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ESTIMATION OF ELECTRIC FIELDS TO HIGH VOLTAGE SUBSTATIONS DESIGN USING ARTIFICIAL NEURAL NETWORKS

ANDRÉ N. DE SOUZA, IVAN N. DA SILVA, MÁRIO E. BORDON

State University of São Paulo – UNESP, Department of Electrical Engineering, CP 473, CEP 17033-360-Bauru-SP, Brazil, e-mail: andrejau@bauru.unesp.br

Abstract. This paper describes a novel approach to map electric fields using artificial neural networks. The networks acts as an identifier of structural features of the high voltage substations design so that output parameters can be estimated and generalised from an input parameter set. Simulation examples are presented to validate the proposed approach. More specifically, the neural networks are used to compute electrical fields intensity and critical voltage taking into account several atmospheric and structural factors, such as pressure, temperature, humidity, distance between phases, height of the bus bars, and wave forms. A comparative analysis with the finite element method is also provided to illustrate this new methodology.

Key Words. Artificial neural networks, High voltage, Electric fields, Substations, Atmospheric impulses.

1. INTRODUCTION

Brazil is the largest tropical country in the world and, in consequence, one of the main countries in terms of lightning activity. About 100 million lightning strikes occur every year in almost all parts of the country. In consequence there is the necessity of understanding the lightning phenomenon intrinsically and evaluating its incidence.

During the last years a great improvement on lightning protection methodology has been made. In fact the major step forward in this field is relevant to the evaluation and identification of risk of damage due to lightning related to the protection of high voltage substations [1,5,6].

On the other hand, the ability of Artificial Neural Network (ANN) on complex non-linear functions realisation makes it identify and estimate electric fields and its parameters in an attractive way.

An artificial neural network is a dynamic system that consists in highly interconnected and parallel non-linear processing elements that shows extreme efficiency in computation. The main benefits of using ANNs on lightning studies are the following: i-) the ability of learning and therefore generalisation; ii-) the facility of implementation in hardware; iii-) the capacity of mapping complex systems without necessity of knowing the eventual mathematical models associated with them; iv-) the possibility of time reduction involved with tests in laboratory.

This paper has three principal aims. The first one is the most important objective that suggests problems about estimation of electric fields. It can be effectively mapped by artificial neural networks. The second objective is to offer an effective method for identification of lightning models. The third objective is to aid the tests to simulate that have been made in laboratories once the network is capable of simulating realistic test scenario.

The paper has the contents as following: In Section 2, the experimental procedures and simulations are showed. In Section 3, the finite element method is used. In Section 4, the basic aspects relative to artificial neural networks are presented. Simulation results are given in Section 5 to validate the developed approach. In section 6, the key for this issue is emphasised by drawing conclusions.

2. EXPERIMENTAL TECHNIQUES

The atmospheric impulses that represents the lightning in high voltage laboratory has been produced by an impulse generator that consists essentially of a number of capacitors which are charged in parallel from a direct voltage source and then discharged in series into a circuit which includes the test object (bus bars).

The standard lightning impulse has been produced full lightning impulse having a virtual front time of 1.2μs and a virtual time to half value of 50μs.

At first, in the high voltage laboratory it was experimentally determined the critical voltage ($V_{50\%}$) for several electrical distances between bus bars. As soon as this procedure finished, the supportable voltage ($V_{10\%}$), was calculated by:

$$V_{10\%} = V_{50\%} (1 - 1.3\sigma) \qquad (1)$$

Where $V_{10\%}$ means the voltage with 90% of non-occurrence of a disruptive discharge and σ is the standard deviation (3%).

The real atmospheric conditions (pressure, temperature, humidity, etc.) were measured in the laboratory. These figures were stored to be used in the training process of the neural network.

Fig.1 shows the assembling of the parallel bus bars (A and B).

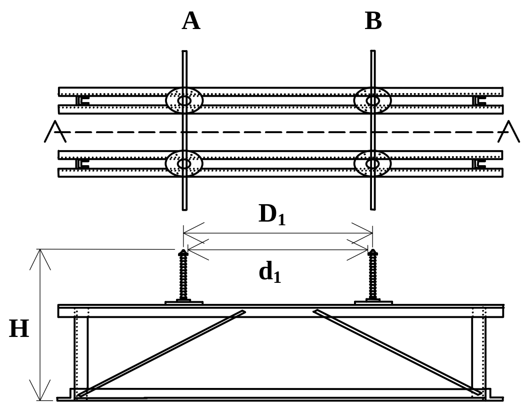

Fig.1. Parallel bus bars

Where D_1 is the distance between phases, d_1 is the distance of the electric arc and H is the height of the bus bar far from the ground.

On the parallel bus bars were applied atmospheric impulses of positive polarity in one side, having the other side grounded. The $V_{50\%}$ potential for several electric distances and bus bars heights were determined.

Fig.2 outlines the several tests that took place in laboratory.

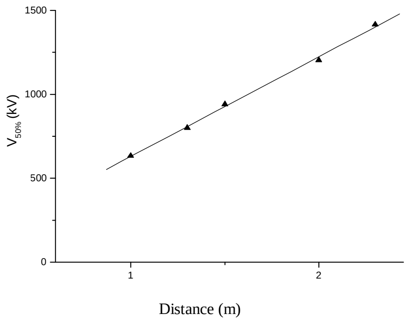

Fig.2. Profile of the critical voltage $V_{50\%}$, H = 3m

It is essential to mention that this methodology is the most used to determine the $V_{50\%}$ even though it is a expensive and slow procedure to achieve the $V_{50\%}$.

Besides that, it is also possible to estimate the $V_{50\%}$ by using statistics. However, in this case the rate of failure is very high.

3. FINITE ELEMENT SIMULATIONS

In order to make use of the experimental results presented in the last section, simulations were realised by using the finite element considering the structure as it was shown in Fig. 1.

It was used an electrostatic finite element program to get an initial approach regarding numerical analysis although this procedure represents a transient behaviour. This approach was possible in sake of the symmetrical structure.

Fig.3 shows the topology for the finite element model. V_0 represents the applied voltages, D is the distance between the bus bars and H is the height far from the ground (3 m). Zero potential (V = 0) was imposed on the whole boundary of the high voltage laboratory, which means to consider V = 0 on the ground and walls. This is the most critical situation, because it represents a more rapid variation in the gradient of the potential, in comparison with non zero potential on the walls.

As the distance between the bus bars are less than their length, a 2D finite element mesh could be used.

The simulations were done with finite element meshes of the 8561 nodes and 16400 triangular first order elements.

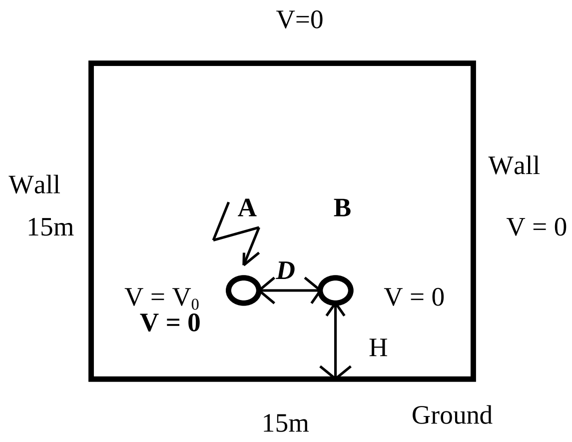

Fig.3. Topology for the finite element analysis

Fig.4 and Fig.5 show the intensity of electrical field in the region between bus bars (A and B) for the distances 1.30 and 1.75 meters and the voltages 450kV, 550kV and 650kV.

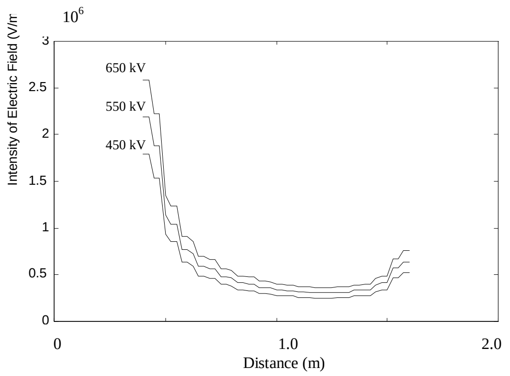

Fig.4. Distance between the bus bar : 1.30 m

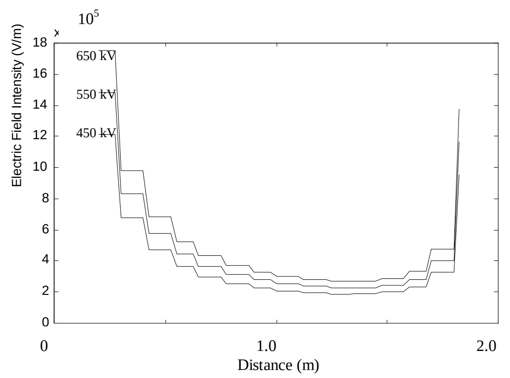

Fig.5. Distance between the bus bar : 1.75 m.

Observing Fig. 4 and Fig. 5, it was realised some oscillations caused by the interpolation problems, which is a featured aspect of the finite element.

4. IDENTIFICATION WITH NEURAL NETWORKS

The motivation for use an ANN is to speed up the analysis or design of process substantially. The main advantage of an ANN is in its ability to approximate functional relationships, particularly non-linear relationships [4].

The ANN, when presented with appropriate input and output data related to a specific functional relationship, can adjust itself such that it can give a good representation of that relationship. This feature is particularly useful when the relationship is non-linear and/or not well defined, and thus difficult to model by conventional means.

ANNs were also developed to mimic some of the learning processes of the human brain. In this paper, feedforward ANNs are used to map the relationships between the variables associated with the process of specification (identification) on lightning studies.

The system identification is the determination, on the basis of input and output, of a system within a specified class of systems. The identification process usually consists of two stages - model selection and parameter estimation. In neural networks, the selection of the neural architecture corresponds to the model selection stage.

In this paper, the selected architecture is defined by a feedforward ANN. The learning algorithm used to compute the weights of the network corresponds to the parameter estimation.

A typical feedforward ANN is depicted in Fig.6, with "m" inputs and "p" outputs, and each circle representing a single neuron. The name feedforward implies that the flow is one way and there are not feedback paths between neurons. The output of each neuron from one layer is an input to each neuron of the next layer. The initial layer where the inputs come into the ANN is called the input layer, and the last layer, i.e., where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layer.

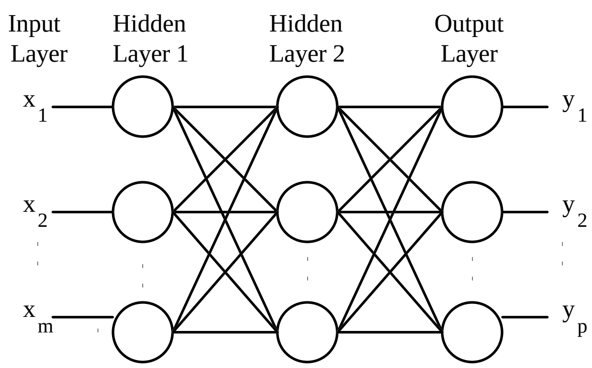

Fig.6. Typical feedforward ANN

Each neuron can be modelled as shown in Fig.6, with "n" being the number of inputs to the neuron. Associated with each of the n inputs x_i is some adjustable scalar weight, w_i (i=1,2,...,n), which multiplies that input. In addition, an adjustable bias value, b, can be added to the summed scaled inputs.

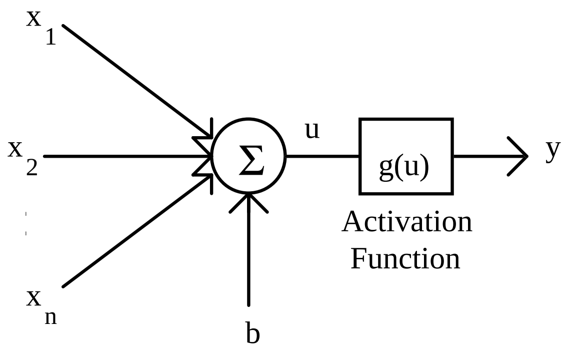

Fig.7. Single artificial neuron

These combined inputs are then fed into an activation function, which produces the output y of the neuron, that is:

$$y = g\left(\sum_{i=1}^{n} w_i x_i + b\right) \qquad (2)$$

where g is a sigmoid function $g(u)=(1+e^{-u})^{-1}$.

For network training was used the Levenberg-Marquardt Algorithm [2,3].

5. SIMULATION RESULTS

In this section, some simulations for the arrangement shown in Fig.1 have been done. The general architecture of the neural system is shown in Fig.8. This architecture is composed by two feedforward networks.

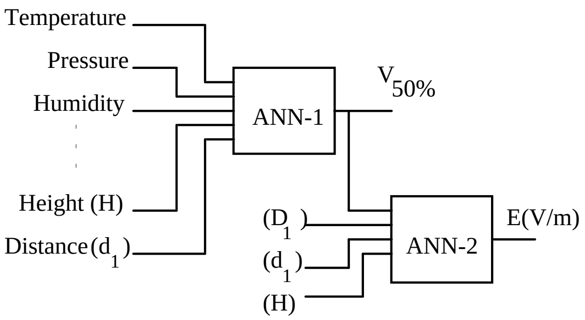

Fig.8. General architecture of the ANN

The first network (ANN-1) is responsible by the computation of the critical voltage ($V_{50\%}$). The training data for ANN-1 were directly obtained from experimental values acquired in high voltage laboratory. It were used nearly three hundred training vectors of $V_{50\%}$. It is important to notice that this network has taken into account several atmospheric and structural factors.

Fig.9 shows the variation of $V_{50\%}$ computed by ANN-1 when the temperature has been modified (25.0 ^{0}C to 25.3 ^{0}C).

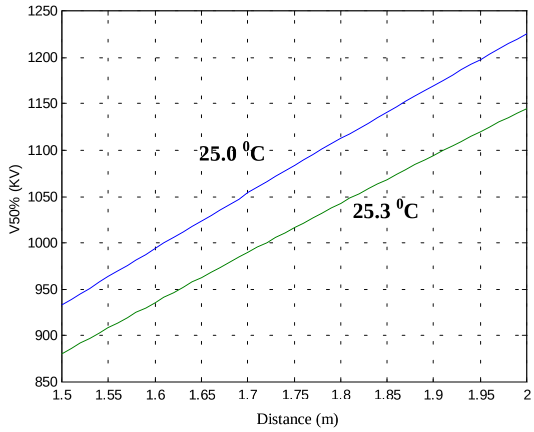

Fig.9. Variation of $V_{50\%}$ when the temperature has been modified

It is important to mention that this kind of verification is impossible to be observed through experimental procedures.

The second network (ANN-2) is responsible by the computation of the electric field intensity between the bus bars. For this network, the training data were obtained by an electrostatic finite element method. It was used around two thousand and five hundred training vectors.

Fig.10 illustrates the variation of the electrical field intensity with three different values of $V_{50\%}$ computed by ANN-2 (650 kV, 550 kV and 450 kV).

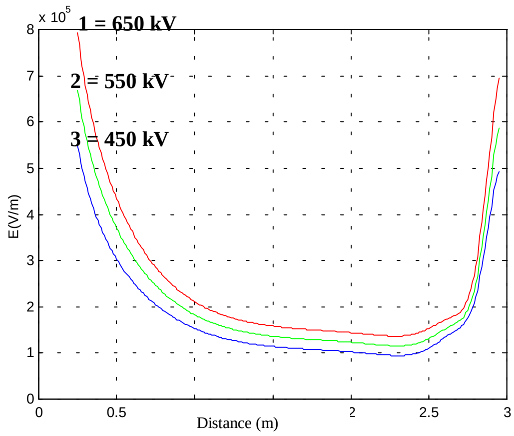

Fig.10. Variation of the electrical field intensity

As observed in Fig.8, the ANN-1 output is provided as an input parameter to the ANN-2. Therefore, all atmospheric and structural factors are also taken into account to compute the electric field intensity. This is one of the main advantages related to the finite element method approach. This procedure was adopted to verify the sensitivity of the network and also to set the limits and extreme conditions to future researches .

Fig.11 and Fig.12 compare the electric field intensity considering finite element method and artificial neural network (alleviated curve).

Fig.11 shows the electric field intensity between the bus bars (1.5m), and applied voltage of 550 kV.

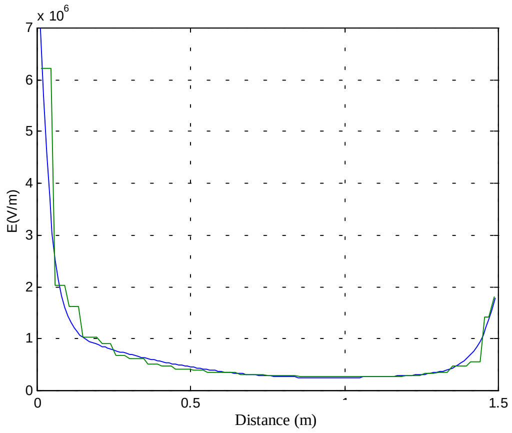

Fig.11. Electric field intensity

Fig.12 shows the electric field intensity between the bus bars (1.5m), and applied voltage of 650 kV.

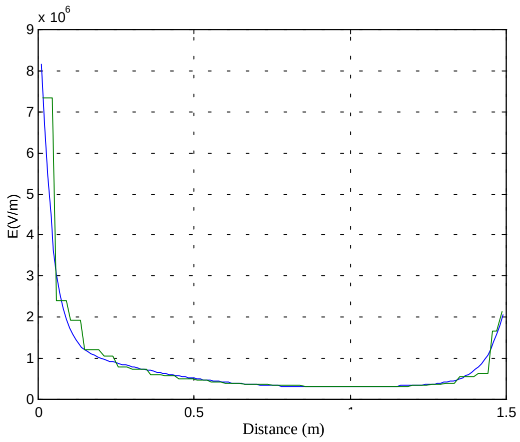

Fig.12. Electric field intensity

Observing Fig. 11 and Fig. 12, it can be verified that the network might get a good estimation electric field intensity. Besides that, the network was capable of decreasing the interpolation problems (oscillations) when compared to results provided by the finite element method.

6. CONCLUSIONS

This paper has presented a novel methodology to map electric fields of high voltage substations using artificial neural networks. The simulation results can be useful in the elaboration of new criteria, more consistent and adequate, for on substations design.

Artificial neural networks were considered within its context of identification of high-voltage process. The training of the neural networks has been made using data (atmospheric and structural factors) from experimental simulations. After the training, the network was been able to generalise novel inputs that were not simulated in laboratory. This property allows to reduce the time spend with simulations in the laboratories.

All these results evidence that problems involving identification on electric fields intensity can be effectively mapped by artificial neural networks.

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7. REFERENCES

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