Sensoring Leakage Current to Predict Pollution Levels to Improve Transmission Line Model via ANN

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ABSTRACT

Pollution insulator is a serious threat to the safety operations of electric power systems. Leakage current detection is widely employed in transmission line insulators to assess pollution levels. This paper presents the prediction of pollution levels on insulators based on simulated leakage current and voltage in a transmission tower.The simulation parameters are based on improved transmission line model with leakage current resistance insertion between buses. Artificial neural network (ANN) is employed to predict the level of pollution with different locations of simulated leakage current and voltage between two buses. With a sufficient number of training, the test results showed a significant potential for pollution level prediction with more than 95% Correct Classification Rate (CCR) and output of the ANN showed high agreement with Simulink results.

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1. INTRODUCTION

Accumulation of pollutants on the surface of high-voltage (HV) insulators is the main reason for the decrease in insulation levels between phase and ground in transmissionline towers [1]. The transmission lines of electrical insulation exposed to open air for long periods lead to solid, liquid and gaseous filthy particle deposition outside the electric insulation surface. The electric strength of the insulator will be greatly reduced under severe weather conditions, such as fog, dew, drizzle, melting ice and snow [2]. These conditions lead initially to partial discharges whereby the rate and severity can grow to generate a full line-to-ground discharge known as a flashover. Partial discharges are caused by salt contaminants or by non-soluble substances on the insulator surface in the presence of humidity.Insulator flashover phenomenaare closely related to leakage current. Therefore leakage current online monitoring has become the most effective method [3], [4].

Several techniques have been proposed in the literature to measure the quantity of pollutants deposited on an insulator surface, such as measurement of equivalent salt deposit density (ESDD), determination of non-soluble deposit density (NSDD) and measurement of surface resistance (SR) [5]. This paper presents a correlation study comparing information obtained from the optical sensor network, the traditional visual inspections performed by CHESF's maintenance team [6]. At present, measuring leakage current of insulator strings is one of the means to monitor contamination levels of the insulator surface of transmission lines. However, given the complex environment of transmission lines, a large amount of electromagnetic interference will produce much noise at the time of collecting leakage current. Therefore, the leakage current of the insulator strings was measured, in which a light emitting diode (LED) was used to detect current signals as photoelectric conversion and light signal stability [7]. Many numerical methods have been introduced to ease the difficulty of precise measurements of electric fields including the use of charge simulation method to calculate the electric field distribution of insulators [8].

Most leakage current measurement methods in the time domain include the maximum value of leakage current pulses, pulse count, highest peak value of leakage current before approaching contamination flashover, and leakage current root-mean-square (RMS) value. Leakage currents can be classified into three stages on the basis of test results: security stage (< 50 mA), forecast stage (< 150 mA) and dangerous stage (> 150 mA). Results can be obtained through experiments in the laboratory via measurement of leakage current and its classification into three stagesfollowed by prediction ofcontamination level [9]. This study measures leakage current and voltage on insulators by using simulation Matlb for the 5-bussystem withan improved transmission line model [10], which includesa leakage current parameter. The leakage current and voltage information are recorded at different locationsas well asthe level of pollution between two buses (0.25, 0.5 and 0.75). The collected data are trained to feedforward back- propagation algorithm for both short and medium transmission lines in the test system. Voltage and leakage current information on the transmission tower with different levels of R_{LC} insertion is manipulated as an input for the ANN. The output of FFBP provides informationabout the pollution level of the insulator surface.

2. SIMULATION MODULE

2.1. Data Collection

The simulation study is based on a 5-bus test system. This test system comprised three short transmission lines, three medium transmission lines and two generators with 100MVA capacity. R_{LC} is inserted in the transmission line tower, which is located at 0.25, 0.5 and 0.75 between two buses. Studies of an improved transmission line model with R_{LC} effect has been discussed in [10]. Based on this paper, it allows for the manipulation of a few parameters purposively for the classification of pollution levels by measuring leakage current and voltage magnitude on polluted towers. The Simulink model of the test system is shown in Figure 1. A base voltage of 138 KV and base power of 100MVA is used in this analysis.

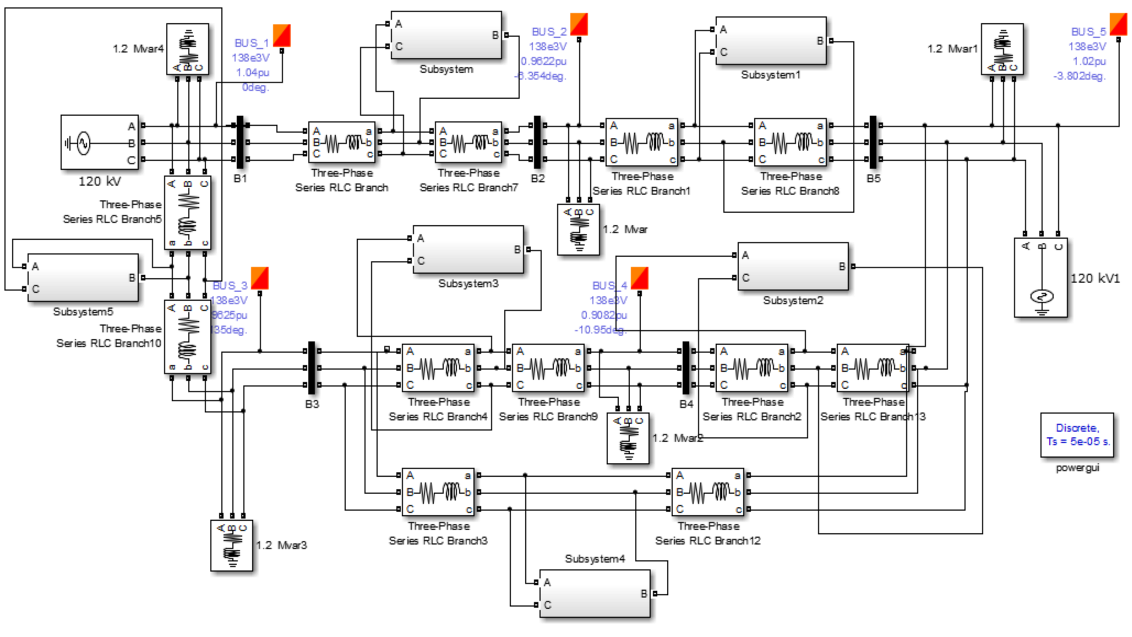


Figure 1. Simulink Model of the Test System

The sub system block in each short and medium transmission line is explained in Figure 1. The block measures leakage current and voltage magnitude in rms value on resistant insulators for three levels of pollution as shown in Figure 2. These classifications are listed as follows and are assumed to be fixed during simulation works [11]. On the other hand, changes such as effects of weather, temperature and humidity are excluded from this study.

a. Low pollution (7MΩ).
b. Medium pollution (3MΩ).
c. High pollution (0.4MΩ

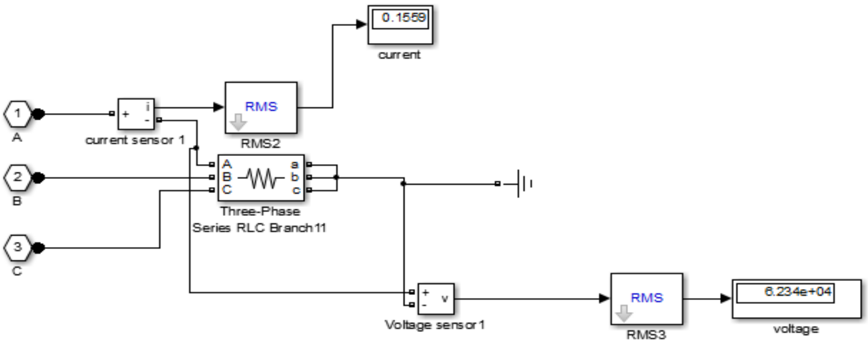


Figure 2. Simulink Sensor System for Measuring Leakage Current on Post Insulator

The impedance (Z) and admittance (Y) of transmission line between two busses in the test system will change with the R_{LC} insertion at the transmission line tower as shown in equation below.

$$Z_{new} = n * Z_{old}/N \tag{1}$$

$$Y_{new} = n * Y_{old}/2/N \tag{2}$$

Where, n is the number of towers between bus and pollution tower, N is the number of towers between two buses. Leakage current magnitude and voltage magnitude are measured on the transmission tower with R_{LC} location used as ANN input for the prediction of pollution levels on the insulator surface. Three levels of leakage current resistance, R_{LC} are selected for this study i.e. 0.4 MΩ, 3 MΩ and 7 MΩ.

2.2. Neural Network for Level of Pollution Prediction

ANN which has a high degree of self-learning, self-organization and adaptive capacity, can be used in many problems requiring function approximation, modelling, pattern recognition and classification, estimation and prediction, etc. [12-13].The most widely used is feed forward back- propagation (FFBP) to predict the level of pollution of insulators.

First, the prediction model is established according to the leakage current of the insulators. Neurons of the input layer include leakage current, leakage voltage and location tower on the transmission line. The hidden layer has three neural units. The output is the level of pollution. ANN techniques have been applied extensively in the domain of power systems. ANN is used to establish a model for the classification of the pollution grade of insulators. As illustrated in Figure 3, input patterns for the ANN is leakage current, voltage leakage and position tower on short or medium transmission lines while the output layer is the pollution level of the network. The output is the pollution level in the range between 0, 5 and 10 [14]. This can be seen in Table 1.

Table 1. Class Labels For Pollution Level Classifier

Pollution level Index (PLI)	Class Category / Label
PLI = 0	Class A : High Pollution
PLI = 5	Class B : Medium Pollution
PLI = 10	Class C : Low Pollution

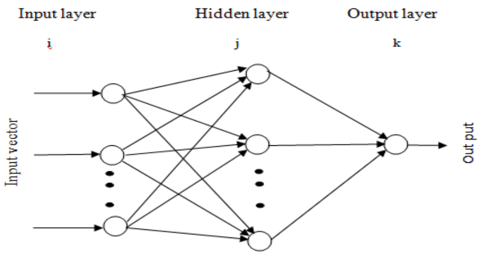


Figure 3. Structure of multilayered FFBP Neural Network

M.E. Aggoune, et al. [15] discussed the mathematical procedure of the FFBP algorithm which consists of output value, trained weights and output error calculations. The NN-based pattern-classification approach for pollution level depends on the assumption that there are some characteristics of leakage current resistance states that give low, medium, and high pollution levels. The task of the NN is to capture these common underlying characteristics of a set of measurement states and to interpolate this knowledge to classify pollution levels. The first step in such an application is to obtain a set of training data which represents the different measurements on resistance insulators. Among the techniquesin ANN, feed forward back propagation algorithm is being extensively used for pollution level classification. In this application, the classifier performance was evaluated by classifying patterns in the test set, which were generated randomly. The accuracy of pollution level state classifications can also be evaluated by the following measures.

1. Correct Classification Rate [CCR(%)]: percentage of data examples categorized properly.

$$\mathrm{CCR}(\%) = \frac{\text{No.of correct samples}}{\text{Total No.of samples}} * 100 \tag{3}$$

2. Misclassification Rate [MCR(%)]: percentage of data samples categorized incorrectly.

$$\mathrm{MCR}(\%) = \frac{\text{No.of false samples}}{\text{Total No.of samples}} * 100 \tag{4}$$

3. Mean Squared Error (MSE)

$$\mathrm{MSE} = 1/N_f \sum_{\mathrm{K}}^{\mathrm{N_f}} (\mathrm{E_K})^2 \tag{5}$$

$$\mathrm{E_K} = |\mathrm{DQ_K} - \mathrm{AQ_K}| \tag{6}$$

where N_f is the number of samples in the data set, DQ_K is the desired output obtained from off-line simulations and AQ_K is the actual output obtained from the AI classified model. The error between the real and desired output values is transmitted backwards from the output layer to the intermediate layer. This process is repeated until each unit receives a proportion of the error signals [16-17].

3. RESULTS AND DISCUSSION

The goal is to assess the severity of contamination on the insulator surface based on the leakage current and voltage of insulator strings. This information should be available from different tower locations in a transmission line. The pollution can be classified into three levels: low, medium and high.

3.1. Classification of Leakage Current in Short Transmission Lines between Bus 1 and 2

R_{LC} is inserted in the transmission line tower, at 0.25, 0.5 and 0.75 between buses1 and 2, and the leakage current and voltage on insulators are measured by simulated sensors. The results are listed in Table 2. R_{LC} is inserted in short transmission lines, at 0.25 between buses1 and 2. Based on the simulation results, leakage currents can be classified into three stages: low pollution (< 25.84mA), medium pollution (< 193.9mA) and high pollution (> 193.9mA). Also, I_{LC} in short transmission lines (0.5 of length) can be classified as follows: low pollution (< 20.78mA) medium pollution (< 155.9mA) and high pollution (> 155.9mA). Finally, at location 0.75 of long short transmission lines, I_{LC} is classified into three stages: low pollution (< 17.30mA), medium pollution (< 129.8mA) and high pollution (> 129.8mA) while leakage current resistance dependent leakage current variable is displayed in Figure 4.

Table 2. R_{LC} with (I_{LC}, V) at 0.25, 0.5 and 0.75 in Short Transmission Lines between Buses1-2

Location on transmission line	R_{LC}(MΩ)	I_{LC}(mA)	V_{LC} (kV)
	0.4	193.9	77.52
0.25	3	25.84	77.52
	7	11.08	77.52
	0.4	155.90	62.34
0.50	3	20.78	62.34
	7	8.906	62.34
	0.4	129.80	51.91
0.75	3	17.30	51.91
	7	7.416	51.91

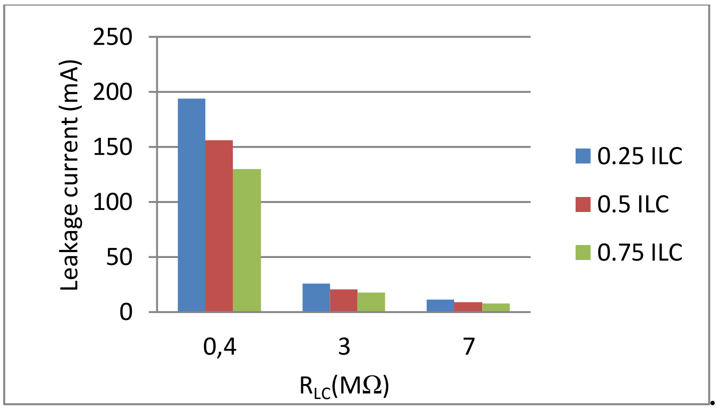


Figure 4. R_{LC} with I_{LC} at 0.25, 0.5and 0.75 in Short Length Transmission Lines

3.2. Classification of Leakage Current in Medium Transmission Lines Between Buses 5 and 4

R_{LC} is inserted in the transmission line tower, at 0.25, 0.5 and 0.75 between buses 5 and 4, and leakage current and voltage are measured on insulators for medium transmission lines. The results are listed in Table 3, and the leakage current resistance dependent leakage current variation is displayed in Figure 5.

Table 3. R_{LC} with ($I_{LC,}$V) at 0.25, 0.5 and 0.75 in Medium Transmission Lines between Buses 5- 4

Location on transmission line	R_{LC}(MΩ)	I_{LC}(mA)	V_{LC} (kV)
	0.4	206.2	82.70
0.25	3	27.49	82.70
	7	11.78	82.70
	0.4	178..5	71.40
0.50	3	23.8	71.40
	7	10.2	71.40
	0.4	153.5	61.38
0.75	3	20.46	61.38
	7	8.769	61.38

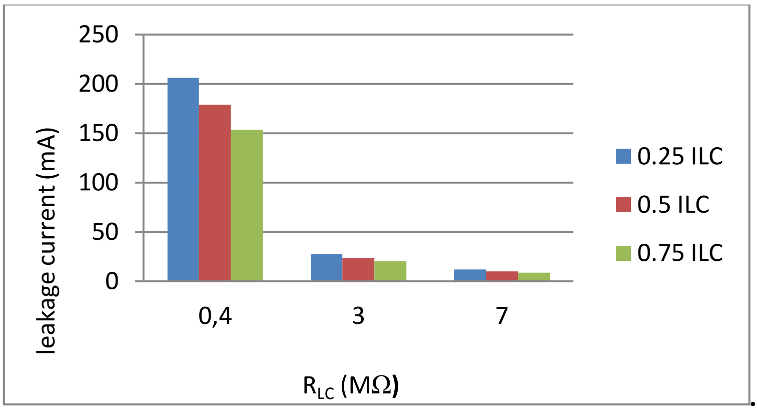


Figure 5. R_{LC} with I_{LC} at 0.25, 0.5 and 0.75 in Medium Length Transmission Lines

From the above results, R_{LC} is inserted in the medium transmission line, at 0.25 between buses 5 and 4. Based on simulation results, leakage currents can be classified into three stages: lower pollution (< 27.49mA), medium pollution (< 206.20mA) and high pollution (>206.20mA). Also I_{LC} in medium transmission lines (0.5 of length) can be classified as follows: low pollution (< 23.80mA) medium pollution (< 178.5mA) and high pollution (>178.5mA). Finally, I_{LC} is classified into three stage in medium transmission lines (0.75 of length): low pollution (< 20.46mA), medium pollution (< 153.5mA) and high pollution (>153.5mA). The R_{LC} dependent on leakage current level is as shown in Figure 5 for 0.25, 0.5 and 0.75 of medium length transmission lines.

From the above results for short and medium transmission lines, leakage current on the insulator is varied a long the transmission line. It is shown that I_{LC} of short or medium transmission lines (0.25 of length) is greater than I_{LC} of short or medium transmission lines (0.75 of length). In addition, leakage current increases with the decrease in leakage current resistance at three locations of the transmission line because of increased contamination deposited on the insulator towers. As observed on the display, accordingly as recorded in the computer, this finding reflects to some extent, the filthy state as well as the development of the discharge process of polluted insulators, which can be used as parameters to evaluate the contamination degree of insulators. Therefore, classification of leakage current to evaluate the level of pollutionis very necessary to the continued operation of transmission lines.

3.3. Implementation of ANN Techniques on Test System

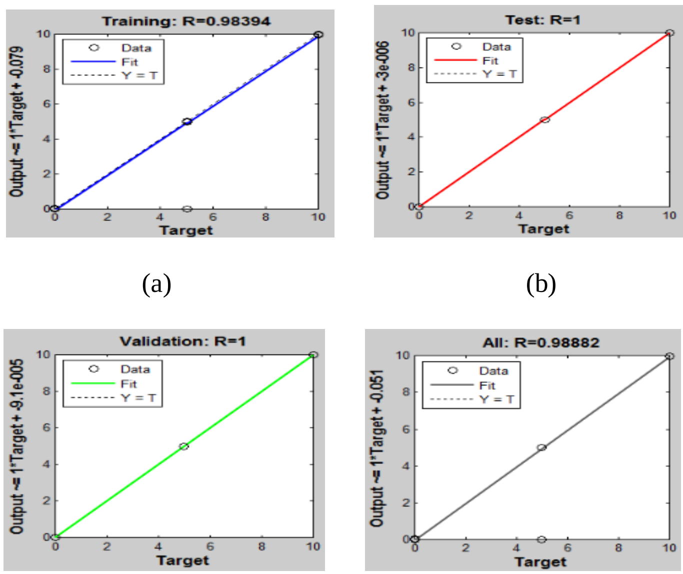
Data on training and testing are obtained from simulation of the 5-bus test systems, ANN techniques are used to predicate the level of pollution under operating conditions. Data obtained from leakage current resistance insertion at 0.25, 0.5 and 0.75 for short and medium transmission lines, leakage current and voltage on insulator resistance are sensoring for both training and testing. It is to be noted here that test data is not part of training data.Test result error is measured in terms of mean square error (MSE) and test result accuracy is measured in terms of CCR (%). There are many types of ANN in this paper in which FFBP is used.

3.3.1. Implementation FFBP Neural Network in Short Transmission Line

In order to predict contamination severity of the insulators, the most widely used feed forward back propagation (FFBP) neural network model (NNM) has been selected to construct a model for the insulator [3]. Neural network uses 125 samples. The data is divided into two groups; 68% is used for training processes and the other, 32% is used for testing. Values for the different levels of pollution that represent the output are stated in Table 4.

Table 4. Result FFBP in Short Transmission Line

Level pollution	CCR(%)	MCR(%)
High	92.30%	7.69%
Medium	100 00%	0.0%
Low	90.90%	9.09%



(a) (b)

(c) (d)

Figure 6. The Neural Network Regression Results: (a) Training, (b) Test, (c) Validation and (d) all

Figure 7 elaborates the implementation of FFBP-NN on the 5 bus test system in short transmission lines between buses 1 and 2 with training, validation, MSE and number of epochs and it can be seen that the training mean square error decreases as the number of epochs increase. The best validation point of the performance is at epoch 33, with the MSE value at 2.064*10^-7. As seen from this result, there is a satisfactory agreement between simulation and ANN predicted values.

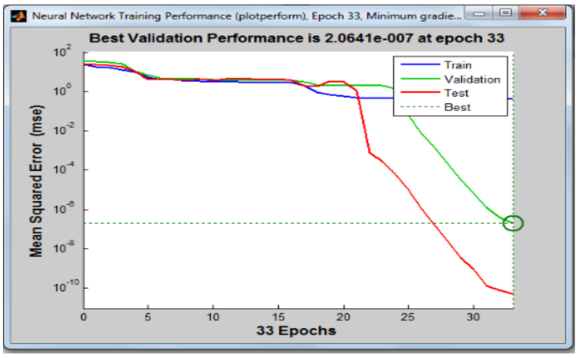


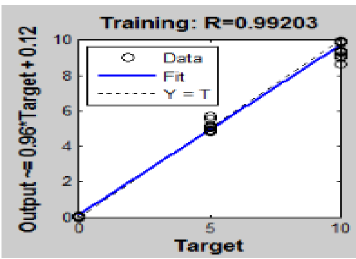
Figure 7. ANN Training for Short Transmission Lines Busses1-2

3.3.2. FFBP Neural Network in Medium Transmission Line

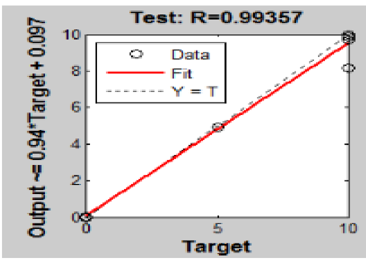
Neural network uses 146 samples. The data is divided into two groups; 68.5% is used for training processes and the other, 31.5% is used for testing. Values of the different levels of pollution that represent the output for the model are stated in Table 5.

Table 5. Result FFBP in Medium Transmission Line

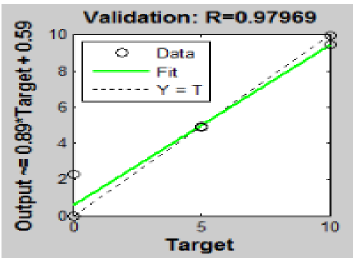
Level pollution	CCR(%)	MCR(%)
High	80.0%	20%
Medium	100.0%	0.0%
Low	100.0%	0.0%



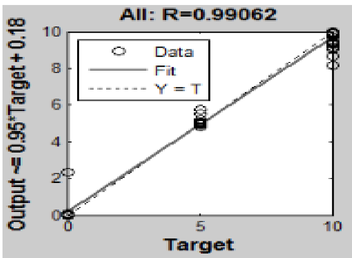
(a)



(b)



(c)



(d)

Figure 8. The Neural Network Regression Results: (a) Training, (b) Validation, (c) Test and (d) all

Figure 8 illustrates the simulation results for training, testing validation and all for medium transmission lines. The results show that the overall CCR and MCR is 98.63% and 1.36%, respectively. The regression correlation coefficients (R) between predicted and simulation values of the leakage current, voltage, location tower are found at 0.99203, 099357 and 0.97969 for training, testing and validation data sets, respectively. It has been shown that there is a very good correlation between predicted values of the ANN model and the simulation values.

Figure 9 elaborates the implementation of ANN on the 5 bus test system in medium transmission lines between buses 5-4 with training, validation, MSE and number of epochs.

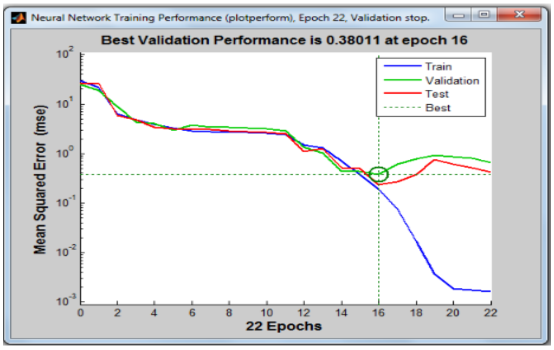


Figure 9. ANN Training for Medium Transmission Line

From Figure 9, it can be seen that the training mean square error decreases as the number of epochs increases. The best validation point of the performance is at epoch 16, and the MSE value is 0.38011. The study indicates that the proposed ANN can be used efficiently for the prediction of pollution levels of insulators at case appear leakage current for short and medium transmission lines.

The FFBP neural network showed high agreement with the Simulink results. The results of medium transmission lines clearly demonstrated that the classification CCR% in case high pollution is 80% as compared to classification CCR% in short transmission lines which is 92.30%, because the numberof towers in medium transmission lines is more and therefore increases pollution.

4. CONCLUSION

In this study, a new method has been proposed to predict severe contamination of insulators which is, based on a measure of leakage current and voltage of the insulator to an improved transmission line model. This paper describes the simulation study of a 5-bus system with R_{LC} insertion between buses. Based on the results, medium transmission lines have greater magnitude of leakage current compared to short transmission lines. The FFBP neural network successfully predicted the level of pollution with at least 95% CCR for both short and medium transmission line types for the test system. In conclusion, information from the improved transmission line model on test systems provided an opportunity for assessing the pollution level of surface insulators. The validation of simulation resultscan be easily proven with the ANN. The results of medium transmission lines clearly demonstrated that the classification CCR% in case high pollution is 80% as compared with classification CCR% in short transmission lines which is 92.30%, because the number of towers in medium transmission lines is more and therefore increases pollution.

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