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Application of artificial neural network methods for the lightning performance evaluation of Hellenic high voltage transmission lines

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Abstract

Feed-forward (FF) artificial neural networks (ANN) and radial basis function (RBF) ANN methods were addressed for evaluating the lightning performance of high voltage transmission lines. Several structures, learning algorithms and transfer functions were tested in order to produce a model with the best generalizing ability. Actual input and output data, collected from operating Hellenic high voltage transmission lines, as well as simulated output data were used in the training, validation and testing process. The aims of the paper are to describe in detail and compare the proposed FF and RBF ANN models, to state their advantages and disadvantages and to present results obtained by their application on operating Hellenic transmission lines of 150 kV and 400 kV. The ANN results are also compared with results obtained using conventional methods and real records of outage rate showing a quite satisfactory agreement. The proposed ANN methods can be used by electric power utilities as useful tools for the design of electric power systems, alternative to the conventional analytical methods.

Keywords: High voltage transmission lines; Lightning performance; Shielding failure rate; Backflashover failure rate; Feed-forward neural networks; Radial basis function neural networks

1. Introduction

Protecting overhead high voltage transmission lines from lightning strokes is one of the most important task to safeguard electric power systems. In order to achieve this effectively, the lightning performance of the lines has to be evaluated accurately. Over the last 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. Clayton and Young [1] were from the first researchers, who tried to estimate the lightning performance of transmission lines introducing an analogue computer method, based on generalized estimating curves. Anderson [2], followed by Bouquegneau, Dubois and Trekat [3] and many others, tried to solve the same problem using Monte-Carlo simulation techniques. Significant was also the study of Fisher, Anderson and Hagenguth [4], where measurements made on geometrical models of the Ohio Valley Electric Corporation's 345 kV transmission towers (small-scale models), agreed well with the calculations of Lundholm, Finn and Price [5], which have been based on the electromagnetic field theory and Maxwell's equations. Travelling wave method was introduced from Bewley [6], in order to calculate overvoltages on transmission line towers, while electrogeometric model, the technique used to determine the target point of a lightning stroke, was extensively studied by Eriksson [7], Rizk [8] and many others.

According to the pre-mentioned methodologies software tools have been developed to facilitate all the necessary and complex calculations [9–11], while today's technology offers several simulation packages [12,13], which can model and represent graphically the transmission lines, lightning and overvoltages in an effort to estimate the lightning performance.

In the recent years ANN have attracted much attention and many interesting ANN applications have been reported in power system areas [14–26], due to their computational speed, the ability to handle complex non-linear functions, robustness and great efficiency, even in cases where full information for the stud-

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ied problem is absent. ANN are widely used in short term load forecasting [14], in fault classification and fault location in transmission lines [15–18], in voltage stability analysis [19], in power system economic dispatch solution problems and in power system stabilizer design [14]. Furthermore the ANNs present to have applications in the solution of the power flow problem [20], to the effective distance protection of the transmission lines [21,22], to the prediction of high voltage insulators' flashover [23] and to the calculation of insulators' surface contamination under various meteorological conditions [24]. Finally studies, which are using ANNs, have been presented for the evaluation of lightning overvoltages in distributions lines [25] and for the protection of high voltage transmission lines [26].

In this paper, two ANN methods, the feed-forward (FF) method and the radial basis function method (RBF), are used to identify the lightning performance of high voltage transmission lines. Each method has been tested by developing several models with different structures, learning algorithms and transfer functions in order the best generalizing ability to be achieved. Actual input and output data, collected from operating Hellenic high voltage transmission lines, as well as simulated output data were used in the training, validation and testing process.

The developed FF and RBF ANN models are applied on operating Hellenic transmission lines of 150 kV and 400 kV in order to validate their accuracy and the obtained results are compared with these produced using conventional methods and with real records of outage rate. Finally a comparison between the FF ANN method and the RBF ANN method is performed stating clearly the advantages and disadvantages of each method.

2. Previous research

The keraunic level, defined as the average number of days per year on which thunder is heard, can be evaluated either from isokeraunic maps or from daily weather records being obtained from ground based-observations. Using the keraunic level, the ground flash density, as well as an approximation to the number of flashes to earth, that intercepted by a transmission line, are calculated using the following equations [9,10]:

$$N_{\mathrm{g}} = 0.04 \times T^{1.25} \tag{1}$$

$$N_{\mathrm{L}} = 0.004 \times T^{1.35} \times (g + 4 \times H^{1.09}) \tag{2}$$

where N_{g} is the ground flash density, flashes per km^2 per year, N_{L} is the number of lightning flashes to a line per 100 km per year, T is the yearly keraunic level in the vicinity of the line in thunderstorm days per year, H is the average height in m of the shielding wires and g is the horizontal spacing in m, between the shielding wires.

The total lightning failure rate N_{T} (number of failures per year) of a transmission line, or the outage rate, is the arithmetic sum of the shielding failure rate N_{SF} and the backflashover failure rate N_{BF}

$$N_{\mathrm{T}} = N_{\mathrm{SF}} + N_{\mathrm{BF}} \tag{3}$$

Shielding failure rate N_{SF} is associated to a required minimum current $I_{\min}$ to cause a line insulation flashover [10]. N_{SF} is defined as follows:

$$N_{\mathrm{SF}} = \frac{2 \times N_{\mathrm{g}} \times l_{\mathrm{line}}}{10} \times \int_{I_{\min}}^{I_{\max}} D_{\mathrm{C}} \times f(I)\,\mathrm{d}I \tag{4}$$

where $f(I)$ is the probability density function of the peak current magnitude of lightning strokes, l_{line} is the line length in km, D_{C} is the shielding failure exposure distance, which is a function of the of the peak current magnitude of lightning strokes, $I_{\max}$ is the maximum lightning current in kA, $I_{\min}$ is the minimum current equal to $2U_{\mathrm{a}}/Z_{\mathrm{surge}}$ [10], U_{a} is the insulation level of the transmission line in kV, Z_{surge} is the conductor line surge impedance under corona equal to $60\sqrt{\ln(4h_{\mathrm{C}}/d) \times \ln(4h_{\mathrm{C}}/D)}$ [9], h_{C} is the conductor height at the tower in m, d is the equivalent conductor diameter without corona and D is the equivalent conductor diameter with corona.

Backflashover failure rate N_{BF} is estimated for transmission lines, according to the method presented in [27] and [28]. N_{BF} is defined as follows:

$$N_{\mathrm{BF}} = N_{\mathrm{L}} \times \int_{0}^{\infty} P(\delta)\,\mathrm{d}\delta \tag{5}$$

where $P(\delta)$ is the probability distribution function of the random variable δ, δ is a function of the two random variables I_{peak} and $\mathrm{d}i/\mathrm{d}t$ as shown in the following relation:

$$\delta\left(I_{\mathrm{peak}}, \frac{\mathrm{d}i}{\mathrm{d}t}\right) = R \times \frac{I_{\mathrm{peak}}}{2} - 0.85 \times U_{\mathrm{a}} + L \times \frac{\mathrm{d}i}{\mathrm{d}t} \tag{6}$$

with δ greater than zero when there is backflashover, R is the tower footing resistance in Ω, L is the total equivalent inductance of the system (tower and grounding system's inductance) in μH, calculated according to the simplified method presented in [9], di/dt is a random variable denoting the lightning current derivative (current steepness) in kA/μs and I_{peak} is a random variable denoting the peak lightning current in kA.

Tower footing resistance can be calculated, either for uniform or two-layer soil, through Eqs. (7) and (8) respectively [30]

$$R = \frac{\rho}{4} \times \sqrt{\frac{\pi}{4}} + \frac{\rho}{l} \tag{7}$$

$$R = 1.6 \times \frac{\rho_2}{P} + 0.6 \times \frac{\rho_1}{l} + \rho_1 \times \frac{n}{A} \tag{8}$$

where ρ, ρ_1, ρ_2 with $\rho_1 \geq \rho_2$ are soil resistivities in Ω-m, measured according to Wenner's method [31], A is the area occupied by the grid in m^2, n is the depth of the upper soil layer in m, P is the grid perimeter in m and l is the total length of grid conductors in m.

3. Artificial neural networks

3.1. Feed-forward (FF) neural networks

A typical three-layer FF ANN is presented in Fig. 1, having four inputs and three outputs with each node to represent a single neuron. The name feed-forward implies that the flow is one way and there are not feedback paths between neurons. The initial layer where the inputs come into the ANN is called the input

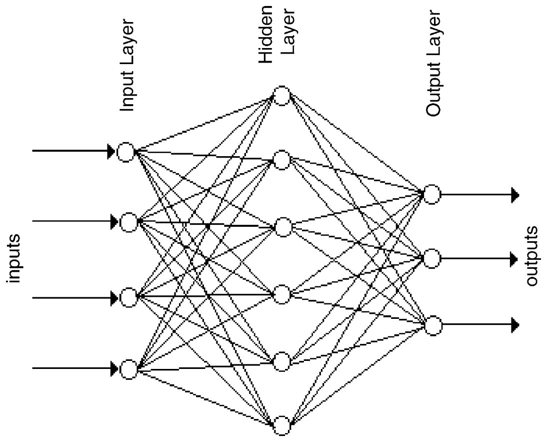

Fig. 1. Structure of a three-layer feed-forward neural network.

layer and the last layer where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layers.

Each neuron can be modelled as shown in Fig. 2, with n being the number of inputs to the neuron. Associated with each of the n inputs x_i are some adjustable scalar weights w_i ($i = 1, 2, \ldots, n$), which multiply that inputs. In addition, an adjustable bias value, b, can be added to the summed scaled inputs. These combined inputs are then fed into an activation function, which produces the output y of the neuron, that is

$$y = k\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{9}$$

where k is a hyperbolic tangent sigmoid $k(u) = (e^{u} - e^{-u})(e^{u} + e^{-u})^{-1}$ or logarithmic sigmoid function $k(u) = (1 + e^{-u})^{-1}$.

3.2. Radial basis function (RBF) neural networks

The architecture of a RBF neural network involves three different layers. The first layer consists of the input nodes. The second layer (hidden layer) is composed of the so-called kernel nodes whose functions are local functions and the range of their effects is determined by their centre and width. The third layer consists of the output nodes, which simply compute the weighted sum of the hidden node outputs

$$f_i(X) = \sum_{j=1}^{q} \Phi_j(||X - C_j||)\theta_{ji}, \quad 1 \le i \le q \tag{10}$$

where q is the output dimension of the network, X is the input vector, C_j is the centre of the qth unit, $||\cdot||$ denotes the Euclidean norm, θ_{ji} is the width of the qth unit and $\Phi(\cdot)$ is a radially symmetric function whose output is maximum at the center and decreases rapidly to zero as the input's distance from the center increases.

The design and training of an RBF network consists of: the determination of how many kernel functions to use, the calculation of their centres and width and finally the calculation of the weights that connect them to the output node.

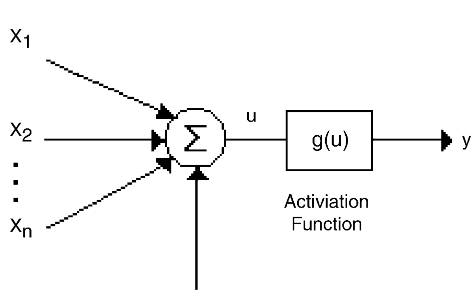

Fig. 2. A single artificial neuron.

Table 1
ANN architectures

No.	Input variables	Output Variables
Case I		
Actual input data/actual output data	Tower footing resistance R Peak lightning current I_{peak} Lightning current derivative di/dt Keraunic level T	Total lightning failure N_T
Case II		
Actual input data/simulated output data	Tower footing resistance R Peak lightning current I_{peak} Lightning current derivative di/dt Keraunic level T	Shielding failure N_{SF} backflashover failure N_{BF}

4. Design of neural networks

4.1. Neural networks architecture

The goal is to develop a neural network architecture that could identify the lightning performance of high voltage transmission lines. Four parameters that play important role to 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 peak lightning current I_{peak}, the lightning current derivative (current steepness) di/dt and the keraunic level T. These data constitute either actual collected data or estimated data based on actual measurements. As far concerning the outputs, the use of one or two output parameters, denotes two cases with two different neural network architectures. In case I, the single output refers to the total lightning failure rate N_T and constitute actual collected data, while in case II, the two outputs refer to the shielding failure rate N_{SF} and the backflashover failure rate N_{BF} and constitute simulation data (Table 1).

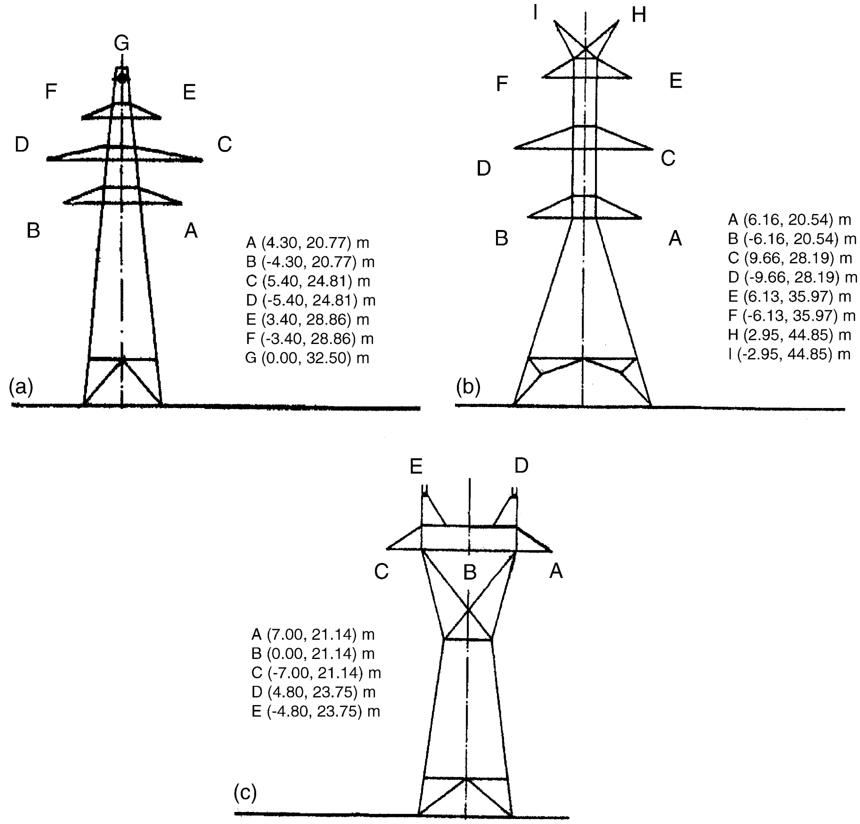

Fig. 3. The towers of the analyzed 150 kV and 400 kV Hellenic transmission lines.

4.2. *Characteristics of the examined transmission lines*

The ANN methods presented in this paper have been implemented and tested on 150 kV and 400 kV operating transmission lines of the Hellenic interconnected system. These lines were selected due to their high failure rates during lightning thunderstorms [29].

The first line called Arachthos–Acheloos is a 150 kV line having a length of 70.300 km. It comprises a three phase double circuit with one shielding wire (Fig. 3a). The line has got 192 towers with an average span of 370 m. The insulation level U_α of the line is 750 kV and the phase conductor dimensions are ACSR 636 MCM.

The second line called Thessaloniki-Kardia is a 400 kV line having a length of 109.908 km. It comprises a three phase double circuit, with two shielding wires (Fig. 3b). The line has got 305 towers with an average span of 360 m. The line's insulation level U_α is 1550 kV and the phase conductor dimensions are ACSR 954 MCM.

The third line called Kilkis–Serres is a 150 kV line having a length of 58.068 km. It comprises a three phase single circuit, with two shielding wires (Fig. 3c). The line has got 162 towers

Table 2
Line parameters of the examined transmission lines [29,32]

Line	Region	Towers	R (Ω) (average regional value)	N_T (average lightning failures 1996–2000)	T (thunderstorm days/year) (average keraunic level 1996–2000)
Arachthos–Acheloos	I	1–70	3.00	1.40	44.8
	II	71–130	3.12	1.40	40.7
	III	131–192	3.56	1.60	41.3
Thessaloniki–Kardia	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
Kilkis–Serres	I	1–46	1.99	0.60	31.8
	II	47–106	4.40	1.80	29.2
	III	107–162	1.78	0.80	27.7

with an average span of 358 m. The line's insulation level U_α is 750 kV and the phase conductor dimensions are ACSR 336.4 MCM.

Each one of these three transmission lines are divided into three regions, due to the different meteorological conditions and the different average values of tower footing resistance, which exist in each one region. The regions and the different parameters that exist in each one of these three lines are presented in Table 2.

4.3. Derivation of training, validation and test data

All the input data used in the proposed neural networks were actual collected data or estimated data based on actual measurements. More specifically, the keraunic level T has been supplied from the National Meteorological Authority of Hellas [32], while 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 [29,33]. Finally, the peak lightning current I_{peak} and the lightning current derivative (current steepness) $\mathrm{d}i/\mathrm{d}t$, were estimated using the statistical lightning parameters distributions presented by Berger and the typical return-stroke current waveform that he has recorded [34,35], in combination with the geographical and meteorological data of the examined area. As far concerning the output data, the total lightning failure rate N_{T}, in case I, were actual collected data provided from the Hellenic Public Power Corporation S.A. [29], while the output data in case II, the shielding failure rate N_{SF} and the backflashover failure rate N_{BF}, were generated from a simulation software program [28].

Five hundred forty values of each input and output data, referring to every one region of the examined transmission lines (nine regions) for every individual month of a 5-year period (1996–2000), were used to train and validate the neural network models. In each training iteration 10% of random samples were removed from the training set and validation error was calculated for these data. This technique, known as *m*-fold cross-validation technique [36], avoids over-fitting. An additional year data were used for test purposes.

4.4. Feed-forward and radial basis function ANN designed models

In order to address the evaluation of the transmission lines' lightning performance two different neural network methods were used and two different cases were considered. As it is mentioned earlier, the two cases refer in the use of actual or simulated output data, while the methods, which were considered, were the feed-forward and the radial basis function neural network methods.

Each ANN model is determined according to its structure, the transfer function and the learning rule, which are used in an effort the network to learn the fundamental characteristics of the examined problem. The learning rules and the transfer functions are used to adjust the weights and biases of networks in order to minimize the network's sum squared error. 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 trying varied combinations for selecting the structure with the best generalizing ability amongst 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 [37]. This approach was followed, since the selection of an optimal number of hidden layers and nodes for a FF network is still an open issue, although some papers have been published in these areas.

The designed and tested FF ANN models were combinations of two learning algorithms, two transfer functions and five different structures selected among others due to their best generalizing ability in comparison with the all other tried combinations. The used learning algorithms were the gradient descent and the Levenberg–Marquardt, while the transfer functions were the hyperbolic tangent sigmoid and the logarithmic sigmoid (Table 3).

Radial basis function neural networks are three layer networks. Each node of the hidden layer of RBF corresponded to one basis function center. In this study, as kernel function was used the Gaussian function. Bias, which determined the size of the receptive field, was a free parameter. The weights in the output layer were derived using the least square error learn-

Table 3
Designed ANN models

Case	ANN methods	Structure (neurons in each layer)	Learning algorithm	Transfer function
I	FF	4/5/5/1 4/10/10/1 4/10/20/1 4/10/5/10/1 4/10/20/10/1	Gradient descent Levenberg–Marquardt	Hyperbolic sigmoid Logarithmic sigmoid
	RBF	4/525/1	Least squares	Gaussian
II	FF	4/5/5/2 4/10/10/2 4/10/20/2 4/10/5/10/2 4/10/20/10/2	Gradient descent Levenberg–Marquardt	Hyperbolic sigmoid Logarithmic sigmoid
	RBF	4/525/2	Least squares	Gaussian

Table 4
Training data of the designed ANN models for case I

No.	Structure	Epochs	Train error	Validation error (%)
FF ANN – gradient descent – hyperbolic sigmoid				
1	4/5/5/1	2351	0.010	16.531
2	4/10/10/1	2724	0.010	9.714
3	4/10/20/1	1371	0.010	9.786
4	4/10/5/10/1	2945	0.010	5.368
5	4/10/20/10/1	3000	0.011	6.491
FF ANN – Levenberg–Marquardt – hyperbolic sigmoid				
6	4/5/5/1	2050	0.010	15.550
7	4/10/10/1	2207	0.010	8.494
8	4/10/20/1	883	0.010	7.136
9	4/10/5/10/1	2347	0.010	5.198
10	4/10/20/10/1	2003	0.010	7.018
FF ANN – gradient descent – logarithmic sigmoid				
11	4/5/5/1	3000	0.062	39.561
12	4/10/10/1	3000	0.063	29.807
13	4/10/20/1	3000	0.050	20.233
14	4/10/5/10/1	3000	0.075	30.377
15	4/10/20/10/1	3000	0.081	21.456
FF ANN – Levenberg–Marquardt – logarithmic sigmoid				
16	4/5/5/1	–	–	–
17	4/10/10/1	3000	0.023	15.204
18	4/10/20/1	2901	0.010	8.151
19	4/10/5/10/1	3000	0.016	9.239
20	4/10/20/10/1	3000	0.021	12.715
RBF ANN – least square error – Gaussian				
21	4/525/1	525	0	4.347

Table 5
Training data of the designed ANN models for Case II

No.	Structure	Epochs	Train error	Validation error	
				N_{SF} (%)	N_{BF} (%)
FF ANN – gradient descent – hyperbolic sigmoid					
1	4/5/5/2	3000	0.077	11.034	12.934
2	4/10/10/2	3000	0.035	9.908	7.277
3	4/10/20/2	3000	0.028	4.557	6.273
4	4/10/5/10/2	3000	0.017	5.414	6.011
5	4/10/20/10/2	3000	0.013	5.011	7.035
FF ANN – Levenberg–Marquardt – hyperbolic sigmoid					
6	4/5/5/2	–	–	–	–
7	4/10/10/2	1070	0.010	4.722	3.386
8	4/10/20/2	2086	0.010	4.146	3.292
9	4/10/5/10/2	1950	0.010	5.014	4.999
10	4/10/20/10/2	1870	0.010	5.015	5.019
FF ANN – gradient descent – logarithmic sigmoid					
11	4/5/5/2	3000	0.032	17.012	21.312
12	4/10/10/2	3000	0.027	18.012	21.781
13	4/10/20/2	3000	0.035	22.014	18.142
14	4/10/5/10/2	3000	0.029	25.124	18.414
15	4/10/20/10/2	3000	0.027	31.567	24.144
FF ANN – Levenberg–Marquardt – logarithmic sigmoid					
16	4/5/5/2	3000	0.027	9.012	14.125
17	4/10/10/2	2950	0.010	12.011	13.123
18	4/10/20/2	3000	0.018	13..012	12.023
19	4/10/5/10/2	3000	0.017	15.781	18.012
20	4/10/20/10/2	3000	0.018	22.341	19.157
RBF ANN – least square error – Gaussian					
21	4/525/2	525	0	3.915	6.083

ing algorithm. At each epoch (iteration), centers were added dynamically until desired minimum square error was achieved. However, performance of the RBF neural network model critically depended upon the chosen centers, which may require an unnecessarily large RBF network to obtain a given level of accuracy and cause numerical ill conditioning (Table 3).

The training process is repeated until the root mean square error between the actual (case I)/simulated (case II) output and the desired output reaches the goal of 1% or a maximum number of epochs (iterations), (it was set to 3000), is accomplished. Finally, the number of the estimated lightning failures of the examined transmission line was validated with the number obtained from situations encountered in the training, i.e. the 5-year period, and others which have not been encountered.

Table 4 presents the training data of all designed ANN models for case I, where the output i.e. the total lightning failure rate N_T, constitute actual data, while Table 5 presents the training data of all designed ANN models for case II, where the two outputs i.e. shielding N_{SF} and backflashover N_{BF} failure rate, constitute simulation data.

It must be mentioned that although in [38] 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 ANN with more than one hidden layers are examined to study the convergence rate for the particular problem of the lightning performance evaluation.

5. Test results

In order to evaluate the lightning performance of the examined Hellenic high voltage transmission lines, it was selected and used from the designed ANN models the model, which presented the best generalising ability, had a compact structure, a fast training process and consumed low memory. According to the training data presented in Tables 4 and 5 the ANN model that had been selected to be applied in the examined transmission lines for case I was No. 9 (FF ANN – Levenberg–Marquardt – hyperbolic sigmoid – 4/10/5/10/1), while for case II was No. 8 (FF ANN – Levenberg–Marquardt – logarithmic sigmoid – 4/10/20/2).

Both models (model No. 9 for case I and model No. 8 for case II) were applied three times to each one of the three examined transmission lines in order to evaluate the lightning failures for years 2001, 2002 and 2003. Thirty six values of each input data (actual collected data or estimated data based on actual measurements corresponding to the examined year) were introduced to the models referring to every one region of the examined transmission line for every individual month of the examined year.

In Table 6 are presented the recorded lightning failures [29] of the examined transmission lines for years 2001, 2002 and 2003, as well as the results obtained according to the simulation software program [28] and these obtained according to the proposed artificial neural network model for case I. Similarly Table 7 presents the shielding failure rate N_{SF} and backflashover fail-

Table 6
Test results of the designed ANN model for Case I

Case I	Line I Arachthos–Acheloos			Line II Thessaloniki-Kardia			Line III Kilkis–Serres		
Year	Recorded lightning failures	Lightning failures using simulation method	Lightning failures using ANN model	Recorded lightning failures	Lightning failures using simulation methods	Lightning failures using ANN model	Recorded lightning failures	Lightning failures using simulation methods	Lightning failures using ANN model
2001	4.00	3.82	3.91	6.00	5.54	6.12	5.00	4.41	4.98
2002	5.00	4.76	5.13	4.00	4.47	4.18	3.00	2.68	2.89
2003	5.00	4.79	5.09	7.00	7.22	6.90	5.00	4.82	4.91

Table 7
Test results of the designed ANN model for case II

Case II	Line I Arachthos–Acheloos				Line II Thessaloniki–Kardia				Line III Kilkis–Serres			
Year	Lightning failures using simulation methods		Lightning failures using ANN model		Lightning failures using simulation methods		Lightning failures using ANN Model		Lightning failures using simulation methods		Lightning failures using ANN model	
	N_{SF}	N_{BF}	N_{SF}	N_{BF}	N_{SF}	N_{BF}	N_{SF}	N_{BF}	N_{SF}	N_{BF}	N_{SF}	N_{BF}
2001	3.09	0.73	2.91	0.78	0.82	4.72	0.83	4.79	3.15	1.26	3.21	1.13
2002	3.14	1.62	3.71	1.67	0.56	3.91	0.62	3.88	2.14	0.54	2.17	0.51
2003	3.21	1.58	3.33	1.41	1.38	5.84	1.19	6.01	4.16	0.66	4.34	0.65

ure rate N_{BF} of the examined transmission lines for years 2001, 2002 and 2003, calculated according to the simulation software program [28] and the proposed artificial neural network model for case II.

It is obvious that the results obtained according to the proposed ANN methods are very close to the actual ones and the results obtained according to the the simulation software program, something which clearly implies that the proposed ANN model is well working and has an acceptable accuracy.

6. Comparison of the FF and the RBF ANN methods

The use of the FF and RBF ANN methods, in the design of the proposed ANN models for evaluating the lightning performance of high voltage transmission lines gave the opportunity for a comparison between the two methods, summarizing the advantages and disadvantages of each one of them.

FF ANN method can provide compact distributed representations of complex data sets, finding a relative solution. It is considered fast method and present small errors during validation process. As a drawback must be mentioned the lack of an exact rule for setting the numbers of neurons and layers for best performance and that there is not an exact match to the training data.

RBF ANN method achieves exact matching between input and output data especially when there is an adequate large number of training data. On the other hand it converges to a quite large number of neurons having as a result the creation of large networks. Furthermore it requires a lot of memory and processing time, while the errors which appear in the validation and test data can not be considered insignificant.

7. Conclusions

The paper describes in detail the design of artificial neural network models in order to evaluate the lightning performance of high voltage transmission lines. 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 method is only using actual input and actual or simulated output line data in its calculations, something that clearly presents its main advantage. Moreover the efficient and economic implementation of the ANN method with today's computer technology, constitute it as an alternative attractive tool. The only drawback that the proposed method presents is that the trained ANN model, which results from the application of the method, can be applied to transmission lines with similar characteristics with these lines, which have been used in the training, validation and testing procedure.

In this paper, the feed-forward and the radial basis function ANN methods where considered, using several different learning algorithms, transfer functions and structures in an effort the problem to be represented accurately. Neural network models were trained and tested and these which presented the best generalising ability, had a compact structure, a fast training process and consumed lower memory, have been selected and applied on three operating Hellenic transmission lines of 150 and 400 kV giving results very close to the actual ones and similar to these of other simulation methods. Finally a comparison between the two neural network methods was presented, stating clearly their advantages and disadvantages. The proposed ANN method can be used by electric power utilities as a useful alternative tool for the design of electric power systems.

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