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Insulator Contour Optimization Using Intelligent Systems & Soft Computational Methods

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Abstract— **The purpose of this study is to give basic concepts of insulator contour optimization by using intelligent systems and soft computational methods. In this sense, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) are used as an optimization method. First training and validation data were collected from electric field distribution of an insulator by using finite element method analysis. Data contains coordinates and electrical field values of the middle point and the top point of the insulator. And then the data sets were used as inputs for ANN and ANFIS to train the algorithms. After the training process, any desired output that the top radius of the insulator was calculated for given input data using both methods. Finally results were compared from each other. The methods successfully are used for insulator contour optimization.**

Keywords-insulator contour optimization; ANN; ANFIS

I. INTRODUCTION

Insulators are one of very important elements of the high voltage power systems. They insulate the live lines from other live parts or grounded parts in order to protect the human beings and system apparatus. Due to its reliability importance, insulators must be well designed in terms of the electrical and mechanical properties. Sometimes the proper design need to be optimized but it is not always easy to make because there are lots of insulator types and proper design parameters should be used for a specific insulator type. Therefore, there is no such a formula that can be used either for design or optimization. Optimized insulator contour should give uniform stress distribution along the insulator surface, and keeping the electric field as low as possible. Obtaining uniform electric field 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.

The most important design parameter for an insulator is its nominal voltage which is creating electrical stress on it. The voltage level gives general information about shape and size of the insulator.

There are many numerical optimization methods widely used but they requires objective function about the it is hard to define such an objective function because there are many design parameters and there is no specific formulas related to shape and size values for every single insulator [1-6]. Genetic algorithm is another well known method but it needs an objective function as well. Also it is very time consuming method because it requires too much iteration [7].

Soft computational methods are easy to apply nonlinear systems for modeling. With the improvement of the computer technology, many algorithms related to soft computing were developed. Two of the important ones are artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS). There are lots of studies in the literature about optimization method for insulator design [8-12].

In this study both ANN and ANFIS were used to optimize geometrical form of a 1 kV shuttle insulator. Top radius of the insulator was calculated according to desired input electrical field value obtained from finite element analysis. The obtained numerical results were compared with the real values. Besides, different configurations (number of neurons, various membership functions. etc.) of the optimization methods were also applied to take into account the system in order to minimize the computational error.

II. ELECTRICAL PROPERTIES OF SHUTTLE INSULATOR AND ITS DESIGN PARAMETER

Figure 1 shows a typical 1 kV shuttle insulator. The insulator is made of resin, and is use as a post insulator under the busbar. Dimensions of the insulator are also shown in same figure. Some of the dimensions which are height of the insulator (h), middle radius (r_m), screw socket height (h_s) and radius (r_s) were kept the same during the optimization. r_T top radius of the insulator was chosen as the design parameter for the optimization problem.

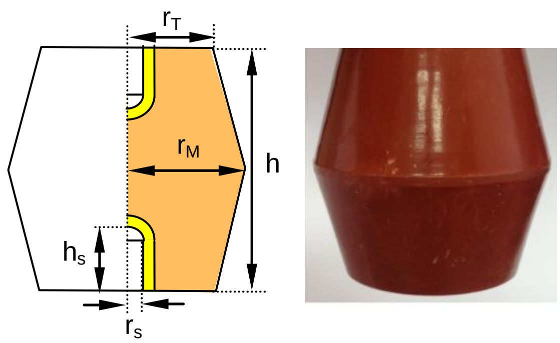


Figure 1. Shuttle insulator

In order to calculate top radius, two optimization parameters which are electrical value at the middle point (E_{MIDDLE}) and tangential electric field (E_{TOP}). These values were calculated using finite element method analysis program. For this purpose, it is assumed that insulator was placed between two plane electrodes and 1 kV AC voltage was applied to the top electrode, and the bottom electrode was grounded. Such a case can easily be simulated.

Figure 2 and 3 shows 2D and 3D simulations done with different top radius values. E_{TOP} and E_{MIDDLE} calculations were done for every 0.25 mm position increments starting from 9 mm to 20 mm. E_{TOP} and E_{MIDDLE} values at 45 different points were calculated as the input data for the optimization methods.

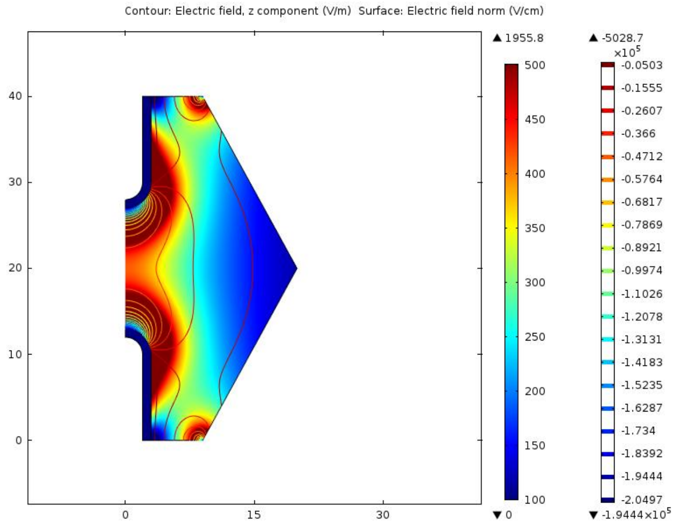


Figure 2. Insulator 2D electrical field simulation

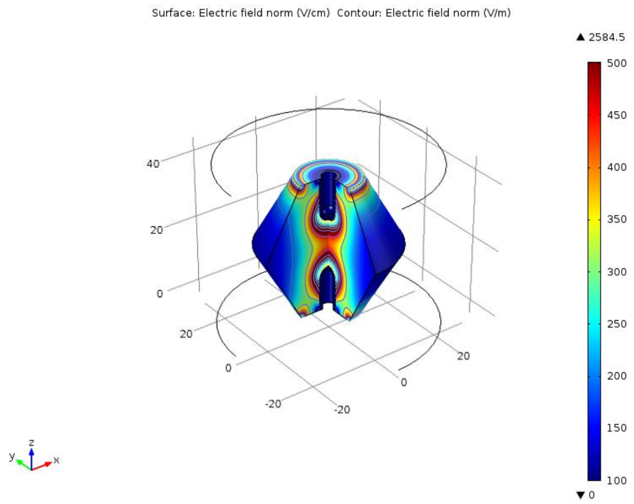


Figure 3. Insulator 3D electrical field simulation

III. Artificial Neural Networks

The electrical field calculations for unconventional geometric insulators contain nonlinearity. Hence it is very difficult to solve these kinds of problems with numerical approaches. ANN is an alternative approach for optimization. Also it is very reliably and adaptive [13-14].

For the calculations, 30 data points that cover the whole workspace and reflect the all characteristic of the maximum value of tangential electric field distribution of the insulator were used to train the NN. 15 data were also chosen among the total of 45 data points for validation as well. On the other hand same amount of data points for training and validation were chosen for tangential electric field value at mid-point (E_{MIDDLE}) of the insulator.

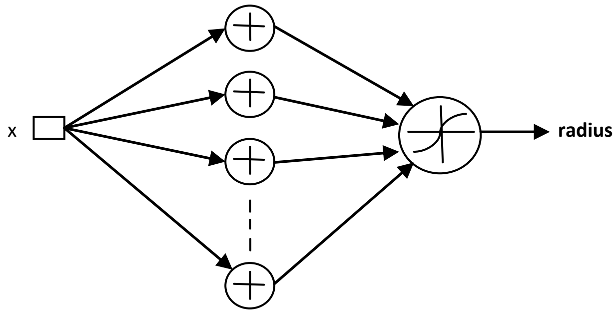


Figure 4. ANN configuration

Figure 4 shows the general representation of feed forward NN architecture used for electrical field calculations. Gradient descent with adaptive learning rate (GDX) and Levenberg-Marquardt (LM) back-propagation algorithms were used as learning algorithm. It was shown that accuracy of Levenberg-Marquardt back-propagation cross validation results is higher than the GDX. Also LM converges with less epoch number that means faster than GDX.

During the simulations, for both training algorithms, training data size, number of hidden layers and number of neurons in layers, activation function types of layers are changed and compared. Mean square error is used for performance comparison and its level is kept constant for this purpose. In addition to that validation data is not changed to provide a clear view for comparison. Network configuration related to system training sequence consists two hidden layer with different hidden neurons. 0.0000001 was chosen as the error goal for the network.

IV. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a widely used modelling and optimization technique and it contains the best properties of neural networks and fuzzy logic. For a given data and initial membership functions, ANFIS deduces trained membership functions by training the input data [15]. Data from ANN section were used to train and validate ANFIS. Input data includes tangential electrical field along the outer surface and electrical field at the middle point of the electrode, so ANFIS become two input and single output system shown in figure 5.

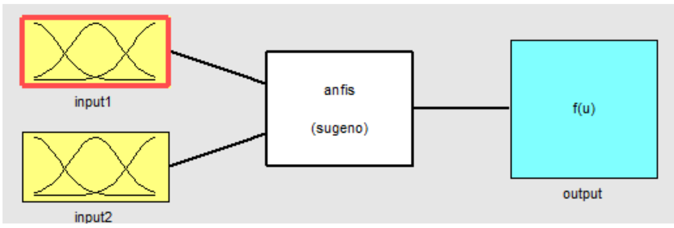
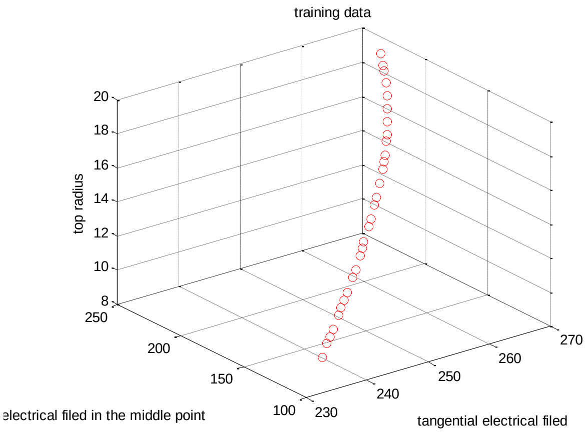
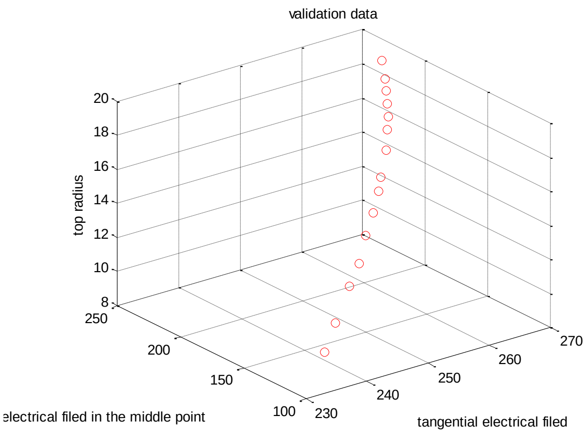


Figure 5. ANFIS structure

In figure 6 a, 3D representation of training and validation data can be seen. Several simulations were made for different membership functions. Besides, simulations were repeated with various number of membership functions (mf) for each type of mf in order to see the effect of number of mfs.



(a)



(b)

Figure 6. Input data for ANFIS a-training data b-validation data

Two input that each of them contains four membership functions and single output FIS system has 16 fuzzy rules given below in figure 7.

1. If (input1 is in1mf1) and (input2 is in2mf1) then (output is out1mf1) (1)
2. If (input1 is in1mf1) and (input2 is in2mf2) then (output is out1mf2) (1)
3. If (input1 is in1mf1) and (input2 is in2mf3) then (output is out1mf3) (1)
4. If (input1 is in1mf1) and (input2 is in2mf4) then (output is out1mf4) (1)
5. If (input1 is in1mf2) and (input2 is in2mf1) then (output is out1mf5) (1)
6. If (input1 is in1mf2) and (input2 is in2mf2) then (output is out1mf6) (1)
7. If (input1 is in1mf2) and (input2 is in2mf3) then (output is out1mf7) (1)
8. If (input1 is in1mf2) and (input2 is in2mf4) then (output is out1mf8) (1)
9. If (input1 is in1mf3) and (input2 is in2mf1) then (output is out1mf9) (1)
10. If (input1 is in1mf3) and (input2 is in2mf2) then (output is out1mf10) (1)
11. If (input1 is in1mf3) and (input2 is in2mf3) then (output is out1mf11) (1)
12. If (input1 is in1mf3) and (input2 is in2mf4) then (output is out1mf12) (1)
13. If (input1 is in1mf4) and (input2 is in2mf1) then (output is out1mf13) (1)
14. If (input1 is in1mf4) and (input2 is in2mf2) then (output is out1mf14) (1)
15. If (input1 is in1mf4) and (input2 is in2mf3) then (output is out1mf15) (1)
16. If (input1 is in1mf4) and (input2 is in2mf4) then (output is out1mf16) (1)

Figure 7. Calculated rules for the 2 input and single output FIS system

The control surface of the system according to rules was also given in figure 8. It can be seen that the sharpness of the surface near the input 2 (electrical field in the middle point) is dominant for the counter optimization, so we have to take into account this input basically.

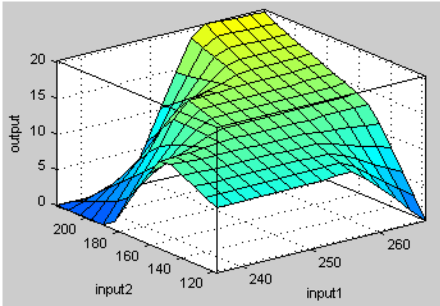


Figure 8. Control surface for a given rule base

V. SIMULATION RESULTS

The ANFIS results for training data given for four triangular membership functions can be seen in figure 9.

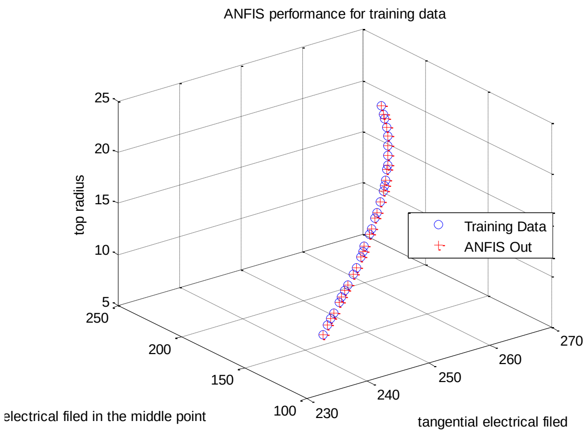


Figure 9. ANFIS performance for training data

The training data and the ANFIS output data fits very well, so the configuration is suitable for the system. Validation data results are also shown in figure 10. Both training and validation data points have better fitting rates rather than ANN results.

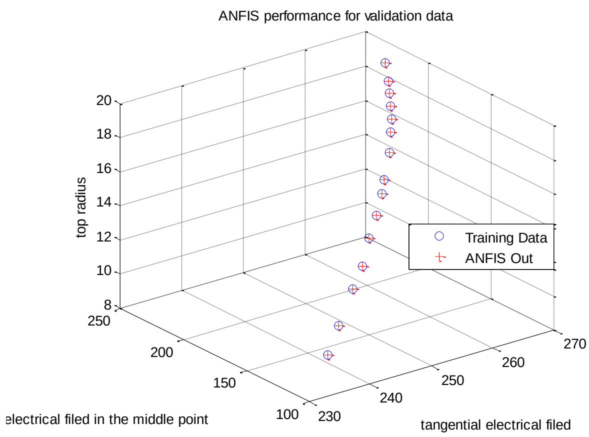


Figure 10. ANFIS performance for validation data

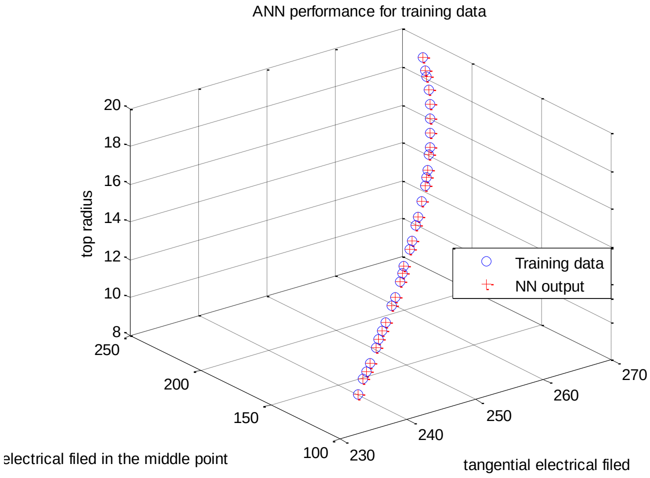
The ANFIS simulations were made with various membership functions and tested different numbers of membership function to find the optimum configuration for the system. Five different membership functions such as triangular, Gaussian, bell, sigmoid and trapezoidal used for input fuzzyfication. For all membership functions, simulations were repeated five different numbers of membership functions from 2 to 6, respectively. After each simulation mean square errors (MSE) were calculated for both training and validation data. The error rates of the simulations are shown in Table I.

TABLE I. ERROR RATES OF THE ANFIS SIMULATIONS WITH DIFFERENT MFS AND DIFFERENT NUMBER OF MFS.

# of MF.	Training error	Validation error	MF
2	8.7502e-07	3.3569e-07	Triangular
3	8.9334e-08	2.0362e-07	
4	2.1956e-08	3.1540e-07	
5	3.1797e-09	2.5081e-05	
6	4.5085e-11	9.2114e-07	
2	1.0012e-05	5.7825e-06	Gaussian curve
3	7.2627e-07	1.3997e-06	
4	3.9236e-08	8.8440e-07	
5	1.7649e-08	1.4149e-06	
6	1.5449e-11	1.4036e-05	
2	3.1589e-05	1.2564e-05	Generalized bell curve
3	1.0030e-06	1.3233e-06	
4	8.8702e-08	1.5504e-06	
5	1.5171e-09	8.3073e-07	
6	1.0098e-09	4.0456e-06	
2	2.9839e-05	1.2312e-05	Sigmoid curve
3	6.2918e-06	1.8375e-05	
4	2.0381e-07	3.3033e-06	
5	1.3854e-08	9.8433e-07	
6	7.6957e-10	7.5130e-06	
2	5.2451e-05	3.8418e-05	Trapezoidal
3	1.2666e-05	1.8817e-05	
4	7.0024e-06	5.8467e-05	
5	5.1164e-06	1.5638e-04	
6	1.0150e-06	5.5310e-04	

According to Table I, it can be said that triangular membership function has minimum training and validation error. Also four membership functions for each input give best error rates seen from Table II as well.

In Figure 11, neural networks output of training and validation data are given for Levenberg-Marquardt learning algorithm. It can be said that for given data LM learning algorithm fits more accurately rather than GDX. This case easily be seen from validation data cross check. The LM algorithm is more reliable than GDX for this kind of low data point optimization problem. Table II shows the performance comparison of learning algorithms with respect to training and validation errors. The best results were obtained by using Levenberg-Marquardt back-propagation algorithm. Also mean square errors of both data sets state that, choosing gradient descent with adaptive learning rate as learning algorithms yields bigger error.



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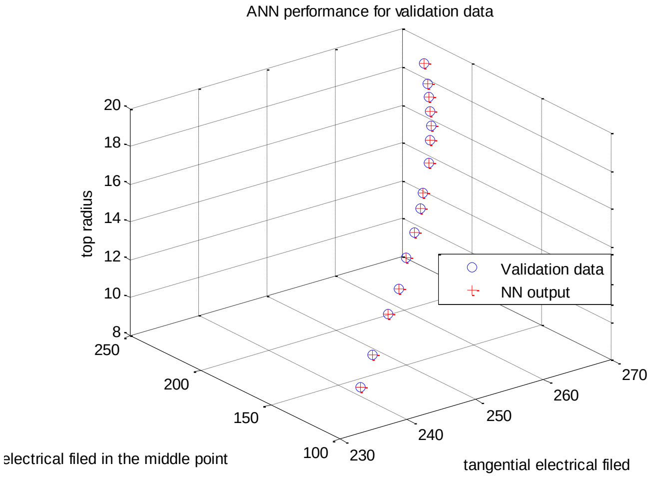

b

Figure 11. ANN performance for training data (a) and validation data (b)

TABLE II. ERROR RATES OF THE ANN SIMULATIONS FOR DIFFERENT LEARNING ALGORITHMS.

Layers	**Training error**		**Validation error**	
	LM	**GDX**	**LM**	**GDX**
[2 1]	6.5619e-06	0.0176	3.2317e-06	0.0097
[2 2]	2.1464e-07	0.0032	1.2546e-07	0.0014
[2 3]	1.0621e-06	0.0680	2.6927e-07	0.0358
[2 4]	6.4434e-06	0.0372	2.3877e-06	0.0142
[2 5]	1.5654e-07	0.0667	8.0458e-08	0.0329
[3 1]	4.2815e-07	0.0756	1.2614e-07	0.0394
[3 2]	1.7639e-06	0.1845	1.0349e-06	0.0775
[3 3]	3.4919e-07	0.0145	1.1136e-07	0.0070
[3 4]	3.0668e-06	0.0261	8.5517e-07	0.0136
[3 5]	5.3221e-06	0.0245	4.1304e-06	0.0162
[4 1]	1.2917e-07	0.0326	6.7251e-08	0.0149
[4 2]	9.0372e-07	0.0977	2.7771e-07	0.0329
[4 3]	7.4101e-06	0.0301	2.8234e-06	0.0124
[4 4]	3.8437e-05	0.0048	2.9607e-05	0.0014
[4 5]	2.8586e-07	0.0093	2.7167e-07	0.0029

The top radius values of the insulator obtained with two optimization technique (ANN & ANFIS) can be seen in Table

III. Real radius values were taken from FEM simulations and they were compared with the proposed methods above. The radius values for the calculations seem very similar to real ones.

TABLE III. ERROR RATES OF THE SIMULATIONS WITH DIFFERENT MFS AND DIFFERENT NUMBER OF MFS.

REAL VALUES	ANFIS OUTPUTS	ANN OUTPUTS
9.25	9.2504	9.2477
10.25	10.2500	10.2470
11.50	11.4996	11.5001
12.25	12.2482	12.2491
13.25	13.2492	13.2492
14.00	14.0011	14.0008
14.75	14.7488	14.7505
15.25	15.2502	15.2496
16.25	16.2487	16.2492
17	16.9994	16.9994
17.50	17.5002	17.5005
18	17.9998	17.9997
18.50	18.4998	18.4995
19	19.0002	19.0003
19.75	19.7506	19.7510

VI. CONCLUSION

In this study, two of optimization technique ANN and ANFIS were applied to a contour optimization problem for a shuttle insulator and their performances were examined. For this purpose first of all, neural network toolbox of Matlab is used for simulation. At first gradient descent with adaptive learning rate back-propagation is used as training algorithm in neural network, but it didn’t give satisfactory results in validation. For this reason Levenberg-Marquardt back-propagation is used next and successfully results gained in validation. On the other hand, it must be taken care that, although Levenberg-Marquardt back-propagation is a fast algorithm, but it needs much more memory in simulation. Then, in order to establish a scientific link to the ANN part of the study, which was realized by a feed-forward back-propagation network, same training data and validation data were used in ANFIS model of the system. Different membership functions with different number of MF configurations were also used to show the system performance

Levenberg-Marquardt back-propagation algorithm is highly faster and reliable than gradient descent with adaptive learning rate back-propagation algorithm. It must be expressed that performance level is very important and efficient for optimizing, small performance level which means small mean square error, provides both better training and validation.

The study carries out that, an ANFIS structure with triangular MFs is more suitable for the problem. In all cases the increase in number of MFs in input layer provides better performance but after 4 in trapezoidal and generalized bell MFs and after 5, in triangular MF overfitting and memorizing occurs.

Consequently, it has been seen that used algorithmic methods are appropriate to determine the insulator contour. Also these methods can be used to determine shed number, shed position, shed form, shed size of an insulator having sheds.

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