# EVALUATION OF FLASHOVER VOLTAGE ON POLLUTED INSULATORS WITH ARTIFICIAL NEURAL NETWORK

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***Abstract:*** *The importance of the research on insulator pollution has been increased considerably with the rise of the voltage of transmission lines. In order to improve understanding of the flashover phenomenon in polluted insulators, several experimental and numerical studies have been made in last years. In this paper, an artificial neural network (ANN) model was built with limited number of measurements for the prediction of the critical flashover voltage of polluted insulators. The proposed network is trained using different variables characteristics of the insulator such as diameter, height, creepage distance, form factor and equivalent salt deposit density. After training, the network can estimate the flashover voltage for different inputs. The obtained results shows that the ANN model can predict the flashover phenomenon parameters without carry out any experiment.*

***Key-Words:*** *High voltage, polluted insulators, critical flashover voltage, artificial neural networks.*

## 1. Introduction

Insulators used in outdoor electric power transmission lines are exposed to outdoor environmental contaminations. The pollution of the insulators is the most essential element in a flashover phenomenon which constitutes one of the factors of first importance in the quality and the reliability of the power transmission. Due to rapid rise of transmission voltages and growth of pollution, this problem has drawn more attention in recent years. The insulators high voltages are covered with a layer of pollution which comes from the atmosphere. Associated the dew of morning, the rain, or the fog, this layer of pollution becomes conducting and allows passage of a leakage current towards the mass of the pylons. Under certain favorable conditions there will be the appearance of the discharges partial on surface of the insulator which lengthen and lead to the complete flashover of the insulator. Experiments concerning the critical flashover voltage *Uc* are time-consuming and have further obstacles, such as high cost and the need for special equipment .This has resulted in the development of several approaches and analytical mathematical relationships for the estimation of the flashover voltage on polluted insulators [1-6].

In last years, the computational intelligence techniques have been successfully applied in many studies. Among of these methods, artificial neural network (ANN) architectures have been widely used, 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 studied problem is absent. The ANNs, present to have applications in the solution of various engineering problems, such as function approximation, modeling, classification, control, estimation and prediction, etc...In the field of high voltage (HV), ANNs have been used to estimate the time-to-flashover [7], to analyze the insulator surface tracking on solid insulators [8], to estimate the pollution level [9], and to predict a flashover voltage [10-11].

In this paper, we will use available experimental data and the results of a mathematical approach, in order to construct a model based on ANN architectures that can estimate the critical flashover voltage on polluted insulators, using as input geometrical characteristics of the insulator and the severity of the pollutant layer.

## 2. Artificial neural networks

Artificial neural network algorithm has been used successfully in many applications, Called "universal approximator", because of their ability to approximate any function, linear or no-linear, simple or complex. It transforms inputs into outputs to the best of its ability. An artificial neural network consists of a set of processing elements called neurons that interact by sending signal to one another along weighted connections (weights) [12]. Each neuron can have multiple inputs and outputs. Inputs to a neuron can be from external stimuli or can be from output of the other neurons. Copies of the single output that comes from a neuron can be input to many other neurons in the network. It is also possible that one of the copies of the neuron's output can be input to itself as a feedback. An ANN can have three types of layers: the input layer, one or more hidden layers and the output layer. When creating an ANN it must be first decided how many neurons there will be in each layer. Therefore, a learning procedure is necessary in which the strengths of the connections are modified to achieve the desired form of activation function. The learning procedure is divided into three types: supervised, reinforced and unsupervised. The type of error signal used to train the weights in the network defines these three types of learning. In supervised learning, an error scalar is provided for each output neuron by an external "teacher", while in reinforced learning the network is given only a global punish/reward signal. In unsupervised learning, no external error signal is provided, but instead internal errors are generated between the neurons, which are then used to modify weights [13]. In a successful learning process, the weights are gradually modified in order to give an output close to the expected. An ANN is usually trained with the error back-propagation algorithm, in which the occurring errors of the output layer return in the input layer to modify the weights iteratively according to equation (1).

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \tag{1}$$

Where: $w_{ji}(n)$ and $w_{ji}(n+1)$ are the previous and the modified weights connected between the $i^{th}$ and the $j^{th}$ adjoining layers. $\Delta w_{ji}(n)$ stands for the correction or modification factor and n stands for the number of the iteration.

If we consider the $j^{th}$ neuron in a single layer neural network, the training efficiency is enhanced by minimizing the error between the actual output of the $j^{th}$ neuron and the output that has been dictated by the teacher. Same criterion can also be achieved by the usage of a Least Squares Method (LSM). Hence, if there are L neurons in a particular network, the cost function to be ultimately minimized is given by (2).

$$e(n) = \frac{1}{2}\sum_{j=1}^{L}\left[d_j(n) - y_j(n)\right]^2 \tag{2}$$

Where $y_j(n)$ and $d_j(n)$ are respectively, the actual and the teacher-requested outputs for the $j^{th}$ neuron in the $n^{th}$ iteration,. The overall measure of the error for all the input-output patterns is given by

$$E(n) = \frac{1}{2}\sum_{n=1}^{N} \sum_{j=1}^{L}\left[d_j(n) - y_j(n)\right]^2 \tag{3}$$

Where $N$ is the number of input-output patterns in the training set.

In this study, the prediction performances of the model are tested using the following statistical error criteria: the root mean square error (RMSE), the mean absolute percentage error (MAPE) and the absolute fraction of variance ($R^2$). These errors have been calculated by the following equations [14]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(d_k - y_k)^2} \tag{4}$$

$$R^2 = 1 - \sum_{k=1}^{N}\left[\frac{d_k - y_k}{d_k}\right]^2 \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left[\left|\frac{d_k - y_k}{d_k}\right|\right].100 \tag{6}$$

## 3. Data of learning and test

The data used for the training and testing of the ANN concerning different types of insulators were collected from both experiments [15–17] and application of a mathematical model for the calculation of the flashover voltage [18].

The equivalent circuit used for the formulation of a mathematical model consists of a partial arc spanning over a dry zone in series with a resistance that represents the pollution layer, as shown in Fig. 1. This model has been used to enrich the training data by the evaluation of the flashover process of a polluted insulator.

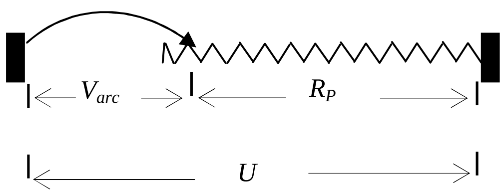


**Fig.1.** Equivalent circuit for the evaluation of the flashover voltage.

Where $V_{arc}$ is the arcing voltage, $R_p$ the resistance of the pollution layer and $U$ a stable voltage supply source.

The critical flashover voltage $Uc$ (in V) is given by the following formula [18]:

$$U_c = \frac{A}{n+1}(L + \pi.n.D_m.F.K).(\pi.A.D_m.\sigma_s)^{\frac{-n}{n+1}} \tag{7}$$

Where L is the creepage distance of the insulator (in cm), $D_m$ is the maximum diameter of the insulator disc (in cm) and F is the form factor. The arc constants A and n have been calculated using a genetic algorithm model [19] and their values are A=124.8 and n=0.409.

The surface conductivity $\sigma_s$ (in $\Omega^{-1}$) is given by the following formula [20]:

$$\sigma_s = (369.05.C + 0.42).10^{-6} \tag{8}$$

Where C is the equivalent salt deposit density (ESDD) in mg/cm$^2$. The coefficient of the resistance of the pollution layer K in the case of cap-and-pin insulators is given by [21]:

$$K = 1 + \frac{n+1}{2.\pi.F.n} . \ln\left(\frac{L}{2.\pi.R.F}\right) \quad (9)$$

Where $R$ is the radius of the arc foot (in cm) and is given by:

$$R = 0.469. (\pi.A.D_m.\sigma_s)^{1/(2.(n+1)}} \quad (10)$$

In the literature, there are many values of the arc constants $A$ and $n$ which depending for the chemical composition of the pollutants [22,23]. The above mathematical model is a result of experiments in specific insulators types and specific pollutants on their surfaces.

In this study, a neuronal model has been developed to estimate accurately the critical flashover voltage of polluted insulators (FOV). This model use as inputs parameters the geometric characteristics of the insulators : the maximum diameter $D_m$ (cm), the height H (cm), the creepage distance L (cm), the form factor F of the insulator and the Equivalent Salt Deposit Density ESDD (mg/cm$^2$), while the output variable is the critical flashover voltage Uc (KV) (Fig.2).

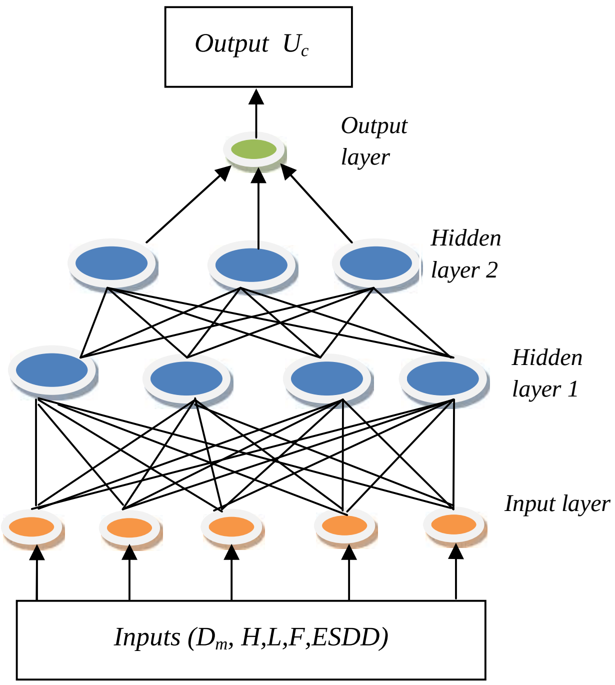


**Fig.2** Structure of a Neuron Network multilayers.

In order to avoid saturation phenomena and for better convergence of the learning process of the ANN model, the input and output variable values are normalized.

The normalization is chosen by the maximum and minimum values of each variable, as shown in the following expression:

$$x_{i,nor} = a + \frac{b-a}{x_{max}-x_{min}}(x_i - x_{min}) \quad (11)$$

Where: $x_{min} = \min(x_i)$, $x_{max} = \max(x_i)$ ,a and b are the respective values of the normalized variable.

All of the input-output variables in the training patterns are normalized within its series before the initiation of the training and test of the neural network.

## 4. Results and discussion

In the present work, an ANN model was implemented by using the MATLAB software in order to estimate the critical flashover voltage on polluted insulators Uc. The input data are the geometric characteristics of an insulator ($D_m$, H, L, F) and the equivalent salt deposit density C. The total number of vectors, which include the input and output variables, was 172. The 80% of these input-output patterns was decided to be used to train the network, while the rest 20% was used to test the function of the network. That means that the training set consisted of 144 vectors and the testing set consisted of 28 vectors. 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 1500), is accomplished. 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.

Architecture and training parameters of ANN were presented in Tables 1.

**Table.1** Architecture and training parameters.

| Architecture | |
|---|---|
| The number of layers: | 3 |
| The number of neuron on the layers: | 5/7/1 |
| The initial weights and biases: | Random |
| Activation functions: | Logarithmic sigmoid |
| **Training parameters** | |
| Learning rule: | Levenberg–Marquardt Back-propagation |
| Learning rate : | 0.25 |
| Momentum constant: | 0.85 |
| Mean-squared error: | 1E-10 |

**Table.2** Characteristic values of the insulators for constructing the training set.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| D(cm) | 26.8 | 26.8 | 25.4 | 25.4 | 29.2 | 27.9 | 32.1 | 28.0 | 25.4 | 20.0 |
| H(cm) | 15.9 | 15.9 | 16.5 | 14.6 | 15.9 | 15.6 | 17.8 | 17.0 | 14.5 | 16.5 |
| L(cm) | 33.0 | 40.6 | 43.2 | 31.8 | 47.0 | 36.8 | 54.6 | 37.0 | 30.5 | 40.0 |
| F | 0.79 | 0.86 | 0.90 | 0.72 | 0.92 | 0.76 | 0.96 | 0.80 | 0.74 | 1.29 |

Figure.3 presents the produced results of the trained ANN model for the estimation of the critical flashover voltage which have been compared to the calculated results produced by the use of equation (7) for the same insulators. The characteristics values of these insulators are given in Table 2.

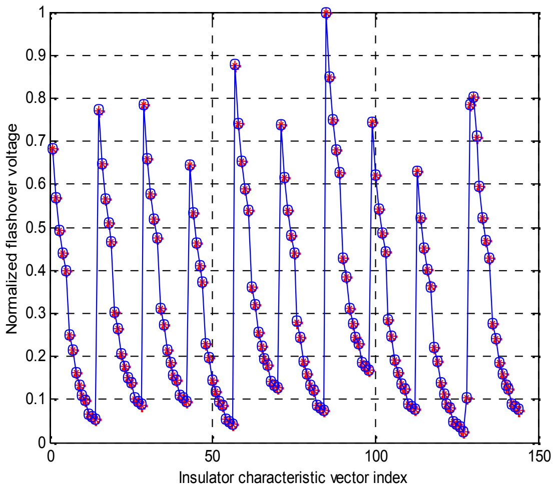


**Fig.3** Training process of the ANN

In order to measure the generalization capability of the neural network model, the output of the neural network model is compared with the actual measured outputs. Two testing sets are carried out, which are, respectively, called Test-I and Test-II. In Test-I, ANN model was tested by values of the critical flashover voltage that were obtained from experimental study [15]. In Test-II, a testing set included the different data points that FOVs were obtained from experimental studies [16,17]. Table.3 illustrates the geometric characteristics of the testing string insulators.

**Table.3** The characteristics values of the testing insulators.

| Insulator type | $D_m$(cm) | H(cm) | L (cm) | F |
|---|---|---|---|---|
| Type I | 25.4 | 14.6 | 30.5 | 0.70 |
| Type II | 25.4 | 14.6 | 27.9 | 0.68 |
| Type III | 25.4 | 14.6 | 43.2 | 0.92 |
| Type IV | 22.9 | 16.6 | 43.2 | 1.38 |

The comparison of the obtained results using ANN model and experimental results for Test-1 and Test-2 is given in Fig. 4. The correlation between real and estimated targets for these cases is shown in Fig. 5 and Fig. 6. The results of comparison show that the ANN results and experimental results are nearly same.

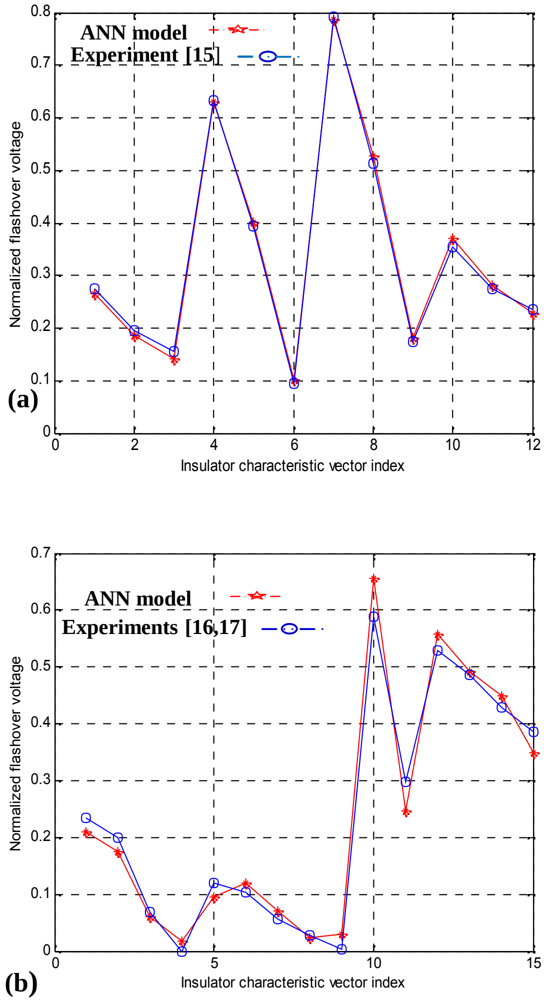


**Fig. 4** The comparison of the results of ANN model and experimental results (a) for Test-1 and (b) for Test-2.

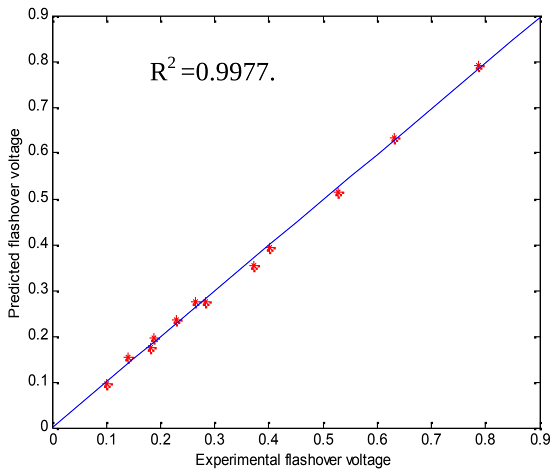


**Fig. 5** Correlation between estimated and real values of FOV for Test-1.

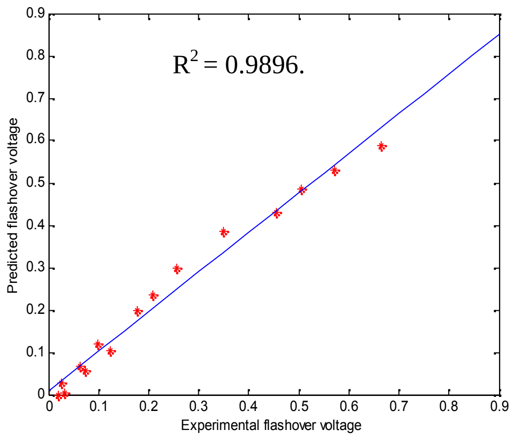


**Fig. 6** Correlation between estimated and real values of FOV for Test-2.

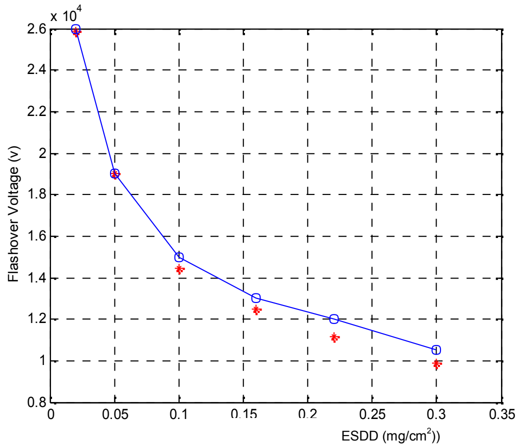


**Fig.8** Comparison between the values of the ANN model and the experimental values for type III.

The performance of the ANN model was measured for both testing sets by evaluation of the root mean square error (RMSE), the mean absolute percentage error (MAPE) and the correlation ($R^2$) between the predicted data and experimental results.Table 4 shows the values of the RMSE, MAPE and $R^2$ for both testing sets.

Moreover, a comparison between the predicted data and experimental data was then made to evaluate the model's prediction performance. The results of comparison for FOV are shown in Fig. 6 and Fig. 7 for two types of insulators (type I and type III, Table.3).

**Table 4.** Performance comparison in terms of the error statistics for Test1 and Test-2.

| | RMSE | $R^2$ | MAPE(%) |
|---|---|---|---|
| **Test-1** | 0.0019 | 0.9977 | 2.41 |
| **Test-2** | 0.0052 | 0.9896 | 5.62 |

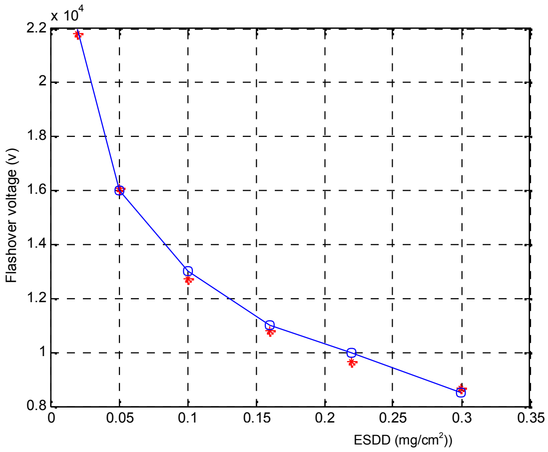


**Fig. 7** Comparison between the values of the ANN model and the experimental values for type I.

## 5. Conclusion

In this paper, an ANN has been successfully applied in order to solve the problem of critical flashover voltage modeling. The ANN model is developed in order to determine the relationship between critical flashover voltage as function of insulator parameters ($D_m$, H, L, F) and the equivalent salt deposit density C. The principal characteristic of the proposed model is the choice of the optimum training parameters such as the number of neurons, learning rate and momentum term. The comparisons of the estimated results with the measured data collected from experimental studies prove the validity of Artificial Intelligence for modeling phenomena in High Voltage Engineering.

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