A.C. POLLUTION FLASHOVER OF COMPOSITE INSULATION AT HIGH ALTITUDE TRANSMISSION

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(With Specialization in Power System Engineering)

By

RISHI KUMAR SHARMA

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE-247 667 (INDIA)

JUNE, 2011

INDIAN INSTITUTE OF TECHNOLOGY, ROORKEE

CANDIDATE'S DECLARATION

I hereby declare that the work that is being presented in this dissertation report entitled **"A.C. Pollution Flashover of Composite Insulation at High Altitude Transmission"** submitted in partial fulfillment of the requirements for the award of the degree of **Master of Technology** in **Electrical Engineering** with specialization in **"Power System Engineering"**, submitted in the **Department of Electrical Engineering, Indian Institute of Technology Roorkee,** Roorkee, is an authentic record of my own work carried out, under the guidance of, **Dr. E. Fernandez,** Associate Professor, Department of Electrical Engineering, Indian Institute of Technology, Roorkee.

I have not submitted the matter embodied in this dissertation report in any other degree.

Date: 30-06-2011

Place: Roorkee

R.K.Sharma

(RISHI KUMAR SHARMA)

Enrollment No. 09529016

CERTIFICATE

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

EFernandez

Dr. E. Fernandez

Associate Professor

Department of Electrical Engineering

Indian Institute of Technology

Roorkee – 247667

ACKNOWLEDGMENT

I would like to express my sincere gratitude to **Dr. E. Fernandez,** Associate Professor, Department of Electrical Engineering, Indian Institute of Technology, Roorkee, for his valuable guidance, support, encouragement and immense help.

I express my deep and sincere sense of gratitude to **Dr. Vinod Kumar**, Head of the Electrical Engineering Department, Indian Institute of Technology and to all the faculty members of Power System Engineering group.

I am thankful to all my friends who have helped directly or indirectly for the completion of this work.

Finally, I would like to express my deepest gratitude to the Almighty for showering blessings on me. I gratefully acknowledge my heartiest thanks to all my family members for their inspirational impetus and moral support during the course of work.

(RISHI KUMAR SHARMA)

Enrollment No: 09529016

ABSTRACT

High voltage insulators form an essential part of the high voltage electric power transmission systems. Any failure in the satisfactory performance of high voltage insulators will result in considerable loss of capital because there are numerous industries that depend upon the availability of an uninterrupted power supply. The importance of the research on insulator pollution has been increased considerably with the rise of the voltage of the transmission lines. In order to determine the flashover behavior of polluted high voltage insulators and to determine the physical mechanisms that govern this phenomenon, the researchers have established many types of modeling.

Artificial intelligent techniques can be used and are being used to estimate the critical flashover voltage (FOV) for polluted insulators, using experimental measurements carried out in an insulator test station and a mathematical model based on the characteristics of the insulator like : diameter, height, creepage distance, form factor , equivalent salt deposit density etc.

In this project work Fuzzy logic technique and Artificial Neural Network technique have been used to make the models of the outdoor insulators: glass, porcelain and composite. These models have four element input vectors. These four elements include surrounding pressure, salt deposit density, creepage distance and maximum diameter of insulators. A comparison between the results of the two types of the models is also done and has been seen that ANN models give results much nearer to experimental values. Then these models have been simulated at some new input values other than the experimental ones. So prediction of flashover voltage has been done by using these models.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

INTRODUCTION

1.1 OVERVIEW:

Electrical network can be divided in three major parts namely Generation, Transmission and Distribution. Of all these three, transmission system is the one which has highest capital cost and complexity. Therefore, for making system more reliable and economical, transmission system has to be monitored for system voltage and power flows etc. Mostly power is transmitted from one location to other by overhead lines at high voltages. For supporting overhead lines steel towers are used widely. Insulators on overhead lines isolate the conducting wires from each other and from the ground (tower), and they also act as load-bearing support for wires. High voltage insulators are an important of high voltage electric power transmission systems . The insulators are fixed at cross arm of supporting structure and the power conductor passes through the clamp of the insulator.

There should not be any insulator failure for reliable and uninterrupted power supply. Uninterrupted power supply is needed at numerous industries now a days. Failure of insulator can cause loss of millions of dollars to both industries and power system utility. So reliability of insulator performance can not be compromised and therefore for knowing performance of insulators different tests and experiments have been done on them.

1.2 TYPE OF INSULATORS:

The principle dielectrics used for outdoor insulators are *Ceramics* and *Polymers*.

1.2.1 Ceramics Insulators:

Ceramic insulators are made up of porcelain or glass. Ceramic insulators were traditionally used in high voltage transmission and distribution lines. Porcelain consists of silica 20%, feldspar 30% and clay 50% [1]. Porcelain insulators are mechanically strong, less affected by temperature and has minimum leakage problem in normal conditions.

Toughened glass is also used for manufacture of ceramic insulators because of its high dielectric strength. The most popular advantage of glass insulator is that being it transparent it can easily be detected for any flaw like air bubble inside etc. It has also low coefficient of thermal expansion. Major drawback of glass insulator is that moisture from atmosphere condenses on its surface very easily and therefore chances of flashover increases.

1.2.2 Composite Insulators:

Since 1960's polymer insulators also called as Composite Insulators have been preferred over porcelain and glass insulators for high voltage outdoor insulators. Polymer insulators have a number of benefits over traditional insulators. Polluted environment performance of polymeric insulators is much better in comparison to ceramic insulators. Some benefits are listed as:

- Light weight
- Relatively low cost
- Increased safety
- Superior pollution performance due to hydrophobic surface
- UV stability
- Non-brittle
- High impact resistance
- Maintenance free

The use of polymeric materials, particularly silicone rubber and Ethylene Propylene Diene Monomer (EPDM) as weather sheds, on outdoor insulators has increased substantially in the last twenty-five years.

Due to hydrophobic property of these polymeric materials continuous water film is not formed but only isolated water droplets are formed. Thus leakage current is reduced much better than porcelain and glass insulators. Hence, they have a much better contamination based flashover performance compared to porcelain [2].

1.3 FLASHOVER MECHANISM:

Outdoor insulators are affected by various operating conditions and environment exposer. Insulators near coastal areas are contaminated by salt particles driven by wind. Salt particles get accumulated on insulators' surfaces and forms a layer. Other pollution factors may also be there e.g. agricultural factors as fertilizers are used in fields, dust particles etc.

These pollutant particles are carried by wind and get deposited on insulators' surface to form a layer.

Figure 1.1: A naturally contaminated silicone rubber insulator

Occasionally, rain washes away some part of the pollution particles and self cleaning by airflow is also there. But after a long time the deposits are stabilized and a thin layer of solid deposit will cover the insulator.

Layer of contaminant particles increases the chances of flashover of insulators. Under dry conditions the contaminated surfaces do not conduct, and thus contamination has little effect in dry condition. In cases when there is light rain, fog or dew, the contamination on the surface dissolves. This creates a conducting layer on the surface of the insulator and the line voltage initiates the leakage current. High current density near the electrodes results in the heating and drying of the pollution layer. An arc is initiated if the voltage stress across the dry band exceeds the withstand capability. The extension of the arc across the insulator ultimately results in flashover. If the concentration of contamination is higher, it will increase the probability of flashover [3].

Atmospheric pressure also plays an important role on flashover voltage of an insulator [4]. Pressure is less at high altitudes regions. As pressure decreases, flashover voltage of an insulator also decreases as has been seen in models formed ahead in this report.

The mechanism above shows that heavy contamination and wetting may cause insulator flashover and it results in service interruptions.

The importance of the research on insulator pollution has been increased considerably with the rise of the voltage of transmission lines. In order to determine the flashover behavior of polluted high voltage insulators and to know the effect of change of diameter and creepage length on flashover voltage, the researchers have done experiments and modeling.

1.4 WORK DONE:

In this project work outdoor Insulators have been modeled with the help of Fuzzy Inference System and Neural Network Tool. These toolboxes are available in Mat-Lab software package. In this project work Mat-Lab 7.6 has been used to create and simulate the models of Glass, Porcelain and Composite Insulators. These models predict the flashover voltage of an insulator in different conditions of severity of pollution and low pressure found at high altitudes etc. These models can also predict the behavior of variation of flashover voltage with creepage length and diameter of insulator disks taken. A comparison has also been shown between the two types of these models.

For new construction, field experience may not be available and laboratory experiments are very time consuming and expensive. A good theoretical model for simulation of flashover process is very useful thing as it helps in reducing need of experimental work. This project work is therefore aimed at developing models by which the FOV based on contamination are to be predicted.

Chapter 2

LITERTURE REVIEW

Hydrophobicity and pollution degree are the basic parameters influencing the pollution performance of insulators. Pollution flashover performance of insulators is also affected by atmospheric pressure. The dependence of flashover voltage on pressure has been told by many researchers in their papers. Many experiments have been done on insulators to know their performance in polluted regions. Different experimental and visual analysis has been done to know the aging mechanism and effect of it on insulators' performance so that flashover of an insulator could be predicted accurately to avoid system collapse. Some literature has been reviewed in this context which is as follows:

Zhijin Zhang et al [4] investigated the ac pollution flashover performance of 4 types of porcelain and glass insulator strings of 21 units as well as 4 types of composite insulators under low atmospheric conditions in a multifunctional artificial climate chamber in Chongqing University. And they also carried out field investigations of the ac pollution flashover performance are at three different high altitudes including Wangkun station (height of altitude 4484 m), Nachitai station (height of altitude 3575 m) located along the Qingzang railway and Geermu urban (height of altitude 2820 m). They told that insulator's electrical performance decreases under low atmospheric condition which is found at high altitudes region. They have given a relationship between flashover voltage and atmospheric pressure which is follows in eqn.(2.1):

$$U = U_0 \left(\frac{P}{P_0}\right)^n \qquad (2.1)$$

Where U_0 is the pollution flashover voltage at the normal air pressure P_0 , n is the exponent describing the influence degree of air pressure on pollution flashover voltage. Different researchers give the different values of n according to their test results.

They found that value of n under ac voltage is greater than that under dc voltage conditions. By experiments they found that the ac pollution flashover voltage of the insulators decreases with the increase of SDD or the decrease of the air pressure. With the increase of SDD, the influence of the air pressure on the pollution ac flashover voltage will become weaker.

J.S.T. Looms [5] has said some laws or rules of insulator behavior which have been established by various tests. These are as follows:

1. The performance of an insulator depends on its altitude. In general, but not always, inclination from the vertical improves performance.
2. If a string of disc insulators is extended by addition of units the electrical performance rises in direct proportion, at least up to 750 kV system voltages. There is controversy about linearity at higher voltages.
3. For a given category of shape and surface, flashover voltages increases with the creepage length.
4. The flashover voltages of insulators fall with increasing core diameter, up to some 0.35 to 0.40 m, above which it levels off. Taper has no effect on performance.
5. In general, internal stress control has no effect on pollution flashover. Exceptions have been claimed for large bushings and for some highly capacitive assemblies.
6. Identical shapes of insulator behave identically whether in porcelain or glass, if insulators have undamaged surfaces. There are strong differences from the performance of polymers, especially when weathered, and from insulators whose surfaces have been treated or coated.

M.T. Gencog lu, M. Cebeci [6] studied model of VC = f (H,D,L,r,n,d) based on ANN which compute flashover voltage of the insulators. This model considers height (H), diameter (D), total leakage length (L), surface conductivity (r) and number of shed (d) of an insulator and number of chain (n) on the insulator. In this paper multilayer feed-forward network with back-propagation learning algorithm was used for modeling. It was seen that ANN model is capable for predict the flashover voltages of different type of the string insulators.

I.F. Gonos et al [8] presented a complex optimization method based on genetic algorithms for the determination of the arc constants, using experimental results from artificially polluted insulators. First the well known model of Obenhaus for pollution flashover is used. The application of genetic algorithms enables the definition of the arc constants, resulting also in the calculation of the critical conditions at the beginning of the pollution flashover mechanism. A mathematical model is established, which simulates accurately the experimental results. This study proposes a complex arithmetic optimization method using genetic algorithms, which leads to more accurate results compared with those from conventional mathematical methods.

Y. Xiong et al [9] studied 400 kV SIR polymeric insulators which were in service for 15 years. This paper describes the ageing as determined by visual observation and the results of material analysis using the surface analysis techniques of SEM (Scanning electron microscopy), EDX (Energy Dispersive X-ray) analysis, Fourier transform infrared spectroscopy (FTIR), and Raman spectroscopy. Visual observation showed non-uniform degradation over the sheds. The degradation can be qualified by using material techniques among which EDX and FTIR have been proved to be the most effective tools. The analysis has shown the ageing is an oxidation process, resulting in the formation of Si-OH groups.

Linjie Zhao et al [10] developed a cold fog test method to evaluate the contamination flashover performance of silicone rubber composite insulators under the winter fog condition. They also showed that ambient temperature is an important parameter influencing the pollution flashover voltage of insulators in clean fog tests. In the test it was shown that in cold fog test method, the flashover voltage found is lower than in steam fog test method. The factor influencing the pollution flashover of the SIR insulators in the cold fog test is the existence of a thin ice layer on the sample surface when the ambient temperature is below freezing point. So it was suggested that the winter fog performance of contaminated SIR insulators should be investigated using the cold fog method at ambient temperatures near 0°C.

S. Sundhar et al [11], studied about chemical structure of silicon rubber and told that silicon rubber contains a repeating silicone-oxygen (Si-O) backbone and two methyl groups (CH_3) for every one silicon atom. According to him methyl groups play a key role in maintaining the highly hydrophobic surface. Due to aging these methyl groups are oxidized in to O-H groups which are hydrophilic in nature. At the same time, the scission and ablation of polymer chains by electrical energy from corona and arcing produces layers of residues composed of hydrophilic substances such as SiO_2 and SiC that are dependent on the discharge temperature. On heating above 200 ^{0}C through discharge activity, the filler alumina trihydrate (ATH) also decomposes in a reaction to produce a residue of alumina. These hydrophilic compounds may be responsible for reduction in surface resistance and flashover may occur.

R. S. Gorur, J. Montesinos, L. Varadadesikan [12] developed a new experimental method for evaluating tracking and erosion performance of high voltage outdoor polymeric insulating materials (Silicon rubber and polyolefin polymers). This test was based on the combining some features of the ASTM D2132 DF (dust and fog) test and the ASTM D2303 (inclined plane) test. Tests were done on materials for different ESDD and NSDD concentrations. Tracking and erosion resistances of different samples of materials were found and then samples were categorized in groups of suitability and non-suitability for HV outdoor applications. They found hot spot temperature as in eqn. (2.2) due to discharge using a theoretical model a theoretical model developed in an earlier paper [10]

$$T = \frac{Q\,R}{K}\left[\frac{2}{\sqrt{\pi}}\left(\frac{\alpha\, t}{R^2}\right)^{1/2}\left(1 - e^{-R^2/4\alpha t}\right) + erfc\frac{R}{2\sqrt{\alpha t}}\right] \tag{2.2}$$

where Q is the heat flux, R the radius of the discharge, K the thermal conductivity of the material, *H* the surface heat transfer coefficient, a the thermal diffusivity of the material, *t* the time duration of the discharge in a particular location, the complementary error function erfc(β) = 1-erf(β), and erf(β) the Gaussian error function. A typical temperature value was obtained above which polymer degradation was expected. They also monitored the waveshape and magnitude of leakage current by which the status of polymeric devices could be indicated.

Models were also made for prediction of flashover voltage of non-ceramic insulators.

Numerous models were developed for ceramic insulators following the Obenaus model. The models are based on different empirical values for the arc constant, reignition constant and the reignition exponent. The generic formulas for E_{arc} and E_P are given in eqn. (2.3) and (2.4) :

$$E_{arc} = N \times I^{-n} \tag{2.3}$$

$$E_P = E_c = 10 * N \times (N - A)^{-n/_{n+1}} \times n^{n/_{n+1}} \times {rpu^{n/_{n+1}}}/{n+1} \tag{2.4}$$

where, E_P - electric field in the polluted layer

Ec - the arc gradient

N- reignition constant

n- reignition exponent (typically 0.5)

A- arc constant (typically 0.15 * N)

I - current entering the pollution layer

rpu - average resistance per unit length

S. Venkataraman and R. S. Gorur [13] developed a theoretical model to predict flashover voltage of non - ceramic insulators. This model is also based on reignition and arc constants that have been derived from electric field simulations and experimental data of flashover voltage and surface resistance measurements. New and field-aged silicone rubber (SIR) and ethylene propylene diene monomer (EPDM) rubber samples were evaluated. Experimental results show that the flashover performance of a new silicone rubber is similar to that of aged silicone rubber that has been allowed to recover its hydrophobicity. Without recovery, this sample behaves like a new EPDM.

The model can be used to predict the flashover voltage of silicone rubber and EPDM and also considers the hydrophobic nature of the surface.

Boubakeur Zegnini, Mohammed Belkheiri, and Djillali Mahi[14] have made ANN model for predicting flashover voltage. The diameter, the height, the creepage distance, the form factor and the equivalent salt deposit density are taken as inputs and critical flashover voltage is the output. The models made can estimate the critical flashover voltage for new designed insulators with different operating conditions and constitute models that can be used in field simulations of various parameters for polluted insulators. The data used for the training, evaluation and testing of the ANN were selected from various sources for different types of insulators.

N. Narmadhai and A. Ebenezer Jeyakumar [15] developed a model of $Vc = f(V, I_{initial}, I_{em}, I_{emax}$ and $I_\sigma)$ based on artificial neural network. This model predicts flashover from the analysis of leakage current. The input to the neural network are mean (I_{mean}), Maximum(Imax) and standard deviation(I_σ) of leakage current extracted along with the initial value of leakage current $I_{initial}$ and the input voltage(V). Inputs were normalized and then given to network. Initially five neurons in input layer, three neurons in hidden layer and one neuron in output layer were used. Hidden layer used tangent sigmoid transfer function and output layer used linear transfer function. Leven-Marquardt algorithm is used for training and the function 'trainlm' is invoked .Using trial and error the numbers of nodes in the hidden layer are determined. The optimization process was carried out based on MSE value.

Chapter 3

METHODOLOGY USED

In this project work fuzzy logic models and Artificial Neural Network models of outdoor insulators have been developed. These models are fed four input parameters namely P (atmospheric pressure in kPa), SDD (Salt deposit density in mg/cm^2), L (Creepage length in mm) and D (maximum diameter of insulator in mm). The output of the models is Uf (Flashover voltage in kV). Value of flashover voltage depends on all these four input parameters.

First of all before modeling of insulators we should have data points or training data with the help of which the models Fuzzy as well as Neural will be trained to predict the flashover voltage of the insulators in different conditions of environment. Input and output data are collected from the experiment results of ref. [4] performed at State Key Laboratory, Chongqing University. By data interpretation some other training datas are also created for training purpose. For this, help is taken from theory of book of J.S.T Looms [5]. These data will be used for making rule base of Fuzzy models of insulators and for training-testing of Artificial Neural models.

Before discussing about exact models of the insulators first some discussion is given below about Fuzzy logic and Artificial Neural Networking.

3.1 FUZZY LOGIC [16]:

The Fuzzy Logic tool was introduced in 1965 by Lotfi Zadeh. This tool is a mathematical tool and it deals with uncertainty in datas. The fuzzy logic is used because of its ability to model uncertain or ambiguous data. Fuzziness describes the ambiguity of an event and randomness describes the uncertainty in the occurrence of an event. It can be generally seen in classical sets that there is no uncertainty, hence they have crisp boundaries, but in the case of a fuzzy set, since uncertainty occurs, the boundaries may be ambiguously specified.

Lotfi Zadeh proposed the Set Membership idea to make suitable decisions when uncertainty occurs. This membership was meant to possess various degree of membership. The interval on the real continuous is taken as [0, 1]. Zadeh formed fuzzy sets as the sets on the universe X which can accommodate degrees of membership between 0 to 1. The values 0 and 1 describe "not belonging to" and "belonging to" a conventional set respectively and the values in between represent "fuzziness".

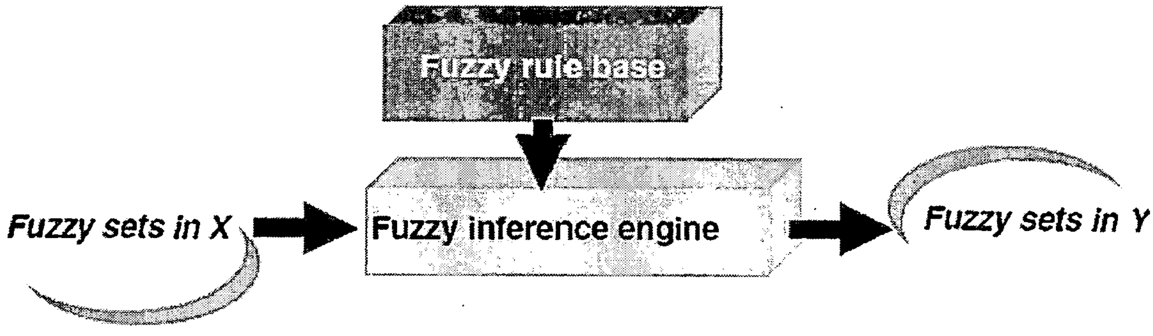


Figure 3.1: Configuration of a pure fuzzy system

Fuzzy systems are used for nonlinear mappings of inputs to outputs. The fuzzy inference engine (algorithm) combines fuzzy *IF–THEN* rules into a mapping from fuzzy sets in the input space X to fuzzy sets in the output space Y based on fuzzy logic principles. Fuzzy systems are rule-based systems that are constructed from a collection of linguistic rules.

3.1.1 Fuzzy Inference System (FIS):

FIS is a major unit of a fuzzy logic system. The decision-making is an important part in the entire system. The FIS formulates suitable rules and based upon the rules the decision is made. FIS uses "IF. . . THEN. . . " statements, and the connectors present in the rule statement are "OR" or "AND" to make the necessary decision rules. The basic FIS can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. When the FIS is used as a controller, it is necessary to have a crisp output. Therefore in this case defuzzification method is adopted to best extract a crisp value that best represents a fuzzy set.

3.1.2 Construction and Working of Inference System:

Fuzzy inference system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface.

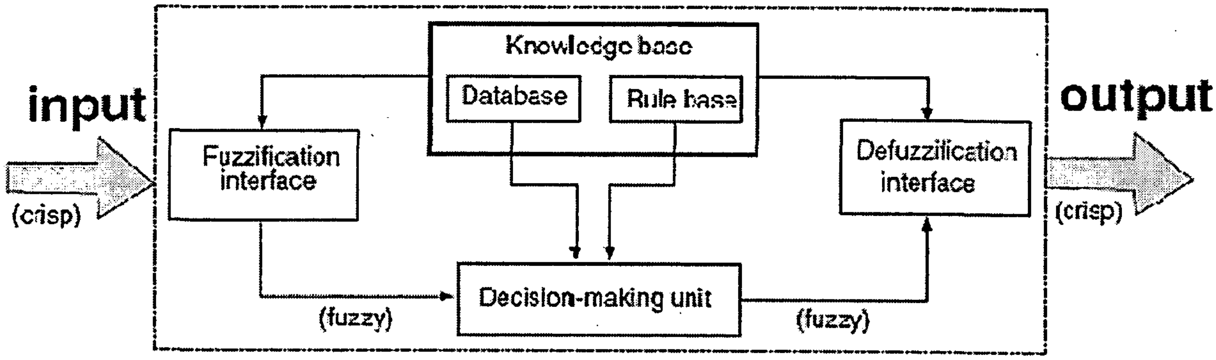


Figure 3.2 :Fuzzy inference system

3.1.3 Function of Blocks:

- a *rule base* containing a number of fuzzy IF–THEN rules;
- a *database* which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- a *decision-making unit* which performs the inference operations on the rules;
- a *fuzzification interface* which transforms the crisp inputs into degrees of match with linguistic values; and
- a *defuzzification interface* which transforms the fuzzy results of the inference into a crisp output.

3.1.4 Fuzzy Inference Methods:

The most important two types of fuzzy inference method are:

1. Mamdani's fuzzy inference method
2. Takagi–Sugeno–Kang method

In this work Mamdani's fuzzy inference method has been used to develop the models. This method was introduced by Mamdani and Assilian 1975. Second inference method is Takagi–Sugeno–Kang method. This method was introduced by Sugeno in 1985. In short we call this method as TS method. The main difference between the two methods is in the consequent of fuzzy rules. Mamdani fuzzy systems use fuzzy sets as rule consequent whereas TS fuzzy systems employ linear functions of input variables as rule consequent.

Steps which are taken in forming model by Mamdani's fuzzy inference method are as following:

1. Determining a set of fuzzy rules
2. Fuzzifying the inputs using the input membership functions
3. Combining the fuzzified inputs according to the fuzzy rules to establish a rule strength
4. Finding the consequence of the rule by combining the rule strength and the output membership function
5. Combining the consequences to get an output distribution
6. Defuzzifying the output distribution

In this project, for fuzzification triangular membership functions have been used for both inputs and output. Then database has been prepared from the experimental datas of reference [3]. From that database rules have been prepared.

It is desired to come up with a single crisp output from an FIS. This crisp number is obtained in a process known as defuzzification. There are two common techniques for defuzzification : 1. Center of mass or centroid and 2. Mean of maximum.

In this work for defuzzification of output value "Centroid" technique has been used.

3.2 ARTIFICIAL NEURAL NETWORK MODELLING [18]:

Warren McCulloch and Walter Pitts presented the first mathematical model of artificial neurons in 1943. An Artificial Neural Network (ANN) processes the information in a way that is similar to the way biological nervous systems does. It is composed of a large number of highly interconnected neurons working all together to solve the problems. ANNs learn by examples in the same way as people learn. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. In ANNs weights are adjusted trough learning process.

3.2.1 A Simple Neuron:

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire or not fire, for particular input patterns. In the using mode, input is examined by the network and it decides which neuron to fire or not to fire depending on its training.

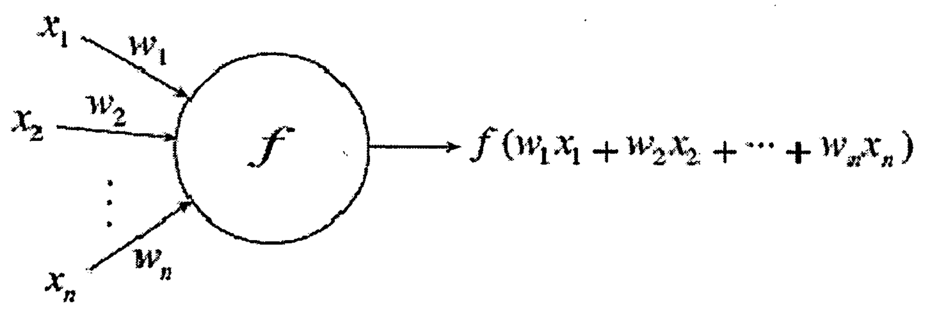


Figure 3.3: A simple neuron

3.2.2 Architecture of Neural Networks:

1. *Feed-forward networks:*

   In Feed-forward ANNs (Fig. 3.4) signals flow in one way only i.e from input to output. There is no feedback or loops. The output of any layer does not affect that same layer. Feed-forward ANNs are straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition.

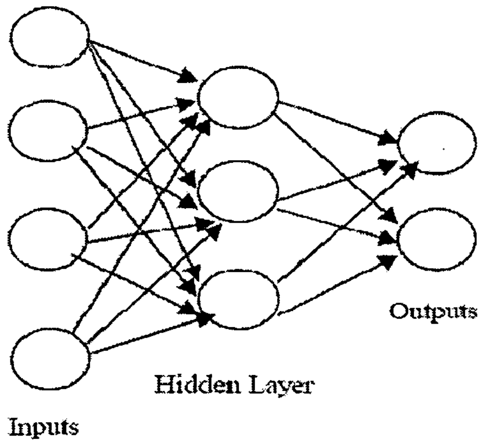


Figure 3.4: A feed forward network

2. *Feed-back networks:*

Feedback networks may have signals coming in back directions also. Loops are formed in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic in nature. Means their 'state' is changing continuously until they reach an equilibrium point. If input is changed their state will change and then new equilibrium point or output value is to be found. Feedback architectures are also called as **recurrent networks.**

3.2.3 Network Layers :

Three types of layers are there in neural networks namely input layer, hidden layer and output layer. Hidden layer is connected to input layer through weight connections and output layer is connected to hidden layers by weight connections.

The activity of the input units represents the raw information that is fed into the network.

The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

3.2.4 The Learning Process:

Information is stored in the weight matrix W of a neural network. Learning is the determination of the weights. Every neural network possesses knowledge which is contained in the values of the connections weights. Modifying the knowledge stored in the network as a function of experience implies a learning rule for changing the values of the weights.

Learning methods used for adaptive neural networks can be classified into two major categories:

1. **Supervised learning:** In this each output unit is externally made to give response according to input. During the learning process global information may be required. An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. Least mean square (LMS) convergence is used as a sign of minimized error.
2. **Unsupervised learning:** In this no external factor is needed and is based upon only local information.

We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

3.2.5 Transfer Function :

The behavior of an ANN depends on both the weights and the input-output function that is specified for the units. This function is called transfer function. This function generally may one of these three types:

1. linear (or ramp)
2. threshold
3. sigmoid

For **linear units**, the output activity is proportional to the total weighted output.

For **threshold units**, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

For **sigmoid units,** the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units.

3.2.6 The Back-Propagation Algorithm:

For training a neural network to perform some task, the weights of each unit are to be adjusted in such a way that the error between the desired output and the actual output is minimized. For this derivative of the weights (dW) are to be calculated. It must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the dW.

The algorithm computes each dW by first computing the dA, the rate at which the error changes. For output units, the dA is simply the difference between the actual and the target output. To get the dA for a hidden unit in the layer just before the output layer, first all the weights between that hidden unit and the output units to which it is connected are to be found. Then those weights are multiplied by the dA s of those output units and add the products. This sum equals the dA for the hidden unit under consideration. After finding all the dAs in the hidden layer just before the output layer, we can compute in same way the dAs for other layers. We move from one layer to other in opposite direction to the way activities propagate through the network. That's why this algorithm is named back propagation.

A three-layer network performs a particular task by using the following procedure:

1. Network is fed with training examples, which consist of a pattern of activities for the input units. It also has the desired pattern of activities for the output units.

2. Actual output of the network is compared with the desired output.

3. Weights of each connection are adjusted so that the network produces a better approximation of the desired output and error is reduced to minimum.

3.3 NEURAL NETWORK IN PROJECT WORK:

Here in this project work back propagation method is used for training the artificial neural network models of outdoor insulators.

According to the universal approximation theorem, a Neural Network with two layers can approximate a given function to a desired precision. Above Fig. 3.4 shows the schematic diagram of a multilayer feed-forward network used in this work. The back-propagation learning algorithm is employed in this work. This learning algorithm is presented here in brief.

For each neuron in the input layer and hidden layer , *tansig* transfer function has been taken as it best represents a human neural in comparison to other linear transfer function.

For each neuron in the hidden layer, the neuron inputs are given by eqn. (3.1)

$$n_k = \sum_{j=1}^{Nj} \mathrm{Wkj}.\mathrm{Okj} \qquad k=1\ldots\ldots N_k \qquad (3.1)$$

where *Wkj* is connection weight between neuron *j* and neuron *k*, and Nj, Nk are the number of neurons in the input and hidden layers, respectively; the neuron outputs are given by eqn. (3.2) :

$$O_k = \frac{2}{1+\exp\left(-(nk+\theta k)\right)} - 1 = f_k(n_k, \theta_k) \qquad (3.2)$$

where θ_k is the threshold of neuron *k*, and the sigmoid function f_k is usually used as an activation function.

For the neurons in the input layer, the input and the outputs are given by the relationships similar to those given in the eqn. (3.1) and (3.2), respectively

For output layer neurons, *purelin* transfer function has been taken. Therefore output of neuron in output layer is given in eqn.(3.3) :

$$O_l = n_l \qquad (3.3)$$

where n_l is the input of neuron *l* and O_l the output of neuron *l*.

The connection weights of the feed-forward network are derived from the input–output patterns in the training set by the application of generalization delta rule [17]. The algorithm is based on minimization of the error function of each pattern *p* by the use of the gradient descent method.

Keeping in mind that output layer has *purelin* transfer function and other layers have *tansig* transfer function, below are expressions to adjust the weights of layers by using Back propagation algorithm:-

$\Delta Wij = \eta_j . (d_i - t_i) . o_i . a_j$ ....for the output layer

$\Delta Wij = \eta_j \ (\sum_k \delta_k \, w_{ki}) \ (1/2) \ (1 - a_i^2) \ a_j$ ......for the hidden layer and input layer

where η_j is the learning rate and $\delta_k = (d_k - o_k) \ (1/2) \ (1 - o_k^2)$

Chapter 4

FORMULATION OF FUZZY MODELS FOR INSULATORS

4.1 Fuzzy Model for Glass insulators:

For preparing the fuzzy model of LXY_4-160 and $LXHY_3$-160 type glass insulators Fuzzy Logic tool box of MatLab 7.6 has been used. By this tool box, model can be made in GUI based windows, which can be run in MatLab command window environment using some commands.

The model for glass insulators is as in Fig. 4.1:

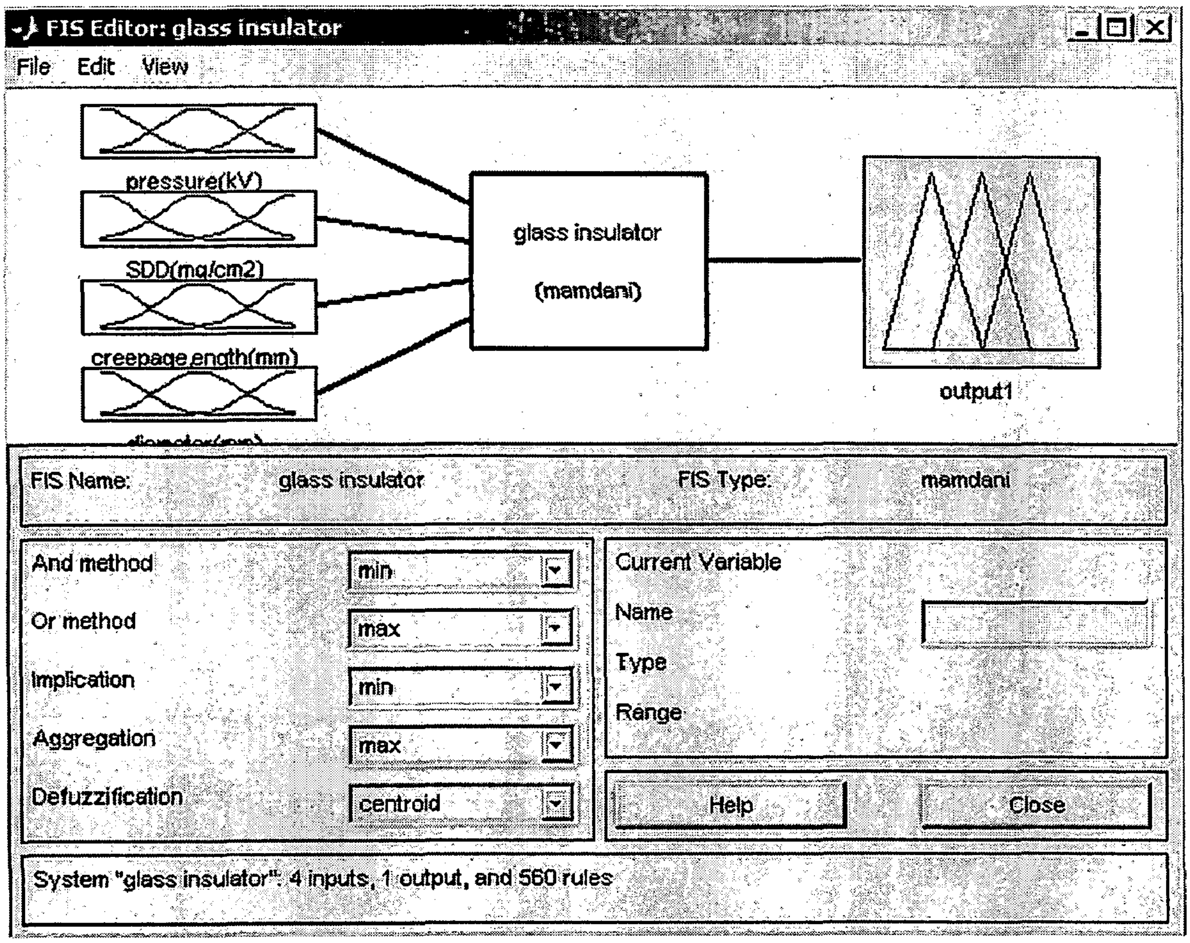


Figure 4.1: FIS Editor for glass insulator model

We can see that four inputs are given as:

1. Pressure (kV)
2. SDD (mg/cm^2)
3. Creepage Length(mm)
4. Diameter(mm)

All input and output names can be seen in above Fig. 4.1 and defuzzification technique used is *centroid.*

4.1.1 Membership Functions:

Different membership functions have been made by fuzzyfying the inputs. Triangular membership functions are used. Membership functions of input Pressure are as shown in Fig. 4.2:

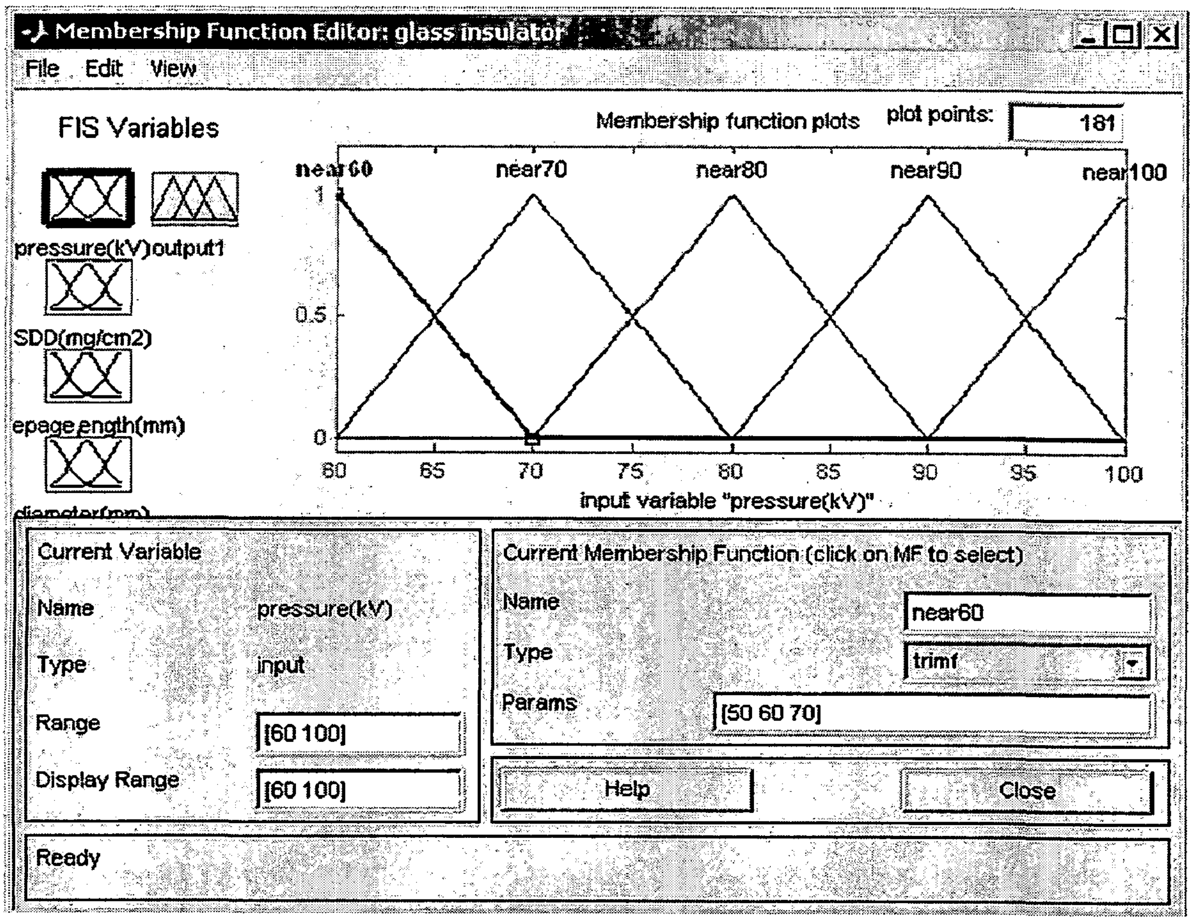


Figure 4.2: Membership functions for pressure

The input SDD has four membership functions named as 'near 0.03', 'near 0.05', 'near 0.08' and 'near 0.15'. These all membership functions are triangular and are spread in range 0.0 to 0.15 as shown in Fig. 4.3:-

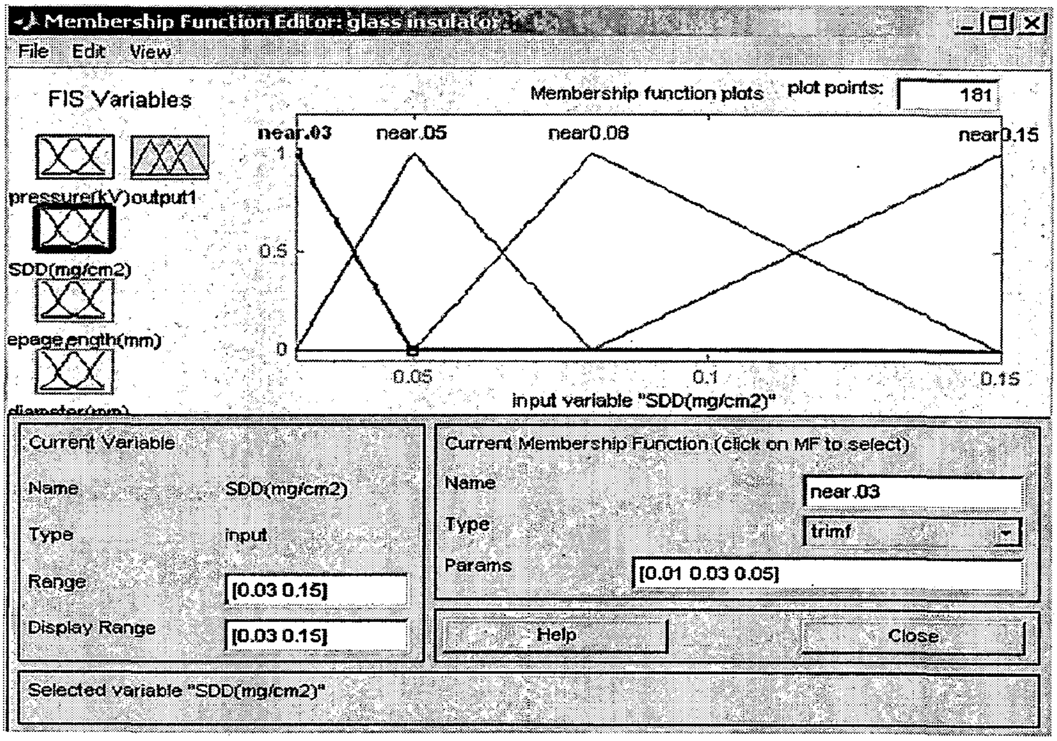


Figure 4.3: Membership functions for SDD

The input, *creepage length* has membership functions which are triangular in shape and are spread evenly in range 0 to 490 mm as shown in Fig. 4.4:-

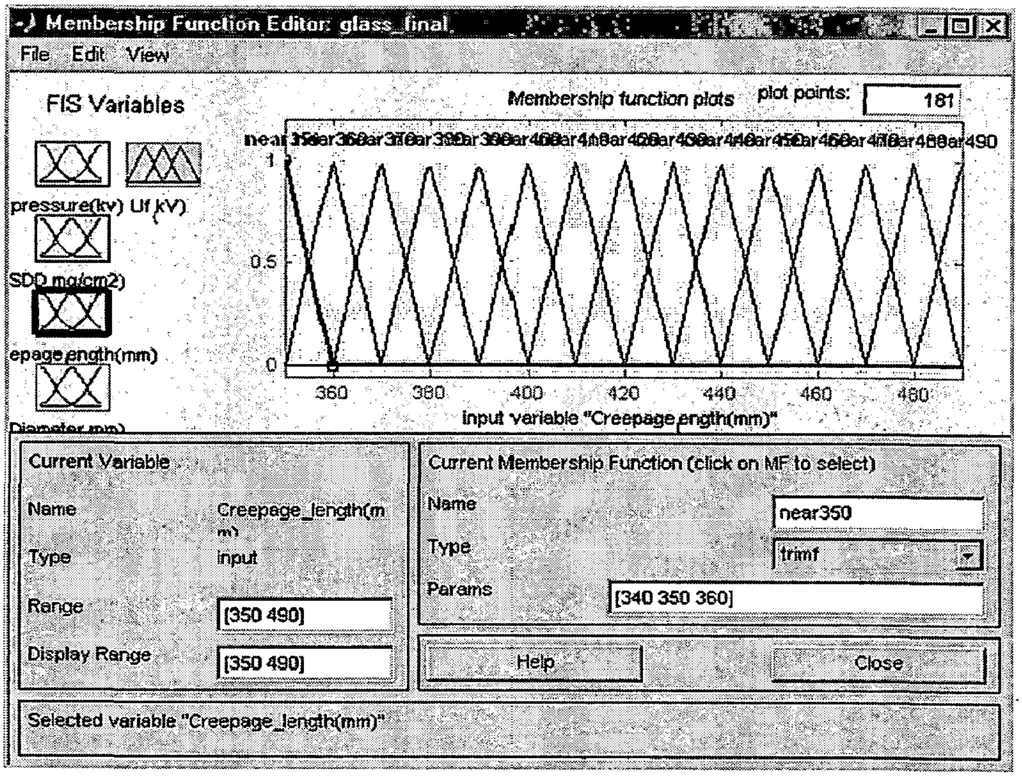


Figure 4.4: Membership functions for creepage length

The input, diameter has membership functions which are also triangular in shape and are spread evenly in range 250 to 320 mm as shown in Fig. 4.5:-

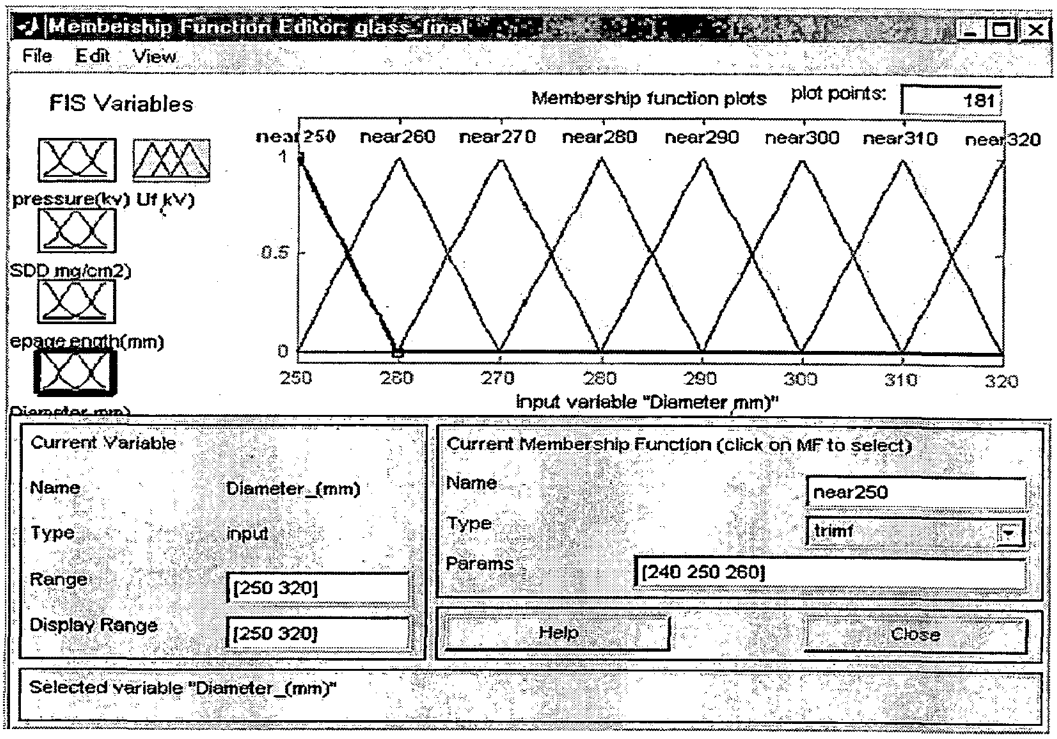


Figure 4.5: Membership functions for diameter

The output, flashover voltage has membership functions which are also triangular in shape and are spread evenly in range 90 to 400 kV as shown in Fig. 4.6:-

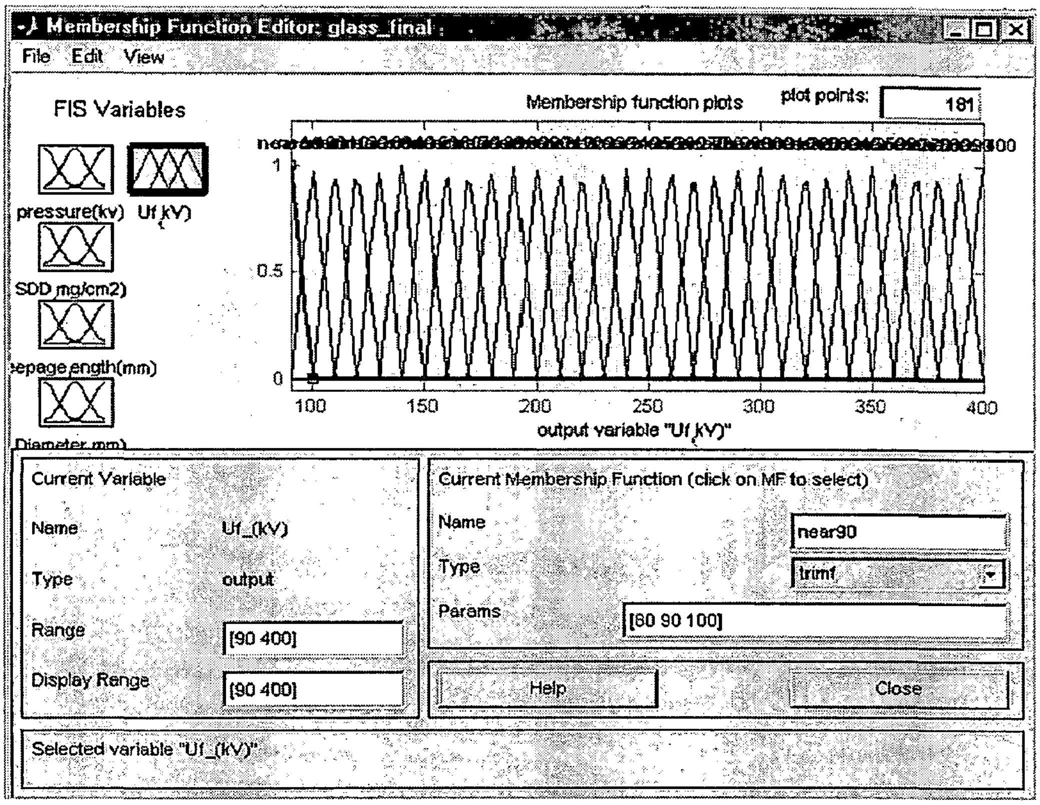
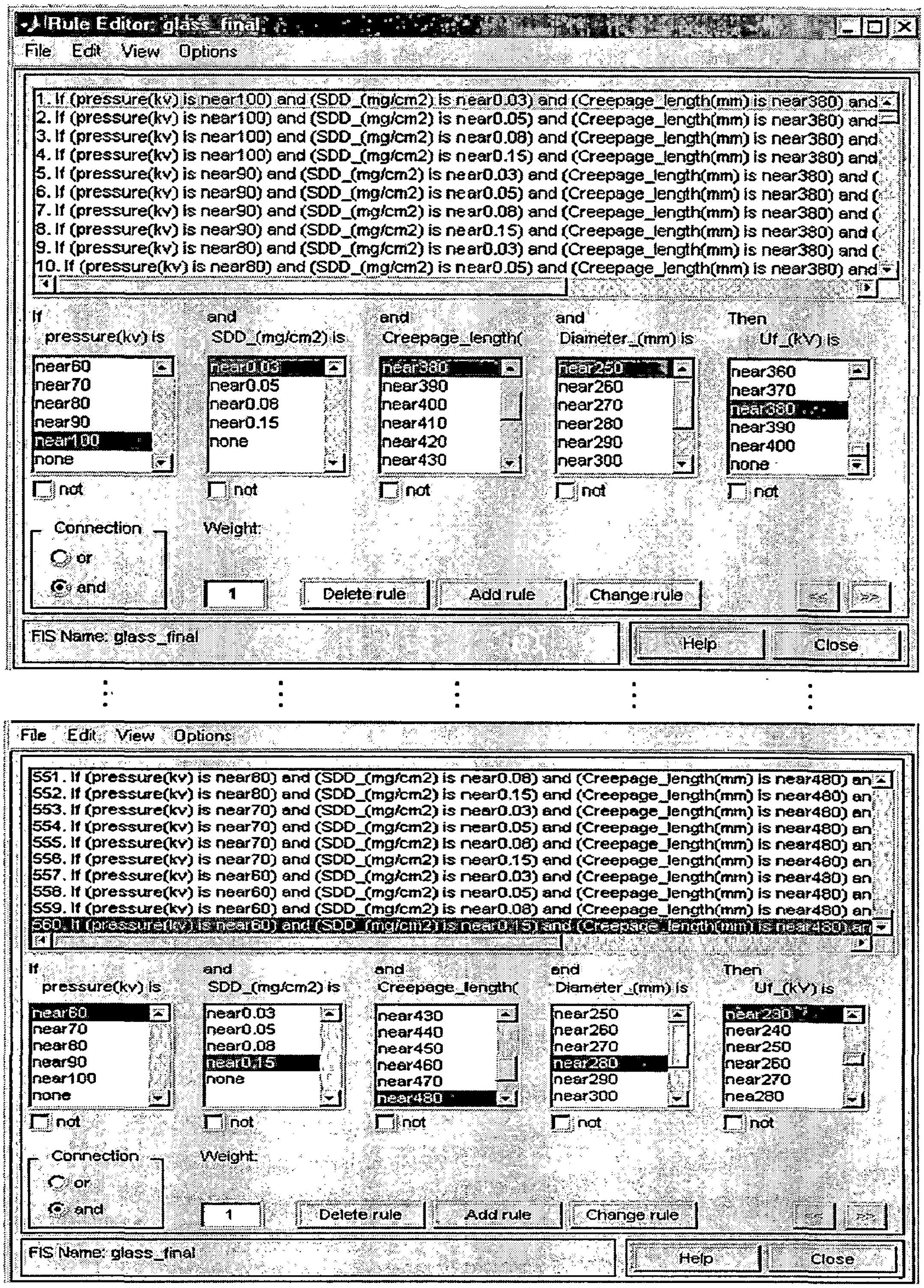


Figure 4.6: Membership functions for flashover voltage

4.1.2 Rule Base: Once all the input and output membership functions have been defined the heart of control now can be defined; the rules. The fuzzy rules are in the form of if-then statements. These statements look at all inputs and determine the desired output. The rules are the defining elements of this system. The rules defined for this model will look as in following Fig. 4.7:-



<u>**Figure 4.7:Rule base for glass insulator**</u>

4.2 FUZZY MODEL FOR PORCELAIN INSULATOR:

Similarly model for porcelain type insulators (XP-160 and XWP_2-160) have been prepared in fuzzy logic tool box.

The model for porcelain insulators is as in Fig. 4.8:

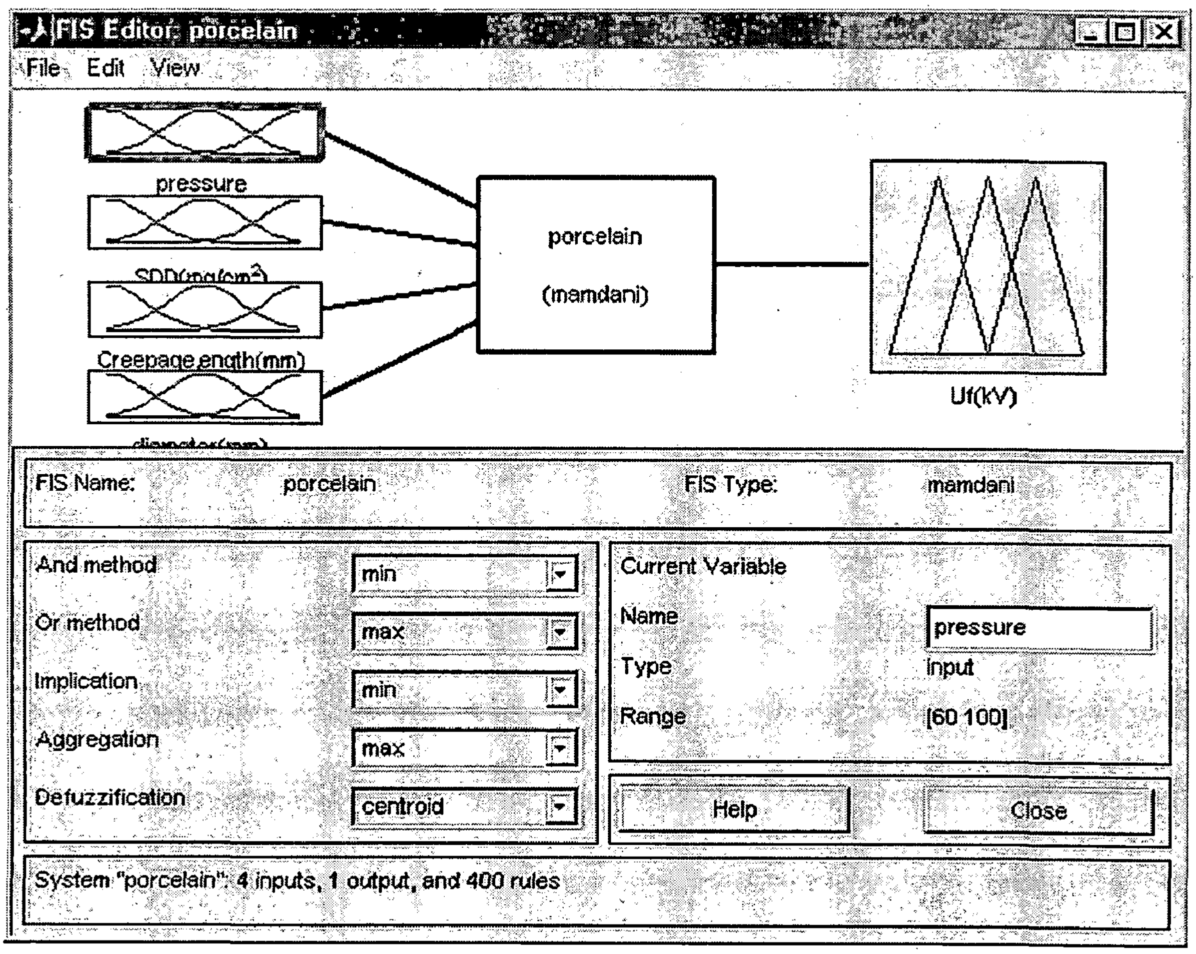


Figure 4.8: FIS Editor for porcelain insulator model

All membership functions for inputs and outputs are *triangular* in shape and methodology used is same as for glass insulator model. Number of rules in rule base are 400. For getting a crisp value of output i.e. Flashover voltage, defuzzification of output is needed. For defuzzification, *centroid* technique is used in this model.

Chapter 5

ARTIFICIAL NEURAL NETWORK MODELS OF INSULATORS

For preparing the ANN model of LXY_4-160 and $LXHY_3$-160 type glass insulators *nntool* (Neural Network Tool) tool box of MatLab 7.6 has been used. By this tool box, model can be made in GUI based windows, which can be run in MatLab command window environment using some commands and programs.

5.1 NEURAL NETWORK GRAPHICAL USER INTERFACE (GUI) IN MATLAB:

When entering in *nntool* toolbox of MatLab, a window is opened looking as shown in Fig 5.1 on next page. The name of this window is **Network/Data Manager window.** Mfiles of input data and target data have been made in Matlab7.6. These Mfiles should have run already in command window environment before opening *nntool*, so that input data and target data can be imported in *nntool* window.

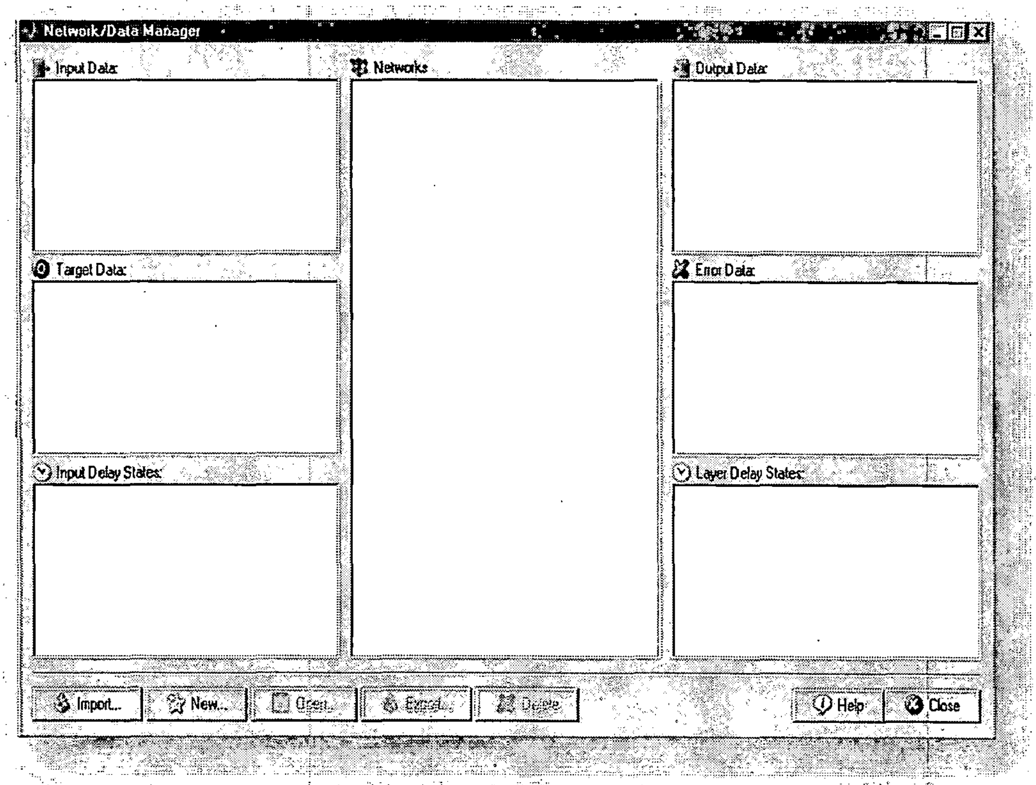


Figure 5.1: window of Network/Data Manager

In window, shown in Fig. 5.1, input data and target data will be concerned to the insulator for which ANN model has to be prepared. Here in this work ANN models of three type of insulators (Glass, Porcelain and Composite) , are made. Therefore, one by one all the ANN models are made by taking corresponding training and testing datas.

Models made here have four-element input having a varying number of sets for each type of insulator. These input sets are used by *nntool* for training the ANN.

5.1.1 Importing the Data from Workspace:

By clicking on 'Import' in Fig. 5.1 , an import wizard is opened by *nntool* as shown in Fig. 5.2 below:

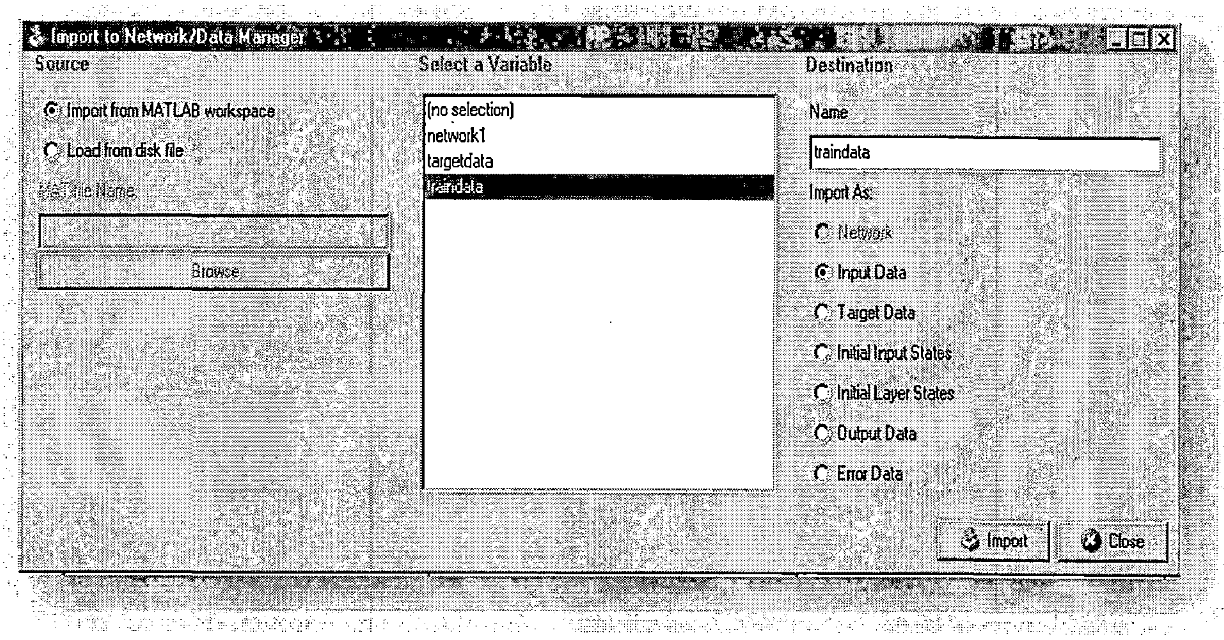


Figure 5.2: Window for Import to Network/Data Manager

The data which are to be imported should be run on workspace and then they will be imported to *nntool* accordingly as shown Fig. 5.2.

After this Neural network is to be created, for this we press 'New' button shown in Fig. 5.1. This opens a new window 'Create Network or Data' for creating Neural Network as shown in Fig. 5.3 below:

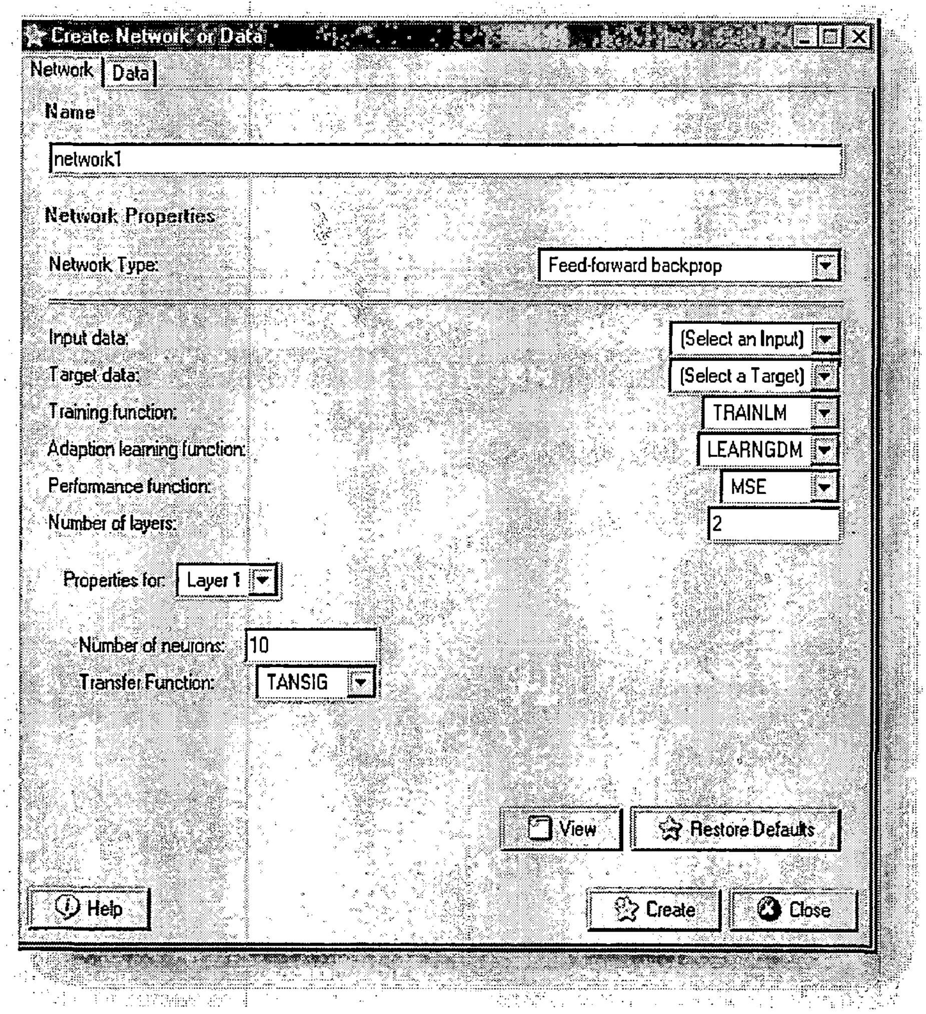


Figure 5.3: Window for Creating Neural Network

In this window name of the network is to be given. Network type is also selected.

Here in all ANN models Feed-forward back propagation is chosen as the type of the network. Then input and target vectors are to be selected for creating and training the network. Training function by default is TRAINLM and in this work also training function is taken as its default i.e. TRAINLM. Adaptive learning function taken is LEARNGDM by default. Performance function can also be changed. Here MSE (Mean Square Error) has been taken as the performance function. Then numbers of layers and the number of neurons in each layer can also be fixed from their respective places in window of Fig 5.3. Transfer functions of layers are also to be selected. In this work output layer transfer function is taken as *'Purelin'* and all other layers' transfer function is taken as *'Tansig'* for all the ANN models of all three type of insulators.

5.1.2 Transfer Functions:

Transfer function taken for output layer is *Purelin* and for all other layers is *tansig*. *Tansig* transfer function best represents human neural and is mostly used for solving non linear type problems. Purelin and Tansig transfer functions are defined as in Fig. 5.4:

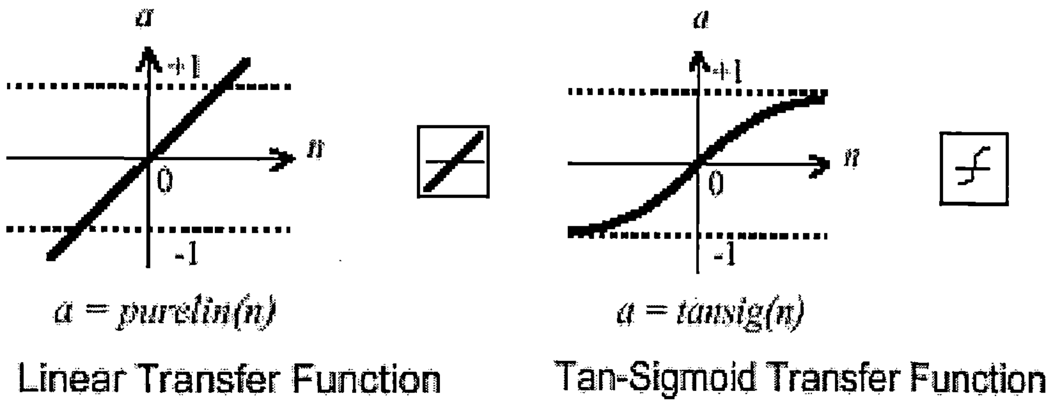


Figure 5.4: Transfer functions

5.1.3 Creating Network:

After setting all parameters for creating a ANN, the 'Create' button shown in Fig. 5.3 ,is pressed. In this way an ANN model is formed of given specifications. To examine the network architecture, click View. We see a window like shown in Fig. 5.5.

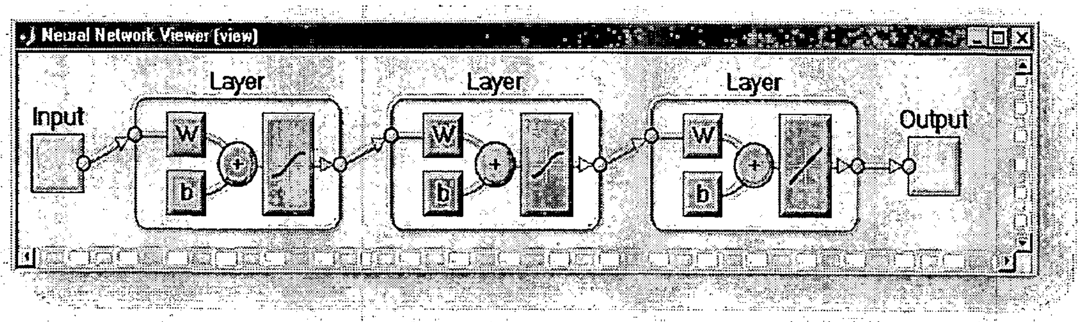


Figure 5.5: Window for viewing architecture of network

After clicking 'Create', a network named as given by you will be added in list of network in Network/Data Manager window shown in Fig.5.1.

5.1.4 Training the ANN:

To train the network, click name of network in Network/Data Manager window shown in Fig.5.1 to highlight it. Then click Open. This leads to a new window as shown in Fig.5.6, labeled by name of the network.

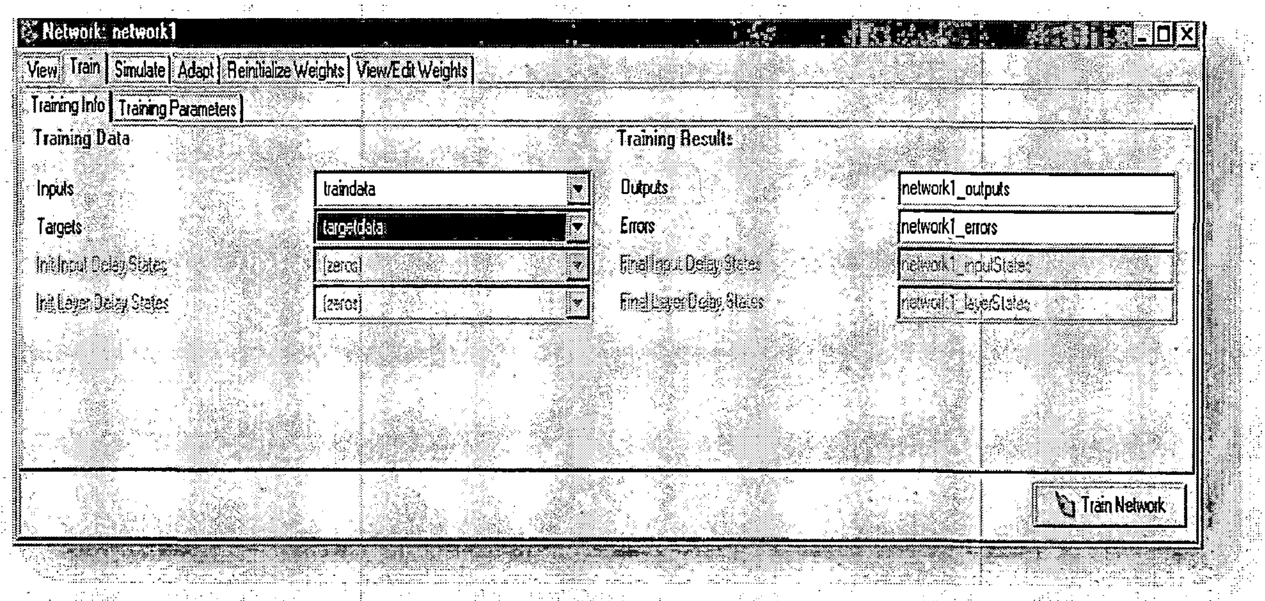


Figure 5.6: Window for Training the network

We can also check on the initialization by clicking the 'Initialize' tab. For training of ANN, click the 'Train' tab. Specify the inputs and output by clicking the 'Training Info' tab and selecting input from the list of inputs and target from the list of targets.

By clicking the 'Training Parameters' tab we can see epochs and error goal. We can change these parameters .

After all this we click 'Train Network' to train the neural network. A window like in following Fig.5.7 is shown by *nntool.*

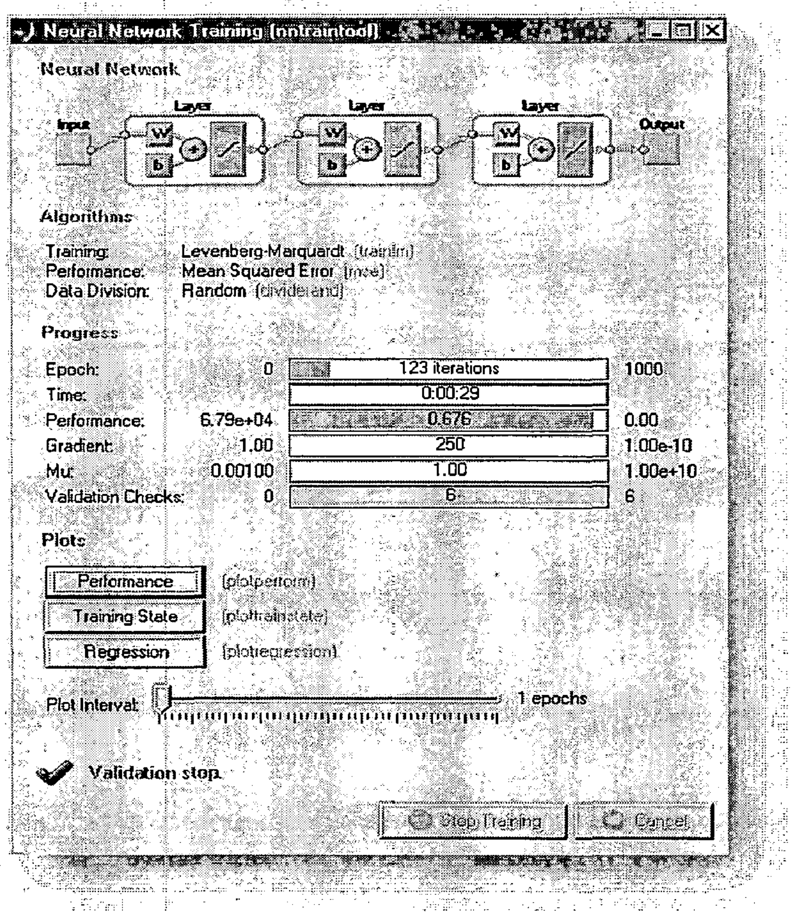


Figure 5.7: Window shown during training

In this way ANN model is trained on given data points. After this the network and other variables, performance index etc. can be exported or saved in workspace and then the model can be run by using some commands from workspace.

Procedures for making ANN model for all three type of insulators are similar to each other. So there is no need of talking about ANN models all three type of insulators separately.

Chapter 6

FLASHOVER VOLTAGE PREDICTION BY FUZZY AND ANN MODELS RESULTS OF FUZZY MODEL

The effect of pressure on flashover voltage is that flashover voltage decreases as pressure decreases. This low pressure is found at high altitude hilly regions. Normal value of atmospheric pressure is 101.325 kPa.

Effect of salt deposit density is that the flashover voltage decreases with increment in concentration of SDD. A range of 0.03 to 0.15 mg/cm^2 has been taken in model.

Effect of creepage distance is that as creepage distance increases the flashover voltage also increases approximately linearly.

Effect of diameter of insulator is that as diameter increases the flashover voltage is going to decrease.

By the model we can get value of flashover voltage at some ranges of inputs: Pressure, Sdd, Creepage distance and Diameter.

Here some characteristics have been shown in the form of result by varying different input vector parameters.

Effect of creepage length variation and diameter variation has also been seen which shows appropriate resemblance with experimental results [4].

6.1 RESULTS FOR GLASS INSULATOR:

6.1.1 Creepage Length Variation:

A variation of flashover voltage with pressure at different creepage lengths is shown in following Fig. 6.1

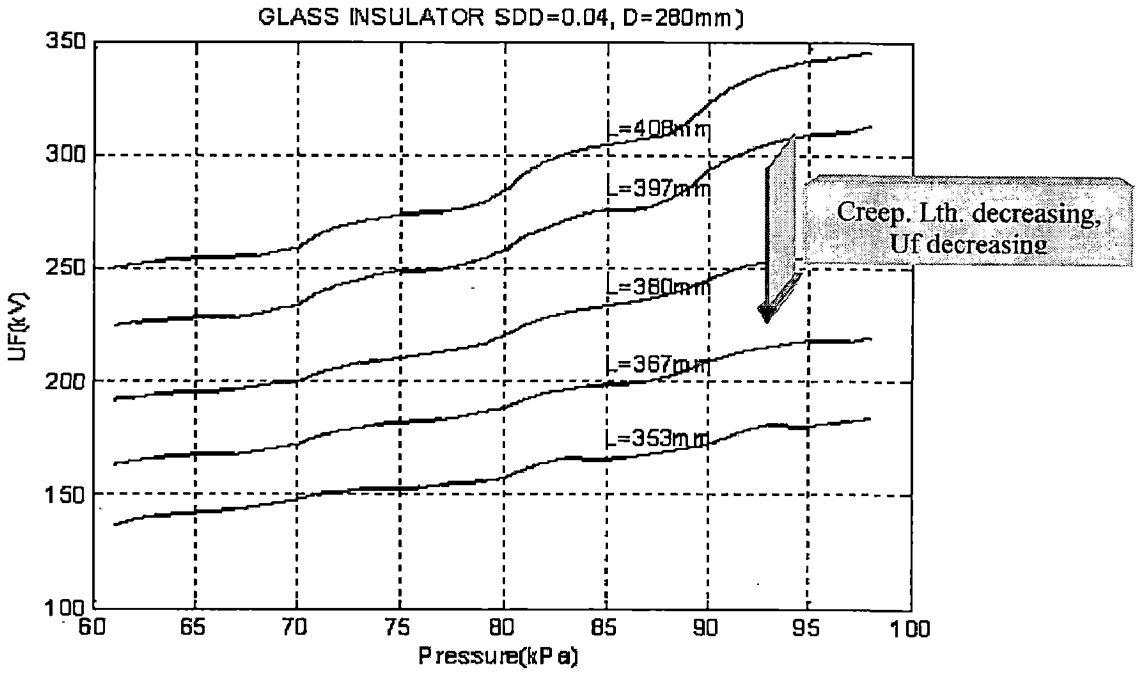


Figure 6.1: Variation of FOV with Creepage length (i)

From this we can see the effect of creepage length on flashover voltage. Flashover voltage decreases with decrease in pressure and flashover voltage increases as creepage length is increased.

One more type characteristic of flashover voltage variation with creepage length can be drawn with flashover voltage at Y-axis and creepage length at X-axis at different values of SDD concentration and pressure, for LXY_4-160 type glass insulator. These characteristics are shown in following Fig.6.2.

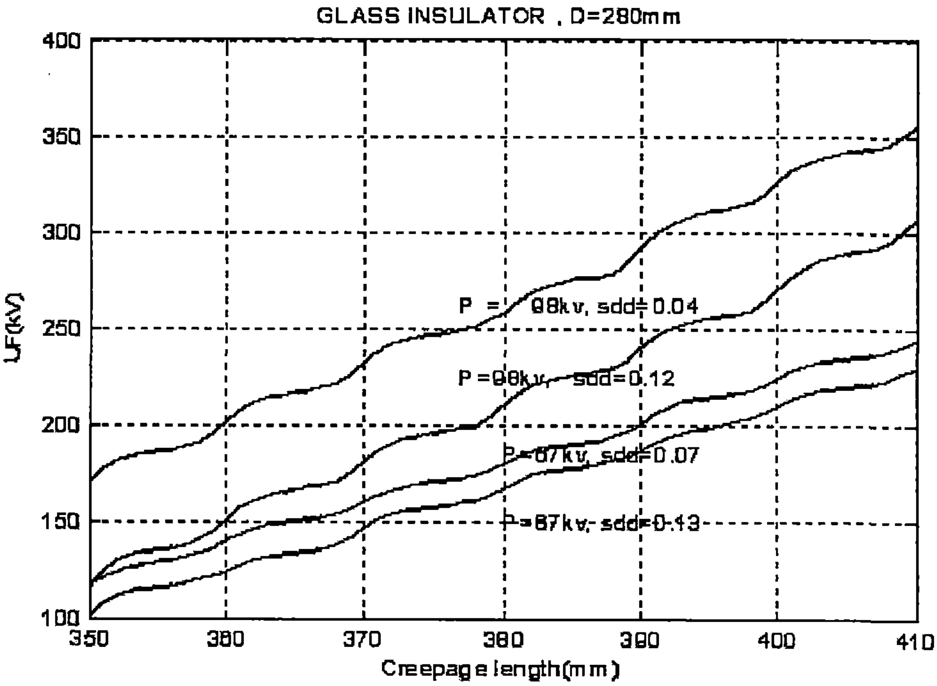


Figure 6.2: Variation of FOV with Creepage length (ii)

6.1.2 Diameter Variation:

Now from the following Fig. 6.3 the effect of diameter variation can be seen on flashover voltage. It is obvious from characteristic that if Diameter increases then flashover voltage decreases as was said in reference [4] and [5].

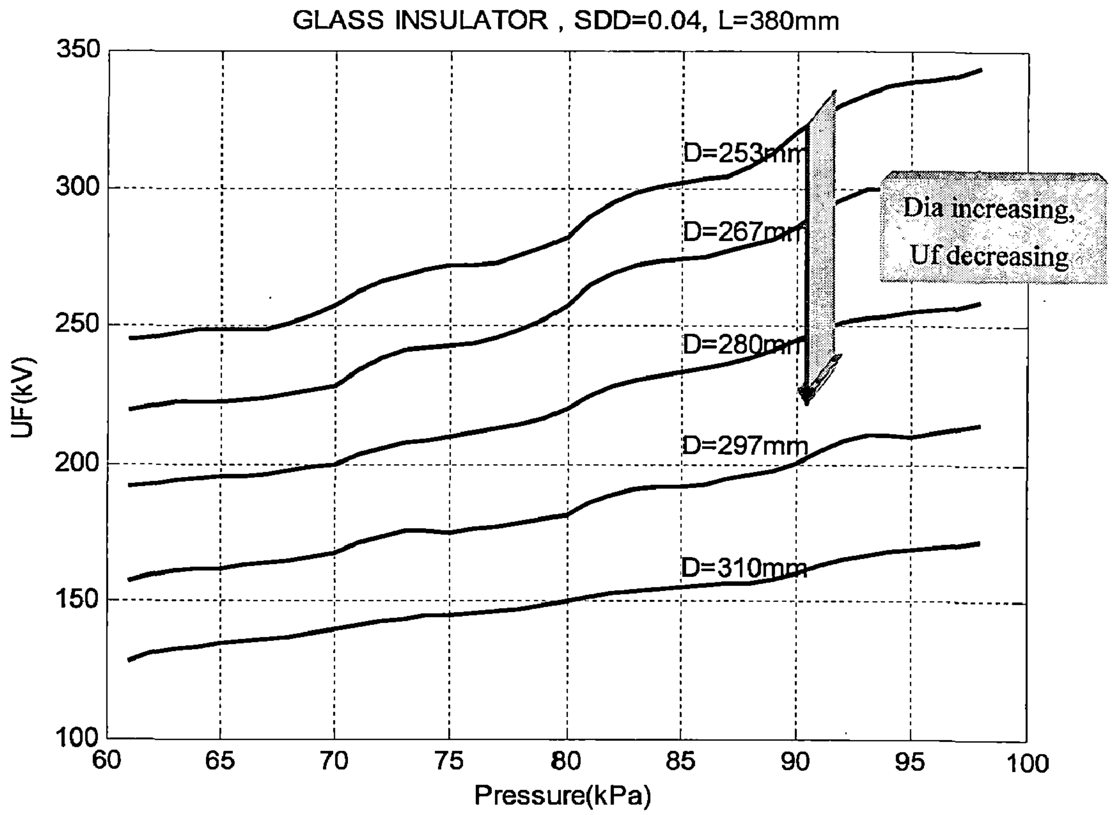


Figure 6.3: Variation of FOV with diameter (i)

Characteristic of flashover voltage variation with diameter can be drawn with flashover voltage at Y-axis and diameter at X-axis at different values of SDD concentration and pressure, for LXY_4-160 type glass insulator. These characteristics are shown in following Fig. 6.4.

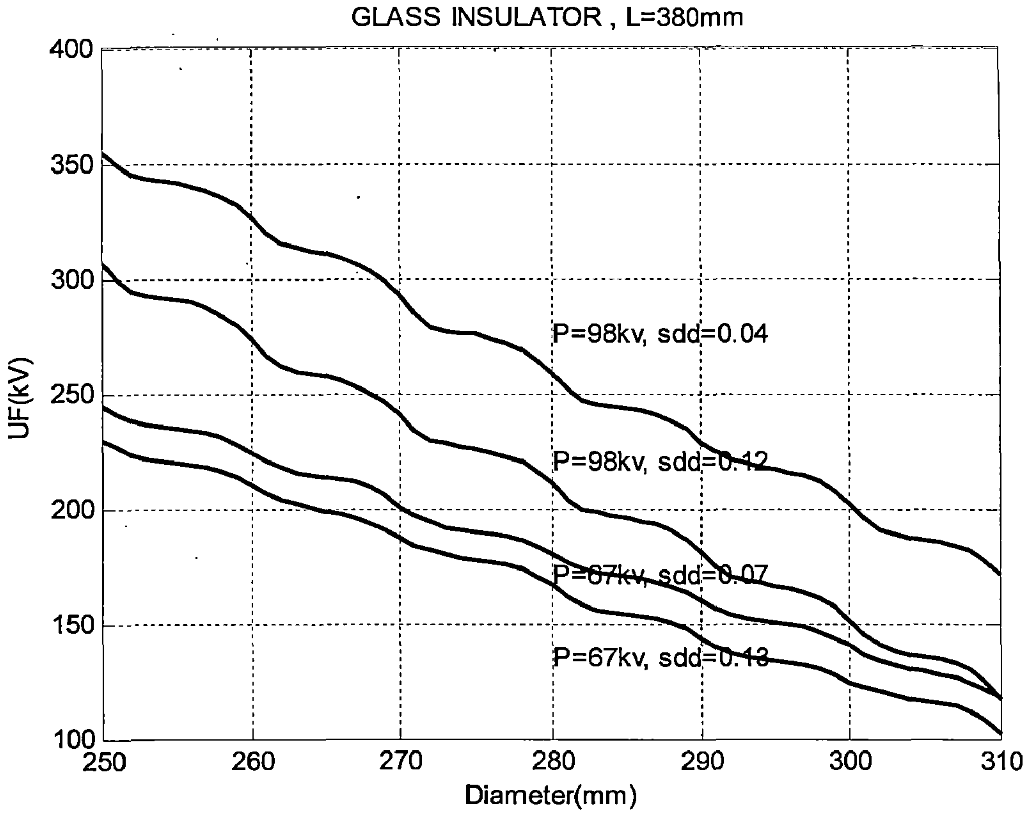


Figure 6.4: Variation of FOV with diameter (ii)

Other characteristics can also be drawn for different values of Pressure, Sdd, Creepage length and Diameter but within specified and limited range.

In this way we can predict the flashover voltage of glass insulators at different pollutant degree concentrations and at low pressures at high altitude region transmissions. The results of fuzzy model have closely matched with the experimental results. So this fuzzy model can predict flashover voltage fairly accurate.

6.2 RESULTS FOR PORCELAIN INSULATOR:

6.2.1 Creepage length Variation:

A variation of flashover voltage with pressure at different creepage lengths for XP-160 is shown in following Fig. 6.5

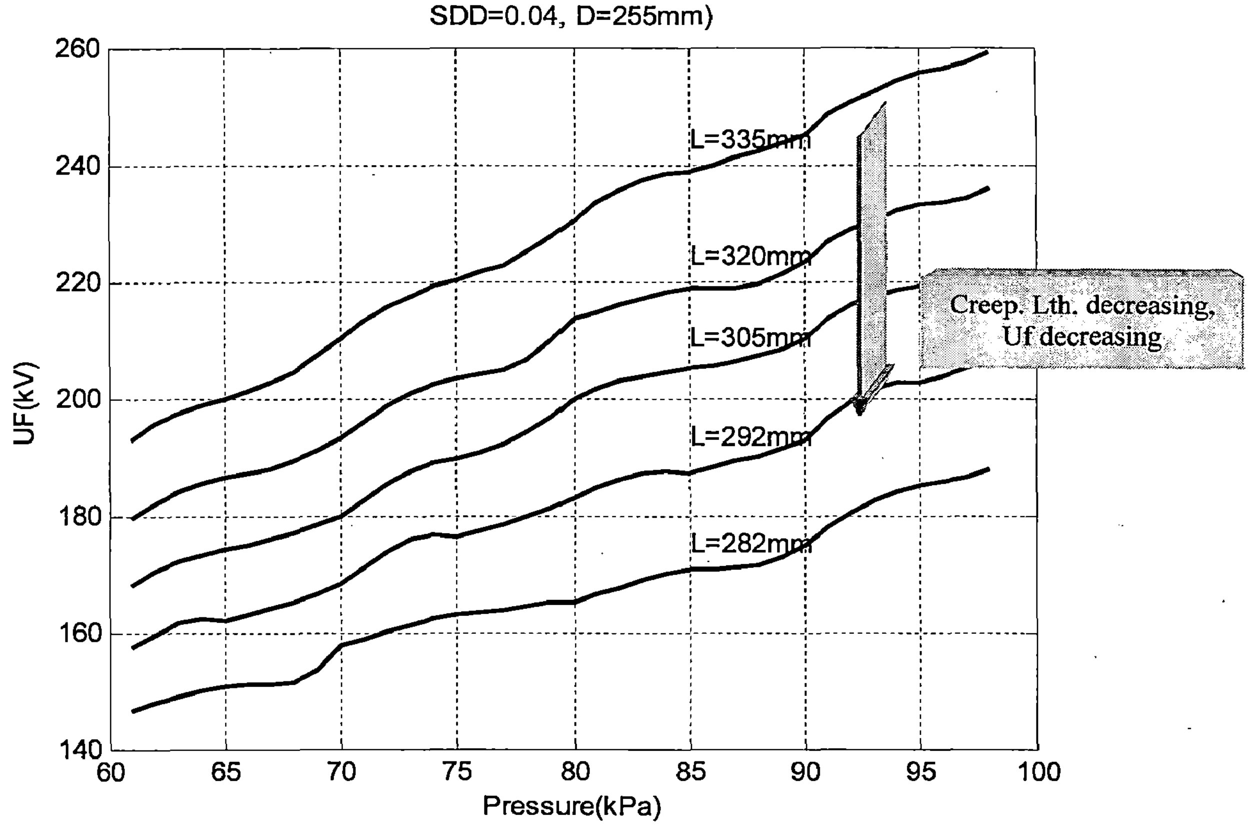


Figure 6.5: Variation of FOV with Creepage length (i)

Flashover voltage variation with creepage length can be drawn with flashover voltage at Y-axis and creepage length at X-axis at different values of SDD concentration and pressure, for LXY_4-160 type glass insulator. These characteristics are shown in following Fig. 6.6.

'Fig. 6.6 on next page'

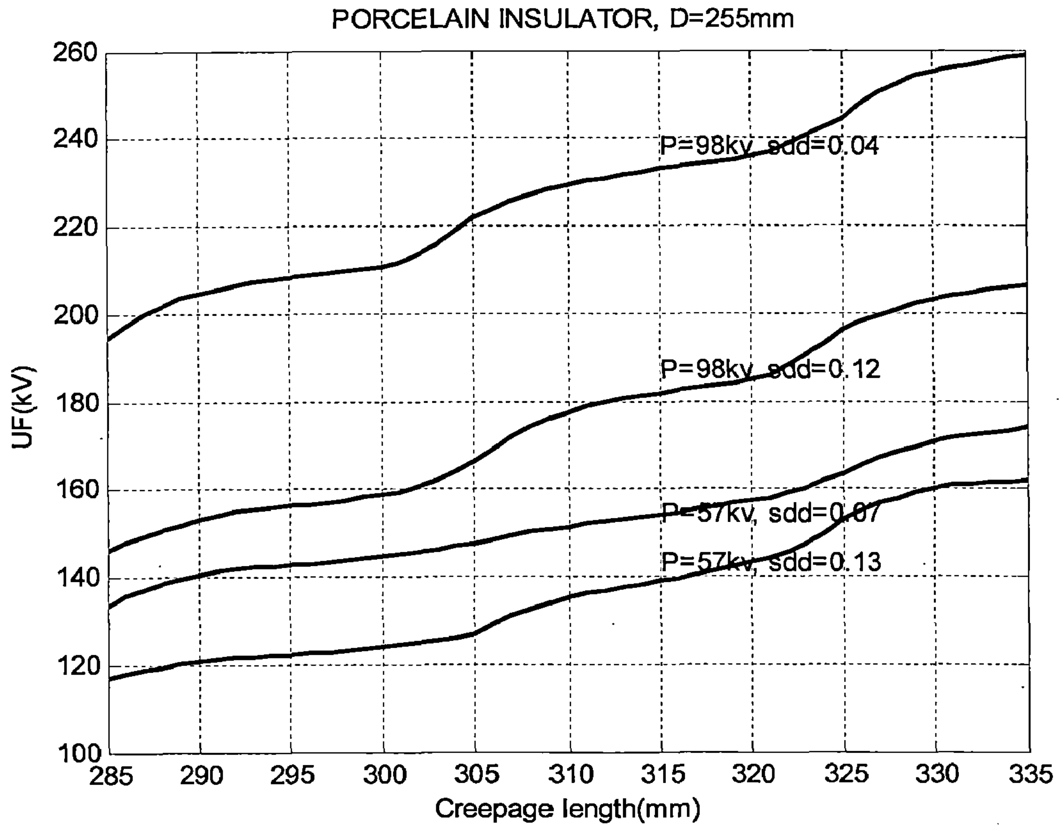


Figure 6.6: Variation of FOV with Creepage length (ii)

6.2.2 Diameter Variation:

Now from the following Fig. 6.7 the effect of diameter variation can be seen on flashover voltage. It is obvious from characteristic that if Diameter increases then flashover voltage decreases as was said in reference [4] and [5].

'Fig. 6.7 on next page'

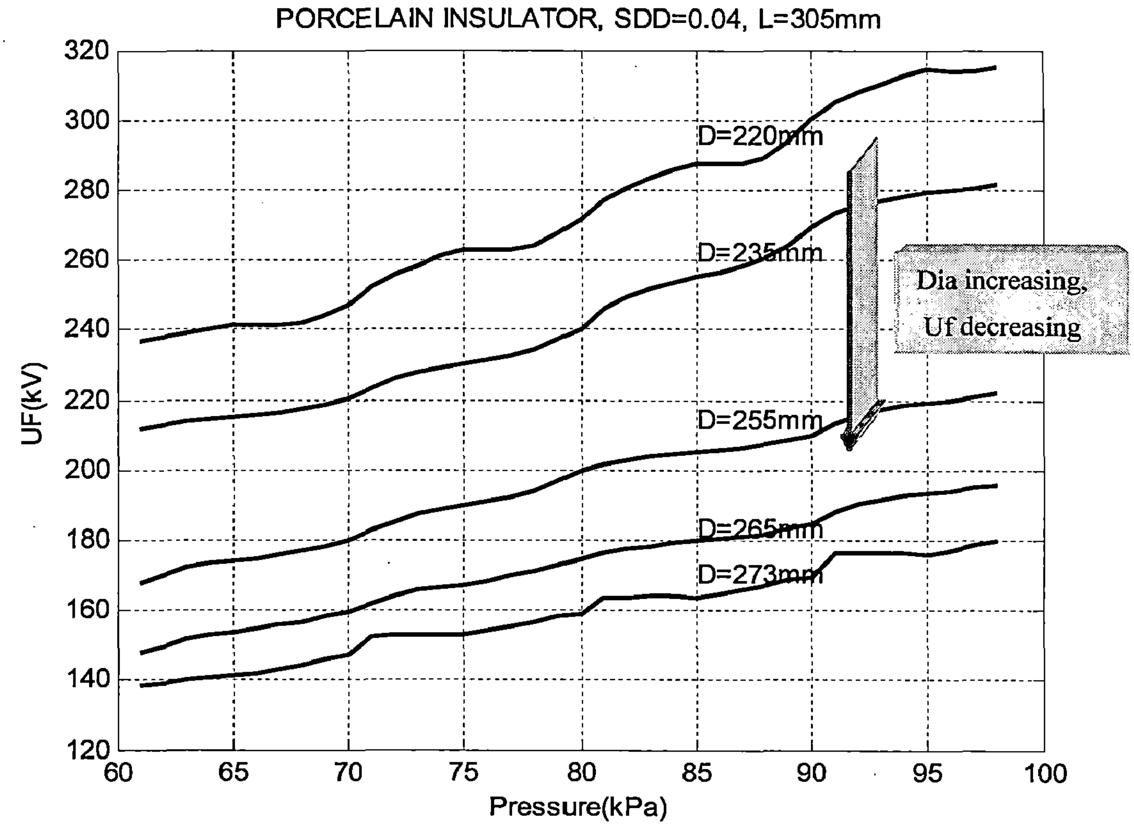


Figure 6.7: Variation of FOV with Diameter (i)

Flashover voltage variation with diameter are drawn in Fig. 6.8 with flashover voltage at Y-axis and diameter at X-axis at different values of SDD concentration and pressure, for XP-160 type glass insulator.

'Fig. 6.8 on next page'

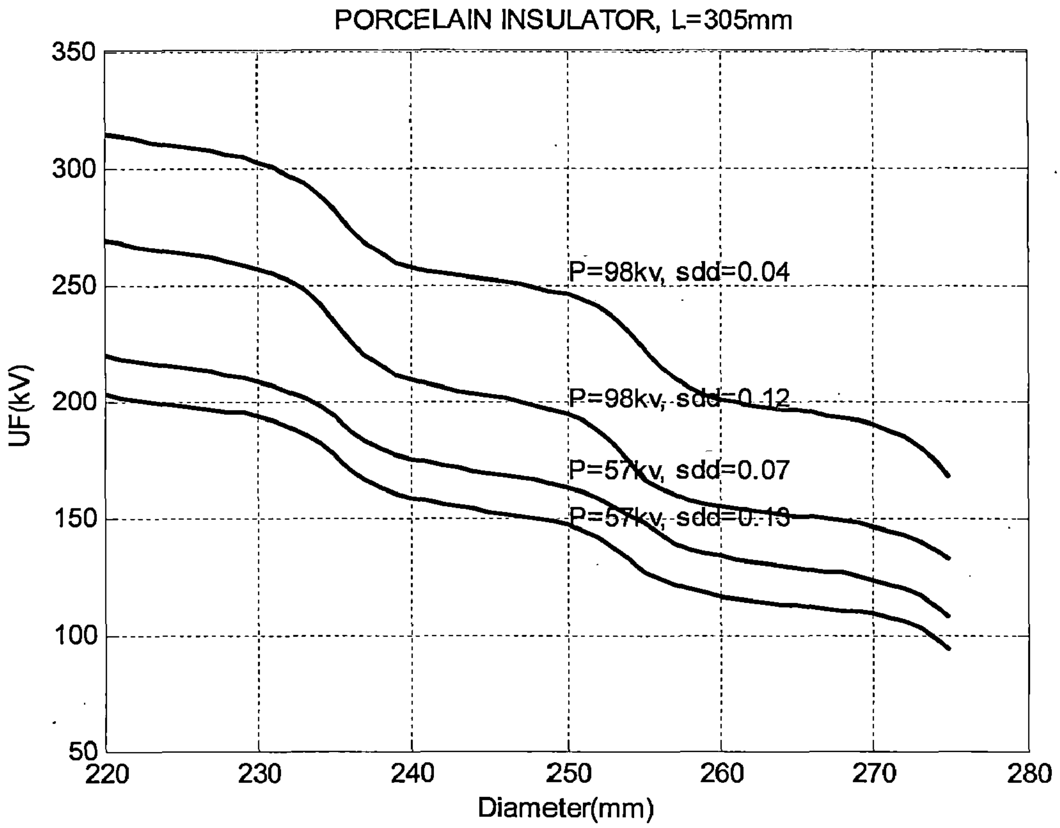


Figure 6.8: Variation of FOV with Diameter (ii)

Other characteristics can also be drawn for different values of pressure, sdd, creepage length and diameter but within specified and limited range.

Different pollutant degree concentrations and pressure values can be given to this model for predicting flashover voltage and predicted results are fairly close to the experimental results taken from reference [4].

Inference:-

- By these characteristics it can be seen that as diameter of insulator increases, the flashover voltage of a polluted insulator decreases linearly. We are not getting exact linear curves because of fuzziness of output values.
- As creepage distance is going to increase, flashover voltage should increase which can also be seen by the characteristics drawn.
- Effect of SDD can also be interpreted from these characteristics. As SDD increases, FOV is decreased which is an obvious phenomena and can also be seen in characteristics.
- As atmospheric pressure decreases, flashover voltage is decreased.

We can get value of flashover voltage of glass insulators (LXY_4-160 and $LXHY_3$-160) and of porcelain insulators (XP-160 and XWP_2-160) by this model at different values of Pressure, Sdd concentration, Creepage length and Diameter of insulators by changing any one of them. So we can have an idea of flashover voltage of an insulator. In this way, the insulators that has to be utilized on a specific transmission line in a given environment conditions can be identified.

RESULTS OF ANN MODELS:

ANN models of glass, porcelain and composite insulators have been made following the procedure said in chapter 5. Different architectures of ANN models were tried for each of the insulators and then optimal architecture of ANN for each one has been found out. Optimal architecture has been found by minimizing the MSE (mean square error) . So MSE has been taken as the performance index.

The data used for the training, evaluation and testing of the ANN were selected from experimental results of reference no. [4] for different types of insulators. The aim of the present work is to apply different Neural Network topologies for flashover modeling to be used for forecasting the flashover voltage for new operating conditions. A multilayer feed forward neural network is constructed and trained with experimental input/output data pairs using *Levenberg-Marquardt optimization algorithm*, to find the optimal network weights (W*) by minimizing mean square error (MSE). Back propagation algorithm has been used for minimizing the error between target and actual output value.

With the help of these tables in excel sheet, m-files in MatLab have been made which are to run in command window environment before calling training data through nntool box. Out of all training data points, 60% have been taken for training the neural network and remaining are used for testing the ANN model. Relative error has been calculated for each testing data and then plotted for each ANN model so that error can be visualized easily.

6.3 ANN MODEL FOR GLASS INSULATOR :

ANN as a function approximator is used to model accurately the relationship between flashover voltage Uf (kV) as the output of the neuronal model and the High voltage insulator parameters the maximum diameter D (mm), the creepage distance L (mm), the Salt deposit density (mg/cm^2), and the surroundings pressure P (kPa).

Different architectures or topologies were used for finding optimal ANN network which gives least MSE. Number of hidden layers and number of neurons in them were changed substantially to find an optimal ANN model for glass insulator of type LXY4-160 and LXHY3-160.

A three layer network i.e. one input layer, one hidden layer and one output layer has given satisfied results. ***This ANN model has 10 neurons in input layer, 7 neurons in hidden layer and 1 neuron in output layer.*** This ANN model has given convincing results in form of flashover voltage values which match fairly with the experimental values of reference no. [4].

During training , the following window as shown in Fig. 6.9 appears:

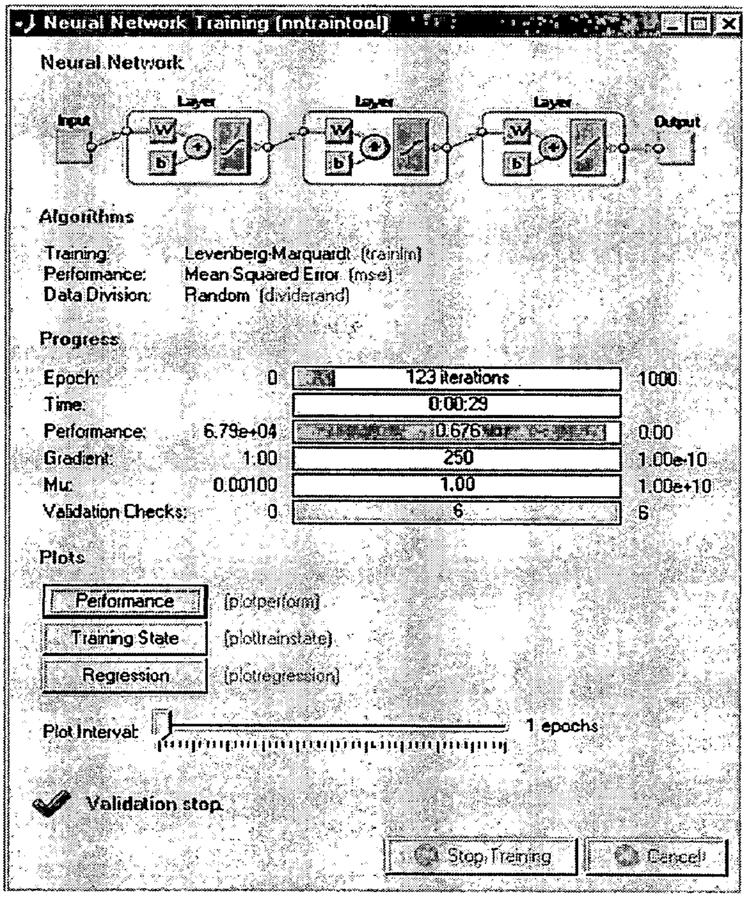


Figure 6.9: Training of Glass insultor ANN

From Fig. 6.9, it can be seen that ANN model has been trained in 123 iterations. Training algorithm used is Levenberg-Marquardt i.e trainlm. Fig.6.10 shows the performance graph of this neural network.

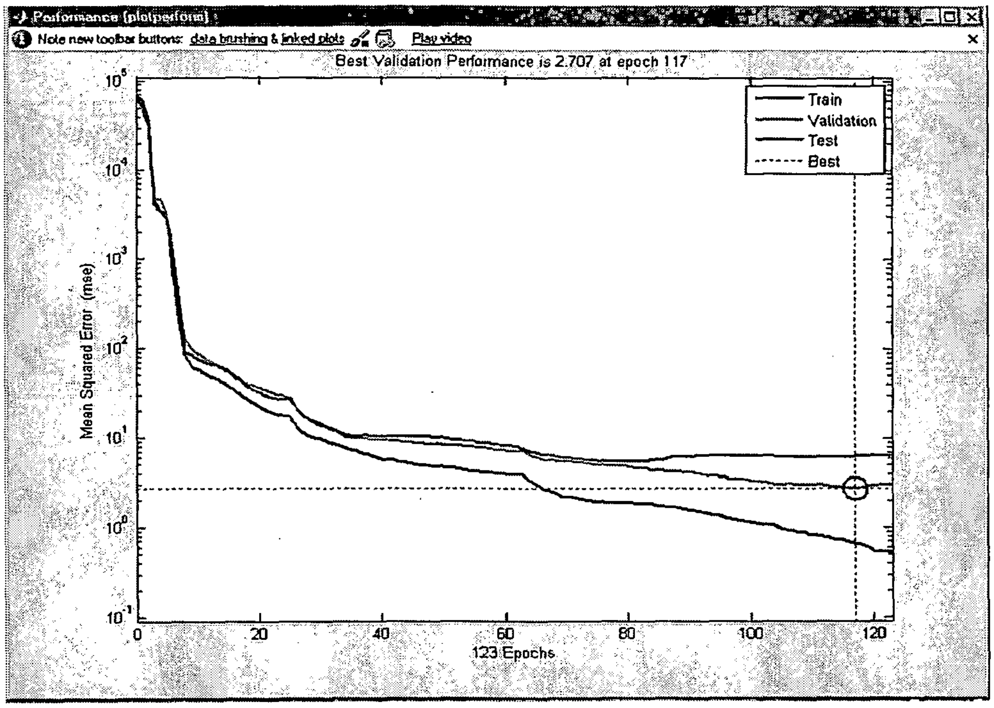


Figure 6.10: Performance graph

The MSE achieved is 2.707 at 117 th iteration or epoch which is quite considerable.

When this ANN model was tested using remaining input data points, the relative error of the output value of model gave plot as shown in Fig.6.11, below:

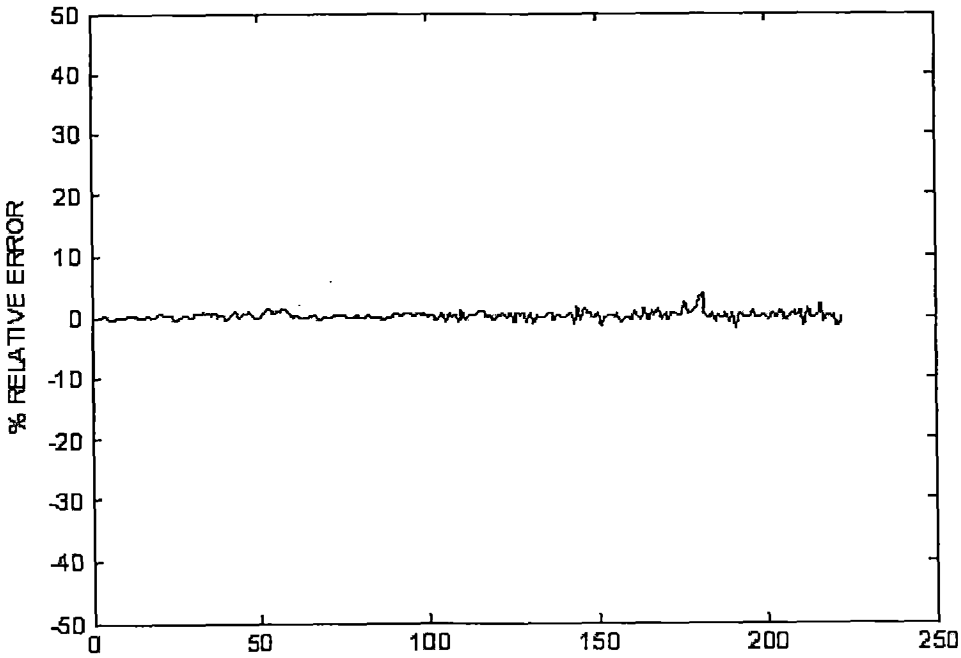


Figure 6.11: Graph of Relative Error

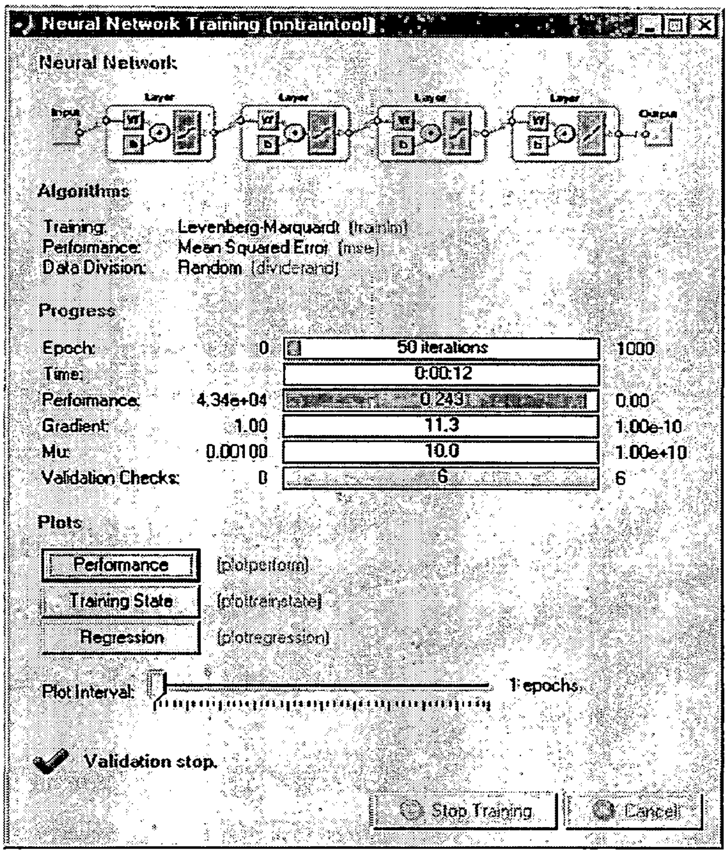
We can see that relative error is not very high. It is in between +/- 4%. So this ANN model is a satisfactory model of Glass insulator of type LXY4-160 and LXHY3-160.

6.4 ANN MODEL FOR PORCELAIN INSULATOR :

In the same way ANN model for porcelain insulators of type XP-160 and XWP2-160 are made. Different architectures or topologies were used for finding optimal ANN network which gives least MSE.

A four layer network i.e. one input layer, two hidden layers and one output layer has given satisfied results. ***This ANN model has 10 neurons in input layer, 10 neurons in first hidden layer, 7 neurons in second hidden layer and one neuron in output layer.*** This ANN model has given convincing results in form of flashover voltage values which match fairly with the experimental values of reference no. [4].

During training , the following window as shown in Fig.6.12, appears:



<u>**Figure 6.12: Training of Network**</u>

By this we can see that ANN model has been trained in 50 iterations. Training algorithm used is Levenberg-Marquardt i.e trainlm. Below in Fig. 6.13, is the performance graph of the neural network.

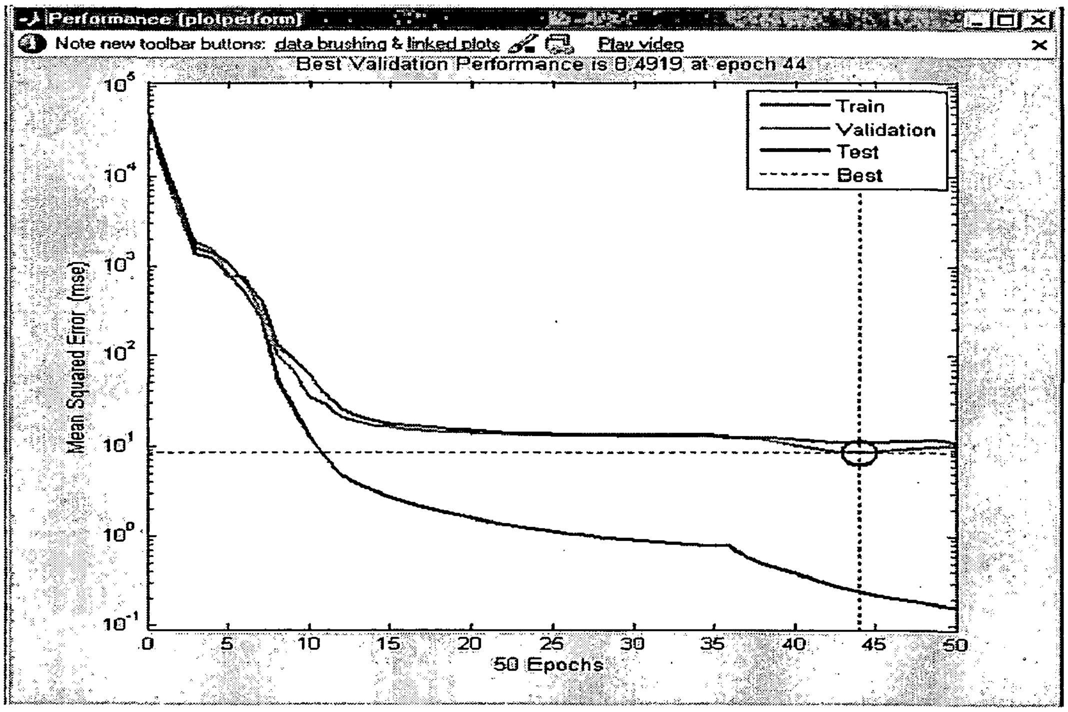


Figure 6.13: Performance Graph

The MSE achieved is 8.4919 at 44th iteration or epoch which is quite considerable.

When this ANN model was tested using remaining input data points, the relative error of the output value of model gave plot as shown in Fig.6.14, below:

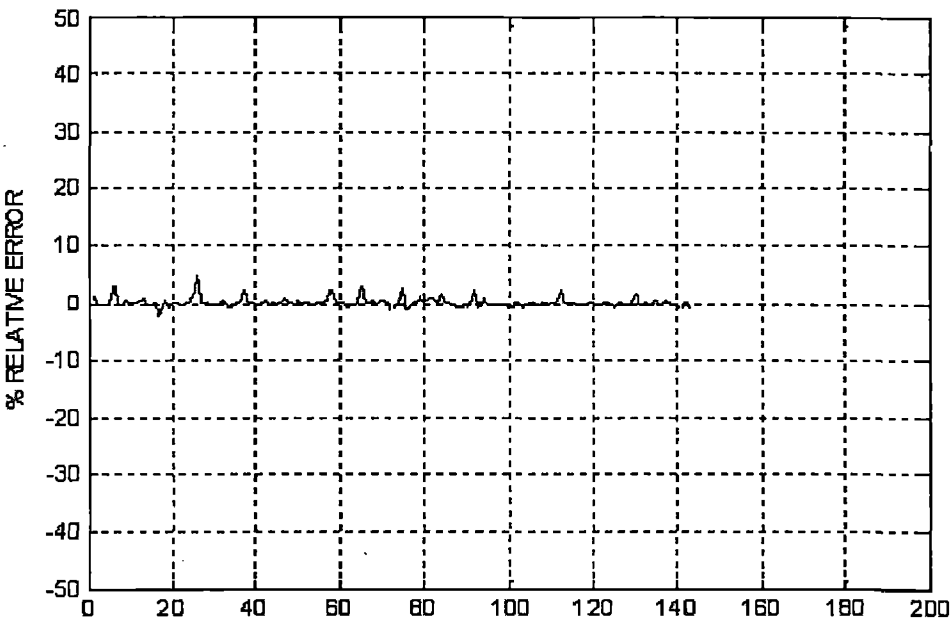


Figure 6.14: Graph of Relative Error

We can see that relative error is not very high. It is in between +/- 4%. So this ANN model is a satisfactory model of Porcelain insulator of type XP-160 and XWP2-160.

6.5 ANN MODEL FOR COMPOSITE INSULATOR :

ANN model for three type of composite insulators are made namely $FXBW_3$-110/70 SIR, FXBW-750/A SIR and FXBW-750/B SIR . Different architecture of topologies were used for finding optimal ANN network which gives least MSE.

Training datas are taken from the experimental results in reference no. [4].

These ANN models for composite insulators have created relationship between flashover voltage Uf (kV) as the output of the neuronal model and the parameters Salt deposit density (mg/cm^2), and the surroundings pressure P (kPa) as the input of the model.

6.5.1 Model for $FXBW_3$-110/70 SIR Composite insulator:

A three layer network i.e. one input layer, one hidden layer and one output layer has given satisfied results. ***This ANN model has 4 neurons in input layer, 8 neurons in hidden layer and one neuron in output layer.*** This ANN model has given convincing results in form of flashover voltage values shown in Table A.1 in appendix, which match fairly with the experimental values of reference no. [4].

During training , the following window as shown in Fig. 6.15, appears :

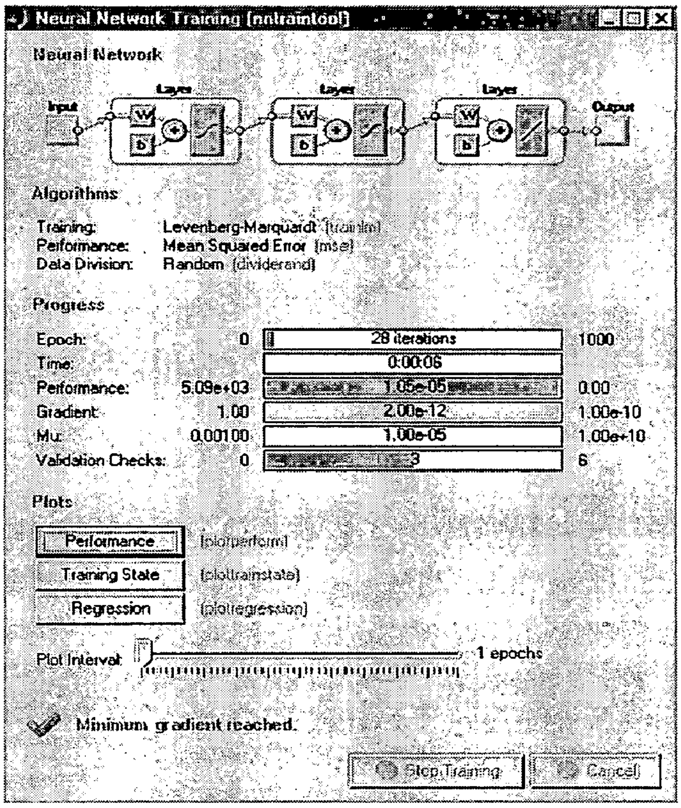


Figure 6.15: Training of Network

By this we can see that ANN model has been trained in 28 iterations. Training algorithm used is Levenberg-Marquardt i.e *trainlm*. Below in Fig.6.16, is the performance graph of the neural network.

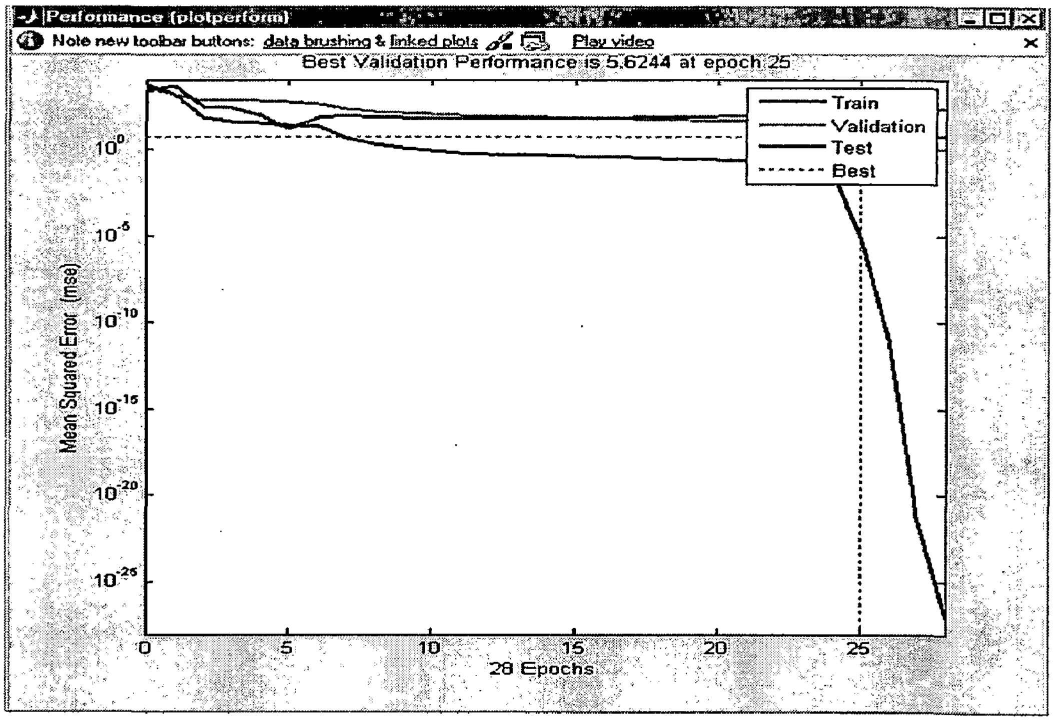


Figure 6.16: Performance graph

The MSE achieved is 5.6244 at 25th iteration or epoch which is quite considerable.

6.5.2 Model For FXBW-750/A SIR Composite Insulator:

A three layer network i.e. one input layer, one hidden layer and one output layer has given satisfied results. ***This ANN model has 6 neurons in input layer, 3 neurons in hidden layer and 1 neuron in output layer.*** This ANN model has given convincing results in form of flashover voltage values shown in Table A.2, which match fairly with the experimental values of reference no. [4].

During training , the following window as shown in Fig.6.17, appears:

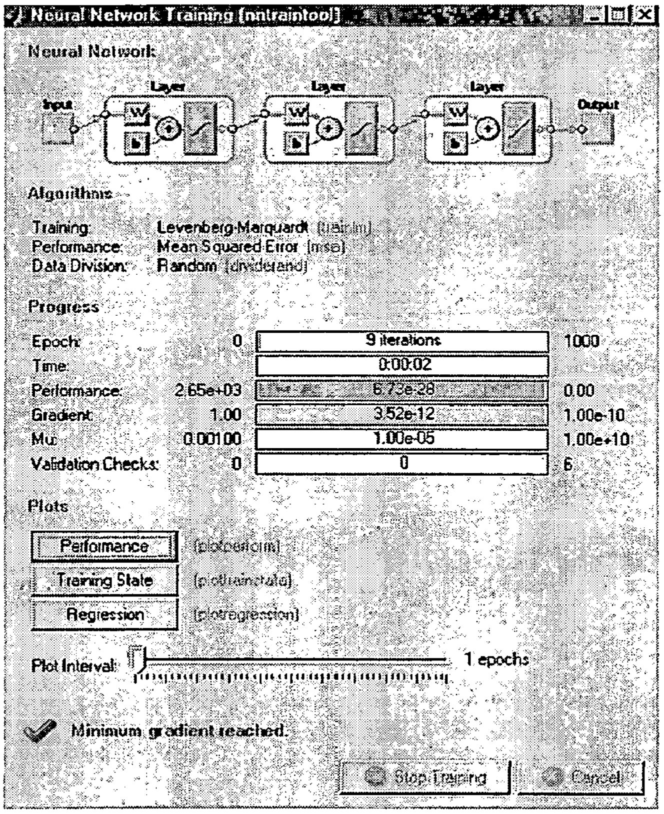


Figure 6.17: Training of network

By this we can see that ANN model has been trained in 9 iterations. Training algorithm used is Levenberg-Marquardt i.e *trainlm*. Below in Fig.6.18 is the performance graph of the neural network.

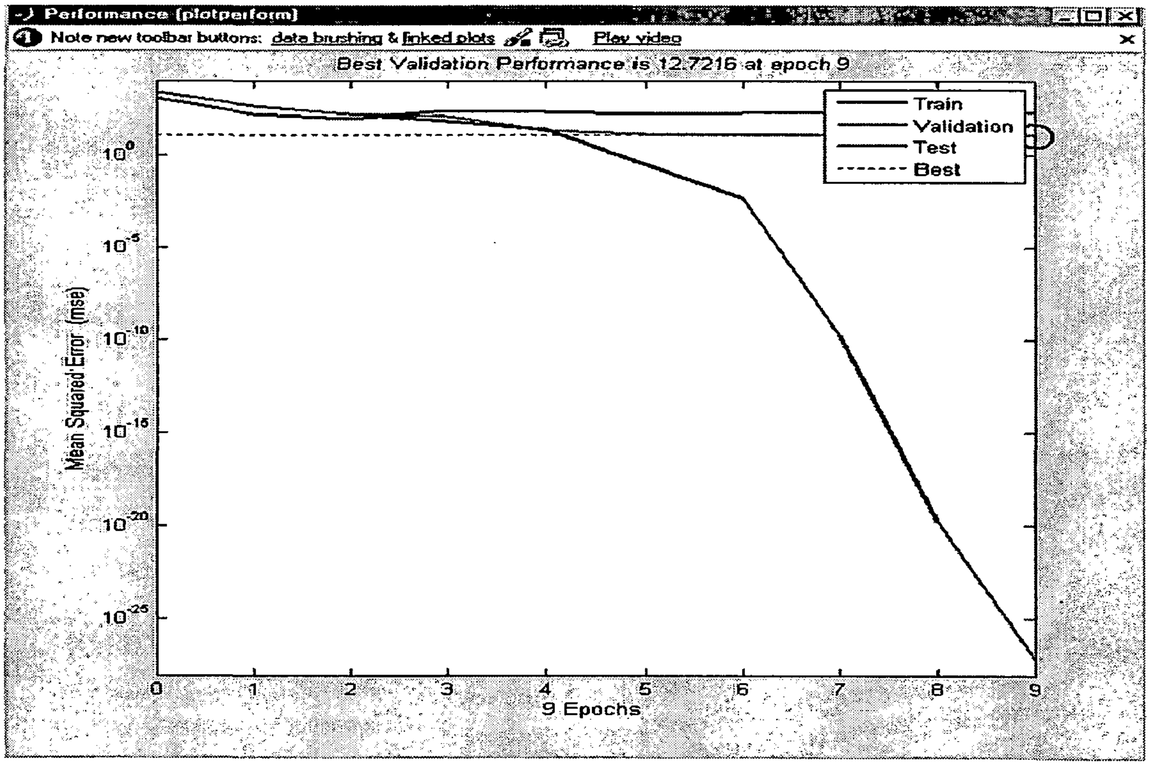


Figure 6.18: Performance Graph

The MSE achieved is 12.7216 at 9th iteration or epoch which is quite considerable.

6.5.3 Model For FXBW-750/B SIR Composite insulator:

A three layer network i.e. one input layer, one hidden layer and one output layer has given satisfied results. ***This ANN model has 5 neurons in input layer, 12 neurons in hidden layer and 1 neuron in output layer.*** This ANN model has given convincing results in form of flashover voltage values shown in Table A.3 which match fairly with the experimental values of reference no. [4].

During training , the following window as shown in Fig.6.19, appears:

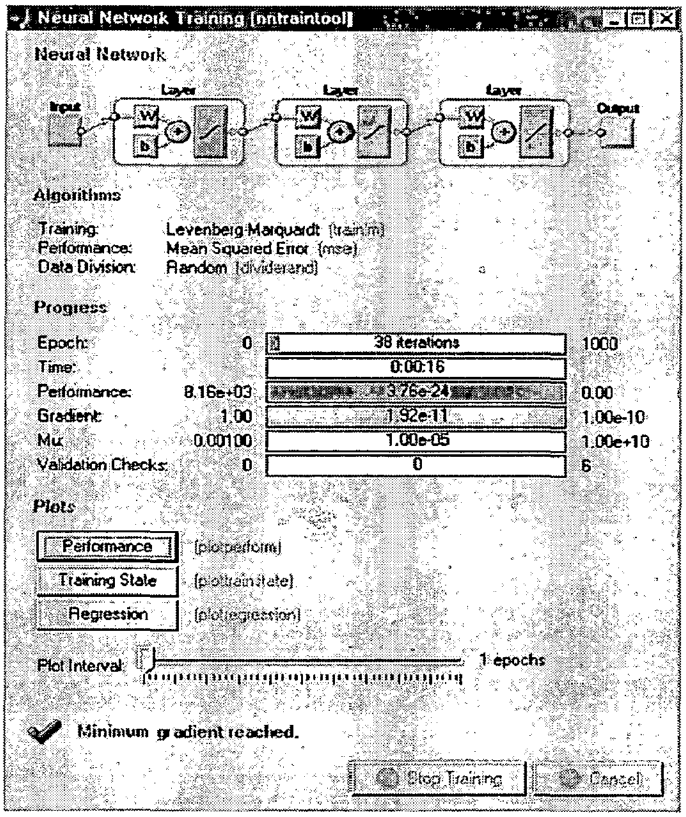


Figure 6.19: Training of network

By this we can see that ANN model has been trained in 38 iterations. Training algorithm used is Levenberg-Marquardt i.e *trainlm*. Below in Fig.6.20, is the performance graph of the neural network.

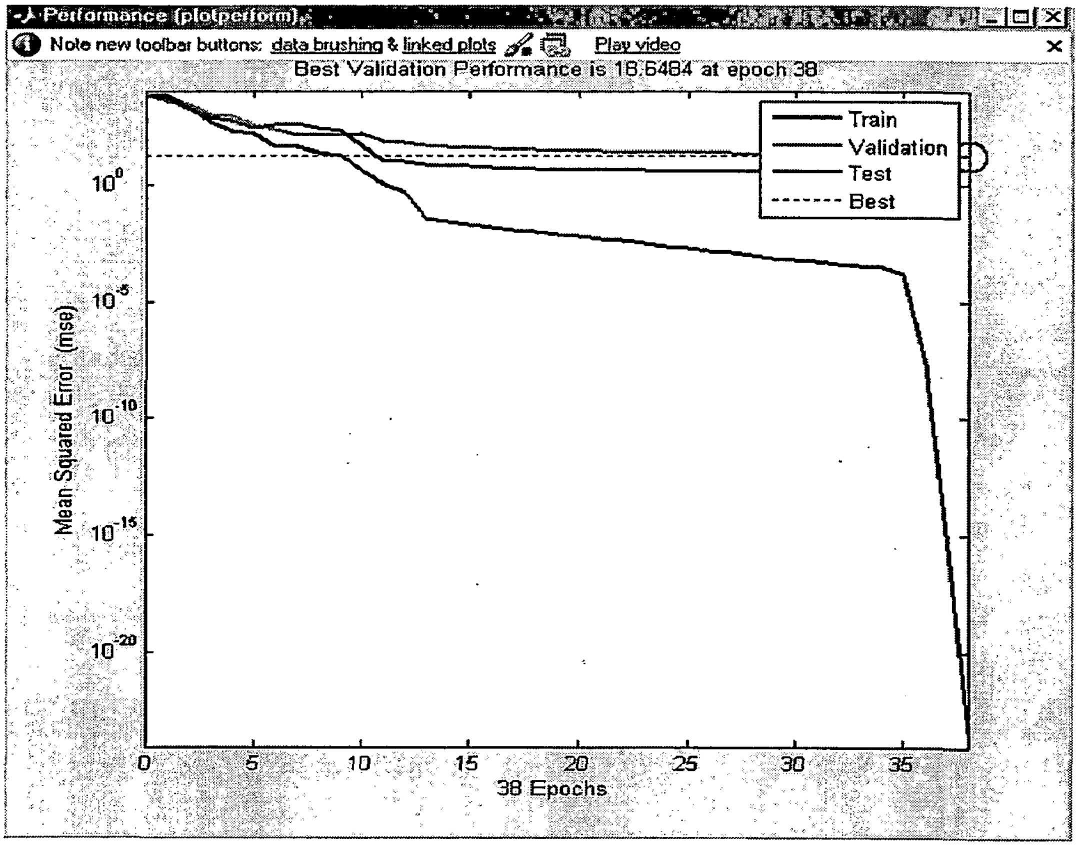


Figure 6.20: Performance Graph

The MSE achieved is 18.6484 at 38th iteration or epoch which is quite considerable.

Chapter 7

COMPARISON OF FUZZY MODEL RESULTS WITH ANN MODEL RESULTS FOR PREDICTION OF FOV

7.1 COMPARISON FOR GLASS INSULATORS:

In order to compare the simulated and the experimental values, simulations were performed and compared with the experimental results.

The ANN model made for glass insulator type LXY4-160 and LXHY3-160 were simulated for the input values given below in Table 7.1 and 7.2 respectively. These input values are corresponding to the experimental values of these insulators in reference no. [4]. Then the experimental values of Flashover voltage is compared with the Flashover voltage values obtained by simulating ANN model.

Similarly the Fuzzy model made for Glass insulators is simulated for same standard input values. The simulated output values for Flashover voltage are compared with the experimental values as given in reference no. [4].

Relative error has also been found out for both type of models and shown in Tables 7.1 and 7.2, below.

'Table 7.1 and7. 2 on next pages:'

Table7. 1: Comparison of results of Fuzzy model and ANN model (i)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length (mm)	Diameter (mm)		Experimental value of FOV(kV)	ANN model value of FOV(kV)	Relative Error ANN (in %)		FuzzyModel value of FOV (kV)	Relative Error Fuzzy (in %)
98.6	0.03	380	280		282.6	281.593	0.35644		275.752	2.42321
89.7	0.03	380	280		258	258.608	-0.2355		258.177	-0.06872
79.7	0.03	380	280		231	231.458	-0.1982		228.982	0.87368
70.1	0.03	380	280		210	209.566	0.20671		210.333	-0.15852
61.6	0.03	380	280		196.5	196.537	-0.0186		201.836	-2.71547
98.6	0.05	380	280		254.1	255.884	-0.7019		245.915	3.22102
89.7	0.05	380	280		234	233.77	0.09825		228.982	2.14453
79.7	0.05	380	280		211.2	211.587	-0.1832		208.897	1.09029
70.1	0.05	380	280		193.8	195.006	-0.622		190.451	1.72786
61.6	0.05	380	280		183	184.571	-0.8586		182.181	0.4477
98.6	0.08	380	280		230.1	230.575	-0.2066		225.715	1.90587
89.7	0.08	380	280		213.9	212.578	0.61786		208.897	2.3388
79.7	0.08	380	280		194.7	195.99	-0.6625		189.563	2.63837
70.1	0.08	380	280		180.3	178.974	0.73544		180.154	0.0812
61.6	0.08	380	280		171	170.358	0.37556		171.994	-0.58111
98.6	0.15	380	280		201.9	201.681	0.10832		198.398	1.73477
89.7	0.15	380	280		189.6	188.734	0.4568		188.954	0.34082
79.7	0.15	380	280		174	173.835	0.09483		169.504	2.58379
70.1	0.15	380	280		163.2	163.045	0.09504		160.155	1.86556
61.6	0.15	380	280		156.9	155.824	0.68598		159.955	-1.94691

Table7. 2: Comparison of results of Fuzzy model and ANN model (ii)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)	Experimental value of FOV(kV)	ANN model value of FOV(kV)	Relative Error ANN(in %)	FuzzyModel value of FOV (kV)	Relative Error Fuzzy(in %)
98.6	0.03	450	280	378.1	379.499	-0.3699	375.9119	0.57871
89.7	0.03	450	280	356	355.182	0.22992	357.8526	-0.5204
79.7	0.03	450	280	318.1	319.379	-0.40217	318.4974	-0.1249
70.1	0.03	450	280	287	285.281	0.59892	290.621	-1.2617
61.6	0.03	450	280	259.1	259.842	-0.28649	266.9735	-3.0388
98.6	0.05	450	280	341.2	340.724	0.13942	333.6507	2.21257
89.7	0.05	450	280	313	313.288	-0.09208	308.9341	1.29901
79.7	0.05	450	280	292	292.57	-0.19534	288.2364	1.2889
70.1	0.05	450	280	260.3	260.698	-0.15282	260.4717	-0.066
61.6	0.05	450	280	241.2	240.151	0.43483	244.5097	-1.3722
98.6	0.08	450	280	304	304.621	-0.20418	298.1689	1.91813
89.7	0.08	450	280	285	284.616	0.13474	288.7535	-1.317
79.7	0.08	450	280	269.9	270.363	-0.17158	268.9595	0.34846
70.1	0.08	450	280	248.1	248.252	-0.06127	250.3777	-0.9181
61.6	0.08	450	280	218	218.436	-0.19995	226.9471	-4.1042
98.6	0.15	450	280	273.2	273.448	-0.09067	268.0835	1.8728
89.7	0.15	450	280	256	255.369	0.24645	258.8909	-1.1293
79.7	0.15	450	280	241.2	242.004	-0.33325	238.8272	0.98375
70.1	0.15	450	280	218	216.644	0.62225	220.3401	-1.0734
61.6	0.15	450	280	207.1	207.993	-0.43134	211.9136	-2.3243

- From these tables it can be seen that Relative Error in flashover voltage (FOV) calculation from Fuzzy model is higher in comparison to calculated from ANN model. So ANN model can be preferred over Fuzzy model of glass insulators for prediction purpose of flashover voltage for different insulator parameters and environmental conditions.

Now below, in Table 7.3 and 7.4, are the simulated results for Glass insulator for input parameters other than the standard values:-

Table7. 3: Simulated results of Fuzzy model and ANN model (i)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)			ANN model value of FOV(kV)		FuzzyModel value of FOV (kV)
98.6	0.03	483	280			424.532		394.718
89.7	0.03	483	280			394.639		387.2236
79.7	0.03	483	280			354.152		347.2804
70.1	0.03	483	280			316.007		310.903
61.6	0.03	483	280			289.098		287.356
98.6	0.05	483	280			385.294		373.1718
89.7	0.05	483	280			354.345		348.7955
79.7	0.05	483	280			328.22		327.71
70.1	0.05	483	280			290.083		290.803
61.6	0.05	483	280			267.899		267.3041
98.6	0.08	483	280			344.754		335.642
89.7	0.08	483	280			323.124		318.9016
79.7	0.08	483	280			304.793		297.8684
70.1	0.08	483	280			278.835		270.6185
61.6	0.08	483	280			244.08		247.3933
98.6	0.15	483	280			314.321		305.5717
89.7	0.15	483	280			292.812		288.6377
79.7	0.15	483	280			275.905		268.8749
70.1	0.15	483	280			249.078		250.412
61.6	0.15	483	280			233.674		234.9051

Table7. 4: Simulated results of Fuzzy model and ANN model (ii)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)			ANN model value of FOV(kV)		FuzzyModel value of FOV (kV)
98.6	0.03	380	263			337.174		328.2497
89.7	0.03	380	263			307.127		306.6244
79.7	0.03	380	263			273.525		270.5606
70.1	0.03	380	263			247.301		243.4766
61.6	0.03	380	263			231.372		234.761
98.6	0.05	380	263			310.256		301.5321
89.7	0.05	380	263			281.715		277.707
79.7	0.05	380	263			253.689		251.122
70.1	0.05	380	263			232.673		229.6603
61.6	0.05	380	263			219.566		221.1705
98.6	0.08	380	263			285.507		273.2263
89.7	0.08	380	263			261.3		257.6182
79.7	0.08	380	263			236.917		231.5863
70.1	0.08	380	263			216.674		213.1853
61.6	0.08	380	263			205.709		204.9184
98.6	0.15	380	263			256.566		251.6488
89.7	0.15	380	263			238.196		237.6816
79.7	0.15	380	263			215.811		211.4006
70.1	0.15	380	263			199.64		199.3503

Here is some difference between values of FOV calculated from Fuzzy and ANN model. But as seen before ANN models are more accurate, therefore, ANN model output values of FOV are more reliable and will be considered for prediction of FOV.

7.2 COMPARISON FOR PORCELAIN INSULATOR

In a similar way the ANN model made for porcelain insulator type XP-160 and XWP2-160 were simulated for the input values given below in Table 7.5 and 7.6 respectively. These input values are corresponding to the experimental values of these insulators in reference no. [4]. Then the experimental values of Flashover voltage is compared with the Flashover voltage values obtained by simulating ANN model.

Similarly the Fuzzy model made for Porcelain insulators is simulated for standard input values. The simulated output values for Flashover voltage are compared with the experimental values as given in reference no. [4].

Relative error has also been found out for both type of models and shown in Tables 7.5 and 7.6 :.

Table7.5: Comparison of results of Fuzzy model and ANN model (i)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)		Experimental value of FOV(kV)	ANN model value of FOV(kV)	Relative Error ANN(in %)		FuzzyModel value of FOV (kV)	Relative Error Fuzzy(in %)
98.6	0.03	305	255		238.5	238.049	0.18906		236.04	1.03145
89.7	0.03	305	255		218	217.063	0.43		219.722	-0.79
79.7	0.03	305	255		205.8	205.951	-0.0736		209.074	-1.5909
70.1	0.03	305	255		191	190.355	0.3378		190.278	0.37822
61.6	0.03	305	255		173.7	172.331	0.78803		174.332	-0.3638
98.6	0.05	305	255		210.3	210.831	-0.2526		208.311	0.94574
89.7	0.05	305	255		197.7	197.621	0.04021		199.595	-0.9584
79.7	0.05	305	255		186	188.305	-1.2395		188.849	-1.5317
70.1	0.05	305	255		171.6	172.105	-0.2941		170.287	0.76515
61.6	0.05	305	255		157	157.009	-0.0055		161.904	-3.1233
98.6	0.08	305	255		184	183.93	0.03826		179.959	2.19609
89.7	0.08	305	255		177.3	176.326	0.54913		179.533	-1.2593
79.7	0.08	305	255		166.5	167.296	-0.478		168.844	-1.4079
70.1	0.08	305	255		152	148.789	2.11257		150.394	1.05658
61.6	0.08	305	255		146.1	145.059	0.71273		149.992	-2.6637
98.6	0.15	305	255		162	160.848	0.7113		158.149	2.3771
89.7	0.15	305	255		153.6	154.032	-0.2812		149.971	2.36237
79.7	0.15	305	255		150	149.581	0.2794		149.539	0.3076
70.1	0.15	305	255		138.6	138.607	-0.0053		140.139	-1.1107
61.6	0.15	305	255		130.8	131.382	-0.445		131.98	-0.9021

Table7.6: Comparison of results of Fuzzy model and ANN model (ii)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)	Experimental value of FOV(kV)	ANN model value of FOV(kV)	Relative Error ANN(in %)	FuzzyModel value of FOV (kV)	Relative Error Fuzzy(in %)
98.6	0.03	450	300	313.5	310.789	0.86488	297.177	5.20673
89.7	0.03	450	300	293	292.55	0.15362	282.933	3.4359
79.7	0.03	450	300	270.7	271.251	-0.2035	263.335	2.72058
70.1	0.03	450	300	245.5	243.55	0.79438	242.337	1.28827
61.6	0.03	450	300	227	227.96	-0.4229	228.939	-0.854
98.6	0.05	450	300	276	276.109	-0.0394	264.073	4.32138
89.7	0.05	450	300	259.8	259.364	0.16798	254.279	2.12525
79.7	0.05	450	300	244.6	243.264	0.54624	236.391	3.35609
70.1	0.05	450	300	221.8	222.994	-0.5384	218.275	1.58927
61.6	0.05	450	300	202	201.452	0.27124	201.599	0.19847
98.6	0.08	450	300	245.4	242.038	1.37005	231.201	5.78606
89.7	0.08	450	300	226.2	230.855	-2.0581	218.721	3.30632
79.7	0.08	450	300	219.8	217.005	1.27157	214.121	2.58385
70.1	0.08	450	300	200	199.052	0.474	194.617	2.6914
61.6	0.08	450	300	180	179.823	0.09839	178.547	0.80717
98.6	0.15	450	300	210	210.689	-0.328	202.5	3.57129
89.7	0.15	450	300	200.4	203.159	-1.3766	194.027	3.18029
79.7	0.15	450	300	191.3	190.525	0.40533	184.691	3.45504
70.1	0.15	450	300	177.7	178.865	-0.6558	174.15	1.99769
61.6	0.15	450	300	161.1	160.931	0.1049	158.388	1.68318

- From the above comparison results it is obvious that Relative Error in flashover voltage (FOV) calculation from Fuzzy model is higher in comparison to calculated from ANN model as was the case with glass insulator. So ANN model can be preferred over Fuzzy model of insulators for prediction purpose of flashover voltage for different insulator parameters and environmental conditions.

Following are the simulated results for Porcelain Insulator for input parameters other than the standard values in Table 7.7 and7. 8:-

Table7.7: Simulated results of Fuzzy model and ANN model (i)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)		Experimental value of FOV(kV)	ANN model value of FOV(kV)		FuzzyModel value of FOV (kV)
98.6	0.03	334	255			275.272		269.58
89.7	0.03	334	255			251.627		253.585
79.7	0.03	334	255			238.912		238.461
70.1	0.03	334	255			217.261		219.849
61.6	0.03	334	255			198.408		204.343
98.6	0.05	334	255			246.185		245.377
89.7	0.05	334	255			230.898		233.753
79.7	0.05	334	255			219.942		218.445
70.1	0.05	334	255			201.806		199.695
61.6	0.05	334	255			180.781		183.996
98.6	0.08	334	255			222.469		217.416
89.7	0.08	334	255			211.16		213.532
79.7	0.08	334	255			200.553		198.148
70.1	0.08	334	255			178.152		179.499
61.6	0.08	334	255			169.62		171.432
98.6	0.15	334	255			196.585		197.303
89.7	0.15	334	255			188.68		188.739
79.7	0.15	334	255			183.792		183.208
70.1	0.15	334	255			166.353		164.983
61.6	0.15	334	255			153.979		156.662

Table7.8: Simulated results of Fuzzy model and ANN model (ii)

Pressure (kPa)	SDD (mg/cm^2)	Creepage Length(mm)	Diameter (mm)		Experimental value of FOV(kV)	ANN model value of FOV(kV)		FuzzyModel value of FOV (kV)
98.6	0.03	450	318			261.93		248.168
89.7	0.03	450	318			241.789		236.795
79.7	0.03	450	318			221.519		218.589
70.1	0.03	450	318			204.168		201.3
61.6	0.03	450	318			187.348		187.785
98.6	0.05	450	318			226.194		214.296
89.7	0.05	450	318			208.179		206.273
79.7	0.05	450	318			195.796		196.907
70.1	0.05	450	318			180.728		180.868
61.6	0.05	450	318			160.839		163.222
98.6	0.08	450	318			185.187		176.467
89.7	0.08	450	318			178.112		164.506
79.7	0.08	450	318			171.258		166.594
70.1	0.08	450	318			161.858		157.822
61.6	0.08	450	318			143.218		143.979
98.6	0.15	450	318			148.837		145.665
89.7	0.15	450	318			147.677		144.941
79.7	0.15	450	318			143.883		139.216
70.1	0.15	450	318			137.603		137.904
61.6	0.15	450	318			123.374		124.398

Some differences are there in FOV values simulated Fuzzy model and ANN model. But as said before ANN models are more accurate. Therefore, ANN model values of FOV will be considered more reliable and therefore ANN model will be preferred over Fuzzy model of insulator to predict the FOV in varying conditions of surrounding environment and for various dimensions of insulators either Glass, porcelain or composite.

CONCLUSION AND FUTURE WORK

Flashover of outdoor insulators due to contamination results in power outages, revenue loss, damage to machines etc. Numerous industries are there which need continuous uninterrupted power supply for their operation. So reliability of insulators should be appropriately high. Therefore prediction of flashover voltage is very helpful and for this modeling has been done here in this dissertation for glass, porcelain and composite insulators.

The influence of the pollution and air pressure on the ac flashover voltage is related to the material of the insulators. The composite insulator is superior in severely contaminated areas because of hydrophobic nature of its surface. The ac pollution flashover voltage of insulators decreases with the decrease of the air pressure and with increase of pollution layer concentration (SDD).

For new construction, field experience may not be available and laboratory experiments are very time consuming and expensive. A good model for simulation of flashover process is very useful thing as it helps in reducing need of experimental work. This project work is therefore aimed at developing models by which the FOV based on contamination are to be predicted.

In this project work, fuzzy models for predicting ac flashover voltages of the polluted glass and porcelain insulators, at different values of pressure, salt deposit density(SDD), creepage length and diameter, are constructed . These models show fair accuracy with experimental results and therefore can be used to predict flashover voltages in different environmental conditions.

For prediction of flashover voltage, ANN models have also been modeled for glass, porcelain and composite insulators. Input and output data are collected from the experiment results of ref. [4] performed at State Key Laboratory, Chongqing University. And these are used in the training, validation and testing process. Several ANN models have been developed using many different structures. The ANN model, that presented the best generalizing ability, had a minimum mean square error (MSE). All the developed ANN models have been selected and applied on contaminated insulators of known contamination presenting very accurate results.

A comparison has also been shown between the results of ANN models and fuzzy models in tabular form. From that it has been seen that ANN models have less error in comparison to fuzzy models. Therefore ANN models have been preferred for predicting flashover voltages of outdoor insulators.

More generalized model can be made by adding some more input parameters to input vector of ANN model. Except this model may also be constructed by larger data base for making it more generalized so that model will be applicable for a number of insulators.

REFERENCES

[1]. M. A. Laughton, D. J. Warne, "Electrical Engineer's Reference Book" , Text Book, ISBN 0-7506-46373,sixteenth edition,pp.7/27-7/30; 2003

[2]. R. S. Gorur, S. Sundhara Rajan, and O. G. Amburgey "Contamination performance of polymeric insulating materials used for outdoor insulation applications," IEEE Trans. Electrical Insulation, vol. 24, no. 4, pp. 713-716, Aug. 1989.

[3]. J. P. Holtzhausen, W. L. Vosioo "The Pollution Flashover of ac Energized Post Type Insulators", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 8 No. 2, April 2001

[4]. Zhijin Zhang, Xinliang Jiang, Yafeng Chao, Caixin Sun and Jianlin Hu , "Influence of Low Atmospheric Pressure on AC Pollution Flashover Performance of Various Types of Insulators" ,IEEE Transactions on Dielectrics and Electrical Insulation Vol. 17, No. 2; April 2010

[5]. J.S.T. Looms, "Insulators for high voltages" Text Book, ISBN 0 86341 116 9, IEE power Engineering series 7, Published by: Peter Peregrinus Ltd., London, UK, pp. 172-192 ; 1988.

[6]. M.T. Gencog lu, M. Cebeci, "Investigation of pollution flashover on high voltage insulators using artificial neural network", ELSEVIER, Expert Systems with Applications 36 , pp. 7338–7345; 2009

[7]. P.S Ghosh., S. Chakravorti., N. Chatterjee, "Estimation of time to flashover characteristics of contaminated electrolytic surfaces using neural networks", IEEE Trans on Dielectrics and electrical insulation, Vol. 2, No. 6, pp.1064-1074, December 1995

[8]. I.F. Gonos, F.V. Topalis and LA. Stathopolos, "Genetic algorithm approach to the modelling of polluted insulators" , IEE Proceedings on Generation, Transmission and Distribution, Vol. 149, No. 3,pp. 373-376 ; May 2002

[9]. Y. Xiong, S. M. Rowland, J. Robertson, " Surface Analysis of Asymmetrically Aged 400 kV Silicone Rubber Composite Insulators", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 15, No. 3, pp. 763-770; June 2008

[10]. Linjie Zhao, Chengrong Li, Jisha Yao, Shuqi Zhang, Jun Xiong, "A Cold Fog Test Method of Composite Insulators", Conference Record of the 2006 IEEE International Symposium on Electrical Insulation, pp.193-196, August 2006

[11]. S. Sundhar, A. Bernstorf, W. Goch, D. Linson and L. Huntsman, "Polymer insulating materials and insulators for high voltage outdoor applications", Electrical Insulation. Conference records of 1992 IEEE International Symposium , pp. 222-228; Jun 1992

[12]. R. S. Gorur, J. Montesinos, L. Varadadesikan, "A Laboratory Test for Tracking and Erosion Resistance of HV Outdoor Insulation", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 4 ,No. 6, pp. 767-774 ;December 1997

[13]. S. Venkataraman and R. S. Gorur, "Prediction of Flashover Voltage of Non-ceramic Insulators Under Contaminated Conditions", IEEE Transactions on Dielectrics and Electrical Insulation Vol. 13 ,No. 4, pp. 862-869 ; August 2006

[14]. Boubakeur Zegnini, Mohammed Belkheiri, and Djillali Mahi, "Modeling Flashover Voltage (FOV) of Polluted HV Insulators Using Artificial Neural Networks (ANNs)" , Electrical and Electronics Engineering, 2009. ELECO 2009. International Conference , Page(s): I-336 - I-340, 2009

[15]. N. Narmadhai and A. Ebenezer Jeyakumar, "Analysis of Leakage Current to Predict Insulator Flashover Using Artificial Neural Network" , Journal of Computer Science 7 (2), Science Publications, ISSN 1549-3636, pp. 167-172; 2011

[16]. S. N. Sivanandam, S. Sumathi and S. N. Deepa , "Introduction to Fuzzy Logic using MATLAB", Text Book ISBN -10 3-540-35780-7, Published by: Springer Berlin Heidelberg New York, 2007

[17]. P.S.Ghosh, S.Chakravorti and N.Chatterjee, "Estimation of time to flashover characteristics of contaminated electrolytic surfaces using a neural network", IEEE Trans. on DEIS., Vol. 2, n° 6, , pp.1064-1074,December.1995

[18]. Jacek M. Zurada, "Introduction to Artificial Neural Systems", Text Book ISBN 0-314-93391-3, Published by: West Publishing Company, St. Paul, 1992

LIST OF PUBLICATIONS

[1]. Rishi Kumar Sharma and E. Fernandez, "Flashover Voltage Determination for Glass Insulators: Fuzzy based Approach", National Conference on Converging Technologies Beyond 2020" Kurukshetra university, Vol. 5; April 2011

TABLE A.2: Results of ANN Model For Composite Insulator Type FXBW-750/A

pressure (kPa)	sdd (mg/cm2)		FOV exp. value (kV)		NN model value (kV)
98.6	0.03		223		223
98.6	0.05		195.4		195.4
98.6	0.08		171		171
98.6	0.15		145.5		120.7159
98.6	0.25		124.7		121.1233
89.7	0.03		203.1		201.3622
89.7	0.05		178.6		179.0694
89.7	0.08		158.4		158.4
89.7	0.15		136.2		135.7
89.7	0.25		117.5		117.1
79.7	0.03		184.2		185.1
79.7	0.05		163.5		163.8
79.7	0.08		145.2		132.6371
79.7	0.15		125.4		125.4
79.7	0.25		110		111.3
70.1	0.03		167.3		167.3
70.1	0.05		149.2		159.3939
70.1	0.08		134.5		132.7969
70.1	0.15		117.2		117.2
70.1	0.25		103.3		99.2661
61.6	0.03		151.6		151.8
61.6	0.05		134.2		142.5899
61.6	0.08		121.3		121.2
61.6	0.15		109.1		115.5183
61.6	0.25		98		99

TABLE A.3: Results of ANN Model For Composite Insulator Type FXBW-750/B

pressure (kPa)	sdd (mg/cm2)		FOV exp. value (kV)		NN model value (kV)
98.6	0.03		208.6		208.8
98.6	0.05		184.1		183.7
98.6	0.08		163.2		165.8943
98.6	0.15		142.5		142.5
98.6	0.25		121.1		129.8707
89.7	0.03		188.3		188.8
89.7	0.05		167.4		167.468
89.7	0.08		151.3		150.6
89.7	0.15		130.4		130.237
89.7	0.25		113.8		113.1
79.7	0.03		171		170.6776
79.7	0.05		153.4		152.757
79.7	0.08		138.2		138.8
79.7	0.15		121.1		121.8
79.7	0.25		106.2		105.0148
70.1	0.03		155.1		155.185
70.1	0.05		137.8		138.6695
70.1	0.08		124.9		124.658
70.1	0.15		111.2		111.2
70.1	0.25		99		96.4623
61.6	0.03		138.8		143.0037
61.6	0.05		127.4		127.4
61.6	0.08		114		114.5149
61.6	0.15		104.9		103.5356
61.6	0.25		92.1		92.5