A Neural Network Applied to Map and to Compute Overvoltages Related to Lightning in Power Systems

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Abstract: - This paper describes a novel approach for mapping overvoltages related to lightning in power system using artificial neural networks. The network acts as identifier of structural features of the grounding processes. So that output parameters can be estimated and generalized from an input parameter set. Simulation examples are presented to validate the proposed approach. More specifically, the neural networks are used to compute the overvoltages of grounding system taking into account time, waveform, soil resistivity and impulse current. The results obtained by the network are compared with other approaches also used to model grounding systems related to lightning.

Key Words: - Power System, Neural Networks, Lightning and Grounding Systems.

1 Introduction

The accurate estimation of features of grounding systems is extremely important to establish the limits of power system protection related to lightning. Once the grounding system directly influence in the magnitude and waveform of the lightning.

However, nowadays there is not any agreement about the relationship among the whole variables which compose the grounding processes to the over voltages related to lightning because it has been almost impossible to represent the behavior of soil ionization phenomenon.

Several experimental tests and theoretical investigations have been carried out to obtain characteristics and parameters associated with the technique of grounding [1-2]. The grounding system involves a lot of parameters, such as impedance behavior with soil resistivity, effect of varying current injection point, impedance behavior, properties of soil ionization, polarity of discharge, so on.

Among the most electric energy systems, lightning is the main cause of unscheduled supplies interruptions and several experimental tests and theoretical investigations have been carried out to obtain characteristics and parameters associated with the grounding system concerning lightning.

The dynamic behavior of grounding systems depends on two different physical processes: the nonlinear behavior of soil due to soil ionization in the immediate proximity of the grounding electrodes and the propagation of electromagnetic waves along grounding electrodes and in soil [3-4].

According to the current literature the core regarding soil resistivity process is to identify and to model those uncertain information on mathematical principles due to the soil ionization.

In this sense, it is crucial to compute the overvoltages, to know and to identify the features of grounding behavior taking into account several parameters such as resistivity, frequency, polarity of the current, waveform, time, impedance that have a nonlinear behavior most of times.

In this context, the identification features of grounding through Artificial Neural Networks (ANN) can be seen as an efficient tool to provide alternatives to the conventional methodologies, generating attractive results, mainly due to the intrinsic characteristics of the technique, such as the generalization capacity and integration facility with other computational tools.

An artificial neural network is a dynamic system that consists of several single processing elements, which explore intrinsically parallel and adaptive computation architectures.

For this purpose, the present paper is organized as following: In Section 2, it is presented the grounding system used in this work. The Section 3 introduces some basic foundations of artificial neural networks. In Section 4, the neural approach used in the proposed methodology is presented. The Section 5 provides the simulation results obtained by the presented technique. Finally, the key issues discussed in this paper and the conclusions drawn are presented in Section 6.

2 Grounding System

The configuration investigated in this work to represent a typical grounding system has been composed for six rods (electrode) distant of 3 meters with 2.4 meters deep.

Fig. 1 shows the electrode configuration with six rods used in the computational model.

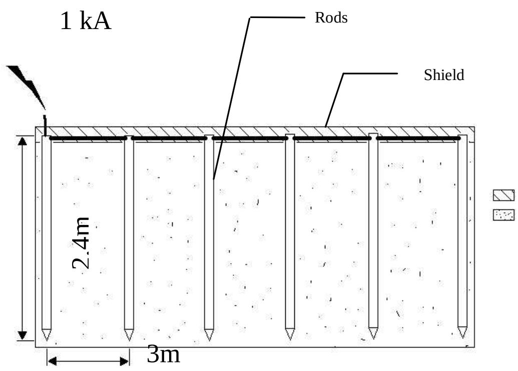

Fig. 1 - Investigated configuration

The data used in this work were based on results reached in [5]. The authors considered that a parameter that can used to summarize in a representative way the overall grounding behavior is the impulse impedance (Z_P), which is defined as the ratio between the peak values of voltage and current waves.

The impulse current is having a virtual front time of 1.2 μs and a virtual time to half value of 50 μs with 1 kA amplitude that was injected in the first rod.

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, as shown in the Figure 2.

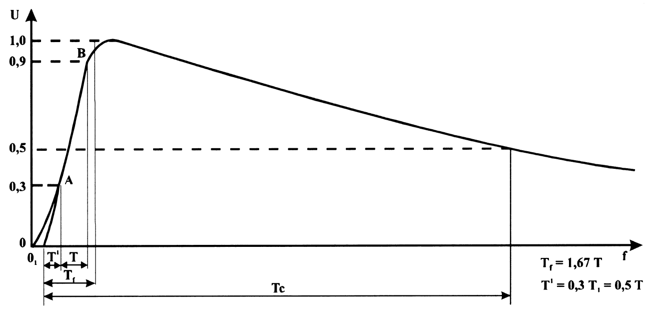

Fig. 2 - Normalized impulse

where 0_1 is the virtual origin, the time instant that precedes the time instant corresponding to the point A of $0{,}3T_1$; T_f is the time of the wave front, parameter defined as 1,67 times the time interval T, between the times corresponding to the times 30 % and 90 %; and T_c is the time until the half value.

An interest aspect verified from [5] is that on all the investigated range the value of this ratio between impulsive impedance and low frequency resistance was constant, around 0.57. The authors explained that this value could be due to the significance of the capacitive current though the soil.

It is important to notice that all results obtained from these simulations were used in the training neural network.

3 Foundations of Artificial Neural Networks

The ability of Artificial Neural Network (ANN) in mapping functional relationships has become them an attractive approach that can be used in several types of problem [6].

This characteristic is particularly important when the relationship among the process variables is non-linear and/or not well defined, and thus difficult to model by conventional techniques.

In this paper, artificial neural networks of the type Multilayer Perceptron have been used to map the relationship among the overvoltages in relation to the several variables that indicate the features to grounding process.

A typical feedforward ANN is depicted in Fig. 3, 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.

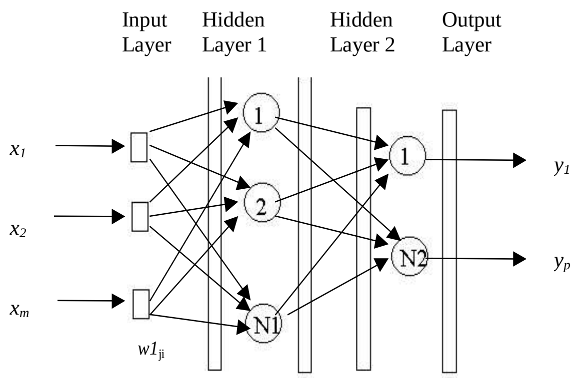

Fig. 3 - Typical feedforward AN

Each neuron can be modeled as shown in Fig. 4, with n as 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.

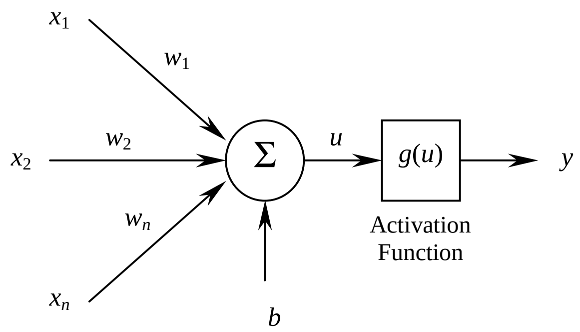

Fig. 4 - Single artificial neuron

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

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

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

The training process of the artificial neural network consists of the successive presentations of input output data pairs. The basic structure having one hidden layer has been shown to be powerful enough to produce an arbitrary mapping among variables.

During the training, the data are propagated forward through the network, which adjusts its internal weights to minimize the function cost (weighted squared deviation between the true output and the output produced by the network) by using the back-propagation technique.

The detail of the derivation of the back-propagation algorithm is well known in literature and its steps can be found in [7].

4 The Neural Approach Used in the Identification of Grounding System

An Artificial Neural Network of the type Multilayer Perceptrons has been employed for the identification of characteristics of grounding system and to compute the overvoltages.

The variables that compose each input vector of the network are defined by those variables that indicate the overvoltages of system. These variables are identified as soil resistivity (ρ), time (T) and impulse current (I).

The output vector of the neural network has been composed by a unique variable, which represents the over voltage (V) of grounding system. The neural architecture used to compute and to estimate the (V) of the system is shown in Fig. 5.

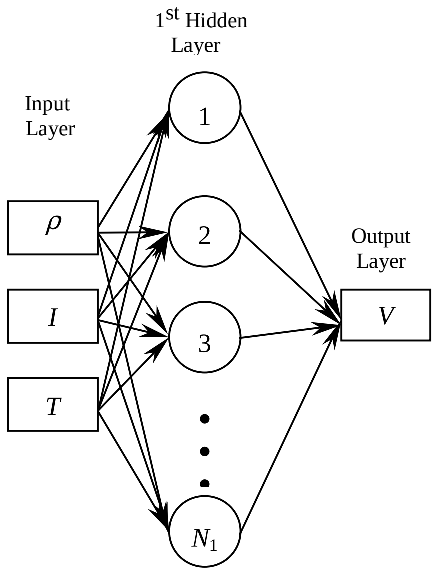

Fig. 5 - General architecture of the ANN

The training network is made by Levenberg-Marquardt algorithm [8] with data obtained from results simulated by [5].

To evaluate the developed architecture, some preliminary tests were accomplished as following:

- Impulse Current: 1 kA (amplitude)
- Wave Form: 1.2x50 μs
- Z_P / R_{LF} : 0.57
- Data Set Training: 150
- Resistivity: 100 Ω.m up to 2000 Ω.m

ANN Topology:

- Architecture: Multilayer Perceptron
- Number of Hidden Layers: 1
- Number of Neurons of the Hidden Layer: 5
- Mean Square Error: 11.14×10^{-4}
- Mean Relative Error (test pattern): 91×10^{-4}

5 Results and Discussions

In this section, some preliminary simulations results and discussions are presented to illustrate the application of the neural network approach developed to identify characteristics of grounding systems and to improve the power system related to lightning.

Fig. 6 shows the behavior of the over voltage in relation to the soil resistivity of 100 Ω.m , taking into account a impulse current of 1 kA.

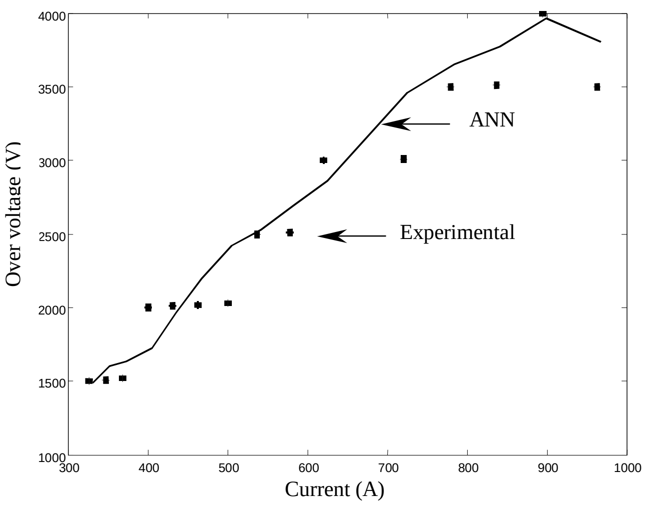

Fig. 6 - Variation of overvoltage with the soil resistivity (100Ω.m)

According to Fig. 6 it has been observed that the highest value of over voltage in the system is around 4 kV considering a resistivity of 100 Ω.m.

Fig. 7 shows the behavior of the overvoltage in relation to two different values of soil resistivity (500 and 800 Ω.m), taking into account a impulse current of 1 kA.

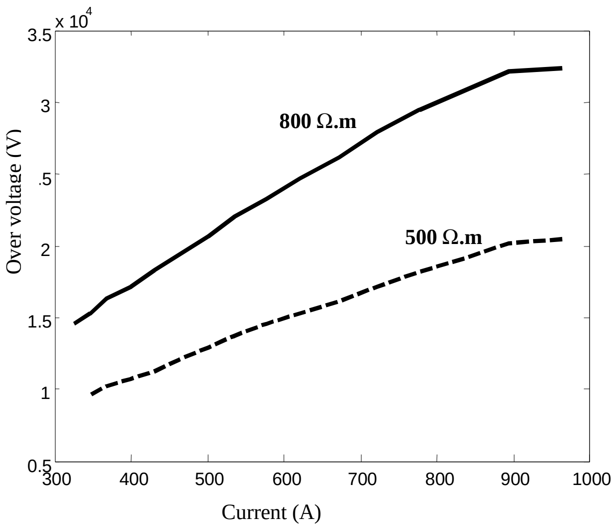

Fig. 7 - Variation of overvoltage with the soil resistivity (500 and 800 Ω.m)

As far as Fig. 7 it has been noticed that the highest value of overvoltage in the system is nearly of 33 kV, taking into account a resistivity of 500 Ω.m, and 20 kV considering a resistivity of 800 Ω.m.

Fig. 8 shows the behavior of the overvoltage in relation to two different values of soil resistivity (1000 and 1300 Ω.m) and a impulse current of 1 kA.

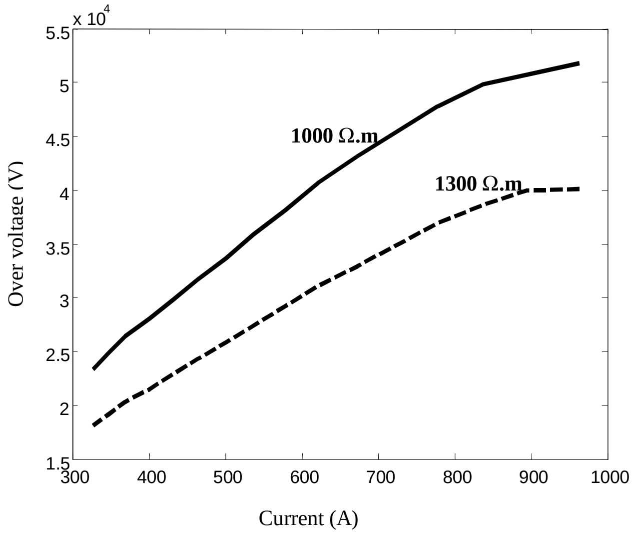

Fig. 8 - Variation of overvoltage with the soil resistivity (1000 and 1300 Ω.m)

Observing Fig. 8 it has been verified that the highest value of over voltage is about 50 kV to a resistivity of 1300 Ω.m and 40 kV to a resistivity of 1000 Ω.m.

Fig. 9 shows the behavior of the over voltage in relation to two different values of soil resistivity (1600 and 2000 Ω.m) and a impulse current of 1 kA.

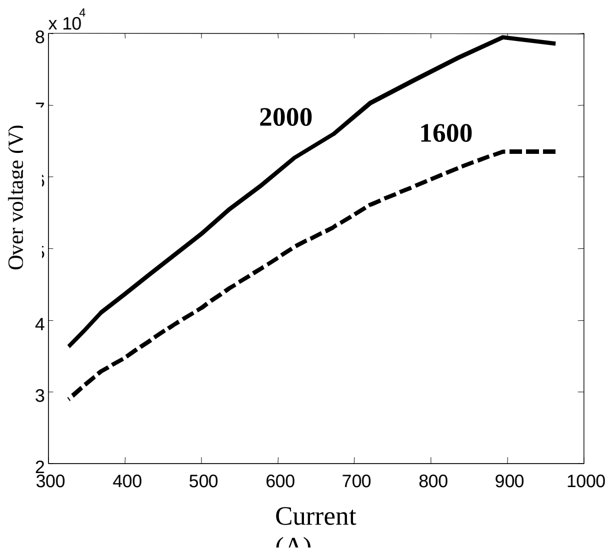

Fig. 9 - Variation of overvoltage with the soil resistivity (1600 and 2000Ω.m)

Based on the obtained results on those former simulations it has been verified that the behavior of the overvoltages are similar for different values of soil resistivity. However, the magnitude of those overvoltages has been totally different when they are compared with each other.

It is important to comment that this kind of particularity has been not considered in the actual project of grounding, once these different magnitudes can to cause any danger to people or damage to installations.

From Table 1, it is observed that the proposed neural approach provides results near to real values. The mean relative error is acceptable for this type of application.

Table 1: Relative error rate (%) of the overvoltages

Time (μs)	Current (A)	Resistivity (Ω.m)	Voltage (kV) ANN	Voltage (kV) Conventional	Error (%)
30	673.68	100	3.0	3.09	3.20
35	621.05	500	15.5	15.42	0.50
80	326.32	500	9.0	9.11	1.24
15	836.84	800	31.0	30.90	0.29
55	463.16	800	19.5	19.44	0.28
25	721.05	1000	35.0	35.07	0.20
45	536.84	1000	27.5	27.44	0.21
10	894.74	1300	51.5	51.60	0.17
25	721.05	1300	45.5	45.68	0.41
20	778.95	1600	58.5	58.61	0.19
55	463.16	2000	49.0	49.06	0.13

It means that, it is really important to kwon not only the relationship that there is between soil resistivity and overvoltage but also dynamic behavior of impulse current.

In this context, this new approach will allow accurate evaluation regarding to grounding system as well the establishment of limits for different protection systems related to lightning.

This particularity is remarkable because it will allow suitable projects for different kind of soil resistivity (selectivity), once the variables that compose the grounding process might be better identified and quantified.

The achieve relative error rate low acceptable demonstrates that ANN has been successful in generalize the data that were not supplied to the network. All these results confirm that artificial neural networks can effectively map problems involving identification of characteristics of grounding systems.

In sake of a better understanding, the process has still been developed towards to an accurate identification of the whole process. Another simulations will be considered to validate the proposed approach.

6 Conclusions

In this paper, artificial neural networks of the type Multilayer Perceptron have been used to map the relationship among the over voltage in relation to the several variables that indicate the features to grounding system.

The training network was based on evaluation of data extracted from [5]. After training, the network was able to generalize novel inputs what were not simulated. It allows decreasing of time involved with tests in experimental laboratory.

This kind of the study can contribute together with other conventional approaches, for a better qualitative evaluation of power system related to lightning.

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