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Evaluation of Flashover Voltage on Hydrophobic Polymer Insulators with Artificial Neural Network

L. S. Nasrat and Saleh Aly*
Electrical & Power Eng. Dept., Faculty of Eng., South Valley Univ.,
*Computer and Systems Eng. Dept., Faculty of Eng., South Valley Univ.,
Aswan, EGYPT

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ABSTRACT

This paper presents an experimental measurement of ac 50 Hz flashover voltage (kV) of hydrophobic polymer insulators. Hundred thirty five different testing conditions were used to evaluate the electrical performance of hydrophobic surfaces of composite polymer insulators. The study of flashover voltages depend on the silicone rubber (SiR) content (%) in Ethylene propylene diene monomer (EPDM) rubber, water conductivity (μS/cm), volume of water droplet (ml) and number of water droplets on the surface of polymer insulators. Artificial neural network (ANN) is used successfully to model nonlinear functions which are difficult to model using classical methods. ANN can estimate the values of flashover voltage (kV) for different polymer insulators. The proposed network is trained using different environmental wet condition such as; water conductivity, volume of water droplet and number of water droplets on the surfaces of composite different polymer. After training, the network can estimate the flashover voltage for different inputs. A comparison between the laboratory measurements of flashover voltages and computational results of ANN were convergent. The results obtained from applying ANN show that it can be used to model the data with accuracy of 96%. These results prove that ANN can be considered a successful model to evaluate the electrical performance of hydrophobic polymer insulators and predicts the best hydrophobic composite surface that withstands higher flashover voltage under wet contaminated weather condition.

Corresponding Author:
L. S. Nasrat,
Electrical Power Eng. Dept., Faculty of Eng.,
South Valley University,
Aswan, Egypt.
Email:loaisaad@yahoo.com

1. INTRODUCTION

Power transmission at high voltages has acquired considerable prominence in the recent times. It has become essential to design and develop compact cost-effective and reliable insulation structures. With the advancement in polymer technology it has become possible to design insulation structures with the enhanced mechanical, electrical and thermal properties. The use of polymeric insulators for outdoor transmission lines has rapidly increased during the last two decades. Both service experience and the laboratory tests demonstrated a better performance in contaminated conditions [1]-[3].

In recent times, composite insulation materials are gaining importance as outdoor insulating structures especially the silicone rubber. Silicone rubber has good pollution performance and high hydrophobicity. In addition, it has high discharge resistance. Water droplets on a polymeric surface increase locally the applied electric field. Local field intensifications lead to partial discharges (PD) and/or localized arcs, causing damage to insulating materials [4]-[7].

The values of flashover voltages of polymer insulators can be affected with some parameters such as; conductivity (µS/cm) of water droplet, number of droplets, volume of water droplet (ml), and percentage of silicone rubber content (%) to the composite polymer. Hydrophobic polymeric surfaces are characterized by a low surface conductivity which in turn gives a low discharge activity and a higher flashover voltage. This holds also for polluted environments. Reduced hydrophobicity implies a higher risk for flashover of the insulator. Hydrophilic materials, on the other hand, are very sensitive to polluted environments, and are characterized by a significant activity of local discharges [8].

Artificial neural networks (ANNs) can be used in problems requiring function approximation, modeling, pattern recognition and classification, estimation and prediction, etc. [9]. In the field of high voltage insulators, ANNs can be used to estimate the pollution level [10], [11], to predict a flashover voltages [12],[13], to analyze surface tracking on polluted insulators [14] and also to estimate the flashover voltage on hydrophobic polymer insulators which will be examined in this paper. Multilayer perceptron is a famous supervised neural network which is used as a universal function approximator. Backpropagation learning algorithm is used successfully to train the network which is subsequently used to estimate the flashover voltage [15]. In this paper, the trained network was employed to evaluate the electrical performance of hydrophobic polymer insulators and predict the best hydrophobic composite surface that withstands higher flashover voltage under wet contaminated weather condition.

2. EXPRIMENTAL PROCEDURE

2.1 Material Details

Composite polymeric insulators were tested during this study. The composite was consisted of EPDM rubber with various content (%) of SiR (0, 25, 50, 75 and 100%), respectively.

2.2 Test Procedure

The ac 50 Hz high voltage was supplied from single phase high voltage transformer (150 kV, 15 kVA). Two copper electrodes used as a shape of half cylindrical rounded edges. The electrodes had very smooth without any irregularities to avoid the non-uniform electric field [16].

2.3 Specimens Dimensions

The dimension of each specimen is 80 mm length, 40 mm width and 3 mm thickness. The water droplets were put on the surface of specimen with a syringe. The volume of water droplets are 0.05, 0.1 and 0.15 ml. The conductivity of the water droplets are 50, 500 and 1000 µS/cm. The distance between the two parallel electrodes is 40 mm. Number of water droplets on the surface of each composite specimen are 1, 3 and 5 droplets. To simulate the surface of composite at outdoor wet and fog weather condition, angle with 10º from the horizontal level was used. The high voltage between electrodes increased gradually until the flashover voltage (kV) occurs.

3. BACKGROUND ABOUT ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are computational networks which attempt to simulate the structure and the behavior of biological nervous system. An artificial neural network consists of a set of processing elements called neurons that interact by sending signal to one another along weighted connections [9]. The connection weights, which can be determined adaptively, specify the precise knowledge representation. It is not possible to specify the weights beforehand, because the knowledge is distributed over the network. Therefore, a learning algorithm is adopted in which the strengths of the connections are modified to achieve the desired form of activation function.

The learning algorithms are divided into three categories: supervised, reinforced and unsupervised. The type of error signal used to train the weights in the network defines these three types of learning. In supervised learning, an error scalar is provided for each output neuron by an external ‘teacher’, while in reinforced learning the network is given only a global punish/reward signal. In unsupervised learning, no external error signal is provided, but instead internal errors are generated between the neurons, which are then used to modify weights [9]. In supervised learning the weights, connecting neurons are set on the basis of detailed error information supplied to the network by an external teacher. In most cases the network is trained using a set of input-output pairs, which are examples of the mapping that the network is required to learn to compute. The learning process may therefore be viewed as fitting a function, and its performance can thus be judged on whether the network can learn the desired function over the interval represented by the training set, and to what extent the network can successfully generalize away from the points that it has been trained on [13]-[15].

3.1. Multilayer Feedforward Network

The simplest network capable of supervised learning is a three-layer feedforward network consisting of an input layer, hidden layer and an output layer. Each neuron of the hidden layer receives a signal from all input neurons along connections with modifiable weights. But such three-layer feedforward networks can compute only linearly separable functions. However, it has also been shown that a feedforward network with more than one hidden layer of adaptive weights can compute very complex functions

The neurons in the network can be divided into three layers: input layer, output layer and hidden layers (Figure 1). It is important to note that in feedforward networks, signals can only propagate from the input layer to the output layer via one or more hidden layers. It should also be noted that only the nodes in the hidden layers and the output layer, which perform activation function, are called ordinary neurons. Since the nodes in the input layer simply pass on the signals from the external source to the hidden layer, they are often not regarded as ordinary neurons.

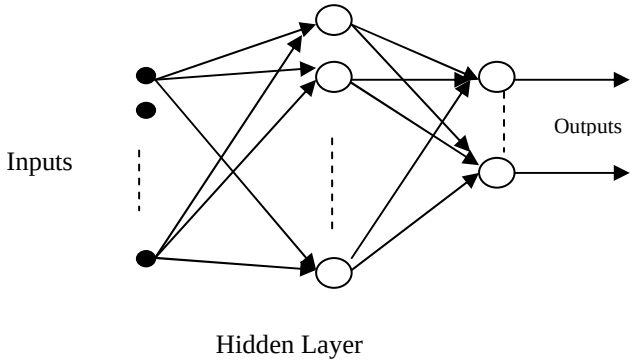

Figure 1. Architecture of three layers Feedforward Network.

3.2. Input-Output Data Normalization

Since the input and output variables of the ANN have different ranges, the feeding of the original data to the network, leads to a convergence problem. It is obvious that the output of the ANN must fall within the interval of (0 to 1). In addition, input signals should be kept small in order to avoid a saturation effect of the sigmoid function. So, the input-output patterns are normalized before training the network. Normalization by maximum value is done by dividing input-output variables to the maximum value of the input and output vector components. After the normalization, the input and output variables will be in the range of (0 to 1).

4. EXPERIMENTAL MEASUREMENTS

The ac (50Hz) flashover voltages (kV) measurements have been recorded for five composite polymer insulators. SiR content (%) in EPDM insulators are (0, 25, 50, 75and100) %.

Figure 2 shows the flashover voltages (kV) of EPDM with different SiR contents (0, 25, 50, 75 and 100) % at various number of water droplets (1, 3 and 5) under constant conditions such as; volume of each water droplet (0.05 ml) and water conductivity (50 µS/cm).

From this figure it can be noticed that, the percentage of SiR content (%) plays an important role on the flashover voltage (kV) values. The flashover voltages are 8, 11, 14, 16 and 19 kV at 0, 25, 50, 75 and 100% SiR content in EPDM respectively, at one water droplet with 0.05 ml volume and 50 µS/cm conductivity. Increasing the number of water droplets from 1 to 5 droplets decreases flashover voltages at the same volume and water conductivity. For example, the flashover voltages are 8, 7 and 6 kV at 1, 3 and 5 water droplets under the same condition of water conductivity and volume of water droplet at 0% of SiR content in EPDM. At one water droplet with conductivity of 50 µS/cm, flashover voltages for different SiR content (%) EPDM for various volumes of water droplet 0.05, 0.1 and 0.15 are illustrated in Figure 3.

It can be seen from this figure that, at higher content of SiR (100%), the flashover voltage decreases by increasing the volume of water droplets. This means that, increasing the volume of water droplets 0.05, 0.10, and 0.15 ml in specimens of 100% SiR content register 19, 17 and 15 kV respectively under water conductivity 50 µS/cm.

Figure 4 shows the relationship between the flashover voltages and SiR content in EPDM at various water conductivity 50, 500 and 1000 µS/cm for 5 water droplets with constant volume of each droplet equal to 0.15 ml.

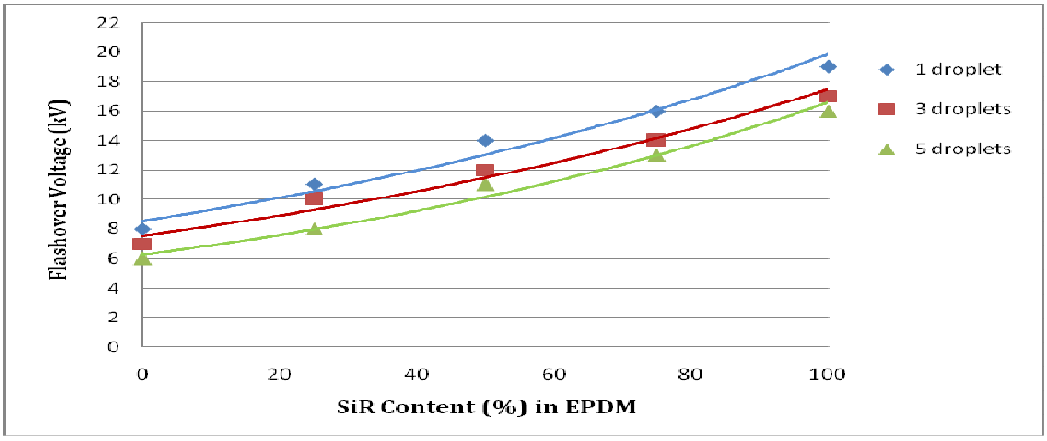

Figure 2. Flashover voltages for different SiR content (%) in EPDM specimens at various number of water droplets (1,3 and 5) with (0.05 ml) volume of water droplet and (50µS/cm) water conductivity.

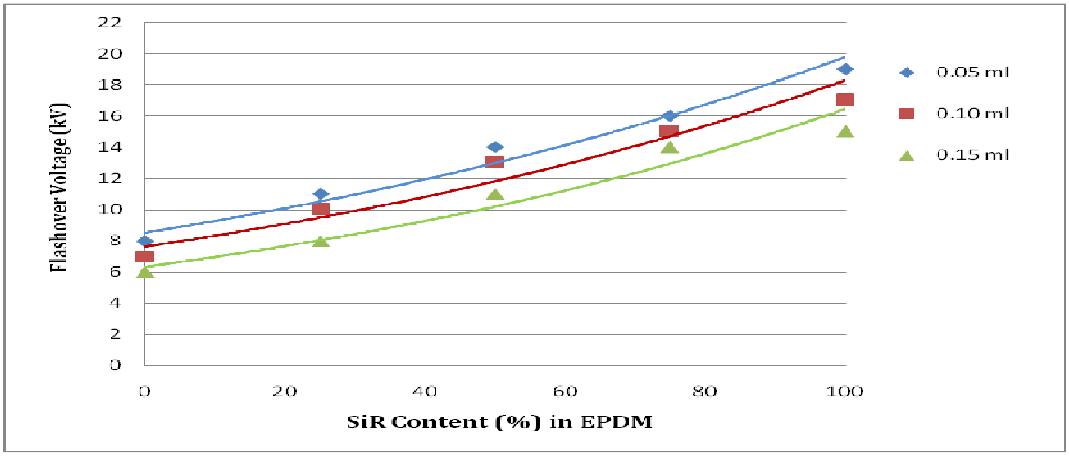

Figure 3. Flashover voltages for different SiR content (%) in EPDM specimens at various volumes of water droplets (ml) for one water droplet with (50µS/cm) water conductivity.

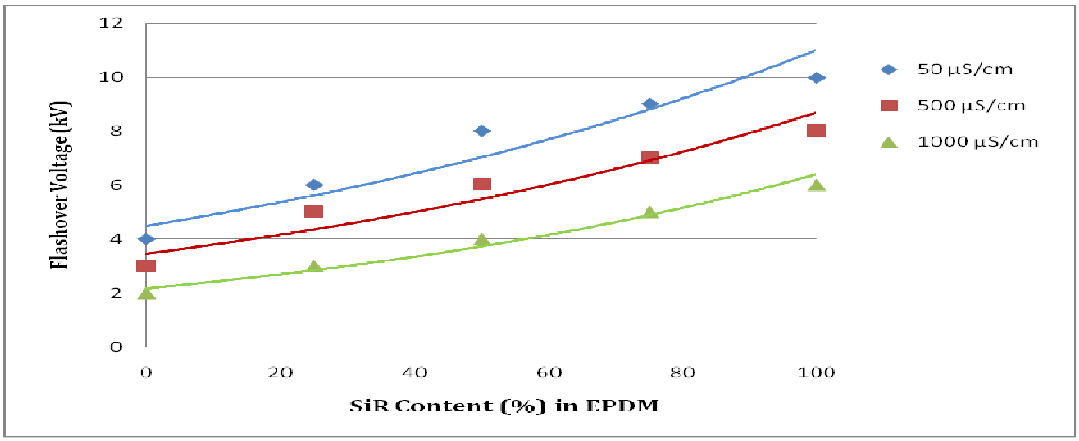

Figure 4. Flashover voltages for different SiR content (%) in EPDM specimens at various water conductivity (µS/cm) for 5 water droplet with (0.15 ml) volume of water droplet.

It can be noticed from this figure that, the values of flashover voltage decrease 8, 6 and 4 kV at water conductivity 50, 500 and 1000 µS/cm, respectively, under 5 water droplets with 0.15 ml volume for specimen of 50% SiR content in EPDM. It can be seen from the experimental work that, the hydrophobic

surface of composite polymer insulators were pronounced effect on the values of flashover voltage. The electrical performance improves with increasing the silicone rubber content. At weather of wet condition with high salinity, the hydrophobic surface withstands the flashover voltage.

5. MECHANISM OF COMPUTING FLASHOVER VOLTAGES

The configuration in figure 5 shows different parameters affecting on the values of flashover voltages of composites rubber. Various parameters are:

i- Silicone rubber content (SiR %) in EPDM rubber, varying from 0% to 100%.
ii- Water conductivity (µS/cm), 50, 500 and 1000 µS/cm.
iii- Volume of water droplets (ml), 0.05, 0.10 and 0.15 ml.
iv- Number of water droplets, 1, 3 and 5 droplets.

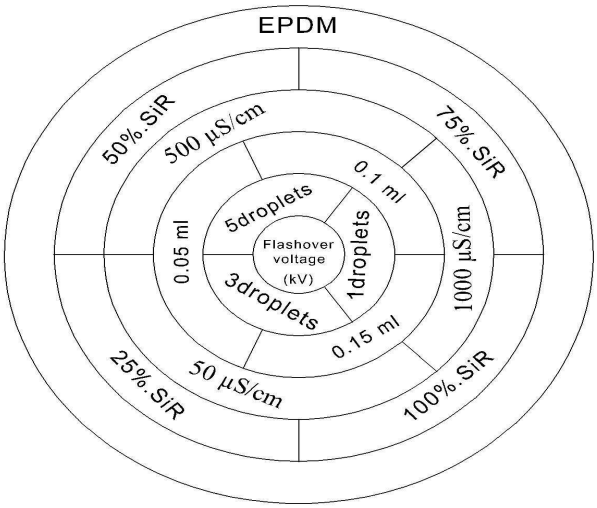

Figure 5. Diagram illustrates the mechanism of computing flashover voltages.

The flashover voltages (kV) can be proportional with SiR content (%), water conductivity (µS/cm), volume of water droplet (ml) and number of water droplets according to the proposed function:

$$\text{Flashover Voltage (kV)} \ \alpha \ \frac{\text{SiR (\%)}}{\text{No. of droplet*Vol.droplet(ml)*water Cond.(µS/cm)}}$$

6. DEVELOPMENT OF THE NEURAL NETWORK FOR FLASHOVER VOLTAGE

The purpose of the ANN developed is to estimate the flashover voltage from the input data, which are obtained from previous experiments results.

1. Input Selection

The inputs to the neural network ANN are silicone rubber content (SiR %) in EPDM rubber, varying from 0% to 100%, water conductivity (µS/cm), 50, 500 and 1000 µS/cm, Volume of water droplets (ml), 0.05, 0.10 and 0.15 ml, Number of water droplets, 1, 3 and 5 droplets. The output of the neural network model consists of one neuron representing the flashover voltage for a specific operating condition. The chosen input data were divided into two groups, the training group, corresponding to 50% of the patterns, and the test group, corresponding to 50% of patterns; so that the generalization capacity of network could be checked after the training phase. The output of the neural network model consists of one neuron representing the flashover voltage for a specific operating condition.

2. Selection of ANN

The ANN used is the multi-layer feedforward type, with one or more hidden layers represented in Figure 6. The number of units in each hidden layer is determined experimentally, from studying the network behavior during the training process taking into consideration some factors like convergence rate and error

criteria. The "logsig" function is used for the units for all the neurons except for those in the input layer. The neural network is trained offline. In this regard, different configurations are tested and the best suitable configuration is selected based on the accuracy level required.

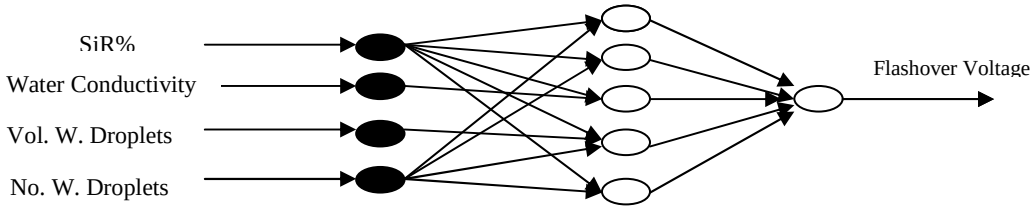

Figure 6. Multilayer Feed-forward Network used in the training stage

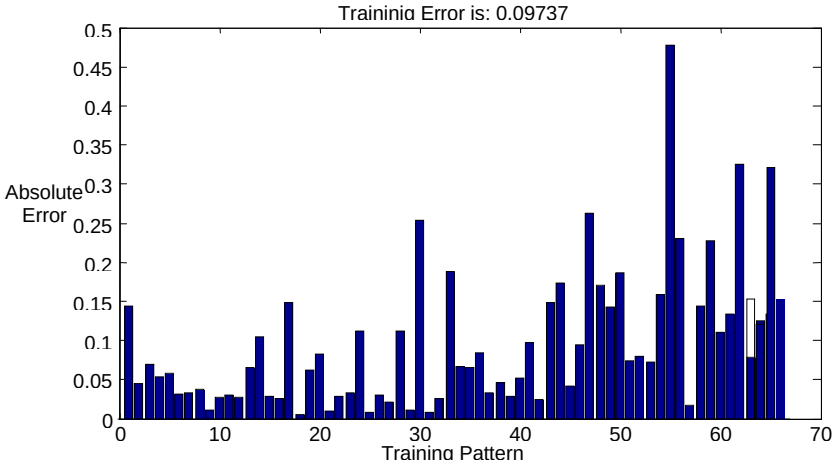

Figure 7-a. Absolute error values for all data used in the training step.

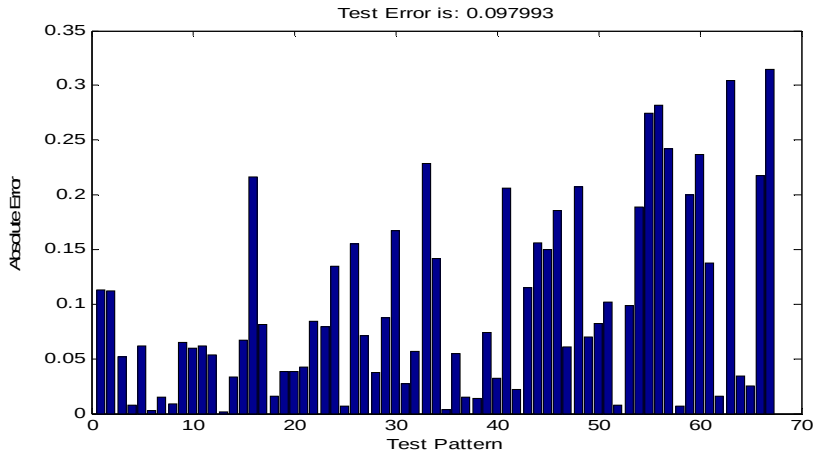

Figure 7-b. Absolute error values for all data used to test the neural network

Table (1) shows the performance of various network structures where the network is specified by the number of inputs, number of neurons in the first hidden layer, number of hidden neurons in the second layer, and the number of output neurons. For example 4×10×1 means that the network has four inputs, ten neurons in the first hidden layer and one output neuron. The training and test error computed as the absolute average of the error for all training data and test data respectively as shown in figures (7-a, b). The network with one hidden layer and 5 hidden neurons is selected in our simulation which gives minimum errors for both training and test data.

Table 1. Training and test errors for various network structures

Network Structure **NI**×NH×NO	**Training Error**	**Test Error**
4×3×1	0.0678	0.0655
4×5×1	0.0484	0.0534
4×10×1	0.0459	0.0599
4×5×3×1	0.0842	0.1134
4×10×3×1	0.0820	0.1118

Table (2) Comparisons between NN output and measured values for various patterns in the test data

Test Pattern	NN Output	Measured Output
[0;50;0.05;3]	7.9	7
[25;500;0.1;1]	8.3	8
[50;50;0.1;5]	9.4	8
[100;500;0.05;5]	13	11

Table (3) Estimated NN output for new unseen data

Test Pattern	NN Output
[0;400;0.05;1]	7.9149
[25;400;0.05;1]	9.9137
[50;400;0.05;1]	11.9198
[75;400;0.05;1]	13.4964
[100;400;0.05;1]	14.5006

In order to measure the generalization capability of the neural network, the output of the neural network is compared with the actual measured outputs. The results in Table (2) shows that the estimated output of NN is very near to the measured one which prove the validity of NN to model the data. The results obtained from applying ANN show that it can be used to model the test data with accuracy of 96%. Table 3 shows the estimated results of flashover voltage for different unseen inputs. For example the input [25;400;0.05;1] means that for SiR=25%, Water Conductivity=400µS/cm, Volume of Water Droplets=0.05ml, and Number of Droplets=1, the estimated flashover voltage equal 9.9137 KV. By analyzing the collected data from laboratory measurements these inputs are closer to the measured values SiR=25%, Water Conductivity=500µS/cm, Volume of Water Droplets=0.05ml, and Number of Droplets=1, which give a measured flashover voltage equal 10 KV. Its mean that the estimated value obtained from neural network is a correct value compared with the measured value which is near to this point. By increasing the water conductivity from 400µS/cm to 500µS/cm, the flashover voltage increases from 9.9137 kV to 10 kV at fixed other parameters such as; SiR, Vol. of Droplets and No. of Droplets.

7. CONCLUSION:

In order to improve the long-term electrical performance of hydrophobic composite insulators, silicone rubber content (%) should be increased. In this study the flashover voltage on the surface of hydrophobic polymer insulators is estimated using neural network. A multilayer feed-forward back-propagation neural network has been used in this work. That model shows a good ability to estimate the flashover voltage to select hydrophobic surface insulators. The advantage of the use of ANN in the design and optimization is that ANN is required to be trained only once. After the completion of training, the ANN gives the flashover voltage for any desired mechanism on hydrophobic polymer insulators. Thus, this model can be used confidently for the design and development of insulators. Developed model has very fast, reliable and robust structure. An accuracy of 96% is obtained from applying ANN which shows that it can be used as a successful model for predicting flashover voltage. These results prove that ANN can be exploited to evaluate the electrical performance of hydrophobic polymer insulators and predicts the best hydrophobic composite surface that withstands higher flashover voltage under wet contaminated weather condition.

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