Modeling the Flashover Voltage Using ANN

Kherfane Riad Lakhdar , Younes Mimoun , Khodja Fouad , Kherfane Naas

Abstract— This work attempts to apply an artificial intelligent technique which is the ANN to estimate the flashover voltage for polluted insulators, based on various studies published in this field and given by reference to the experimental results on insulators artificially polluted. The obtained results are promising and insure that ANN technique can help researchers in this field to understand more deeply and estimate the critical flashover voltage for new designed insulators.

Keywords— high voltage insulator, insulator polluted, ANN, critical flashover voltage.

I. INTRODUCTION

One of the main objectives in the design of equipment for transmission and distribution of electrical energy is to make it reliable, whatever the environmental conditions. These conditions can be related to various factors such as pollution, atmospheric pressure, temperature, etc. From the electrical equipment constituting the air networks a special interest should be worn to insulators which are essential for the proper functioning of these networks and this despite the fact that they represent a small percentage of the total cost of design. Indeed, their failure can have a significant impact on operating costs of electrical networks, since their role is to provide electrical isolation of power phases between them and between them and the parties earthed.

Thus insulators are most exposed to pollution accumulation and can be significantly affected by transients overvoltages who are capable of exceeding their dielectric withstand at all times. This usually results in electrical flashovers, which can lead to interruptions more or less long of the electrical energy distribution, and to economic losses. A flashover is resulting in a short circuit, between scope part to the high voltage and ground, created by establishing of an electric arc which is generally at the insulator surface covered by a layer of pollution.

Measurement results in artificial testing laboratory to determine the profile of insulators and the length of the string that represents the best performance in the conditions of pollution of the studied site. The shape of the insulator is generally designed for a maximum creepage distance between the two conductors. Indeed, these tests are not only very expensive, but require hardware long to achieve to follow very complex phenomena namely the propagation of discharges along the insulators [12]. In addition to the degree of pollution which varies greatly from one region to another and from one year period to another period [11].

Economically, intelligent systems would gain to be used in the domain of high voltage, especially in the study of insulators flashover. These techniques can reduce the experimental work and predict values which influences the parameters characterizing this process which saves considerable time and reducing the number and duration of interruptions in the power supply of consumers.

This work tries to use the experimental values and the results of theoretical approaches to building and establishing an ANN which can estimate the value of the critical flashover voltage, using as data the characteristics of the insulator.

II. NEURAL NETWORKS

II.1. The ANN algorithm: (Neural networks algorithm)

The ANN can use data read to model some problems with high accuracy. This model can be used to estimate the output variables from the data input variables. He tries to simulate the reasoning process of human intelligence and therefore be used instead of mathematical functions.

The ANN may have three types of layers, the layer of inputs, one or more hidden layers and the layer of the outputs. To create the ANN, the first thing is to decide on the number of neurons in each layer. The artificial neural network is generally established with a backpropagation algorithm of the error when the error happens at the output layer, returns to the input layer to modify the weights. This procedure is repeated until reaching values of acceptable errors.

In the present work, an adapted ANN is built in Matlab and developed to estimate the flashover voltage of insulator according to these characteristics. The variable which is given as input is: C: ESDD in mg/cm2, while the output variable is the flashover voltage Uc (in kV).

The input-output data are normalized before the network training to ensure good convergence and accuracy during the training process [4]. We tried nine different schemes to standardize training models input-output. The details of these schemes normalization are discussed [3]. These different schemes for the normalization using the minimum and maximum values of the data vector components of output and also the average value and standard variance (standard deviation) SD input-output variables are presented in the following table:

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Table 1

Number of the schemes	**input**	**output**
1	Max	Max
2	Max	Max Min
3	Max	Mean & S.D
4	Max Min	Max
5	Max Min	Max Min
6	Max Min	Mean & S.D
7	Mean & S.D	Max
8	Mean & S.D	Max Min
9	Mean & S.D	Mean & S.D

A. *Artificial neural networks*

Once the connection weights are adjusted by backpropagation algorithm, the ANN can estimate the experiment flashover voltage. Three points should be noted:

- Stopping criteria:

The calculation is repeated with epoch (an epoch is the representation of group of experiences, inputs and targets, vectors of the network and the calculation of the new weights) until the weights have stabilized or error functions are not still minimized or the maximum number of epochs is reached.

In our case the error function is the square root of the mean error of the evaluation group according to RMSE.

$$RMSE = \sqrt{\frac{1}{m_2\, q_{out}} \sum_{i=1}^{m_2} \sum_{k=1}^{q_{out}} e_k^2 \ \ (i)} \tag{1}$$

Where q_{out} is the number of neuron in the output layer and $e_k(i)$ is the error of the k^{th} output neuron for the i^{th} sample of the evaluation group.

If one of the three criteria is true, the main core of the backpropagation algorithm tends towards the end otherwise the number of epochs is increased by 1, the adaptation rules are applied and the calculation is repeated.

- Validation criteria:

For all evaluation, the root mean square error RMSE, the square of the mean absolute error MAE, and correlation can be calculated.

$$MAE(k) = 100\%. \frac{\sum_{i=1}^{m_2} \left| t_k(i) o_k - (i) / t_k(i) \right|}{m_2} \tag{2}$$

Where $t_k(i)$ and $o_k(i)$ are the real and estimated value of the k^{th} output neuron for the i^{th} sample of the evaluation assembly.

For the estimate of the final flashover voltage, the equations (1) and (2) can be applied.

- Activation functions:

A number of activation functions, called transfer function, can be applied. The "logsig" (sigmoid) function, the "tansig" (hyperbolic) function and the "purelin" (linear) function.

III. Application of the ANN to estimate the flashover voltage

The ANN training is done on a database collected from publications on the domain of flashover of polluted insulators [10] [5] [6] [7] [9] [1] [8][2].

167 values were used for training and 29 values for the test. And we chose in first the hyperbolic function as activation function, α = 0.3, η = 0.9, a single hidden layer, and the number of iterations 500. We varied the number of the schem and the number of layers, the RMSE has assumed values of the figure (1).

Table 2

Types of insulators

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
D_m(cm)	25.4	26.8	25.4	25.4	25.4	27.9	25.4	28	25.4	20	22.9	29.2	32.1	26.8
L (cm)	27.9	40.6	43.2	31.8	30.5	36.8	43.2	37	30.5	40	43.2	47	54.6	33
F	0.68	0.86	0.9	0.72	0.70	0.76	0.92	0.8	0.74	1.29	1.38	0.92	0.96	0.79

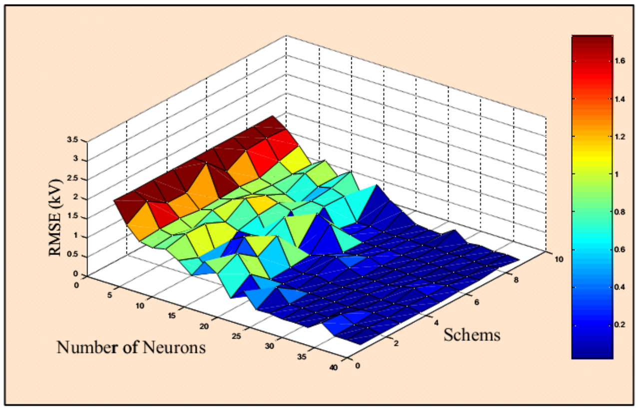

Figure 1
The RMSE for one hidden layer

Fig (1) shows that the number of neurons and the number of the arrangement have a great influence on the RMSE and greater the variation of the error function of these two parameters is not linear, so we had to find the best combination that gives the smallest error. The best results are given for the scheme number 8 and the number of neurons is between 25 and 40 but we take the number 27 which corresponds to the best MAE as shown in figure (2).

This figure also shows that the variation of the MAE in depending on number of neurons is not linear.

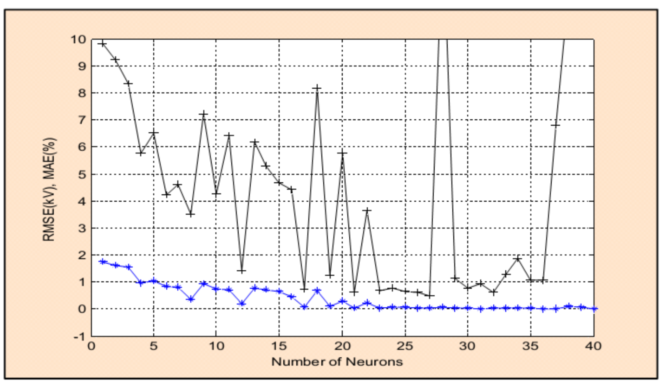

Figure 2
The RMSE and The MAE in depending on number of neurons

After we tried with two hidden layers while keeping $\alpha = 0.3$, $\eta = 0.9$ and 500 iterations, but changing the activation function to the sigmoid function (logsig), fixing the number of scheme to 8 and varying the number of neurons in the first and the second hidden layer, the RMSE values are given in Figure (3).

Even notice the variation of the RMSE is not linear, so we must select the best combination carefully, because we can see that for a larger number of neurons we can find a smaller error, as there may be a greater error.

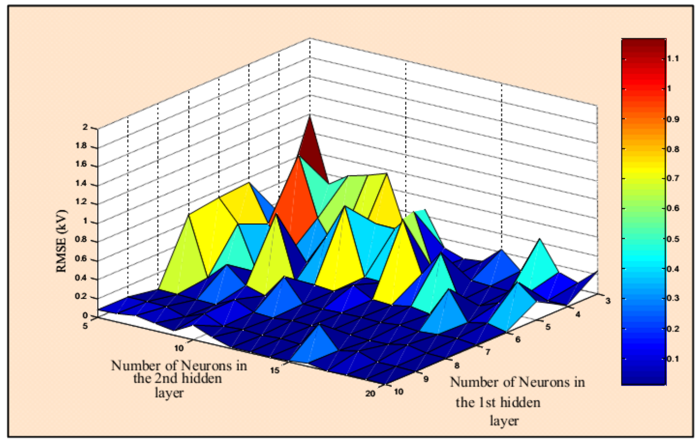

Figure 3
The RMSE for 2 hidden layers

The best result was given for 8 neurons in the first hidden layer and 11 neurons in the second hidden layer where RMSE= 4.10-3 kV.

After we set the number of neurons to 8 for the first hidden layer and 11 for the second hidden layer and we did change the number of iterations we found the RMSE of the figure (6).

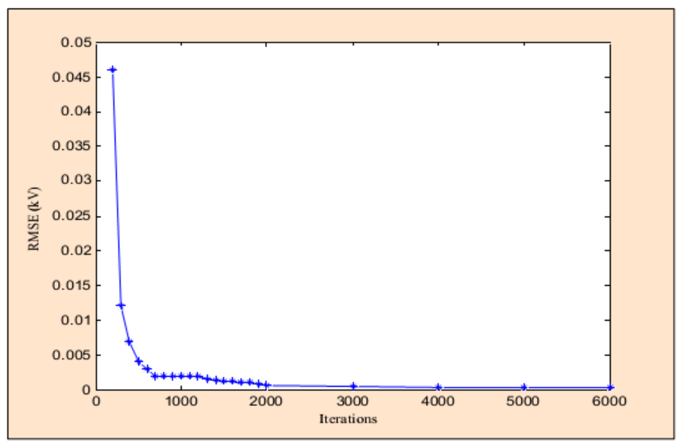

Figure 4
RMSE depending the iterations

It was found that 6000 iterations are a good value for the RMSE (3.10-4kV).

In the end we changed the activation function for the last case i.e. $\alpha = 0.3$, $\eta = 0.9$, S = 8, 8 neurons in the first layer and 11 neurons in the second layer and 6000 iterations, we found the following table which gives the RMSE (kV) as a function of the various combinations of the functions of activation.

Table 3

		The activation function for the hidden layers		
		Logsig	Tansig	Purelin
The activation function for the output layer	Logsig	0.0083	0.04	0.002
	Tansig	0.003	0.192	0.0028
	Purelin	0.0003	0.012	0.0027

We note that the function logsig for the hidden layers and purelin (linear) for the output layer gives the best result.

IV. Validation

After the development of the structure of the ANN we are going to validate the results. Figures (5.6) show that the training and testing of the ANN are done with great success.

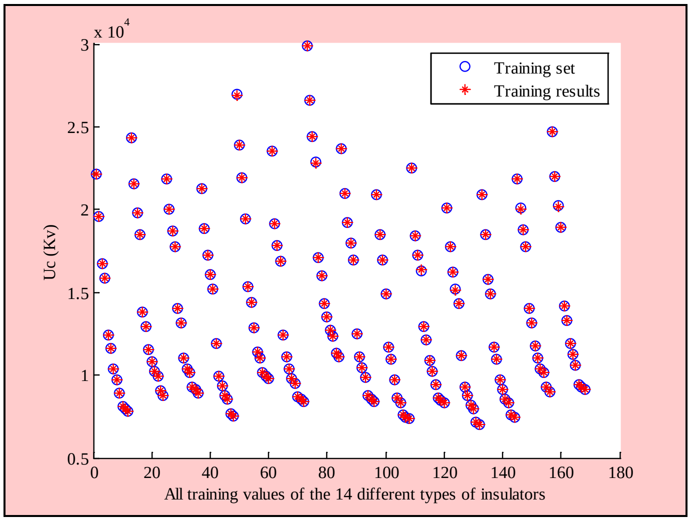

Figure 5
Training results of the ANN

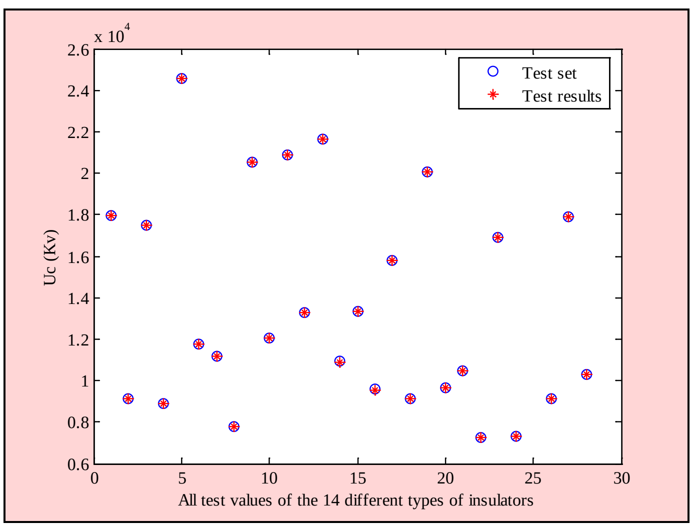

Figure 6
Test results of the ANN

Now we verify the fidelity of ANN by exposing the output values to the input values of learning and testing we find the curves in Figure (7).

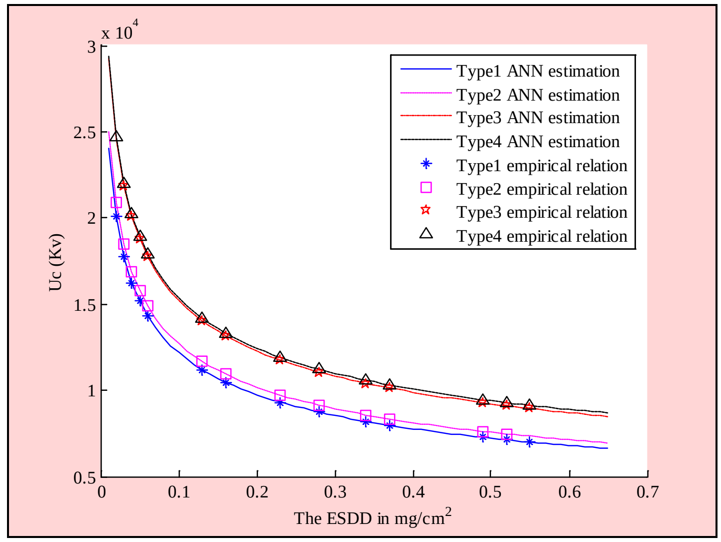

Figure 7
Verifying the ANN fidelity

In the end we proceed with the validation of the results by comparing the estimate values of ANN to experimental values (Table 4) and the mathematical model used by most researchers in this field, established by IF Gonos, based on the equation of Aubenaus, which gave values to the arc constants A and n (A= 124.8 and n=0.409) [7], [13].

Table 4
experimental values

Type	L(cm)	D (cm)	F	C (mg/cm^2)	Uc (KV)
Type 1	27.9	25.4	0.68	0.13	12
	27.9	25.4	0.68	0.16	11.1
	27.9	25.4	0.68	0.23	8.7
	27.9	25.4	0.68	0.28	9.1
	27.9	25.4	0.68	0.34	7.5
	27.9	25.4	0.68	0.37	7.8
	27.9	25.4	0.68	0.49	6.2
	27.9	25.4	0.68	0.52	6.8
	27.9	25.4	0.68	0.55	6.1
Type 2	30.5	25.4	0.70	0.02	22
	30.5	25.4	0.70	0.05	16
	30.5	25.4	0.70	0.1	13
	30.5	25.4	0.70	0.16	11
	30.5	25.4	0.70	0.22	10
	30.5	25.4	0.70	0.3	8.5
Type 3	43.2	25.4	0.92	0.02	26
	43.2	25.4	0.92	0.05	19
	43.2	25.4	0.92	0.1	15
	43.2	25.4	0.92	0.16	13
	43.2	25.4	0.92	0.22	12
	43.2	25.4	0.92	0.3	10.5
Type 4	43.2	22.9	1.38	0.02	23.5
	43.2	22.9	1.38	0.03	20.9
	43.2	22.9	1.38	0.04	19.4
	43.2	22.9	1.38	0.05	18.3
	43.2	22.9	1.38	0.06	16.9
	43.2	22.9	1.38	0.1	15.8
	43.2	22.9	1.38	0.2	13.6

We chose four types of insulators (Those who we have their experimental values (1, 5, 7, 11)), and have been shown separately to avoid overlapping between the curves, whence the figures (8, 9, 10, 11)

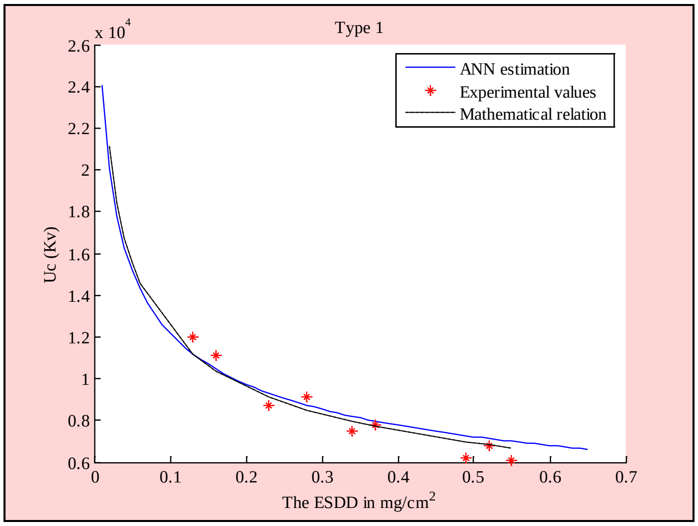

Figure 8
Comparison between the values of the mathematical model and those of ANN taking as a reference the experimental values of type 1

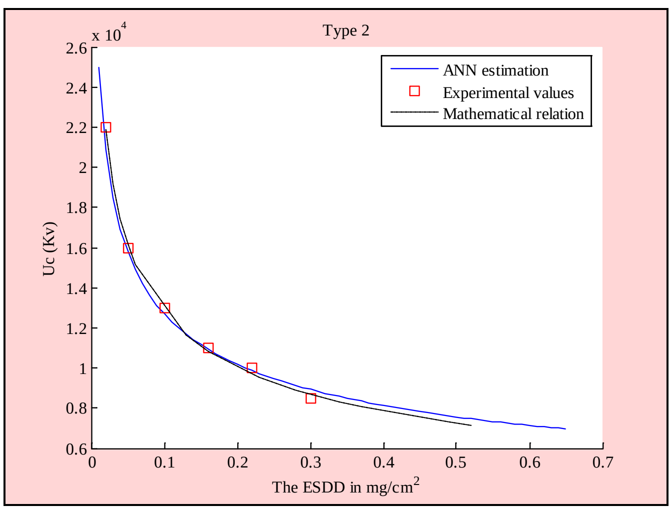

Figure 9
Comparison between the values of the mathematical model and those of ANN taking as a reference the experimental values of type 2

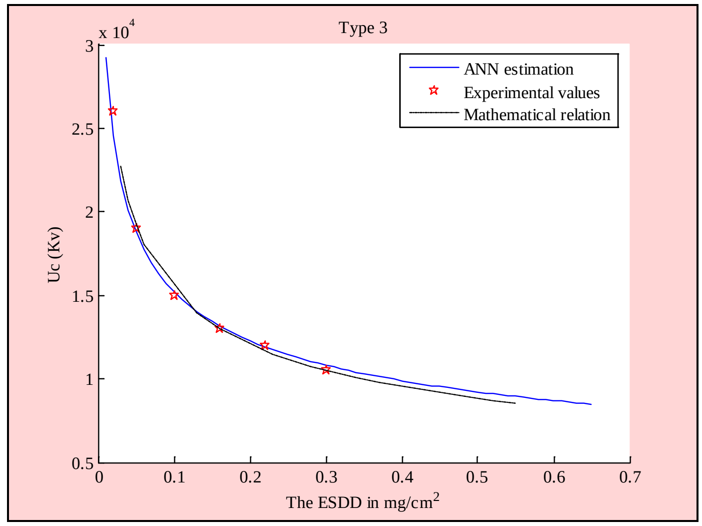

Figure 10
Comparison between the values of the mathematical model and those of ANN taking as a reference the experimental values of type 3

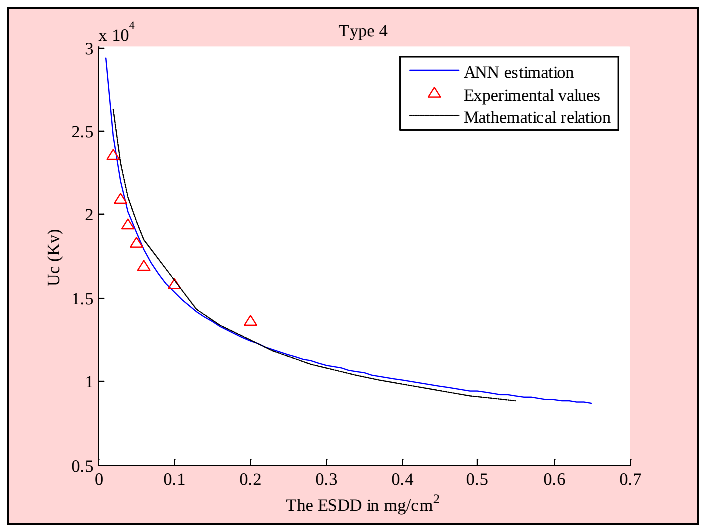

Figure 11
Comparison between the values of the mathematical model and those of ANN taking as a reference the experimental values of type 4

V. Conclusion

The validity of results shows that this method has been successfully applied and that its use in this area can effectively replace the experimental costly works, that time and equipment consuming. And therefore this technique can give a more in research to reduce the flashover defect, and improve the smooth functioning of insulators.

References

[1] G.E. Asimakopoulou V.T. Kontargyri G.J. TsekourasF.E. Asimakopoulou I.F. Gonos I.A. Stathopulos “Artficial neural network optimization

methodology for the estimation of the critical flashover voltage on insulators" National Technical University of Athens, Published in IET Science, pp 90-104, 2009.

[2] G.E. Asimakopoulou V.T. Kontargyri G.J. Tsekouras, Ch.N. Elias F.E. Asimakopoulou, I.A. Stathopulos "A fuzzy logic optimization methodology for the estimation of the critical flashover voltage on insulators" National Technical University of Athens, Published in IET Science, pp 580-588, 2010.

[3] M. Belkheiri,B. Zegnini, and D. Mahi "Modeling the Critical Flashover Voltage of High Voltage Insulators Using Artificial Intelligence" Journal of Intelligent Computing and Application (JICA), pp137-154, December 2009.

[4] A.S. Farag , "Estimation of Polluted Insulators Flashover Time Using Artificial Neural Networks" King Fahd University of Petroleum and Minerals IEEE,pp. 184-192, 1997

[5] M.T. Gencoglu, M. Cebeci "Computation of AC Flashover Voltage of Polluted HV insulators using a dynamic arc model" Euro.Trans.Electr.Power, pp689-701, 2008.

[6] M.T. Gencoglu, M. Cebeci "Investigation of Pollution Flashover on High Voltage Insulators Using Artificial Neural Network" Science Direct, pp7338-7345, 2009.

[7] I. F.Gonos, F.V. Topalis and LA. Stathopolos "Genetic Algorithm Approach to the Modelling of Polluted Insulators" IEE,pp. 373-376, May 2002

[8] A. Kazemi, M.T.Hassanzadeh and A.Gholami "Artificial Neural Network for Insulator Leakage Currents Prediction from Environmental Data" IEEE International Conference on Power and Energy, Malaysia , pp. 13-17,2008

[9] V.T. Kontargyri, A.A. Gialketsi, G.J. Tsekouras,I.F. Gonos, I.A. Stathopulos "Design of an Artificial Neural Network for the Estimation of the Flashover Voltage on Insulators" National Technical University of Athens, pp. 1532-1540, December 2006.

[10] Muhsin Tunay Gencoglu, Mehmet Cebeci "The Pollution Flashover on High Voltage Insulators", Science Direct, pp. 1914-1921, 2008

[11] Z. Sahli, et al. «Prediction parameters of dimensioning of insulators under non-uniform contaminated conditions by multiple regression analysis », Electr. Power Syst. Res. (2010), doi:10.1016/j.epsr.2010.11.017

[12] M. El-A. Slama, A. Beroual, and H. Hadi ''Analytical Computation of Discharge Characteristic Constants and Critical Parameters of Flashover of Polluted Insulators '' IEEE, pp1764-1771, July 2010.

[13] F. OBENAUS, Fremdshichtuberschlag und kriechweglang, deutch elektrotechnick, vol, 4, PP. 135-136, (1958).