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Research Article

Adaptive Neurofuzzy Inference System-Based Pollution Severity Prediction of Polymeric Insulators in Power Transmission Lines

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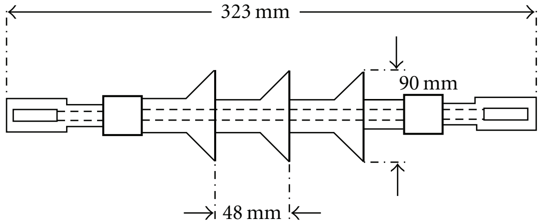
This paper presents the prediction of pollution severity of the polymeric insulators used in power transmission lines using adaptive neurofuzzy inference system (ANFIS) model. In this work, laboratory-based pollution performance tests were carried out on 11 kV silicone rubber polymeric insulator under AC voltage at different pollution levels with sodium chloride as a contaminant. Leakage current was measured during the laboratory tests. Time domain and frequency domain characteristics of leakage current, such as mean value, maximum value, standard deviation, and total harmonics distortion (THD), have been extracted, which jointly describe the pollution severity of the polymeric insulator surface. Leakage current characteristics are used as the inputs of ANFIS model. The pollution severity index "equivalent salt deposit density" (ESDD) is used as the output of the proposed model. Results of the research can give sufficient prewarning time before pollution flashover and help in the condition based maintenance (CBM) chart preparation.

1. Introduction

In a power system, outdoor insulators play an important role in maintaining the reliability of the system. Ceramic insulators are widely used in power transmission and distribution lines for a long time. In recent times, polymeric insulators are mostly preferred because of their superior insulation performance, in terms of contamination endurance compared with conventional ceramic insulators [1, 2]. When these insulators are installed near industrial, agricultural, or coastal areas, airborne particles are deposited on these insulators, and the pollution builds up gradually, which result in the flow of leakage current (LC) during wet weather conditions such as dew, fog, or drizzle. The LC density is nonuniform, and in some areas sufficient heat is developed leading to the formation of dry bands. Voltage redistribution along the insulator causes high electric field intensity across dry bands leading to the formation of partial arcs. When the surface resistance is sufficiently low, these partial discharges will elongate along the insulator profile which may eventually cause the insulator flashover. Pollution flashover along power line insulator has been a long-standing problem for the security and reliability of power transmission line. Considering the recent developments in extra high voltage power transmission in India, it is imperative to predict the pollution severity of insulator surface before pollution flashovers occur and to provide an early warning for the operators. It is important to point out that the failure at any single point of the transmission network can bring down the entire system. Recent reports [3, 4] on grid disturbance in India indicate the loss of five thousand million rupees and 97% of interconnected generation on 2nd January 2001. Similar disturbances of lesser magnitudes were also observed during the period of December 2002 and 2005, Febuary and December 2006, January/Febuary 2007 and March 2008. One of the major causes identified was the pollution/contamination-induced flashovers. These events have amply portrayed that the performance of overhead transmission line string insulators and those used in outdoor substations are critical factors which govern the reliability of power delivery systems.

Quantities recommended to express pollution severity are the equivalent salt deposit density (ESSD), the leakage current, the air pollution measurements, and the nonsoluble



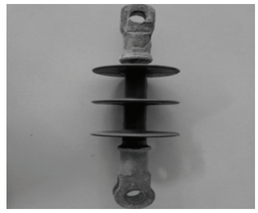


Figure 1: Photo and dimensions of the 11 kV composite insulator.

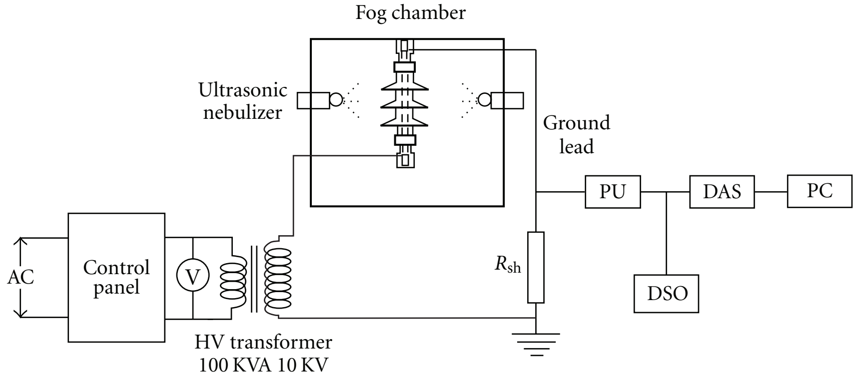


Figure 2: Schematic diagram of the experimental setup.

deposit density (NSDD) [5]. It has been verified that the leakage current affected by the operating voltage, temperature, and humidity can provide more comprehensive description about the state of the polluted insulators than other methods.

Suda [6] studied the LC waveforms and frequency characteristics of an artificially polluted cap and pin type insulator and classified the transition of LC waveforms into six stages in order to predict the flashover. Reddy and Nagabhushana [7] studied the leakage current behavior on artificially polluted ceramic insulator surface and derived the relationship between the surface resistance and leakage current. Sarathi and Chandrasekar [8] have shown that application of moving average technique for the trend analysis of leakage current signal could be useful to predict the surface condition of outdoor polymeric insulators. Chandrsekar and Kalaivanan [9] have investigated the harmonic content in polluted porcelain insulator and concluded that the harmonic content analysis is the effective diagnosis tool for outdoor insulators.

Neural networks have been intensively studied in the past decades. Cline et al. [10], Kontargyri et al. [11], and Saleh Al Alawi et al. [12] have implemented the neural network to predict the insulator flashover. Ahmad et al. [13] have successfully implemented the ANN model to predict the ESDD for contaminated porcelain insulators, but in this work, meteorological data like rainfall, wind velocity and so forth. are considered as the input to ANN model, which will vary according to the area and climate. Li et al. [14] have studied the time domain parameter of leakage current and give these parameters as input to ANN to predict the ESDD value. Considering the above facts, it is important to predict the pollution severity of the transmission line insulators taking into account both time and frequency domain characteristics of LC. In ANN, the number of learning steps is high, and also the learning phase has intensive calculations. For complex problems, it may require days or weeks to train the network. The trained ANN can respond only if the input parameters are within training limits (minimum value to maximum value). Suppose that the inputs slightly deviate from the training limits, it may not give accurate results. The pollution problem in the outdoor insulator is very fuzzy due to external environmental factors, so the inputs selected to train the network and inputs given in real-time implementation may be slightly varying. So a new network model needs to be developed to overcome the drawbacks of simple artificial neural network model [11–14], and ANFIS-based model will be most suitable for prediction of ESDD values of power transmission line insulators. Having known all this, present paper focuses on prediction of pollution severity (ESDD value) on the surface of polymer insulators by using an adaptive neurofuzzy inference system (ANFIS).

2. Experimental Setup and Data Collection

A11 kV silicone rubber insulator was used for the contamination experiments. Figure 1 shows the overall dimension of a11 kV silicone rubber insulator used in this study. Figure 2 shows the schematic diagram of the experimental setup, where PU is protection unit, DSO is digital storage oscilloscope, DAS is data acquisition system, and PC is personal computer. The test insulator was suspended vertically inside the fog chamber (1.5 m $\times$ 1.5 m $\times$ 1.5 m). The test voltage was 11 kVrms, 50 Hz. Pollution tests were conducted as per

Table 1: Leakage current time and frequency domain features.

ESDD (mg/cm^2) [o/p of model]	Leakage current features [input to model] Mean value (I_{em}), mA	Maximum value (I_{emax}), mA	Standard deviation (σ)	Total harmonic distortion (THD)%
0.01	0.039	0.13	0.0495	78.56
0.06	0.047	0.14	0.0583	54.35
0.08	0.286	2.07	0.3892	37.34
0.12	1.428	4.11	2.0302	24.34
0.25	2.160	4.24	3.6160	12.23

IEC 60507 clean fog test procedure [15]. Before tests, the insulator surfaces were cleaned by washing with isopropylic alcohol and rinsing with distilled water, in order to remove any trace of dirt and grease. To reproduce saline pollution typical of coastal areas, a contamination layer consisting of NaCl and 40 g of kaolin mixed with 1 litre of deionized water was applied to the surface of insulator. The concentration of NaCl salt was varied to give Equivalent salt deposit density (ESDD) in mg/cm^2. Four ultrasonic nebulizers were used to maintain the required relative humidity level inside the fog chamber. Relative humidity inside the fog chamber was measured using a wall-mounted hygrotherm instrument.

2.1. Leakage Current Measurement. The leakage current was measured through a series resistance in the ground lead. A high sampling rate data acquisition system (National Instruments, 1.25 MSa/sec) was used in the present study. In this study, all the signals were captured at a sampling rate of 5 kHz, and the data was stored in PC for further processing. Laboratory tests were carried out in silicone rubber insulator at different pollution levels varying from 0.01 ESDD to 0.25 ESDD, at a constant 100% relative humidity conditions. 50 leakage current signals were recorded at each ESDD level. The mean, maximum, standard deviation, and total harmonic distortion (THD) were calculated based on the formulas as follows:

$$
\begin{gathered}
I_{em} = \frac{\left(\sum_{i=1}^{N} I_e(i)\right)}{N}, \\
I_{emax} = \max(I_{em}(i)), \\
\sigma = \sqrt{\frac{\sum_{i=1}^{N}\left(I_e(i) - I_{em}\right)^2}{N}}, \\
\mathrm{THD} = \frac{\sqrt{\sum_{h=2}^{\infty} I_{h,\mathrm{rms}}^2}}{I_{\mathrm{rms}}} \times 100\%, \\
I_{\mathrm{rms}} = \sqrt{\sum_{h=1}^{\infty} I_{h,\mathrm{rms}}^2},
\end{gathered} \tag{1}
$$

where N is the total number of sampling points in the test time; $I_e(i)$ is the leakage current value in one sampling period; I_{em} is the mean value of leakage current in the test time; I_{emax} is the maximum value of leakage current in the test time; σ is the standard deviation of leakage current in the test time. The total data set 250 (50×5) is divided into three parts as training, validation, and testing. Training sets varied from 60 to 180 sets. The remaining 70 data sets are divided into 40 for validation and 30 for testing the model. The one set of recorded leakage current signal is shown in Figure 3, and its features are tabulated in Table 1.

The present work has been carried out in the high voltage pollution testing laboratory. However, the proposed methodology can be applied at selected highly polluted areas, and suitable leakage current sensors will be installed in the composite insulators. The acquired leakage current signals from all such sensors on towers will be transmitted to central data logging system in substation. The data logging system will be connected with a high-end configuration computer, which will process the data continuously and simultaneously for all insulators and features are extracted and given to the ANFIS model. This is not a simple task, and it probably requires an expensive infrastructure. The laboratory-based measurement leakage current signal was verified with real-time leakage current signal in literature work [16].

3. Performance Measure

Assessment of the performance of ANFIS model is done by optimal values of Root mean square error (RMSE), coefficient of determination (R^2), and correlation coefficient (r).

Root Mean Square Error (RMSE). The formula for RMSE is

$$
\mathrm{RMSE} = \left(\frac{\sum_{k=1}^{n}\left(X_{\mathrm{obs}} - X_{\mathrm{est}}\right)^2}{n}\right)^{1/2}, \tag{2}
$$

where n is number of data points, X_{obs} is observed value X_{est}, and estimated value.

Correlation Coefficient (r). Correlation coefficient is a measure of strength and direction of a linear relationship between two random variables. In this work, Pearson's product moment correlation coefficient, denoted by r, has been adopted to determine the value of correlation efficient between two signals. If a series of n measurements of X and Y are written as x_i and y_i where $i = 1, 2, \ldots, n$, then the

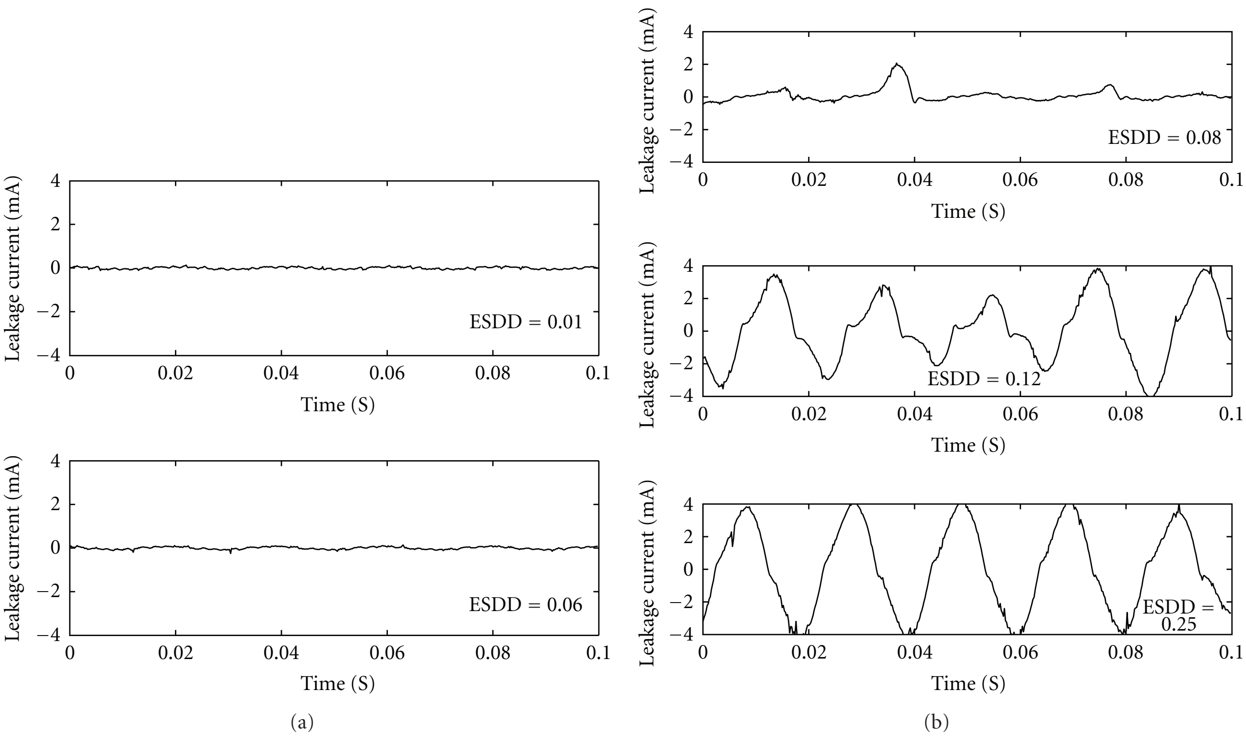


Figure 3: Leakage current signals for different ESDD values.

Pearson product-moment correlation coefficient to estimate the correlation of X and Y is written as

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{(n-1)S_x S_y}, \tag{3}$$

where x and y are the sample means of X_{obs} and X_{est}, S_x and S_y are the sample standard deviations of X_{obs} and X_{est}. The value of correlation coefficient is between -1 and $+1$ which measures the degree to which two signals are linearly related. If there is perfect linear relationship with positive slope between the two signals, then the correlation coefficient will be $+1$. If there is a perfect linear relationship with negative slope between the two signals, then the correlation coefficient will be -1. Correlation coefficient of 0 indicates that there is no linear relationship between the signals.

Coefficient of Determination (R^2). There are different definitions of R^2. In the case of linear regression,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{\text{obs}} - X_{\text{est}})^2}{\sum_{i=1}^{n}\left(X_{\text{obs}} - \overline{X}_{\text{obs}}\right)^2}. \tag{4}$$

4. Back Propagation Neural Network

Artificial neural networks are highly parallel, adaptive learning system that can learn a task by generalizing from case studies of the tasks. If a problem can be posed as an input-output mapping problem, an ANN can be used as a black box that learns the mapping from input-output examples from known cases of task. In the present work, ANN has been applied to the problem of predicting the pollution severity of polymeric insulators. Among the various ANN architectures available in the literature, the multilayer feed-forward network with back propagation learning algorithm has been used for the present study because of its simple approach and good generalization capability [17, 18]. The details of the optimized neural network used in the present study are shown in Table 2.

Table 2: Back propagation neural network specifications.

No. of inputs	4
No. of neurons in hidden layer	11
No. of neurons in output layer	1
Learning rate (η)	0.01
No. of iterations	2500
No. of training sets	180
No. of test input sets	70
Convergence criteria	0.001

The convergence property and accuracy of the learning process for the BNN are significantly dependent on the scaling of the input-output data set. Hence, before training BPNN, the normalization of input-output data should be carried out. So their input values are normalized to 1 based on the following:

$$\overline{y}_i = \frac{(y_i - y_{\min})}{(y_{\max} - y_{\min})}. \tag{5}$$

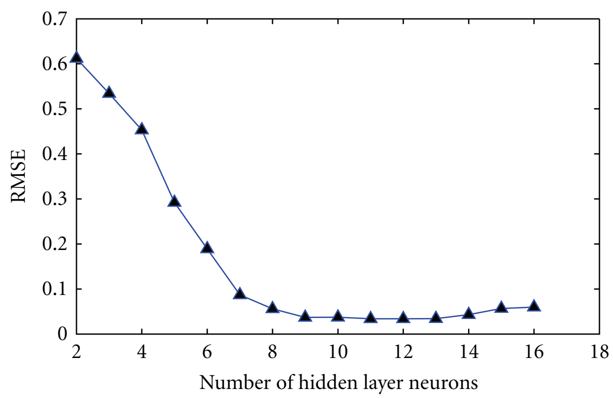


FIGURE 4: RMSE evaluation for different hidden layer neurons.

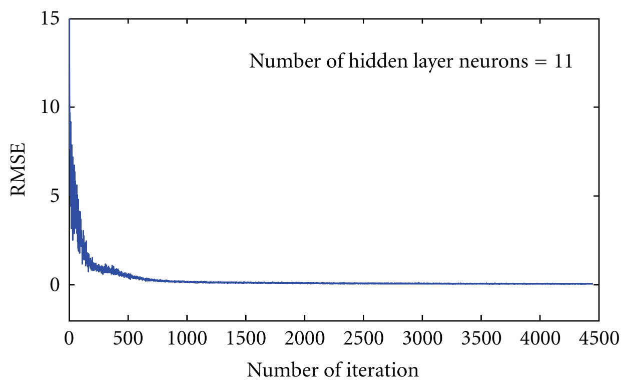


FIGURE 5: RMSE evaluation for different number of iteration.

The important factors influencing the performance of the neural network are the number of processing elements in the hidden layer and the number of iterations. Figure 4 shows the root mean square error value obtained with the different number of hidden layer neurons. It clearly indicates that the root mean square error value obtained with 11 hidden layer neurons was the minimum. As the number of hidden layer neurons increases, the neural network takes more time to learn. To obtain an optimum value for the number of iterations, the mean square error value of the network has been evaluated by maintaining the value of learning rate to be 0.01 with 11 hidden layer neurons. Figure 5 shows the performance of the network for different iteration numbers. It clearly indicates that during training the present network reaches the convergence criteria near 3000 iterations. It indicates that 3000 iterations are sufficient for the successful training of the optimized neural network.

5. Adaptive Neurofuzzy Inference System

A unique approach in neurofuzzy system is the adaptive neurofuzzy inference system (ANFIS), which has been proven better performance in modeling nonlinear function [19]. The ANFIS models possess human-like expertise within a particular domain which adapts itself and learns to do better in changing environment condition [20]. An ANFIS aims at automatically generating unknown fuzzy rules from a given input and output data sets [21]. Figure 6 shows a typical architecture of ANFIS.

Notice that in Figure 6, each circle shows a fixed node, whereas every square indicates an adaptive node. So the rule base system has two if-then rules of Takagi-Sugeno's type as:

Rule i : if x is A_i and y is B_i, then $f_i = p_i x + q_i y + r_i$, $i = 1, 2$.

Layer 1. Each node i in this layer is an adaptive node and outputs of these nodes are given by

$$\begin{aligned} O_{1,i} &= \mu A_i(x), \quad \text{for } i = 1, 2, \quad \text{or} \\ O_{1,i} &= \mu B_{i-2}(y), \quad \text{for } i = 3, 4, \end{aligned} \tag{6}$$

where $\mu A_i(x)$ and $\mu B_{i-2}(y)$ are membership functions that determine the degree to which the given x and y satisfy the quantifiers A_i and B_{i-2}. In this work, the membership function for A can be any appropriate parameterized membership function, such as the generalized bell function

$$\mu A(x) = \frac{1}{1 + |(x - c_i)/a_i|^{2b}}, \tag{7}$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly. Parameters in this layer are referred to as *premise parameters.*

Layer 2. In this layer, each node is a fixed node labeled Π that determines the firing strength of related rule, whose output is the product of all the incoming signals

$$O_{2,i} = \omega_i = \mu A_i(x) \mu B_i(y), \quad i = 1, 2. \tag{8}$$

Layer 3. In this layer, every node is a circle node labeled N, which computes the ratio of firing strength of each rule to the sum of all of them; the so-called normalized firing strength.

$$O_{3,i} = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. \tag{9}$$

Layer 4. The output of each adaptive node in this layer is

$$O_{4,i} = \varpi_i f_i = \varpi_i (p_i x + q_i y + r_i), \tag{10}$$

where ϖ_i is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ are called as *consequence parameters.*

Layer 5. Final layer, the single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals,

$$\text{overall output} = O_{5,i} = \sum_i \varpi_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}. \tag{11}$$

Thus, an adaptive network has been constructed. The proposed ANFIS-based pollution severity system is based upon Jang's ANFIS [19], which is a fuzzy inference system

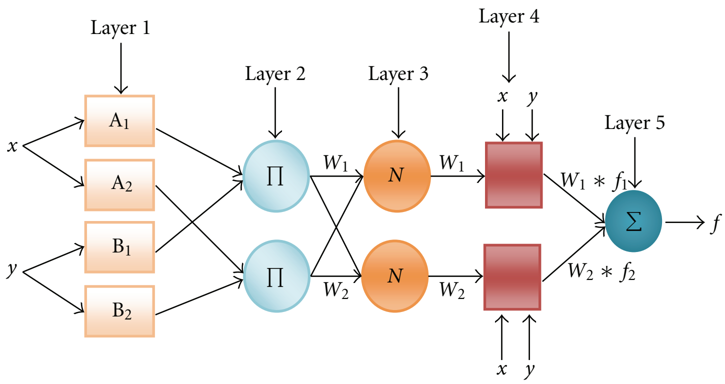


Figure 6: Architecture of typical ANFIS.

Table 3: Two passes in the hybrid learning procedure for ANFIS.

	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least squares estimate	Fixed
Signals	Node output	Error rates

Table 4: Summary of general specifications of the used architecture.

Adaptive FIS type	Adaptive architecture	Algorithmic learning structure	Partition of spaces	Required initial knowledge	Structural change	Extracted knowledge type
ANFIS	Multilayer feed-forward network	Hybrid: supervised (gradient descent)	Adaptive fuzzy grid	Numerical data	No	If-then fuzzy rules

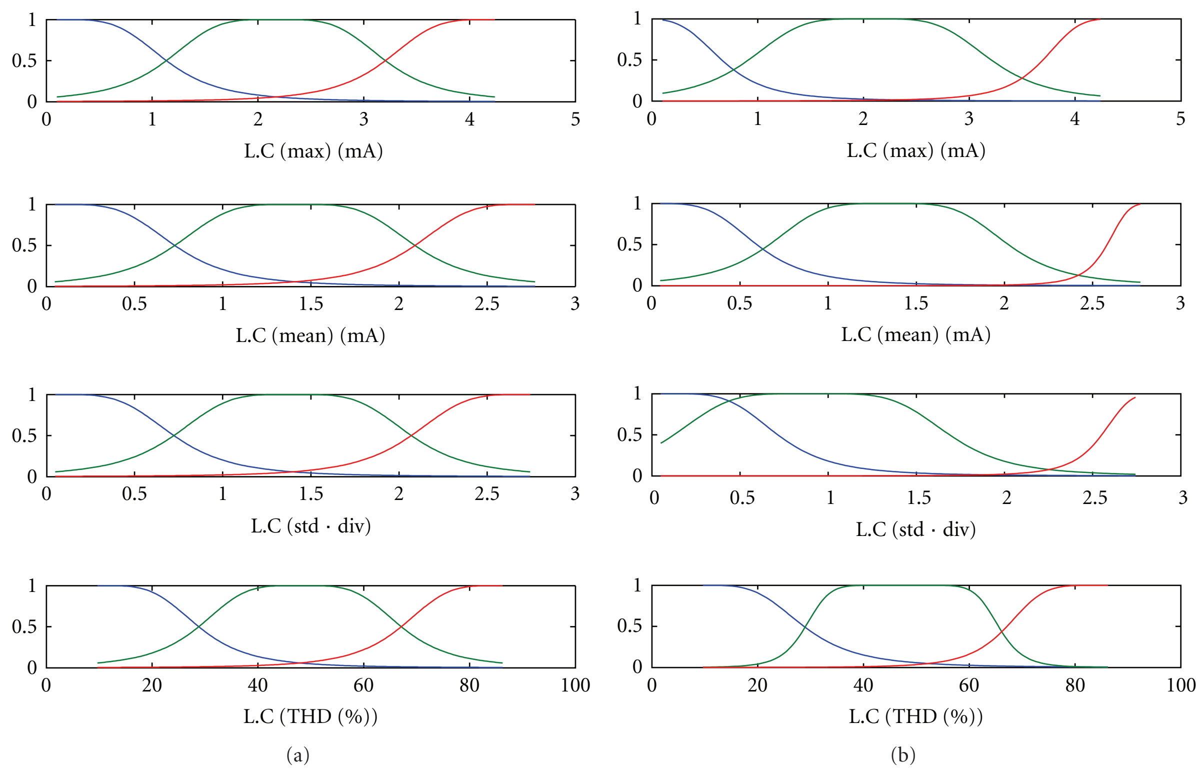


Figure 7: MFs parameters before and after ANFIS model bell-shaped MFs.

Table 5: Statistical indices for performance assessment of the different types of ANFIS models.

Type of Mf	No. of MF	RMSE		RMSE	R^2	r
		Training	Validation	Testing		
Trimf	2	0.007213	0.01282	0.00689	0.945	0.8462
	3	0.005301	0.01155	0.00683	0.967	0.9167
	4	0.003438	0.01485	0.02847	0.875	0.8413
	5	0.001705	0.00602	0.00282	0.974	0.9122
gaussmf	2	0.014395	0.00962	0.01609	0.962	0.8642
	3	0.016005	0.01687	0.01742	0.879	0.8932
	4	0.002167	0.00141	0.00031	0.999	0.9812
	5	0.009562	0.01225	0.00934	0.979	0.9232
gbellmf	2	0.009173	0.01072	0.01048	0.899	0.8652
	3	**0.001831**	**0.00513**	**0.00323**	**0.998**	**0.9945**
	4	**0.001245**	**0.00496**	**0.00289**	**0.999**	**0.9952**
	5	0.003399	0.01258	0.00894	0.969	0.9171

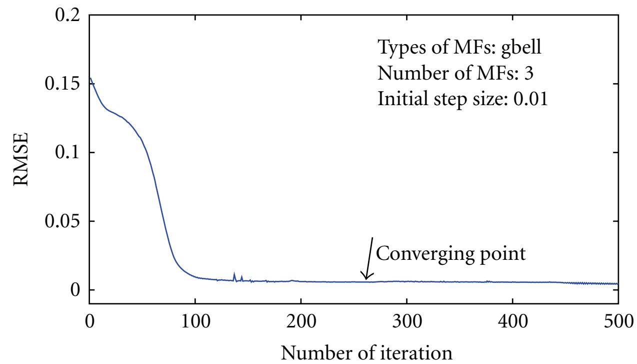


Figure 8: RMSE evaluation of different no. of integration for ANFIS model.

implemented on the architecture of a five-layer feed-forward network. Using a hybrid learning procedure, the ANFIS model can construct an input-output mapping based on both human knowledge (in the form of if-then rules) and input-output data observations. In the hybrid learning algorithm, in the forward pass, the functional signals go forward till layer 4, and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. The consequent parameters thus identified are optimal (in the consequent parameter space) under the condition that the premise parameters are fixed. Accordingly, the hybrid approach is much faster than the strict gradient descent. Table 3 summarizes the activities in each pass. A summary of the general specifications including the learning algorithm, required initial knowledge, domain partitioning, rule structuring, and extracted knowledge type are given in Table 4.

6. Results and Discussion

In this study, automatic pollution prediction system was developed based on the leakage current feature measurement. The time and frequency domain feature of leakage current were extracted from the laboratory testing, and these data were given as inputs to train the ANFIS. 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), and generalized bell-shaped built-in membership function (gbellmf); each MF was tested with different linguist variables (2 [HIGH LOW]3[HIGH MEDIUM LOW] 4[HIGH MEDIUM LOW VERY LOW] 5[VERY HIGH HIGH MEDIUM LOW VERY LOW) to each input. The ANFIS model was trained by hybrid learning algorithm. Figure 7 illustrates the gbellmf membership functions before and after training. The std and mean inputs boundaries were adapted well, and max, THD inputs boundaries were slightly adapted, because the initial assignment of these boundaries was very close to actual input data. Figure 8 shows the training error curves with initial step size equal to 0.01. The converging criterion was obtained at 250th iteration. The performance of each model was tested by performance-measured coefficients. The detailed simulated results obtained by the developed ANFIS model for predicting the ESDD value of the polymer insulator were tabulated in Table 5.

According to Table 5, generalized bell-shaped (gbell) with 3 or 4 MFs is the best architecture model to predict the pollution severity of the polymeric power line insulators, because it gives lowest RMSE value during the training, validation process and lowest RMSE, highest R^2, and r during the testing process. Even though two architecture models are fit for this problem, 3 MFs architecture model was selected, because it has been trained with less time compared with the 4 MFs architecture model. The final performance of any model strictly depends on the number of training data sets, and initially different architecture ANFIS model was trained with 180 training data sets for getting best fit architecture model, then the training data sets vary from 60 to 180 sets to train the best fit model (gbell, 3 MFs) in order to get optimal training data sets to train the model.

The performance of the ANFIS model was compared with back propagation neural network (BNN) model. The same input training and testing data sets were applied to BNN model, and the performance measurement indices were

Table 6: Comparative performance assessment of models.

Models	Performance measures		
	RMSE	R^2	r
BNN	0.02524	0.943	0.9732
ANFIS	0.00323	0.998	0.9945

tabulated in Table 6. According to Table 6, ANFIS model gives more accurate results than BNN. The output of ANFIS-based model was mostly matching the tested values, because it gives lowest RMSE [0.00323], highest R^2[0.998], and r[0.9945] compared to BNN model. This was because of the highly nonlinear mapping capability and self-adaptive nature of the fine tuning of the MFs of ANFIS. After the initial training step of the ANFIS model, which was the optimization of the consequence parameters, the system adapts such that the pollution severity index value (ESDD) predicting was significantly close to the actually tested values of the polymer insulators. The RMSE to predict the ESDD values based on neural network is 0.02524 at developed BNN model and 0.035 at literature work [14], which was recently a published work with the same kind of input feature used to train the BNN model. Considering the above test results, the ANFIS model would give better accuracy than BNN models.

The accurate prediction of pollution severity index [ESDD] of polymeric insulator in power transmission line is automated by ANFIS model by on-line training. Actually, the pollution flashover may take place once the pollution severity index reaches it critical value. If the ANFIS model predicts the ESDD value prior to critical value, then the operator will get a warning instruction to wash the particular polluted polymeric insulator in the transmission tower to avoid the pollution flashover.

7. Conclusion

A methodology for the prediction of the pollution severity of polymeric insulators using ANFIS model was presented. The ANFIS model was designed based on the time and frequency domain characteristics of the polymeric insulator leakage currents. The performance of the developed model was justified by root mean square error, coefficient of determination (R^2), and correlation coefficient (r). The respective results are quite satisfactory and superior compared to BNN model. The new prediction model helps to automate the process of identification surface condition of the polymeric insulator, installed near industrial and agricultural or coastal areas. Hence, the present model could be used to predict the pollution severity of polymeric insulator and, therefore, can be used to establish condition-based maintenance practices.

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