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MODELING OF BREAKDOWN VOLTAGE OF SOLID INSULATING MATERIALS BY ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This paper presents a model to find out the breakdown voltage of solid insulating materials under AC excitation condition by employing the artificial neural network method. The paper gives a brief introduction to multilayer perceptrons and resilient back-propagation. A relation between input variables and output variables i. e. breakdown voltage is demonstrated. The inputs to the neural networks are the thickness of material, diameter of void, depth of void and permittivity of materials. Neural network methodology is the one of the most popular and widely used method for the analysis of voids. ANN is built to train the multilayer perceptrons in the context of regression analysis. Back-propagation algorithm is used for learning and to train the ANN and it is provides a custom choice of activation and error function. MATLAB software is used for designed, trained and tested in the ANN.

KEYWORDS:Permittivity, Breakdown Voltage, ANN, Insulation Sample, Multilayer Feed-forward Neural Network, Voids, Thickness.

INTRODUCTION

In present day, the care of insulation is the most important in electrical power system and high voltage engineering. The insulation is used for any electrical system, power sectors, research laboratories etc. even foe all technical systems, we are using at this time. The main cause of insulation failure in the high voltage equipment is the void i.e. present inside the solid insulating materials during manufacturing process. The void is generally found in electrical power system and they are more hazardous which may cause in to big loss of money and lives so, it is very important to monitor such cases. A many research paper has been published on the subject of void analysis with experimental performed on equipment such as cables, capacitors, transformers, motors etc under AC and DC voltage as well as impulse voltage conditions, these things are in action from early 19th century[1] breakdown voltage is influence by the many external parameters such as temperature, humidity, duration of testing, AC, DC, impulse voltage etc. but here, we are analysis only the four main factors as thickness of material, depth of void, diameter of void and permittivity of material. The fundamental mechanism of breakdown voltage of solid insulating materials is understood with the help of this parameters and breakdown voltage tester. Here we are represents a breakdown voltage of three solid insulating materials namely such as lather minilex, white minilex, glass cloth. There are two sample of thickness of each material. The sigmoidal function is used for the activation function for all the neurons. The breakdown voltage is modeled as output of the ANN and it is done with the help of MATLAB software.

CREATION OF VOID

Void may be defined as electrical breakdown incident which occurs in solid insulating materials, when rapidly changes in the electrical activities that causes a current flow into the material to external world [2]. Partial discharge is the group of breakdown phenomenon i.e. this phenomenon may starts as many ways like (1) From a bubble in gas (2) as corona in air and liquids (3) from void in solid dielectric (4) as floating discharge (5) due to surface discharge etc. but we are focused on this paper only void in solid dielectrics or solid insulating materials. Void or cavities can be generated artificially also by many different methods for the aim of its analytical study in high voltage laboratories by research scholars. The voids of different sizes are artificially created with the help of a spacer made of Kapton film with a circular punched hole at the center. The diameter of void is 1.5mm; 2mm and 3mm. the thickness of Kapton spacer used are of 0.025mm and 0.125mm. Therefore, the size of the created void i.e. 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 punched lines.

BREAKDOWN VOLTAGE

The breakdown voltage of any insulating material is that minimum value of voltage above which the insulating material starts behaving like a conducting material is called breakdown voltage of solid insulating material. Hence the purpose of any material is defeated and it is of great importance to calculate the breakdown voltage of any insulating material. Breakdown voltage is the characteristics that can be applied across the insulating material before the materials get collapse and conducts. In solid insulating materials, this usually creates a weakened path within material which is permanently created inside the material. Breakdown voltage is sometimes called 'strike voltage' [3]. In general partial discharges are a consequence of local stress concentration in insulation or on the surface of insulation such electrical discharges are appeared as impulse i.e. various forms of voltage impulse and current impulse having duration of much less than 1sec. [4-12].

ARTIFICIAL NEURAL NETWORK

ANN may be defined as an information processing model that is inspired by the way of biological nervous system such as show in fig (a) & (b).

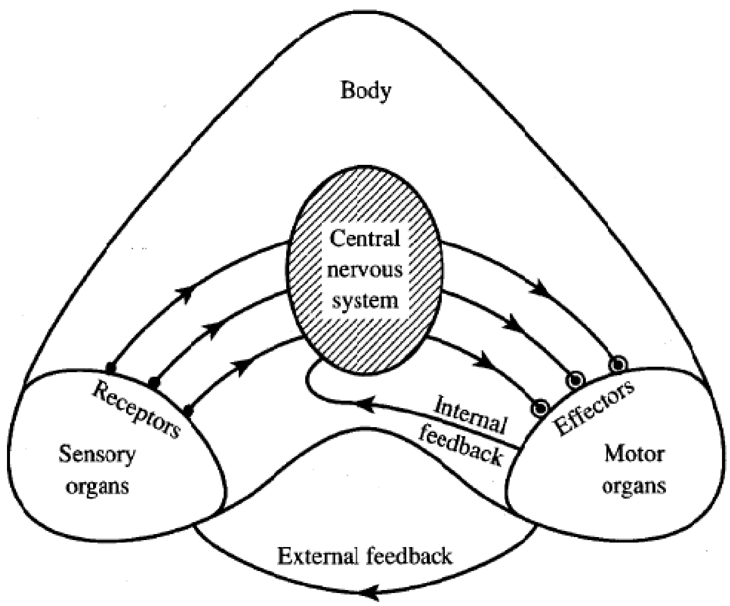


Fig (a) Information flow in nervous system [13]

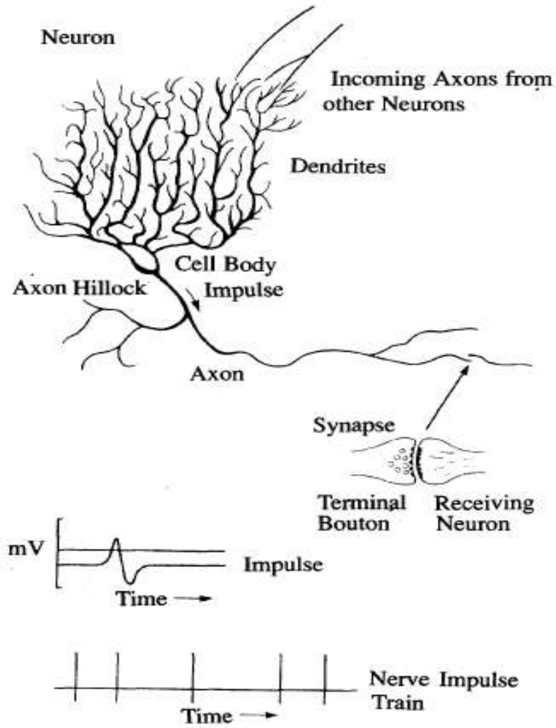
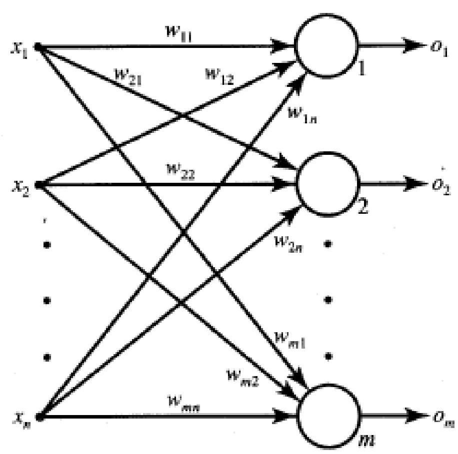


Fig (b) Schematic diagram of a neuron and a sample of train pulse [13]

Similarly, ANN offers an unusual scheme based programming standpoint and exhibit higher computing speeds compared to other conventional methods [14]. The artificial neural network has a function of f(x) which shows relation between inputs, weights, bias and the activation function. The activation function relates the output of a neuron to its input based on the neurons input activity level. Some of commonly function used in ANN includes: the threshold value, tangent hyperbolic, pieces wise linear and the Gaussian [3]. The single layer feed-forward neural network shown in fig (c). Here are only two layers namely one is input layer and another is output layer so it is called single layer feed-forward neural network. The input and output is connected to each-other with weights which is a source of information processing element. It's carry the information from input layer to output layer. ANN is to the data by supervised learning algorithm during a training process. These learning algorithms are functioned by the usage of a given output that is compare to predicted output value.



Input layer ***output layer***
Fig (c) Single layer feed-forward network [13]

The parameters are connected with the weights which are usually initialized by random values. Fixed weights ANNs do not need any learning process. Supervised learning ANNs are the most commonly used method because this system makes use for both input and output data for every set of input and output data, weights and biases are updated.

Multilayer Feed-Forward Network

The MFFN (multilayer feed-forward network) are most commonly used network in the ANN. Its fall into the supervised learning process [3]. The MFFN as shown in fig (d)

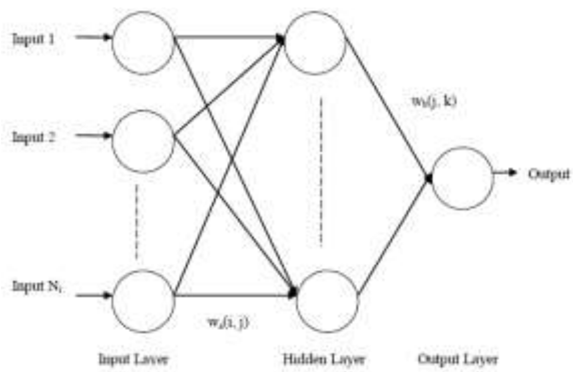


Fig (d) multilayer feed-forward network

The multi layer feed-forward network are consisting of three layers namely input layer, hidden layer and output layer as representing in fig (d). 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 [15-17] 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)…………………………….. (1)

Choice Of Ann Parameters

The learning rate, η and the momentum factor, α have a very important effect on the learning rate of BPA. BPA provides an approximation to the path in the weight space computed using the method of steepest descent [18]. If the value of η is very small, this result in very slow rate of learning, whereas if the value of η is too huge in order to accelerate the rate of learning, the MFNN may become unstable (oscillatory). A simple method of improving the rate of learning without making MFNN unstable is by addition of the momentum factor [19]. The value of η and α should lie between 0 and 1 [15].

Weight Update Equations

The weights between the hidden layer and the output layer are updated based upon the equation as follows:

$$w_b(j,k,m+1) = w_b(j,k,m) + \eta_2 \times \delta_k(m) \times S_b(j) + \alpha \times (w_b(j,k,m) - w_b(j,k,m-1))$$

$$j = 1, \ldots, N_h \qquad \ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

Where m is the number of iteration, j varies from 1 to N_h. $\delta_k(m)$ is the error for the k^{th} output at the m^{th} iteration. $S_b(j)$ is the output from the hidden layer. Similarly, the weights between the hidden layer and the input layer are updated as follows:

$$w_a(i,j,m+1) = w_a(i,j,m) + \eta_1 \times \delta_j(m) \times S_a(i) + \alpha \times (w_a(i,j,m) - w_a(i,j,m-1))$$

………………… (3)

Where i varies from 1 to N_i as there are N_i inputs to the network, $\delta_j(m)$ 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 (2) and δ_j in equation (3) are related as:

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

…………… (4)

Evaluation Criteria

The Mean Square Error E_{tr} for the training patterns after the m^{th} iteration is defined as:

$$E_{tr} = \left(\sum_{p=1}^{P} \left(V_{b1p} - V_{b2p}(m) \right)^2 \right) \times \left(\frac{1}{P} \right) \quad \ldots\ldots\ldots\ldots (5)$$

Where V_{1p} is the experimental data of breakdown voltage, P is the number of training patterns and $V_{2p}(m)$ is the estimated value of the breakdown voltage after m^{th} iteration.

Mean Absolute Error

The Mean Absolute Error E_{ts} is 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 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:

$$E_{ts} = \left(1/S \right) \times \left(\sum_{s=1}^{S} \left| \left(V_{b4s} - V_{b3s} \right) \right| / V_{b3s} \right) \times 100 \quad \ldots\ldots (6)$$

Where V_{3s} is the experimental value of the breakdown voltage taken for testing pupose, V_{4s} is the output value of the breakdown voltage after the testing input data is passed the train network and S is the number of testing patterns.

EXPERIMENTAL SETUP

30kv insulation testers: High voltage tester place a vital role in the industry and research institutes, this tester enable the operator to measure the high voltage withstand level at the require place of the require material. The diagram of 30kv insulation tester is shown in below fig (e). This apparatus is on air cooled single unit consisting of high voltage transformer and the control. This transformer has primary and secondary winding separated from each other with proper insulation.

Fig (e) 30kv insulation tester

Specification:

Input	0-230V, AC, 50 C/S, single phase
Output	0-30 KV AC
Leakage current	30mA
Type of cooling	Air cooling
Timer	0-30hours

Table1 specification of 30 kV insulation testers

There are three types of sample insulating materials as follows with thickness of material:
Lather minilex- 0.25mm, 0.50mm
White minilex- 0.125mm, 0.25mm
Glass cloth- 0.25mm, 0.50mm

Now the four types of input variables are used to find-out the breakdown voltage of given solid insulating materials as thickness of materials, permittivity of materials, depth of voids and the diameter of voids. The experimental value of materials with breakdown voltage as output of30 kV insulation tester as shown in table no. 2 of given insulating materials.

Insulating material	t (mm)	t_1 (mm)	d (mm)	ε_r	$V_{b\,(KV)}$
White minilex	0.125	0.025	1.5	4.4	17.5
	0.125	0.025	2	4.4	14.82
	0.125	0.025	3	4.4	12.80
	0.25	0.125	1.5	4.4	19.5
	0.25	0.125	2	4.4	18
	0.25	0.125	3	4.4	16.30
Lather minilex	0.25	0.025	1.5	5.74	8.7
	0.25	0.025	2	5.74	6.9
	0.25	0.025	3	5.74	5.2
	0.50	0.125	1.5	5.74	9.8
	0.50	0.125	2	5.74	8.5
	0.50	0.125	3	5.74	7.2
Glass cloth	0.25	0.025	1.5	4.97	2
	0.25	0.025	2	4.97	1.8
	0.25	0.025	3	4.97	1.95
	0.50	0.125	1.5	4.97	2.8
	0.50	0.125	2	4.97	1.9
	0.50	0.125	3	4.97	1.2

Table no. 2. Experimental data

Whereas t = thickness of material, t_1 = depth of void, d = diameter of void, ε_r = permittivity of material and V_b = breakdown voltage of solid insulating material (experimental value).

Further, we correlate the breakdown voltage to the output response of the ANN using MATLAB software. The below fig (f) shows the ANN with input variable and one output variables using MFNN system

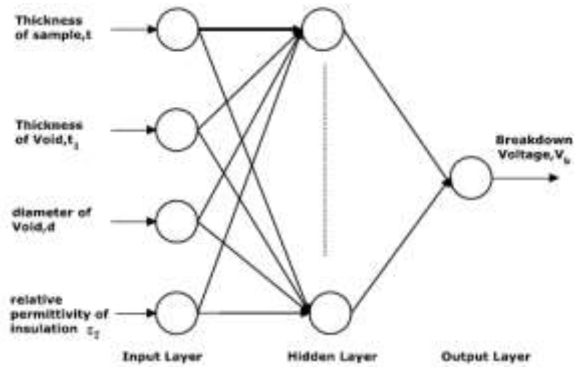


Fig (f) MFNN structure

RESULT AND DISCUSSION

The training process of neural network provides the opportunity to explain the required number of hidden neurons according to the needed complexity. The complexity of any neural network increases with the increasing of hidden neurons. As we know that the neural network learns from examples and this learning process is named as training of the neural network for this purpose we already have obtained the 18 set of three insulating materials. We are able to get the mathematical value of breakdown voltage by using the MATLAB software action. All input and output variables are formed as matrix namely input matrix and target matrix. The data will be trained and it is compared to the output values and target values, and then gives the error between them. The status of trained network can be seen in fig (g) with its various facilities of plot.

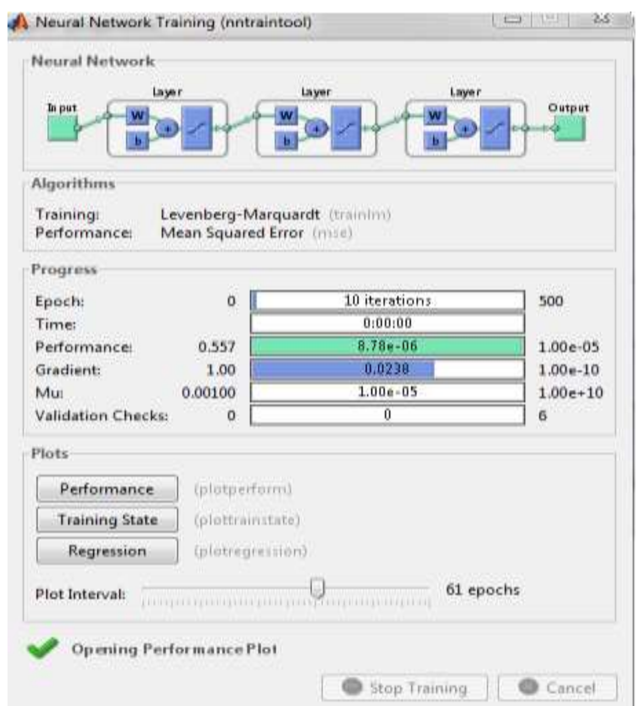


Fig (g) neural network training

The neural network train tool show the various plot which gives the mean square error it can be seen to given below fig (i), (j) and (k) here, the mean square error is obtained $\mathbf{8.78\times10^{-6}}$ in 10 iterations which is very less. The output is obtained within the one sec. during training. During trains hidden layers are taking 5 neurons, learning rate is taken as 0.5 and momentum constant is 0.8. The training process is done with the Levenberg-Marquardt learning methods.

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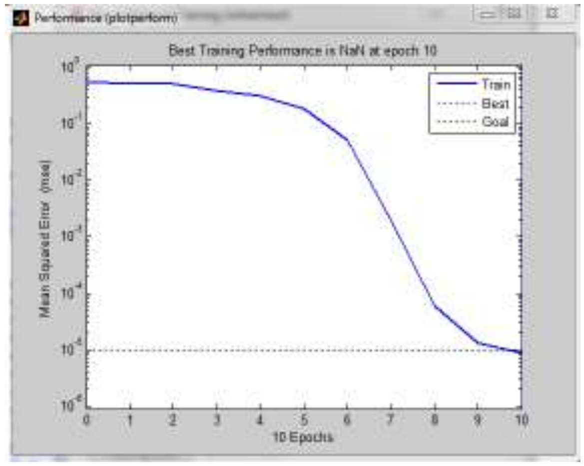

Fig (i) Performance plot

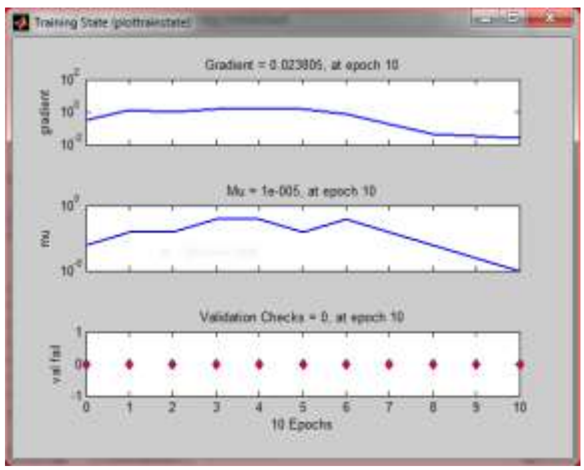

Fig (j) training state

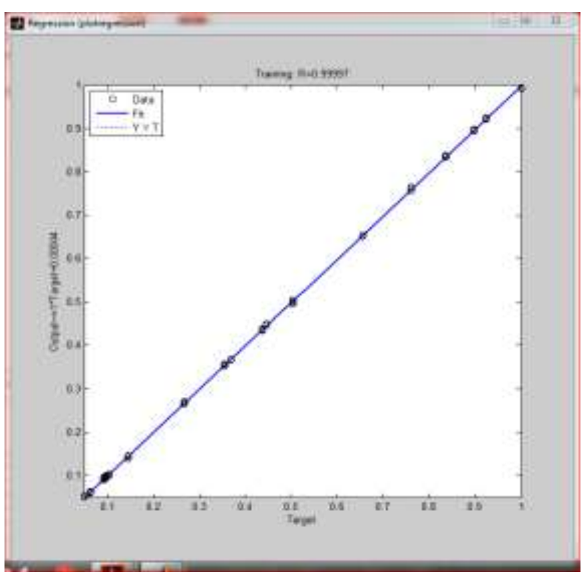

Fig (k) regression analysis

The given training plot shows the gradient about 0.023805 at epochs 10 and validation check is zero. The regression analysis shows correlation between output and target value and its give in my trained network is 0.99997 i.e. output value is approximate equals to the target value.

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