TO MODEL BREAKDOWN VOLTAGE USING ARTIFICIAL NEURAL NETWORKS OF SOLID INSULATING MATERIALS

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A Thesis submitted in partial fulfillment for the degree of

Bachelor of Technology in Electrical Engineering

By

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CERTIFICATE

This is to certify that the thesis entitled "**To Model Breakdown Voltage using Artificial Neural Networks of Solid Insulating Materials**", submitted by **Niranjan Sureddi (**Roll. No. **110EE0214) and Ashish Shrivas (**Roll.No. **110ee0154)** in partial fulfillment of the requirements for the award of **Bachelor of Technology** in **Electrical Engineering** at National Institute of Technology, Rourkela is a bona- fide record of research work carried out by him under my supervision and guidance.

All the prescribed requirements are fulfilled by the candidate.

The Thesis which is based on candidates' own work, have not submitted elsewhere for a degree/diploma.

The thesis is of standard required for the award of a bachelor of technology degree in Electrical Engineering in my opinion.

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Ashish Shrivas

ABSTARCT

During manufacture, insulating materials may have voids which are source to electrical trees. Due to partial discharge, the insulating material degrades and breakdown occurs. The factors contributing to the breakdown are difficult to determine. As the equation describing the function is unknown, function estimation, which has some of its own useful properties, a major field of Artificial neural networks, is used. In this project using Artificial Neural Network, we develop models which intakes four different possible inputs that effect the breakdown which are the insulating sample thickness (t), void thickness (t_1), void diameter(d) and the materials' permittivity (ε_{r}) predicts the breakdown voltage as a function of these four inputs. The Neural Network needs to be trained to be able to predict the Breakdown Voltage as close as possible. For the purpose of training , experimental data using a cylinder plane electrode system is used. The different dimensions used will be used to create the voids artificially. The parameters are selected after detail studying of the models as to which would generate best results. After the training is completed, the breakdown voltage as a function of the four input parameters is predicted. The results are very convincing as the error with which it is predicted is very less. Hence, this again proves the capability and effectiveness of using simulation models. MATLAB 2010 is used for doing the simulation process.

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ABBREVIATIONS

ANN	-	Arterial Neural Networks
MFNN	-	Multi Layer Feed Forward Neural Network
RBFN	-	Radial Basis Function Network
BPA	-	Back Propagation Algorithm
LMS	-	Least Mean Square
AC	-	Alternative Current
RBF	-	Radial Basis Functions
FCSR	-	Fixed Centers Selected at Random
η_1	-	Learning rate in MFNN
α	-	Momentum factor
E_{tr}	-	Mean Square Error
N_h	-	Number of hidden layer neurons
η_2	-	Learning rate in RBFN
m_1	-	Number of centers in hidden layer in RBFN

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

Solid Insulators are used in several areas, but especially in areas concerning high voltage or very high voltage such as national or state grids, they are costly and need to be tested properly. Materials with very high breakdown voltage should be used. Aging causes the defects to grow that are present during manufacturing. Changes in the parameters change the breakdown voltage of the insulating material but are very difficult to determine. The minimum voltage that causes the insulator to conduct electrically is called Breakdown Voltage. Due to high voltage stress, a localized breakdown occurs in a solid insulating material is called Partial discharge. In finding the best insulation material that suits the needs, they have to be tested properly and modeling the process is a very efficient way to do it. Artificial Neural Network prove to be very flexible and reliable model in testing the materialsas they can be improved by just giving extra data.

1.2 AIM OF THESIS

The objective of the project is to model the breakdown voltage of the insulating materials under consideration using 2 different ANN models namely MFFNN and RBFN. The results are found out using these 2 models and then it is to be proved that modeling also generates the same results that are generated experimentally with very less error.

1.3 TIMELINE OF THESIS:

The thesis report is broadly divided into 4 chapters. The timeline of the thesis is detailed in this section. The experimental data used in the project is perquisite.

The whole thesis is divided into 4 chapters namely the Introduction, Experimental Procedure, Literature and Modeling Procedure, and Results and Discussion

Chapter 1, Introduction deals primarily with the motivation that drove to do the project. It emphasizes the use of modeling procedure over experimental procedure by telling the advantages if the model should be proved effective and about the main aim of doing this project.

Chapter 2 is titled Experimental Procedure, as it describes the detailed procedure of experimental set up, the creation of void, measurement of relative permittivity and also the measurement of Breakdown voltage. The results obtained here are used both for training the model developed so as to find the varying parameters and also to test the data upon. Only after testing can the model be proved worthy enough to be done.

Chapter 3 is Literature and Modeling procedure. It starts with the basic literature needed to complete the project. The basics of Artificial Neural Networks is discussed in the chapter simultaneously along with the procedure required for modeling the breakdown voltage. It describes about weight updating, the BPA for MFNN and LMS for RBFN and also the evaluating criteria for both the models

Chapter 4 deals firstly with finding the parameters values , Number of hidden neurons, learning rate, momentum factor in case of MFNN and number of centers in hidden layer and learning rate of LMS algorithm in case of RBFN. After the parameters are set, then the testing data is used to test the model and the results are compared with already available experimental data. It also discusses about which model performs better.

CHAPTER 2

EXPERIMENTAL PROCEDURE

For the purpose of checking the modeled Neural Network, experimental values are required. So, firstly the experimental step by step procedure is to be discussed. In this project we intend to use five solid insulating materials which are Manila Paper, Lather Minilex. White Minilex Paper, Leatheroid Paper and Glass Cloth. The experimental procedure is as follows

2.1 PREPARATION OF SAMPLE

Firstly, the samples to be tested are to be prepared. Preparation means using different thickness and the thickness values used for different materials is as shown below

TABLE 1 THICKNESS OF INSULATING MATERIALS

Insulation material	Thickness		
White Minilex Paper	0.26mm	0.18mm	0.125mm
Leatheroid Paper	0.235mm	0.175mm	0.13mm
Lather Minilex	0.245mm	0.185mm	0.12mm
Glass Cloth	0.195m	0.155mm	
Manila Paper	0.06mm	0.035mm	

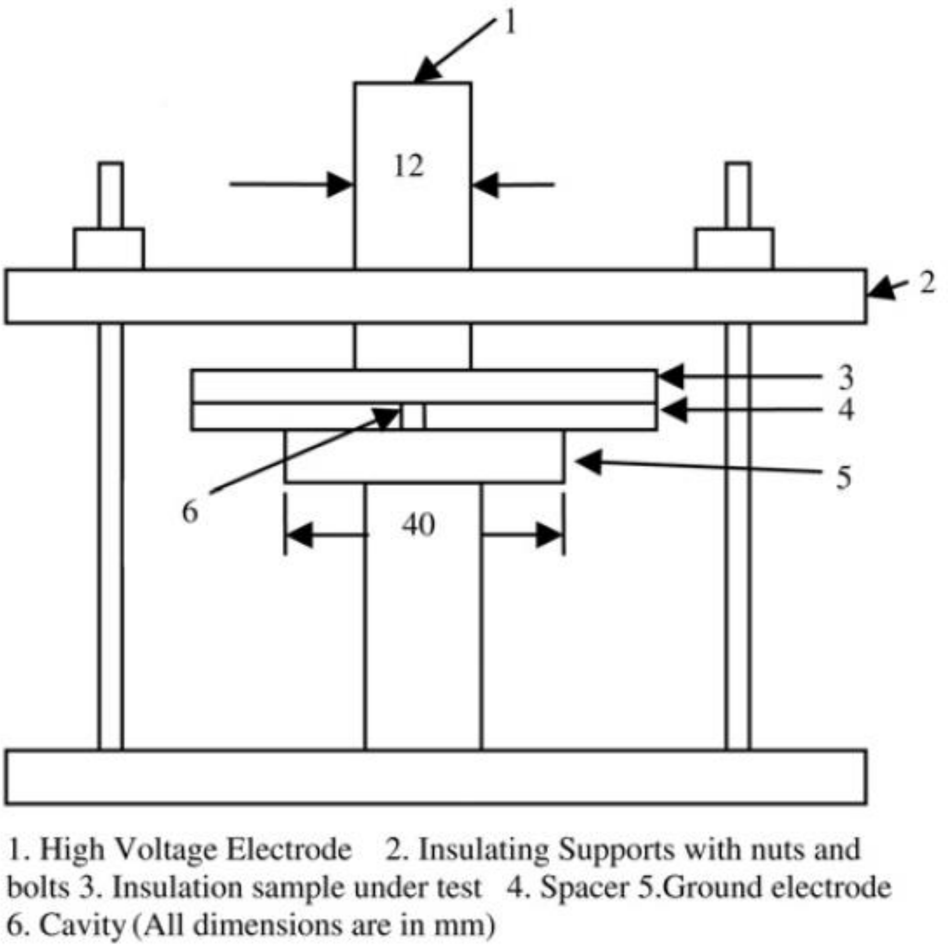

FIGURE 1 EXPERIMENTAL SET UP FOR MEASURING BREAKDOWN VOLTAGE

2.2 VOID CREATION

A spacer made of Kapton film is used to make voids of different sizes. 1.5mm, 2mm, 3mm, 4mm, 5mm are the diameter of the voids and 0.025mm, 0.125mm being the thickness of Kapton spacer. Thickness of spacer and diameter of hole are the two factors on which the size of the void depends upon.

2.3 AC BREAKDOWN VOLTAGE MEASUREMENT

40 kV AC/DC Series Hipot Tester is used to obtain the 50 Hz AC voltage applied to the insulating samples. Until the breakdown occurs, for 30 seconds a voltage is applied and then raised to next level by increasing in steps of 200 V. The time taken from starting till the breakdown is noted. For the purpose of modeling, condition of the void and the mean voltage value is taken. For a sample under consideration 5 data points are taken. Temperature and pressure influence the results at which the data is collected, so every reading is adjusted to room temperature and pressure.

2.4 SOLID INSULATING MATERIALS' RELATIVE PERMITTIVITY MEASUREMENT

To measure the relative permittivity, the insulating samples coated on both sides with silver of 12 mm diameter are used. The two sample holder electrodes, which are made of brass, of Impedance gain/phase analyzer are used to press hold the samples which are silver coated. An AC voltage of 0.1 V (r.m.s.) at 50 Hz was applied to the samples from the impedance gain/phase analyzer. At 50 Hz the relative permittivity values of the insulating materials are recorded.

TABLE 2 RELATIVE PERMITTIVITY OF MATERIALS

Insulating Material	Relative permittivity ε_r
Lather Minilex	5.74
Glass Cloth	4.97
White Minilex	4.4
Leatheroid Paper	4.21
Manila Paper	4.68

CHAPTER 3

LITERATURE AND MODELING PROCEDURE

Artificial Neural Networks is to be used in modeling of the breakdown voltage of these materials. Artificial Neural Networks resemble brain, both have neurons and develop outputs based on the previous results when a new input is given. There are two types of Neural Network Models that are used in the process namely Multi Layer Feedforward Neural Network(MFNN) and Radial Basis Function Network. An overview of the two models is written below.

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3.1 MULTI LAYER FEED FORWARD NEURAL NETWORK

3.1.1 MFNN MODEL

As shown in the figure below, the MFNN structure has three layers which are the input layer, the hidden layer and the output layer. Corresponding to each of the inputs, thickness of void, thickness of insulation, diameter of void and Relative permittivity the input layer has 4 neurons. The output of the model is a single output which is the breakdown voltage of the insulating material making the number of neurons 1 in the output layer. There is another layer also which is called the hidden layer. As the name suggests, the number of neurons in the hidden layer can be varied according to our convenience but it has a limit. The network is to be trained first so as to predict the results when pertained to new inputs. For this purpose, the MFNN model uses the Back Propagation Algorithm (BPA). There is an activation function that connects the output from one layer to input of other layer. So, therefore the input layer doesn't have an activation function. Equation 1 represents the activation function for the layers.

It is a sigmoidal function

$S(x) = \frac{1}{1+e^{-x}}$ -- (1)

As told before the number of neurons in hidden layer is not fixed. It can be varied according to our convenience. But, that is where a clever decision is to be made. The computational time depends upon number of hidden layers. So, as the number of hidden layers increase, the complexity increases and there by the time taken. But, the error decreases.

The maximum values given by (2) and (3) are maximum values of input and output layers respectively.

$n_{i,max} = \max(n_i(p))$, $p=1, \ldots, N_p$, $i = 1, \ldots, N_i$ ---(2)

where N_p in the training set is the number of patterns and ,N_i in the input layer is used to represent number of hidden neurons

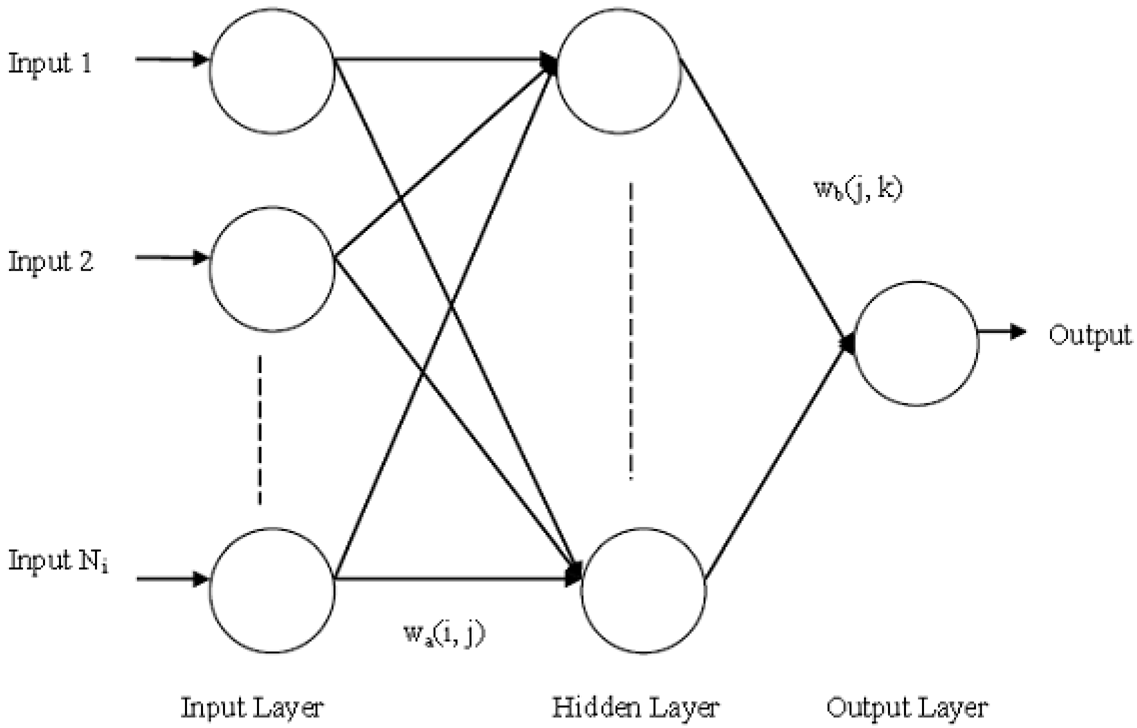

FIGURE 2 MULTI LAYER FEED FORWARD NETWORK

$O_{k,\,max} = \max(O_k(p)),\ p = 1, \ldots, N_p,\ k = 1, \ldots, N_k$ ---(3)

Where N_k in the output layer represents number of neurons.

Every value in the input and output layer are to be normalized and they are done according to equations (4) and (5)

$n_{i,\,nor}(p) = \frac{n_{i\,(p)}}{n_{imax}} p = 1, \ldots, N_p,\ i = 1, \ldots, N_i$ and --(4)

$O_{k\,,nor}(p) = \frac{O_{k(p)}}{O_{kmax}} p = 1, \ldots N_p,\ i = 1, \ldots, N_k.$--(5)

3.1.2 ANN PARAMETERS:

Apart from number of hidden layer neurons, there are a few more Network parameters that effect the networks process in generating the output.

They are

1. Learning rate
2. Momentum factor
3. Training factor
4. Epoch
5. Minimum Error

Learning rate controls the size of the weights in each layer. If fast, the rate of learning increases causing the networks to performs faster due to fast learning, but too much learning rate makes the MFNN unstable and oscillatory.

Momentum helps the network in not converging at a local minimum point by adding a fraction of the previous weight to the current one.

Training type, Epoch and Minimum error are evaluation parameters which assist in better performance of the network like by stopping after a particular number of iterations.

3.1.3 WEIGHT UPDATION

Weight updating takes place every time when an output passes from one layer to another layer. The weights between input-hidden layer and between hidden-output layer contribute to the output so, weight updating is very necessary. During training the outputs are known, so the weights are adjusted so as to get the desired output. After a long number of iterations, the weights when seemed satisfactory, the test data are given. As the updated weights are now in place, the output is estimated with least amount of error.

Now, the weights are updated first in hidden-output layer and then in the input-hidden layer. This is what happens in Back Propagation Algorithm. The output is known and the required hidden layer weights are updated accordingly so as to get the desired output.

The weights between the hidden layer and the output layer are updated as follows

$\mathbf{W_x(a, b, c+ 1) = w_x(a, b, c) +(\eta_1 * \delta_k(c) * S_x(a))+\alpha*(w_x(a, b, c) - w_x(a, b, c - 1))}$ ----- (6)

where c is the number of iterations, a varies from 1 to N_h , where N_h is number of hidden neurons in consideration and estimated output parameters is represented by b. As breakdown voltage is the only output present, the value of c is 1. $\delta_b(m)$ is the error for the b^{th} output at the c^{th} iteration. $S_b(a)$ in the hidden layer represents the output.

After the weights between hidden and output are updated, the weights between input and hidden are to be updated so as to get the required hidden layer parameters to get the final output.

So as needed, the weights between the hidden layer and the input layer are also to be updated as follows

$$\mathbf{w_y(i, a, c + 1) = w_y(i, a, c) + \eta_1 * \delta_j(c) * S_y(i) + \alpha * (w_y(i, a, c) - w_y(i, a, c - 1))} \text{ ---------------- (7)}$$

as there are four inputs to the network, i varies from 1 to 4. after the c^{th} iteration , $\delta_a(c)$ is the error for the a^{th} output and Sa(i) is the output from the first layer.

The errors are taken after every iteration completes and a relation can be found between both the errors.

They both can be related as

$$\boldsymbol{\delta_b(c) = \sum_{b=1}^{b} \delta_b(c) * w_x(a, b, c)} \text{ ---(8)}$$

3.1.4 CRITERIA FOR EVALUATION

MEAN SQUARE ERROR:

As like any model, this ANN model too requires some criteria so it that it can be evaluated Mean square error is a basic and efficient way to evaluate most of the processes. So we also use the same method to find the error and evaluate the theory.

The mean square error E_{tr} after the c^{th} iteration for the training patterns is defined as

$$\mathbf{E_{tr}(c) = \left(\sum_{p=1}^{P} (V_{x1p}(c) - V_{x2p}(c))2 \right) * 1/P} \text{ ---(9)}$$

WhereV_{x1p} is the experimentally value of the breakdown voltage taken for training purpose, V_{x2p}(c) is the modeled value of the breakdown voltage after c^{th} iteration and P is the number of training patterns

MEAN ABSOLUTE ERROR:

This is used for judging the accuracy with which the model is working. The disadvantage of using only Mean Square Error is that it tells only how well the network is adapted to the data. It tells if there is any contaminated data. The Mean Absolute Error is calculated as follows

$$\mathbf{E_{ts}=(1/S) *(\sum_{s=1}^{S}\frac{|\,V_{x4s}-V_{x3s}|}{V_{x3s}}) * 100} \quad \text{---(10)}$$

3.2 RADIAL BASIS FUNCTION NETWORK

3.2.1 RBFN MODEL

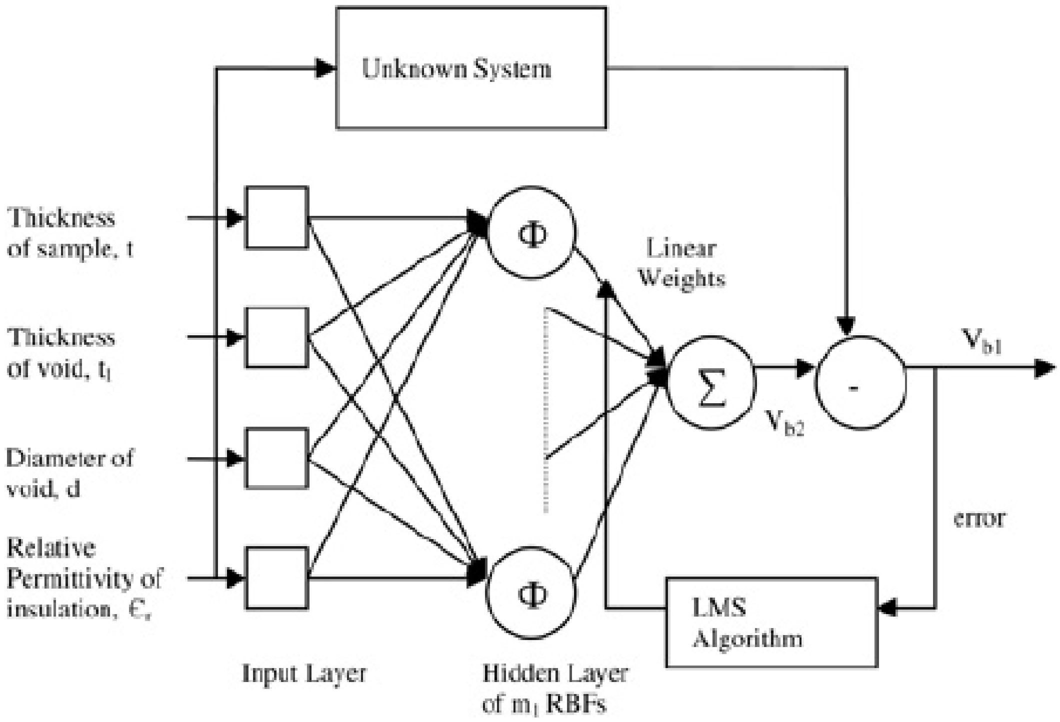

FIGURE 3 RADIAL BASIS NEURAL NETWORK

Apart from MFNN, the other model used is RBFN, Radial Basis Function Network. RBFN also has 3 layers an input layer, a hidden layer and output layer. The hidden layer has a nonlinear RBF activation function and the output has a linear function. The name Radial basis function is given because they only depend upon the distance from the center.

The centers are to be selected and a strategy which selects them at random, Fixed Centers Selected at Random (FCSR) is used. Apart from FCSR, there are two strategies available, Clustering based and Orthogonal Least Squares. FCSR gives better results with large training data.

The Radial Basis Functions(RBF) ar of different types such as Linear, Cubic, Gaussan, Multi-Quadratic, Generalized Multi-Quadratic etc. In RBFN, the hidden and output layer play a very different role. It is appropriate to use different learning algorithm for each: first the node centers are determined and the the output layer weights are trained.

The RBFs are assumed to be isotropic Gaussian function whose standard deviation is fixed according to the spread of the centers.

3.2.2 RADIAL BASIS FUNCTION

The fixed RBFs are defined as follows

$$\mathbf{G}(\|\mathbf{o_1}\text{-}\mathbf{o_2}\|^2) = \boldsymbol{e}^{\frac{-c_1 * \|o_1 - o_2\|^2}{d^2{}_{max}}} \text{ --(11)}$$

where a_1 is the input pattern, a_2 is the coordinates of the center, c_1 is the number of chosen centers and d_{max} is the maximum distance between the chosen centers. $\|\mathbf{o_1}\text{-}\mathbf{o_2}\|$ is the Euclidean distance between o_1 and o_2

Euclidean distance is the least distance i.e. a straight line between any two points.

The RBFs are multiplied by the respective weights and then are summed. The trained output at the cth iteration is given as

$$\mathbf{V_{x2p}(c)} = \sum_{a=1}^{c_1} \mathbf{1} * \boldsymbol{G}(\|\boldsymbol{o_1} - \boldsymbol{o_2}\|)^2 * \boldsymbol{w_{ya}(c)} \text{ --(12)}$$

Where w_{ay} are the weights connected between the hidden layer and the output layer.

The error at the cth iteration is given by

$$\mathbf{e_{1p}(c) = V_{x1p}(c) – V_{x2p}(c)} \text{ -- } (13)$$

3.2.3 WEIGHT UPDATION

The weights w_{aj} are updated through a linear optimization strategy which is the LMS algorithm. LMS Algorithm: LMS stands for Least Mean Square. In this algorithms, the LMS is found and the weight path is optimized.

The weight update equation as per the LMS algorithm is given by

$$\mathbf{W_{ya}(c + 1) = W_{ya}(c) + \eta_2 * G(\| o1 - o2 \|^2) * e_{1p}(c)} \text{ --}(14)$$

Here η_2 is learning rate parameter of the LMS algorithm.

3.2.4. CRITERIA FOR EVALUATION

The same criteria used for MFNN can also be used to evaluate RBFN. Both Mean Square Error and Mean Absolute Error prove to be better criteria for evaluating the RBFN process too.

CHAPTER 4

RESULTS AND DISCUSSIONS

After the model is developed, the training data set is fed into it and network model is set with the updated weights. Both the training and testing data is obtained from experimental values. Now, firstly we would test the data with MFNN model and compare the results with the available experimental data.

4.1 MFNN MODELING

4.1.1 DETERMINING PARAMETER VALUES

In MFNN modeling, there are certain factors that contribute to the output of the system such as Number of hidden neurons, learning rate, and momentum factor. Now, change in the Evaluation criteria that is E_{tr} is checked against every factor.

Firstly, we have the results for change in Mean Square Error with the change in Number of Hidden neurons. When doing this, the other factors i.e. momentum factor, learning rate are kept constant.

Now, for testing the data we need to find the parameters which give the least Mean Square Error. Now, after all the parameters are found at which we get the least error, we need to use these values for training so as to get the least error

TABLE 3 VARIATION OF MEAN SQUARE ERROR WITH NUMBER OF HIDDEN NEURONS

Number of Hidden Neurons, N_h	Mean Square Error, E_{tr}
2	$5.4230 * 10^{-5}$
3	$4.0314 * 10^{-5}$
4	$1.9982 * 10^{-5}$
5	$1.4723 * 10^{-5}$
6	$6.1108 * 10^{-6}$
7	$2.6104 * 10^{-6}$
8	$1.3039 * 10^{-6}$
9	$9.4792 * 10^{-7}$
10	$7.7447 * 10^{-7}$

Iterations = 500, Momentum factor $\alpha = 0.7$, Learning rate $\eta_1 = 0.3$

As the number of hidden neurons increase, the error decreases which shows that as the number of hidden neurons increase is very helpful in decreasing the error. But, there isn't any need for increasing after a certain number as the change in error is not significant.As we can see we get the least error when the value of number of hidden neurons is 10.

TABLE 4 VARIATION OF MEAN SQUARE ERROR WITH MOMENTUM FACTOR

Momentum factor, α	**Mean Square Error, E_{tr}**
0.6	$2.1241 * 10^{-9}$
0.65	$1.3818 * 10^{-9}$
0.7	$7.9446 * 10^{-10}$
0.75	$3.4829 * 10^{-10}$
0.8	$1.0010 * 10^{-10}$
0.85	$5.9116 * 10^{-9}$
0.9	$5.9874 * 10^{-9}$

Learning rate η_1=0.9, Number of Hidden Neuron N_h = 8, iterations =500

We are getting the least value of error when the momentum factor is 0.8. As we can see, as the momentum factor increases after 0.8, the error goes on increasing. So, we should not increase the momentum after a certain value as it may converge at a minimum.

TABLE 5 VARIATION OF MEAN SQUARE ERROR WITH LEARNING RATE

Learning rate, η_1	**Mean Square Error, E_{tr}**
0.1	$7.7447 * 10^{-6}$
0.2	$1.0855 * 10^{-7}$
0.5	$1.0235 * 10^{-8}$
0.6	$6.6281 * 10^{-9}$
0.7	$4.6376 * 10^{-9}$
0.8	$3.4236 * 10^{-9}$
0.9	$2.6276 * 10^{-9}$
0.99	$2.1241 * 10^{-9}$

Iterations = 500, Momentum factor $\alpha = 0.8$, Number of Hidden Neurons N_h=8. Learning rate decreases the error significantly as it goes on increasing. But increasing the learning rate too much can cause the system to be unstable and become oscillatory

Variation of Mean Square Error E_{tr} with number of iterations is given by the following figure. As the number of iterations increase the mean square error decreases, but doing a lot of iterations doesn't change the error value much, so advised to stop after a certain value.

(Learning rate =0.99, Momentum factor = 0.9, Number of hidden neurons N_h = 8)

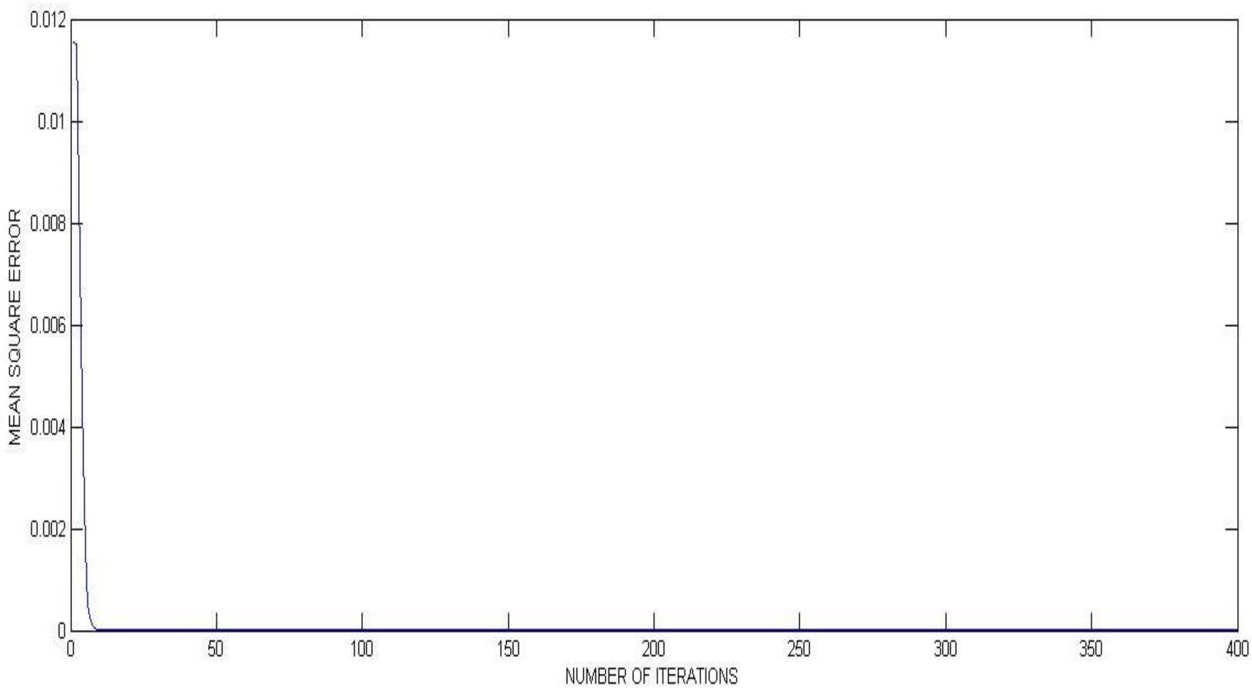

FIGURE 4 CHANGE OF MEAN SQUARE ERROR WITH NUMBER OF ITERATIONS

From the results above, for the training data Mean Square Error is lowest when number of hidden neurons (N_h) is 10, learning rate is 0.99 and momentum factor is 0.8. The lowest value of Mean Square Error obtained is $1.0010 * 10^{-10}$

Now that we have all the parameters set, we need to find out the breakdown voltages and check it with the experimental data and find the Mean Absolute Error thereby proving the model to be very efficient.

TABLE 6 : MODELED DATA AGAINST EXPERIMENTAL DATA USING MFNN MODEL

Insulating Material	t, mm	T_1, mm	D, mm	E_r	Breakdown voltage(exp), KV	Breakdown voltage(model)KV	E_{ts}, %
Lather Minilex	0.125	0.125	3	5.74	2.4000	2.3856	0.0800
	0.185	0.025	4	5.74	2.2000	2.2000	
	0.245	0.125	5	5.74	2.4000	2.3856	
Glass Cloth	0.155	0.125	1.5	4.97	2.3000	2.3000	
	0.195	0.125	3	4.97	2.2000	2.2000	
	0.155	0.025	5	4.97	2.3000	2.3000	
White Minilex	0.18	0.125	2	4.4	2.2000	2.2000	
	0.125	0.025	4	4.4	2.3000	2.3000	
	0.26	0.125	1.5	4.4	2.2000	2.2000	
Leatheroid Paper	0.235	0.125	1.5	4.21	2.2000	2.2000	
	0.175	0.025	2	4.21	1.8000	1.8000	
	0.13	0.025	3	4.21	1.2000	1.2000	
Manila Paper	0.06	0.025	3	4.68	0.9000	0.9000	
	0.06	0.125	5	4.68	0.9000	0.9000	
	0.035	0.025	2	4.68	0.8000	0.8000	

Mean Absolute Error which is a very effective method for calculating error and which also takes into account the condemnation of data is of very less value at 0.0800 % proving MFNN a better model.

4.2 RBFN MODELING

4.2.1 DETERMINING PARAMETER VALUES

In RBFN modeling, we have 2 parameters to be varied while testing. One is number of centers in the hidden layer and the other being learning rate. In RBFN, we are using Fixed Centers selected at random strategy to select the centers. The number of centers have a large effect on the processing rate, complexity and time taking.

TABLE 7 CHANGE OF MEAN SQUARE ERROR AGAINST NUMBER OF CENTERS

Number of centers, m_1	**Mean Square Error, E_{tr}**
2	$7.74 * 10^{-5}$
4	$5.87 * 10^{-5}$
6	$2.35 * 10^{-5}$
7	$1.36 * 10^{-6}$
8	$5.09 * 10^{-6}$
9	$3.87 * 10^{-5}$

Learning rate is 0.7 and the number of iterations is 500. As we can see, MSE is least when number of centers is 7. As RBFN is different from MFNN, increasing the number of chosen centers doesn't mean decreasing the error.

TABLE 8 CHANGE OF MEAN SQUARE ERROR AGAINST LEARNING RATE

Learning rate η_2	**Mean Square Error E_{tr}**
0.40	$9.83 * 10^{-7}$
0.80	$7.74 * 10^{-7}$
1.20	$5.76 * 10^{-7}$
1.68	$8.64 * 10^{-7}$
1.75	$6.08 * 10^{-7}$
1.82	$4.05 * 10^{-7}$
1.89	$4.37 * 10^{-7}$
1.90	$4.57 * 10^{-7}$
1.915	$4.42 * 10^{-7}$
1.927	$4.01 * 10^{-7}$
1.936	$4.49 * 10^{-7}$
1.949	$4.48 * 10^{-7}$
1.959	$5.85 * 10^{-7}$
1.965	$5.98 * 10^{-7}$
1.99	$5.57 * 10^{-5}$

Number of centers is taken to be 7 and number of iterations is 500. When learning rate is 1.927, MSE is least with a value of $4.01 * 10^{-7}$ The two parameters in RBFN is number of centers and Learning rate. Change of MSE with respect to each variable is obtained.

From the above tables, it is derived that Mean Square Error is minimum when number of centers is 7 and has a value of $1.36 * 10^{-6}$

And also it has a minimum value when the learning rate is 1.927 and has the minimum value of $4.01 * 10^{-7}$. So, to obtain the least error during testing the parameters to be used is number of centers (m_1) = 7 and learning rate (η_2) is 1.927.

After the training the values of number of centers and learning rate are known. Now, the experimental and modeled data are to be compared and the results are to compared. The experimental data is perquisite and is available to compare.

TABLE 9 MODELED DATA AGAINST EXPERIMENTAL DATA USING RBFN MODEL

Insulating material	T, mm	T_1, mm	D,mm	$€_r$	Breakdown voltage(experimental)	Breakdown voltage(modeled)	E_{ts}, %
Lather Minilex	0.185	0.025	3	5.74	2.2000	2.1884	0.3091
	0.125	0.125	5		2.4000	2.3984	
	0.245	0.125	2		2.4000	2.4007	
Glass Cloth	0.155	0.125	2	4.97	2.3000	2.3000	
	0.155	0.025	4		2.3000	2.3093	
	0.195	0.125	1.5		2.2000	2.1989	
White Minilex	0.125	0.025	5	4.4	2.3000	2.3000	
	0.18	0.125	4		2.2000	2.2000	
	0.26	0.125	2		2.2000	2.2016	
Leatheroid Paper	0.175	0.025	3	4.21	1.8000	1.8004	
	0.13	0.025	1.5		1.2000	1.1951	
	0.235	0.125	3		2.2000	2.2000	
Manila Paper	0.035	0.025	4	4.68	0.8000	0.7996	
	0.06	0.125	3		0.9000	0.8036	
	0.06	0.025	5		0.9000	0.9096	

In RBFN also as in MFNN the Mean Absolute Error is found to be a very insignificant number at 0.3091 % . Although a bit higher than MFNN it also proved to a model worthy enough to be tried.

CONCLUSION

2 ANN models, MFNN and RBFN are both used to model the breakdown voltage and we got satisfying results in both the models. Firstly the parameters required for both the models are obtained and then the models are tested for data available during experimentation. Both the models prove to be effective although MFNN gave a better result when compared to RBFN. The errors in MFNN and RBFN are 0.0800% and 0.3091 % respectively. This, thus proves that the simulation models can very efficiently and accurately determine the breakdown Voltage under AC conditions. This model paves the way for usage of Artificial Neural Networks in a very large wide of applications.

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