PREDICTION OF FLASHOVER VOLTAGE OF INSULATORS USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Sid Ahmed Bessedik
Electrical Engineering DPT, University Ammar Telidji Laghouat,
PO BOX 37G, Laghouat (03000), Algeria
Ahmed_7b@yahoo.fr

Hocine Hadi
Electrical Engineering Laboratory of Oran (LGEO), University of Sciences and Technology of Oran,
Mohamed Boudiaf, USTO BP1505 El Mnouar Oran, Algeria
hadihocine@yahoo.com

Abstract: *High voltage insulators form an essential part of the high voltage electric power transmission systems. Any failure in the satisfactory performance of high voltage insulators will result in considerable loss of capital, as there are numerous industries that depend upon the availability of an uninterrupted power supply. The importance of the research on insulator pollution has been increased considerably with the rise of the voltage of transmission lines. In order to determine the flashover behavior of polluted high voltage insulators and to identify to physical mechanisms that govern this phenomenon, the researchers have been brought to establish a modeling. This paper describes the application of adaptive neuro-fuzzy inference system (ANFIS) model 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. In order to train the network and to test its performance, the data sets are derived from experimental results obtained from the literature and a mathematical model. The obtained results are promising and insure that ANFIS techniques can estimate the critical flashover voltage for new designed insulators with different operating conditions and constitute an indispensable model that can be used in field simulations of various parameters for polluted insulators.*

Key words: *High voltage insulators, Polluted insulators, Critical flashover voltage, ANFIS.*

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1. Introduction

Pollution flashover, observed on insulators used in high voltage transmission, is one of the most important problems for power transmission. Pollution flashover is a very complex problem due to several reasons such as modeling difficulties of the insulator complex shape, different pollution density at different regions, non-homogenous pollution distribution on the surface of insulator, and unknown effect of humidity on the pollution.

Under severe environmental conditions, a pollution layer is deposited on the insulator surface. When the surface of a polluted high voltage insulator is dampened due to dew deposition, fog or rain, a wet conducting film is formed and a leakage current flows through the surface [1, 2]. The leakage current begins to dry the pollution layer and the resistivity of the layer rises in certain areas.

This leads to dry band formation, usually in the areas where the current density is highest. The dry band supports most of the applied voltage. The air gap flashes over, with the arc spanning the dry band gap which is in series with the wet portion of the insulator. The arc may extinguish at zero current and the insulator may return to working conditions. Dry band formation and rewetting may continue for many hours [3]. These arcs will burn in series with the wet surface resistance. If this resistance is sufficiently low, the partial arcs will elongate along the insulator profile and may eventually cause the full insulator flashover. In this way, the performance of a polluted insulator may be represented by the flashover voltage and the flashover current defined as the maximum leakage current magnitude immediately before flashover [4].

Several researches concerning the insulators performance under pollution conditions have been conducted, in which mathematical or physical models have been used [5- 9], experiments have been conducted [10-12] or simulation programmes have been developed [13–15].

In recent years, a variety of prediction models have been proposed in the literature, ANN artificial neural networks models are developed for the qualitative control of the insulators by determining important parameters (such as leakage current or the critical flashover voltage) [16–21], an adaptive neuro-fuzzy inference system (ANFIS) [22], least squares support vector machines (LS-SVM) [23-24].and fuzzy logic model [25] have been applied in order to estimate the critical flashover voltage on polluted insulators, additionally an multiple regression analysis has been used in order to prediction parameters of dimensioning of insulators under non-uniform contaminated conditions [26]. Present paper focuses on prediction of the critical flashover voltage of polluted insulators by using an adaptive neuro-fuzzy inference system (ANFIS).

2. Experimental measurements and data collection

Data concerning cap and pin type insulators was used for the training and testing of the ANFIS. Specifically, the following geometric characteristics were used as input variables: the maximum diameter Dm (in cm) of the insulator, its height H (in cm), the creepage distance on it L (in cm), its form factor F and the layer conductivity σs (in μS), while the output variable was the critical flashover voltage Uc (in kV). The dataset was built using data acquired from experiments and the application of a mathematical model. In particular, the experiments were carried out in an insulator test station installed in the High Voltage Laboratory of Public Power Corporation's Testing, Research and Standards Center in Athens [27] according to the IEC standard 507:1991 [28]. Following the application of artificial pollution on the insulators, the critical flashover voltage was measured. This set of measurements was enriched by measurements from experiments performed by Sundararajan et al. [29] and Zhicheng and Renyu [30]. In addition, the mathematical model of an equivalent circuit for the evaluation of the critical flashover voltage presented by Topalis et al. [31] is used for the enlargement of the available dataset, the ANFIS is successfully implemented for the estimation of the critical flashover voltage of 24 artificially polluted insulators, whereas the training set is formed by 140 vectors from the mathematical model [31] and other four experimental vectors (different from the test set).

3. Mathematical model of the flashover process

Flashover modeling has been a topic of interest for many researchers [5, 32-34]. A major problem in all those investigations is the definition [35, 36] of the value of the arc constants that affect the flashover process. Unfortunately the values of the constants determined from several investigations diverge substantially.

This investigation targets the precise calculation of the arc value parameters, using relevant experimental results and close simulation of the insulator's behaviour under polluted conditions using a suitable mathematical model [37].The flashover process over polluted insulators is described by well-known analytical equations, published by various scientists, mainly Boeme and Obenaus and Alston and Zoledziowski. These procedures have been used for the formulation of a mathematical model that permits determination of the parameters of the flashover under pollution of the insulators. The most known model for the explanation and evaluation of the flashover process [31, 34] of a polluted insulator consists of a partial arc spanning over a dry zone and the resistance of the pollution layer in series. Therefore, the voltage across the insulator will be:

$$U = xAI^{-n} + (L - x) r_p I \tag{1}$$

where xAi-n is the stress in the arc and (L –x)rp I is the stress in the pollution layer. x is the length of the arc, L is the leakage path of the insulator in cm, rp is the resistance per unit length of the pollution layer, I is the leakage current and A and n are the arc constants. Their values
A = 124.8, n = 0.409 have been determined using a complex optimization method [38] based on genetic algorithms. It has been found experimentally that the value of the flashover voltage of a polluted insulator is not constant even under identical conditions.

This is mainly due to random arc phenomena on the polluted surface. Such phenomena are the arc bridging between sheds or ribs, the arc drifting away from the surface of an insulator as well as the number of consecutive arcs before flashover. These random arcs will certainly affect the flashover.

The measurement of the resistance rp of the wet zone is quite complicated. Therefore it may be substituted by the surface conductivity σ_S of the pollution layer:

$$\sigma_S = \frac{1}{r_p} F \tag{2}$$

F is the form factor of the insulator that is given as follows:

$$F = \int_0^L \frac{l}{\pi D(l)} dl \tag{3}$$

where D(l) is the diameter of the insulator that varies across the leakage path.

For the equivalent salt deposit density C (ESDD) [3], the surface conductivity σ_S in Ω-1 is given by the following equation:

$$\sigma_S = (369.05.\mathrm{C} + 0.42).10^{-6} \tag{4}$$

Where C is the equivalent salt deposit density in mg/cm2.
The critical condition for propagation of the discharge along the surface of the insulator to cause flashover is [31].

$$\frac{dl}{dx} > 0 \tag{5}$$

The voltage under this critical condition yields

$$U = xAI^{-n} + (L - x)Kr_p I \tag{6}$$

Here the coefficient K was added to validate (1) at the critical instant of the flashover. Wilkins introduced this coefficient in order to modify the resistance rp of the pollution layer considering the current concentration at the arc foot point. A simplified formula for the calculation of K for cap-and-pin insulators is [2, 30].

$$K = 1 + \frac{L}{2\pi F(L - x_C)} \ln\left(\frac{L}{2\pi F \sqrt{\frac{(\pi D_m \sigma_S A)^{\frac{1}{n+1}}}{1.45\pi}}} \right) \tag{7}$$

At the critical condition the length of the arc takes the value [34].

$$x_C = \frac{1}{n+1} L \tag{8}$$

Further analysis [31] of the system equations at the moment of flashover yields for the critical current

$$I_C = (\pi D_m \sigma_S A)^{\frac{1}{n+1}} \tag{9}$$

and for the critical voltage

$$U_C = \frac{A}{n+1}(L + \pi D_m FKn)(\pi D_m \sigma_S Ax)^{\frac{-n}{n+1}} \tag{10}$$

where D_m is the maximum diameter of the insulator in cm.

4. Adaptive Neuro-Fuzzy Inference System

Fuzzy logic and ANN are modeling methods used influ-entially and effectively in the problems of engineering. The modeling of fuzzy logic method is a rule-based method using the feature of human thinking and decision making. On the other hand, ANN learns the problem by using its ability of learning and comes through successfully for data sets it did not come across before. The method of ANFIS was suggested by Jang [39] in 1993 considering these advantages of ANN and fuzzy logic methods. The combination of fuzzy logic with architectural design of neural network led to creation of neuro-fuzzy systems which benefit from feed forward calculation of output and back-propagation learning capability of neural networks, while keeping inter-pretability of a fuzzy system [40]. The Takagi-Sugeno-Kang (TSK) [41, 42] is a fuzzy system with crisp functions in consequent which perceived proper for complex applications. It has been proved that a TSK system could approximate every plant with convenient number of rules [39–42]. TSK systems are widely used in the form of neuro-fuzzy systems called ANFIS [39]. Because of crisp consequent functions, ANFIS uses a simple form of scaling implicitly. This adaptive network, ANFIS, has good ability and performance in system identification, prediction and control and has been applied in many different systems. The ANFIS combines the ability of neural network and fuzzy system. The training and updating of ANFIS parameters are the main problems. The training of this network in the antecedent part is more difficult than the conclusion part, because it must go through all layers which cause much calculation in Gradient Decent (GD) method. The most of the training methods in the antecedent part are based on gradient and calculation of gradient in each step is very difficult and chain rule must be used also may causes local minimum.

Both Neural Network (NN) and Fuzzy Logic (FL) are model-free estimators and share the common ability to cope with the uncertainties and noise. Both of them encode the information in a parallel and distribute architecture in a numerical framework. Hence, it is possible to convert fuzzy logic architecture to a neural network and vice-versa. This conversion makes it possible to combine the advantages of neural network and fuzzy logic.

A. *Architecture of ANFIS*

To present the ANFIS architecture, two fuzzy if–then rules based on a first-order Sugeno model are considered:

Rule 1: If (x is A1) and (y is B1), then (f1= p1x+ q1y + r1)
Rule 2 : If (x is A2) and (y is B2), then (f2 = p2x + q2y + r2)

where x and y show the inputs of ANFIS system, Ai and Bi show the original fuzzy sets, pi, qi, and ri show the outcome parameters determined during training process. The structure of ANFIS architecture having two inputs, in which these two rules are applied in one output for Sugeno type fuzzy inference system, is shown in Fig.1. In Fig. 1, each circle indicates a fixed node and each square indicates an adaptive node. As seen in Fig.1, ANFIS includes 5 layers. The node function in each layer can be described as follows [39]:

Layer 1: First layer executes fuzzyfication process. Each i node in this layer is an adaptive node whose output is described below.

$$O_i^1 = \mu_{Ai}(x), \qquad i = 1,2 \tag{11}$$

$$O_i^1 = \mu_{Bi-2}(y), \quad i = 3,4 \tag{12}$$

where x or y is the input of node, A_i or B_{i-2} is a linguistic label related to this node. The output of node is calculated with membership functions given in (11) and (12). Various membership functions such as triangular, gaussian, and bell-shaped can be used for this. Frequently preferred [22] triangular function has been used in this study.

Layer 2: Each node in this layer is a fixed node labeled with M giving the multiplication of the signals coming to it as output. Any node function performing fuzzy AND process can be used in this layer. The outputs of this layer can be calculated as in the (13).

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(x), \quad i = 1,2 \tag{13}$$

Layer 3: This layer is where membership functions are normalized. Each node in layer 3 is a fixed node labeled with N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths. The output of each node in this layer is described with (14).

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \tag{14}$$

where w_i describes the weight degree belonging to ith rule.

Layer 4: All nodes in this layer are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order poly-nomial. Layer 4 is described with (15).

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i x + r_i), \ i = 1,2 \tag{15}$$

where $\overline{w_i}$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: This layer consists of only one node and is labeled with the symbol S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by (16):

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\left(\sum_{i=1}^{2} w_i f_i\right)}{w_1 + w_2} \tag{16}$$

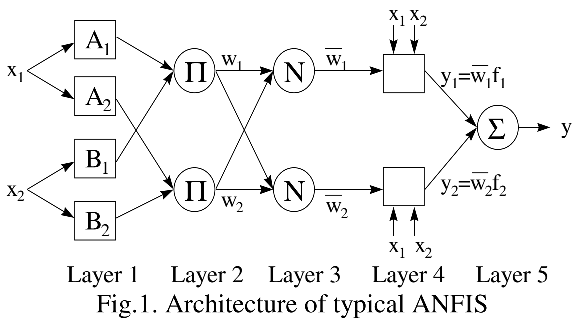

Fig.1. Architecture of typical ANFIS

The ANFIS uses fuzzy MFs for splitting each input dimension. The input space is covered by MFs with overlapping that means several local regions can be activated simultaneously by a single input. Since simple local models are adopted in ANFIS model, the approximation ability of ANFIS will depend on the resolution of the input space partitioning, which is determined by the number of MFs in ANFIS and the number of layers. Four different types of MFs are used usually such as bell-shaped, Gaussian, trapezoidal and triangular type MFs with maximum equal to 1 and minimum equal to 0:

$$bell(x;a,b,c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \tag{17}$$

$$gauss(x;\sigma,c) = e^{\left\{-\left|\frac{x-c}{a}\right|^2\right\}} \tag{18}$$

$$trap(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{19}$$

$$triang(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{20}$$

where {a, b, c, d, σ} are the parameters of MFs which are effected in shape of MFs.

B. Learning algorithm

Two types of learning algorithm are used for the determination of membership functions during the training of ANFIS. The first one is ''Backpropagation Algorithm,'' and the other is the algorithm known as ''hybrid algorithm'' and in which ''least squares'' method and ''gradient descent'' method are used together. Here, gradient descent method is used in the arrangement of non-linear input parameters and least squares method is used in the arrangement of non-linear output parameters. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [39]. Table 1, summarizes the learning procedures performed for this network.

	Forward pass	**Backward pass**
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least-square estimator	Fixed
Signals	Node outputs	Error signals

Table 1. Two passes hybrid learning procedure of ANFIS

Assessment of the performance of ANFIS model is done by optimal values of Root Mean Square Error (RMSE), the RMSE is given as:

$$RMSE = \left\{ \frac{\sum_{k=1}^{n} (y_{tes,k} - y_{pre,k})}{n} \right\}^{1/2} \quad (21)$$

Where n is the number of data patterns in the data set, $y_{pre,k}$ indicates the predicted and $y_{tes,k}$ the testing value of one data point k. Moreover, several statistical methods, the Coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE), are used to compare predicted and testing values for computing the model validation, the R^2 and MAPE parameters are calculated from:

$$R^2 = 1 - \frac{\sum_{k=1}^{n} (y_{tes,k} - y_{pre,k})^2}{\sum_{k=1}^{n} (y_{test,k} - \overline{y_{tes,k}})^2} \quad (23)$$

$$MAPE = 100\%.\frac{\sum_{k=1}^{n} \left| y_{tes,k} - y_{pre,k} \right| / y_{tes,k}}{n} \quad (24)$$

where $\overline{y_{tesk}}$ is the mean value of all data points. A very good fit yields an R^2 value of one, whereas a poor fit results in a value near zero.

In order to avoid saturation phenomena during the training process of the ANFIS model, the input and output variable values are normalized. Through preliminary algorithm executions, normalization is chosen by the maximum and minimum values of the input and output data, as shown in the following type:

$$y_{nor} = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}} \quad (25)$$

where y_{max} and y_{min} are the upper and lower values of variable y_i for the training set.

5. Critical flashover voltage estimation using anfis

The developed ANFIS is applied for the critical flashover voltage estimation of polluted insulators.

The data from the mathematical model and a set of the experimental data are used to train the ANFIS model, while the rest of the experimental data was used to test its performance. The training set consists of 144 patterns/vectors (of which140 vectors are derived from the model and 4 vectors are real values), and the ANFIS model is tested using 24 patterns (experimental data).

In order to get a good performance for ANFIS, all of the used data sets for both training and test stages were selected as randomly, the ANFIS model was constructed in MATLAB and has been trained with several MATLAB training functions.

Results and discussion

There are many parameters one can select to obtain better results in ANFIS. For the most common case, these parameters are: the number and type of membership function for each input, the output membership function type (either 'linear' or 'constant'), the training epoch number, the training error goal, the initial step size, the step size decrease rate and the step size increase rate. In addition to the parameter selection one can also ensure that appropriate test data are used to detect over fitting of the training data set. The test data have the same format as the training data. Over fitting can be detected when the test error (difference between the measured and predicted outputs) starts increasing while the testing error is still decreasing.

Initially the system was developed with different types of Membership Functions (MFs) like Triangular-shaped built-in membership function (trimf), Gaussian curve built-in membership function (gaussmf), Generalized bell-shaped built-in membership function (gbellmf) each MFs was tested with two linguist variables (2[High Low] 3[High Medium Low] to each inputs. The ANFIS model was trained by hybrid learning algorithm.

The detailed simulated results obtained by the developed ANFIS model for predicting the critical flashover voltage of polluted insulators was tabulated in Table 2.

According to Table 2, the Triangular-shaped built (trimf) with 2 MFs is the best architecture model to predict the critical flashover voltage, because it gives lowest MAPE value (3.9789%) and highest R^2 value (0.9843) during the testing process.

Type of mf	No of MF	Step-size	Data normalized	No Epoch	$RMSE_{tr}$	$RMSE_{Test}$	R^2_{tr}	R^2_{test}	$MAPE_{tr}$	$MAPE_{test}$
gbellmf	2	0.05/0.6/1.6	No	300	0.0319	0.7429	1.0000	0.9727	0.2023	4.8474
	2	0.001/0.2/1.6	Yas	300	0.0045	0.0258	0.9996	0.9792	1.1716	21.2116
	3	0.05/0.6/1.6	No	30	0.0340	3.8157	1.0000	0.3656	0.2072	16.9346
	3	0.05/0.6/1.6	Yas	30	0.0297	0.0988	0.9836	0.7131	6.6400	42.9010
Gaussmf	2	0.05/0.6/1.6	No	300	0.1339	0.8566	0.9995	0.9638	0.8296	5.8731
	2	0.001/0.9/1.1	Yas	300	0.0115	0.0295	0.9975	0.9729	5.1022	29.2391
	3	0.05/0.6/1.6	No	30	0.1002	4.0142	0.9997	0.3223	0.5748	15.4005
	3	0.01/0.9/1.1	Yas	30	0.0115	0.0875	0.9975	0.7722	3.6811	39.3295
trimf	**2**	**0.05/0.6/1.6**	**No**	**300**	**0.2426**	**0.5641**	**0.9983**	**0.9843**	**1.6915**	**3.9789**
	2	0.001/0.9/1.1	Yas	300	0.0214	0.0522	0.9914	0.9153	6.8294	28.3971
	3	0.05/0.6/1.6	No	30	0.0655	1.4512	0.9999	0.8982	0.3775	7.3165
	3	0.001/0.9/1.1	Yas	30	0.0125	0.0426	0.9971	0.9437	4.9279	58.7402
trapmf	2	0.05/0.6/1.6	No	63	0.5447	1.0781	0.9912	0.9439	3.5478	7.3286
	2	0.0009/0.9/1.1	Yas	300	0.0106	0.0394	0.9979	0.9524	5.0512	27.2888
	3	0.001/0.6/1.6	No	30	0.4000	4.5075	0.9953	0.2163	2.0979	21.3876
	3	0.001/0.9/1.1	Yas	30	0.0097	0.0439	0.9983	0.9415	2.7408	23.0487

Table 2. Statistical indices for performance assessment of the different types of ANFIS models:

Using selected data from within the series of the training pattern, the results of the tested ANFIS were compared the computed results using the mathematical model is shown in Fig.2.

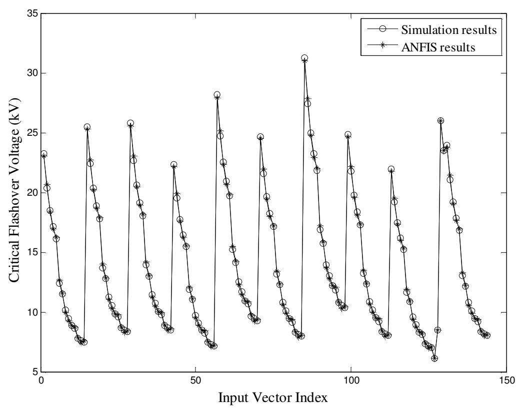

Fig. 2. The performance of ANFIS model for Training

The comparison between the predicted data and Test data was then made to evaluate the model prediction performance is shown in Fig.3, and the correlation between estimated and Actual values of Uc for the testing set was illustrated in Fig. 4.

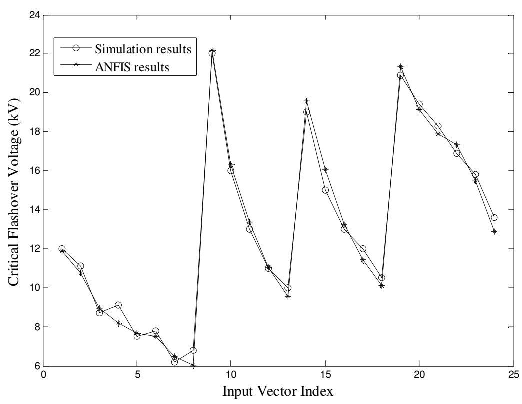

Fig. 3. The performance of ANFIS model for Testing.

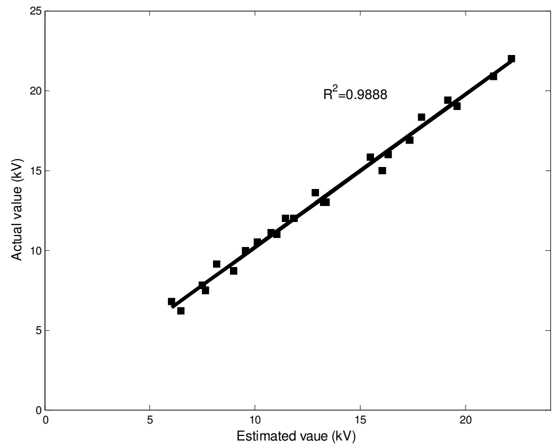

Fig.4. Correlation between estimated and Actual values of Uc for the testing set

The corresponding Root Mean Square Error (RMSE), the Coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE) values for this comparison are given in Table 3. In addition, the performance of the ANFIS model was compared with the previous results given in Ref. [18, 25] for the testing set. This was carried out under the following conditions: Data normalized = No, number of MFs = 2, type of MFs = triangular (low and high), initial step size = 0.05, step size decrease rate = 0.6, step increase rate = 1.6, maximum number of epochs = 5851 epochs, learning type = hybrid method, the output MF type = linear.

Models	R_{tr}^2	$RMSE_{test}$	$MAPE_{test}$	R_{tes}^2
ANFIS	0.9989	0.4766	3.5185	0.9888
ANN [18]	0.9972	-	3.84	0.9853
FL [25]	0.9840	-	-	0.9670

Table 3. Performance comparison in terms of statistical model validation parameters

Conclusion

A methodology for the prediction of the critical flashover voltage of polluted insulators using ANFIS model was presented, in this paper ANFIS model is developed by getting the relationship between critical flashover voltage (FOV) and input variables, such as insulator height, insulator diameter, leakage length of the insulator, form factor and the layer conductivity, In order to train the ANFIS structure, four different MFs were used, the triangular MFs is the best to predict flashover voltage, choosing the number of MFs for each input reflects the complexity of ANFIS for choosing parameters, However when the number of MFs for each input is increased superior to two MFs the training stage is more time-consuming procedure [22].

The performance of the developed model was justified by root mean square error, coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE). The respective results are quite acceptable and superior compared to artificial neural network optimization methodology model [18], and a fuzzy logic optimization methodology model [25].

The ANFIS could also be applied in various types of insulators with higher accuracy than the mathematical model by changing the data set.

Appendix

Values that were used in the mathematical model for the calculation of the flashover voltage and experimental results were given in Tables 4 and 5, respectively. The flashover voltage was calculated with the aid of mathematical model in Eq. (1) using the data given in Table 4 and the following values for the equivalent salt deposit density C (in mg/cm2): {0.02, 0.03, 0.04, 0.05, 0.06, 0.13, 0.16, 0.23, 0.28, 0.34,0.37, 0.49, 0.52, 0.55}. The experimental data are also given in Table 5.

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

Table 4. Values that were used in the mathematical model

Dm, cm	H, cm	L, cm	F	C, mg/cm2	Uc (kV)
25.4	14.6	27.9	0.68	0.13	12.0
25.4	14.6	27.9	0.68	0.16	11.1
25.4	14.6	27.9	0.68	0.23	8.7
25.4	14.6	27.9	0.68	0.28	9.1
25.4	14.6	27.9	0.68	0.34	7.5
25.4	14.6	27.9	0.68	0.37	7.8
25.4	14.6	27.9	0.68	0.49	6.2
25.4	14.6	30.5	0.70	0.52	6.8
25.4	14.6	30.5	0.70	0.02	22.0
25.4	14.6	30.5	0.70	0.05	16.0
25.4	14.6	30.5	0.70	0.10	13.0
25.4	14.6	30.5	0.70	0.16	11.0
25.4	14.6	43.2	0.92	0.22	10.0
25.4	14.6	43.2	0.92	0.05	19.0
25.4	14.6	43.2	0.92	0.10	15.0
25.4	14.6	43.2	0.92	0.16	13.0
25.4	14.6	43.2	0.92	0.22	12.0
25.4	14.6	43.2	1.38	0.30	10.5
22.9	16.6	43.2	1.38	0.03	20.9
22.9	16.6	43.2	1.38	0.04	19.4
22.9	16.6	43.2	1.38	0.05	18.3
22.9	16.6	43.2	1.38	0.06	16.9
22.9	16.6	43.2	1.38	0.10	15.8
22.9	16.6	43.2	1.38	0.20	13.6

Table 5. Experimental values

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