INSULATOR CONTOUR OPTIMIZATION BY ARTIFICIAL NEURAL NETWORK

S Bolat Ö Kalenderli

Istanbul Technical University, Türkiye

ABSTRACT

In this paper, optimized form of a support insulator has been determined by Artificial Neural Networks (ANN) to obtain stress distribution along the insulator surface not only as ideally uniform as possible but also as low as possible. To train ANN, tangential electric field values of the insulator are calculated by Finite Element Method (FEM). A half of calculated values are used for training, the other half of the field values are used for testing in order to determine the performance of ANN. r-coordinates of optimized contour are searched by applying the desired stress distribution to the ANN. The results show that optimized contour has been obtained with an acceptable degree of accuracy by ANN.

INTRODUCTION

Insulators used in high voltage technique, transmission lines, transformers, and high voltage connection equipment provide insulation between conductors as well as insulation between earth and conductors. In addition of providing electrical insulation, insulators are an important element in electrical installations because they also allow mechanical connections to be made.

In the high voltage technology, designing a cost-effective high voltage electrode system with performance requires knowledge about the devices, which composed the electrode system, such as, insulator and electrode. The classical approach to design of an insulating system is based on the usage of simple geometrical formed elements. However, that leads to nonuniform stress distribution and results increasing in the cost of insulation. For a better economy, it is necessary to have a uniformly distributed stress along the surface of insulator and electrode, and keeping the electric field as low as possible. To obtain uniform stress distribution in any insulation is important for the reliability and life of electrical system. Otherwise, electric field is non-uniform and breakdown or partial discharge phenomena early become in the insulation.

Since the electric field heavily depends on geometric shape of the system, to have a uniform field distribution in a high voltage arrangement the optimized electrode and insulator profiles are preferred. In order to have optimum contours with complex geometries, it is necessary to optimize electrode and insulator contour by means of electrical field calculation. In the determination of electric fields is used various methods as analytical, numerical or experimental methods.

Different methods have been developed for electrode and insulator contour optimization [1-15]. One of these methods, to obtain desired electric field distribution, insulator contours are modified iteratively by linear interpolation [1-4, 7]. In these iterative methods, since the electric fields have to be computed iteratively for each step, computation time is very long. Therefore, iterative methods are not useful for every problem. As another way, optimum stress distribution can be obtained by the method based on Artificial Neural Network (ANN) faster [12-15]. The training set including a limited number of detailed field computations is sufficient for train the ANN.

For the last couple of years very wide range of research works has been carried out on the application of ANN in various fields successfully. Therefore, the literature on ANN has growth very rapidly not only in its applications but also in development of ANN algorithmic structure. ANN has been adapted extensive applications including machine vision, speech processing, sonar analysis, radar analysis, pattern recognition, robotic control etc. In electrical power systems, ANN has been used accurately for load forecasting, security evaluation, capacitor control, alarm processing etc. In high voltage techniques, applications of ANN have been reported for pattern recognition of partial discharges, and lightning prediction. One of the most important applications of ANN is optimization of electrode and insulator contours [12-19].

In this study, contour optimization of a shuttle insulator in plane – plane electrode system to have a uniform field distribution along the insulator surface is performed by using artificial neural network. ANN is trained by applying electric field values and r-coordinates of the points that electric fields calculated to the network. Among the various ANN structures presented so far, the Generalized Regression Neural Network (GRNN), which is a multilayer feedforward network, is used for training.

ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a method that consists of a set of processing elements called neurons that interact by sending signal to one another along weighted connections. The connection weights, which can be determined adaptively, specify the precise knowledge representation. Connection weights are usually determined by a learning procedure. By using the weights which can be determined by different learning procedure one can reach the result knowledge [20].

GENERALIZED REGGRESSION NEURAL NETWORK

GRNN is a multilayer feedforward network which is a special case of a Radial Basis Function (RBF) ANN. The network structure of GRNN consists of a radial basis layer and a linear layer. Detailed schematic of the GRNN is given in Figure 1 with n_i input neurons, n_h radial basis functions and n_o output neurons [16-19].

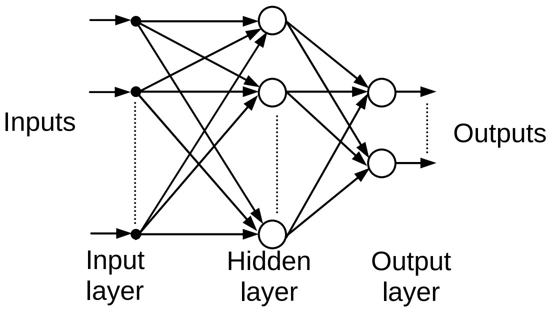

Figure 1. Schematic diagram of GRNN

Each input neuron x_i ($i = 1, 2, \ldots, n_i$) corresponds to the element in the input vector $x = [x_1, x_2, \ldots, x_{ni}]^T$, h_j ($j = 1, 2, \ldots, n_h$) is the radial basis function where n_h is varied. Output of each neuron y_k is calculated as

$$y_k = \frac{1}{\delta}\sum_{j=1}^{n_h} w_{j,k}\, h_j \qquad (1)$$

where:

$$\delta = \sum_{k=1}^{n_o}\sum_{j=1}^{n_h} w_{j,k}\, h_j\ , \qquad (2)$$

$$w_j = \left[w_{j,1}, w_{j,2}, \cdots, w_{j,n_o}\right]^T \qquad (3)$$

$$h_j = f(x, c_j, \sigma_j) = \exp\left(-\frac{\left\|x - c_j\right\|_2^2}{2\sigma_j^2}\right) \qquad (4)$$

where c_j is called the centroid vector, σ_j is the radius of RBF which is also known as smoothing parameter, and w_j denotes the weight vector between the j^{th} RBF and the output neurons [20].

As shown in Figure 1, the structure of a GRNN is similar to the well-known multilayered perceptron neural network (MLP-NN) except that RBFs are used in the hidden layer and linear functions in the output layer [18]. In comparison with the conventional RBF-NNs, the GRNNs have a special property, namely that no iterative training of the weight vectors is required. That is, like other RBF-NNs, any input-output mapping is possible, by simply assigning the input vectors to the centroid vectors and fixing the weight vectors between the RBFs and outputs identical to the corresponding target vectors. This is quite attractive, since conventional MLP-NNs with back-propagation type weight adaptation involve long and iterative training, and there even may be a danger of their being stuck in local minima (this is serious as the size of the training set becomes large) [20].

Moreover, the special property of GRNNs enables us to flexibly configure the network depending on the tasks given, which is considered to be beneficial to real hardware implementation, with only two parameters, c_j and σ_j, to be adjusted. The only disadvantage of GRNNs in comparison with MLP-ANNs seems to be, due to the memory-based architecture, the need for storing all the centroid vectors into memory space, which can sometimes be exhaustive for on-line data processing, and hence, the utility is slow in the reference mode (i.e., the testing phase). Nevertheless, with the flexible configuration property, the GRNNs can be exploited for interpretation of the notions relevant to actual brain, such as "intuition," or other psychological functions.

In Figure 1, when the target vector d(x) corresponding to the input pattern vector x is given as a vector of indicator functions

$$d(x) = \left(\delta_1, \delta_2, \cdots, \delta_{n_o}\right),$$
$$\delta_j = \begin{cases} 1 & \text{if x belongs to the class} \\ & \text{corresponding to } y_k \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

when the RBF h_j is assigned for, with utilizing the special property of GRNNs, $w_j = d(x)$, the entire network becomes topologically equivalent to the network with a decision unit [18, 20].

In summary, the network configuration by means of a GRNN is simply achieved as in the following.

Network Growing: Set c_j = x and fix σ_j, then add the term $w_{jk}h_j$ in equation (2). The target vector d(x) is thus used as a class "label" indicating the sub-network number to which the RBF belongs.

Network Shrinking: Delete the term $w_{jk}h_j$ from equation (2).

CALCULATION OF ELECTRIC FIELDS

In this study, the electric field data applied to the network input is determined by FEMM 4.0 packet program of finite element method [21].

Although the differential equations of interest appear relatively compact, it is typically very difficult to get closed-form solutions for all but the simplest geometries. This is where finite element analysis comes in. The idea of finite elements is to break the problem down into large number regions, each with a simple geometry (e.g. triangles). The insulating region is broken down into triangles. Over these simple regions, the true solution for the desired potential is approximated by a very simple function. If enough small regions are used, the approximate potential closely matches the exact solution [21-23].

The advantage of breaking the domain down into a number of small elements is that the problem becomes transformed from a small but difficult to solve problem into a big but relatively easy to solve problem. Through the process of discretization, a linear algebra problem is formed with perhaps tens of thousands of unknowns. However, algorithms exist that allow the resulting linear algebra problem to be solved, usually in a short amount of time. Specifically, FEMM 4.0 discretizes the problem domain using triangular elements. Over each element, the solution is approximated by a linear interpolation of the values of potential at the three vertices of the triangle. The linear algebra problem is formed by minimizing a measure of the error between the exact differential equation and the approximate differential equation as written in terms of the linear trial functions [21].

After approximation of the potential in the triangular elements, electric fields can be easily calculated in them. Figure 2 shows the mesh of the problem after the discretization process. For accurate solution the region is divided into more than 10000 triangles for each case.

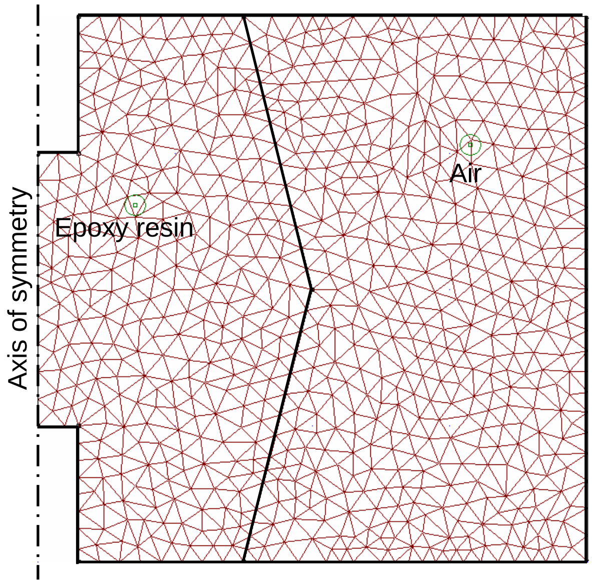

Figure 2. A finite element mesh used in solution for the shuttle insulator.

INPUT – OUTPUT DATA

In this study, optimum insulator geometry has been searching. To obtain the optimum contours of an insulator in order to keep the field distribution along the insulator surface uniform and as low as possible, electric field values should have been known [15]. Electric field calculations have been carried out by FEMM 4.0 packet program as mentioned.

Figure 3 shows the schematic of a support insulator having a conical contour form. The cast resin insulator is a shuttle type insulator placed between plane – plane electrode system. It is considered that the magnitude of the potential difference as 1 kV which represents percent potential difference for studying the efficiency of ANN.

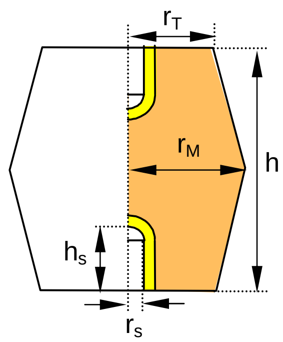

Figure 3. Support insulator having a shuttle type.

Insulator profile is taken as linear as shown in Figure 3. For the axi-symmetric insulator, the values of r_M, and h are kept constant at r_M = 20 mm and h = 40 mm, which are radius of the insulator, and height of the insulator respectively. The radius (r_s) and the height (h_s) of screw socket using for connections are also kept constant during the calculations. The dimensions of the screw sockets are r_s = 3 mm, and h_s = 10 mm. In this study, by varying only one parameter, r – coordinate of the top point of the insulator (r_T), different contours are obtained.

For obtaining the different training and test patterns by means of field calculation, 110 different values of the top point of insulator are considered, e.g. 9 to 19.9 mm in steps of 0.1 mm. Hence, altogether 110 electric field data obtained from the results of calculations. The electric stresses are calculated at 45 different points on the surface of the insulator which have equal distance from each other for all cases.

Stress distribution along the insulator surface is symmetrical according to mid-point of the insulator. Because of the symmetry, only the 22 points from the top point to mid-point are taken for computations. These 22 points are taken such that their heights, z – coordinates, remain the same for each contour.

The computed tangential electric fields at the above mentioned 22 points are applied to the network as input pattern vectors. The r – coordinates of the 22 points on the insulator surface as mentioned above are applied to the network as the output pattern vectors. Because the z – coordinates of these points are fixed, they are not used in ANN.

PREPROCESSING OF INPUT-OUTPUT DATA

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 – 1). In addition, input signals should be kept small in order to avoid a saturation effect of the radial basis function. Therefore, the input-output patterns are normalized before training the network [23]. 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).

Both input and output pattern vectors of training and test sets have 22 items. Therefore, the ANN has 22 input neurons and 22 output neurons.

With the input – output pattern vectors for training available, the GRNN is trained to give optimized insulator contour. After the training is completed, test phases which are within the range of input data but not included in the training set are applied to the network for the ANN accuracy estimation.

In the study, 2 – fold cross – validation method is used for data set. All data set which contains 110 computed electric field data and r – coordinates of the points that the calculations made is divided into two subsets which consist of 55 and 54 patterns. In case 1, the 1st subset is used for training ANN and the 2nd subset is used for testing. In case 2, 2nd subset is used for training and 1st subset is used for testing. By using that method generalization abilities of the networks are examined. The errors of the training and test phases are shown in Table 1.

TABLE 1 - Training and test errors for both cases

	Training errors			Test errors
	sse (%)	mse 10^{-6} (%)	rms (%)	mae (%)
1st case	0.0064	5.2653	0.0229	0.6123
2nd case	0.0020	1.7140	0.0131	0.6174

It is to be noted here that in this study the error in training is represented by mean squared error (mse), sum squared error (sse), and root mean squared error (rms), and the error in test is represented by mean absolute error (mae). The formulae used for computation of errors are given below [23].

$$sse = \sum_{j=1}^{N} e_j{}^2(n) \qquad (6)$$

$$mse = \frac{1}{N}\sum_{n=1}^{N}\sum_{j\in C} e_j^2(n) \qquad (7)$$

$$rms = \sqrt{\frac{1}{N\,n_o}\sum_{j=1}^{N}\sum_{k=1}^{n_o}(d_{jk} - y_{jk})^2} \qquad (8)$$

$$mae = \frac{1}{n_t\ n_o}\sum_{j=1}^{n_t}\sum_{k=1}^{n_o}\left[\frac{|d_{jk} - y_{jk}|}{d_{jk}}\right]100 \qquad (9)$$

where N denote the total number of patterns contained in the training set, C includes all the neurons in the output layer of the network, n_o is the number of output neurons, and n_t is the number of test phases.

The result of 2 – fold cross – validation method is shown that the 1st case represents the all data set better than the 2nd case. Therefore, 1st case is used for the other computations.

APPLICATION OF ANN

The smoothing parameter σ of GRNN is determined by trial – error method. In both of the cases, it has been shown that σ determined as 0.015 gives the best possible result. The ANN is trained by using that value of σ.

The desired input variables are determined by using minimum values of the training set and the field distribution along the cylindrical insulator in a way that the desired field distribution is ideally as uniform as possible. The desired field distribution and the field distribution of the training set are shown in Figure 4.

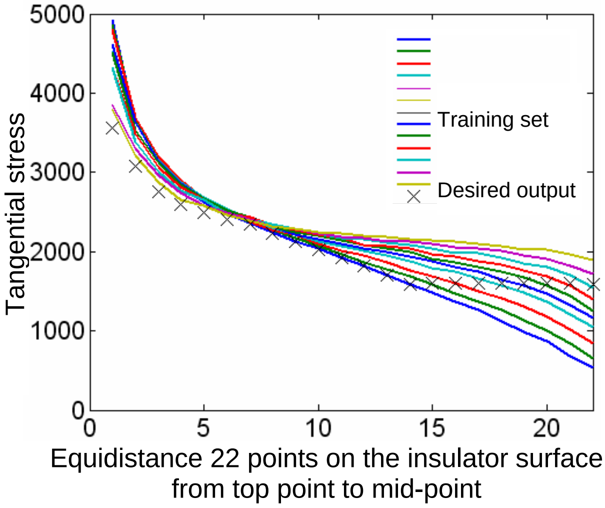

Figure 4. Surface field distributions of shuttle insulators

After training and testing is completed, the desired field distribution is applied to the ANN in order to give the optimum insulator contour. The optimum insulator contour obtained by ANN is shown in Figure 5 for case 1. All the above – mentioned ANN studies have been carried out by using MATLAB 6.5 Neural Network Toolbox.

CONCLUSIONS

In this paper, GRNN has been employed for optimizing the form of an axi - symmetric support insulator.

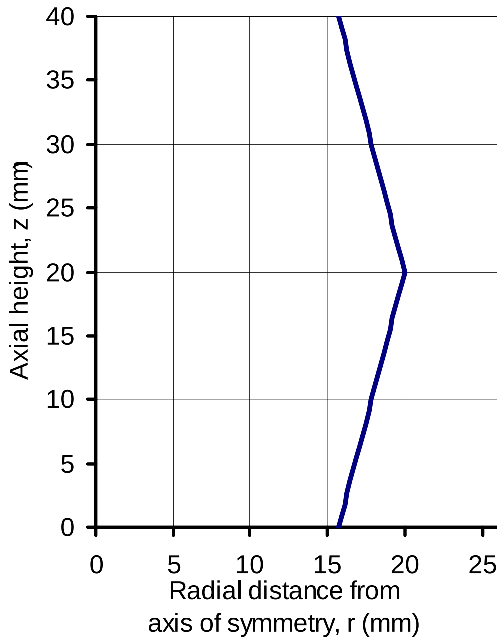

Figure 5. Optimum shuttle insulator contour obtained by ANN

In order to supply data for training ANN, surface electric field values of the insulator is calculated by FEM. Half of the calculated values is used for training and the rest is used for testing ANN. By 2 – fold cross – validation method, it had been determined that which half of the calculated data is represents the system better. After the decision, tangential stresses as input and r – coordinates as output are applied to the network. The results show that the ANN with GRNN gives output with less than 0.3 % error for training set and less than 0.6 % for test set. When the desired tangential stress is applied to the network, the optimum contour coordinates can be obtained.

The network structure and learning algorithm is very available for optimization problems. It can be easily applied to any prediction and classification problem with accurate results. Another significant advantage is having a very short computation time due to other learning algorithms, because the GRNN has no iteration.

As a numerical method of solving optimization problems, ANN gives efficient results very fast. The flexibility and the speed of the method make ANN very preferable in the optimization of the design of an insulating system.

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