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PREDICTION OF CRITICAL FLASHOVER VOLTAGE OF POLLUTED INSULATORS UNDER SEC AND RAIN CONDITIONS USING ANFIS

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Abstract **–** High voltage insulators are critical components of high voltage electric power transmission networks. Any failure in the satisfactory performance of high voltage insulators would result in significant capital loss, since various industries rely on the availability of an uninterrupted power supply. With the growth in transmission line voltage, the relevance of insulator contamination study has grown significantly. The researchers established a modeling to evaluate the flashover behavior of contaminated high voltage insulators and to uncover the physical factors that drive this phenomena. This paper describes the application of adaptive neuro-fuzzy inference system (ANFIS) model to estimate the critical flashover voltage (FOV) under rain and sec condition . The approach takes as input variable insulator properties such as diameter, height, creepage distance, and the number of pieces on an insulator chain, the data sets used to train and test the network are drawn from experimental results gathered from the literature. The approach's validity was tested by testing numerous insulators with varying shapes. The accuracy and quality of ANFIS are demonstrated by a comparison with the Grouping Multi-Duolateration Localization (GMDL) technique and LS-SVM. Furthermore, ANFIS provides a good estimate of findings that are confirmed by experimental experiments.

Keywords – High Voltage , Flashover, Modelling, Polluted Insulator, ANFIS, GMDL, LSSVM

1.Introduction

Outdoor high-voltage insulators are critical components of transmission lines. Pollution is one of their primary restrictions[1] [2] . The pollution enables a modest leakage current to flow in dry conditions, but in the presence of light rain, fog, or dew, the surface becomes extremely conductive, potentially leading to a flashover [3]. The reason for this is that when pollution gets moist, its presence causes an increase in leakage current as well as a widening of the dry band. As a result, it is possible to claim that the flashover phenomena caused by insulator contamination follow a well-defined process. The first is the deposition of pollutants on the insulator's surface. Second, the dirty surface becomes moistened. Thirdly, the value of the leakage current will grow. Finally, the flashover expresses itself along the insulator's surface through contaminated patches [4].

The insulator's surface properties may alter with time and under certain circumstances, potentially leading to premature aging [5]. The critical flashover voltage of a contaminated insulator is an important characteristic for power system dependability. Several methods for estimating the flashover voltage have been devised. Experimentation takes time and adds to the cost of the system. To address this issue, high voltage engineering research groups presented certain mathematical models based on physical modeling, employing electrical equivalent models, or mathematical regressions using artificial intelligence approximates [6] [7] .The quantity and kind of contamination in a location are linked to the pollution sources that cause it, as well as local weather considerations.

Seasonal changes impact the propensity of pollutant buildup over the insulator's surface when the weather effect is stronger than the pollution source influence.

In some circumstances, the pollution level's behavior is quite dynamic, with the maximum and lowest pollution levels occurring in the same year. The coastlines are typical examples [8]. Time-series models, regression models, artificial neural network (ANN) models[9], adaptive Neuro-fuzzy inference system (ANFIS), and support vector machine (SVM)[10] models have all been proposed in the literature. The use of genetic algorithms allows for the definition of the arc constants, as well as the computation of the critical circumstances at the start of the pollution flashover process. A mathematical model has been developed that accurately mimics the experimental data .

The primary goal of this research is to forecast the flashover voltage under sec and rain conditions, and the suggested ANFIS model has been evaluated to assess its performance.

2.ADAPTIVE NEURO-FUZZY INFERNCE SYSTEM

Fuzzy logic and ANN are modeling approaches that are influential and successful in engineering challenges.The modeling of fuzzy logic technique is a rule-based method that makes use of human thinking and decision-making capabilities. ANN, on the other hand, understands the issue through its ability to learn and succeeds with data sets it has never seen before. Jang [11] proposed the ANFIS approach in 1993, taking into account the benefits of ANN and fuzzy logic methodologies. The combination of fuzzy logic with neural network architectural design resulted in the development of neuro-fuzzy systems, which benefit from the output feed forward computation and backpropagation learning capabilities of neural networks while maintaining the inter-pretability of a fuzzy system [12]. Considered appropriate for difficult applications It has been demonstrated that a TSK system can approximate any plant with a manageable set of rules [11-14].

TSK systems are commonly employed in the form of neuro-fuzzy systems known as ANFIS [11].Because of the sharp consequent functions, ANFIS applies a simple type of scaling implicitly. This adaptive network, ANFIS, has demonstrated high ability and performance in system identification, prediction, and control and has been used in a variety of systems.

The ANFIS combines the capabilities of a neural network and a fuzzy system. The key issues are ANFIS parameter training and updating. The training of this network in the preceding section is more complex than the training in the next section because it must travel through all layers, which requires a lot of calculation in the Gradient Decent (GD) approach.

The majority of the training methods in the preceding section are gradient-based, and calculating gradient in each step is quite complex. Using a chain rule may also result in a local minimum.

Both Neural Network (NN) and Fuzzy Logic (FL) are model-free estimators that can deal with uncertainties and noise.

They both encode data in parallel and distribute architecture in a numerical framework. As a result, it is feasible to transform a fuzzy logic architecture into a neural network and vice versa. This conversion enables the benefits of neural networks and fuzzy logic to be combined.

2.1. 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 represent the ANFIS system's inputs, Ai and Bi represent the initial fuzzy sets, and pi, qi, and ri represent the outcome parameters computed during the training phase. Figure 1 depicts the construction of an ANFIS architecture with two inputs, in which these two rules are applied in one output for a Sugeno type fuzzy inference system. Each circle in Fig. 1 represents a fixed node, whereas each square represents an adaptive node. ANFIS has five layers, as shown in Fig.1. Each layer's node function may be characterized as follows [11]:

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

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

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 (1) . Various membership functions such as triangular, gaussian, and bell-shaped can be used for this. Frequently preferred [15] triangular function has been used in this study.

Layer 2: Each node in this layer is a fixed node designated with M that multiplies the signals that come to it as output.
In this layer, any node function that performs the fuzzy AND procedure can be utilized. This layer's outputs may be computed as in (2).

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(x), \; i = 1,2 \qquad (2)$$

Layer 3: Membership functions are normalized in this layer. Layer 3 consists of fixed nodes identified with N.The ith node computes the ratio of the ith rule's firing strength to the total firing strength of all rules. Each node in this layer's output is specified by (3).

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2}, \; i = 1,2 \qquad (3)$$

where w_i denotes the weight degree associated with the ith rule.

Layer 4: This layer's nodes are all adaptable.Each node in this layer simply outputs the product of the normalized firing strength and a first order polynomial. Layer 4 is defined as (4).

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

where $\bar{w}_i$is the output of layer 3 and {p_i, q_i, r_i} is the parameter set..

Layer 5: This layer has only one node and is denoted by the symbol S. This node computes the total of all incoming signals. As a result, the model's overall output is provided by (5):

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

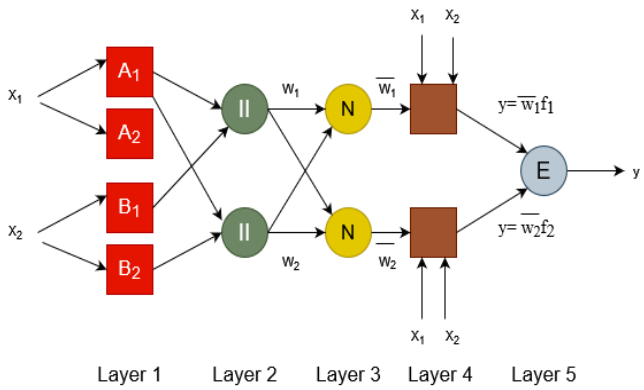

Fig.1. Architecture of typical ANFIS

The ANFIS splits each input dimension using fuzzy MFs. Because the input space is spanned by MFs that overlap, a single input can activate numerous local areas at the same time. Because ANFIS uses basic local models, its approximation ability is governed by the resolution of the input space partitioning, which is dictated by the number of MFs in ANFIS and the number of layers. MFs of four main forms are commonly employed, including bell-shaped, Gaussian, trapezoidal, and triangular MFs with maximum equal to 1 and minimum equal to 0:

$$\text{bell}\;(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad (6)$$

$$\text{gauss}\;(x; \sigma, c) = e^{\left\{\left|\frac{x-c}{a}\right|^2\right\}} \qquad (7)$$

$$\text{trap} = \text{m}\ \left(\text{m}\ \left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \qquad (8)$$

$$\text{traing}\ (x; a, b, c) = \text{m}\ \left(\text{m}\ \left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \qquad (9)$$

2.2. Learning algorithm

During ANFIS training, two types of learning algorithms are employed to determine membership functions. The first is known as the "Backpropagation Algorithm." The other is the "hybrid algorithm," which employs both the "least squares" approach and the "gradient descent" method. In this case, the gradient descent approach is utilized to arrange nonlinear input parameters, while the least squares method is used to organize nonlinear output parameters. This hybrid approach has been shown to be particularly efficient in training the ANFIS [11]. The learning techniques for this network are summarized in Table 1.

Table 1. Two passes hybrid learning procedure of ANFIS

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

The performance of the ANFIS model is evaluated using optimal values of Root Mean Square Error (RMSE), which is provided as:

$$RMSE = \left\{\frac{\sum_{i=1}^{NU} \left(y_{tes,i} - y_{pre,i}\right)}{NU}\right\}^{\frac{1}{2}} \quad (10)$$

NU stands for the number of instances, y_{prei} and $y_{tes,i}$ indicates the predicted and the testing value of one data point i, respectively[9] .

To assess the quality of the ANN models, determination coefficient (R^2) and mean absolute percentage error (MAPE), were used as the indicators of the model's performances. We express the mathematical formulation of R^2 and MAPE as follows:

$$\text{R2} = 1 - \frac{\sum_{i=1}^{NU} \left(y_{\text{tes},i} - y_{\text{pre},i}\right)^2}{\sum_{i=1}^{NU} \left(y_{\text{tess},i} - \overline{y_{\text{tes},i}}\right)^2} \qquad (11)$$

$$MAPE = 100\% \cdot \frac{\sum_{i=1}^{NU} \frac{\left|y_{\text{tes},i} - y_{\text{pre},i}\right|}{y_{\text{tes},i}}}{NU} \qquad (12)$$

3.COMPUTATIONOF CRITICAL FLASHOVER VOLTAGE OF POLLUTED INSULATORS USING ANFIS

In this study a training set containing adequate representative data points is constructed. This is a considerable step in building an ANFIS model that can represent insulators critical flashover voltage. In this work, insulator height (H-mm) insulator diameter (Dm-mm), leakage length of the insulator of an element (L-mm), and number of elements in a chain of insulators are used as input vector to the approximate and the flashover critical voltage (Vc-kV) as the output of the approximate in two cases; sec condition and rain condition. Therefore, the training set with input–output data was constructed in the training process. We used in this study twelve kinds of insulators; U70BS, U160BS, U300B, U400B, U530B, U160BSP, U300BP, U120AD, U160AD, U210AD, 52-3 and 52-8 [16]. The characteristics of these insulators are given in Table 2. Each pattern of the training set contains six inputs which characterize parameters of H, Dm, L, NE, and one output which represent VC critical flashover voltage. Constructing a testing set is also a significant step in evaluating the prediction performance of the ANFIS model with representative data points of different insulators that are not used during training. We used for each kind of insulators 24 training data and 5 test data. In global, we have 300 training data and 90 testing data.

The computation is divided into two sections; the first is to find the critical flashover voltage in sec conditions and the second in rain condition; the data of experimental tests are used from previous researches [16].

Table 2. Characteristics of the investigated Insulators

INSULATOR TYPE	D_m(mm)	H(mm)	L(mm)
U70BS	255	127	320
U160BS	285	146	325
U300B	320	195	390
U400B	360	205	555
U530B	360	240	600
U300BP	360	146	545
U300BP	360	195	617
U120AD	380	127	365
U160AD	420	146	400
U210AD	420	170	400
52-3	255	146	320
52-8	280	146	385

3.1. 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.

This was carried out under the following conditions: Data normalized = No, number of MFs = 2, type of MFs = trapmf
(low and high), initial step size = 0.05, step size decrease rate = 0.6, step increase rate = 1.6, maximum number of epochs = 4000 epochs, learning type = hybrid method, the output MF type = linear.

Fig. 2 (a) and Fig.2(b) shows The results of the training ANFIS were compared to the testing data utilizing selected data in sec and rain condition from within the series of the training pattern.

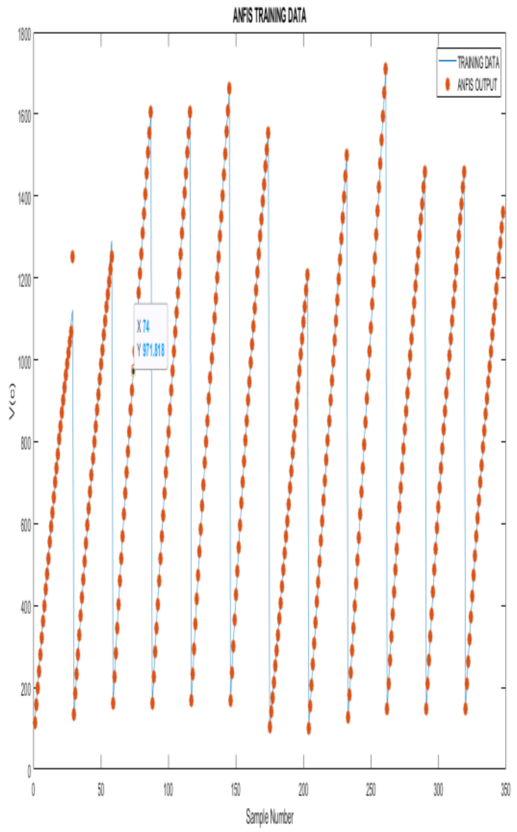

Fig 2. (a) The performance of ANFIS model for Training For sec condition

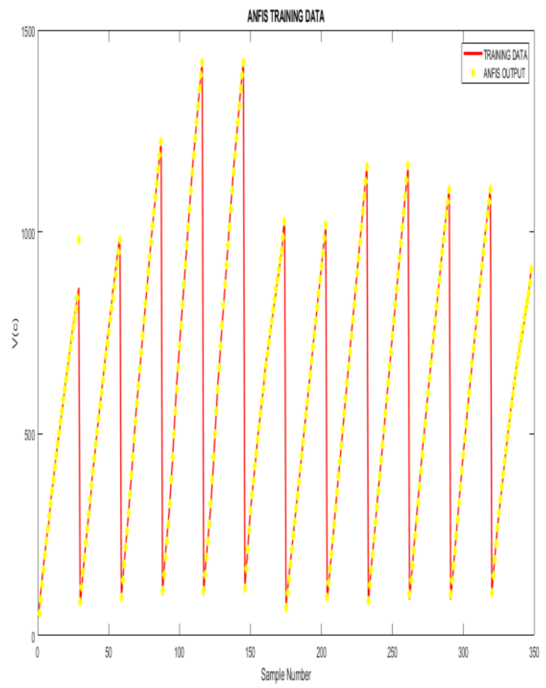

Fig 2(b) The performance of ANFIS model for Training For rain condition

We see that the model of ANFIS gives the best performance for the training data for the two condition.

The comparison between the predicted data for rain and sec condition and Test data was then made to evaluate the model prediction performance is shown in Fig.3 and Fig .4.

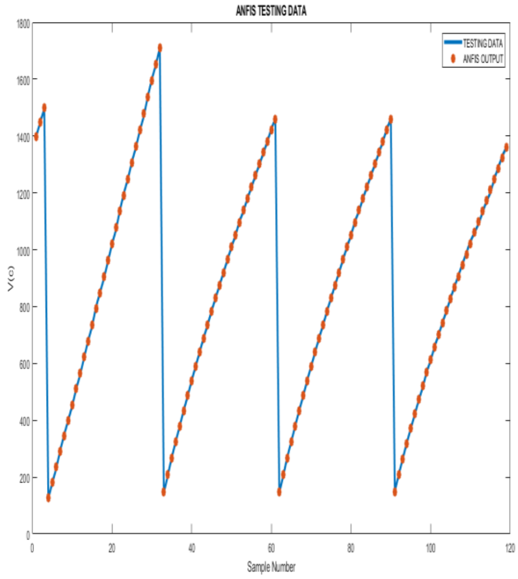

Fig. 3. The performance of ANFIS model for Testing for Sec condition.

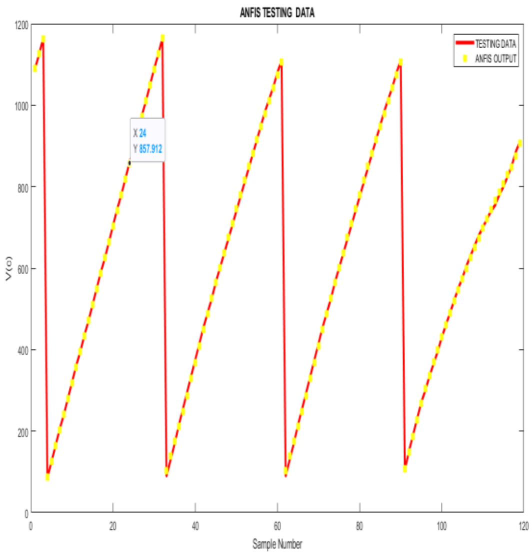

Fig. 4. The performance of ANFIS model for Testing For Rain Condition.

Based on results obtained, we can note that the flashover voltage in rain condition is lower than shown in sec condition. That explains the effect change of resistance R_p by the deposit of water drops on the surface of insulators.

By comparison between values of flashover voltage in sec condition and rainy, we can do the mean proportion like:

$$\frac{\text{Vsec}}{\text{Vrain}} = 1.29 \qquad (13)$$

Compared to other intelligent techniques in modeling fashover, we see clearly that the proposed model achieves higher correlation coefficient R=0.99986 with very small root mean square error (RMSE=0.005307) and outperforms other modeling strategies. For this comparison, the relevant Root Mean Square Error (RMSE) and Coefficient of determination (R^2) and the mean absolute percentage error (MAPE) values are presented in table 3.

From Table 3, the results show that ANFIS is powerful in the prediction of flashover voltage on insulators. As given in Table 3, the proposed model has a smaller RMSE for the test set than the ANFIS. Moreover, it can be observed that the proposed model gives comparable values for the MAPE and R2 with the previous values given in [16].

Table 3: Comparison of the proposed ANFIS models with others modeling strategies.

modelling strategies	RMSE train	RMSE test	MAPE	R^2 train	R^2 test
ANFIS sec	0.00053	0.000446	0.00053	0.9993	0.9997
ANFIS rain	0.00098	0.005107	0.00636	0.9957	0.9986
GMDL rain [14]					0.9989
LSSVM sec [14]		0.0389			0.9970
LSSVM rain [14]		0.0371			0.9983

4. Conclusion

In this paper, the ANFIS model is developed to determine the relationship between critical flashover voltage as a function of insulator height, insulator diameter, leakage length of the insulator for an element, the number of elements on a chain. Two kinds of conditions are used in this study; sec condition and rainy to show the influence of water drops of rain in decreasing of flashover voltage. The comparisons and the results presented in this investigation, such as with other methods like the GMDL model and LSSVM, reveal the the capability of the proposed ANFIS modelling strategy in predicting critical flashover voltage values of different insulator types in any region by giving detailed information on electrical transmission system.

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