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Evaluation of Flashover Voltage Levels of Contaminated Hydrophobic Polymer Insulators Using Regression Trees, Neural Networks, and Adaptive Neuro-fuzzy

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Abstract

Polluted insulators at high voltages has acquired considerable importance with the rise of voltage transmission lines. The contamination may lead to flashover voltage. As a result, flashover voltage could lead to service outage and affects negatively the reliability of the power system. This paper presents a dynamic model of ac 50Hz flashover voltages of polluted hydrophobic polymer insulators. The models are constructed using the regression tree method, artificial neural network (ANN), and adaptive neuro-fuzzy (ANFIS). For this purpose, more than 2000 different experimental testing conditions were used to generate a training set. The study of the ac flashover voltages depends on silicone rubber (SiR) percentage content in ethylene propylene diene monomer (EPDM) rubber. Besides, water conductivity (µS/cm), number of droplets on the surface, and volume of water droplet (ml) are considered. The regression tree model is obtained and the performance of the proposed system with other intelligence methods is compared. It can be concluded that the performance of the least squares regression tree model outperforms the other intelligence methods, which gives the proposed model better generalization ability.

Keywords: *Flashover voltage, EPDM rubber, Regression tree, Artificial neural network (ANN), Adaptive neuro-fuzzy (ANFIS)*

1. Introduction

Recently, polymeric high voltage insulators have been used on distribution and transmission lines. They increasingly replace glass and porcelain insulator around the world. They weigh 10% lighter and have less breakage than porcelain and glass. Polymeric high voltage insulators lend themselves as attractive high voltage insulators. They have low installation cost, easy handling, low surface energy, higher mechanical strength to weight ratio, resistance to vandalism and better performance in the contamination and wet conditions [1]. Both practical service and laboratory experimental tests on polymeric high voltage insulators have demonstrated a better performance in contaminated conditions [2-5]. Contamination on the insulator surface increases the possibility of flashover voltage. Under light rains, fog, or dew, the insulator surface contamination starts to dissolve. This results in a conducting layer on the surface of the insulator. The line voltages invoke leakage currents. High current density near the electrodes leads to heating at the polluted layer. Heating results in dry areas. Water droplets on a surface of a polymer increase the applied electric field. An arc is initiated if the electric field strength across the dry band exceeds the withstanding capability. The extension of the arc results in flashover voltage [6-8].

Many environmental factors such as conductivity (µS/cm) of water droplets, droplets number, water droplet volume (ml), and percentage ratio of silicone rubber contents to the composite polymer have a strong impact on determining the the flashover voltages values of polymer insulators [9-10]. Consequently, the authors of this work are motivated to consider and develop numerical evaluation or accurate modeling of flashover voltages levels plays a significant role in studying the dynamic behavior of polymeric materials. Another motivation arises from the polymeric surfaces of hydrophobic insulators, which have low surface conductivity [11]. This problem in turn gives a low discharge activity and hence a higher

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flashover voltage. On the other hand, hydrophobicity reduction leads to a higher risk insulator flashover voltage values. Hydrophobic materials lie in a vulnerable position regarding polluted environments. They are characterized by a significant activity of local discharges [12].

In the last decades, various prediction or evaluation models have been proposed in electrical engineering literature research. Artificial neural network (ANN) model was presented in [13-15]. In [6], the support vector models were introduced. The time-series models are introduced in [16]. The adaptive neuro-fuzzy interface models (ANFIS) are reported in [17-18] respectively. Various regression modes are investigated in [19].

The prediction models in engineering using artificial neural network modeling have been increased gradually. ANN gives satisfactory results in many research cases [6]. However, this accuracy tends to come at the expense of over-fitting the training data [6,15]. In [20], a fuzzy Logic (FL) model has been applied in order to estimate the critical flashover voltage on polluted insulators. Recently, the least squares regression tree has been used to describe the groundwater potential mapping [21].

The main target of this research is to investigate a dynamic function approximation, pattern recognition, classification, and prediction or evaluation of EPDM high voltage polymeric insulators under wet contaminated conditions. The investigated trained network uses experimental investigations of EPDM under various testing conditions. The proposed work mainly contributes to find a fast and effective function approximation and classification modelling between EPDM fashover voltage and the prediction variables. Correllation analysis will be employed to determine such relation [22]. Consequrntly, this research work investigates three modern artifitial intelligent regression models: regression trees, artifitial neural netwoks, and adaptive neuro-fuzzy [23-25].

Recently, regression trees were used to solve many engineering problems. In [25], regression tree was used as a base for data-driven to machine condition prognoses. In [26], it was used to predict the wind speed with local models or algorithms being discussed for the short term operating wind conditions. In [27], it was used sucessfuly to predict an airport weather conditions. Besides, it was utilized to predict the blood pressure and recession problems in [28,29] respectively. In power system applications, regression trees were applied to fault diagnosis in the transmission lines [30]. Regression trees are developed with the help of the learning informative technique and classification methods [31]. The usage of casting in regression tree dates back to 1963 by Morgan and Sonquist [31-32]. The most valuable book related to the regression tree is introduced by Breiman et al in 1984 [33-34]. In [35], regression trees were adopted to solve a sequential power flow problem for active distribution systems. Although regression tree has a piecewise constant approximation, however it has several merits that make it promising in multiple regression problems [31]. Regression tree provides an automatic variable data selection. This makes it highly intensive to the irrelevant data variables. It has a significant computational efficiency that enables addressing large data related problems. It can handle both numerical and predictor variables with insensitivity to predictors scale. Also, it is interpretable for most domains. Therefore, regression tree is very attractive and promising technique for modelling the flashover voltage.

Artfitial neural networks (ANNs) has been significantly developed in the field of power system protection and flashover voltage approximation. Also, ANNs were widely utilized in regression and control [36]. Multlayered perceptron with back propbagation training algorithm is a famous and supervised neural network for function approximation [15,24]. On the other hand, the adaptive neuro-fuzzy is developed by using fuzzy rules into neural network construction using appropriate training [23]. ANFIS introduces a technique to use fuzzy with Sugeno sytems to investigate the output of the data sets. The back back propbagation training algorithm can be employed in ANFIS systems to train the input and output data sets [37].

The superiority and effectiveness of the regression trees are achieved in [25-35]. Furthermore, it is clear from the literature survey that the application of regression trees algorithm of flashover voltage prediction has not been discussed. This incourages the authors to adopt this algorithm with this problem. In this research, a dynamic model of the ac 50Hz flashover voltages of polluted hydrophobic polymer insulators is constructed using the least squares regression trees. The training data are obtained from various experimental conditions that include the silicone rubber (SiR) percentage content in the EPDM rubber insulators. In addition to that, the water conductivity (µS/cm), number of droplets on the surface, and volume of water droplet (ml) are considered while executing the experiments. The trained data were employed to predict the performance of the hydrophobic polymer insulators and to predict the composite hydrophobic surface that can withstand higher flashover voltage under wet polluted weather conditions. In order to evaluate the effectiveness of the investigated model, the least squares regression tree model is compared with ANN and ANFIS regression techniques for the same data sets. Finally, the obtained model is employed to investigate the surface at which the EPDM composites can withstand higher flashover voltages.

The remainder of the paper is organized as follows. Section 2 introduces an idea about the experimental work and test procedures. A theoretical background about the developed regression and function approximation models is presented in section 3. The discussions and simulation results are explained in section 4. Finally, the conclusions are presented section 5.

2. Experimental Setup and Test Procedures

2.1. Material Details

In this study, composite polymeric insulators were tested experimentally. The composite was composed of EPDM rubber insulator with various percentages of SiR.

2.2. Test Procedures

The fixed frequency 50Hz alternating current high voltage was fed from a single phase high voltage transformer as shown in Figure 1. The transformer rating is 15kVA with 150kV. The resistors R1 and R2 are used for voltage dividing. Two half cylindrical copper electrodes with round edges are used. They are designed to have similar smooth profile without any irregularities in order to avoid the non-uniform electric field.

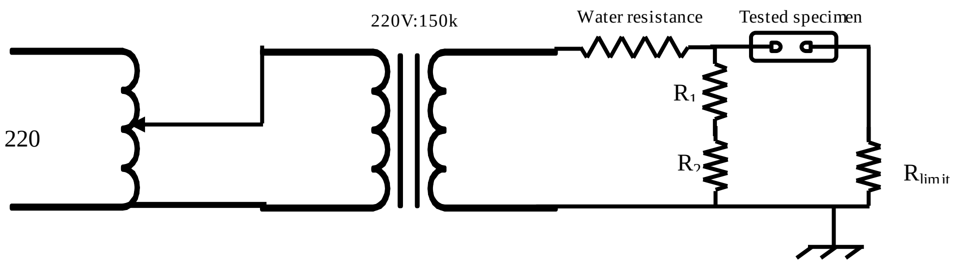


Figure 1. Connection diagram of EPDM flashover voltage testing

2.3. Dimensions of the Specimens

The dimensions of each sample are 80mm in length, 40mm width, and 3mm thickness. The droplets water conductivity is 50, 500, and 1000 µS/cm. The water droplets volume is 0.05, 0.1, and 0.15ml respectively. The water droplets were put on the specimen surface using a syringe. The two electrodes are 40mm far from each other. The water droplets number on each specimen is 1, 3, and 5 droplets respectively. To emulate the outdoor fog and wet weather conditions, the composite surface was inclined by an angle of 10^o from the horizontal level.

3. Theoritical Background

3.1. Regression Trees Analysis

A method or an approach of nonparametric regression that could overcome the presence of higher order interactions among some of the explanatory variables is called the classification and regression tree (CART) [34]. The basic of such tree technique is the extraction of subgroups of observation (in this study, the various experimental condition). The subgroup data can be of any type (i.e. binary, numeric, categorical, etc.). Among these subgroups, the outcome (in this study, the flashover voltage) is distinctive. The creation of subgroups occurs according to a tree structure. Figure 2 shows the basic idea of the regression tree. The tree consists of two variables, and it has three layers of nodes. The first layer is the unique root node, at the top of Figure 2a. In the second layer, there is one internal circle node. The three terminal nodes (shown by boxes) are located in the second and third layers. Both the root and the internal nodes are divided into two nodes in the next layer as shown in Figure 2 b (called the left and right daughter nodes). The terminal node does not have offspring nodes. The terminal nodes of a tree are known as leaves.

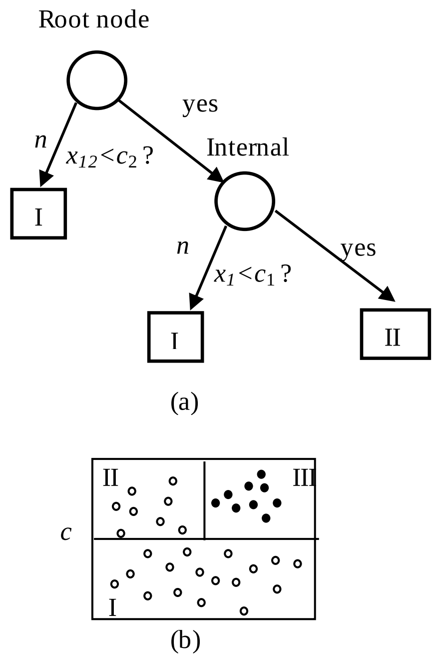


Figure 2. An illustrative tree structure (circle and dots are different outcomes) (adopted from [34])

For a given set of data D= $\{(x_{i,1},x_{i,2}...,x_{i,p},y_i)\}_{i=1}^{n}$, regression tree provide a tree-based approximation $\hat{f}$ of a known regression function Y as given in (1) [31]. A hierarchical model of logical tests according to the values of the variables of predictor p is obtained.

$$Y = f(x) + \varepsilon, Y \in R \quad (1)$$

where, ε is a perturbation around f(x). Tests on numerical real variables have the form of (2). Whereas, tests on nominal variables take the form of (3).

$$x_i < \alpha, \alpha \in R \quad (2)$$

$$x_j \in \{v_1,...,v_m\} \quad (3)$$

Regression trees employ an algorithm known as binary recursive portioning [21,31,34]. The algorithm proceeds recursively to divide the tested sample into two partitions test in order to obtain a left and right branches of a node. One partition related to the cases verifying the test. The other is concerned with the remaining data of the sample. The algorithm has three components to characterize the regression tree: the termination criteria, constant, and way to find the best test one of the predictor's. The decision to choose these components is related the preference criteria in order to build a tree. The most common criterion is the least squares. This criterion depends on the minimization of the square of errors as given in (4).

$$err = \frac{1}{n_g}\sum_{(x_t,y_t)\in D_g}(y_i - k_t)^2 \quad (4)$$

where, y_i is the measured output or outcome value, D_g is the sample of the cases or data in node t, n_g is the total number of elements of the sample, and k_t is the average target value.

3.2. Pruned Regression Tree

As previously stated, regression tree is nonparametric modeling. Nonparametric techniques may over-fit the measured data. This would imply that the regression tree may fitted too exactly at the trained data points. However, it may not give good results by any other data [31,34]. An algorithm called pruning algorithm is used to avoid the overfitting. Let n_g is the total number of cases in g, and let the target or response average in g is given in (5).

$$\bar{y}(g) = \frac{1}{n_g}\sum_{i\in g} y_i \tag{5}$$

The within-node summation of squares for node g will be given by (6).

$$SS(g) = \sum_{i\in g}[(y_i - \bar{y}(g))]^2 \tag{6}$$

For a split s that divides g into left and right daughter nodes, the equation of least squares split function is given in (7).

$$\phi(s,g) = SS(g) - SS(g_L) - SS(G_R) \qquad (7).$$

The best split s^* of g is obtained such that (8) is obtained.

$$\phi(s^*,g) = max_{(s\in\Omega)}\phi(s,g) \tag{8}$$

where, Ω is the split of all allowable splits in s $\in g$. A least squares repression tree proceeds recursively splitting nodes to maximize the function ϕ [34].

3.3. Multilayer Feed-Forward Nueural Network

ANNs consist of input layer, hidden layers, and output layer. In ANN systems, an element called neuron process the data. Each neoron of hidden layers is given a signal from the input neurons. Signals can propagate from the input layer to the output layer through single or multiple hidden layers. The signals are transferred via connecting links with associated weights. The output regression or trained signal is obtained by applying activations to the input signal. ANNs occupy a wide and mature area [36,37]. A simple structure of artificial neuron is shown in Figure 3.

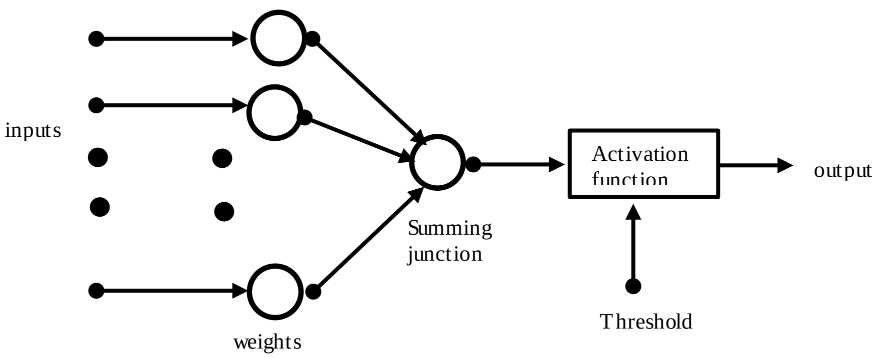


Figure 3. Simple construction of ANN neuron

3.4. Adaptive Neuro-Fuzzy Inference System

Adaptive neuro-fuzzy inference system (ANFIS) combines the merits of fuzzy as well as the adaptability of ANN. ANFIS approach is used as a teaching method for sugeno-type fuzzy systems subjected to the following limitations [37-40]:

a. First order sugeno-type fuzzy systems
b. Single output obtained by weighted average defuzzification stage
c. Unity weight for every rule
d. AND logic represented by prod, OR by max, implication by prod, and Aggregation method by max.

The user is required to provide ANFIS by number of membership functions (MFs) for each input and output, the MFs' type, the number of training and checking data, and the optimization criterion for reducing the measured error. Normally, the optimization criterion is defined by the number of the squared difference between the actual and linearized N curve [40-41].

4. Results and Discussions

Figure 4 shows the various parameters affecting the EPDM rubber composites flahover voltages. The contents of SiR in EPDM vary from 0% to 100% with 25% step increase in each test. For each SiR percentage content test, the water conductivities in µS/cm were 50, 500, and 1000 respectively. Again, for each water conductivity, the droplets volume in milli-litre (ml) was 0.05, 0.1, and 0.15. For every water droplet volume, the experiments were repeated for 1, 3, and 5 droplets respectively. This culiminates into 2025 different experimental testing conditions could be used to generate a training set.

The pruned regression tree model was implemented for prediction of flashover voltages of various contaminated levels. The model is constructed using Matlab software, version 2015b. The model was performed using the following procedures:

a. Training and testing the measured data sets.
b. The regression tree is pruned as described above.
c. The tested and estimated values are compared.

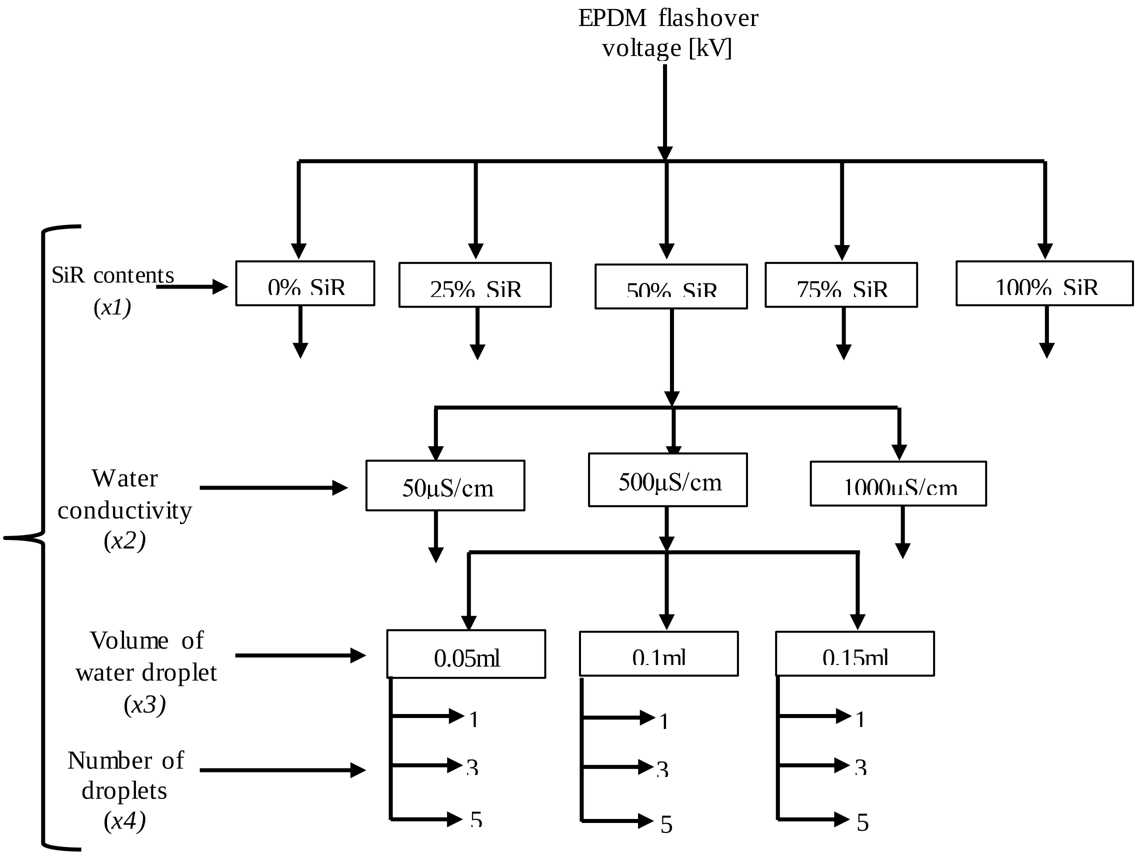


Figure 4. Configuration of computing EPDM flashover voltages

Several statistical parameters are calculated. The root mean square error (RMSE) and the relative error (RE) is calculated according to (9) and (10) respectively. The correlation coefficient (R) is calculated according to (11), in which the superscript *e* refers to the estimated or predicted values, and *t* refers to the tested data values. It should be noted that, the designation y in (9)-(11) is used to stand for the flashover voltage. The absolute normalized error is given in (12).

$$RMSE = \sqrt{\frac{1}{n_g}\sum_{(x_t,y_t)\in D_t}(y_e - y_t)^2} \tag{9}$$

$$RE = \frac{RMSE}{n_g} \tag{10}$$

$$R = \frac{\sum_{i\in g}(y_e-\bar{y}_e)\sum_{i\in g}(y_t-\bar{y}_t)}{\sqrt{\sum_{i\in g}(y_e-\bar{y}_e)}\sqrt{\sum_{i\in g}(y_t-\bar{y}_t)}} \tag{11}$$

$$E = \frac{|(y_e-y_t)|}{|(y_t)|} \tag{12}$$

Part of the obtained regression tree is shown in Figure 5. A comparison between the predicted and test data was made for 100 different samples to evaluate the model prediction performance. The simulation is shown in Figures 6 and 7 respectively. The corresponding RMSE, RE, and R values are given in Table 1. In addition, another 100 tested samples were chosen. The results of simulation are given in Figures 8 and 9 respectively. Table 2 shows the statistical model validation results for this testing set. The comparison of Figures in Tables 1 and 2 with the straight lines regression approximations of Figure 6 and 8 indicates perfect prediction. The perfect prediction is also confirmed by the results of the normalized error as given in Figures 6 and 8.

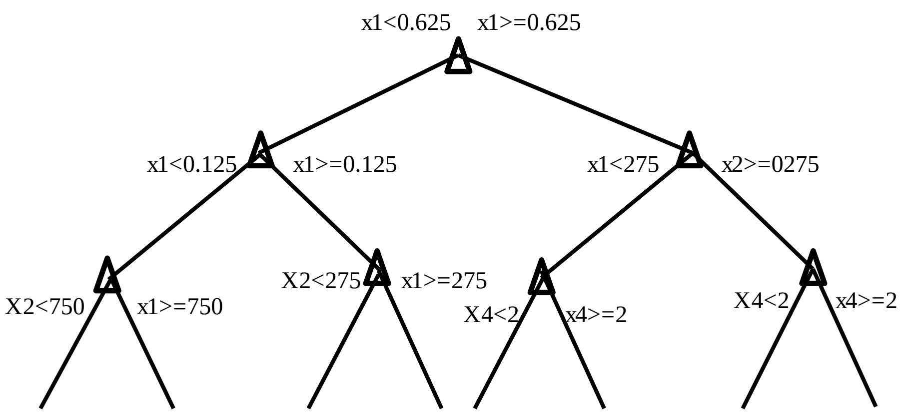


Figure 5. Regression tree profile

Table 1. Regression Tree Performance for the first tested samples

Parameter	Value
RMSE	0.1379
RE	0.0165
R	0.9992

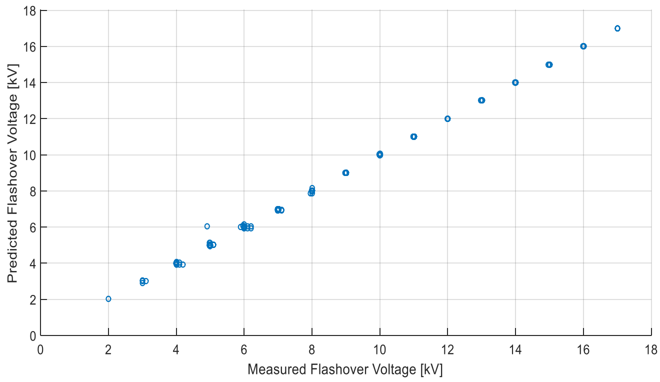


Figure 6. The regression Tree prediction vs. the measured data for data set#1

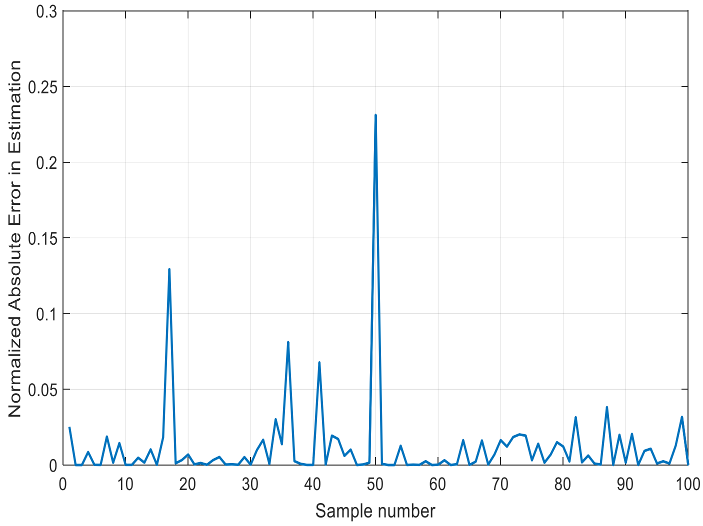


Figure 7. The regression tree absolute normalized error vs. the selected samples for data set#1

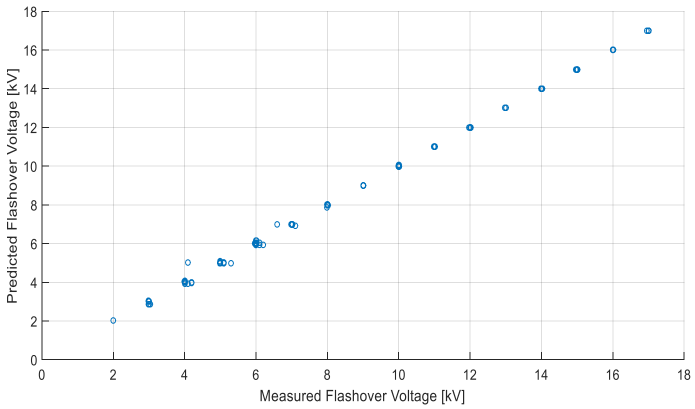


Figure 8. The regression tree prediction vs. measured data for data set#2

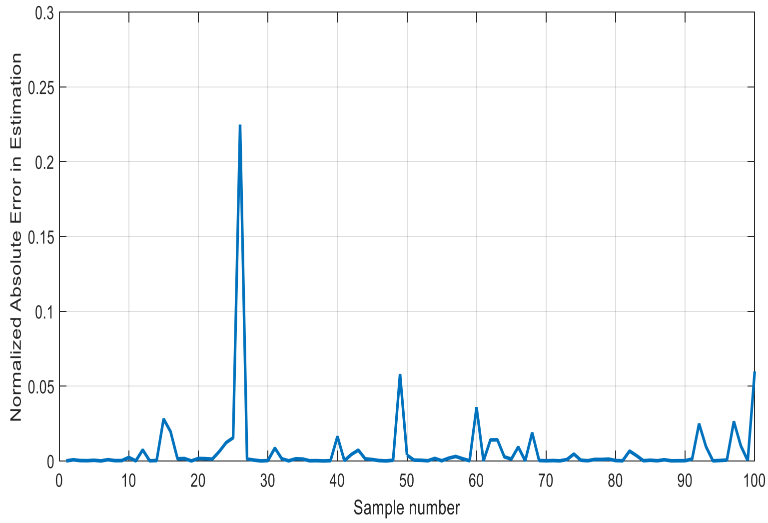


Figure 9. The regression tree absolute error vs. the selected samples for data set#2

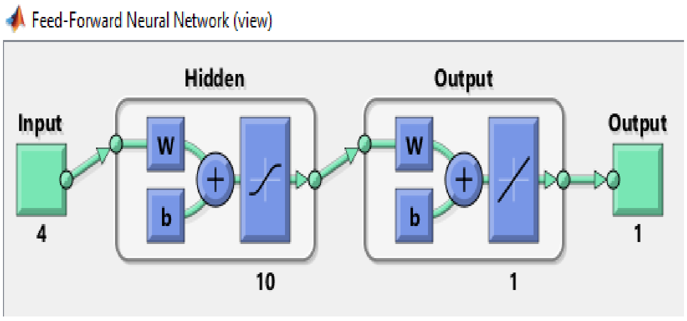
Table 2. Regression tree performance for the first tested samples

Parameter	Value
RMSE	0.0900
RE	0.0103
R	0.9970

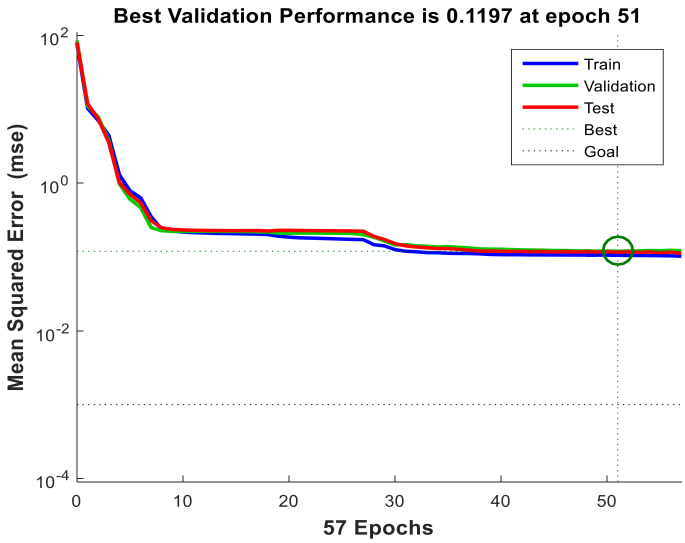
In order to estimate prediction performance of the pruned regression tree model, a comparison was made between the perceptron results of a multilayer feed-forward neural network with back propagation and the adaptive neuro-fuzzy approach. Since the multilayer feed-forward neural network is a well-known universal estimator for researchers, half of the measured data is used for training. Then, the results of the implemented regression tree model, with the same training data sets, of the remaining data are compared with the multilayer feed-forward neural network. The training data of the multilayer feed-forward neural network used in this study are given in Table 3. The developed matlab structure and the mean squared error of the multilayer feed-forward neural network are shown in Figure 10 a and b respectively. In Figures 11 and 12, the predicted flashover voltage and the normalized absolute error are shown.

Table 3. multilayer feed-forward neural network architecture and training parameters

Number of layers	2
Number of hidden layers	10
Number of inputs	4
Number of outputs	1
Number of weighting elements	61
Training function	Levenberg-Marquardt backpropagation



(a)



(b)

Figure 10. Developed neural network model. (a) Constructed neural network (b) Mean squared error vs. the number of iteration. (total number of iteration is 57)

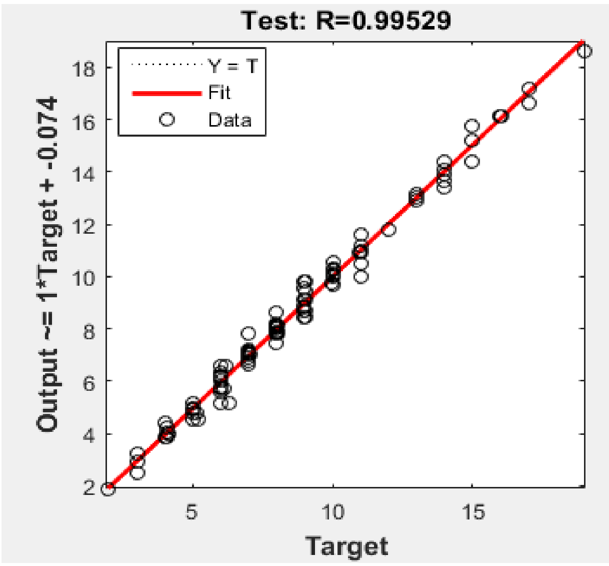


Figure 11. The neural network prediction vs. measured data (vertical axis: predicted values, Target: measured data)

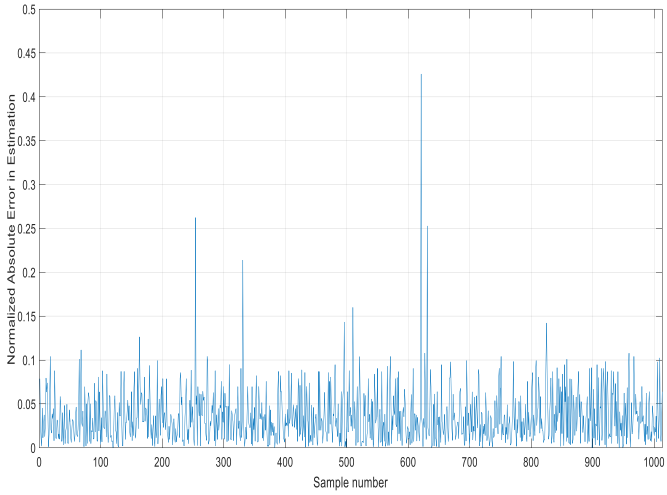


Figure 12. The neural network absolute error vs. the selected samples

A great advantage of ANFIS regression model is related to the small number of input and output membership functions with maximized number of fuzzy rules. Hence, the rule base cccupied memory becomes small [33]. The developed training design parameters used in the developed ANFIS model are given in Table 4. Using the same training data sets as ANN and regression tree models, the membership functions and the structure of the ANFIS are given in Figures 13 and 14 respectively. In Figures 15 and 16, the predicted flashover voltage and the normalized absolute error obtained by ANFIS regression approach are shown. The corresponding results of the regression tree are given in Figures 17 and 18 respectively.

Table 4. ANFIS parameters information

Number of nodes	193
Number of linear parameters	405
Number of nonlinear parameters	4
Total number of parameters	441
Number of training data pairs	1012
Number of Fuzzy Rules	81
Final epoch error	0.1336
Membership function type	gbellmf
Number of membership functions	9

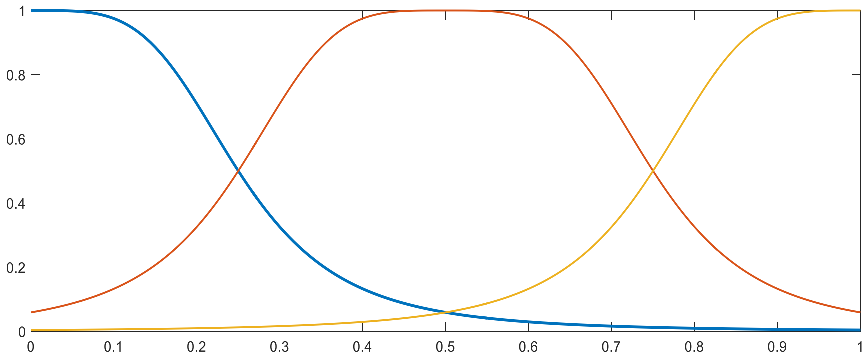


Figure 13. adaptive neuro-fuzzy membership functions for each input

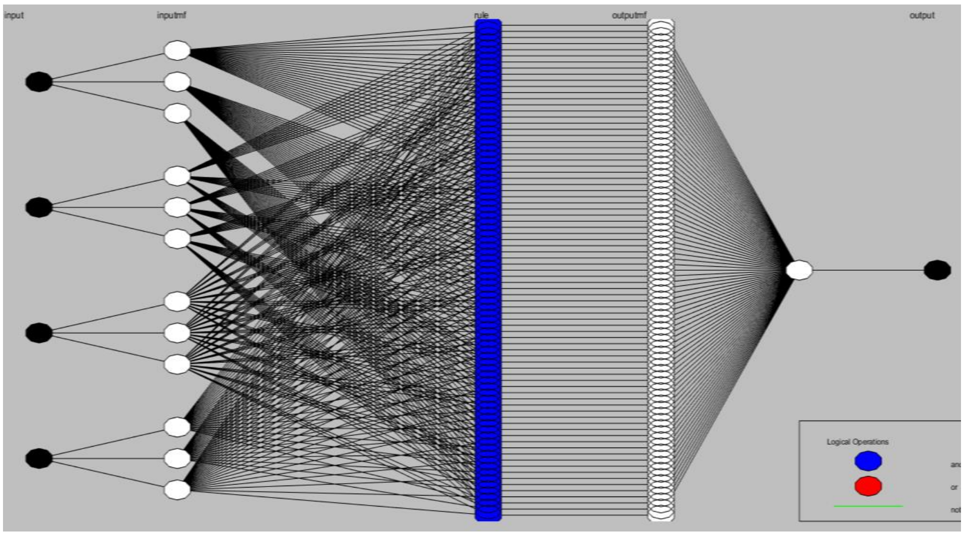


Figure 14. Structure of adaptive neuro-fuzzy developed by Matlab

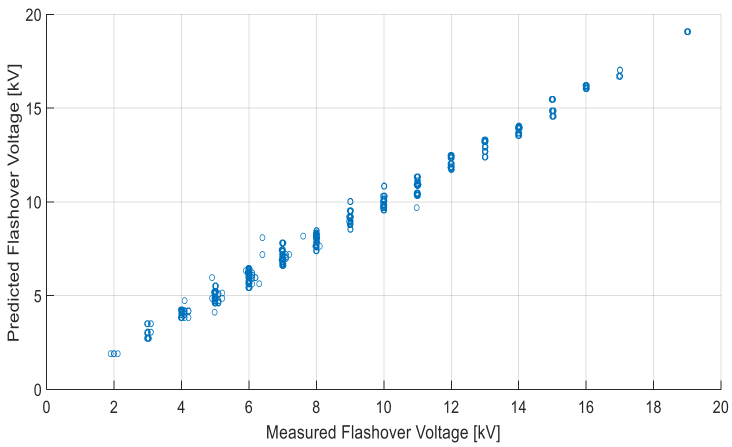


Figure 15. The adaptive neuro-fuzzy prediction vs. measured data

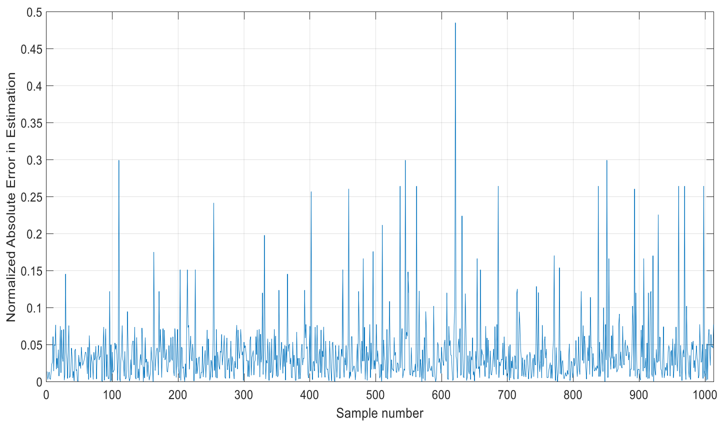


Figure 16. The adaptive neuro-fuzzy absolute error vs. the selected samples

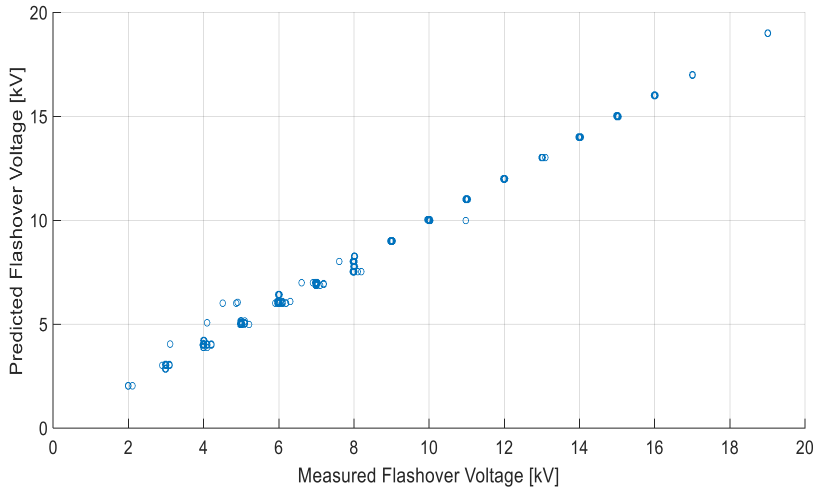


Figure 17. The regression tree prediction vs. measured data

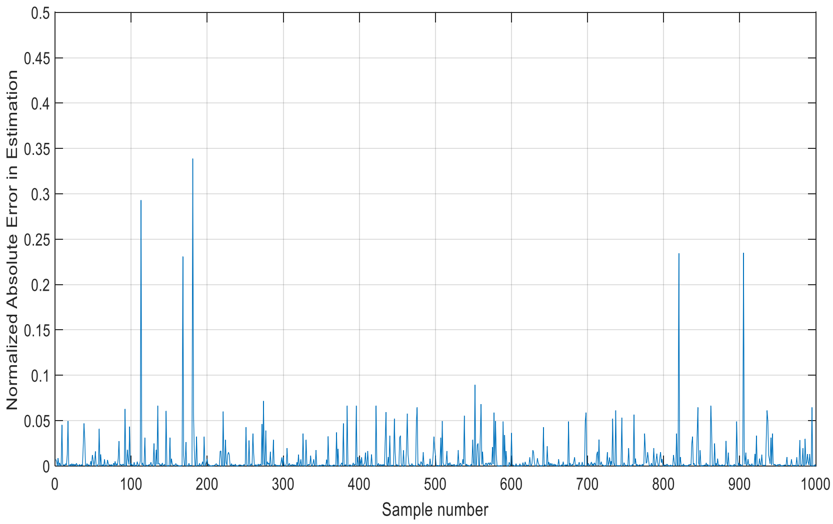


Figure 18. The regression tree absolute error vs. the selected samples

The performance comparison in terms of the statistical parameters is given in Table 5. The obtained results reveal that the regression tree model prediction and the other investigated regression methods are competitive. However, the big appeal for the regression tree is the time elapsed in training the measured data. Using a computer with a processor Intel(R) Core(TM) i3-4160 CPU of speed 3.5GHz and 8GB ram, the required time for training the data is reported in Table 6.

Table 5. Regression tree performance for the first tested samples

Parameter	Regression tree	Neural network	ANFIS	Neural network [15]
RMSE	0.1225	0.3504	0.3408	-
RE	0.0143	0.0404	0.0394	0.0484
R	0.9994	0.9952	0.9955	-

Table 6. Time required for training

Regression approach	Elapsed time [s]
Regression tree	0.323274
Neural netw ork	2.409496
ANFIS	0.688565
Neural netw ork [15]	unknow n

Because of the aforementioned appeal of the regression trees technique, it will be used to investigate the behavior of EPDM composite insulators against the SiR contents based on the recorded experimental work. The percentage SiR contents in EPDM composites are 0, 25, 75 and 100% respectively. Generally, the EPDM composite polymer insulator properties are enhanced with increasing the SiR contents percentage as shown in Figures 17 to 19.

Figure 19 shows the effect of water droplet number upon the EPDM behavior with fixed water droplets volume and conductivity. Increasing the number of droplets decreases the flashover voltage at the same droplet size and water conductivity. For instance, at 1, 3, 5 droplets, the flashover voltages are 19, 17, 16kV and 11, 9.99, 8kV for 100% and 50% SiR contents with constant water conductivity and droplets volume.

Figure 20 shows the effect of water size upon the flashover voltage. The droplets volumes are 0.01, 0.1, and 0.15ml respectively. The larger the droplets volume is, the lower the flashover voltage is obtained. For constant water conductivity, it is noted that the impact of the droplet volume appears clearly and strongly for one droplet. However, the increase of droplets volume from 0.1 to 0.15ml has less impact on the flashover voltage at 3 and 5 droplets. For instance, at 100% SiR, the flashover voltages record 19, 17, 15kV respectively for one droplet at volumes of 0.05, 0.1, 0.15ml respectively. The corresponding data for 3 and 5 droplets are 17, 14, 13kV and 16, 11, 10kV respectively with 1kV difference.

Figure 21 illustrates the relationship between the flashover voltages and SiR contents in EPDM at various water conductivities with three droplets. The tested water conductivities are 50, 500, and 1000μS/cm. For 100% SiR contents, 0.1ml water droplet volume, and 3 droplets, the flashover voltages record 14, 12, 10kV at 50, 500, and 1000μS/cm. For constant droplets number and volume, it can be noticed that as the droplet water conductivity increases, the EPDM flashover voltage decreases.

It can be concluded from the prediction values in Figures 19 to 21 that the hydrophobic surfaces of EPDM composites polymer insulators were pronounced impact on the values of flashover voltages. The electrical properties of EPDM composite insulators were improved with increasing the silicon rubber contents. At wet conditions weather with high salinity (i.e. low conductivity), the hydrophobic surface of EPDM composite insulator withstands more flashover voltages.

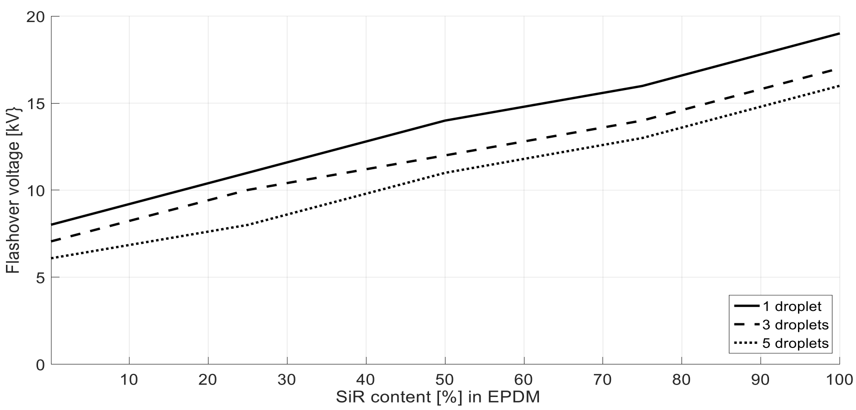
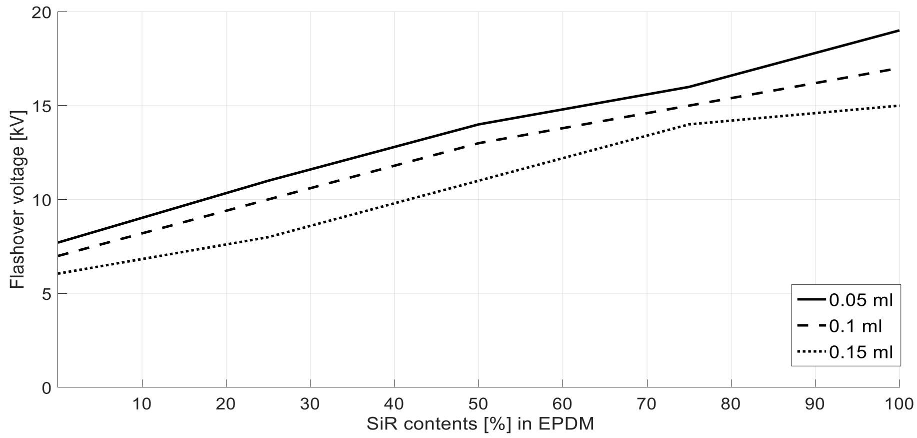
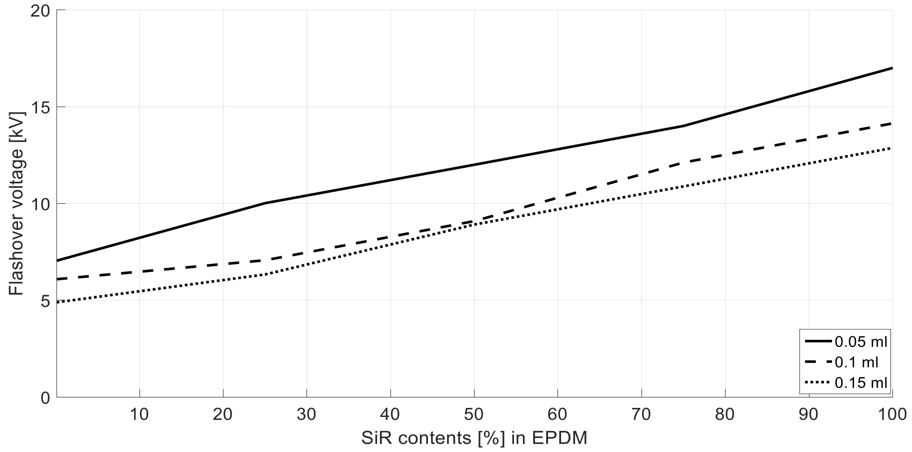


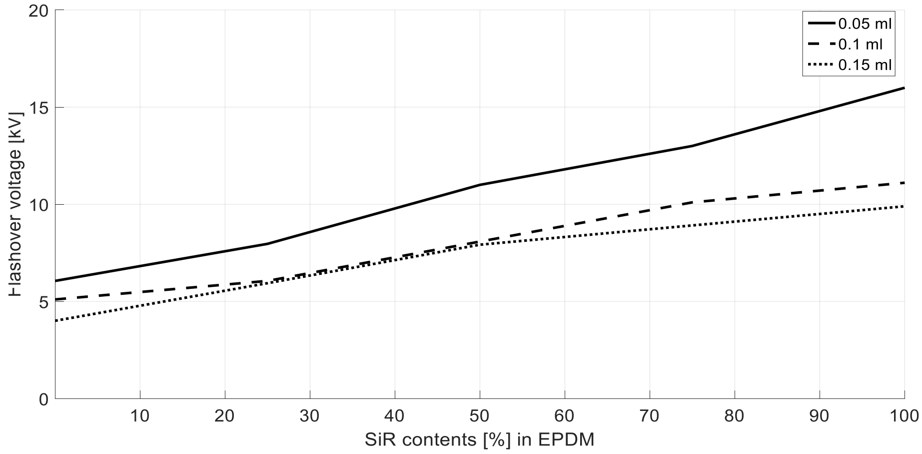
Figure 19. Predicted flashover voltage versus SiR contents in EPDM specimens with 0.05ml water droplet conductivity and 50μS/cm water conductivity.



(a) One droplet



(b) Three droplets



(c) Five droplets

Figure 20. Predicted flashover voltage versus SiR contents in EPDM specimens at various water droplet volumes with 50µS/cm water conductivity

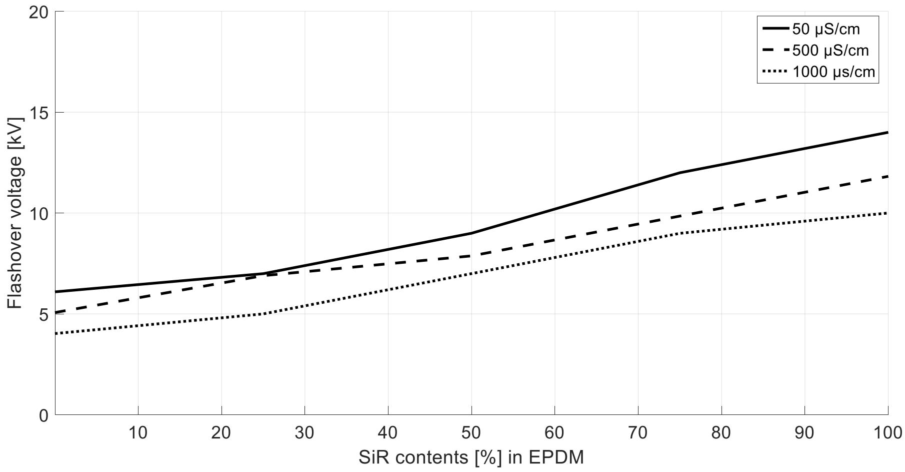


Figure 21. Predicted flashover voltage versus SiR contents at various water conductivities in EPDM specimens with three droplets and 0.1ml water droplet volume

5. Conclusions

In this study, a regression tree modeling is proposed for the flashover voltage on the surface of the hydrophobic EPDM polymer insulators. The regression tree is developed by correlating the measured flashover voltage and input variables such as the silicone rubber percentage, water conductivity, size and number of water droplets. The close agreement of the statistical performance shows the good ability of the model to estimate the flashover voltage. The results obtained by the regression tree are compared with the results obtained by the feed-forward neural network and adaptive neuro-fuzzy. Based on the results, the regression tree model is more powerful in terms of time required in training the measured data. In addition to that, it gives a great potential to decide the insulator surface by giving detailed information of the region.

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