Study of Electric Fields on High Voltage Composite Insulators under Polluted Conditions Using Artificial Neural Network

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***Abstract*—This paper attempts to apply artificial intelligent techniques in high voltage applications and especially to estimate the electric field distribution on a polluted insulator surface. The paper presents, a three-dimensional (3D) electric fields estimation program, to calculate the field distribution along the leakage distance of an insulator under polluted conditions using artificial neural network (ANN). Alternate Sheds type composite suspension insulator has been used for calculations. Firstly, electric fields have been calculated for different line voltages and pollution conductivities using finite element method (FEM) in previous study. Some of the calculated data sets have been used for training the ANN and the other sets of data have been used for testing. The x, y and z coordinates and pollution level of the surface have been used as inputs of ANN to estimate the electrical fields on the polluted insulator surface. Several ANN models were addressed to identify the electrical fields on the insulator surface. Each model has been constructed using different structures, learning algorithms and performance functions in order the best generalizing ability to be achieved. These developed models make it possible to determine the electrical fields easier and shortens the calculation time. The results show that the estimated values of electrical field have been obtained with acceptable degree of accuracy.**

Keywords— Insulators; Electric Fields; Pollution; Artificial Neural Networks (ANN); Back Propagation.

I. INTRODUCTION

The electric field calculation is one of the essential factors in the design and development of high voltage insulators. The calculation of the electric-field distribution is very important for the design of high-voltage transmission lines. High electric-field strength can cause strong corona around the conductor surface, audible noise, radio interference, partial discharge, premature aging of insulation, and other electromagnetic (EM) pollution. [1]

The reliability of the power system mainly depends on the environmental and weather conditions which cause flashover on polluted insulators leading to system outages. It is generally recognized that the main causes leading to the contamination of insulators are marine pollution-found in the immediate neighborhood of the coastal regions and solid pollution-found in the dense industrial areas. [2]

The problems of contamination on electrical insulators take place when the environment that surrounds them contains diverse substances, especially saline and industrial ones, which are deposited on insulators, forming a polluting layer on their surface. In dry conditions, this layer does not cause great problems, but under the presence of light rain, humidity, dew or fog, the dielectric characteristics of the insulator surface are decreased, allowing the flow of leakage current between the insulator electrodes leading to a failure on the high-tension electrical system. [3].

Polymer insulators, which have been used increasingly for outdoor applications, give better characteristics over porcelain and glass types: they have better contamination performance due to their surface hydrophobicity, lighter weight, possess higher impact strength, and so on. Polymer insulators are quite different from the conventional porcelain and glass insulators. [4].

In previous study the electric field distribution was calculated on surface of polluted composite insulator using finite element method (FEM). [4].

In this work an alternate sheds composite insulator will be investigated, the (FEM) will be used to calculate the electric fields at a number of points on the insulator surface. These calculated electric field values will be used to train the artificial neural network, and hence the estimated and calculated electric field values will be compared together, in order to explore the efficiency of ANN abilities as a universal approximator. In other words, ANNs were addressed in order to estimate the electric field across medium voltage composite insulator, information which is very useful for diagnostic tests and design procedures. Actual electric field values and model geometric coordinates, which were calculated using finite element method-simulation software on a medium voltage polymeric (silicon rubber) insulator, are used in order to train, validate and test the presented ANNs. [5]

Several structures, learning algorithms, and performance functions for an ANN multi-layer feed-forward back-propagation network are tested in order to produce the ANN models with the best generalizing ability. In the method, based on ANN presented in this study, the estimation time is very short for the electric field strengths of HV insulator when compared with the FEM calculation. The applications have been presented in this paper will be used to estimate the electric fields along the leakage distance on the composite insulator surface by pollution conductivities.

Training and testing data have been prepared as a six groups of different pollution conductivities. The multilayer feed-forward network is used for supervised learning. To determine the connection weights of the ANN, the back-propagation algorithm is employed in the training process. To validate the model, some data sets have been used for testing.

II. E ELECTRIC FIELD CALCULATION USING FEM

The Finite Element Method (FEM) is a numerical method of solving Maxwell's equations in the differential form. The basic feature of the FEM is to divide the entire problem space, including the surrounding region, into a number of non-separated, non-overlapping sub regions, called "finite elements". This process is called meshing. These finite elements can take a number of shapes, but generally triangles are used for 2-D and 3-D analysis [6].

The analyst defines the geometry and material properties of the structure and the type of element to use. The finite element model, or mesh, is created by defining the shapes of element, the sizes of element and any variation of these throughout the model. Fig 1 show the geometrical solid model used in this study.

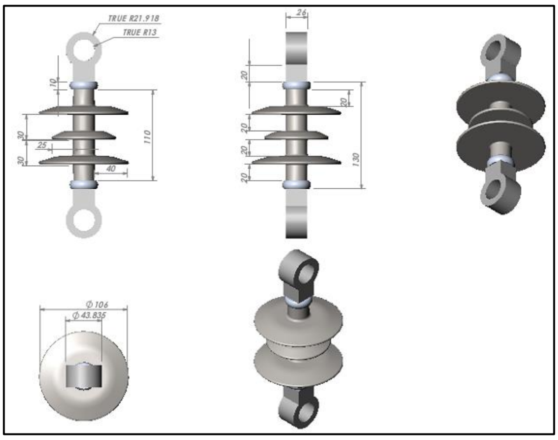


Fig. 1. *3D Insulator geometrical model*

The alternate sheds type composite insulator meshed with tri-angular elements used this work has been shown in Fig. 2. The surface of insulator has been considered as polluted. The conductivity of the pollution is assumed to be uniform. The values of electric field along the leakage distance on the insulator surface for training and testing have been determined using the finite element method. [7]. Fig 2 show the Finite element Mesh results.

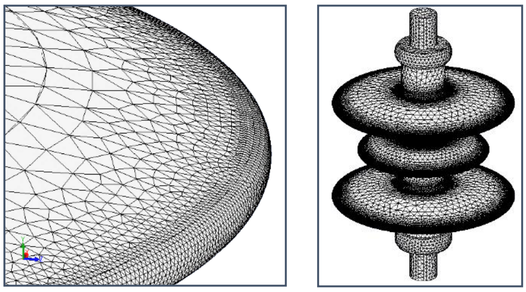


Fig. 2. *Finite element Mesh*

The meshing program has been calculated of the Electric field distribution in the insulator and selected external region as shown in Fig. 2 is considered as a Laplace problem. The functional of the Laplace equation for the problem region is given as follows:

$$w_e = \int_s \rho_s \left[\left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial z}\right)^2 \right] dx \cdot dy \cdot dz \qquad (1)$$

where $\rho_s = \rho / h$, is the surface conductivity and h the polluted layer thickness. With the minimization of energy function, the potential distribution for the solution region can be obtained. The electric field values along the insulator leakage distance, are determined. These values are calculated from the nodal potentials obtained by the FEM. x, y and z components of the electric field are as follows:

$$E_x = -\frac{\partial v}{\partial x} \qquad (2)$$

$$E_y = -\frac{\partial v}{\partial y} \qquad (3)$$

$$E_z = -\frac{\partial v}{\partial z} \qquad (4)$$

From above equations, magnitude of E is:

$$\left|\vec{E}\right| = \sqrt{E_x^2 + E_y^2 + E_z^2} \qquad (5)$$

For calculating the differentiations, corner potentials belonging to the triangular element, the area of the triangle, and the interpolation functions are used [8].

III. ARTIFICIAL NEURAL NETWORK (ANN)

The neural network is one of Artificial intelligence techniques it's a data modeling tool that is capable to represent complex input/output relationships. A NN typically consists of a set of processing elements called neurons that interact by sending signals to one another along weighted connections. The connection weights, which can be determined adaptively, specify the precise knowledge representation. Usually it is not possible to specify the connection weights beforehand, because knowledge is distributed over the network.

Therefore, a learning procedure is necessary in which the strengths of the connections are modified to achieve the desired form of activation function. 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. For the problem of electric field calculation, we know the input–output training sets. Thus for this problem we need an ANN with supervised learning. Feed-forward network with more than one layer of adaptive weights can compute very complex functions. [9]. [9].

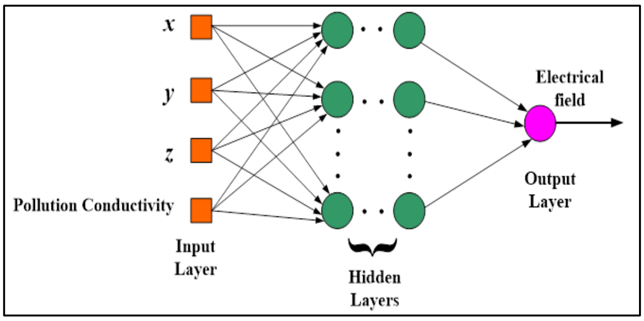


Fig. 3. *Multilayer feed-forward neural network.*

Fig. 3 shows the schematic diagram of a multilayer feed-forward network. The neurons in the network can be divided into three layers: input layer, output layer and hidden layers. The back-propagation learning algorithm is the most frequently used method in training the networks, and proposed as a pollution electric field methodology in this paper. It is important to note that the feed-forward network signals can only propagate from the input layer to the output layer through the hidden layers.

A. ANN Performance Functions

Two different performance functions "Mean square error" (MSE), and "Maximum-likelihood estimators" (M-estimators) are used in this study:

The authors in [10] introduced a family of robust statics M-estimators as alternative traditional performance functions of MSE. It is well known that this family provided high reliability for robust NN training in the presence of contaminated data. Therefore, they recommended that this family of estimators as a good alternative of MSE performance function, in the presence of clean and contaminated data [10].

IV. NETWORK STRUCTURES

In this paper, a multilayer feed-forward back-propagation neural network has been used for structure of the ANN. The learning algorithms "Levenberg-Marquardt" and "Bayesian-Regulation" are used in this study due to its high speed and accuracy. The input/output training patterns are known for the insulator, supervised learning is used by training multilayer feed-forward network. A sigmoidal function (Tangent sigmoid) is taken to be the activation function for all the hidden layers and a "pure line" function is taken to be the activation function for output layer. In this work, the input/output data are normalized using their maximum values. The x, y and z coordinates of the nodes and pollution level (conductivity) have been used as inputs [11].

The goal is to develop an artificial neural network model capable to estimate the electric field stress on contaminated high voltage insulators. Four parameters that play important role to the insulators design were selected as the inputs to the artificial neural network these were: three-dimensional coordinates for each mesh node (x, y, z) and pollution level (conductivity). Output parameter was considered the calculated values of electric field on each mesh node (resultant Er calculated using FEM). Table I. Show all the input and output data for neural network.

TABLE I. DATA SET FOR ANN

ANN	
Input	Output
X coordinate	Resultant Electric Field E_r $E_r = \sqrt{E_x^2 + E_y^2 + E_z^2}$
Y coordinate	
Z coordinate	
S Pollution conductivity	

In this work several different multilayer perceptron models were developed and tested. These were combinations of two different backpropagation learning rules, two different performance functions (MSE & M-estimators) and several different structures consisted of 1 to 3 hidden layers with 2 to 60 neurons in each hidden layer (Table II).

TABLE II. DESIGNED ANN STRUCTURE

Structure	**Learning Algorithm**	**Performance Functions**
- 1 to 3 hidden layers - 2 to 60 neurons in each hidden layer	- Levenberg-Marquardt -Bayesian-Regulation	-Mean square error (MSE) Cauchy (M-estimators)

V. SIMIULATION RESULTS

A. The electric fields on the insulator surface and choosing the input/output data:

The electric field values along the leakage distance on the polluted insulator surface (for V= 15 kV) are determined for clean and different five pollution levels (50, 75, 100, 125 and 150 μS). These values are calculated from the nodal potentials obtained by the FEM. The electric field distribution results for composite insulator (Alternate Sheds type) under various pollution levels obtained by FEM software for six different pollution levels are shown in Fig.4 and the maximum field strength for each case are shown in Table III [4].

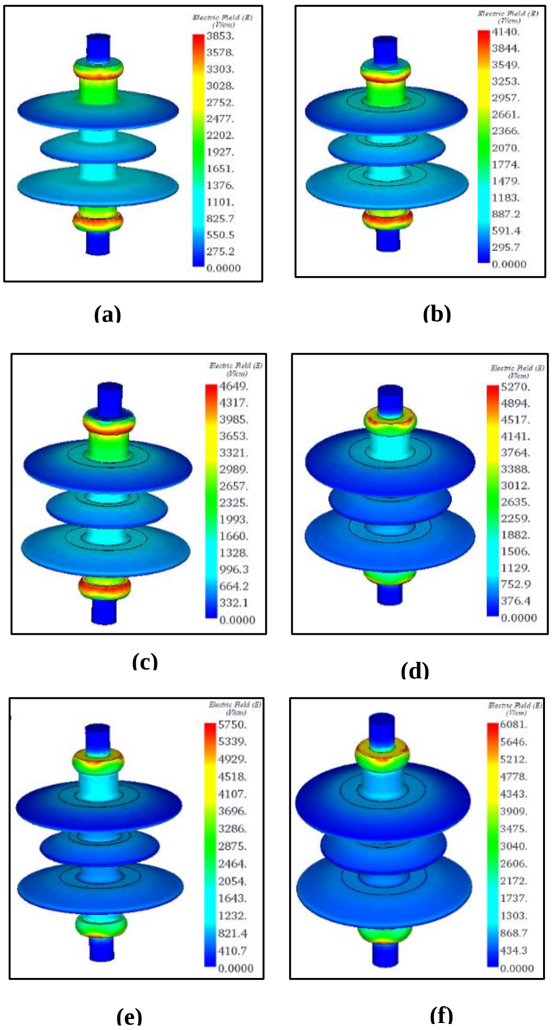


Fig. 4. *Electric field distribution results for clean and five pollution levels for composite insulator.*

TABLE III. MAXIMUM ELECTRIC FIELD FOR DIFFERENT VOLTAGE LEVELS.

Fig.	Pollution Levels (µS)	Maximum electric field V/cm
(a)	clean	3853
(b)	50	4140
(c)	75	4649
(d)	100	5270
(e)	125	5750
(f)	150	6081

The field calculations have been taken for 120 nodes on the insulator surface. 60 point are presented in Fig. 5. Five groups of calculated data (clean, 50, 75, 100, 125 µS) have been used for training of the ANN2 and the other groups of data (150 µS) have been used for testing. Input/output data have been presented graphically in Fig. 5 instead of giving as a table to avoid confusion.

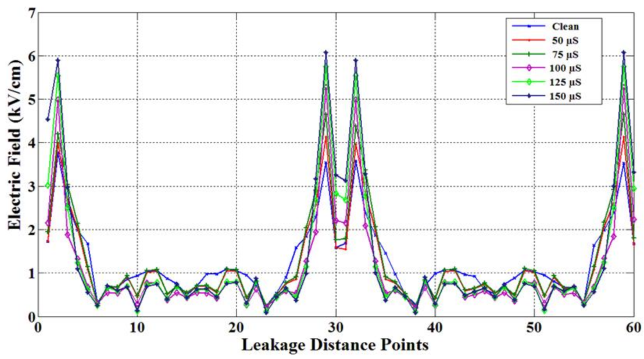


Fig. 5. *Electric field on nodes of the insulator leakage distance for clean and five pollution levels .*

B. Input and 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 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) [12].

C. Training of ANN

The MATLAB® neural network toolbox was used to train the defined neural network models. [12]. Seven hundred and twenty value of each inputs and outputs data (datasets) have been used for train and validate the neural network models.

The inputs to the neural network ANN are consists of four neurons: the x, y and z coordinates of the nodes and pollution level (µS). The output of the neural network model consists of one neuron representing the Field strengths on the nodes. The chosen input data were divided into two groups, the training group, corresponding to 90% of the patterns, and the test group, corresponding to 10% of patterns; so that the generalization capacity of network could be checked after the training phase.

The ANN used is the multi-layer feedforward type, with one or more hidden layers represented in Fig.3. 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.

Several simulations with all possible combinations of the 2 backpropagation learning rules, the two different performance functions, the 1 to 3 hidden layers and the 2 to 60 neurons in each hidden layer have been performed. The training process was repeated until a training performance reached the goal of 10-5 or a maximum number of epochs, it was set to 10,000, was accomplished.

TABLE IV. TRAINING DATA OF THE LEVENBERG-MARQUARDT ANN MODEL

No.	Structure	Mean Square Error			M-estimator		
		Epochs	RMSE	Perf	Epochs	RMSE	Perf
1	4/7/9/1	836	0.0225	5.0578e-004	1505	0.0277	1.6654e-004
2	4/7/9/12/1	862	0.0314	9.8866e-004	1186	0.0242	1.2763e-004
3	4/7/9/14/1	1079	0.0306	9.3722e-004	1102	0.0254	1.3969e-004
4	4/7/9/16/1	723	0.0296	8.7384e-004	1065	0.0296	1.9049e-004
5	4/7/9/17/1	1012	0.0461	0.0021	1061	0.0398	3.4388e-004
6	4/7/9/18/1	174	0.0294	8.6671e-004	1030	0.0376	1.9136e-004

TABLE V. TRAINING DATA OF THE BAYESIAN-REGULATION ANN MODEL

No.	Structure	Mean Square Error			M-estimator		
		Epochs	RMSE	Perf	Epochs	RMSE	Perf
7	4/7/9/1	576	0.0177	3.1482e-004	100	0.0172	6.4398e-005
8	4/7/9/12/1	890	0.0166	2.7527e-004	432	0.0191	7.9491e-005
9	4/7/9/13/1	1863	0.0129	1.6570e-004	314	0.0130	3.6669e-005
10	4/7/9/15/1	1676	0.0181	3.2687e-004	1031	0.0142	4.3630e-005
11	4/7/9/18/1	1158	0.0102	1.0121e-004	381	0.0101	2.2738e-005
12	4/7/9/20/1	1249	0.0137	1.8755e-004	490	0.0100	2.1763e-005

Tables IV and V, presents the training data of the best 12 developed ANN models which have presented the best generalizing ability among all the others developed.

The performance of two different learning rules Levenberg-Marquardt and Bayesian-Regulation with two performance functions are presented in tables IV and V respectively,

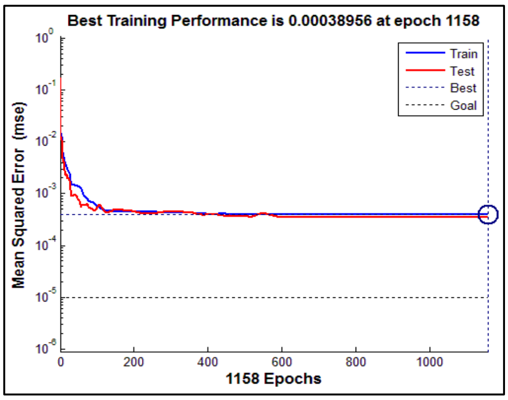
. Two ANN models are selected from 12 models presented in tables 5 with minimum RMSE and Perf, are models numbers 11, 12 with errors 0.0101, 0.0100, respectively. The training performance of two ANN models is shown in fig.6a, 6b, respectively.

D. Testing of ANN

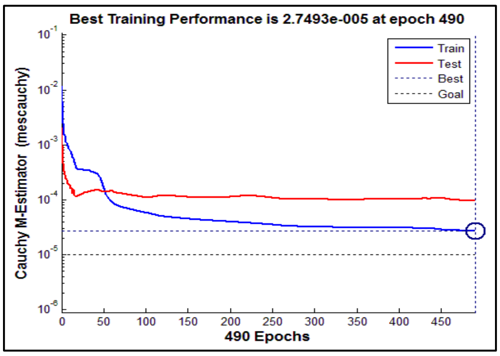
After the completion of training, the trained ANN models has been tested for given Pollution Levels of 150 µS. Test results for 150 µS are given in Fig. 12. From all of these simulations in tables 4, 5, it was selected and used further to assess the field strength value the ANN model with the following characteristics:-

1) Model No.11 with 3 hidden layers, with 7, 9 and 18 neurons in each one of them, Bayesian-Regulation backpropagation learning rule and Mean Square Error performance function. The mean square error was minimized to the final value of 0.0101, and performance value (2.2738e-005) within 381epochs, the test results for this model is shown in fig.7a.

2) Model No.12 with 3 hidden layers, with 7, 9 and 20 neurons in each one of them, Bayesian-Regulation backpropagation learning rule and M-estimator performance function. The mean square error was minimized to the final value of 0.010, and performance value (2.1763e-005) within 490 epochs, the test results for this model is shown in fig.7b.



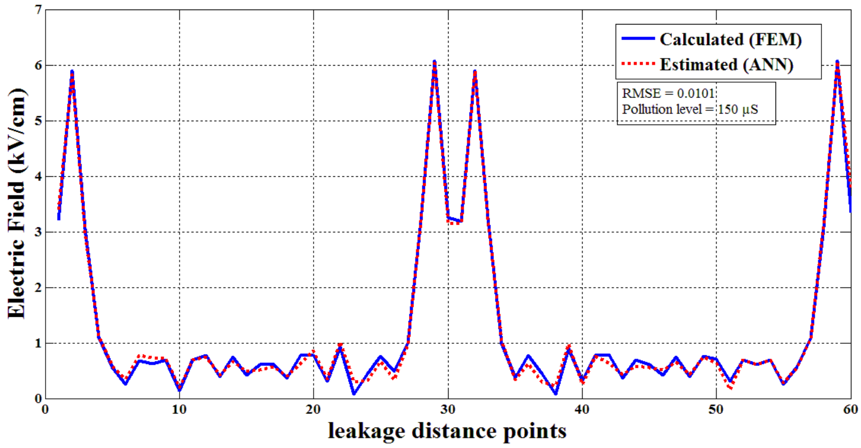
(a)



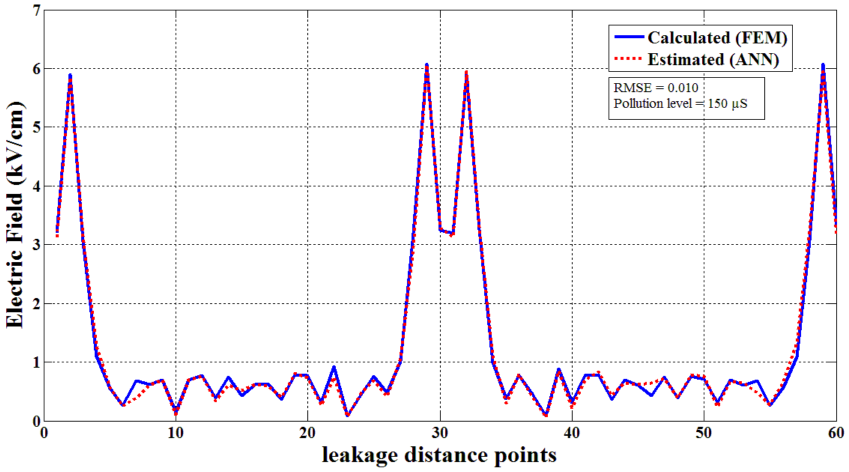
(b)

Fig. 6. *Training performance of ANN models.*

The errors between the calculated and estimated results during the validating process for each model are shown in Tables VI. The maximum errors of test results are 13.7% in model No.11, and the minimum error is 0.08 % in model No.12. The comparison between the results of four models are shown in fig.8. The results indicate successful achievement of the estimation by the ANN.



(a)Test results of ANN model No. 11, with 0.0101 RMSE at 150 µS operating pollution level.



(b) Test results of ANN Model No. 12, with 0.010 RMSE at 150 µS operating pollution level.

Fig. 7. *Test results of ANN models.*

TABLE VI. TESTING RESULTS FOR ANN (RANDOMLY CHOSEN NODES).

Node No.	Node Coordinates			Calculated E(kV/cm)	Model No. 11 at 150 µS Pollution Level		Model No. 12 at 150 µS Pollution Level	
	x	y	z		Estimated E(kV/cm)	Error (%)	Estimated E(kV/cm)	Error (%)
1	4.24E-02	-6.42E-03	3.78E-02	3.2	3.3927	6.02%	3.1229	2.41 %
2	4.24E-02	3.58E-03	3.78E-02	5.9	5.8354	1.09 %	5.8446	0.94 %
11	4.04E-02	3.66E-02	5.18E-02	0.698	0.6964	0.23 %	0.6974	0.08 %
12	4.04E-02	5.21E-02	5.28E-02	0.776	0.7481	3.6 %	0.7573	2.4 %
18	4.19E-02	6.36E-02	602E-02	0.359	0.4082	13.7 %	0.3984	10.1 %
27	4.04E-02	9.66E-02	7.08E-02	1.01	0.9826	2.7 %	1.0703	5.97 %
29	4.24E-02	1.14E-01	7.63E-02	6.08	6.0387	0.68 %	6.0627	0.28 %
30	4.24E-02	1.24E-01	8.12E-02	3.25	3.1506	3.06 %	3.2796	0.91 %
39	-2.56E-02	8.36E-02	9.01E-02	0.892	0.9741	9.2 %	0.8472	5.02 %
41	1.44E-02	8.21E-02	9.00E-02	0.771	0.754	2.21 %	0.6993	9.3 %
48	1.29E-02	5.36E-02	9.08E-02	0.394	0.4271	8.4 %	0.3881	1.5 %
52	7.17E-04	3.36E-02	1.06E-01	0.698	0.688	1.43 %	0.6722	3.69 %
59	1.24E-02	3.58E-03	9.08E-02	6.08	6.056	0.39 %	5.9502	2.13 %

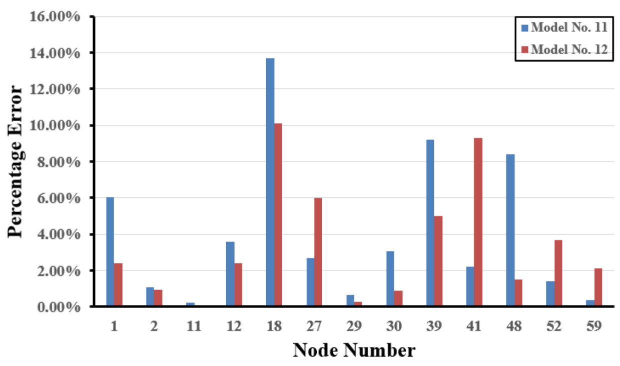


Fig. 8. *Percentage Error for randomly chosen nodes.*

VI. CONCLUSIN

It is very economical to use artificial neural networks in various fields, and particularly in the HV polluted insulators. In this paper the electric fields on the surface of a HV composite suspension insulator has been estimated under pollution conditions using artificial neural network. A multilayer feed-forward back-propagation neural network has been used in this work. Two different backpropagation learning rules “Levenberg - Marquardt” and “Bayesian-Regulation” are used in this paper due to its high speed and accuracy. Also two different performance functions (MSE & M-estimators) and several different structures consisted of 1 to 3 hidden layers with 2 to 60 neurons in each hidden layer, has been presented in study in order to produce the ANN models with the best generalizing ability.

For this purpose, several ANN models have been developed using many different structures, learning rules and performance functions in MATLAB. The data have been prepared by using FEM in previous study. ANN is developed to estimate the electric fields by using x, y and z coordinates and pollution levels. The ANN models, that presented the best generalizing ability, and have a fast training process, consumed lower memory, and presenting accurate results among all the developed ANN models has been selected and applied on ANN models.

The maximum errors of testing the ANN is 13.7%, and the minimum error is 0.08 %. The results shown that the use of M-estimators, as a Performance function, led to improve the performance of ANN. In this study, also the estimation time was very short for determination of electric fields for pollution levels, compare with FEM calculations, because in FEM iterative calculations have been performed and this causes the time consumption. 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 electric fields for any desired pollution level without any iterative process. Thus, this model can be used confidently for the design and development of insulators. The results presented in this work indicate an acceptable degree of accuracy while providing considerable saving in computation time.

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