Comparison of Pollution Level of Aged Porcelain and Silicon Rubber Insulators

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Abstract—In this paper, an artificial neural network (ANN) has been used to compare the pollution level of aging long-rod silicon rubber and porcelain insulators. High regression values and effective correlation of equivalent salt deposit density (ESDD) have been found using MATLAB neural network toolbox. It has been found that the bottom surface of the porcelain insulator contains more pollution than the top surface. Higher pollution has also been measured in case of silicon rubber (SiR) insulator. Pollution levels in case of both insulators have been found to be exceptionally high compared to IEEE and CIGRE standards.

Keywords—long-rod insulators; ESDD; determination of coefficient

I. INTRODUCTION

Day by day demand in electric power is increasing due to the rapid growth in industrial sectors, commercial buildings and residential areas. To meet this demand, new power stations need to be built and the efficiency of transmission systems needs to be improved. However, maintaining efficiency of a transmission system is a challenging task due to the presence of unpredictable faults. Failure to mitigate these unpredictable faults results in economic losses for companies and consumers. One such challenge is encountered when high voltage insulators cause flashover and discontinuity of power supply on a large scale, after being affected by different pollution sources [1]. In Brunei Darussalam, porcelain, glass and silicon rubber insulators are used in 66 kV transmission lines. These insulators are polluted with sea salt, dust, chemicals, and ashes. The ashes are normally the outcome of bush fire during the months of March and April in each year. Sometimes, there are some power outages in the Brunei transmission networks due to combination of different types of pollutions. Pollution is one of the main problems which affect the efficiency of the insulators. Over the period of time, pollution in the air settles on the surface of the insulators and mixed with dews and rain which offers conductive layer. The leakage current flows in the conductive layer of the insulator and creates uneven surface voltage. This uneven surface voltage finally triggers insulator flashover [2]. In the recent past, the leakage current measurement method has been used to prepare the exact pollution maps and optimal design of insulators for the transmission lines and substations [3]. In Brunei Darussalam, the length of the transmission lines

falls into the category of short transmission and medium transmission lines due to the country's small geographical size. The transmission lines pass along the highways near coastal area. There are two types of arrangements installed for the insulators used, double-I-string and V-string [4]. It is important to measure the level of pollution which helps to improve the efficiency of transmission lines. The pollution level in high voltage insulators can be measured by several methods, namely, equivalent salt deposit density (ESDD), non-soluble deposit density (NSDD) and pollution index (PI). In this study, the ESDD has been used to measure the pollution level. An artificial neural network (ANN) has been chosen to analyze the measurement of ESDD due to ANN's popularity in this domain [5].

II. MEASUREMENT OF POLLUTION LEVEL

Two heavily polluted, and approximately 30 years old insulators were brought in from a local utility company, for the pollution-measurement experiment. Some parts of those insulators were found to be cracked. However, extreme cautions were taken during collection of the pollutants. The insulators were brought to the laboratory, where, the pollutants were collected by brushing it off, and later on mixed with distilled water for making salt-solution. These two insulators are long-rod porcelain and long-rod silicon rubber (SiR) ones. The long-rod porcelain insulator has 15 layers, 'a' to 'o', where 'o' has the highest potential and 'a' has the lowest potential. The long rod silicon insulator has 7 layers, 'a' to 'g', where 'a' has the highest potential and 'g' has the lowest potential.

The equipment YSI Model 63 has been used to measure the solution temperature, pH and conductivity. These measured conductivities at different temperatures are then converted to the corrected conductivities at 20°C by the following formula [6]:

$$\sigma_{20} = \sigma_{\theta} [1 - b(\theta - 20)] \quad (1)$$

In addition, the value of salinity, S_a of the solution can be expressed by the following empirical formula:

$$S_a = (5.7 \sigma_{20 \mu S/cm} \times 10^{-4})^{1.03} \quad (2)$$

Finally, the Equivalent Salt Deposit Density (ESDD) is determined by using the following expression,

$$ESDD = \frac{(S_a \times V)}{A} \quad (3)$$

The pollution levels in terms of ESDD at the bottom and top surfaces of both the long-rod porcelain and silicon rubber insulators have been measured.

III. ARTIFICIAL NEURAL NETWORK

A neural network tool has been developed using MATLAB 2014a and represented as ANN model as shown in Fig. 1. In Table 1, four inputs, two hidden layers with five neurons each and an output layer with only one neuron have been considered [6]. The selected inputs are salinity, conductivity, volume of water and surface area of insulators and the output of this model is Equivalent Salt Deposit Density (ESDD).

Fig. 1. Neural network modeling.

The input value varies from -1 to 1 and the input layer distributes the values to each of the neuron in the hidden layer. The constant input of this network is called bias whose value is 1.0 and it is contributed to each of the hidden layers. The bias is multiplied by a weight and added to the sum going into the neuron. In hidden layers, the value from each neuron is multiplied by a weight. The weighted values are added together into a transfer function. Then the outputs are distributed into the output layer. Likewise, the output layer has the same calculations with hidden layer but producing different output values. Both ANN values and predicted values for each insulator have been implemented into the network.

In this model, there are three different sets of performing neural networks, training, validation and testing. The training set has been used to adjust weights on the neural network and the validation set has been used to determine the accuracy of the data. If the accuracy of the data stays the same or below the threshold, the neural network is over-fitting and the network should be stopped. Testing set is used for testing the final solution in order to confirm the actual predictive power of the network.

Table I. The characteristics of the ANN model.

Item	Value
Network Type	Feed Forward
No. of Layers	3
Input Layer Nodes	4
Hidden Layer Nodes	5
Output Layer Nodes	1
Transfer Function	LOGSIG

There are four basic steps in the training process. These are: assemble the training and predicted data, create different network layers, train the network and simulate the network

layers to generate new outputs. Artificial neural network algorithm has been used successfully in many applications. It is important that it acts as a model of real-world system or function. The formulae given in [5, 7, 8, 9, 10] can determine the output from its input accordingly. For each neuron in the input layer, the neuron outputs are given by,

$$O_i = net_i \quad (4)$$

Where net_i is the input of neuron i , and O_i is the output of neuron i . Also, for each neuron in the output layer, the neuron inputs are given by,

$$net_k = \sum_{j=1}^{N_j} w_{kj} O_j, \quad k=1 \dots N_k \quad (5)$$

Where w_{kj} is connection weight between neuron j and neuron k , and N_j , N_k are number of neurons in the hidden and output layers, respectively. The neuron outputs are given by,

$$O_k = \frac{1}{1 + \exp\left(-\left(net_k + \frac{\theta_k}{\theta_o}\right)\right)} = f_k(net_k, \theta_k, \theta_o) \quad (6)$$

Where θ_k is threshold of neuron k , and the activation functions f_k is a sigmoidal function. For the neurons in the hidden layers, the inputs and the outputs are given by the relationships similar to those given in equations (5) and (6), respectively.

IV. RESULTS AND DISCUSSIONS

In MATLAB, measured data have been implemented into the workspace namely, input, output and predicted data from the Microsoft's Excel workspace, as shown in Fig. 2.

The screenshot shows the MATLAB Workspace window. It has a table with four columns: Name, Value, Min, and Max. There are three rows of data: 'input' with value 0, 'output' with value 0, and 'predicted' with value 0. All values are 0.

Name	Value	Min	Max
input	0	0	0
output	0	0	0
predicted	0	0	0

Fig. 2. Workspace on MATLAB window.

The input variables of workspace are inserted by the selected inputs. These input parameters show better correlation with the given formulae to calculate ESDD. The measured input, output and predicted parameters must be in between -1 and 1 because the network has been created based on the sigmoidal neuron model. An artificial neural network's command 'nntool' was used to activate the simulation. The input and predicted data are considered as input variable for getting output as target variable.

The input and output variables are placed into the workspace for evaluating the predicted values by considering an average of each input parameter respectively. All readings

are normalized before starting the simulation. Different network layers have been created using feed-forward back propagation algorithm. The network type used is feed-forward in which the information is propagated in one direction.

The data are trained depending on how long it takes. When more time is consumed, more accurate the outputs become by inserting a value of 1000 into *max_fail* in training parameters. The parameter, *max_fail* represents the maximum number of validations. As the number of training cycle increases, the input-output relationship show better correlation within the same data-range.

In Fig. 3, the data are trained to give new predicted ESDD in terms of training, validation and testing.

Fig. 3. Neural network training.

The predicted ESDD values are considered as the output, and calculated ESDD values are considered as target. The output for silicon rubber and porcelain insulators are plotted against the target for training, validation and testing as shown in Figs. 4, 5, and 6, respectively. The input parameters have been trained to get the target ESDD (measured ESDD). The input layers from the ANN values of either long-rod silicon rubber insulator or long-rod porcelain insulator are being calculated depending on number of cycles. This gives the results in terms of output for all three stages namely training, validation and testing. The performance of the neural network model is measured by using regression R value. The term regression R value is the measurement of the correlation between outputs and targets. A total of 7 discs of long rod silicon rubber insulator have been considered for data collection for both top (*T*) and bottom (*B*) surfaces as shown in Table II. Each reading has been used to evaluate a different set of ESDD values. These readings have actual ESDD and predicted ESDD. Unlike the values of actual ESDD which are being calculated, the values of predicted ESDD are evaluated by using the neural network in MATLAB. The comparison between actual ESDD and predicted ESDD shows that the values are more or less the same for each disc respectively.

In case of long rod porcelain insulator, the values of R are 0.98139, 1 and 1 in training, validation and testing, respectively. The regression line for training, validation and testing stages are determined as shown in Figs. 4, 5, and 6 accordingly. Unlike silicon rubber insulator, a total of 15 discs of porcelain insulator have been considered for data collection for both top (*T*) and bottom (*B*) surfaces as shown in Tables III. As the values of corrected ESDD, which are being calculated, the values of predicted ESDD are evaluated by using the neural network in MATLAB too. The ANN is used in this paper to find the better coefficient of determination between the measured and predicted ESDD.

Fig. 4. Training regression line for long rod silicon rubber insulator.

Fig. 5. Validation regression line for long rod silicon rubber insulator.

Fig. 6. Testing regression line for long rod silicon rubber insulator.

Table II. ESDD comparison for long-rod silicon rubber insulator.

Insulators from pin side	Corrected ESDD (mg/cm ²)	Predicted ESDD (mg/cm ²)
<i>a (T)</i>	0.337	0.36221
<i>b (T)</i>	0.359	0.33712
<i>c (T)</i>	0.361	0.33903
<i>d(T)</i>	0.36	0.33732
<i>e (T)</i>	0.363	0.33755
<i>f (T)</i>	0.368	0.33781
<i>g (T)</i>	0.369	0.33794
<i>a (B)</i>	0.385	0.33715
<i>b (B)</i>	0.399	0.33714
<i>c (B)</i>	0.396	0.33713
<i>d (B)</i>	0.4	0.33713
<i>e (B)</i>	0.397	0.33712
<i>f (B)</i>	0.396	0.33712
<i>g (B)</i>	0.396	0.33712

Table III. ESDD comparison for long-rod porcelain insulator.

Insulator from pin side	Corrected ESDD (mg/cm ²)	Predicted ESDD (mg/cm ²)
<i>a (T)</i>	0.257	0.22751
<i>b (T)</i>	0.238	0.24152
<i>c (T)</i>	0.215	0.22113
<i>d(T)</i>	0.234	0.21994
<i>e (T)</i>	0.219	0.22006
<i>f (T)</i>	0.232	0.22096
<i>g (T)</i>	0.232	0.2232
<i>h (T)</i>	0.236	0.22757
<i>l (T)</i>	0.232	0.23314
<i>j (T)</i>	0.236	0.23746
<i>k (T)</i>	0.234	0.23979
<i>l(T)</i>	0.235	0.24082
<i>m (T)</i>	0.235	0.24124
<i>n (T)</i>	0.235	0.24141
<i>o (T)</i>	0.235	0.24148
<i>a (B)</i>	0.245	0.24151
<i>b (B)</i>	0.269	0.24152
<i>c (B)</i>	0.282	0.24152
<i>d (B)</i>	0.263	0.24152
<i>e (B)</i>	0.259	0.24152
<i>f (B)</i>	0.279	0.24152
<i>g (B)</i>	0.281	0.24152
<i>h(B)</i>	0.281	0.24152
<i>l (B)</i>	0.282	0.24152
<i>j (B)</i>	0.253	0.24152
<i>k(B)</i>	0.281	0.24152
<i>l (B)</i>	0.281	0.24152
<i>m (B)</i>	0.282	0.24152
<i>n (B)</i>	0.281	0.24152
<i>o (B)</i>	0.285	0.24152

V. CONCLUSION

Pollution level of long rod porcelain, and silicon rubber insulators have been measured. The pollution levels are found to be more than the IEEE and CIGRE standards which are identified as exceptionally high values. In case of long-rod porcelain insulator, the bottom surface has more pollution than

the top surface. It means that the pollution on the bottom surface cannot be removed by the natural rain. The frequency of the rain in this tropical country is significantly high compared to other countries. The overall pollution level in the long-rod porcelain insulator is higher than the long-rod silicon rubber insulator. It is due to the pollution that adheres to the silicon rubber insulator surfaces for long time, and cannot be automatically removed by the rain. An artificial neural network has been applied to the measurement results and a good agreement has been achieved with the high determination of coefficients (more than 90%). These high coefficients exhibit the strong correlation between the outputs and the targets.

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