Modeling Flashover Voltage (FOV) of Polluted HV Insulators Using Artificial Neural Networks (ANNs)

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Abstract

This paper attempts to apply artificial intelligent techniques in high voltage applications and especially to estimate the critical flashover voltage (FOV) for polluted insulators, using experimental measurements carried out in an insulator test station according to the IEC norm and a mathematical model based on the characteristics of the insulator: the diameter, the height, the creepage distance, the form factor and the equivalent salt deposit density and estimates the critical flashover voltage. Two types of artificial neural networks (ANNs) are designed to establish a nonlinear model between the above mentioned characteristics and the critical flashover voltage. The ANNs models, algorithms, and tools have been developed using the software package Matlab. The obtained results are promising and insure that artificial intelligent techniques can estimate the critical flashover voltage for new designed insulators with different operating conditions and constitute an indispensable models that can be used in field simulations of various parameters for polluted insulators. Further comparative analysis of the estimated results with the measured data collected from the site measurement amply demonstrate the effectiveness of the use of Artificial intelligent techniques for modeling (ANNs) of FOV.

1. Introduction

The reliability of the power system mainly depends on the environmental and weather conditions which cause flashover on polluted insulators leading to system outages. It is generally recognized that the main causes leading to the contamination of insulators are marine pollution-found in the immediate neighborhood of the coastal regions and solid pollution-found in the dense industrial areas. A major problem of insulation systems is the accumulation of airborne pollutants due to natural, industrial or even mixed pollution, during the dry weather period and their subsequent wetting, mainly by high humidity. At the coastal areas the high voltage insulators are affected by salt particles that settle on the insulators surfaces. The winds that blow from the sea carry the salt particles. These particles are not dangerous in its dry condition but with high environmental humidity or drizzle rain conditions the salt can absorb the water and form a thin film with high conductivity. This layer gives an ideal path for the leakage current to pass through between the high voltage side and the ground side. The conductivity of this layer depends on the type of salts which this layer consists of [1],[2]. High failure rate of polluted insulator due to the flashover has been found near the coastal areas [3]. This problem was the motivation for the installation of a test station performs laboratory tests on artificially polluted insulators.

Experiments concerning the critical flashover voltage 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 for the estimation of the flashover voltage on polluted insulators. Most are based on circuit models for the calculation of the analytical mathematical relationship for either dc or ac flashover voltage on polluted insulators.

The proposed approach will help in the establishment of maintenance policy and for addressing an effective solution against pollution flashover of high voltage insulators.

2. Mathematical Model

The simplest model that has been developed by Obenhaus [4] consists of a partial arc bridging the dry zone and the resistance of the polluted wet zone in series (Figure 1).

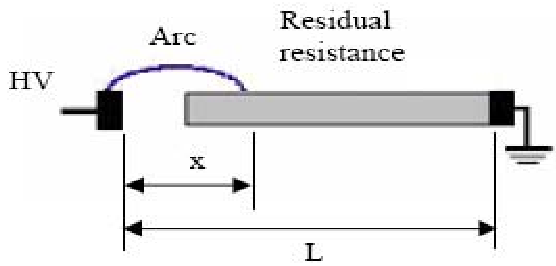

Fig. 1. Obenhaus model

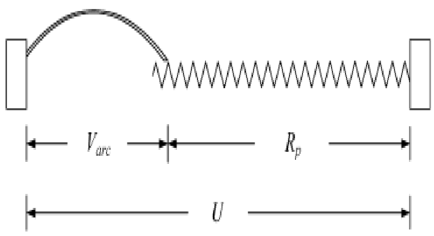

Fig. 2. Equivalent circuit

The mathematical model 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 the resistance of the pollution layer and U a 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 [5]:

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

where

L is the creepage distance of the insulator (in cm),

Dm the maximum diameter of the insulator disc (in cm) and

F is the form factor. A and n are the arc constants

The surface conductivity σ_s (in Ω^{-1}) is given by the following type:

$$\sigma_s = (369.05.C + 0.42).10^{-6} \quad (2)$$

where C is the equivalent salt deposit density in (mg/cm^2).

The coefficient of the pollution layer resistance K in case of cap-and-pin insulators is given by

$$K = 1 + \frac{n+1}{2.\pi.F.n}.\ln\left(\frac{L}{2.\pi.R.F}\right) \quad (3)$$

where R is the radius of the arc foot (in cm) and is given by

$$R = 0.46.(\pi.A.D_m.\sigma_s)^{\frac{1}{2.(n+1)}} \quad (4)$$

The above mathematical model is a result of experiments in specific insulators types and specific pollutants in their surface. There are many values for the arc constants A and n in the literature [6,7]. As a result, the above mathematical model could be applied with satisfactory accuracy in specific insulator types and pollutants.

3. ANNs modelling

An artificial neural network (ANN) is made up of a number of simple, and highly interconnected processing elements called neurons, which processes information by its dynamic state response to external inputs. ANN models have been applied for different engineering applications including machine vision [14], speech processing [15] and system identification, diagnosis and control [16]. In electrical power systems, ANN have been used for accurate load forecasting, alarm processing, etc [12,13]. In these applications, the property of universal function approximation of ANN is widely exploited in which ANN is useful because it acts as a model of a real-world system or function by adjusting the network parameters (weights). Then, this model can be used for prediction or forecasting. The useful properties of ANN, like, adaptable and non-linearity are well suited to many function estimation tasks in many engineering fields [10,16].

3.1 Multilayer feed forward network

According to the universal approximation theorem, a Neural Network with two layers can approximate a given function to a desired precision. Fig. 4 shows the schematic diagram of a multilayer feed-forward network used in this paper. The Network is made of three layers: input layer, output layer and hidden layer. Each neuron of the output layer receives a signal from all input via hidden layer neurons along connections with adjustable weights.

The neural network can identify input pattern vectors, once the connection weights are adjusted by means of the learning process. The back-propagation learning algorithm which is a generalization of Widrow–Hoff error correction rule is the most popular method in training the ANN [16] and is employed in this work. This learning algorithm is presented here in brief. For each neuron in the input layer, the neuron outputs are given by

$$O_i = n_i \quad (6)$$

where n_i is the input of neuron i and O_i the output of neuron i. Again, for each neuron in the output layer, the neuron inputs are given by

$$n_k = \sum_{j=1}^{N_j} w_{kj} O_j, \qquad k = 1,\ldots,N_k \quad (7)$$

where w_{kj} is connection weight between neuron j and neuron k, and Nj, Nk are the number of neurons in the hidden and output layers, respectively; the neuron outputs are given by

$$O_k = \frac{1}{1+\exp(-(n_k+\theta_k))} = f_k(\mathrm{n_k}, \theta_k) \quad (8)$$

where θ_k is the threshold of neuron k, and the sigmoid function f_k is usually used as an activation function.

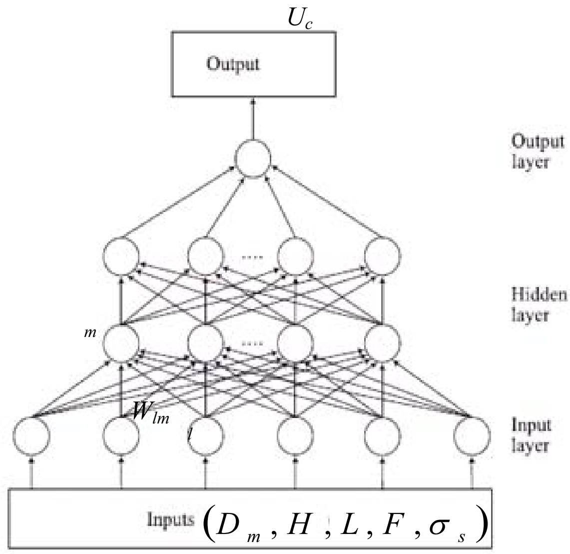

Fig. 4. The structure of a multilayer perceptron

For the neurons in the hidden layer, the input and the outputs are given by the relationships similar to those given in the Eqs. (7) and (8), respectively. The connection weights of the feed-forward network are derived from the input–output patterns in the training set by the application of generalization delta rule [16]. The algorithm is based on minimization of the error function of each pattern p by the use of the steepest descent method. The sum of squared errors which is the error function of each pattern is given by

$$E_p = \frac{1}{2}\sum_{k=1}^{N_k}(t_{pk}\text{-}O_{pk})^2 \qquad (9)$$

where t_{pk} and O_{pk} are target and calculated outputs for output neuron k, respectively. The overall measure of the error for all the input–output patterns is given by

$$E = \sum_{p=1}^{N_p} E_p \qquad (10)$$

where N_p is the number of input–output patterns in the training set.
The hidden and output layer weights are adjusted according to the following expressions:

$$\Delta W_{kj}(p) = \eta_j \delta_{pk} O_{pj} + \alpha_j \Delta W_{kj}(p-1) \qquad (11)$$

$$\delta_{pk} = \begin{cases} O_{pk}(t_{pk} - O_{pk})(1 - O_{pk}) & \text{for the output layer} \\ O_{pk}(1 - O_{pk})\sum_{j=1}^{N_k} \delta_{pj} W_{jk} & \text{for the hidden layers} \end{cases} \qquad (12)$$

where η_j, α_j are the learning rate and momentum constant, respectively.

Most of the proposed optimization methods for updating the Neural Network weights are based on Equations (11-12), the difference relies on either fixing the learning rate and momentum for some variants or using adaptive searching methods.

3.1 The modeling of an insulator by ANN

In this paper, a new approach using ANN as a function approximator is used to model accurately the relationship between critical flashover voltage U_c (kV) as the output of the neuronal model and the High voltage insulator parameters the maximum diameter D_m (cm), the height H (cm), the creepage distance L (cm), the form factor F of the insulator and the layer conductivity σ_s (mS).

$$U_c = f(D_m, H, L, F, \sigma_s) \qquad (13)$$

The data used for the training, evaluation and testing of the ANN were selected from various sources for different types of insulators. The aim of the present work is to apply different Neural Network topologies for flashover modeling to be used for forecasting the critical flashover voltage for new operating conditions. A multilayer feedforward neural network is constructed and trained with normalized experimental input/output data pairs using Levenberg-Marquardt optimization algorithm, a variant based on equations (11,12) to find the optimal network weights (W*) that minimize equation (10).
Different normalization schemes have been tested for normalizing the input-output training patterns. They detailed in table 1 [16].

TABLE 1: Normalization Schemes

Scheme Number	Input	Output
1	MAX	MAX
2	MAX	MAX MİN
3	MAX	MEAN & S.D
4	MAX MİN	MAX
5	MAX MİN	MAX MİN
6	MAX MİN	MEAN & S.D
7	MEAN & S.D	MAX
8	MEAN & S.D	MAX MİN
9	MEAN & S.D	MEAN & S.D

After normalisation , the input ans output variable ranges are within (0,1) [13] .Each input –ouput variable was normalized one by one using scheme number 8 in this work.

$$net_{i,nor}(p) = \frac{net_i(p) - net_{i,av}(p)}{\sigma_i} \qquad (14)$$

where : $net_{i,nor}$ is the average value of the ith component of the input vector;

σ_i is the standard deviation value of the ith component of the input vector.

$$O_{k,nor}(p) = \frac{O_k(p) - O_{k\min}}{O_{k,\max} - O_{k\min}} \qquad (15)$$

where: $O_{k,\min} = \min(O_k(p))$

4. Results and discussion

Modeling using Neural Networks is a not straightforward especially in selecting the number of hidden layers, the number of neurons per layer and the activation functions for each layer. In this paper we have worked on Two and Three Layer Feedforward Neural Networks.
Our methodology of designing a neural network, as depicted in figure 5, is summarized as follows:

- Among the available experimental data for different insulator types illustrated in tables (II, III) , we have constructed two sets, a training set to find the optimal Network parameters and weights, and a validation set
- To validate the obtained model for generalization.
- For all the patterns in the training set, the respective parameters of the network are optimised through a set of trials where we have tried different number of neurons per layer (2-12 neurons) and we have tested different activation functions the linear, the logistic or hyperbolic).
- For each combination of the parameters, the ANN training process is updated using the respective training set. After the respective convergence, the Absolute Mean square Error is used as a comparison index between the experimental and estimated values of the critical flashover voltage for the evaluation set is calculated and the lowest index is chosen as the best one with the respective parameters.

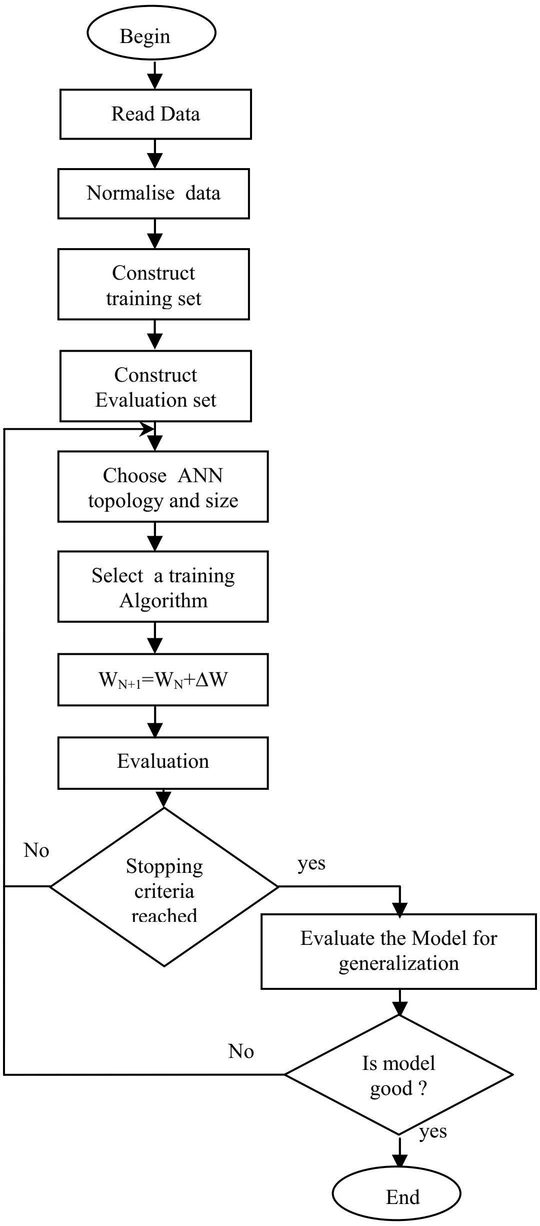

Fig.5. Flowchart of the ANN optimisation methodology for the estimation of the critical flashover voltage of insulators

It has been verified that using two hidden layers have better effect on the learning accuracy than the use of one hidden layer, with the same number of hidden layer nodes. The effect of different learning rates and momenta in different layers on the convergence property of the learning process is also presented in details.

Figure 6 illustrates the best obtained black box model using a 2 Hidden Layer Network (4,7,7,1) and the training data for insulators of 4 different types whereas figure 7 shows the ANN capability of predicting the Critical Flashover Voltage for two new types of insulators.

Table 2. Properties of the investigated insulators

Insulator	**Type (I)**	**Type (II)**	**Type (III)**	**Type (VI)**
Maximum diameter D_m *(mm)*	254	254	254	254
Distance between centers H *(mm)*	146	146	146	146
Creepage distance *L* *(mm)*	431	279	279	305
Form factor *F*	0.916	0.684	0.680	0.696

Table 3 Experimental data for validation

Insulator Type	**C (mg/cm^2)**	**Uc (kV)[10]**
T(V) D=254 mm H=146 mm F=.68	0.13	12.0
	0.16	11.1
	0.23	8.7
	0.28	9.1
	0.34	7.5
	0.37	7.8
	0.49	6.2
	0.52	6.8
	0.55	6.1
T(IV) D=254 mm H=146 mm F=.68	0.02	22.0
	0.05	16.0
	0.10	13.0
	0.16	11.0
	0.22	10.0
	0.30	8.5

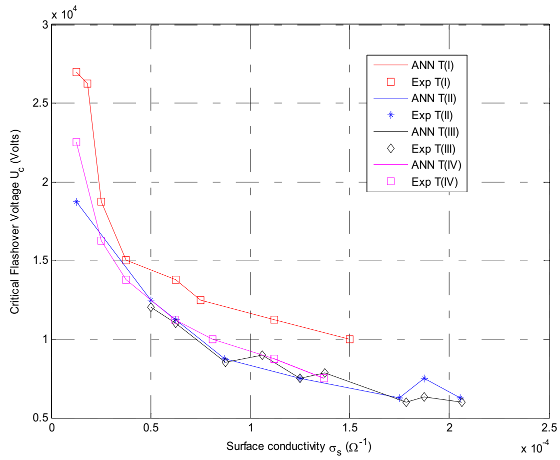

Fig. 6. Trained ANN - Critical voltage against the surface conductivity

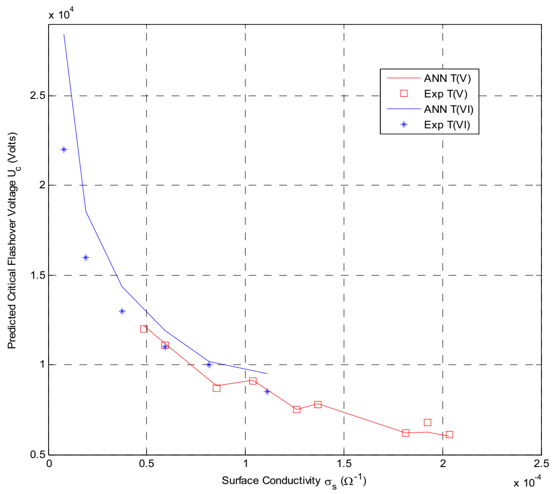

Fig.7. ANNs in Estimating Critical voltage against the surface conductivity

5. Conclusions

In this work, the ANNs optimisation models are successfully applied to solve the problem of critical flashover voltage modeling and estimation along the insulator surface when given some of the insulator's geometrical types. Then, ANNs are designed as black-box models to estimate the unknown relationship between the insulator parameters and the critical flashover voltage.

Therefore, finding a model based on ANNs helps in computing the critical conditions for flashover which leads to better understanding of the transient phenomena in polluted insulators. Simulation results were obtained from experimental studies and from application of a mathematical model for the estimation of the flashover voltage on polluted insulators.

The results prove the validity of Artificial Intelligence for modeling phenomena in High Voltage Engineering. The method proposed in the paper can be used to eliminate the flashover fault and in the establishment of maintenance policy and for addressing an effective solution against pollution flashover of high voltage insulators.

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