Artificial neural network-based software tool for calculating the lightning performance of high-voltage transmission lines

L. Ekonomou, P. Liatsis, I.F. Gonos and I.A. Stathopulos

Abstract: An artificial neural network (ANN) is addressed for evaluating the lightning performance of high-voltage transmission lines. Several structures, learning algorithms and transfer functions were tested to produce a model with the best generalising ability. Actual input and output data, collected from operational Hellenic high-voltage transmission lines, were used in the training, validation and testing process. The method is coded in a comprehensive software program to be used by electric power utilities as a useful tool for the design of electric power systems, as an alternative to the conventional analytical methods. The aims of the paper are to describe in detail the proposed ANN method and the developed software tool and to present the results obtained by its application to operational Hellenic transmission lines of 150 kV and 400 kV. The ANN tool's results are compared with results produced from a conventional method and real records of outage rate showing a quite satisfactory agreement.

1 Introduction

Nowadays, artificial neural networks (ANNs) are being applied to an increasing number of real-world problems of considerable complexity owing to computational speed, their ability to handle complex non-linear functions, robustness and great efficiency, even in cases where full information about the studied problem is absent. They offer ideal solutions to a variety of classification problems such as speech and signal recognition, in function prediction, system modelling, control problems etc.

Many interesting ANN applications have been reported also in power system areas [1], where they are widely used short-term load forecasting, fault classification and fault location in transmission lines [2–5], voltage stability analysis [6], power system economic dispatch solution problems and power system stabiliser design [1]. Furthermore, ANNs have been shown to have applications in the solution of power flow problems [7], the effective distance protection of transmission lines [8, 9], the prediction of high-voltage insulator flashovers [10] and the calculation of insulator surface contamination under various meteorological conditions [11]. Finally, studies using ANNs have been presented for predicting the magnetic performance of strip-wound magnetic cores [12], for the evaluation of lightning overvoltages in distributions lines [13] and for lightning protection of high-voltage transmission lines [14].

The calculation of the lightning performance of overhead transmission lines presents many uncertainties owing to the random nature of the lightning phenomenon and the lack of reliable data. This is why all the existing methods for the calculation of lightning performance are based on empirical and approximating equations. ANNs can be an effective alternative solution to this problem, as they can present great accuracy and, in many cases, better results using only actual line data in the lightning performance calculations. Moreover, the efficient and economic implementation of ANNs with today's computer technology makes them very attractive tools.

In this paper, an ANN method is proposed to identify the lightning performance of high-voltage transmission lines. By testing several combinations of different structures, learning algorithms and transfer functions, we have developed an ANN that presented the best generalising ability among all the other combinations. Actual input and output data, collected from operational Hellenic high-voltage transmission lines were used in the training, validation and testing process. The developed method was coded in a comprehensive software program and applied to several operational Hellenic transmission lines of 150 kV and 400 kV so that its accuracy could be validated. The results obtained are compared with those produced using conventional methods and with real records of outage rate.

IEE Proceedings online no. 20050074

doi:10.1049/ip-smt:20050074

Paper first received 21st October 2005 and in final revised form 13th June 2006

L. Ekonomou, I.F. Gonos and I.A. Stathopulos are with the School of Electrical & Computer Engineering, High Voltage Laboratory, National Technical University of Athens, 9 Iroon Politechniou St., Zografou GR 157 80, Athens, Greece

P. Liatsis is with School of Engineering & Mathematical Sciences, Division of Electrical, Electronic & Information Engineering, Information & Biomedical Engineering Centre, City University, Northampton Square, London EC1V 0HB, UK

E-mail: igonos@softlab.ntua.gr

2 Previous research efforts

The protection of overhead high-voltage transmission lines from lightning strikes is one of the most important tasks to safeguard electric power systems. To achieve this effectively, the lightning performance of the lines has to be accurately calculated. Over recent decades, several studies have been conducted, and many methodologies have been proposed in the technical literature in an effort to estimate the lightning performance of transmission lines, and consequently, to improve the performance of power systems.

Extending the first method proposed by the AIEE Committee [15], the researchers tried to estimate the lightning performance of transmission lines by introducing an analogue computer method, based on generalised estimating curves [16]. Satisfactory results were also presented by the studies that tried to solve the same problem using Monte Carlo simulation techniques [17, 18]. Also significant in the study of lightning performance were the measurements made on small-scale geometrical models of the Ohio Valley Electric Corporation's 345 kV transmission towers [19], which agreed very well with the theoretical calculations based on electromagnetic field theory and Maxwell's equations [20], verifying at the same time both approaches. The travelling wave method was introduced by Bewley [21], to calculate overvoltages on transmission line towers, and an electrogeometrical model, the technique that determines the target point of a lightning stroke [22, 23], was extensively studied, extended and modified by many researchers, as it was proved a reliable tool in the estimation of lightning performance.

According to the above-mentioned methodologies, which all tried to evaluate with accuracy the lightning performance of high-voltage transmission lines, several software tools have been developed and presented in the technical literature, so that all the necessary calculations can be facilitated [24, 25].

Reference [25] is used in this paper so that its results can be compared with those produced from the proposed ANN method. The method presented in [25] determines the lightning performance of high-voltage transmission lines, taking into consideration both shielding failures and backflashover rates. The method calculates the shielding failures using the methodology presented in [26], uses the electrogeometric model to estimate the incidence of lightning strokes on transmission lines, employs the Monte Carlo statistical technique to select lightning and power system parameters and finally calculates the backflashover phenomenon according to the method presented in [27].

3 Artificial neural networks

The ANNs represent a parallel multilayer information processing structure. The characteristic feature of these networks is that they consider the accumulated knowledge acquired during training and respond to new events in the most appropriate manner, given the experience gained during the training process. In this work, an ANN called feed-forward has been used. The name feed-forward implies that the flow is one way and there are not feedback paths. A typical two layer feed-forward ANN is presented in Fig. 1.

In its basic form, a feed-forward ANN consists of an input layer, an output layer and one or more hidden layers. Each layer consists of a set of neurons or nodes that are fully connected to the neurons in the next layer. The connections have multiplying weights associated with them. The neuron receives its input either from other neurons or from the outside world. The sum of all weighted inputs represents the neuron transfer function. The number of neurons and hidden layers to be used depends on the problem studied. The process of determining the weights is called the training process. In the training process, sets of input and output data are associated by proper adjustment of the weights in the network such that a sum of squared error function is minimised. This is achieved using a specified learning rule. Thus each ANN model is

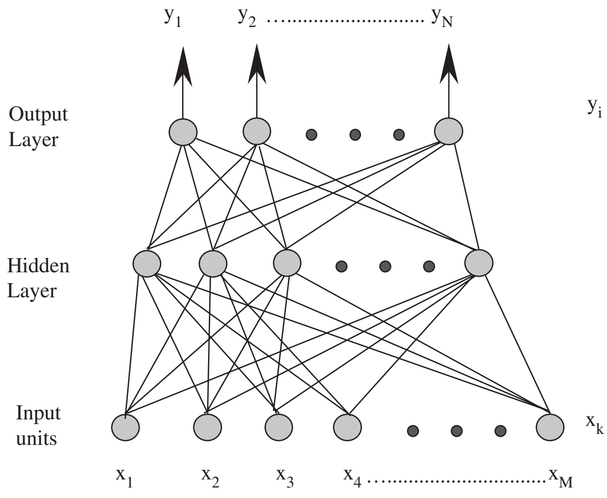

Fig. 1 *Two-layer feed-forward neural network*

determined according to its architecture, the transfer function and the learning rule.

4 Design of the proposed ANN

The goal was to develop a neural network architecture that can identify the lightning performance of high-voltage transmission lines. Five parameters that play an important role in the lightning failure rate of a transmission line were selected as the inputs to the neural network. These are: the tower footing resistance R, the insulation level U_α the peak lightning current I_{peak}, the lightning current derivative di/dt and the keraunic level T. The lightning failure rate N_T (i.e. number of faults) is the output (Table 1).

Table 1: ANN inputs and outputs

Input variables	Output variables
Keraunic level T	lightning failure rate N_T
Tower footing resistance R	
Insulation level U_α	
Peak lightning current I_{peak}	
Lightning current derivative di/dt	

These input and output data comprise either actual collected data or estimated data based on actual measurements. More specifically, the keraunic level T was supplied by the National Meteorological Authority of Hellas. The tower footing resistance R, was supplied by the Hellenic Public Power Corporation S.A. [28] and refers to the value measured during construction, or is estimated using the geometric characteristics of grounding grid [28] and actual measurements of the resistivity of the soil [29]. The insulation level U_α was supplied by the Hellenic Power Corporation S.A. [28] and refers to the nominal value of construction. For the last two input data, i.e. the peak lightning current I_{peak} and the lightning current derivative di/dt, the lightning measurements of Berger [30] and of Katz [31] and the work published by the Lightning and Insulator Subcommittee of the T&D Committee [32] were studied, with the proportional behaviour of the lightning parameter distributions being observed. Based on this, it was considered that the peak lightning current I_{peak} and the lightning current derivative di/dt were also proportional for the Greek territory and could be approximated well by a lognormal distribution. A lognormal random number generator was used for the generation of I_{peak} and di/dt using statistical lightning parameter distributions taken from the literature, in combination with geographical and meteorological data of the area examined, provided by the National Meteorological Authority of Hellas. As far as the output data we concerned, the lightning failure rate N_T, was based on collected data provided by the Hellenic Public Power Corporation S.A. [28].

The structure of the networks, i.e. the number of hidden layers and the number of nodes in each hidden layer, is generally decided by trial of various combinations and selection of the structure with the best generalising ability from among the tried combinations, considering that one hidden layer is adequate to distinguish input data that are linearly separable, whereas extra layers can accomplish non-linear separations [33]. This approach was followed in this work, as the selection of an optimum number of hidden layers and nodes for a feed-forward network is still an open issue, although some papers have been published in these areas.

As has been mentioned earlier, each ANN is determined also according to the learning algorithm and the transfer function that are used. In this work, two different learning algorithms (gradient descent and Levenberg–Marquardt) and three different transfer functions (hyperbolic tangent sigmoid, logarithmic sigmoid and hard limit) were examined so that the combination that presented the best generalising ability could be selected.

5 Transmission lines examined

The ANN method presented in this paper has been implemented and tested on two 400 kV and three 150 kV operational transmission lines of the Hellenic interconnected system (Table 2). These five lines were carefully selected among others owing to their high failure rates during lightning thunderstorms and the different characteristics that exist along their length (source: National Meteorological Authority of Hellas; [29]). The different characteristics, which refer to the different meteorological conditions and the different average values of tower footing resistance, are the reason for the division of the lines into regions.

It must be mentioned that the majority of the transmission lines in the Hellenic interconnected system present different characteristics along their length, as they run through plain regions, coastlines and/or mountainous regions. The number of regions and the different characteristics that exist in each one of these five lines, used in this study, are presented in Table 3.

6 Training, validation and testing

The proposed ANN was trained using the MATLAB Neural Network Toolbox [34]. Nine hundred and sixty

Table 2: Line characteristics of analysed transmission lines

Number	Line	Voltage, kV	Length, km	Number of towers	Insulation level, kV	Conductor dimensions, (ACSR MCM)	Number of circuits
1	Athens–Acheloos	400	250.557	717	1550	954	2
2	Thessaloniki–Kardia	400	109.908	305	1550	954	2
3	Arachthos–Igoumenitsa	150	75.802	239	750	336.4	1
4	Megalopoli–Sparti	150	64.472	173	750	336.4	1
5	Aktio–Argostoli	150	81.409	224	750	336.4	1

Table 3: Line design parameters of analysed transmission lines

Line	Region	Towers	R (measured during construction), Ω	T (average keraunic level, 1998–2002)
Athens–Acheloos	I	1–130	28.9	17.4
	II	131–318	6.5	21.9
	III	319–578	26.8	34.6
	IV	579–717	5.4	38.5
Thessaloniki–Kardia	I	1–195	1.9	26.1
	II	196–260	8.8	28.4
	III	261–305	18.2	30.2
Arachthos–Igoumenitsa	I	1–80	5.2	36.3
	II	81–163	13.0	38.4
	III	164–239	45.4	39.0
Megalopoli–Sparti	I	1–45	5.1	28.0
	II	46–75	39.7	29.7
	III	76–173	11.2	31.2
Aktio–Argostoli	I	1–55	4.8	37.2
	II	56–137	64.9	34.1
	III	138–224	126.3	30.9

values of each input and output datum, were used to train and validate the neural network model. These data refer to every region of the five examined transmission lines (16 regions in total), for each month of a 5-year period (1998–2002). In each training iteration, 20% of random data were removed from the training set, and a validation error was calculated for these data. The training process was repeated until a root mean square error between the actual output and the desired output reached the goal of 0.5%, or a maximum number of epochs (it was set to 10 000) is accomplished. Finally, the number of estimated lightning failures of the examined transmission lines was checked with the number obtained from situations encountered in the training, i.e. the 5-year period (1998–2002), and others that were not encountered.

It must be mentioned that, although in [35] it is proved that any non-linear function can be approximated by a feed-forward neural network, with one hidden layer without any minimum convergence time guarantee, in this work, ANNs with more than one hidden layer were examined so that the convergence rate for the particular problem of lightning performance evaluation could be studied.

After extensive simulations with all the possible combinations of transfer functions, learning algorithms, between one and four hidden layers and between two and 50 neurons in each hidden layer, it was found that the ANN architecture with two hidden layers, 12 and 15 neurons in the first and second hidden layer, respectively, the logarithmic sigmoid transfer function and the Levenberg–Marquardt learning algorithm presented the best generalising ability, had a compact structure, a fast training process and consumed lower memory than all the other combinations tried . In this ANN model, the mean square error was minimised to the final value of 0.005 within 5871 epochs.

7 Developed software tool

The proposed ANN model (two hidden layers with 12 and 15 neurons, logarithmic sigmoid transfer function, Levenberg–Marquardt learning algorithm), which was trained using MATLAB, can be used not only in the lightning performance calculation of the five lines used for its training, validation and testing, but also in the lightning performance calculation of other lines of the Hellenic interconnected system with similar characteristics. So that it can be easily used, flexible and user friendly and can be compared with other tools used by electric power utilities, it was coded in the software tool (written in MATLAB), presented in the simple flow chart of Fig. 2 and is organised as follows:

(*a*) Determination of the line's regions: the user determines the number of regions of the analysed transmission line.

(*b*) Introduction of insulation level U_α: the insulation level is entered into the software tool for each region of the analysed transmission line.

(*c*) Introduction of keraunic level T: the keraunic level in the vicinity of each analysed region of the transmission line is entered into the software tool for each month of the year studied.

(*d*) Decision concerning the use of tower footing resistance R, measured during construction (case 1), or soil resistivity parameters (case 2), for each region of the analysed transmission line.

(*e*) In case 1, the measured tower footing resistance for each region of the analysed line, as well as the month that this measurement was taken, is introduced into the software

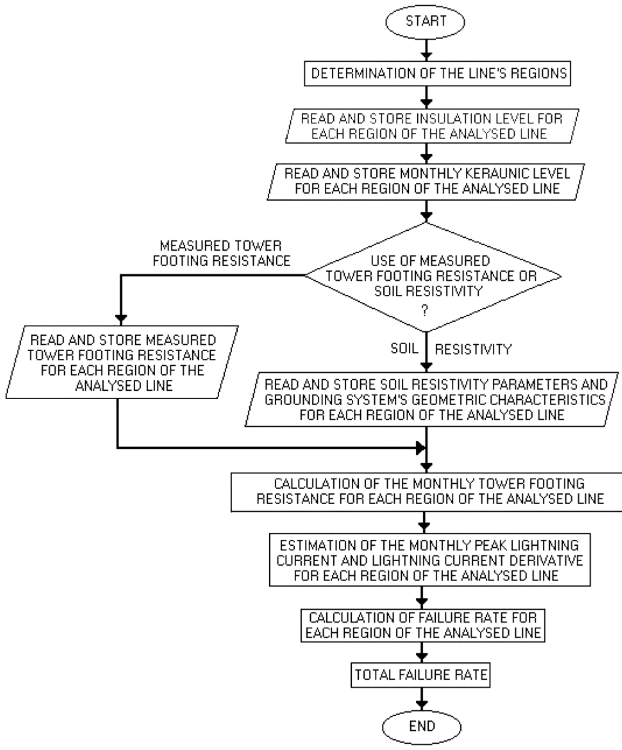

Fig. 2 *Simplified flow chart of developed software tool*

tool. These data were recorded during the transmission line's construction.

(*f*) In case 2, the soil resistivity parameters, the month that these measurements were taken and the grounding system's geometric characteristics are introduced into the software tool for each region of the analysed line.

(*g*) Then, the monthly tower footing resistance for each region of the analysed line is estimated, with the data introduced in step (*f*) used in the calculations. A methodology presented in [37] is used to estimate the monthly tower footing resistance using either the soil resistivity parameters and the grounding system's geometric characteristics or the tower footing resistance measured during construction.

(*h*) Estimation of the monthly peak lightning current I_{peak} and the lightning current derivative di/dt for each region of the analysed transmission line: the peak lightning current and lightning current derivative are estimated through the lognormal random number generator using the statistical lightning parameter distributions presented by Berger, in combination with the geographical and meteorological data of the examined area.

(*i*) Lightning performance calculation of the examined transmission line is performed, producing as an output the lightning failure rate (number of lightning faults) for each month and region of the analysed transmission line.

(*j*) Total failure rate: the yearly lightning failure is presented.

8 Results

Table 4 presents the recorded lightning failures [28] of the examined transmission lines for years 2003 and 2004, as well as the results obtained according to the conventional method presented in [25] and those obtained according to the proposed ANN-based software tool.

Table 4: Test results of developed ANN model

Year	2003			2004		
	Lightning failures:			Lightning failures:		
Line	recorded	using conventional method	using ANN	recorded	using conventional method	using ANN
Athens–Acheloos	7.00	7.28	6.92	9.00	8.73	8.65
Thessaloniki–Kardia	7.00	6.64	7.27	6.00	6.39	6.08
Arachthos–Igoumenitsa	5.00	4.71	5.43	6.00	6.13	5.87
Megalopoli–Sparti	3.00	2.72	2.81	2.00	1.78	1.89
Aktio–Argostoli	6.00	6.14	6.26	6.00	5.85	6.16

It is obvious that the results obtained according to the proposed ANN-based software tool are very close to the actual ones and the results obtained according to the conventional method, something that clearly implies that the proposed ANN-based software tool works well and has an acceptable accuracy.

9 Conclusions

The paper describes in detail an artificial neural network-based software tool for the calculation of the lightning performance of high voltage transmission lines. A feed-forward artificial neural network was used, and several different learning algorithms, transfer functions and structures were considered so that the ANN model could be selected that presented the best generalising ability, had a compact structure and a fast training process, consumed lower memory and represented the problem accurately, among all the tried combinations. The neural network model developed, which was trained and tested using actual input and output data, was coded in a comprehensive software program so that it can be easily used by electric power utilities. The developed software has been applied to five operational Hellenic transmission lines of 150 kV and 400 kV, giving results very close to the actual ones and similar to those of other simulation methods. The efficient and economic implementation of the ANN-based software tool with today's computer technology, the use of only real data in its calculations and the avoidance of empirical and approximating equations make it an attractive alternative tool to the conventional analytical methods.

10 Acknowledgments

The authors want to express their gratitude to the Hellenic Public Power Corporation S.A. for the supply of various technical data, and the National Meteorological Authority of Hellas for the supply of meteorological data.

11 References

1 Aggarwal, R., and Song, Y.: 'Artificial neural networks in power systems. III Examples of applications in power systems', *Power Eng. J.*, 1998, **12**, (6), pp. 279–287

2 Mahanty, R.N., and Gupta, P.B.D.: 'Application of RBF neural network to fault classification and location in transmission lines', *IEE Proc.-Gen. Trans. Distr.*, 2004, **151**, (2), pp. 201–212

3 Mazon, A.J., Zamora, I., Gracia, J., Sagastabeutia, K.J., and Saenz, J.R.: 'Selecting ANN structures to find transmission faults', *IEEE Comp. Appl. Power*, 2001, **14**, (3), pp. 44–48

4 Vasilic, S., and Kezunovic, M.: 'An improved neural network algorithm for classifying the transmission line faults'. Power Eng. Society Winter Meeting, Vol. 2, 2002, pp. 918–923

5 Gardoso, G., Rolim, J.G., and Zurn, H.H.: 'Application of neural-network modules to electric power system fault section estimation', *IEEE Trans. PWRD*, 2004, **19**, (3), pp. 1034–1041

6 Schmidt, H.P.: 'Application of artificial neural networks to the dynamic analysis of the voltage stability problem', *IEE Proc.-Gen. Trans. Distr.*, 1997, **144**, (6), pp. 371–376

7 Paucar, V.L., and Rider, M.J.: 'Artificial neural networks for solving the power flow problem in electric power systems', *J. Electr. Power Syst. Res.*, 2002, **62**, pp. 139–144

8 Dash, P.K., Pradhan, A.K., and Panda, G.: 'Application of minimal radial basis function neural network to distance protection', *IEEE Trans. PWRD*, 2001, **16**, (1), pp. 68–74

9 Coury, D.V., and Jorge, D.C.: 'Artificial neural network approach to distance protection of transmission lines', *IEEE Trans. PWRD*, 1998, **13**, (1), pp. 102–108

10 Cline, P., Lannes, W., and Richards, G.: 'Use of pollution monitors with a neural network to predict insulator flashover', *J. Electr. Power Syst. Res.*, 1997, **42**, pp. 27–33

11 Ahmad, A.S., Ghosh, P.S., Aljunid, S.A.K., Said, H.A.I., and Hussain, H.: 'Artificial neural network for contamination severity assessment of high voltage insulators under various meteorological conditions'. AUPEC, Perth, 2001

12 Miti, G.K., and Moses, A.J.: 'Neural network-based software tool for predicting magnetic performance of strip-wound magnetic cores at medium to high frequency', *IEE Proc.-Sci. Meas. Tech.*, 2004, **151**, (3), pp. 181–187

13 Martinez, J.A., and Gonzalez-Molina, F.: 'Statistical evaluation of lightning overvoltages on overhead distribution lines using neural networks'. Power Engin. Society Winter Meeting, 2001, Vol. 3, pp. 1133–1138

14 Sidhu, T.S., Singh, H., and Sachdev, M.S.: 'Design, implementation and testing of an artificial neural network based fault direction discrimination for protecting transmission lines', *IEEE Trans. PWRD*, 1995, **10**, (2), pp. 697–706

15 AIEE Committee Report: 'A method of estimating the lightning performance of transmission lines', *AIEE Trans.*, 1950, **69**, pp. 1187–1196

16 Clayton, J.M., and Young, F.S.: 'Estimating lightning performance of transmission lines', *IEEE Trans. PAS*, 1964, **83**, pp. 1102–1110

17 Anderson, J.G.: 'Monte Carlo computer calculation of transmission-line lightning performance', *AIEE Trans.*, 1961, **80**, pp. 414–420

18 Bouquegneau, C., Dubois, M., and Trekat, J.: 'Probabilistic analysis of lightning performance of high-voltage transmission lines', *J. Electr. Power Syst. Res.*, 1986, **102**, (1–2), pp. 5–18

19 Fisher, F.A., Anderson, J.G., and Hagenguth, J.H.: 'Determination of lightning response of transmission lines by means of geometrical models', *AIEE Trans. PAS*, 1960, **78**, pp. 1725–1736

20 Lundholm, R., Finn, R.B., and Price, W.S.: 'Calculation of transmission line lightning voltages by field concepts', *AIEE Trans. PAS*, 1958, **77**, pp. 1271–1283

21 Bewley, L.V.: 'Traveling waves on transmission systems' (John Wiley & Sons, Inc., NY, 1951, 2nd edn.)

22 Brown, G.W., and Whitehead, E.R.: 'Field and analytical studies of transmission line shielding-II', *IEEE Trans. PAS*, 1969, **88**, pp. 617–626

23 Rizk, F.A.M.: 'Modeling of transmission line exposure to direct lightning strokes', *IEEE Trans. PWRD*, 1990, **5**, (4), pp. 1983–1997

24 IEEE Working Group on Estimating the Lighting Performace of Transmission Lines: 'Estimating the lightning performance of transmission lines II – Updates to analytical models', *IEEE Trans. PAS*, 1993, **8**, (3), pp. 1254–1267

25 Ekonomou, L., Gonos, I.F., Stathopulos, I.A., and Topalis, F.V.: 'Lightning performance evaluation of Hellenic high voltage transmission lines'. ISH 2003, Delft, The Netherlands, 2003

26 IEEE Working Group on Lighting Performance of Transmission lines: 'A simplified method for estimating lightning performance of transmission lines', *IEEE Trans. PAS*, 1985, **104**, pp. 919–927

27 Gonos, I.F., Ekonomou, L., Topalis, F.V., and Stathopulos, I.A.: 'Probability of backflashover in transmission lines due to lightning strokes using Monte-Carlo simulation', *Int. J. Electr. Power Energy Syst.*, 2003, **25**, (2), pp. 107–111

28 PPC, S.A.: 'Transmission lines characteristics'. Hellenic Public Power Corporation S.A., Athens, 2004

29 Gonos, I.F., and Stathopulos, I.A.: 'Estimation of multi-layer soil parameters using genetic algorithms', *IEEE Trans. PWRD*, 2005, **20**, (1), pp. 100–106
30 Berger, K., Anderson, R.B., and Kroninger, H.: 'Parameters of lightning flashes', *Electra*, 1975, **41**, pp. 23–37
31 Katz, E.: 'The lightning detection system in Israel'. MedPower04, Cyprus, 2004
32 Lighting and Insulator Subcommitte of the T&D Committee.: 'Parameters of lightning strokes: a review', *IEEE Trans. Power Deliv.*, 2005, **20**, (1), pp. 346–358
33 Lippmann:, R.: 'An introduction to computing with neural nets', *IEEE ASSP Magazine*, 1987, **4**, (2), pp. 4–22
34 Demuth, H., and Beale, M.: 'Neural network toolbox user's guide for use with MATLAB', 2002
35 Hornik, K.: 'Some new results on neural network approximation', *Neural Networks*, 1993, **6**, (8), pp. 1069–1072
36 Gonos, I.F., Kontargyri, V.T., Stathopulos, I.A., Kontaxis, P.A., and Moronis, A.X.: 'Variation of multilayer structure of the soil during the year'. Greek CIGRE 2005, Athens, Greece, 2005