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Lightning performance identification of high voltage transmission lines using artificial neural networks

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The paper presents a novel approach to lightning performance identification of high voltage transmission lines using artificial neural networks (ANNs). This approach is described in detail and results obtained by its application on an operating 400 kV Hellenic transmission line are presented. The conventional multilayer perceptron (MLP) technique, based on a backpropagation algorithm was considered in order to train the model. Actual input and output data collected from operating Hellenic high voltage transmission lines were used in the training process. The computed lightning failure rate is compared with real records of outage rate and with results obtained using the analytical algorithms. The presented methodology can be proved valuable to the studies of electric power systems designers, intended in a more effective protection of transmission lines against lightning strokes.

Keywords: High voltage transmission lines, lightning performance, artificial neural networks

1. INTRODUCTION

Lightning causes a significant part of the disturbances, damages and unscheduled supply interruptions in the modern power systems. This is the reason why over the last years, many lightning performance estimation methods have been presented in the technical literature.

Clayton and Young [1] tried to estimate the lightning performance of transmission lines introducing an analogue computer method. Anderson [2] tried to solve the same problem using Monte-Carlo simulation techniques. Fisher, Anderson and Hagenguth [3], used geometrical models, while Lundholm, Finn and Price [4] proposed a methodology based on the electromagnetic field theory and Maxwell's equations. Furthermore, several software tools which evaluate the lightning performance of transmission lines, have been developed and presented combining the above techniques and facilitating all the necessary complex calculations [5–8].

The current work presents an artificial neural network (ANN) method, capable to predict the lightning failure rate of high voltage transmission lines, using lines' past actual data. The efficient and economic implementation of ANN methods with today's computer technology and the accurate results that these methods provide, constitute them as alternative attractive tools in the identification of high voltage transmission lines lightning performance. The developed method has been applied on an operating 400 kV

Hellenic transmission line. Performance of proposed artificial neural network model is compared with real records of outage rate and the conventional analytical algorithms.

2. LIGHTNING FAILURE RATE OF A TRANSMISSION LINE

The total lightning failure rate N_T of a transmission line, or the outage rate, is the arithmetic sum of the shielding failure N_{SF} and the backflashover failure rate N_{BF}:

$$N_T = N_{SF} + N_{BF} \tag{1}$$

2.1 Shielding Failure Rate

An approximation to the number of flashes to earth that are intercepted by a transmission line is calculated using the equation [5]:

$$N_L = 0.004 \cdot T^{1.35} \cdot (b + 4 \cdot h^{1.09}) \tag{2}$$

where
N_L is the number of lightning flashes to a line per 100km per year,
T is the lightning level in the vicinity of the line,
h is the average height in meters of the shielding wires and
b is the horizontal spacing, in meters, between the shielding wires.

Shielding failure rate N_{SF} is associated to a required minimum current I_{min} to cause a line insulation flashover [6]. N_{SF} is defined as follows:

$$N_{SF} = N_L \cdot \int_{I_{\min}}^{I_{\max}} f(I)dI \tag{3}$$

where
$I_{\max}$ is the maximum lightning current,
$I_{\min}$ is the minimum current equal to $2U_a / Z_{surge}$ [4],
U_a is the insulation level of the transmission line,
Z_{surge} is the conductor line surge impedance in ohms, equal to

$$60\sqrt{\ln \frac{4h}{d} \cdot \ln \frac{4h}{D}} \text{ [6]}$$

d is the equivalent conductor diameter without corona and
D is the equivalent conductor diameter with corona.

2.2 Backflashover Failure Rate

Backflashover failure rate N_{BF} is estimated for transmission lines according to the method presented in [9] and is given from the equation:

$$N_{BF} = N_L \cdot \int_0^{\infty} P(\delta)\, d\delta \tag{4}$$

where
$P(\delta)$ is the probability distribution function of δ,
δ is an auxiliary variable given from the equation:

$$\delta = R \cdot I/2 - 0.85 \cdot U_a + L \cdot di/dt \tag{5}$$

R is the tower footing resistance,
I is the peak lightning current,
L is the total inductance of the system and
di/dt is the lightning current derivative.

3. ARTIFICIAL NEURAL NETWORKS

The ANN represents a parallel multilayer information processing structure. The characteristic feature of this network is that it considers the accumulated knowledge acquired during training, and responds to new events in the most appropriate manner, giving the experience gained during the training process. The model of the ANN is determined according to the network architecture, the transfer function and the learning rule.

In this study a typical neural network model known as conventional multilayer perceptron model (MLP) has been used. The conventional MLP network consists of nonlinear differentiable transfer functions. The backpropagation learning rules are used to adjust the weights and biases of networks so as to minimize the sum squared error of the network. This is achieved by continually changing the values of the network weights and biases in the direction of steepest descent with respect to error [10].

In order to train the network, a suitable number of representative examples of the relevant phenomenon must be selected so that the network can learn the fundamental characteristics of the problem. The backpropagation training may lead to a local rather than a global minimum. The local minimum that has been found may be satisfactory, but if it is not, a network with more layers and neurons may do a better job. However, the number of neurons or layers to add may not be obvious. Conventional MLP architecture, is generally decided by trying varied combinations of number of hidden layers, number of nodes in a hidden layer etc. and selecting the architecture which has a better

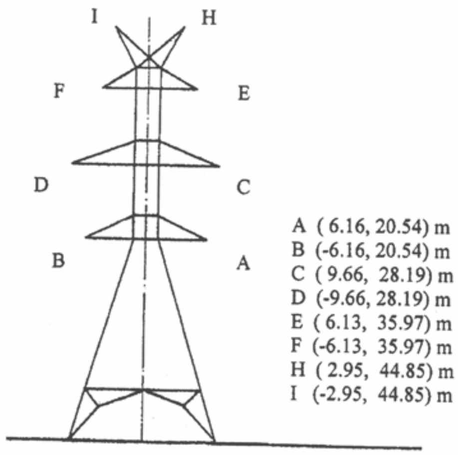

Figure 1 Typical tower of the analyzed 400kV Hellenic transmission line

generalizing ability amongst the tried combinations [11].

Once the training process is completed and the weights and bias of each neuron in the neural network is set, the next step is to check the results of training by seeing how the network performs in situations encountered in training and in others not previously encountered.

4. ANN APPLICATION TO THE LIGHTNING PERFORMANCE IDENTIFICATION

4.1 Transmission line characteristics

The goal is to develop a neural network architecture that could identify the lightning performance of a 400 kV operating transmission line of the Hellenic interconnected system. The line, which was selected among others, due to its high failure rate during lightning thunderstorms [12], is called Thessaloniki–Kardia and is running through a plain region. It has a length of 109,908 km and comprises a three phase double circuit, with two shielding wires (Figure 1). The line has got 305 towers with an average span of 360 m and the insulation level of the line (U_a) is 1550 kV.

The transmission line is divided into three regions, due to the different meteorological conditions and the different average values of tower footing resistance, which exist in each one of these. The regions and the different parameters that exist in each one of them are presented in Table 1.

4.2 Neural Network Training

In the development of a neural network model for the lightning performance identification of high voltage transmission lines, tower footing resistance *R*, peak lightning current I_{peak}, lightning current derivative *di/dt* and lightning level *T* were considered to be the inputs to the neural network model. The output of the neural network was considered to be the number of lightning failures of the line N_T.

It must be mentioned that these input-output data refer to each one individual month of a five-year period and constitute either actual collected data or estimated data based on actual measurements. More specifically, the number of lightning failures of the line N_T, has been provided from the Public Power Corporation of Hellas [12], while the lightning level *T* has been supplied from the National Meteorological Authority of Hellas [13]. The tower footing resistance *R*, has been estimated using the geometric characteristics of the grounding grid and actual measurements of the resistivity of the soil [14, 15]. Finally, the peak lightning current I_{peak} and the lightning current derivative *di/dt* were estimated using the statistical lightning parameters distributions presented by Berger, based on his measurements in Monte San Salvatore [16], in combination with the geographical and meteorological data of the examined area.

Having decided the number of network's inputs and outputs, the number of hidden layers and the number of neurons per layer were considered. Varied combinations of number of hidden layers and number of neurons in a hidden layer were tried and the selection of this architecture, which had a better generalizing ability, was made. It was decided to use a multilayer neural network with four input layers, two hidden layers each one consisting of ten neurons and one output layer neuron as shown in Figure 2.

The MATLAB neural network toolbox [11] was used for training the network. The function 'trainlm' was used which converges in less time as well as in few epochs compared to the training function 'trainbpx', of the neural network toolbox. Each epoch or training iteration represents the presentation of the set of training vectors to a network and the calculation of new weights and biases. The training function 'trainlm', is a backpropagation method based on the Levenberg–Marquardt optimisation algorithm [17], which is a more sophisticated method compared to the gradient descent approach, but requires more computer memory. Although the training function 'trainlm', requires significant memory, with today's technology this is unlikely to be a drawback.

One hundred eighty values of each input and output data, referring to every one region of the transmission line for every individual month of a five-year period, were used to train the network, i.e. to determine the weights and bias of each neuron in the neural network. The training

Table 1 Line parameters of Thessaloniki-Kardia transmission line [12,13]

Region	Towers	R(ohms) (Average regional value)	N_T (Average lightning failures 1996-2000)	T (Average lightning level 1996-2000)
I	1–195	1.93	0.40	32.2
II	196–260	8.83	1.20	29.6
III	261–305	18.24	1.80	30.4

Table 2 Recorded average annual lighting failures versus conventional analytical algorithms and artificial neural networks results

Period	Line	Average Annual Lightning Failures	Average Lightning Failures using Conventional Analytical Algorithms	Average Lightning Failures using ANN Identification Method
1996-2000	Thessaloniki–Kardia	3.40	3.26	3.46
2001	Thessaloniki–Kardia	6.00	5.54	5.87

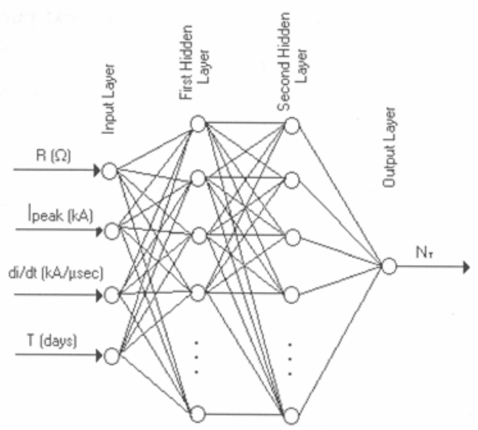

Figure 2 Artificial neural network architecture of the developed model

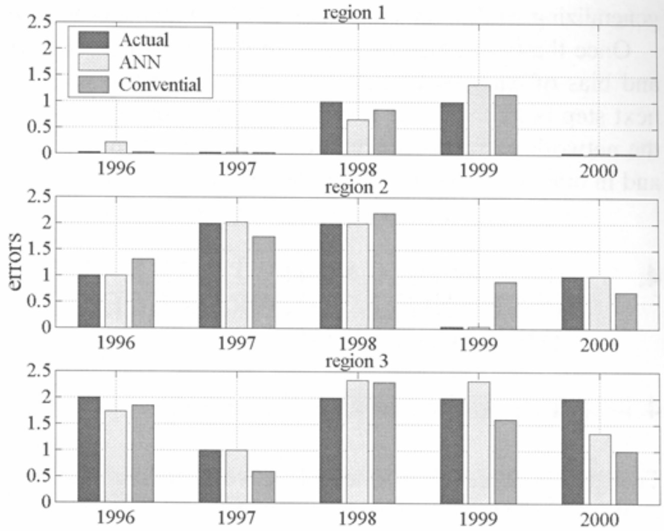

Figure 3 Yearly recorded lightning failures for each one region of the line versus conventional analytical algorithms and ANN results

process was repeated until an error goal of 0.1% was achieved. Finally, the number of the estimated lightning failures of the examined transmission line was checked with the number obtained from situations encountered in the training, i.e. the five-year period, and others which have not been encountered.

5. RESULTS AND DISCUSSION

In Table 2 are presented the recorded average annual lightning failures [12] of the examined transmission line, as well as the results obtained according to the conventional analytical algorithms [8] and these obtained according to the proposed artificial neural network identification method. The first period (1996-2000) refers to data used in the training process, while the second period (2001) refers to data, which have not been encountered in the training process. Figure 3 presents the monthly lightning failures of each one region for the five-year period as it has been evaluated from the proposed ANN method, the conventional analytical algorithms and the recorded actual data. It is obvious that the results obtained according to the proposed ANN method are very close to the actual ones and these results obtained according to the conventional analytical algorithms, something which implies that the proposed ANN identification method is well working and has an acceptable accuracy.

Although several conventional analytical methods are published in the technical literature, which describe satisfactory the lightning performance of high voltage transmission lines, most of them are based on empirical and approximating equations. In contrast to these methods, the proposed ANN identification method is using only actual line data in its calculations, something that clearly presents its main advantage. Moreover the efficient and economic implementation of ANN methods with today's computer technology and their easy application to almost every problem, constitute them as alternative attractive tools.

6. CONCLUSIONS

The paper describes in detail an artificial neural network identification method, which evaluates the lightning performance of high voltage transmission lines. A conventional MultiLayer Perceptron (MLP) technique based on a backpropagation method was used. The neural network model was trained using actual input and output data, The neural network identification has been applied on an operating Hellenic transmission line of 400 kV giving results very close to the actual ones and similar to these of other conventional analytical methods. The presented method can be used by electric power utilities as a useful tool for t he design of electric power systems.

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REFERENCES

1 Clayton JM, Young FS, Estimating lightning performance of transmission lines, *IEEE Trans on Power Apparatus and Systems*, Vol 83 (1964) pp 1102–1110
2 Anderson JG, Monte Carlo computer calculation of transmission-line lightning performance, *AIEE Transactions*, Vol 80 (1961) pp 414–420
3 Fisher FA, Anderson JG, Hagenguth JH, Determination of lightning response of transmission lines by means of geometrical models, *AIEE Trans on PAS*, Vol 78 (1960) pp 1725–1736
4 Lundholm R, Finn RB, Price WS, Calculation of transmission line lightning voltages by field concepts, *AIEE Trans on PAS*, Vol 77 (1958) pp 1271–1283
5 IEEE Working Group on Lightning Performance of Transmission Lines, A simplified method for estimating lightning performance of transmission lines, *IEEE Trans on PAS*, Vol 104 No 4 (1985) pp 919–927
6 IEEE Working Group on Estimating the Lightning Performance of Transmission Lines, Estimating Lightning Perfor-

mance of Transmission Lines II – Updates to Analytical Models, *IEEE Trans on PAS*, Vol 8 No 3 (1993) pp 1254–1267

7 CIGRE, Guide to procedures for estimating the lightning performance of transmission lines, *WG 01 (Lightning) of SC 33 (Overvoltages and Insulation Coordination)* (1991)

8 Ekonomou L, Gonos IF, Stathopulos IA, Topalis FV, Lightning performance evaluation of Hellenic high voltage transmission lines. *Proceedings of 13th International Symposium on High Voltage Engineering, (ISH 2003)*, Delft, The Netherlands (2003)

9 Gonos IF, Ekonomou L, Topalis FV, Stathopulos IA, Probability of backflashover in transmission lines due to lightning strokes using Monte-Carlo simulation, *International Journal of Electrical Power & Energy Systems*, Vol 25 No 2 (2003) pp 107–111

10 Lippmann R, An introduction to computing with neural nets, *IEEE ASSP Magazine*, Vol 4 No 2 (1987) pp 4–22

11 Demuth H, Beale M, Neural Network Toolbox: For use with MATLAB, *The Math Works* (1994)

12 PPC, Transmission lines characteristics, *Hellenic Public Power Corporation*, Athens, Greece (2002) (in Greek)

13 Data supplied from the National Meteorological Authority of Hellas (in Greek)

14 Gonos IF, Transient behavior of grounding system, *PhD Thesis*, National Technical University of Athens, Greece (2002) (in Greek)

15 Nahman J, Salamon D, Analytical expressions for the resistance of grounding grids in nonuniform soil, *IEEE Trans on PAS* Vol 103 No 4 (1984)

16 Berger K, Anderson RB, Kroninger H, Parameters of Lightning Flashes, *Electra*, Vol 41 (1975) pp 23–37

17 Hagan MT, Menhaj MB, Training feedforward networks with the Marquardt algorithm, *IEEE Trans on Neural Networks*, Vol 5 (1994) pp 989–993