Modeling of Breakdown voltage of Solid Insulating Materials Using Soft Computing Techniques

A THESIS SUBMITTED IN PARTIAL FULFILMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Power Control and Drives

By

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CERTIFICATE

This is to certify that the thesis entitled, **"Modeling of Breakdown voltage of solid Insulating Materials Using Soft computing Techniques"** submitted by Mr. **Sreedhar Kumar Teella** in partial fulfillment of the requirements for the award of Master of Technology Degree in electrical Engineering with specialization in **"Power Control and Drives"** during session 2011-13 at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.This work has not been submitted at other University/ Institute for the award of any degree or diploma.

Date:

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Sreedhar Kumar Teella

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ABSTRACT

The voids or cavities within the solid insulating material during manufacturing are potential sources of electrical trees which can lead to continuous degradation and breakdown of insulating material due to Partial Discharge (PD). To determine the suitability of use and acquire the data for the dimensioning of electrical insulation systems breakdown voltage of insulator should be determined. A major field of Artificial Neural Networks (ANN) and Least Square Support Vector Machine (LS-SVM) application is function estimation due to its useful features, they are, non-linearity and adaptively. In this project, the breakdown voltage due to PD in cavities for five insulating materials under AC conditions has been predicted as a function of different input parameters, such as, the insulating sample thickness 't,' the thickness of the void 't_1' diameter of the void 'd' and relative permittivity of materials ε_r by using two different models. The requisite training data are obtained from experimental studies performed on a Cylinder-Plane Electrode system. Different dimensioned voids are artificially created.. On completion of training, it is found that the ANN and LS-SVM models are capable of predicting the breakdown voltage $V_b = f(t, t_1, d, \varepsilon_r)$ very efficiently and with a small value of Mean Absolute Error. The system has been predicted using MATLAB.

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ABBREVIATIONS USED

ANN	Artificial Neural Networks
BPA	Back Propagation Algorithm
LS SVM	Least Square Support Vector Machine
MAE	Mean Absolute Error
MSE	Mean Square Error
SVM	Support Vector Machine

Variables USED

d	Diameter of void
ε_r	Relative Permittivity of insulation,
Etr	Mean Square Error
Ets	Mean Absolute Error
m	Number of iterations
N_h	Number of hidden neurons,
N_k	Number of neurons in the output layer
N_p	Number of patterns in the training set
N_s	Number of test patterns.
η_1	Learning rate parameter

t	Thickness Of sample
t_1	Thickness Of void,
V_{1p}	Experimental value of the breakdown voltage
$V_{2p}(m)$	Estimated value of the breakdown voltage after m^{th} iteration.
α_1	Momentum factor,

CHAPTER - 1

INTRODUCTION

1.1 INTRODUCTION

In modern times, industry, research laboratories and much power system are using high voltages for wide variety of applications. And with ever increasing demand of electricity, the power system is increased in both in size and complexities. To get the modern civilization such applications play the vital role. The generating capacities of power plants and transmission voltage are on the increase because of their inherent advantages.So it's very much essential to know the property of the insulation material for optimum solution in terms of cost and insulating capability. The power transfer capability of the system becomes four times if the transmission voltage is doubled and the line losses are also reduced. As a result of that system becomes a stronger and economical system. In our country India we already using 400 KV lines in operation and 800 KV lines are being planned. In big cities, for the distribution voltages we are using the conventional transmission voltages (110 kV–220 kV etc.) because of increased demand. A system (transmission, distribution, switchgear, insulator etc.) designed for 400 kV and above using conventional insulating materials is both bulky and expensive and, therefore, latest insulating materials are being investigated to bring down both the cost and space requirements. On insulating materials the electrically live conductors are supported and sufficient air clearances are provided to avoid flashover or short circuits between the live parts of the system and the ground. Sometimes, a live conductor is to be inserted in an insulating liquid to bring down the size of the container and at the same time provide sufficient insulation between the grounded container and live conductor.The quality of a solid insulation is adjudged in several ways, out of these, the breakdown voltage continues to evoke a lot of interest to the Electrical Engineers in general and High Voltage Engineers in particular. Hence, it is extremely important to develop solid insulating materials with excellent breakdown strength and any attempt at modelling the phenomenon with the presence of void would go a long way in assessing the insulation quality.

Under normal working conditions, insulating material gradually loses its dielectric strength and overvoltage capacity because of general aging as well as due to local defects appearing in the form of voids in the insulation during manufacture, particularly in extruded and cast type insulation. The quality of a solid insulation is judged in several ways, such as, hydrophobicity, electroluminescence, crystallization kinetics, hydrothermal, breakdown voltage etc.

1.2 BREAKDOWN OF SOLID INSULATING MATERIALS

The minimum voltage above which the insulator starts behaving like a conductor is known as the breakdown voltage of insulator. This defeats the purpose of insulator and hence it is of utmost importance to calculate the breakdown voltage of the insulator. Breakdown voltage is an intrinsic property of the insulator. It defines the maximum potential difference that can be applied across the insulator before the breakdown occurs and the insulator conducts. In an insulator a weakened path is happened within the insulator due to permanent molecular or physical changes by the sudden current. For inert gases found in lamps, breakdown voltage is also said to be the "striking voltage".

The alternate meaning of the term breakdown voltage specifically refers to the breakdown of the insulation of an electrical wire or any other electrical equipment. In such cases breakdown results in short circuit or blown fuse. Generally insulation breakdown occurs in high end voltage applications. This sometimes causes the opening of a breaker. “Breakdown” term is also applicable for the failure of solid or liquid insulating materials used inside transformers or capacitors in the electricity distribution system. Electrical breakdown also occurs across the suspended insulators in overhead power lines, within underground cables, or lines arcing to nearby tree branches. Under enough electrical stress electrical breakdown can occur within vacuum, solids, liquids or gases. However, the breakdown mechanisms are significantly different for each medium, particularly in different kinds of dielectric mediums. Electrical breakdown leads to catastrophic failure of the instruments causing immense losses.

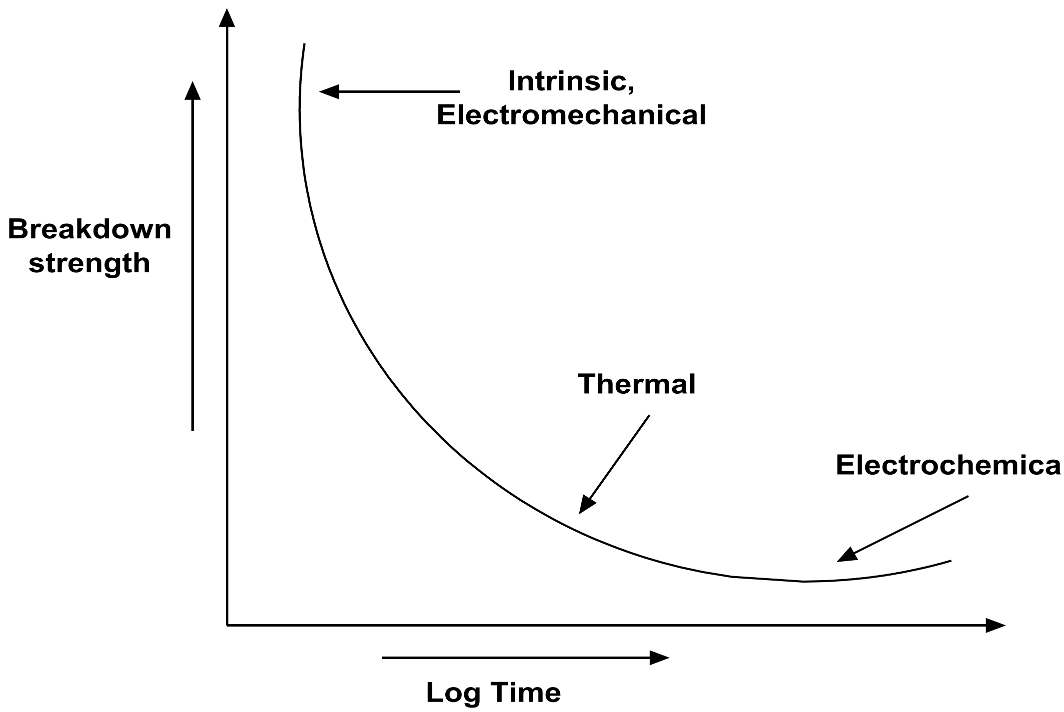


FIG.1.1 VARIATION OF BREAKDOWN STRENGTH AFTER THE APPLICATION OF VOLTAGE

Basically, breakdown of solid insulating materials occur due to intrinsic, electromechanical [3], multi-stress aging [4] or failure due to treeing and tracking, relative humidity [5], thermal, electrochemical, partial discharges (PD) in the cavities [6].

1.2.1 INTRINSIC BREAKDOWN

When voltages are applied only for short durations of the order of 10^{-8} sec the dielectric strength of a solid dielectric increases very rapidly to an upper limit called the intrinsic electric strength. By experimentally, this highest dielectric strength can be obtained only under the best experimental conditions when all extraneous influences have been isolated and the value depends only on the temperature and structure of the material. It is recorded that 15 MV*/cm* for polyvinyl-alcohol at -196^0C is the maximum electrical strength. The obtainable range of maximum strength is from 5MV/cm to 10MV/cm.

The presence of free electrons plays the vital role in intrinsic breakdown which are capable of migration through the lattice of the dielectric. Mostly, a few number of conduction elections are present in dielectrics, with some structural imperfections and small amounts of impurities. The molecules or impurity atoms or both act as traps for the conduction electrons up to certain ranges of electric fields also temperatures. When these exceed the range, electrons in addition to trapped electrons are produced, and those electrons participate in the conduction. Based on above principle, two types of Intrinsic breakdown mechanisms have been proposed and they are (a) Electronic Breakdown and (b) Avalanche or Streamer Breakdown.

ELECTRONIC BREAKDOWN

As mentioned earlier, intrinsic breakdown is assumed to be electronic in nature because it occurs in time of the order of 10^{-8}s.The initial density of conduction (free) electrons is very large, and electron-electron collision occur. When electric field is applied, electrons attain energy from the electric field it cross the forbidden energy gap from the valence to the conduction band. When this process is repeated continuously, more electrons become available in the band of conduction, obviously leading to breakdown.

AVALANCHE OR STREAMER BREAKDOWN

Avalanche or Streamer Breakdown is similar to breakdown in gases due to cumulative ionization. Free electrons gain sufficient energy above a certain electric field and cause liberation of electrons from the lattice atoms by collisions. Under certain uniform field conditions, if in the specimen the electrodes are embedded, breakdown will occur when an electron avalanche bridges the electrode gap.

An electron under the dielectric, starts from the cathode will penetrates towards the anode and during this motion profits energy from the field and loses it while collision. When the energy eared by an electron exceeds the lattice ionization potential and an additional electron will be liberated due to collision of the first electron. This process repeats itself and resulting in the formation of an electron avalanche. When the avalanche exceeds a certain critical size then breakdown will occur.

In practice, breakdown does not occur by the single formation of avalanche itself, but it occurs as a result of so many avalanches formed within the dielectric and extending step by step through the entire full thickness of the material. This can be easily demonstrated in a laboratory by applying an impulse voltage between point-plane electrodes with point embedded in a transparent solid dielectric such as Perspex.

1.2.2 ELECTROMECHANICAL BREAKDOWN

When solid dielectrics are kept in high electric field, failure occurs due to electrostatic forces which can exceed the mechanical compressive strength. If the thickness of the specimen is d_0 and it is compressed to a thickness d under an applied voltage V, then the electrically developed stress is in equilibrium if

$$\varepsilon_0 \varepsilon_r \frac{V^2}{2d^2} = Y \ln\left[\frac{d_0}{d}\right] \qquad (1.1)$$

Where Y is the Young's modulus

$$V^2 = d^2 \left[\frac{2Y}{\varepsilon_0 \varepsilon_r}\right] \ln\left[\frac{d_0}{d}\right] \qquad (1.2)$$

Usually, mechanical instability occurs when $d/d_0 = 0.6$ or $d_0/d = 1.67$.

Substituting this in Eq 1.2, the highest apparent electric stress before breakdown,

$$E_{\max} = \frac{V}{d_0} = 0.6\left[\frac{Y}{\varepsilon_0 \varepsilon_r}\right]^{\frac{1}{2}} \qquad (1.3)$$

The above equation is only approximate if Y depends on the mechanical stress. When the material is subjected to high stresses then the elasticity theory does not hold good and plastic deformation has to be considered.

1.2.3 BREAKDOWN DUE TO TREEING AND TRACKING

When a solid dielectric subjected to electrical stress for long time, then we can observe two kinds of visible markings in the dielectric materials. Given below:

(a) A conduction path presents across the insulation surface;

(b) A mechanism whereby leakage current passes through the conducting path finally leading to the formation of a spark. Insulation deterioration occurs as a result of these sparks.

The spark channels spreads during tracking, in the form of the branches of a tree is called treeing.

Consider a system of a solid dielectric having a conducting film and two electrodes on the surface. In practice, conducting film is formed due to moisture. When voltage applied, the film conduction starts that results in heat generation, and the surface starts becoming dry. Because of drying the conducting films separates and insulation failure occurs when carbonized tracks bridge the distance between layers of Bakelite, paper and similar dielectrics built of laminates.

On the other hand treeing occurs due to the erosion of materials at the spark tips. Result of Erosion s the roughening of the surfaces, and then becomes a source of contamination and dirt. This will cause increment in conductivity results either in the formation of a conducting path bridging the electrodes or in a mechanical failure of the dielectric.

1.2.4 THERMAL BREAKDOWN

The breakdown voltage of a solid dielectric increases with material thickness. But only up to a certain thickness this is true above which the heat generated in the dielectric due to the flow of current determines the conduction.

When an electric field is applied to a dielectric, a small amount of conduction current flows through the material. This current heats up the specimen as a result the temperature rises. The generated heat is transferred to the surrounding medium by conduction through the solid dielectric and by radiation from its outer surface.

This of great importance to engineers, as most of the insulation failures in power apparatus occur due to the thermal breakdown. An upper limit sets up by Thermal breakdown for increasing the breakdown voltage when the thickness of the insulation is increased. To loss angle and applied stress, hence heat generated is proportional to the frequency and hence thermal breakdown is more serious at high frequencies.

1.2.5 ELECTROCHEMICAL BREAKDOWN

Whenever cavities are formed in solid dielectrics, The dielectric strength in these solid specimen decreases. When the gas in the cavity breaks down, the surfaces of the specimen provide instantaneous anode and cathode. Some of the electrons dashing against the anode with sufficient energy shall break the chemical bond of the insulation. Similarly positive ions collides against the cathode may increase the surface temperature and produce local thermal stability. Similarly, chemical degradation may also occur from the active discharge products e.g. O_3, NO_2 etc. formed in air. The net effect of all these processes is a slow erosion of the material and a consequent reduction in the thickness of the specimen. Normally it is desired that with the ageing the dielectric strength decreases with time of voltage application or even without voltage application and in many cases; the decrease in dielectric strength (E_b) with time follows the following empirical relation

$$t E_b^n = \text{constant} \qquad (1.4)$$

Where the exponent *n* depends upon the dielectric material, the ambient temperature humidity and the quality of manufacture. This is the main reason why a.c. voltage testing is not recommended.

1.2.6 BREAKDOWN DUE TO INTERNAL DISCHARGES

Partial discharge is localized discharge process in which the distance between two electrodes is only partially bridged *i.e.*, the insulation between the electrodes is partially punctured. Partial discharges may originate directly at one of the electrodes or occur in a cavity in the dielectric.

The Partial Discharge study has been an important topic in the field of solid insulations, which is very much evident from the large number of literatures associated with it [7-16]. It is well known that voids within the solid insulating materials are the main sources of Partial Discharge (PD). These voids or cavities are essentially gas-filled and can result from many causes. If the Electrode voltage is raised to the point that the field within the cavity goes above the breakdown strength for the gas within the cavity, a PD can take place. The time taken for breakdown to occur depends on the applied voltage and the size of the cavity [17-18]. If an electron is present within the critical volume of the cavity, the electron is accelerated in the electric field and produces electron gain during collisions. Across the cavity a resistive channel is developed in few ns. At the end of the Partial discharge process, cavity field can be reduced to zero.

The breakdown voltage due to PD in cavities is a nonlinear phenomenon and the magnitude of this voltage is critical for judging the quality of the insulation for industrial purpose. However, it is extremely difficult to predict this voltage. Hence, it is necessary to resort to the process of modeling in order to predict the magnitude of this breakdown as a function of different variables. Some literatures can be found in which this voltage is predicted as a function of the thickness of the material [19-21] or as a function of position, size and shape of the void [17]. All these models described there are essentially conventional models, which are extremely rigid. However N.P. Kolev et.al. [22] have proposed an ANFIS structure for the prediction of the PDIV and PDEV using the experimental data from CIGRE Method II Electrode System provided in [23]. Similarly S. Ghosh et. al. [24-25] has proposed ANN models for predicting the PDIV and PDEV of insulation samples. Hence the rigidity in the conventional models has been appropriately taken care of by utilizing an ANFIS and ANN structure respectively.

The Soft Computing (SC) model on the other hand is highly flexible and a model can be improved simply by providing additional training data [26]. In addition, this kind of model can be developed more accurately in a shorter time. The SC is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision . The SC approach consists of several computing paradigms such as Artificial Neural Network (ANN), Fuzzy Logic (FL), approximate reasoning, derivative-free optimization methods, such as, Genetic Algorithms (GA) and Simulated Annealing (SA). These problems are usually imprecisely defined and require human intervention. Thus, the SC with their ability to incorporate human knowledge and adapt their knowledge base via optimization techniques plays an important role in the design of intelligent systems.

1.3 MOTIVATION

The SC model is an important and a flexible model in predicting the breakdown voltage due to PD in voids. To overcome the modern energy demand, it’s required highly complex and reliable power system from transmission to distribution unit, for that it’s very much essential to develop the better quality insulating material. One of the main reasons of degradation of insulating material is PD within the cavities. The breakdown voltage due to PD in cavities is a nonlinear phenomenon. The magnitude of this voltage is critical for judging the quality of the insulation for industrial purpose. However, it is extremely difficult to predict this voltage. Hence, it is necessary to resort to the process of modeling in order to predict the magnitude of this breakdown as a function of different variables. The use of this model in order to tackle this PD issue needs further exploration as the prediction of this breakdown voltage is so important industrially.

1.4 OBJECTIVES

Prediction of the breakdown voltage using Least Square Support Vector Machine (LS-SVM) and ANN structures, namely the Multilayer Feed forward Neural Network (MFNN) is the main objective of this project

1.5 THESIS OUTLINE

This thesis primarily attempts at modelling of PD initiated breakdown voltage of solid insulations by different SC techniques. The requisite experimental breakdown voltage data under AC conditions are generated in the laboratory with artificially created void and insulation dimensions using Cylinder-Plane Electrode System. This thesis contains five chapters; out of which Chapter 3 and Chapter 4 are the contributory Chapters.

Chapter 1 has reviewed the existing literatures on the breakdown voltage of the solid insulating materials in general while giving more emphasis on the breakdown due to PD in cavities. The advantage of using SC models over the Conventional models in solving the prediction of breakdown due to PD in cavities have been discussed thoroughly in this Chapter.

Chapter 2 has discussed the experimental set up for the Cylinder-Plane Electrode System used for obtaining the breakdown voltage data under AC conditions.

Chapter 3 has described a brief theory of the Multiforward Neural Network. This structure is then used to propose three breakdown voltage models using the experimental data obtained from the Cylinder-Plane Electrode System.

Chapter 4 has described the theory of another Soft Computing technique, namely, Least Square Support Vector Machine (LS-SVM). The model explored with this structure has used the experimental data obtained from the Cylinder Plane Electrode System.

Finally, **Chapter 5** summarises the main findings, draws certain conclusions arising out of the thesis work and compares of the MAE of the test data E_{ts} obtained from the various models of Chapter 3 and 4 using similar data to show the effectiveness of the SC techniques used here. At the end, it outlines the scope for the future research.

CHAPTER - 2

EXPERIMENTAL SETUP

2.1 INTRODUCTION

As mentioned in Chapter 1, the primary objective of this thesis work is to develop different soft computing models, which will be able to predict the breakdown voltage of solid insulating materials due to PD in cavities. For modelling purpose, breakdown voltage data are generated experimentally on application of AC power frequency voltages. The chapter 2 covers total experimental procedure for predicting the experimental breakdown voltage of five insulating materials namely, White Minilex, Leatheroid Paper, Glass Cloth, Manila paper and Lather Minilex

2.2 EXPERIMENTAL PROCEDURE

The procedure adopted for the generation of experimental value of the breakdown voltage is as follows:

2.2.1 SAMPLE PREPARATION

The samples are prepared from five commercially available insulation sheets, namely White Minilex Paper, Leatheroid Paper, Lather Minilex, Glass Cloth and Manila paper of different thicknesses. The variation of thicknesses is as follows:

White Minilex Paper:	0.26 mm, 0.18 mm and 0.125 mm.
Leatherite Paper:	0.235 mm, 0.175 mm and 0.13 mm.
Lather Minilex:	0.245 mm, 0.185 mm and 0.12 mm.
Glass Cloth:	0.195 mm and 0.155 mm.
Manila paper:	0.06 mm and 0.035 mm.

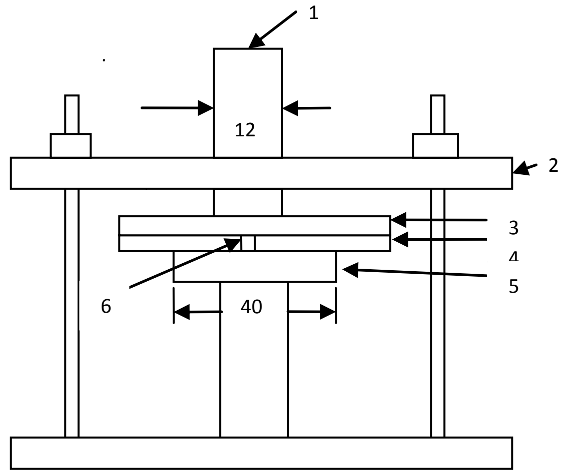
It was ensured that the surfaces of the insulating sample were cleaned and dry, since the contamination on the insulating specimen or absorption of moisture may affect the breakdown voltage.

2.2.2 CREATION OF VOID

The voids of different sizes are artificially created by means of a spacer made up of Kapton film, with a circular punched hole at the canter. The diameter of the voids is 1.5 mm, 2 mm, 3 mm, 4 mm and 5 mm. The thickness of the Kapton spacer used is of 0.025 mm and 0.125 mm. Thus, the sizes of the void, that is, the volume of air space, depends on a typical diameter of the punched hole and thickness of the spacer. Utmost care has been taken to maintain the surface smoothness of the holes whish are punched.

2.2.3 ELECTRODE GEOMETRY

The Cylinder-Plane electrode system as shown in the Figure 1 is used for breakdown voltage measurements. The electrodes, both high voltage and low voltage, were made of brass. They were polished, buffed and cleaned with ethanol before the start of the experiment. And then contact surfaces of electrodes are cleaned by ethanol between two consecutive applications of voltage to avoid contaminations that may arise due to application of voltage. Sufficient care had been taken to keep the electrode surfaces untouched. The insulation sample is sandwiched between the electrodes with the help of insulating supports as shown.



1. High Voltage Electrode 2. Insulating Supports with nuts and bolts 3. Insulation sample under test. 4. Spacer 5.Ground electrode 6. Cavity (All dimensions in mm)

Fig.2.1. Cylinder-Plane Electrode System used for Breakdown Voltage Measurement

2.2.4 MEASUREMENT OF BREAKDOWN VOLTAGE

The 50 Hz AC voltage applied to the insulating samples was obtained from a 40 kV AC/DC Series Hipot Tester (MODEL HD 100) manufactured by Hipotronics, USA. The voltage is raised in steps of 200V and held constant for a period of 30 sin each level until the breakdown occurs. The total time from the application of voltage to the instant of breakdown were noted down. Five data points were obtained for a particular type of sample and void condition and the mean value of the voltage is taken for modeling. All the tests were carried out in air at room temperature and atmospheric pressure. The breakdown data obtained are then corrected for atmospheric condition before being used for modeling.

2.2.5 MEASUREMENT OF RELATIVE PERMITIVITY OF SOLID INSULATING MATERIALS

To measure the relative permittivity, 12mm diameter of the insulating samples was silver coated at the identical zone on both the sides. The silver coated samples were then pressed between the two brass sample holder electrodes of the Dielectric Interface of an Impedance Gain / Phase analyzer (Solartron, U.K.). An ac voltage of 0.1 V (r.m.s) at 50 Hz was applied to the samples from the Impedance Gain / Phase Analyzer and relative permittivity values of the insulating materials are recorded. Table I shows the measured values of the relative permittivity of materials at 50 Hz frequency.

TABLE.2.1 RELATIVE PERMITTIVITY AGAINST MATERIALS

Insulating Materials	ε_r
White Minilex	4.4
Leatheroid paper	4.21
Glass Cloth	4.97
Manila Paper	4.68
Lather Minilex	5.74

2.3 SUMMARY

This Chapter has provided the groundwork for prediction of the breakdown voltage of five insulating materials namely White Minilex, Leatheroid Paper, Glass Cloth, Manila paper and Lather Minilex due to PD in cavities by carrying out experimental data generation with the help of cylinder-plane electrode system.

CHAPTER - 3

MULTI-LAYER FEED FORWARD

NEURAL NETWORK THEORY

3.1 INTRODUCTION

The work on Neural Networks was inspired from the way the human brain operates. It has the ability to organize its structural constituents known as neurons, so as to carry out certain computations (e.g. perception, pattern recognition and motor control) much faster than the fastest digital computer in existence today. This ability of our brain has been utilized into processing units to further excel in the field of artificial intelligence. The theory of modern neural networks began by the pioneering works done by Pitts (a Mathematician) and McCulloh Pitt(a psychiatrist) in 1943.

3.2 ARTIFICIAL NEURAL NETWORKS

It is a mathematical or a computational model derived from the aforementioned human brain. Neural networks got great reputation in recent times for non-linear computations and modeling of complex relationships between inputs and outputs.

In artificial neural networks, there is a function f(x) comprising of various other functions $g_i(x)$, which further is a composition of other functions. This is generally pictorially represented with the help of arrows depicting the dependency of different variables on each other. The relation can be given as:

$$F(X) = K\left(\sum W_i g_i(X)\right) \qquad (3.1)$$

Where W_i is weights provided to various functions and K is known as activation function.

3.3 THEORY OF MFNN

Two ANN structures used for modeling of the breakdown voltages are the Multilayer Feed forward Neural Network (MFNN) and the Radial Basis Function Network (RBFN). The following presents briefly outline of the two networks used here.

3.3.1 INTRODUCTION

The MFNN used here consists of three layers they are input, output and, hidden layer and output layer as shown in figure no 3.1. The Input layer of MFNN consists of different number of inputs variables according to the modeling of MFNN. The input variables are thickness of the material, void diameter, void depth and permittivity of the insulating material. The number of output neuron is decided by the number of estimated parameters; therefore in this model only one output neuron is taken corresponding to breakdown voltage V_b.

The Back Propagation Algorithm (BPA) is used to give training to the network. Equation (3.1) represents sigmoid function and is by is used as the activation function for all the neurons except for those in the input layer.

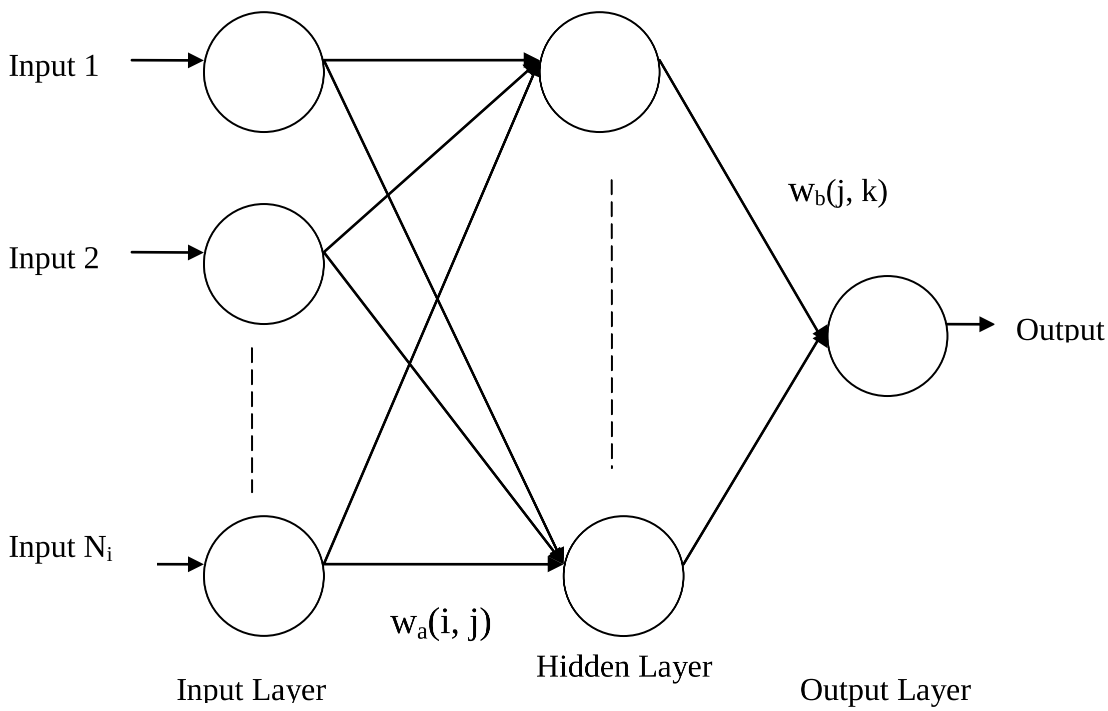


Fig. 3.2. Multilayer feed forward Neural Network

The input layer consists of N_i neurons corresponding to the N_i inputs. The number of output neurons is decided by the number of predicted parameters. The Back Propagation

Algorithm (BPA) is used to train the network. The sigmoidal function represented by equation (1) is used as the activation function for all the neurons except for those in the input layer.

$$S(x) = 1 / (1+e^{-x}) \qquad (3.2)$$

3.3.2 CHOICE OF HIDDEN NEURONS

The choice of optimal number of hidden neurons ($N_{h)}$ selection of number of hidden neurons is the most important aspect in the MFNN designing. There are many methods in deciding the value of $N_{h.}$ Simon Haykin has specified that N_h should lie between 2 and ∞. Hecht-Nielsen uses ANN interpretation of Kolmogorov's theorem to arrive at the upper bound on the N_h for a single hidden layer network as $2(N_i+1)$, where N_i is the number of input neurons. A high value of N_h might reduce the training error related with the MFNN, but the computational complexity and time will increase.

NORMALIZATION OF INPUT-OUTPUT DATA

The input and the output data are normalized before being processed in the network. In this scheme, the input and output vector components maximum values are determined as follows:

$$n_{i,\max} = \max(n_i(p)) \quad p = 1,\ldots\ldots, N_p, \ i = 1,\ldots\ldots, N_i \qquad (3.3)$$

Where N_p is the number of training set patterns

$$o_{k,\max} = \max(o_k(p)) \quad p = 1,\ldots\ldots N_p, \ i = 1,\ldots\ldots N_k \qquad (3.4)$$

Where N_k is the number of neurons in the output layer, that is, the number of

predicted parameters.

Normalized by these maximum values, the input and output variables are obtained as follows:

$$n_{i,nor}(p) = \frac{n_i(p)}{n_{i,\max}} \quad p = 1,\ldots\ldots, N_p, \ i = 1,\ldots\ldots, N_i \qquad (3.5)$$

and

$$o_{k,nor}(p) = \frac{o_k(p)}{o_{k,\max}} \qquad p = 1, \ldots\ldots N_p,\ i = 1,\ldots\ldots N_k \qquad (3.6)$$

After normalization, the input and output variables lie in the range of 0 to 1.

3.3.3 CHOICE OF ANN PARAMETERS

The learning rate, η_1 and the momentum factor, α_1 have a very significant effect on the BPA learning speed. The BPA provides an approximation to the trajectory in the weight space computed by the method of steepest descent method. If the value of η_1 is taken very small, that causes in slow rate of learning, where as if the value of η_1 taken too large in order to speed up the rate of learning, the MFNN may become unstable. Addition of momentum factor α_1 is a simple method of increasing the rate of learning without making the MFNN unstable is by adding the. Preferably, the values of η_1 and α_1 should lie between 0 and 1.

3.3.4 WEIGHT UPDATE EQUATIONS

The weights between the hidden layer and the output layer are updated based on the equation (3.7) as follows:

$$w_b(j, k, m+1) = w_b(j, k, m) + \eta_1 * \delta_k(m) * S_b(j) + \alpha_1 [w_b(j, k, m) - w_b(j, k, m-1)] \qquad (3.7)$$

Where m is the number of iteration, j = 1 …. N_h and k = 1…. N_k. $\delta_k(m)$ is the error of the k^{th} output at the m^{th} iteration. the output from the hidden layer is $S_b(j)$.

Similarly, the weights between the hidden layer and the input layer are updated as follows:

$$w_a(i, j, m+1) = w_a(i, j, m) + \eta_1 * \delta_j(m) * S_a(i) + \alpha_1 [(w_a(i, j, m) - w_a(i, j, m-1)] \qquad (3.8)$$

Where i varies from 1 to N_i . Network has N_i inputs, $\delta_j(m)$ is the error for the j^{th} output after the m^{th} iteration and $S_a(i)$ is the output from the first layer. The $\delta_k(m)$ in equation (3.7) and $\delta_j(m)$ in equation (3.8) are related as

$$\delta_j(m) = \sum_{k=1}^{K} \delta_k(m) * w_b(j, k, m) \quad (3.9)$$

3.3.5 EVALUATION CRETERIA

The Mean Square Error Etr of training data after the m^{th} iteration is defined as

$$E_{tr}(m) = (1/N_p) * [\sum_{p=1}^{Np} \{V_{1p} - V_{2p}(m)\}^2] \quad (3.10)$$

Where V_{1p} is the experimental value of the breakdown voltage.V_{2p} (m) is the estimated value of the breakdown voltage after m^{th} iteration. The training comes to stop when the least value of E_{tr} has been obtained and this value does not change much with the number of iterations.

3.3.6 MEAN ABSOLUTE ERROR

The Mean Absolute Error Ets is a good performance measure for judging the accuracy of the MFNN System. The E_{tr} tells how well the network has adopted to fit the training data only, even if the data are contaminated. The E_{ts} indicates how well a trained network behaves on a new data set not included in the training set. The value of E_{ts} is calculated based on the least value of E_{tr}. The E_{ts} for the test data expressed in percentage is given by

$$E_{ts} = (1/N_S) * [\sum_{s=1}^{Ns} | (V_{4s} - V_{3s}) | / V_{3s}] * 100 \quad (3.11)$$

Where V_{3s} is the experimental value of the breakdown voltage taken for testing purpose, V_{4s} is the estimated value of the breakdown voltage after the test input data is passed through the trained network and N_s is the number of test patterns.

3.4 MODELING OF BREAKDOWN VOLTAGE USING MFNN

This section details the attempt at modeling of breakdown voltage due to PD in voids under AC conditions using MFNN. These models predicts the breakdown voltages as a function of different void parameters, namely, void diameter and void depth and insulation sheet thickness both under AC conditions. The network is provided with both input data and desired response; and is trained in a supervised fashion using the back propagation algorithm. The back propagation algorithm performs the input to output mapping by making weight connection adjustment following the discrepancy between the computed output value and the desired output response. The training phase is completed after a series of iterations. In each iteration, output is compared with the desired response and a match is obtained. Figure 3.shows the flowchart for the MFNN.

In order to predict the breakdown voltage under AC conditions a software program has been developed in MATLAB 7.1 to solve equations (3.1) to (3.11). The program is suitably modified for different models based on input – output parameters.

3.5 RESULTS AND DISCUSSION

In this study, the optimum values of network parameters are obtained based on Mean Square Error E_{tr} for the training patterns. The network is trained in a sequential mode. In applying the BPA for the proposed prediction work the following key issues are addressed

1. Network parameters
2. Number of hidden neurons
3. Number of iterations

The equations of MFNN model have been used to predict the breakdown voltage of White Minilex, Leatheroid paper, Glass cloth, Lather minilex and Manila paper under AC condition in the presence of voids. Figure 3.2 has been derived from Figure 3.1 by substituting N_i=4. The inputs are the thickness of the insulating material, void depth, void diameter and relative permittivity of the insulating materials while the output is the breakdown voltage.

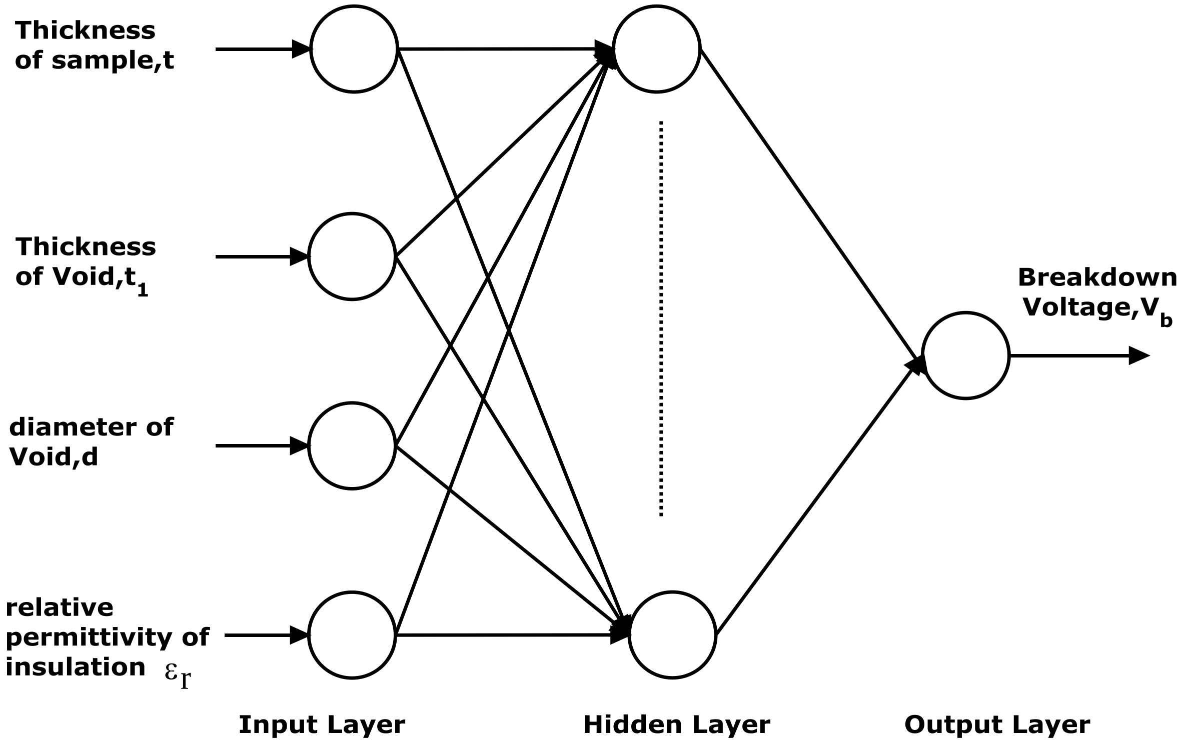


FIG.3.3. MFNN STRUCTURE

With the help of 130 sets of experimental input-output patterns, the proposed modeling are carried out; 115 sets of five insulating materials (27 sets of White Minilex, 27 sets of Leatheroid Paper, 17 sets of Glass Cloth, 17 sets of Manila Paper and 27 sets of Lather Minilex) are chosen input-output patterns used for training both networks and for testing purpose the remaining 15 sets of the five materials are used. The software programs developed are used for implementation using MATLAB version 9.1.

Table 3.1: **Variation of E_{tr} with η_1 (N_h = 5, α_1 = 0.8, Number of iterations = 100)**

η_1	E_{tr}
0.2	$1.5896*10^{-5}$
0.5	$7.5657*10^{-7}$
0.6	$4.3204*10^{-7}$

0.7	$2.3203*10^{-7}$
0.8	$1.4353*10^{-7}$
0.9	$9.2787*10^{-8}$
0.99	**$6.4728*10^{-8}$**

Table 3.2: Variation of E_{tr} with $\alpha 1$ (N_h= 2, η_1 = 0.99, Number of iterations = 100)

α_1	E_{tr}
0.1	$3.100*10^{-3}$
0.3	$2.400*10^{-3}$
0.5	$1.700*10^{-3}$
0.6	$1.300*10^{-3}$
0.65	$1.000*10^{-3}$
0.7	$7.539*10^{-4}$
0.75	$4.906*10^{-4}$
0.8	$2.544*10^{-4}$
0.85	$9.823*10^{-5}$
0.86	**$9.218*10^{-5}$**
0.87	$9.894*10^{-5}$

Table 3.3: Variation of E_{tr} with N_h (η_1 = 0.99, α_1 = 0.86, Number of iterations = 100)

N_h	E_{tr}
2	$2.1301*10^{-4}$
3	$2.0679*10^{-4}$
4	$\mathbf{1.3522*10^{-4}}$
5	$9.2183*10^{-4}$

Finally, the breakdown voltage V = f (t, d) for the test data are calculated by simply passing the input data in the forward path of the network and using the updated weights of the network. Table 3.4 shows the comparison of the experimental and the modeled breakdown voltage using this model after 100 iterations**.**

Table 3.4: Comparison of the experimental and modeled breakdown voltage

Insulating Material	t(mm)	t_1(mm)	d(mm)	ϵ_r	Breakdown Voltage (kV) Experimental	Breakdown Voltage (kV) Modeled	MAE of the Test data E_{ts} (%)
White Minilex	0.26	0.025	3	4.4	5.2	5.1339	
	0.125	0.125	2	4.4	6.2	6.1212	
	0.18	0.025	1.5	4.4	4.3	4.2453	
Leatherite Paper	0.13	0.125	5	4.21	3.3	3.2529	
	0.175	0.125	4	4.21	2.3	2.2672	
	0.235	0.025	2	4.21	2.6	2.5669	

Glass Cloth	0.195	0.025	5	4.97	3.8	3.7458	0.05968
	0.195	0.025	3	4.97	7.2	7.0972	
	0.155	0.125	1.5	4.97	7.4	7.3059	
Manila Paper	0.035	0.125	3	4.68	0.6	0.5924	
	0.06	0.025	2	4.68	1.2	1.1847	
	0.06	0.125	4	4.68	1.4	1.3844	
Lather Minilex	0.245	0.025	5	5.74	1.6	1.5797	
	0.185	0.125	1.5	5.74	8.3	8.1944	
	0.125	0.025	2	5.74	8.8	8.6744	

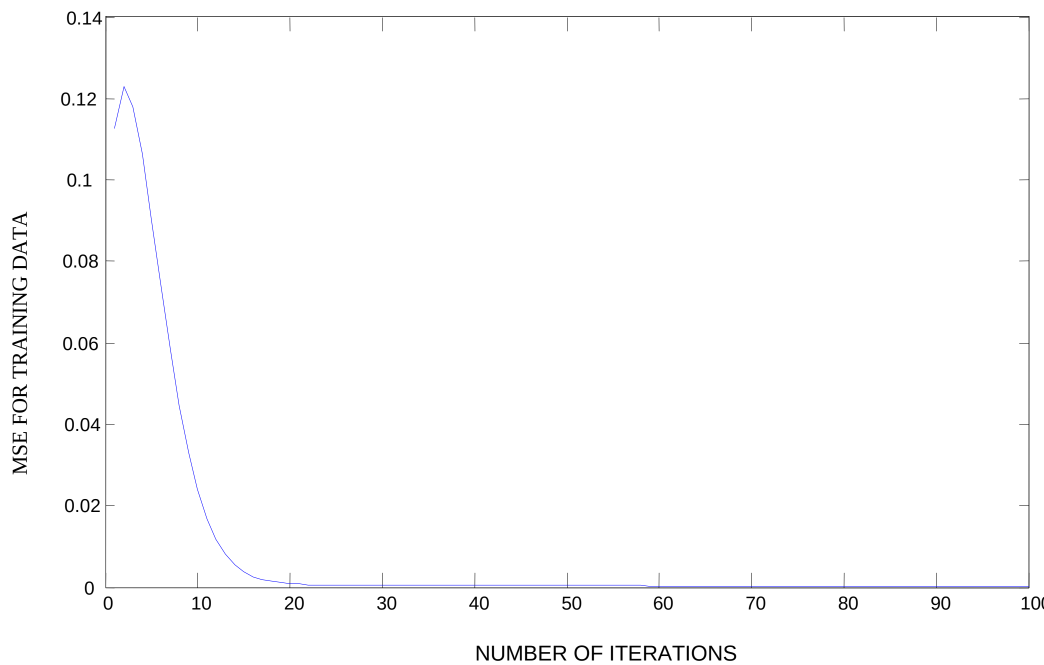


Fig. 3.4 .E_{tr} of the training data as a function of Number of iterations

CHAPTER - 4

LEAST SQUARE SUPPORT VECTOR MACHINE

4.1 INTRODUCTION

The Support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and pattern reorganization, used for classification , regression analysis. The basic SVM takes input data sets and predicts, for each input given. Given a set of examples for training, each belongs to one of two categories; a SVM algorithm constructs a model that assigns new examples into one category or the other.

A support vector machine constructs a hyper plane or set of hyper planes in a high dimensional space, which can be used for data classification and regression. A good separation is acquired by the hyper plane that has the largest distance to the nearest training data point of any class .In general the larger the margin the lower the generalization error of the classifier.

SVM has attracted attention and gained extensive application.. Not only LS-SVM has been used for classification in various areas of pattern recognition [36] but also it has handled regression problems successfully [37].

LS-SVM has additional advantage than SVM. In LS-SVM, a set of only linear equation (Linear programming) is solved which is much easier and computationally more simple. Thus, it is very attractive for the modeling breakdown voltage on insulator.

In this paper, by LS-SVM model we are predicting the PD breakdown voltage of five insulating materials under AC condition, with a cylindrical plane electrode system. LS-SVM techniques have been exploited for breakdown voltage estimation under artificially created air cavities of different size at the center of the sample.

BASICS OF SVMS

The SVMs are a new technique suitable for binary classification problems. Like classical techniques. This function is neither linear nor parametric. The formal basics of SVMs will be subsequently explained.in linear SVM case of a, where the score function is still linear and parametric. After that the SVM will be made non-linear and non-parametric by introducing a kernel. As explained further, it is this characteristic that makes SVMs a useful tool for credit scoring, in the case the distribution assumptions about available input data cannot be made or their relation to the PD is non-monotone.

4.2. LEAST SQUARE SUPPORT VECTOR MACHINE

The formulation of LS-SVM is introduced as follows. Consider a given training set $\{x_i, y_i\}, i=1,2,...,N,$ with input data $x_i \in R$ and output data $y_i = R$ .The following regression model can be constructed by using non-linear mapping function $\phi(\cdot)$[38].

$$y = w^T \phi(x) + b \tag{4.1}$$

Where weight vector given as *w* and bias term as *b*. in SVM, cost function C is to be reduced, as

$$\min C(w,e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{N} e_i^2 \tag{4.2}$$

Subject to equality constraints

$$y = w^T \phi(x_i) + b + e_i,\ i = 1,2,....,N \tag{4.3}$$

The first part of this cost function is a weight decay which is used to regularize weight sizes. Due to this regularization, the weights converge to nearer value. Large weights deteriorate the generalization ability of the LS-SVM because they can cause excessive variance. The second part of (4.2) is the regression error for all training data. The parameter γ, which has to be optimized. Lagrange function is used to solve this problem, and is given as

$$L(w,b,e,\alpha) = \frac{1}{2} \|w\|^2 + \gamma \sum_{i=1}^{N} e_i^2 - \sum_{i=1} \alpha_i \left\{ w^T \phi(x_i) + b + e_i - y_i \right\} \tag{4.4}$$

Where α_i are the Lagrange multipliers the solution of (4.4) can be obtained by partially differentiating with respect to w, b, e_i and α_i

Then

$$w = \sum_{i=1}^{N} \alpha_i \phi(x_i) = \sum_{i=1}^{N} \gamma e_i \phi(x_i) \tag{4.5}$$

A positive Kernel is used as follows:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{4.6}$$

An important result of this approach is that the weights (w) can be written as linear combination of the Lagrange multipliers with the corresponding data training (x_i). Putting the result of (4.5) into (4.1), the following result is obtained as

$$y = \sum_{i=1}^{N} \alpha_i \phi(x_i)^T \phi(x) + b \tag{4.7}$$

For a point y_i to evaluate it is:

$$y_i = \sum_{i=1}^{N} \alpha_i \phi(x_i)^T \phi(x_j) + b \tag{4.8}$$

from solving a set of linear equations vector follows as

$$A \begin{bmatrix} \alpha \\ b \end{bmatrix} = \begin{bmatrix} y \\ 0 \end{bmatrix} \tag{4.9}$$

Where A is a square matrix given by

$$A = \begin{bmatrix} K + \frac{I}{\gamma} & 1_N \\ 1_N^T & 0 \end{bmatrix} \tag{4.10}$$

Where K denotes the kernel matrix with *ij*th element in (4.5) and I denotes the identity matrix $N \times N$, $1_N = [1\ 1\ 1 \ldots.. 1]^T$. Hence the solution is given by:

$$\begin{bmatrix} \alpha \\ b \end{bmatrix} = A^{-1} \begin{bmatrix} y \\ 0 \end{bmatrix} \tag{4.11}$$

All Lagrange multipliers (the support vectors) are integers, that means all training objects participates to the solution and it can be seen from (4.10) to (4.11). In contrast with standard SVM the LS-SVM solution is generally not sparse.

Depends on the number of training data set an iterative solver such as conjugate gradients methods (for large data set) can be used or direct solvers, in both cases with numerically reliable methods.

In application involving nonlinear regression it is not enough to change the inner product of $\left\langle \phi(x_i), \phi(x_j) \right\rangle$ (4.7) by a kernel function and the ijth element of matrix K equals to (4.5).

This show to the nonlinear regression function as follows

$$y = \sum_{i=1}^{N} \alpha_i K(x_i, x) + b \tag{4.12}$$

For a point x_j to be evaluated, it is:

$$y_j = \sum_{i}^{N} \alpha_i K(x_i, x_j) + b \tag{4.13}$$

For LS-SVM, there are lot of kernel functions they are defined by:

$$K(x_i, x_j) = \exp\left(-\frac{\| x_i - x_j \|^2}{\sigma_{sv}^2} \right) \tag{4.14}$$

$$K(x_i, x_j) = \left(x_i^T x_j + t \right)^d \tag{4.15}$$

Where d is the polynomial degree and σ_{sv}^2 is the squared variance of the Gaussian function, it should be optimized by user to obtained support vector. For α of the RBF kernel and polynomial kernel is d, in order to achieve a good generalization model it is very important to select model of the tuning parameters, as a combination of the regularization constant γ.

4.3 MEAN ABSOLUTE ERROR

For judging the accuracy of the LS-SVM the mean absolute error is good performance measure. Even if the data are contaminated the E_{tr} tells how well the network has adopted to fit the training data only. On the other hand, the E_{ts} indicates how well a trained network behaves on a new data set not include in the training set.

The E_{ts} for the test data expressed in percentage is given by

$$E_{ts} = \left(1/S\right) \times \left(\sum_{s=1}^{S} \left|\left(V_{b4s} - V_{b3s}\right)\right| \Big/ V_{b3s} \right) \times 100 \qquad (4.17)$$

where S is the number of testing patterns, V_{b4s} is the modeled value of the breakdown voltage after the testing input data are passed through the trained network and V_{b3s} is the experimental value of the breakdown voltage taken for the testing purpose.

4.4 RESULTS AND DISCUSSIONS

Table 4.1.Variation of E_{tr} with m (η_1 = 0.99, α_1 = 0.86)

No .of iterations (m)	Mean square error (E_{tr})
100	9.65×10^{-4}
200	6.82×10^{-4}
300	9.65×10^{-4}
400	9.65×10^{-4}
500	9.65×10^{-4}
600	9.65×10^{-4}
700	9.65×10^{-4}

TABLE 4.2 COMPARISONS OFTHE EXPERIMENTAL AND THE MODELLED DATA

Insulating material	**t, mm**	**t_1, mm**	**d, mm**	ε_r	**Breakdown voltage, kV (experimental)**	**Breakdown voltage, kV (modeled)**	**E_{ts}, %**
White Minilex	0.26	0.025	3	4.4	2.2	2.2000	0.0407
	0.125	00125	2	4.4	2.3	2.3000	
	0.18	0.025	1.5	4.4	2.2	2.2000	
Leatheroid Paper	0.13	0.125	5	4.21	1.2	1.2000	
	0.175	0.125	4	4.21	1.8	1.8000	
	0.235	0.025	2	4.21	2.2	2.2000	
Glass Cloth	0.195	0.025	5	4.97	2.2	2.2000	
	0.155	0.025	3	4.97	2.2	2.2000	
	0.155	0.125	1.5	4.97	2.3	2.3000	
Manila Paper	0.035	0.125	3	4.68	0.8	0.8000	
	0.06	0.025	2	4.68	0.9	0.9000	
	0.06	0.125	4	4.68	0.8	0.8000	
Lather Minilex	0.245	0.025	5	5.74	2.2	2.2000	
	0.185	0.125	1.5	5.74	2.4	2.3861	
	0.125	0.025	2	5.74	2.4	2.3861	

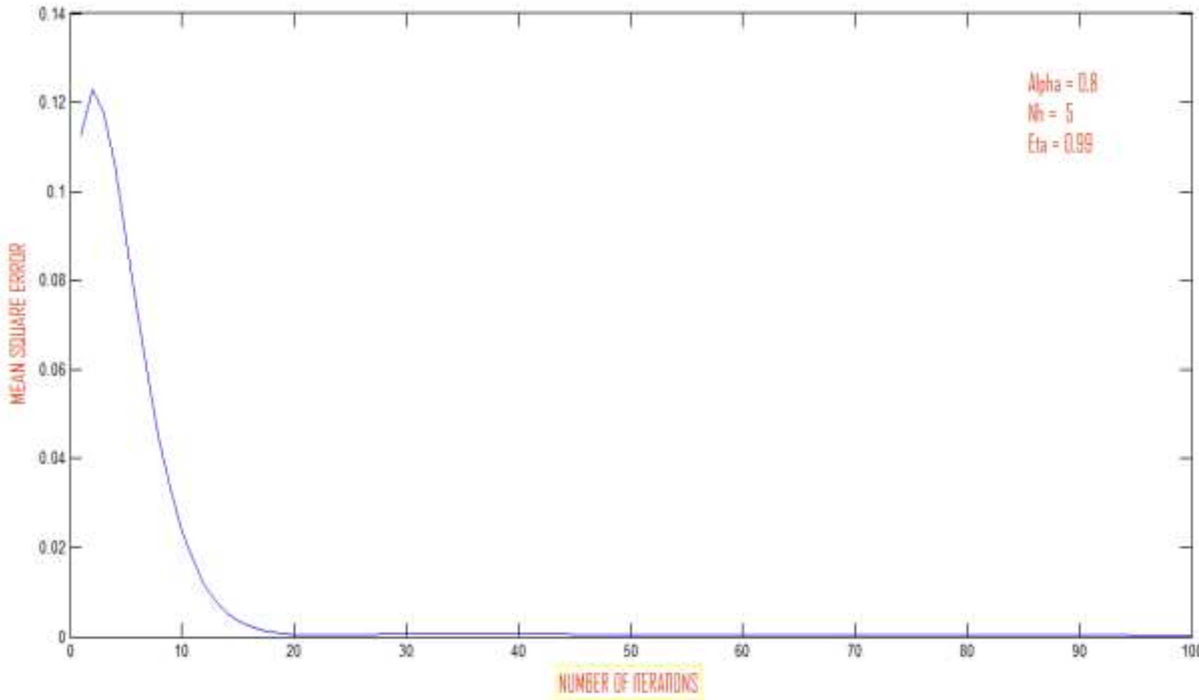


Fig 4.1.**E_{tr} of the training data as a function of Number of iterations**

Finally, the function $V_b = f\left(t, t_1, d, \varepsilon_r\right)$ for the test data are calculated by simply passing the input data in the LS-SVM and using α and b for the kernel parameter. Table 4.2 shows a comparison of the experimental and modeled data test data using LS-SVM model after 10000 iterations.

From Table 4.2 it may be seen that the measured values and the modeled values are almost same and E_{ts} is found to be 0.0407%, thus shows the effectiveness of the proposed breakdown voltage modeling.

CHAPTER - 5

CONCLUSION

5.1 INTRODUCTION

This thesis work deals with the modeling using soft computing techniques. Detailed discussions have been presented in different chapters and conclusions have been made at the end of each chapter. Therefore, this concluding chapter is devoted to the summarization of the main contributions of the work and arriving at general conclusions.

5.2 SUMMARY

The major studies reported in this thesis pertain to:

1. The experimental procedure adopted in the laboratory in order to generate breakdown voltage data under AC conditions has described in Chapter 2. The experimental data are obtained with artificially created voids of various dimensions and with different insulation thicknesses of five common insulating materials, namely, White Minilex Paper, Leatheroid Paper, Glass Cloth, Lather Minilex and Manila Paper using Cylinder-Plane Electrode System.

2. In Chapter 3, MFNN model is proposed for the prediction of the breakdown voltage of solid insulating materials due to PD in cavities as a function of four input parameters. The Mean Square Error E_{tr} for the training patterns and the Mean Absolute Error E_{ts} for the testing patterns has been calculated.

3. In Chapter 4 attempt has been made to use LS-SVM model for the purpose of breakdown voltage prediction. Here also the Mean Square Error for the training patterns and the Mean Absolute Error for the testing patterns is calculated.

5.3 CONCLUSIONS

Before the thesis draws to a close, the general conclusions that emerge out from this work are highlighted. These conclusions are mainly arrived at based on the performance and the capabilities of the soft computing techniques presented here for breakdown voltage modeling. Based on such a critical appraisal, the current state of technology, its promises and pitfalls are charted. This finally leads to an outline of the future directions for research and development efforts in this subject area.

The main conclusions drawn are:

1. The combination of parameters for the best results in each of the models has been identified. A comparison of modeled and experimental results indicates that Soft Computing techniques can be very well employed for estimation of breakdown voltage as a function of insulation and void dimensions.

2. Tables 5.1 depict the comparison between the MSE for the training data E_{tr} obtained from two different models using different techniques. As may be seen from Table 5.1 that LS-SVM model is efficient than MFNN model. This can be concluded from the values of E_{tr}.

TABLE 5.1 COMPARISON OF E_{tr} OF TWO MODELS BASED ON THE SC TECHNIQUES

Model	$\mathbf{E_{tr}}$
MFNN	0.15×10^{-3}
LS-SVM	0.12×10^{-4}

3. Tables 5.2 depict the comparison between the MAE for the test data E_{ts} obtained from two different models using different techniques. As may be seen from Table 5.2 that in LS-SVM model the value of E_{ts} is less compared to MFNN model after the training is over.

5.2 COMPARISON OF E_{ts} OF TWO MODELS BASED ON THE SC TECHNIQUES

Model	$\mathbf{E_{ts}}$
MFNN	0.05968 %
LS-SVM	0.0407 %

Thus, this work is successful in applying SC techniques for prediction of breakdown voltages under AC conditions as a function of insulation and void parameters.

As a future work a more generalization of the models to be developed, it would be interesting to include more parameters responsible for breakdown of insulating materials.

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