Q-V Characteristics Simulation through Artificial Neural Network

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Abstract – **The charge-voltage (Q-V) curves have been used to characterize the Corona Phenomena in overhead conductors and conductor bundles. Several approaches have been proposed in recent years to incorporate the phenomena in EMT calculations, and most of these are based on approximations of the Q-V curves.**

A structure composed by two Artificial Neural Networks (ANN), each having two layers, was developed to simulate the Q-V characteristics. The training set presented to the network had data of sixteen experimental Q-V curves of one single conductor, consisting of four voltage conditions (lightning and switching impulses) at four voltage levels.

Keywords: Transient Analysis, Corona Effect, Neural Networks Application.

I. Introduction

It is well known that the attenuation and distortion produced by the corona phenomena on surges propagating along overhead transmission lines can be very substantial. Since these effects can contribute to reduce insulation levels at the substations, there is considerable interest in incorporating corona models in Electromagnetic Transients Programs.

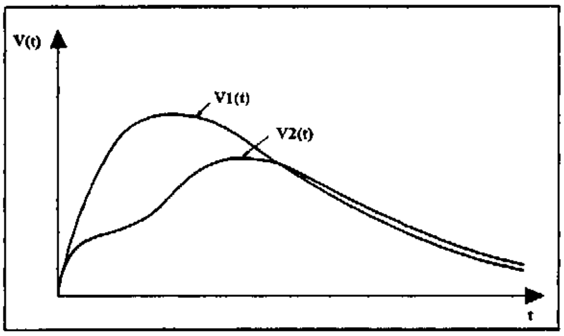

Fig. 1. Overvoltage attenuation due to the Corona Effect

Extensive work has been done to develop realistic corona models [6 - 11], and to interface such models with EMTP type programs.

Most corona models are based on the charge-voltage (Q-V) conductor characteristics, which are determined experimentally. The first attempts to represent the Q-V characteristics for the calculation of surge propagation were based on analog models of the phenomena [1]. A fairly crude piece-wise linear approximation of the Q-V curve can be obtained using diodes, capacitors and resistors. Analog circuits of different topologies were proposed by several authors to reproduce the main aspects of the phenomena. It was later established that, for a given single conductor or conductor bundle under steady atmospheric conditions, the shape of the Q-V curves are considerably affected by the time to crest and by the crest value of the applied surge [2]. Thus a 'wide-band' analog corona model has been proposed to reproduce such behaviour [10].

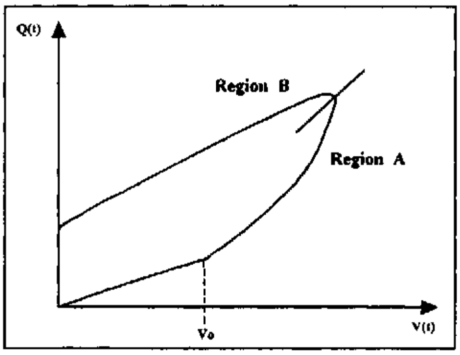

Fig. 2. Typical Q-V curve

The main drawback of the analog models arises from the inherent difficulty associated with their application in multi-phase systems. Also, to approximate the distributed nature of corona, the line has to be divided into short sections, and the analog corona circuit has to be connected at each intersection.

Careful consideration of the nature of the curves obtained by Maruvada et al [2] led to the proposal of a set of linear differential equations which had been applied in studies of visco-elasticity phenomena. The analytical equations proposed by Suliciu and Suliciu [4] have been studied at IREQ [7] and have also been adopted for the development of an efficient recursive scheme to simulate surge propagation on overhead single and multi-phase transmission lines [9, 11]. Suliciu's Model is based on analytical equations, the coefficients of which have to be estimated empirically, using a trial and error process.

Artificial Neural Networks (ANN's) are particularly suitable for the representation of non-linear systems and have been applied successfully to several difficult function approximation problems [13]. It was thus decided to examine their performance for the approximation of Q-V characteristics. The ultimate aim of the investigation would be to develop ANN's that would be capable to efficiently obtain the parameters of Suliciu's model from a set of Q-V curves of a given conductor.

It was decided to start the project by developing ANN structures that would reproduce the Q-V curves measured at IREQ [2]. The curves were obtained when the conductor was subjected to different voltage surge conditions, ranging from lightning type surges, and for several crest values.

The progress obtained in this work will be reported in this paper.

II. Artificial Neural Network Development

Maruvada et al [2] presented measurements of Q-V characteristics, obtained through the application of surges of different shapes and magnitudes, on conductors in an experimental cage arrangement. Sixteen of these Q-V curves, measured on a single 1.2″ diameter conductor, using positive polarity surges and under fair weather conditions, have been selected to form the ANN training set.

The set of characteristics shown in Figures 3 to 6 correspond to four crest values of the applied surge, 280 kV, 340 kV, 390 kV and 450 kV. Figures 3 and 4 are representative of switching impulses (260/2700 μs and 75/2500 μs), whereas Figures 5 and 6 were measured using lightning type impulses (15/1000 μs and 2.5/60 μs).

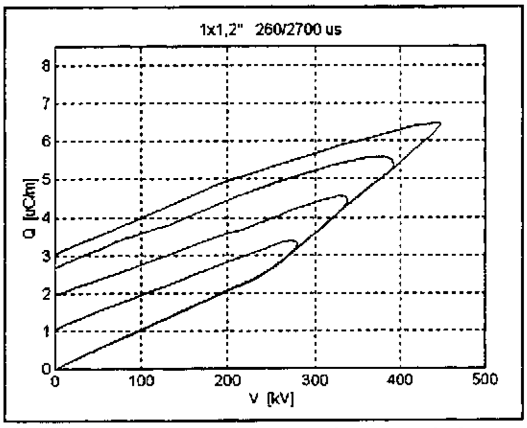

Fig. 3. 260/2700 μs Q-V Characteristic

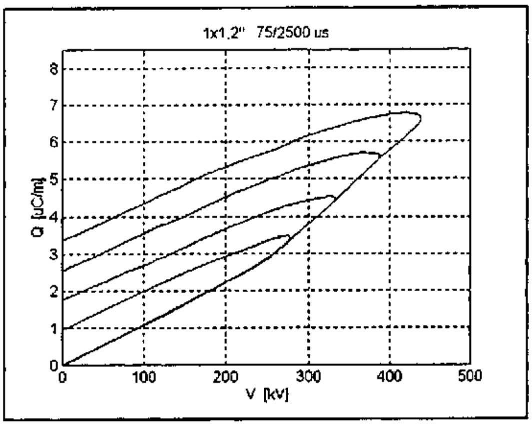

Fig. 4. 75/2500 μs Q-V Characteristic

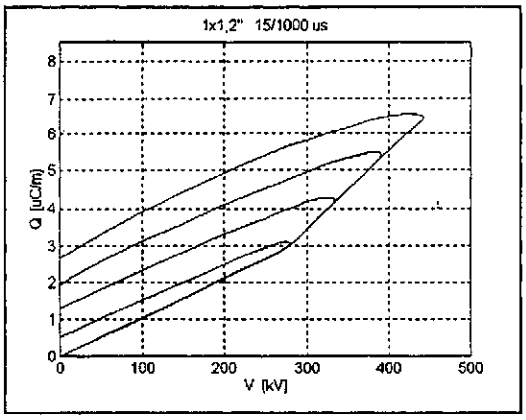

Fig. 5. 15/1000 μs Q-V Characteristic

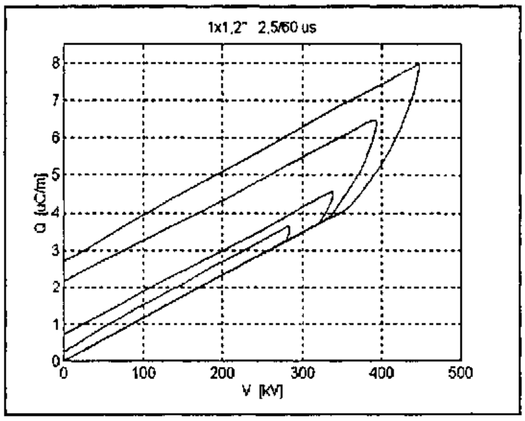

Fig. 6. 2.5/60 μs Q-V Characteristic

The set of four characteristics in each Figure can be defined by three parameters:

- V_{max} → maximum overvoltage
- t_r → rise time
- t_t → tail time

Therefore, an ANN that uses these three parameters, should be able to produce, on its output, the correct charge value associated with a given voltage input.

A structure composed by two Artificial Neural Networks was developed to simulate the Q-V characteristics. Theoretically the use of two ANNs is not necessary, but this simplifies the ANN task because as shown in Fig. 2, Region A is much more complex than Region B. The use of only one ANN has been tested, but its training has evidenced that this is not the best choice. Thus one ANN is used for Region A, and the other is used for Region B.

A very simple test shown in Fig. 7 can be used to determine which ANN should be activated at any given time t: if $V(t) > V(t-1)$ the voltage is on Region A, otherwise it is on Region B.

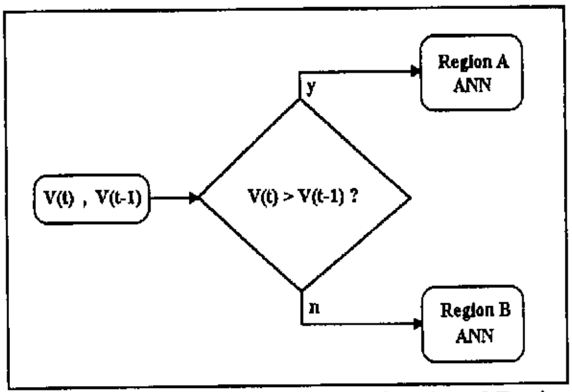

Fig. 7. Test for decision between Region A and Region B

Theoretically a feedforward neural network having two neuron layers could be trained to approximate any practical function arbitrarily well [12]. Thus the architecture adopted for the two ANNs is shown in Fig. 8 and consists of feedforward networks with two layers. The first network uses the hyperbolic tangent for the activation function, and the second uses linear activation. All neurons use bias synapses. The ANNs have four inputs, namely V_{max}, TR, t_t and V(t), and one output Q(t). The first layer has fifty neurons, and the second layer has one neuron. The choice of the number of neurons to be used in the first layer has been decided after a series of tests, in which ten, twenty, thirty and fifty neurons were used. Perhaps fifty neurons are not the better choice, but this number produces very good results as will be seen from the results.

MATLAB™ was chosen to train and test the ANN's, as it provides heavy-duty numeric computation, advanced graphics and visualization, a high-level programming language based on vectors, arrays and matrices, and a useful collection of application functions, such as the *Neural Network Toolbox* [12].

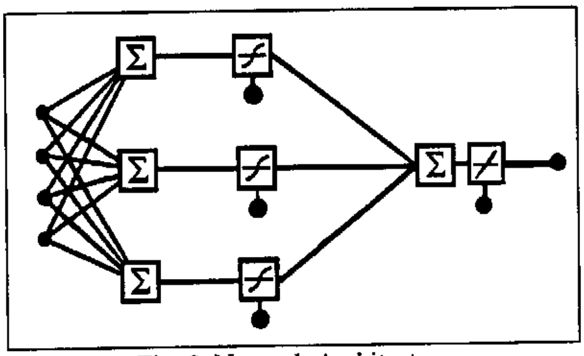

Fig. 8. Network Architecture

The ANNs have been trained by backpropagation, using momentum and adaptive learning rate technique [12]. The backpropagation learning rules are used to adjust the synaptic weights so as to minimize the mean square error of the network output. In the present case better solutions were found when the momentum technique was used; the training time was shortened by the use of an adaptive learning rate for each synapse.

The Nguyen-Widrow method has been used to find the initial conditions of the first layer weights and biases, and small random values have been used for the second layer. The inputs and the output were normalized to values in a range between -0.9 and 0.9; this action is important to warrant a fast convergence of the training process.

A Mean Square Error- MSE- value of $5x10^{-4}$ was the criterion used to stop the training operation.

The error criterion of the Region A ANN (see Fig. 2) has been reached after approximately 10^6 epochs (steps) of training, whereas the Region B ANN has been trained after approximately 10^5 epochs. This difference is easily explained by the differences in the corona charge behaviour in the Regions A and B.

Even though the training can be a slow process, the use of the trained ANN is very simple and practically immediate.

III. Results

Figures 9 to 24 show the comparison between the experimental Q-V characteristics (solid lines) and their respective ANN simulations (dashed lines). It is important to mention that only one neural structure was able to simulate, with a good degree of precision, all the proposed sixteen curves, covering overvoltages from switching to lightning impulse shapes.

Although not tested (because no experimental data was available) the ANNs are supposed to generalize to other values of maximum overvoltage and rise and tail time in the range covered by the training process.

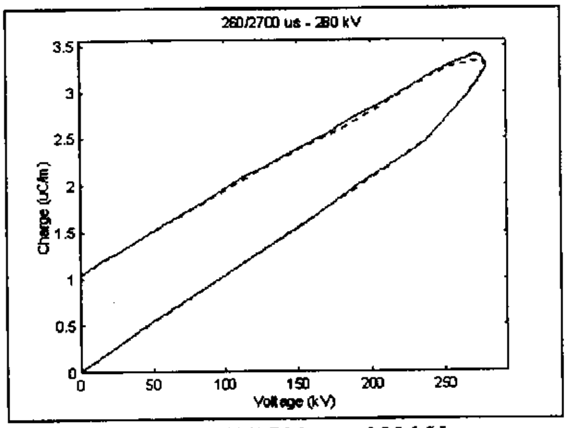

Fig. 9. 260/2700 μs - 280 kV

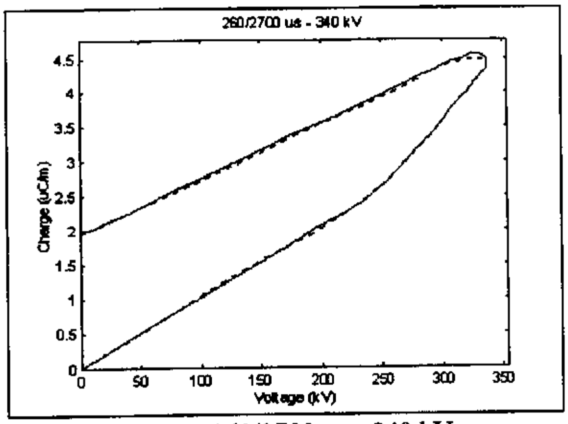

Fig. 10. 260/2700 μs - 340 kV

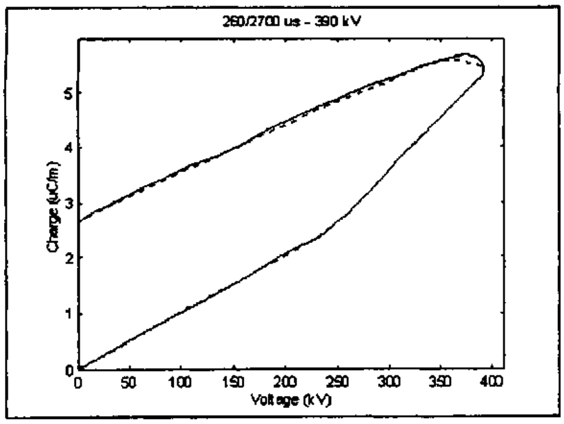

Fig. 11. 260/2700 μs - 390 kV

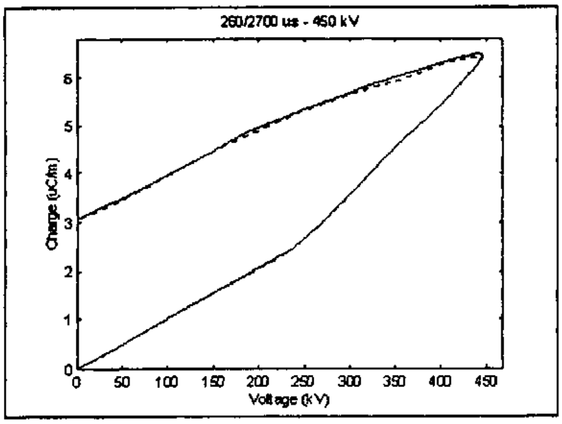

Fig. 12. 260/2700 μs - 450 kV

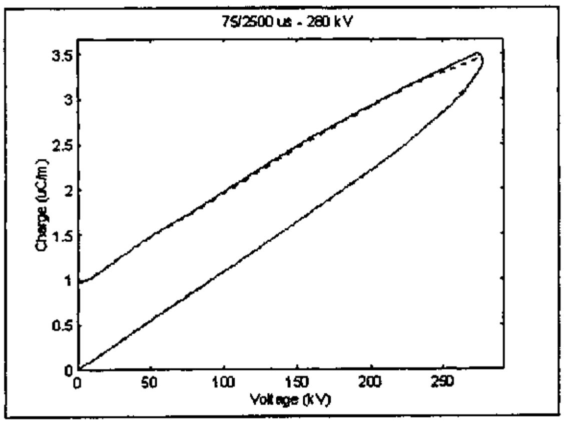

Fig. 13. 75/2500 μs - 280 kV

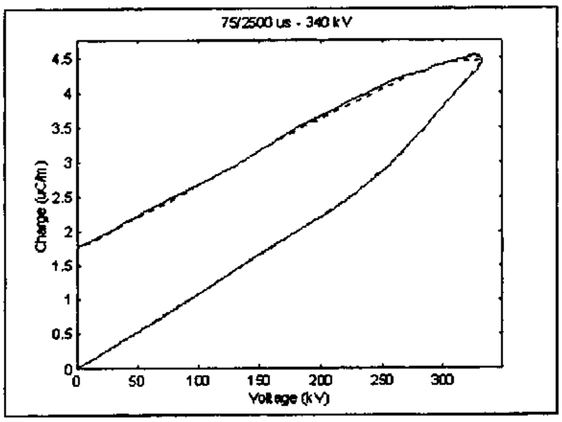

Fig. 14. 75/2500 μs - 340 kV

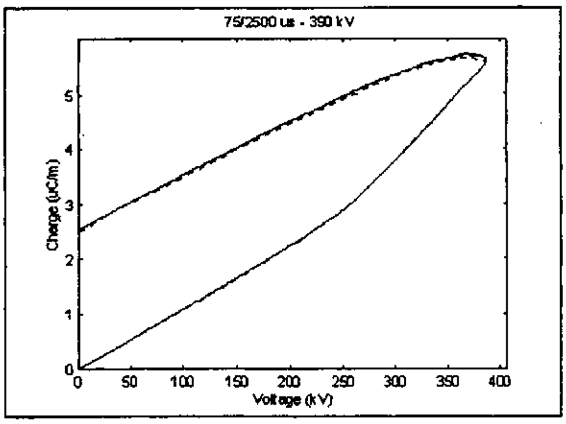

Fig. 15. 75/2500 μs - 390 kV

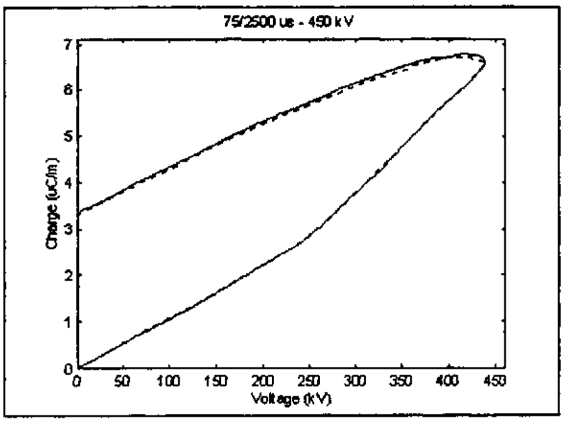

Fig. 16. 75/2500 μs - 450 kV

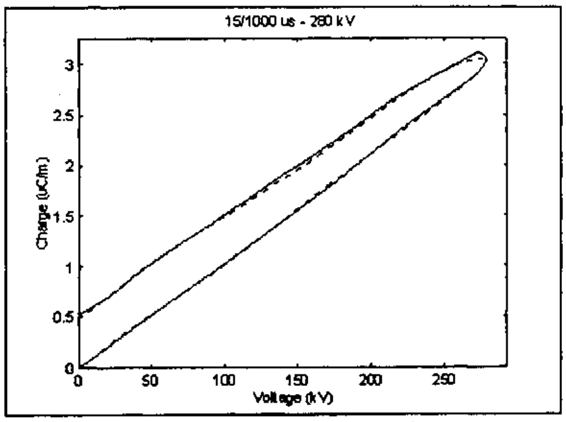

Fig. 17. 15/1000 μs - 280 kV

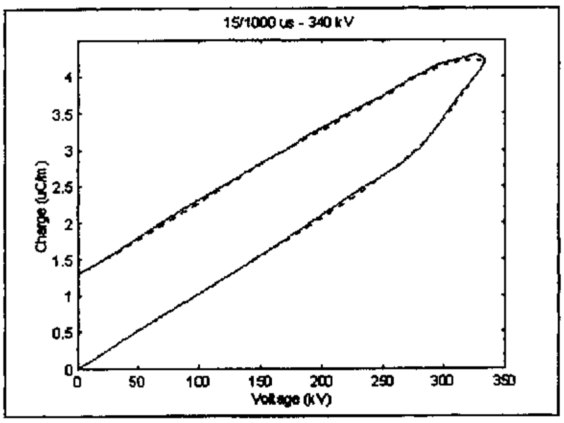

Fig. 18. 15/1000 μs - 340 kV

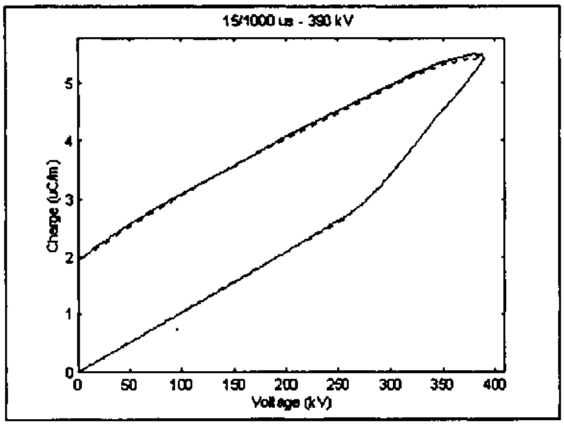

Fig. 19. 15/1000 μs - 390 kV

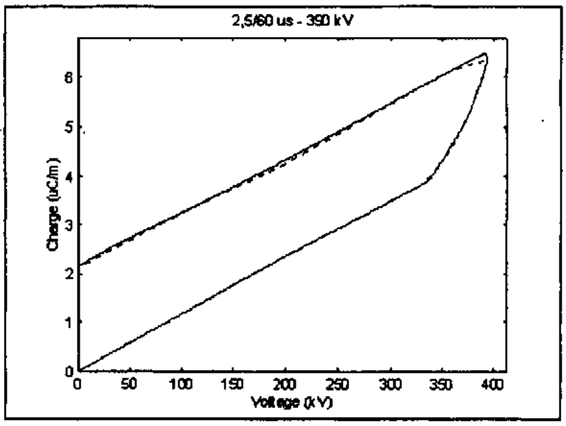

Fig. 23. 2.5/60 μs - 390 kV

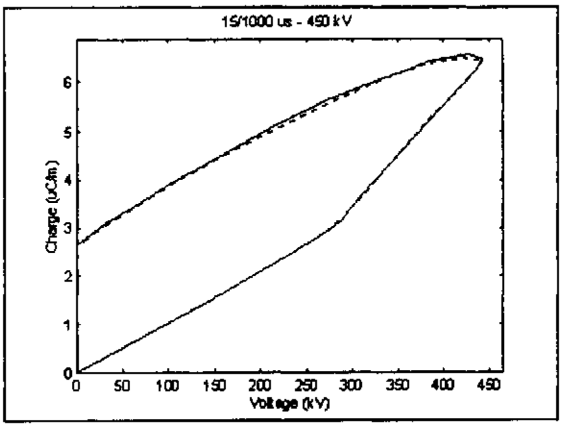

Fig. 20. 15/1000 μs - 450 kV

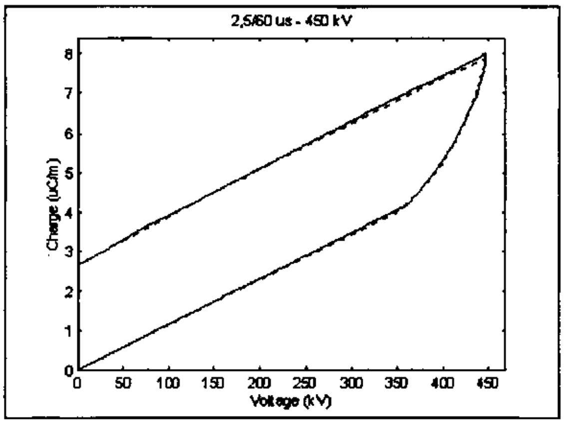

Fig. 24. 2.5/60 μs - 450 kV

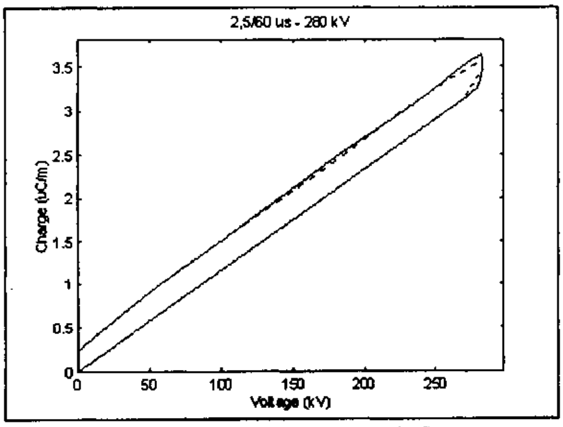

Fig. 21. 2.5/60 μs - 280 kV

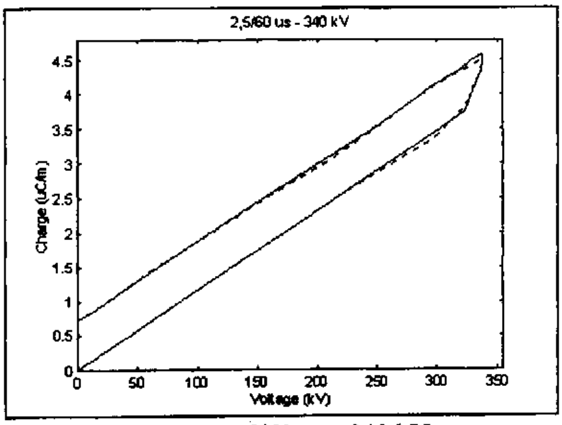

Fig. 22. 2.5/60 μs - 340 kV

IV. CONCLUSIONS

The first conclusion of this work is the evidence that the adopted ANN architecture is capable to reproduce the Q-V characteristics, for lightning and switching impulses, with a very good degree of accuracy, as long as two ANNs are used, one for increasing and the other for decreasing voltage surges. Once the two ANNs are trained, they are capable of responding correctly to different overvoltages and pulse shapes.

Two applications can be envisaged to represent corona phenomena using the trained ANNs in Electromagnetic Transients calculations.

An almost immediate application could consist of using the ANNs to model the corona "nonlinear branches" distributed along the transmission line divided in sections [8], [9]. This approach will require a simple routine to interface the ANNs with the EMTP using the Compensation Method. This routine would use the ANNs output to compute the corona current through the nonlinear branches at every time step.

A second application could be the training of ANNs to obtain the coefficients that define the equations of the dynamic model proposed by Suliciu and Suliciu [7]. This application would replace the cumbersome trial and error process that has to be adopted to determine the coefficients.

Work using both the above approaches is in progress and will be reported in the future.

V. References

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