IOP Publishing — Measurement Science and Technology

Meas. Sci. Technol. **18** (2007) 2239–2244 doi:10.1088/0957-0233/18/7/058

Artificial neural networks in high voltage transmission line problems

L Ekonomou[1], V T Kontargyri[2], St Kourtesi[1], T I Maris[3] and I A Stathopulos[2]

[1] Hellenic Public Power Corporation SA, Distribution Division, 22 Chalkokondyli Str., 104 32 Athens, Greece
[2] National Technical University of Athens, School of Electrical and Computer Engineering, High Voltage Laboratory, 9 Iroon Politechniou St., Zografou Campus, 157 80 Athens, Greece
[3] Technological Educational Institute of Chalkida, Department of Electrical Engineering, 334 40 Psachna Evias, Greece

E-mail: leekonom@gmail.com, vkont@central.ntua.gr, stavriani_kourtesi@yahoo.gr, maris@teihal.gr and stathop@power.ece.ntua.gr

Received 25 December 2006, in final form 15 April 2007
Published 19 June 2007
Online at stacks.iop.org/MST/18/2239

Abstract

According to the literature high voltage transmission line problems are faced using conventional analytical methods, which include in most cases empirical and/or approximating equations. Artificial intelligence and more specifically artificial neural networks (ANN) are addressed in this work, in order to give accurate solutions to high voltage transmission line problems using in the calculations only actual field data. Two different case studies are studied, i.e., the estimation of critical flashover voltage on polluted insulators and the estimation of lightning performance of high voltage transmission lines. ANN models are developed and are tested on operating high voltage transmission lines and polluted insulators, producing very satisfactory results. These two ANN models can be used in electrical engineers' studies aiming at the more effective protection of high voltage equipment.

Keywords: artificial neural networks, critical flashover voltage, high voltage transmission lines, polluted insulators

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Artificial neural network (ANN) methods have seen increased usage in recent years in various fields such as finance, medicine, industry and engineering due to their computational speed, their ability to handle complex nonlinear functions, robustness and great efficiency, even in cases where full information for the studied problems is absent.

Many interesting ANN applications have been reported also in power system areas, where they are widely used in short term load forecasting, in fault classification and fault location in transmission lines [1–3], in voltage stability analysis [4] and in power system economic dispatch solution problems. Furthermore the ANNs have applications in the solution of the power flow problem, the effective distance protection of the transmission lines [5] and the prediction of magnetic performance of strip-wound magnetic cores [6]. Finally very interesting ANN applications have been reported in high voltage engineering problems such as the identification of fault insulators using corona discharges [7], the recognition of leakage current wave forms and their harmonic content on several different types of polluted insulators and polymeric surfaces [8, 9], the evaluation of lightning overvoltages in distribution lines [10] and the lightning protection of high voltage transmission lines [11].

In this paper, the authors have focused their study on two different crucial high voltage transmission line problems, which have been extensively studied in previous decades mainly using conventional analytical methods, empirical and/or approximating equations and simulations. These problems are the estimation of critical flashover voltage on polluted insulators and the estimation of lightning performance

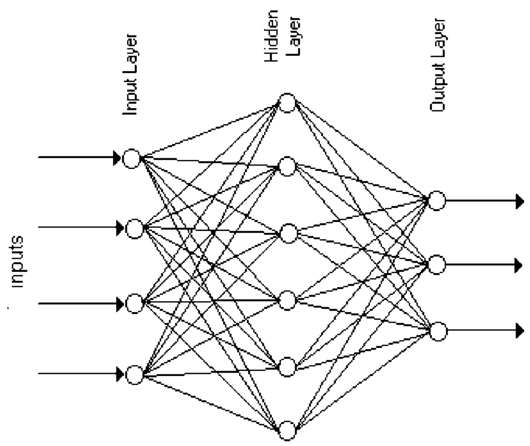

Figure 1. Structure of a typical artificial neural network.

of high voltage transmission lines. The authors have addressed ANNs in order to give accurate solutions in these two problems and satisfactory results are produced using in the calculations only actual field data.

2. Artificial neural networks' design

ANNs can model with great accuracy a certain problem, utilizing the data from a learning set. This model can then be used to estimate the output variable for given values of the input variables without requiring certain mathematical functions, but examples in order to be trained.

An ANN consists of a number of single units, called neurons, bonded with weighted connections. In a successful learning process, the weights are gradually modified in order to give an output close to the expected. An ANN can have three types of layers: the input layer, one or more hidden layers and the output layer (figure 1). When creating an ANN it must be first decided how many neurons there will be in each layer [12]. Afterwards, the training method and the transfer function to be used in the training process must be decided. An ANN is usually trained with the error backpropagation algorithm, in which the occurring errors of the output layer return in the input layer to modify the weights. This procedure is repeated until the occurring errors reach acceptable values.

In the present work two different ANN models have been designed and trained using the MATLAB Neural Network Toolbox [13], in order to estimate (a) the critical flashover voltage on polluted insulators and (b) the lightning performance of high voltage transmission lines. The first ANN model, that will estimate the critical flashover voltage, will consist of five inputs and one output. These are the following: the maximum diameter D_m of the insulator, its height H, the creepage distance L on it, its form factor F and the layer conductivity σ_s, while the output variable is the critical flashover voltage U_c. The second ANN model that will estimate the lightning performance is to consist of four inputs and one output. These are the following: the tower footing resistance R, the peak lightning current I_{peak}, the lightning current derivative $\mathrm{d}i/\mathrm{d}t$ and the keraunic level T. For the output, the lightning failure rate N_T is considered.

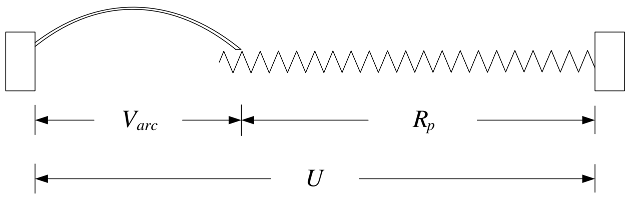

Figure 2. Equivalent circuit for the evaluation of the flashover voltage.

It must be mentioned that all the data used in the training process of both ANN models constitute either actual collected/measured data or estimated data based on actual measurements. More specifically the data that concern the insulators have been derived from experiments carried out in an insulator test station, installed in the high voltage laboratory of Hellenic Public Power Corporation SA's Testing, Research and Standards Center in Athens, Greece [14] and according to the IEC standard 507 (1991). Apart from this set of experimental measurements, other measurement data were also used [15, 16]. As far as the data used in the ANN model for the estimation of the lightning performance are concerned, these have been supplied by the National Meteorological Authority of Hellas (2005), the PPC SA [17] and the lightning measurements of Berger *et al* [18] in Monte San Salvatore in combination with the geographical and meteorological data of the examined areas.

3. Case studies

Conventional analytical solutions, which include in most cases empirical and/or approximating equations, are mainly the tools used by researchers all over the world, in all high voltage transmission line problems. The current work tries to solve two of the most important high voltage transmission line problems using an alternative approach, the ANNs.

3.1. Case I: critical flashover voltage on polluted insulators

The first case study concerns the critical flashover voltage estimation of polluted cap and pin type insulators. The critical flashover voltage is a significant and crucial parameter for the reliability of power systems and that is the reason why there are very interesting research efforts in this area.

One of the mathematical models existing in the literature for the evaluation of the flashover process of a polluted insulator consists of a partial arc spanning over a dry zone and the resistance of the pollution layer in series, as shown in figure 2, where V_{arc} is the arcing voltage, R_p is the resistance of the pollution layer and U_a is the stable voltage supply source.

The critical voltage U_c (in V), which is the applied voltage across the insulator when the partial arc is developed into a complete flashover, is given by the following formula [19]:

$$U_C = \frac{A}{n+1} \cdot (L + \pi \cdot n \cdot D_m \cdot F \cdot K) \cdot (\pi \cdot A \cdot D_m \cdot \sigma_S)^{-(\frac{n}{n+1})}, \quad (1)$$

where A and n are the arc constants. Even though the above equation calculates effectively the critical flashover voltage giving very good results, it constitutes an empirical

Table 1. Line characteristics of the examined transmission lines.

Line	Region	Towers	R (Ω)	N_T (average lightning failures 1996–2003)	T (average lightning level 1996–2003)
Thessaloniki–Kardia	I	1–195	1.93	0.63	29.80
	II	196–260	8.83	1.38	25.40
	III	261–305	18.24	2.00	27.20
Thessaloniki–Amideo	I	1–208	5.20	1.88	29.80
	II	209–249	11.40	3.63	32.50
Acheloos–Arachthos	I	1–70	3.00	3.25	37.60
	II	71–130	3.10	1.50	30.40
	III	131–192	3.60	2.75	37.30
Kilkis–Serres	I	1–46	1.99	1.00	29.45
	II	47–106	4.40	3.50	28.90
	III	107–162	1.78	0.88	27.20

and approximating equation. Furthermore, generally the experiments related to the critical flashover voltage are time consuming and they also meet obstacles, such as the high equipment cost and the need for special equipment.

These drawbacks are attempted to be overcome in this work, utilizing the experimental data available from the literature , producing an effective and reliable ANN estimation tool. The actual data, which have been used in the training, validation and testing processes, have been derived from the studies of Ikonomou [14], Guan [15] and Sundarajan [16].

3.2. Case II: lightning performance of transmission lines

The second case study concerns the lightning performance estimation of high voltage transmission lines. In the last decade, several methods based on many different techniques such as analogue computers [20], geometrical models [21], Monte Carlo simulation [22], travelling waves [23] electrogeometric models [24] and many extensions and improvements of these methods have been proposed. Their common characteristic is that all of these methods use empirical and/or approximating equations. The improvement and modification of these equations, as well as the invention of others was the aim of researchers all over the world, in an effort to successfully and accurately estimate the lightning performance of transmission lines of their own interest.

In this work actual field data from two 400 kV and two 150 kV operating transmission lines of the Hellenic interconnected system are used in order the developed ANN tool to be trained, validated and tested. These four lines were carefully selected among others due to their high failure rates during lightning thunderstorms and the different characteristics that exist along their length according to the data supplied from the National Meteorological Authority of Hellas and the PPC SA. The line characteristics (tower footing resistance, average lightning failures and average lightning level) and their division into regions due to their different characteristics are presented in table 1.

4. Training, validation and testing

Having decided the inputs and outputs of each ANN estimation model, the next step was to define the number of hidden layers, the number of neurons in each layer, the training method, the transfer function and the number of epochs. The total number of data for each input and output was 228 for the first case study, referring to equal numbers of experimental data, while the total number of data for the second case study was 1056, referring to each region of the four examined transmission lines (11 regions in total), for every individual month of an 8 year period (1996–2003). In each training iteration, for each ANN model, 20% of random data was 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 reaches the goal of 1.0% or a maximum number of epochs (it was set to 12 000), is accomplished. Finally, the number of estimated data for both ANN models was checked with the numbers obtained from situations encountered in the trainings, and others which have not been encountered.

Four training methods were tested: the gradient descent, the gradient descent with an adaptive learning rate, the adaptive learning rate with momentum training and the Levenberg–Marquardt and two transfer functions: the hyperbolic tangent sigmoid and the logarithmic sigmoid.

For every ANN model (case studies I and II) and for each one of these training methods a set of scenarios was taken with an inner change of hidden layers (1 or 2) and number of neurons in each hidden layer (2 to 25), in order to find the best architecture for the network, i.e. the number of neurons in the hidden layer that gives the minimum root mean square error.

After extensive simulations with all possible combinations of transfer functions, training methods, hidden layers and neurons in each hidden layer, it was found that the ANN architectures: two hidden layers (16 and 21 neurons respectively in each of them), a logarithmic sigmoid transfer function and the Levenberg–Marquardt training method for the first case study and one hidden layer (18 neurons), a logarithmic sigmoid transfer function and gradient descent with an adaptive learning rate training method for the second case study have presented the best generalizing ability, had a compact structure, a fast training process and consumed lower memory than all the other tried combinations. In these ANN models the mean square error was minimized to the final value of 0.01 within 9582 epochs for the first case study

Table 2. Test results of the developed ANN model for the critical flashover voltage estimation.

No.	D_m (cm)	H (cm)	L (cm)	F	C (mg cm^{-2})	Measured U_c (kV)	Calculated U_c (kV)	ANN U_c (kV)
1	25.4	14.6	27.9	0.68	0.13	12.0	13.4	13.2
2	25.4	14.6	30.5	0.70	0.05	16.0	17.1	15.8
3	25.4	14.6	43.2	0.92	0.02	26.0	26.5	23.7
4	22.9	16.6	43.2	1.38	0.02	23.5	23.1	24.3
5	22.9	16.6	43.2	1.38	0.05	18.3	17.5	19.1

Table 3. Test results of the developed ANN model for the lightning performance estimation.

		Lightning failures in 2004			Lightning failures in 2005		
No.	Line	Recorded	Using conventional method	Using ANN	Recorded	Using conventional method	Using ANN
1	Thessaloniki–Kardia	6.00	6.39	5.68	4.00	4.67	3.86
2	Thessaloniki–Amideo	7.00	7.72	7.34	6.00	5.63	5.44
3	Acheloos–Arachthos	6.00	5.59	6.11	5.00	4.01	5.27
4	Kilkis–Serres	4.00	4.12	4.38	6.00	5.84	5.85

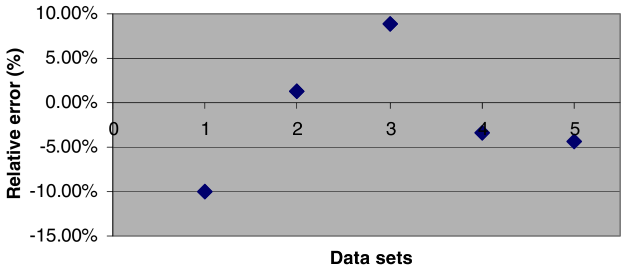

Figure 3. Relative error for the critical flashover voltage between measured and ANN calculated values.

and to the value of 0.01 within 10 375 epochs for the second case study.

5. Results

The trained ANN model for the estimation of the critical flashover voltage has been applied to polluted insulators and the produced results have been compared to actual critical flashover values measured during experiments for the same insulators and to the calculated results produced by the use of equation (1) (table 2). The second trained ANN model for the estimation of high voltage transmission lines has been applied to the same four transmission lines used for the training process, but for the years 2004 and 2005, and the results have been compared to the results obtained according to the conventional method [25] and real records of the outage rate supplied from PPC SA [17] (table 3).

It is obvious that the results obtained according to the proposed ANN methods are very close to the measured ones and the calculated ones (using equation (1)) for case study I and the actual ones and the calculated ones (using the conventional method) for case study II, something which clearly implies that the proposed ANN method and the proposed ANN models are well working and have an acceptable accuracy. Figure 3 presents the percentage absolute error for the critical flashover voltage between the measured and ANN calculated values. Figures 4 and 5 present the percentage absolute error for the lightning failures between actual − conventional calculated values and actual − ANN calculated values for years 2004 and 2005, respectively.

It must be mentioned that the two developed ANN models can be applied to any high voltage polluted insulator and high voltage transmission line with similar characteristics to

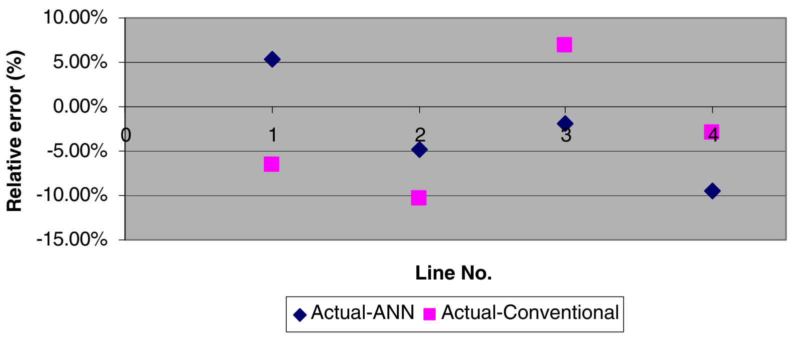

Figure 4. Relative error for the lightning failures between actual − conventional calculated values and actual − ANN calculated values for the year 2004.

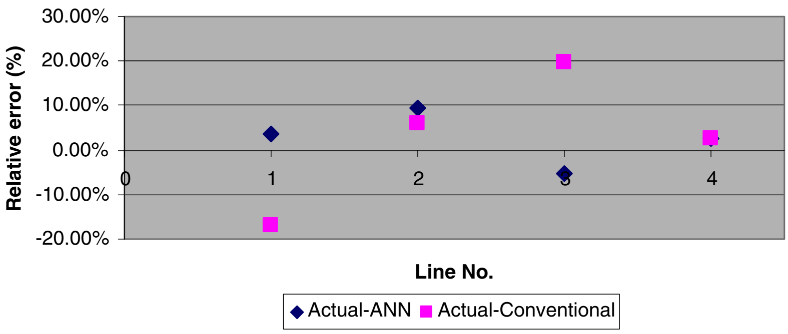

Figure 5. Relative error for the lightning failures between actual − conventional calculated values and actual − ANN calculated values for the year 2005.

those of the Hellenic transmission system. For another high voltage transmission system with different characteristics, we absolutely require retraining, revalidation and retesting of the ANN models using the measured/actual field data of the new transmission system.

6. Conclusions

In this work artificial intelligence and more specifically artificial neural networks are addressed in order to give accurate and reliable solutions to high voltage transmission line problems faced up-to-date using conventional analytical methods and simulations. The models have been applied to real, significant high voltage transmission line problems (estimation of critical flashover voltage on polluted insulators and lightning performance estimation of transmission lines), giving very satisfactory results. The efficient and economic implementation of the ANNs with today's computer technology, the use of only actual data in the calculations and the avoidance of empirical and/or approximating equations mean they constitute alternative attractive tools to the conventional analytical methods. The two developed ANN models can be used in the Hellenic electrical engineers' studies, aiming at the more effective protection of Hellenic high voltage equipment.

Acknowledgments

The authors want to express their gratitude to the Hellenic Public Power Corporation SA and the Meteorological Authority of Hellas for the supply of various technical data.

References

[1] Mahanty R N and Gupta P B D 2004 Application of RBF neural network to fault classification and location in transmission lines *IEE Proc. Gener., Transm. Distrib.* **151** 201–12

[2] Mazon A J, Zamora I, Gracia J, Sagastabeutia K J and Saenz J R 2001 Selecting ANN structures to find transmission faults *IEEE Comput. Appl. Power* **14** 44–8

[3] Gardoso G, Rolim J G and Zurn H H 2004 Application of neural-network modules to electric power system fault section estimation *IEEE Trans. PWRD* **19** 1034–41

[4] Schmidt H P 1997 Application of artificial neural networks to the dynamic analysis of the voltage stability problem *IEE Proc. Gener., Transm. Distrib.* **144** 371–6

[5] Dash P K, Pradhan A K and Panda G 2001 Application of minimal radial basis function neural network to distance protection *IEEE Trans. PWRD* **16** 68–74

[6] Miti G K and Moses A J 2004 Neural network-based software tool for predicting magnetic performance of strip-wound magnetic cores at medium to high frequency *IEE Proc. Sci. Meas. Technol.* **151** 181–7

[7] Li C R, Shi Q, Cheng Y C, Yu C and Yichao Y 1998 Identification of faulty insulators by using corona discharge analysis based on artificial neural networks *Proc. Int. Symp. on EI (Arlington, USA)* pp 382–5

[8] Fernando M A R M and Gubanski S M 1999 Leakage current patterns on contaminated polymeric surfaces *IEEE Trans. Dielectr. Electr. Insul.* **6** 688–94

[9] Fernando M A R M and Gubanski S M 1996 Leakage current patterns on artificial polluted composite insulators *IEEE Annual Report: Conf. on Electrical Insulation and Dielectric Phenomena (San Francisco, USA)* pp 394–7

[10] Martinez J A and Gonzalez-Molina F 2001 Statistical evaluation of lightning overvoltages on overhead distribution lines using neural networks *Power Eng. Soc. Winter Meeting* **3** 1133–8

[11] Sidhu T S, Singh H and Sachdev M S 1995 Design, implementation and testing of an artificial neural network based fault direction discrimination for protecting transmission lines *IEEE Trans. PWRD* **10** 697–706

[12] Haykin S 1994 *Neural Networks: A Comprehensive Foundation* (Englewood Cliffs, NJ: Prentice-Hall)

[13] Demuth H and Beale M 2002 Neural network toolbox user's guide for use with MATLAB

[14] Ikonomou K, Katsibokis G, Panos G and Stathopoulos I A 1987 Cool fog tests on artificially polluted insulators *5th Int. Symp. on High Voltage Engineering (Braunschweig)* vol 2 paper 52.13

[15] Guan Z and Zhang R 1990 Calculation of DC and AC flashover voltage of polluted insulators *IEEE Trans. Electr. Insul.* **25** 723–9

[16] Sundarajan R, Sadhureddy N R and Gortur R S 1995 Computer-aided design of porcelain insulators under polluted conditions *IEEE Trans. Dielectr. Electr. Insul.* **2** 121–7

[17] Hellenic Public Power Corporation SA (PPC SA) 2005 *Transmission lines characteristics* Hellenic Public Power Corporation SA (Athens)

[18] Berger K, Anderson R B and Kkoninger H 1975 Parameters of lightning flashes *Electra* **41** 23–37

[19] Topalis F V, Gonos I F and Stathopoulos I A 2001 Dielectric behavior of polluted porcelain insulators *IEE Proc. Gener., Transm. Distrib.* **148** 373–6

[20] Clayton J M and Young F S 1964 Estimating lightning performance of transmission lines *IEEE Trans. PAS* **83** 1102–10

[21] Fisher F A, Anderson J G and Hagenguth J H 1960 Determination of lightning response of transmission lines by means of geometrical models *AIEE Trans. PAS* **78** 1725–36

[22] Anderson J G 1961 Monte Carlo computer calculation of transmission-line lightning performance *AIEE Trans.* **80** 414–20

[23] Bewley L V 1951 *Travelling Waves On Transmission Systems* 2nd edn (New York: Wiley)

[24] Lundholm R, Finn R B and Price W S 1958 Calculation of transmission line lightning voltages by field concepts *AIEE Trans. PAS* **77** 1271–83

[25] Ekonomou L, Gonos I F, Stathopoulos I A and Topalis F V 2003 Lightning performance evaluation of Hellenic high voltage transmission lines *ISH 2003 (Delft, The Netherlands)* (P.05.10)