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Leakage Current Prediction of Composite Insulator using Artificial Neural Network

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Abstract**: *The uninterrupted power supply is one of the main concerns for the power utility which is often adversely affected by the flashover of the outdoor insulators. The main cause of the flashover of outdoor insulator is the contaminated pollution on its surface which is more severe for the insulators located nearer to the seashore. At such sites, insulators have to be washed regularly to avoid flashover which is an expensive and time-consuming process. So it is required to optimize the washing schedule. When the contamination is severe on the surface of the insulator, it allows the flow of the leakage current (LC) which turns into the flashover. The LC is a good indication for predicting the flashover. LC measurement and instrumentation system in real tower insulator is complex and expensive. In this paper, a prediction method is developed which predicts the LC at the level of starting of the arc which may turns into a flashover. An artificial neural network based model is developed which predicts the leakage current for the different polluted condition and humidity level. An experimental setup is prepared and subsequently data is taken to acquire LC on different relative humidity and equivalent salt deposit density (ESDD). Subsequently, a neural network model is constructed with the experimental data to predict LC. A single layer feed forward network based a predictive model performs LC prediction with the average error of 5.46% from the real values which is acceptable in case of alarming situations.***

Index Terms**: *ANN, ESDD, Flashover, Insulator, Leakage current***

I. INTRODUCTION

The outdoor insulators are absolutely necessary part in the electrical power transmission and distribution network and hence the reliability of the network depends on the mechanical and electrical quality of the insulators. Though the cost of the insulator is very less compared to the total capital cost of the line, they are incorporated with more than 75% of line outages and approximately 50% of line maintenance costs. manufacturing defects, surface contamination, aging and damage due to improper handling are the major causes leading to failure of the insulators[1-2]

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Here we are concentrating the outage of the insulator due to surface contamination.

As the outdoor insulator has to work in open environment, they are always subjected to pollution of different nature and severity. Depending on the working environment, the pollution which contaminates surface of insulator has different composition [3]. For the transmission line passing through the coastal area, the main constituents of pollution are NaCl and slurry. The pollution contains soluble conductive particles as well as non soluble conductive particles which are measured in as Equivalent salt deposit density (ESDD) and non-soluable deposit density (NSDD), repectively. The ESDD has been considered to classify the pollution severity of the outdoor insulator according to IEC-60815 [4].This conductive layer when becomes wet, allows the flow of the LC. Insulator has to work continusiously under the voltage stess, this LC creates arcing which degrade the insulator surface and finally turn into the flashover. As the LC is the cause of the flashover,several studies has been done to understand the relation between LC and the degradation of the insulator. Leakage current is related with level of the contemination build up and wetting on insulaor material surfaces. Surface free energy of the material is responsible for wettiing on mateial surfaces [5,6]. Due to hydropobic nature of polymer the surfae free energy is much lower than the porcelain and glass because this property opposes the wetting and development of electrolyte film on the surface. However, when exposed to the electic stress, the hydropobic property is detoriate and allows the flow of LC.In Maxico, the real time measurement of LC is used as a diagnosis tool for the transmisssion line insulators degredation[7]. But the LC measurement and instrumentation system in real tower insulator is complex and expensive. In [8], it concluded that to measure the leakage current above 150 mA is not an easy task and hence some indirect method like prediction of leakage current has to be adopted. In[9], the leakage current is characterized into three stages and suggested that the security stage has to be consider as pre-warning stage for contemination flashover. It is also concluded that if the creepage distance of porcelain insulator is increase compared to the ordinary available insulator then the chances of the flashover may reduce for the same pollution level. Here the work is on porcelain and not on polymer which are nowadays widely used also the increse in the creepage distance increase the cost. In this paper, an ANN based mathematical model is proposed to predict the LC for the 11 kV working voltage insulator. It is observed that leakage current depaneds on environmental factors like temprature, humidity and polution.

However, because temprature and humidity are related therefore only humidity and constituents of polution are taken as inputs for the predictive model to predict LC.
The reason behind selecting the humidity as an enriomental factor that detemines leackage current is because it is found that as long as pollutants are dry they are not responsible for the flow of the LC on the surface of the insulator but when they are wet due to humidity then allow the LC to flow [10,11]. Hence, two parameters are taken as inputs, i.e. conductivity of the pollution and the environment humidity. The magnitude or the LC is the output of the network. In order to obtain the data for the LC predictive model and validation an experiental setup, consisiting high voltage supply source, fog chamber, humidifier, was prepared.
The paper is structured as follows: in the second section the process of sample prepration (insulator with deposited pollutants) is illustrated. Third section includes details of the experimental setup. Fourth section describes and a preliminary mahtematical backgroud for artificial neural network and architecture of the model for LC prediction. This section also includes various combinations of the parameters and specifications in the process of obtaining the most apt model for LC prediction. In the fifth section, a results and discussion are shown. And, finally some conclusion is withdrawn in the last section.

II. SAMPLE PREPARATION

A. Preparation of pollutant

It is required to predict the LC for different level of polluted conditon. Literature review shows that Equivalent salt deposit density (ESDD) is the universaly adopted method for showing the electrical conductivity of an contemination depositon with unknown composition. As the conductive pollution level is more intense in areas located near the sea, we have considered constitutes of pollution which is likely present in this area. The major constitute are kaolin slurry and the Sodium Chloride NaCl[1].According to IEC 60507, the polluted area may be classified into 5 category as shown in Table1[3].

Table I Classification of contamination severity as per IEC 60507

Class	Pollution severity	ESDD (mg/cm^2)
a	Very light	<0.01
b	light	0.01-0.04
c	Medium	0.04-0.15
d	Heavy	0.15-0.40
e	Very heavy	>0.40

Four different sollutions are prepared to acheive different ESDD level. The sollution are prepared by desolving kaolin and NaCl in the half litre of distiled water. A normalised mixture according to IEC 60507 containsonly 40 grams of Kaolin, so the proprtion of Kaolin is fixer 40 gm but the amonut of NaCl is dirrerent to create different severity of polution[3].The detailed is mentioned in Table II. The exact value of ESDD of sollution is measured which is explained infollowing subsection.

Table II Composition of solution

Pollution level	ESDD (mg/cm^2)	NaCl(gm)	Kaolin
Light	0.01-0.04	10	40
Moderate	0.04-0.15	20	40
Heavy	0.15-0.40	30	40
Very Heavy	>0.40	40	40

B. Preparation of artificially polluted specimen

Prior to performing test on the specimen, it has been wash and clean carefully by distilled water and clean cloth.The sollutions of different ESDD shown in fig. 1 are sprinkled on tne surace or the insulators to create coating of contemination and allowed to dry for 24 hrsas shown in fig.2.According to IEC 60507 standards,this method is known as the solid layer method. The area of the insulator surface is1026 cm^2 which has been polluted.

Fig. 1: Solution poured in the bottle

Fig. 2: Samples prepared for the experiment

B. ESDD Calculation Procedure

The conteminant which has been deposited on the surace is wiped out as per rag-wipe method. When the surface deposit has been wiped clean, the rag is put back into the wash water. The conductivity is measuresd at the solution temperature as shown in fig. 3. The display of conductivity meter showsσ_T, 19.3 mS/cm conductivity at temperature T, 24.6 C.

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Fig. 3: Conductivity measurement

The procedure to find ESDD from σ_T and T is shown below.

The ESDD is given by the following formula(1)[3]

$$ESDD = Sa \times V/A \qquad (1)$$

Where Sa is the salinity measured in(kg/m^3), V is the volume of deionozed water which is used to prepare solution and measured in (cm^3). A is the area of the insulator surface which is artificially polluted.

The salinity(Sa) is calcualted by the following equation (2).

$$Sa = (5.7\sigma_{20})^{1.03} \qquad (2)$$

Where $\sigma_{20}$is conductivity of the NaCl solution corrected at 20°C (S/m) from the existing temperature of the solution. It is corrected by the following equation (3).

$$\sigma_{20} = \sigma_T[1 - b(T - 20)] \qquad (3)$$

Where T is the solution temperature (°C), σ_T is conductivity of the NaCl solution at T°C (S/m). The σ_T at temperature T of the solution is measured by the conductivity meter as shown in fig 1.The conductivity(σ_T) and temperature(T) of each solution is measured and then after using equations 3,2,and 1, σ_{20}, Sa and $ESDD$ has been measured respectively. These calculation has been shown in Table 3.

Table III Calculation of ESDD

Insulator surface area, A (cm^2)	Volume of deionized water, V (ml)	Electrical conductivity at temp. T, σ_T (mS/cm)	Solution temp., T (^{0}C)	Electrical conductivity at 200 C,σ_{20} (S/m)	Sa Salinity (kg/m^3)	ESDD (mg/cm^2)
1026	500 ml	54.5	24.2	5.78	1.144	0.572
1026	500 ml	41.8	24.5	3.628	0.560	0.343
1026	500 ml	30.8	24.6	2.506	0.256	0.087
1026	500 ml	19.3	24.6	1.275	0.114	0.037

III. EXPERIMENTAL SET UP AND DATA DESCRIPTION

Five insulator of 11kV voltage rating areused to predict the LC. These insulators are prepared as mentioned in the III. Theclean fog chamber as shown in fig.4 is used to test the insulator and the measure the LC. The dimensions of the chamber are 1590mm *1560mm*1330mm (2m3) which is according to IEC standards.The insulator is subjected to the electric sterss with the $11/\sqrt{3}$kV phase voltage under the humid environment. As here the interest is to observe the flashover due to contemination, the supply voltage was only the nominal voltage and not the flashover voltage. The activity of arcing due to LC is only observed for the wet insulator surface,clean fog was generated in the chamber with the help of humidifier to saturate the chamber before hanging the insulator in the test chamber. During the testing, few insulators are failed due to the severe flashover.The ultrasonic humidifier with adjustable relative humidity is used to create fog in the chamber. The leakage current is measured with the current transformer and the wavform and the readings are displyed on the laptop with the help of a data acquisition system. At the different himidity the magnitude of LC are different or the same ESDD level. Table IV shows the reading of the leakage current.

Fig. 4: Experimental set-up

Table IV Experimental data

Sr. No.	ESDD (mg/cm^2)	%RH	Leakage Current (uA)
1	0.08	95%	2747
2	0.08	90%	2126
3	0.08	85%	2010
4	0.08	80%	1987
5	0.08	75%	1940
6	0.08	70%	1809
7	0.08	65%	1750
8	0.08	60%	1700
9	0.08	55%	1669
10	0.08	46%	630
11	0.12	95%	3870
12	0.12	90%	3046
13	0.12	85%	2213
14	0.12	80%	2126
15	0.12	75%	1987
16	0.12	70%	1850
17	0.12	65%	1793
18	0.12	60%	1712
19	0.12	55%	1693
20	0.12	46%	637
21	0.18	95%	6547
22	0.18	90%	6130
23	0.18	85%	5780
24	0.18	80%	3921
25	0.18	75%	3220
26	0.18	70%	2800
27	0.18	65%	2010
28	0.18	60%	1860
29	0.18	55%	1780
30	0.18	46%	768
31	0.2	95%	7300
32	0.2	90%	6801
33	0.2	85%	5800
34	0.2	80%	4237
35	0.2	75%	3737
36	0.2	70%	3128
37	0.2	65%	2298
38	0.2	60%	2273
39	0.2	55%	1804
40	0.2	46%	785
41	0.5	95%	8725
42	0.5	90%	7543
43	0.5	85%	6801
44	0.5	80%	5438
45	0.5	75%	4088
46	0.5	70%	3286
47	0.5	65%	2874
48	0.5	60%	2463
49	0.5	55%	1908
50	0.5	46%	890

IV. Prediction Model with Artificial Neural Network

A predictive mathematical model is constructed based on artificial neural network-based architectures. ANN is powerful class of computational methods that is used for prediction, detection, and creation problems. The reason for choosing ANN for prediction (also known as function approximation) is because of its ability to construct a model based on the supervised learning. In this section, a description of a basic ANN model is given, then the steps taken to build a reliable model for LC prediction based when some environmental information like ESDD and RH are known are explained.

A. Basics of ANN based feed forward model

ANN is widely used techniques for the forecast or prediction problem regardless of the field of engineering or science. Since reliable ANN based models require a supervised learning therefore the LC data that is shown in table 4 are prepared and arranged for supervised learning in which some percentages of the data are given to ANN model for learning and some to test the model's suitability. A well-known fact related to ANN is about its incapability to auto-select some of the important elements in the configuration of the model, such as number of neurons in hidden layer, deepness of the hidden layer, activation function, training algorithms, and learning rate, etc., in order to find the best performing architecture [13-14]. Therefore, various combinations of parameters specifications of networks are experimented. The parameters which are taken to prepare the models are: number of neurons in hidden layers, depth of hidden layers, learning rate, momentum constant, training algorithms and activation function in attempt to obtain the minimum squared error in the training process. The basic model of the ANN is shown in the fig. 5, where inputs as humidity and ESDD and output as leakage current are indicated. The main task in building of an ANN based model is two parameters adjust weights of connections between two neurons while minimizing the error between the target output and predicted output during learning process.

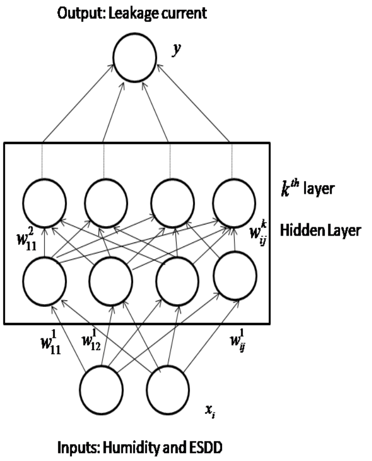

Fig. 5: Basic ANN model for LC prediction

$$w_{ij}^{l}(k+1) = w_{ij}^{l}(k) - \eta\frac{\partial f}{\partial w} + \alpha[w_{ij}^{l}(k) - w_{ij}^{l}(k-1)] \quad (4)$$

Where, w_{ij}^{l} are the weights of the connection between neurons, f is activation function, η is learning rate, and α momentum constant in k iteration required to obtain convergence in the learning process. Output of the model is estimated by linearly multiplying the weights of the neuron to the inputs. The error predicted data and real output is minimized in the learning process. Mean square error (MSE) calculated in each step (epoch) to during the training process in either of the training algorithms. The MSE is calculated as the equation (5), where t_i is the target output and $y_i$is the estimated output.

$$e_{mse} = \frac{1}{n}\sum_{i=1}^{n}(t_i - y_i)^2 \quad (5)$$

This error has to be minimized in order to obtain a best trade-off model. In fact, this also determines when the training process is complete. If MSE is high for test data then training process continues with modified network architecture.

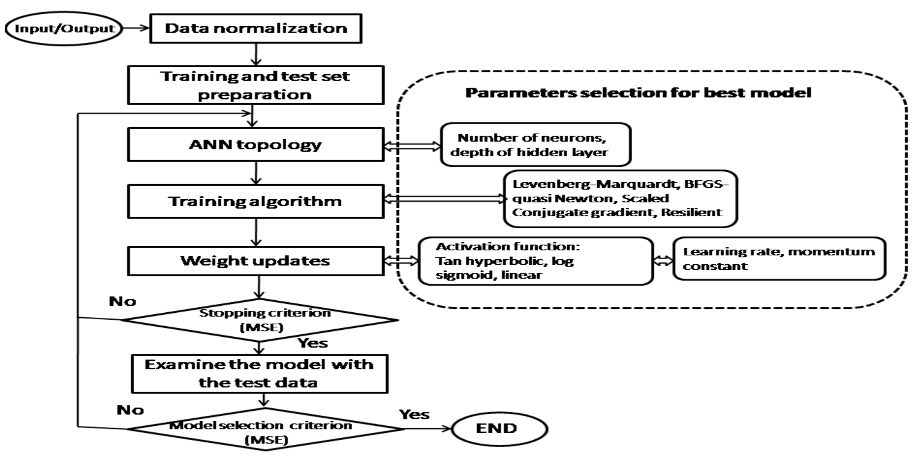

Fig. 6 ANN model construction for prediction of Leakage current

B. Process for constructing a predictive model

ANN based model for prediction of leakage current with the depending variables, ESDD and RH, are constructed as described in the flow chart shown in Fig6. It shows that, input and output data is normalized or pre-processed. Then, simulation experiments are performed to select the best performing model. As flow chart depicts, first number of neuron and depth of hidden layer are determined with selected training algorithm, activation function, learning rate and momentum constants. Once this is defined, rests of the parameters are changed within a range in order in order to reduce MSE and convergence time. The process of selecting a model by performing some steps are following is elaborated here.

B.1 Pre-processing or Data normalization

Input data, ESDD and Relative Humidity, have different range of variations hence it requires to be normalized in order to accelerate learning process and avoid over fitting in the model. In this work, input data is normalized between 0 and 1 using the relation given in (6).

$$x = \frac{x_{max} - x}{x_{max} - x_{min}} \tag{6}$$

In (6), x is data raw data, x_{max} and x_{min} are maximum and minimum, respectively, of the input data, Some other methods of normalization like mean-standard deviation and normalising between any given values (e.g. -1 and 1) were also attempted but max-min method was discovered to be empirically suited in the prediction of the leakage current.

B.2 Data preparation

Data preparation constitutes partition for target data set and test dataset has been shown in Table IV. Almost 85% of the total 50 recording is taken as target set and rest is chosen for testing, while taking care that both sets includes recordings from each ESDD.

B.3 Neuron and hidden layer

In order to find a simple and less computational ANN model, depth of the hidden layer must less. Therefore, first experiment is performed with varying number of neurons in each block of the hidden layer. Table V includes the suitable number neuron in the network, as it can be observed that 4 neurons in a single hidden layer is showing the least MSE.

B.4 Activation function

Decision making in the neuron is taken by activation function. Usually, activation function is selected as nonlinear one because mostly experimental input data is nonlinear. Various nonlinear activation can be taken in training process however in this work three following activation functions are taken:

Tan sigmoid function (tansig),

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{7}$$

Logarithmic sigmoid function (logsig), $f(x) = \frac{1}{1+e^{-x}}$ (8)

Linear function (purelin), $f(x) = x$ (9)

Table V Neurons in the hidden layer

Neuron	Learning rate	Momentum Constant	Maximum Epoch	MSE (test data)
2	0.0001	0.9	68	0.467997
3	0.0001	0.9	1001	0.75849
4	0.0001	0.9	988	0.076339
5	0.0001	0.9	547	0.142976
6	0.0001	0.9	258	0.664445
7	0.0001	0.9	841	0.10595
8	0.0001	0.9	1001	0.51924
9	0.0001	0.9	1001	1.078463
10	0.0001	0.9	1001	5.927686
11	0.0001	0.9	1001	0.982614
12	0.0001	0.9	1001	0.457357
13	0.0001	0.9	1001	2.573551
14	0.0001	0.9	1001	4.105947

Table VI shows nonlinear activation functions tan sigmoid and log sigmoid, showing the less MSE than the linear function. Nonlinear nature of tan sigmoid seems to perform best when test data is given the prepared model in which hidden layer has signal layer of four neurons.

B.5 Learning rate

Learning rate is an important factor that determines the quantum of weight adjustment calculated from the gradient-descent. Learning rate is chosen between 0 and 1. In this experiment, four values of learning rate is used, i.e. 0.0001, 0.001, 0.01 and 0.1. MSE convergence is met sooner when learning rate is high. In fact, effect of the learning rate is on MSE is not seen in terms of minimizing its value but reducing the time of convergence. Table 7 shows the effect of learning rate on MSE and convergence time. It is evident that MSE does not reduce further when learning rate is varied however on the other hand convergence time is reduced significantly.

Table VI MSE of the model on training algorithms and activation functions[12].

Training Algorithm	Transfer function	Neuron	Learning rate	Momentum Constant	Maximum Epoch	MSE (test data)
Levenberg-Marquardt	tansig	4	0.0001	0.9	1001	0.68583
	logsig	4	0.0001	0.9	1001	0.797547
	purelin	4	0.0001	0.9	5	0.765067
BFGS-quasi Newton	tansig	4	0.0001	0.9	988	0.076339
	logsig	4	0.0001	0.9	1001	0.751296
	purelin	4	0.0001	0.9	17	0.765067
Scaled Conjugate gradient	tansig	4	0.0001	0.9	1001	0.112945
	logsig	4	0.0001	0.9	1001	0.751296
	purelin	4	0.0001	0.9	17	0.765067
Resilient	tansig	4	0.0001	0.9	1001	0.419248
	logsig	4	0.0001	0.9	1001	0.186242
	purelin	4	0.0001	0.9	47	0.765067

B.6 Momentum constant:

Momentum constant gives momentum to learning rate in the process of training. From equation 4, it can be noticed that momentum constant α plays significant role in weight updating in each iteration of the leaning process. Table VII shows the MSE on varying momentum constants, 0.5, 0.7 and 0.9. It can be observed in the table that convergence time is more when momentum constant is less. Similar to learning rate it does not have any effect on the final value of MSE but the timing to the training process is reduced as its value changes.

Fig.7 shows the performance of the four training algorithms. BFGS-quasi Newton (trainbfg) algorithm exhibits slow convergence but less error compared to the Levenberg-Marquardt (trainlm)[12]. Fast convergence is not a matter of concern when training process is performed offline therefore the model built with BFGS-quasi Newton training algorithm is selected for prediction.

Table VII MSE and Convergence on model on different learning rate and momentum constant[12].

Neuron	Training algorithm	Transfer Function	Learning rate	Momentum Constant	Maximum Epoch	MSE (test data)	Convergence time (sec)
4	trainbfg	tansig	0.0001	0.9	988	0.076339	1.694
4	trainbfg	tansig	0.0001	0.7	988	0.076339	1.669
4	trainbfg	tansig	0.0001	0.5	988	0.076339	1.707
4	trainbfg	tansig	0.001	0.9	988	0.076339	1.706
4	trainbfg	tansig	0.001	0.7	988	0.076339	1.861
4	trainbfg	tansig	0.001	0.5	988	0.076339	1.709
4	trainbfg	tansig	0.01	0.9	988	0.076339	1.766
4	trainbfg	tansig	0.01	0.7	988	0.076339	1.696
4	trainbfg	tansig	0.01	0.5	988	0.076339	1.681
4	trainbfg	tansig	0.1	0.9	988	0.076339	1.74
4	trainbfg	tansig	0.1	0.7	988	0.076339	1.704
4	trainbfg	tansig	0.1	0.5	988	0.076339	1.687

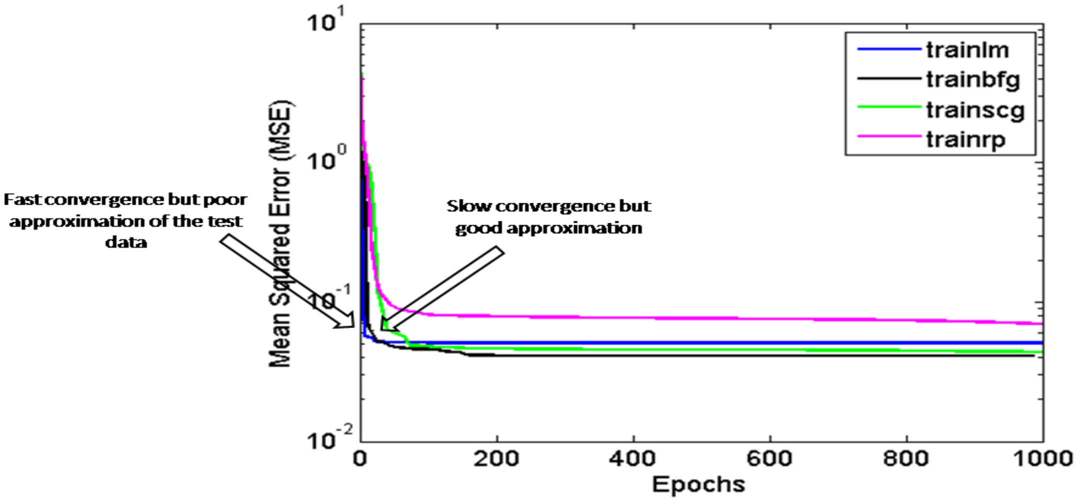

Fig.7 Convergence (Performance) of training algorithms

V.RESULTS AND DISCUSSIONS

After constructing the model suggested above, test dataset in which almost 15 percent ESDD and RH are taken to examine the model. Table VIII shows the selected input members of ESDD and RH as test data set and corresponding predicted and original leakage currents, respectively. It can be observed that the average error 5.46 % is found in predicted result which is quite significant according to the convention for issuing a warning of damaging LC.

A pictorial illustration of the measured LC with respect to ESDD and RH in the HV lab is shown in fig. 4. Original LC, those are taken for modelling building as well as for testing the model, are shown in fig.8. Besides, in the same figure approximated or predicted values of LC in using the build ANN based model is shown which almost overlapping the originals ones.

It is evident that the prediction error, MSE, can be even further minimised if LC is measured on narrower incremental value of ESDD. Furthermore, it can be noted in the Fig.8 that LC from ESDD's 0.2 to 0.4 are not measured which is amounting to induce yeilded error. Prediction for a continuously recorded data can be excersied with more precision. In future work, measurment of LC will be performed with less interval of ESDD and RH to develop a model to predicted values with least error.

Table VIII Approximated or predicted leakage current with the obtained neural network model

ESDD (mg/cm2)	RH(%)	Original Leakage Current (mA)	Predicted Leakage Current (mA)	Error (%)	Average Error (%)
0.5	46	0.890	1.0675	19.94	5.46
0.02	46	0.608	0.6328	4.07	
0.08	75	1.94	1.9204	1.01	
0.08	70	1.809	1.8540	2.48	
0.12	60	1.712	1.7585	2.71	
0.18	55	1.780	1.7064	4.13	
0.18	46	0.768	0.7020	8.59	
0.2	55	1.804	1.7909	0.72	

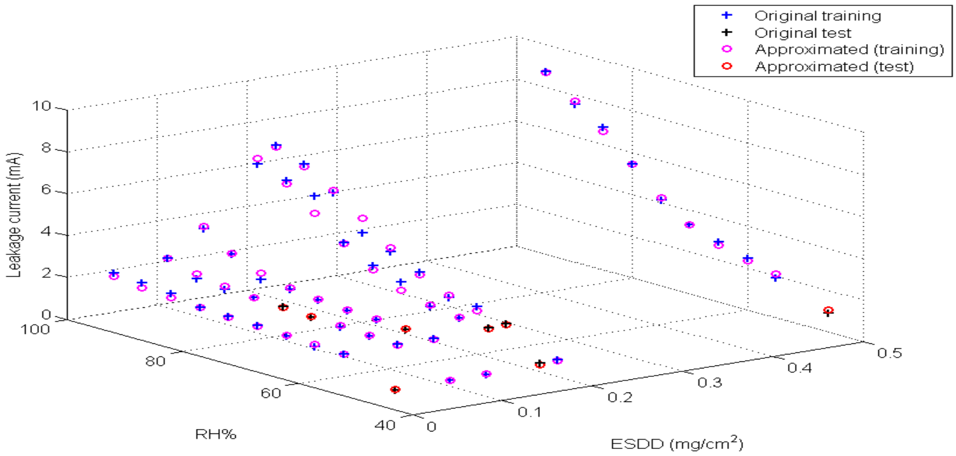

Fig. 8 Predicted values of Leakage Current

VI. CONCLUSION

In the paper an artificial neural network based mathematical prediction model is proposed that takes ESDD and RH as inputs in order to predict an estimated value of leakage current. A feedforward network with a single hidden layer is constructed by varying several toplogies along with the tranining parameters such traning algorithms, activation function, momentum constant and learning rate. BFGS-quasi Newton back propagation with the activation function hyperbolic tangent as an activation function showed the best predicted values. Average predicted error is under the tolerance limit therefore when this value goes higher than a set value (according the standard), then warning for insulator washing can be given.

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