for estimating the propagation phenomena in functions of very important parameters.

I. INTRODUCTION

Formation of a streamer is due to photo ionization mechanisms 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 photon. The head of the avalanche is home of a significant release of photons that are absorbed by the surrounding gas.

If the electron produced is located in the vicinity of the primary avalanche, it will create a new so-called secondary avalanche, with the same mechanism of electron multiplication, but the avalanche is now growing in a field that is enhanced by the presence of the positive space charge. Indeed, in an electric field sufficient to create the boot, the electron velocity is about 100 times higher than that of positive ions, so that the avalanche develops as a cloud of electrons leaving behind positive ions near stationary, then the avalanche leads to the formation of a dipole structure as shown in fig.1:

-a region (towards the anode) of high electron density,
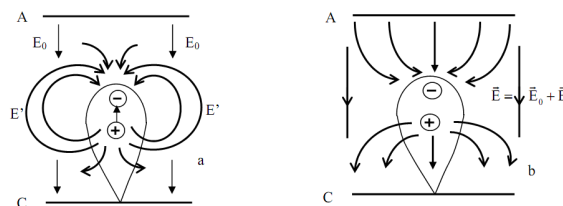-a region (towards the cathode) of a high density of positive ions.

Fig. 1. Electron Avalanche

Therefore the separation of electrons and ions generates a significant space charge produces an electric field ($\overrightarrow{E'}$) of dipolar structure and opposing the separation, which is vectorially added to the external field (Fig.1).

II. MEASUREMENT TECHNIQUES

A. Optical Measurement

The luminous phenomena occurring within the range can be recorded by cameras, streak cameras called ultra fast image converters, photomultipliers, spectroscopy and strioscopy. Cameras whose optical axes are placed at 90° from one another possible to reconstruct the actual length of the discharge in all three dimensions.

The image converter restores both the axial development of the discharge and its temporal development.

Photomultipliers can be used to measure streamers in relatively small intervals [4] over large intervals in Fig. 2.
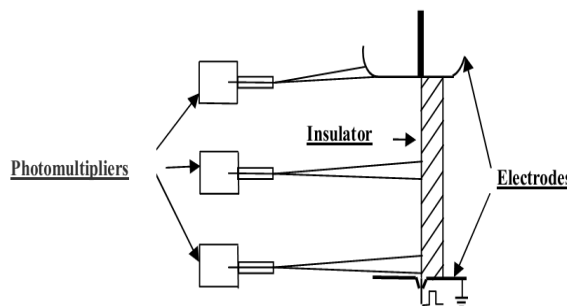

Fig. 2. Schematic diagram of the arrangement of electrodes with photomultipliers

B. Insulated Materials Used

Intervals involved in Fig. 2 are polymers. In the electrical field, the scope of application of insulating organic solids (polymers) is expanded: power transmission lines, telecommunication cables, capacitors, alternators, electric motors, electronic systems and terrestrial power components and on board satellites...

The use of these materials in electrical insulation has several advantages such as, excellent electrical properties (resistivity, stiffness, and permittivity), good mechanical strength and easy implementation, low weight and for some possibility of recycling [5]. These materials had excellent electrical insulating properties because of its low relative permittivity, low dissipation factor, good stability over a wide frequency range, and high dielectric breakdown strength [6].

The polymeric materials have a complex structure which leads to different properties within the same material. Knowledge of the structure of an individual macromolecule, but also the arrangement of the macromolecules relative to each other, is essential to understand the complexity of these systems. The microstructure of a polymer insulator dictates the physical, mechanical and electrical properties that are expected of this material [5].

Insulating materials used in the experimental [4] are:

1 Polytetrafluoroethylene (PTFE).

2 PTFE carbonized (CPTFE).

3 Molybdenumdisuflide PTFE (MPTFE).

4 Nylon.

5 Ceramic coating (CERG).

III. Neural Networks

A. Learning Process

Among the desirable properties for a neural network, probably the most fundamental is the ability to learn from its environment, to improve its performance through a learning process [7].

Learning is a dynamic and iterative process for changing the parameters of a network in response to the stimuli it receives from its environment. The type of learning is determined by how parameter changes occur. Thus, the network may improve overtime [7].

That to say the weight $w_{i,j}$ connecting the neuron i to its input j. At time t, a change $\Delta w_{i,j}$ of weight can be simply expressed as follows:

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

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 is called learning algorithm of the network [7].

B. 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 [8].

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 [7]. This is the error backpopagation method.

The multilayer perceptron is a neural network used for most problems of approximation, classification and prediction. It usually consists of two or three layers of neurons fully connected [7].

One problem of using neural networks is in the choice of topology. For example there is no general rule that gives the number of neurons to remember for the intermediate layer. This choice is application-specific and, in general, these are just arbitrary choices of which we verify later the validity [8].

C. Radial Basis Function Networks

Neural networks Feedforward (NNF) and neural networks based on radial basis function (RBFN) are a class of models widely used in nonlinear system identification [9], [10]. Justification for this is that these networks with one hidden layer can approximate any continuous function having a finite number of discontinuities [11], [12].

A net boost for RBFN neural networks has been observed in recent years because they offer major advantages over commonly used to NNF. These benefits include the complexity of the model and not a lighter load during learning [13].

Neural networks RBFN (Radial Basis Function Network) have been developed by Moody and Darken [14]. They have proven successful in several areas since they can approach several types of functions [15].

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 [16].

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 [17].

IV. PROBLEM FORMULATION

The algorithms of artificial neural networks (ANN) have been applied successfully in many applications in many fields. In the field of high voltage, the ANN has also been applied effectively to the first partial discharges [18].

The major field of application of ANN is the estimation of functions, because the useful properties such as adaptability and nonlinearity are in agreement with the estimation of the equation describing functions when the function is unknown and the only requirement is to have a representative sample of the behaviour of the function. In this work, learning the important data have been made of experimental studies on the propagation of streamers on the surface of insulators [4].More detailed studies and tests were conducted to determine the parameters of the ANN to give better results and to have a quality model. A certain approach using ANN as an estimator function was used to effectively model the propagation velocity of streamers V depending on several parameters:

The nature of the polymer, represented by T .

The initiation voltage u .

The relationship is as follows:

$$V = f(D,T) \tag{3}$$

It was found that when learning is complete, the ANN is able to estimate the speeds of different functions efficiently and effectively. This study attempts to show the effectiveness of ANN as function estimator in studies of the propagation of streamers [4]. Modelling the propagation velocities of the streamer as a function of the applied voltage u and the type of material T by neural networks as a function estimated with the aid of experimental data.

Each learning model includes two input parameters u and T , and an output parameter which is the corresponding values of V

The neural network model has two input nodes and one output node [4].

Once the neural network trained by the training data, the network is tested by the test data.

The collection of experimental data was obtained from the experimental curve from article [4]. The shape of the curve of the measured velocities as a function of applied voltage is given as follows:
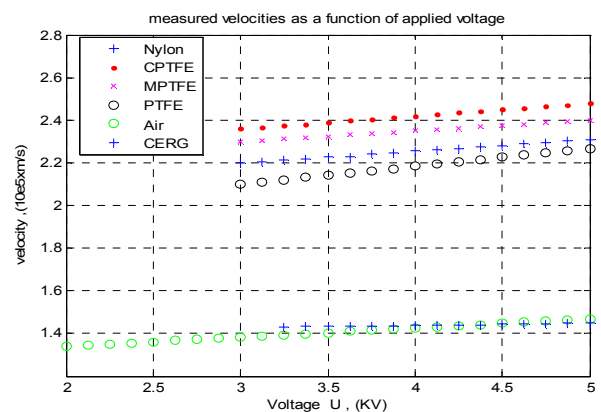

Fig. 3. Velocities measured by the voltages applied

A. The Learning Algorithm

The root mean square error learning RMSE is given by:

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

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:

$$\%MAE = \frac{\sum \left[\left| t_K - O_k \right| \middle/ t_k \right]}{n} \times 100 \tag{5}$$

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.

V. RESULTS AND DISCUSSION

A. Choice of the Arrangement and the Number of Neurons

We begin by a single neuron in the first layer, all calculations are performed for the second arrangement, and the number of neurons in the 1st, 2nd and 3rd layer is applied to other arrangements. We do the same thing with two neurons in the first layer, then three and four neurons the following summary table is obtained.

TABLE I.   CHOICE OF THE ARRANGEMENT AND THE NUMBER OF NEURONS FOR LOGSIG FUNCTION

	Logsig Function, Arrangement 8, Number of layers : 3		
	Number of epochs	RMSE	MAE
1st layer: 1 neuron 2nd layer: 1 neuron 3rd layer: 7 neurons	2000	2.8577e-004	0.0213
1st layer: 2 neurons 2nd layer: 2 neurons 3rd layer:11 neurons	1000	3.1362e-004	0.0204
1st layer: 3 neurons 2nd layer: 9 neurons 3rd layer:12 neurons	1000	2.5530e-004	0.0208
1st layer: 4 neurons 2nd layer: 3 neurons 3rd layer: 9 neurons	2000	2.9046e-004	0.0208

The best result was obtained for 02 neurons in the first hidden layer, 02 neurons in the second hidden layer and 11 neurons in the third hidden layer. The number of iterations is now 1000 iterations.

We change the number of iterations from 500 iterations to 10000 iterations.

TABLE II.   EFFECT OF THE NUMBER OF ITERATIONS FOR LOGSIG FUNCTION

Logsig Function, Arrangement 8, Number of layers : 3		
1st layer: 2 neurons	2nd layer: 2 neurons	3rd layer:11neurons
Number of epochs	RMSE	MAE
500	3.6131e-004	0.0211
1000	3.1362e-004	0.0204
2000	3.0301e-004	0.0205
3000	2.9838e-004	0.0206
4000	2.9530e-004	0.0208
5000	2.9324e-004	0.0210
10000	2.4590e-004	0.0217

The best result is obtained for 1000 iterations, for the case of 02 neurons in the first hidden layer.

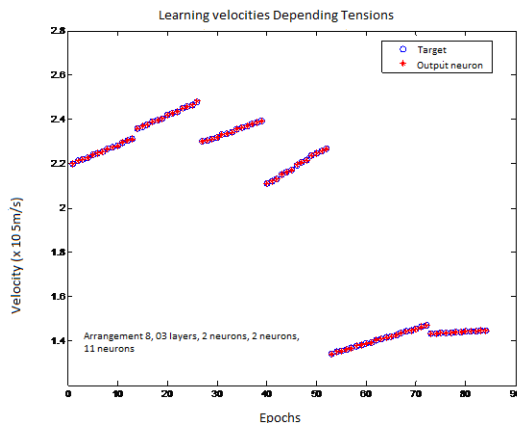The learning of the neural network is represented by the following Figure:

Fig. 4.   Learning of the neural network
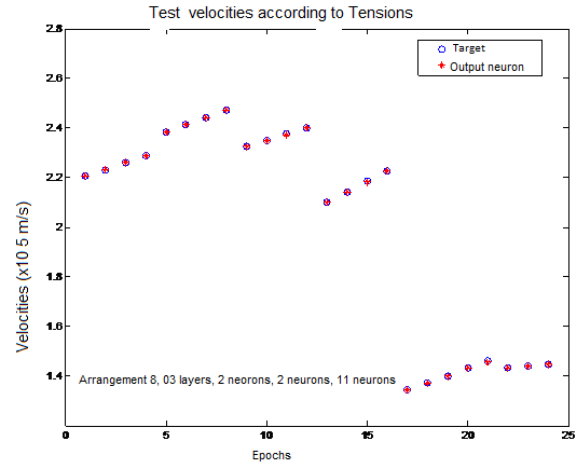
Testing the neural network is that of Fig. 5.

Fig. 5.   Test of the neural network

B. Effect of changing activation function on RMSE and MAE

TABLE III.   CHOICE OF THE ARRANGEMENT AND THE NUMBER OF NEURONS FOR TANSIG FUNCTION

	Tansig Function, Arrangement 6, Number of layers : 3		
	Number of epochs	RMSE	MAE
1st layer: 1 neuron 2nd layer: 1 neuron 3rd layer: 7 neurons	2000	0.0103	0.2717
1st layer: 2 neurons 2nd layer: 2 neurons 3rd layer:11 neurons	1000	0.0505	1.5603
1st layer: 3 neurons 2nd layer: 9 neurons 3rd layer:12 neurons	1000	1.8818e-004	0.0343
1st layer: 4 neurons 2nd layer: 3 neurons 3rd layer: 9 neurons	2000	0.0030	0.1053

The best learning error for tansig function for 1000 iterations, while for the test error MAE, the lowest being for logsig function for 1000 iterations too.

TABLE IV.   EFFECT OF THE NUMBER OF ITERATIONS FOR TANSIG FUNCTION

Tansig Function, Arrangement 6, Number of layers : 3		
1st layer: 3 neurons	2nd layer: 9 neurons	3rd layer:12neurons
Number of epochs	RMSE	MAE
500	2.0609e-004	0.0259
1000	1.8818e-004	0.0343
2000	1.4680e-004	0.0477
3000	1.4124e-004	0.0526
4000	1.3299e-004	0.1147
5000	1.0685e-004	0.3703
10000	1.2829e-005	0.5559

The increase in the number of iterations in this case has the effect of reducing the learning error for tansig function for

10,000 iterations. The error on the test remains the lowest for logsig function for only 1000 iterations.

C. *Comparison between Feedforward and Radial Basis Function Networks*

TABLE V. SUMMARY TABLE BETWEEN FEEDFORWARD AND RBF NETWORKS

	Feedforward Network (Trainlm function)		Radial Basis Function Networks (Newrb)
	Logsig	*Tansig*	*RMSE*
	RMSE	*MAE*	
01 layer	2.3910e-004	2.2327e-004	
02 layers	2.3292e-004	2.1608e-004	2.9883E-004
03 layers	2.4590e-004	1.2829e-005	

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

The comparative curves of the experimental velocities (measured) and simulated according to voltages applied to the streamer, for different insulations and for air, are given in Figure the 8 following:
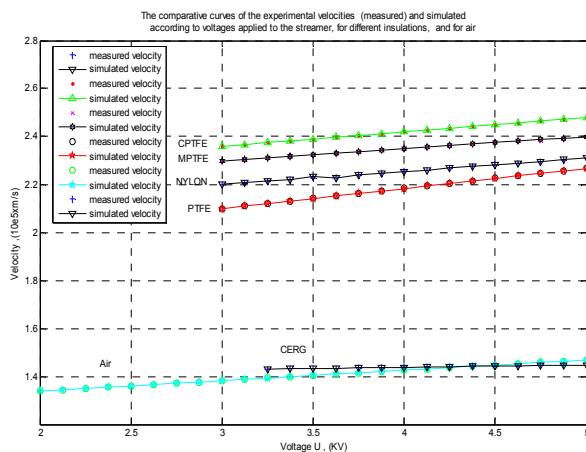

Fig. 6. Comparative curves of measured and simulated speeds depending on applied voltages

VI. CONCLUSIONS

The best result concerning the error of learning or RMSE is given for 03 hidden layers.

The number of iterations that gave the best result is 10000.

The best arrangement is the arrangement No. 06.

The activation function used in hidden layers is the function tansigmoïde.

The function used in learning is trainlm.

Concerning the learning error for the RBF network, the number of iterations is small (100 iterations) which increases the speed of learning.

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