Neural Network Estimator for Electric Field Distribution on High Voltage Insulators

Mohamed H. Essai,
Member IEEE,
Electrical Engineering Department,
Al-Azhar University, Qena, Egypt,
mhessai@azhar.edu.eg

Mahmoud. A-H. Ahmed,
Electrical Engineering Department,
Al-Azhar University, Qena, Egypt,
eng.mahmoud.ali2015@gmail.com

Ali. H.I. Mansour,
Electrical Engineering Department,
Al-Azhar University, Qena, Egypt,
drali_mansour@yahoo.com

Refai. A. Refai
Electrical Engineering Department,
Al-Azhar University, Cairo, Egypt,
dr_refai@yahoo.com

Abstract**-- This paper introduces, a three-dimensional (3D) neural network electric fields estimator, which will be used to determine the electric field distribution on high voltage insulator surface. A 15 KV composite suspension insulator has been used. In the course of collection the training data sets the finite element method (FEM) have been used. The collected/used training data sets consists of x, y and z coordinates of the investigated points on the insulator surface and operating voltage as NN inputs, and the electrical fields as NN outputs, i.e. training pairs (input, and output). Several ANN models have been built, and examined based on number of NN design considerations, such as number of layers, number of neurons in each layer, used learning algorithms, and used performance functions, in order to get the most efficient trained NN-estimator, which provides the best generalized approximation ability of NN These developed NNs make it is possible to determine the electrical fields at any point on the insulator surface easier and faster. The obtained results show that the estimated values of electrical field on an acceptable degree of accuracy. Therefor the ANN models which has been presented in this paper can be used easily for design and development processes of the composite insulators for various line voltages levels.**

Keywords: *Insulators; Electric Fields; Artificial Neural Networks (ANN); Back Propagation*

I. Introduction

High voltage insulators is a very important part of the high voltage electric power transmission systems. Any failure in the High voltage insulators performance will result in considerable loss of capital, as there are many industries that depend upon the continuance of a power supply. The importance of the research on insulator has been increased with the rise of energy demand [1].

For high voltage transmission applications, the electric field and potential distribution calculations, are widely performed in the design and development operations of the composite insulators. Control of the electric field within and around high voltage equipment as conductors, transmission lines, insulators and associated line hardware, surge arresters, switchgear, power transformers and rotating machines is a very important aspect of the design of such equipment. Composite insulators are being increasingly used by utilities to replace porcelain and glass insulators because of the advantages obtained from lower weight, ease of handling, reduced installation and maintenance cost, increased resistance to vandalism, and superior contamination performance. Through more than 25 years, of service experience, the manufacturers and utilities have learned the importance of controlling the electric field in the vicinity of the insulators to prevent degradation of the polymeric insulating materials from corona-related phenomena [2].

In previous study the electric field distribution was calculated on the surface of the composite insulator using finite element method (FEM), where a three-dimensional model for two types of the composite insulators (Alternate Shed and Straight Shed) were developed, the electric field values on insulator surface were simulated in two cases: clean/dry, and contaminated/wet environmental conditions, finally a comparison of the estimated electric fields on the insulators surfaces were investigated for the two types [3].

Currently artificial neural networks (ANNs) are being applied to an increasing number of complex problems due to their calculation speed, their ability to solve complex non-linear functions, great efficiency, and robustness and, also in cases where most of the information for the studied problem is absent. Many interesting ANN applications have been reported in power system areas [4].

In this work an alternate sheds insulator will be investigated, the (FEM) will be used to calculate the induced electric fields at a huge 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.

Various 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 this paper, and in the presented ANNs models, the estimation time is very short to calculate the electric field distribution of HV insulator, compared with electric field calculations based on the Finite Element Method.

II. 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 [5].

A. Model generation and assigning materials:

Pre-processing, or model generation, is the most user intensive part of the analysis. Perhaps up to 90% of the analyst's time is taken up creating the finite element mesh. In pre-processing, 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.

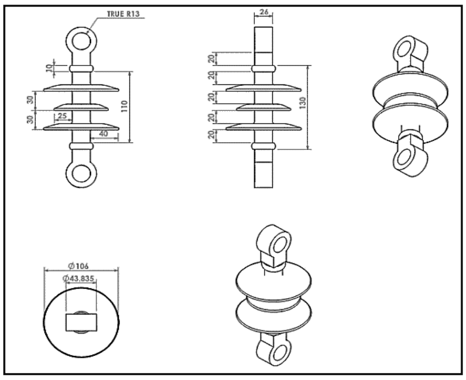


Fig.1 3D Insulator geometrical model

B. Mesh generation:

In most modern finite element programs, mesh generation is a two stage process. The first stage is to create a solid model of the structural geometry in terms of geometrical entities such as points, lines, areas and volumes. Once the geometry is defined, the solid model is automatically discretized into a suitable finite element mesh using a variety of meshing tools. Usually, the mesh is created to give smaller elements in areas of stress concentration to enhance the accuracy of the solution [6]. Fig 2 show the Finite element Mesh results.

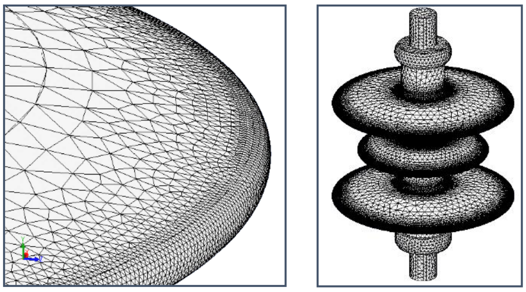


Fig.2 Finite element Mesh

C. Mesh Points analysis:

Before meshing the model, and even before building the model, it is important to think about whether a free mesh or a mapped mesh is appropriate for the analysis. A free mesh has no restrictions in terms of element shapes, and has no specified pattern applied to it. A mapped mesh is restricted in terms of the element shape it contains and the pattern of the mesh. A mapped area mesh contains either only quadrilateral or only triangular elements, while a mapped volume mesh contains only hexahedron elements. In addition, a mapped mesh typically has a regular pattern, with obvious rows of elements. If one wants this type of mesh, so must build the geometry as a series of fairly regular volumes and/or areas that can accept a mapped mesh [7].

D. Laplace equation

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

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

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:

$$E_x = -\frac{\partial v}{\partial x} \tag{2}$$

$$E_y = -\frac{\partial v}{\partial y} \tag{3}$$

$$E_z = -\frac{\partial v}{\partial z} \tag{4}$$

From above equations, magnitude of E is:

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

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. ANN 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.

Most often, the training of artificial neural network is using a group of input/output pairs of data, which are examples of the mapping that the network is desired to learn to calculation. The learning procedure, it can be seen as fitting a function, and its performance therefore can be judged on whether the network can learn the required function over the period represented by the training group, and to how far the network can successfully generalize away from the points that it has been trained.

In the problem of field strength calculations, we already have the input/output training group, that were obtained by FEM, therefore for this problem the ANNs with supervised learning will be used. [9].

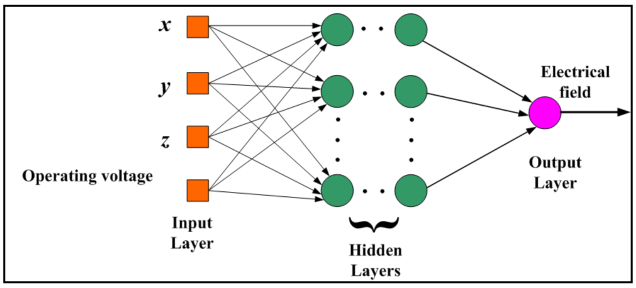


Fig.3. Multilayer feed-forward neural network.

Fig. 3 shows the diagram of a multilayer feed-forward neural 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.

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. Each neuron of the output layer receives a signal from all input via hidden layer neurons along connections with modifiable weights. The neural network can identify input pattern vectors, once the connection weights are adjusted by means of the learning process [10].

The ANN can identify input pattern vectors once the connection weights are adjusted by means of the learning process. The back-propagation learning algorithm is the most popular method in training the ANN and is employed here. This learning algorithm is presented below in brief.

A. ANN Performance Function

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

Feed-forward neural networks are commonly trained by the back propagation learning algorithm based on the minimization of the Mean Square Error MSE for the training data set. The use of MSE in data modeling is commonly known as the least mean squares LMS method. The basic idea of LMS is to optimize the fit of a model with respect to the training data by minimizing the square of residuals. Mean squared error MSE is the preferred measure in many data modeling techniques. Tradition and ease of computation account for the popularity of MSE [11].

M-estimators have gained popularity in the neural networks community. The term M-estimator denotes a broad class of estimators of maximum likelihood type, which play an important role in robust statistics. Recently many researches exploited M-estimators as performance function in order to robustify the NN learning process. M-estimators use some cost functions which increase less than that of least square estimators as the residual departs from zero. When the residual error goes beyond a threshold, the M-estimator suppresses the response instead. Therefore, the M-estimator based performance function is more robust for the presence of the outliers than MSE based performance function [12].

The authors in [11] 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 the use of this family of estimators as a good alternative of MSE performance function, in the presence of clean and contaminated data [11].

IV. NEURAL NETWORK STRUCTURE

In this paper, a multilayer feed-forward neural network structure was used. A sigmoidal function (Tangent sigmoid) was chosen to be the activation function for all neurons in the hidden layers and a "pure line" activation function was chosen to be the activation function for the neuron in output layer. The back-propagation learning algorithms such as "Levenberg-Marquardt" and "Bayesian-Regulation" were used in this study due to its high speed and accuracy. Where we already have the input/output training patterns for the examined insulator, the supervised learning mode was considered.

In this work, the input/output data are normalized using their maximum values. The x, y and z coordinates of the nodes and operating voltage have been used as inputs [13].The goal is to develop an artificial neural network that is capable to estimate the electric field stress on high voltage insulators. Four different parameters that play important role in the insulators design were selected as the inputs to the artificial neural network these are: three-dimensional coordinates for each mesh node (x, y, and z) and operating voltage. Output parameter was considered the calculated values of electric field on each mesh node (resultant E_r calculated using FEM).

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	
V operating voltage	

Table I show all the input and output data for the neural network. In this work several multilayer perceptron structures, with two different performance functions (MSE & Cauchy M-estimators) and consisted of 1 to 3 hidden layers with 2 to 60 neurons in each hidden layer (Table II) were developed and tested.

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

Step 1: The electric fields calculation and, input/output data preparation:

The electric field values along the leakage distance on the clean insulator surface are determined for five different randomly chosen voltage levels (8.7, 12, 15, 18, 25kV). These values are calculated from the nodal potentials obtained by the FEM. The electric field distribution results for composite insulator (Alternate Sheds type) under dry/ clean conditions obtained by FEM software for five different operating voltage levels are shown in Fig.4 and the maximum field strength for each case are shown in Table III [3].

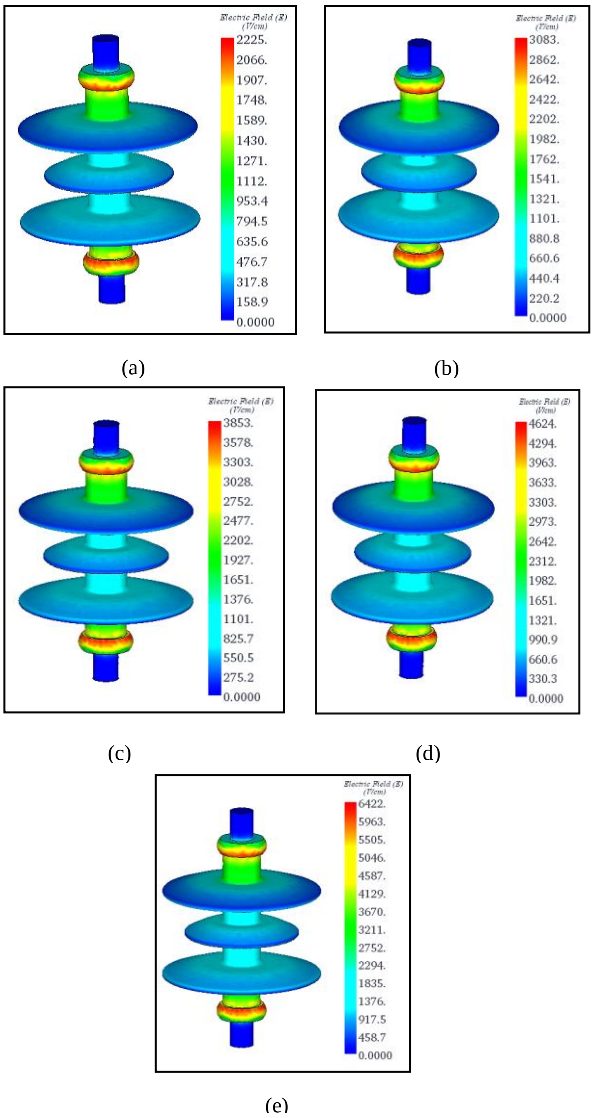


Fig.4 Electric field distribution results for clean composite insulator.

TABLE III. Maximum electric field for different voltage levels.

Fig.	Operation voltage KV	Maximum electric field V/cm
(a)	8.7	2225
(b)	12	3083
(c)	15	3853
(d)	18	4624
(e)	25	6422

The field calculations have been taken for 120 nodes on the insulator surface. 60 point are presented in Fig. 5. Four groups of calculated data (8.7, 12, 15, 18kV) have been used for training of the ANN1 and the other groups of data (25 kV) have been used for testing. Input/output data have been presented graphically in Fig. 5 instead of giving as a table to avoid confusion.

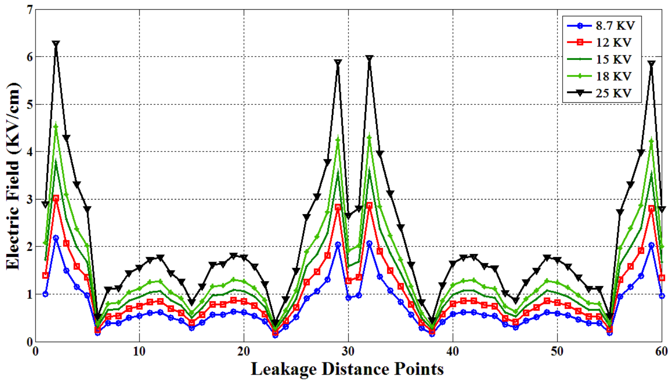


Fig.5 Electric field on nodes of the insulator leakage distance based on the voltages level.

Step 2: 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) [14].

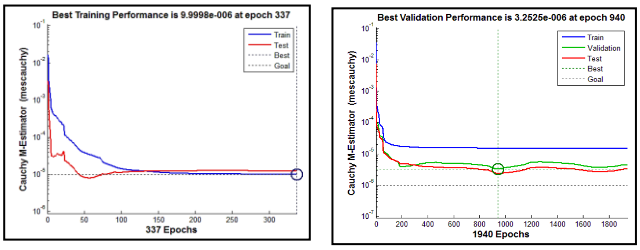
Step 3: Training of ANN1

The MATLAB® neural network toolbox was used to train the defined neural network models [15]. Six hundred value of each inputs and outputs data (datasets) have been used for training and validating 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 operating voltage (KV). 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 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 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.

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,

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, number of hidden neurons in the third layer and the number of output neurons Also the training error (performance or Perf) and test error (root mean square error between the actual output and the desired output or RMSE) are presented in tables IV, V for various training algorithm with two different performance functions.



(c) (d)

Fig.6 Training performance of ANN models.

Step 4: ANN models testing

The next step after the completion of training, is that the trained ANN models will be tested for given voltage level of 25 kV. Test results for 25 kV are given in Fig. 7. From all of these simulations in tables IV, V, it was selected and used the ANN models with the following characteristics:-

a) Structure No.3, in Table IV, consists of 3 hidden layers, each has 7, 9 and 14 neurons respectively, uses Levenberg-Marquardt backpropagation learning algorithm, and Mean Square Error as a performance function. The examined structure provides RMSE = 0.0062, and performance value (3.8285e-005) within 10,000 epochs, the obtained results for this structure can be shown in Fig.7a.

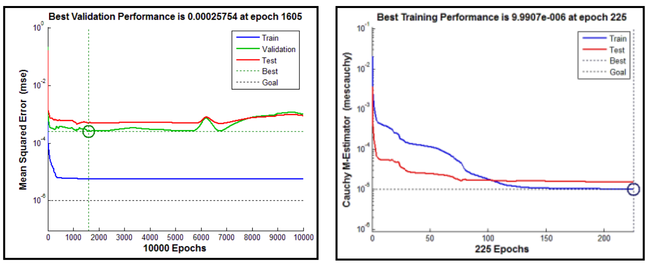
TABLE IV. Training data of the Levenberg-Marquardt ANN model

No.	Structure	Mean Square Error			Cauchy M-estimator		
		Epochs	RMSE	Perf	Epochs	RMSE	Perf
1	4/7/9/1	10,000	0.0272	7.4171e-004	10,000	0.0161	5.6511e-005
2	4/7/9/12/1	9,212	0.0371	0.0014	7450	0.0097	2.0494e-005
3	4/7/9/14/1	10,000	0.0062	3.8285e-005	10,000	0.0261	1.4819e-004
4	4/7/9/16/1	10,000	0.0804	0.0065	10,000	0.0269	1.5744e-004
5	4/7/9/17/1	10,000	0.2318	0.0537	10,000	0.0202	8.8260e-005
6	4/7/9/18/1	10,000	0.0494	0.0024	10,000	0.0157	5.3226e-005

TABLE V. Training data of the Bayesian-Regulation ANN model

No.	Structure	Mean Square Error			Cauchy M-estimator		
		Epochs	RMSE	Perf	Epochs	RMSE	Perf
7	4/7/9/1	577	0.0180	3.2460e-004	152	0.0167	6.0245e-005
8	4/7/9/12/1	1491	0.0134	1.7955e-004	578	0.0096	2.0017e-005
9	4/7/9/14/1	3239	0.0166	2.7658e-004	697	0.0113	2.7542e-005
10	4/7/9/15/1	1049	0.0236	5.5718e-004	380	0.00972	2.0494e-005
11	4/7/9/17/1	3725	0.0164	2.6930e-004	254	0.0212	9.7308e-005
12	4/7/9/19/1	3557	0.0182	3.3012e-004	303	0.0163	5.7889e-005

Four ANN models are selected from 12 models presented in tables IV, V with minimum RMSE and Perf, are models numbers 3, 8, 2, 10 with errors 0.006 (MSE), 0.0096 (Cauchy), 0.0097 (Cauchy) and 0.00972 (Cauchy) respectively. The training performance of four ANN1 models is shown in fig.6a, 6b, 6c, and 6d respectively.

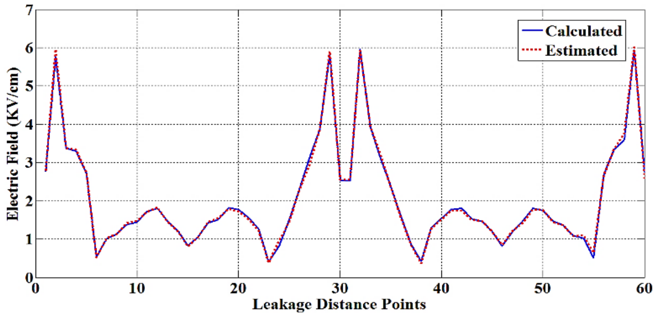


(a) (b)

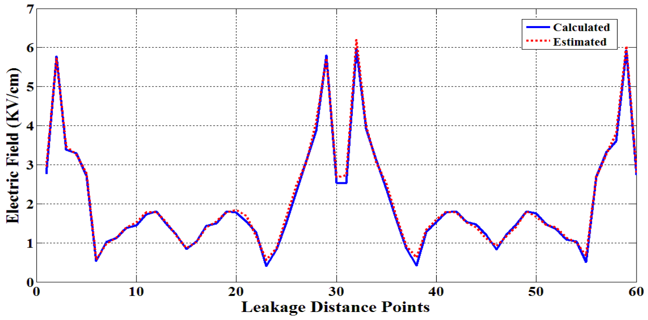
b) Structure No.8, in Table V, consists of 3 hidden layers, each has 7, 9 and 12 neurons respectively, use Bayesian-Regulation backpropagation learning algorithm, and Cauchy M-estimators performance function. The examined structure provides RMSE = 0.0096, and performance value (2.0017e-005) within 578 epochs, the obtained results for this structure can be shown in fig.7b.

c) Structure No.2, in Table IV, consists of 3 hidden layers, each has 7, 9 and 12 neurons respectively, use Levenberg-Marquardt backpropagation learning algorithm and Cauchy M-estimators performance function. The examined structure provides RMSE = 0.0097, and performance value (2.0494e-005) within 7450 epochs, the obtained results for this structure can be shown in fig.7c.

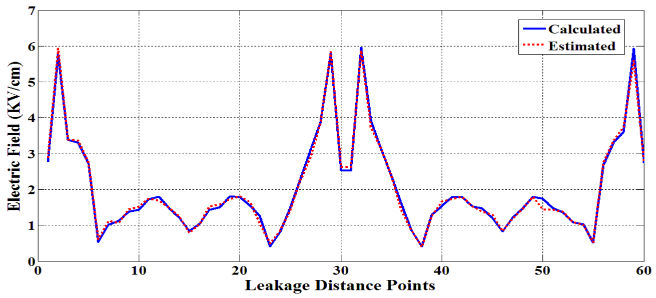
d) Structure No.10, in Table V, consists of 3 hidden layers, each has 7, 9 and 15 neurons respectively, use Bayesian-Regulation backpropagation learning algorithm and Cauchy M-estimator performance function. The examined structure provides RMSE = 0.00972, and performance value (2.0494e-005) within 380 epochs, the obtained results for this structure can be shown in fig.7d.



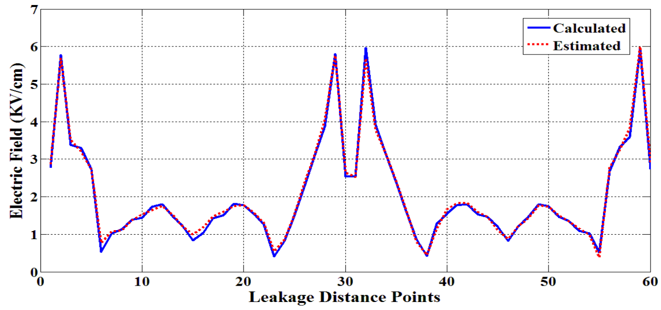
(a)



(b)



(c)



(d)

Fig.7 Test results 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 7% in model No.10, and the minimum error is 0.11 % in model No.2. The comparison between the results of four models are shown in fig.8. The results indicate successful achievement of the estimation by the ANN.

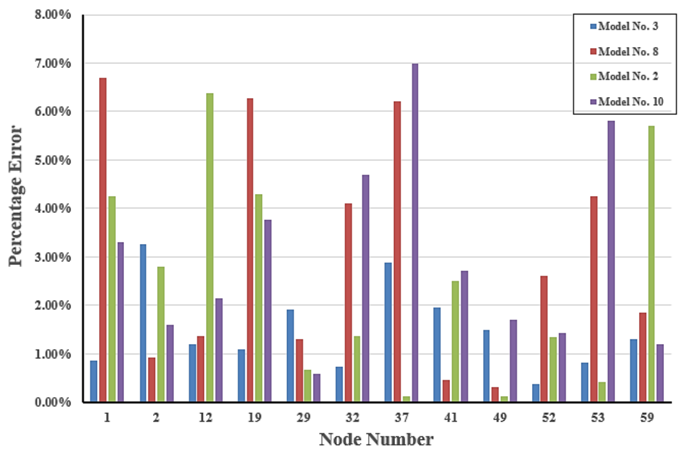


Fig.8 Percentage Error for randomly chosen nodes.

TABLE VI. Percentage Error for ANN (randomly chosen nodes).

Node No.	Node Coordinates			Calculated E(KV/cm)	Model No. 3 at 25 KV operation voltage		Model No. 8 at 25 KV operation voltage		Model No. 2 at 25 KV operation voltage		Model No. 10 at 25 KV operation voltage	
	x	y	z		Estimated E(KV/cm)	Error (%)	Estimated E(KV/cm)	Error (%)	Estimated E(KV/cm)	Error (%)	Estimated E(KV/cm)	Error (%)
1	4.24E-02	-6.42E-03	9.08E-02	2.76	2.7836	0.85 %	2.9447	6.69 %	2.8722	4.25 %	2.851	3.3 %
2	4.24E-02	3.58E-03	9.08E-02	5.77	5.9588	3.27 %	5.7171	0.92 %	5.9315	2.8 %	5.6786	1.6 %
12	4.04E-02	5.21E-02	9.08E-02	1.8	1.8222	1.2 %	1.7978	1.37 %	1.6854	6.37 %	1.7613	2.15 %
19	4.04E-02	6.51E-02	9.08E-02	1.81	1.7899	1.1 %	1.7753	6.28 %	1.7319	4.3 %	1.7418	3.77 %
29	4.24E-02	1.14E-01	9.16E-02	5.8	5.9114	1.92 %	5.7232	1.3 %	5.8391	0.67 %	5.7657	0.59 %
32	1.24E-02	1.14E-01	9.00E-02	5.96	5.9165	0.73 %	6.2033	4.1 %	5.879	1.36 %	5.681	4.7 %
37	-1.17E-02	9.15E-02	9.08E-02	0.859	0.8342	2.88 %	0.9126	6.2%	0.858	0.12 %	0.7985	7 %
41	1.44E-02	8.21E-02	9.08E-02	1.78	1.745	1.96 %	1.788	0.45%	1.7354	2.5 %	1.8284	2.72 %
49	1.44E-02	5.21E-02	9.08E-02	1.8	1.7726	1.5 %	1.8056	0.31 %	1.798	0.11 %	1.7695	1.7 %
52	7.17E-04	3.36E-02	9.08E-02	1.36	1.3651	0.37 %	1.3953	2.6 %	1.3783	1.34 %	1.3405	1.43 %
53	-1.16E-02	3.16E-02	9.08E-02	1.09	1.0811	0.82 %	1.1352	4.25 %	1.0854	0.42 %	1.1535	5.82 %
59	1.24E-02	3.58E-03	9.08E-02	5.93	6.007	1.3 %	6.039	1.84 %	5.59	5.7 %	6.0004	1.19

VI. CONCLUSIN

In this paper the electric fields on the surface of a HV composite suspension insulator has been estimated under environmental clean conditions using artificial neural network. A multilayer feed-forward back-propagation neural network has been used in this work. Two different backpropagation learning algorithms “Levenberg-Marquardt” and “Bayesian-Regulation” are used in this study due to its high learning speed and accuracy.

Also two different performance functions (MSE & Cauchy M-estimator) and several different structures consisted of 1 to 3 hidden layers with 2 to 60 neurons in each hidden layer, has been investigated in order to get ANN models with the best generalized approximation ability.

The developed ANN were used to estimate the electric fields by using x, y and z coordinates and the line potentials. The ANN models, which provided the best generalized approximation ability, have a compacted structure, trained faster, consumed lower memory, and presented more accurate results among all examined ANN models. The examined ANNs provided estimation maximum errors equal 7%, while the estimation minimum error equal 0.11 %.

The trained NN can easily be used as a robust approximator (estimator), where it provides the most accurate estimation of electric field for any desired line voltage level, as soon as you apply the desired electric field, in other words so fast obtained estimation. In contrast FEM, which consumes long processing time for the iterative calculations which may last for more than one hour in order to get the same estimation for the same desired electric field.

The features of the use of ANN in the design and development processes is that ANN is required to be trained only once. After the completion of training, the ANN gives the electric fields for any desired line voltage level without any iterative process. Therefore, this model can be used efficiently for the design and development processes of insulators.

The presented results, indicate that the well trained NNs provides an acceptable degree of accuracy while providing considerable saving in calculation time.

REFERENCES

[1] M.T. Gençogˇlu, M. Cebeci, “Investigation of pollution flashover on high voltage insulators using artificial neural network”, Elsevier, Expert Systems with Applications 36 7338–734, (2009).

[2] Tiebin Zhao, Michael G. Comber, “Calculation of Electric Field and Potential Distribution along Non ceramic Insulators Considering the Effects of Conductors and Transmission Towers”, IEEE Transactions On Power Delivery, Vol. 15, No. 1, January(2000).

[3] R. Ahmed Refai, A. H. Mansour, M. A-H.Ahmed, “Estimation of the Electric Field and Potential Distribution on Three Dimension Model of Polymeric Insulator Using Finite Element Method”, IJEDR | Volume 3, Issue 2 | ISSN: 2321-9939, (2015).

[4] Aggarwal, R., Song, Y.: Artificial neural networks in power systems. III Examples of applications in power systems. Power Engin. Journal 12(6), 279–287 (1998)

[5] K. Hameyer, R. Mertens,, R. Belmans, “Numerical Methods to Evaluate the Electromagnetic Fields below Overhead Transmission Lines and their Measurement” IEEE International Caracas Conference on (1995).

[6] B. Marungsri, W. Onchantuek, A. Oonsivilai “Electric Field and Potential Distributions along Surface of Silicone Rubber Polymer Insulators Using Finite Element Method” World Academy of Science, Engineering and Technology, (2008).

[7] EMS 2013 Program User’s guide, http://www.emworks.com.

[8] Aydogmus, Z., & Cebeci, M. A new flashover dynamic model of polluted HV insulators. IEEE Transactions on Dielectrics and Electrical Insulation, 11(4), 577–584, (2004).

[9] Amari, S. Mathematical foundations of neuro-computing. Proceedings of IEEE, 78(9), 1443–1462, (1990).

[10] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. Learning internal representation by error propagation. Parallel Distributed Processing, 1, 318–362, (1986).

[11] Mohamed M. Zahra, Mohamed H. Essai, Ali R. Abd Ellah, "Performance Functions Alternatives of Mse for Neural Networks Learning", International Journal of Engineering Research & Technology (IJERT), Vol. 3, Issue 1, pp. 967-970, January – (2014).

[12] Ali R. Abd Ellah, Mohamed H. Essai, Ahmed Yahya, “Robust Backpropagation Learning Algorithm Study for Feed Forward Neural Networks”, Thesis, Al-Azhar University, Faculty of Engineering, -(2016).

[13] Z. Aydogmus, “A neural network-based estimation of electric fields along high voltage insulators”, Expert Systems with Applications 36 8705–8710, www.elsevier.com/locate/eswa, (2009).

[14] Nasrat L. S., & Aly.Saleh, “Evaluation of Flashover Voltage on Hydrophobic Polymer Insulators with Artificial Neural Network”, International Journal of Electrical and Computer Engineering (IJECE) Vol.2, No.4, pp. 487~494, August (2012)

[15] Neural Network Toolbox: For use with MATLAB, the Math Works, http://www.mathworks.com