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A Study on Breakdown Voltage Estimation of CO_2+SF_6 Mixture Using Feedforward Neural Network Approach

E. Önal Ö. Kalenderli S. Şeker E. Ayaz
Istanbul Technical University
Electrical and Electronics Faculty
80626 Maslak, Istanbul, TURKEY

Abstract: In this paper, AC breakdown strengths of a mixture of 99.875%CO_2+0.125%SF_6 in nonuniform field were studied. The relative gas pressure and the electrode gap spacing were varied within the range of 100-500 kPa and of 5-15 mm, respectively. The results were first measured experimentally and then estimated by means of Feedforward Neural Network Approach. The comparison of measured and computed values show that there is a good agreement between two values. The breakdown voltages of the mixture can be found correctly by the Feedforward Neural Network (FNN) Approach. Therefore, the Feedforward Neural Network Approach can be considered an alternative tool to estimate the new values at the out of the measurement range.

Keywords: Breakdown Voltage, Feedforward Neural Network, Back Propagation

1. INTRODUCTION

It is well known that SF_6 has excellent dielectric characteristics and is the most commonly used insulating gas at present. However, its disadvantages such as green house effect, high sensitivity to conductor surface roughness and high cost limit its applications. Using a mixture of SF_6 with an inexpensive simple gas like CO_2, N_2 and air can minimise the above problems. These gases are used as electrical insulation purposes for high voltage equipment.

Several investigations have been reported in the literature on the breakdown behaviour of SF_6, CO_2 and CO_2+SF_6 mixtures [1-3]. Most of the published data refer to uniform or nearly uniform field gaps [4]. However, there is still insufficient information regarding the alternating breakdown of such mixtures with small amount of SF_6 in nonuniform field gaps. The present paper describes a study of breakdown strength of 99.875%CO_2+0.125%SF_6 mixture in rod-plane gap under alternating voltages. These results were first measured experimentally and then estimated by means of the Feedforward Neural Network (FNN).

Earlier measurements have shown that CO_2+SF_6 might have some advantages over N_2+SF_6, because gas-film insulation and highly nonuniform problems are encountered. In negative rod-plane gaps under direct applied voltages, at high pressures, CO_2+SF_6 mixtures had breakdown voltages higher than the corresponding values for SF_6+air and SF_6+N_2 mixtures but in the low pressure range, breakdown voltages of negative and positive gaps have similar values. However, at higher pressures, negative breakdowns are significantly higher than the positive ones. Under positive direct voltages, the dielectric strength of CO_2+SF_6 is higher than N_2+SF_6 in highly nonuniform fields [5]. Earlier experiments under negative impulse conditions have shown that at high pressures, mixture containing low SF_6 content can have breakdown voltages lower than the corresponding values in pure CO_2 [6]. Furthermore, the results indicate that CO_2+SF_6 mixtures perform somewhat better than N_2+SF_6 and SF_6+air mixtures at lower pressures.

The present paper at first describes a study of breakdown strength of a mixture of 99.875%CO_2+ 0.125%SF_6 experimentally and then estimates the breakdown strengths in or above the measuring range. These results may be compared with previous investigations.

2. FEEDFORWARD NEURAL NETWORK (FNN) ARCHITECTURE

One of the most known FNN structure is back-propagation algorithm. In literature, there are so many application of the back-propagation in diverse engineering fields [7-9]. In this study, this algorithm is applied to a high voltage measurement system and measurement results are used as training data set of the FNN. The training data (TD) set having *d* measurement values, can be presented as follows

$$TD = (p_1,V_1), ..., (p_d,V_d) \qquad (1)$$

where p_i is input vector to the neural network, and V_i is the target vector for the given input. The training data set TD used in this study is given as Table 1.

The basic idea of this algorithm is gradient descent method. In the gradient descent method, expected value of squared error (e^2) is required to be minimum so that the minimum value of performance surface formed by weights is searched. Hence, the squared error function (e^2) related to any node in the output layer of the FNN structure can be defined as

$$e_k^2 = \left| V_k - f\left[\sum_j w_{ho,j} \cdot f\left(\sum_i w_{ih,i} \cdot p_i\right)\right]\right|^2 \quad (2)$$

$$i = 1, ..., n_{inp} \qquad j = 1, ..., n_{hid} \qquad k = 1, ..., n_{out}$$

where w_{ih} is weight vector between input layer and hidden layer and w_{ho} is weight vector between hidden layer and output layer. n_{inp}, n_{hid} and n_{out} are the number of input nodes, hidden nodes and output nodes respectively. Here, $f(.)$ is a nonlinear function. In this study, it is considered as a sigmoidal function. For an arbitrary variable x, it is defined as follows

$$f(x) = \frac{1}{1+\exp(-x)} \quad (3)$$

Total error for TD is defined by

$$E(w) = \sum_{pattern} \sum_k e_k^2 \quad (4)$$

Initially the weight vector w, is set to a random value vector. The general procedure, which minimizes the error E(w) given in equation (4), is to find the $\partial E/\partial w$. Updated weight coefficients $w_{ho,k}^{(n+1)}$ between the output layer and hidden layer are given as

$$w_{ho,k}^{(n+1)} = w_{ho,k}^{(n)} + \Delta w_{ho,k}^{(n)} \quad (5)$$

Where $\Delta w_{ho,k}^{(n)}$ is

$$\Delta w_{ho,k}^{(n)} = -\eta \cdot \delta_{ho,k}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right) \quad (6)$$

Here, η is learning rate $(0 < \eta < 1)$, n is iteration number and $\delta_{ho,k}^{(n)}$ is

$$\delta_{ho,k}^{(n)} = 2\left\{V_k - f\left[\sum_j w_{ho,j}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)\right]\right\} \cdot f'\left[\sum_j w_{ho,j}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)\right] \quad (7)$$

Where f '(.) is

$$f'\left[\sum_j w_{ho,j}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)\right] = f\left[\sum_j w_{ho,j}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)\right] \cdot \left\{1 - f\left[\sum_j w_{ho,j}^{(n)} \cdot f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)\right]\right\} \quad (8)$$

Updated weight coefficients $w_{ih}^{(n+1)}$ between the hidden layer and input layer are given as

$$w_{ih,j}^{(n+1)} = w_{ih,j}^{(n)} + \Delta w_{ih,j}^{(n)} \quad (9)$$

where

$$\Delta w_{ih,j}^{(n)} = \eta \cdot p_i \cdot \sum_k \delta_{ih,j}^{(n)} \quad (10)$$

and

$$\delta_{ih,j}^{(n)} = \delta_{ho,k}^{(n)} \cdot w_{ho,k}^{(n)} \cdot \frac{\partial f\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)}{\partial\left(\sum_i w_{ih,i}^{(n)} \cdot p_i\right)} \quad (11)$$

Another technique to reduce training time is the use of momentum term. The momentum term enhances the stability of the FNN training algorithm. Using this approach, the updated weights can be given as

$$\Delta w_{ij}^{(n+1)} = \Delta w_{ij}^{(n)} + \alpha\left[\Delta w_{ij}^{(n)} - \Delta w_{ij}^{(n-1)}\right] \quad (12)$$

Equation (12) is called as the delta rule. It is a commonly used method to adapt the network weights. The $\alpha[\Delta w_{ij}^{(n)} - \Delta w_{ij}^{(n-1)}]$ term is called the momentum term and is used to avoid a local minimum. In this equation, α is called as the momentum rate ($0< \alpha <1$) and it is considered as 0.5. In this application, the learning rate η is considered as 0.9 and the iteration number n is 50000.

The established neural network architecture has 1 input, 4 hidden and 1 output processing elements. Hence, the neural network structure used in this application can be shown in Fig. 1.

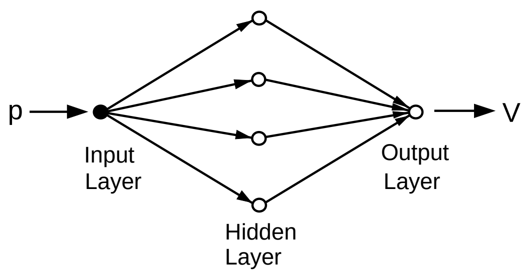

Figure 1. The neural network structure.

In Fig. 1, p and V indicate the relative gas pressures and breakdown voltages as the input and output data. Also, to obtain a perfect performance of the Neural Network, noisy output patterns V_n are used as the following way

$$V_n = V_m + 0.1 \cdot V_m \cdot r \quad (13)$$

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where V_m is the measured breakdown voltages in kV_{rms}. r is a random sequence in the Gaussian distribution to emulate the noise.

3. EXPERIMENTAL SET-UP

Experiments were carried out using a rod-plane electrode system with a rod tip radius of 1 mm and plane disc diameter of 75 mm (Fig. 2). All experiments were used over a pressure range extending from 100 kPa to 500 kPa and gap spacings ranging from 5 to 15 mm. Electrodes were mounted in a pressure vessel of 120 mm diameter and 600 mm length. In rod plane arrangement, the rod was connected to the high voltage supply while the plane was earthed.

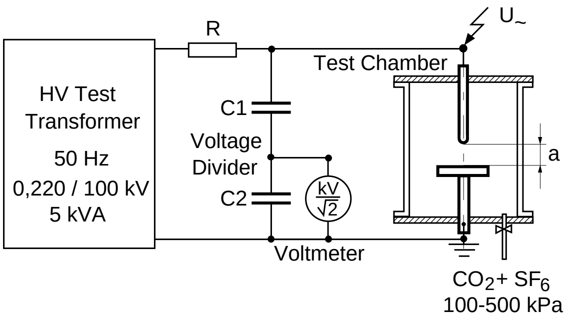

Figure 2. Test Circuit

The test vessel was first evacuated for at least two hours and then filled with the desired gas up to a relative pressure of 500 kPa. 99.875%CO_2+ 0.125%SF_6 gas mixture was obtained according to dilution method. The gas mixture was left for at least 2 hours before test, for the purpose of obtaining a uniform mixture. For the 50 Hz AC tests with voltages up to 100 kVrms a high voltage transformer was employed. AC breakdown voltage was measured by means of a capacitive divider. The mean value of breakdown voltage and standard deviation were calculated by means of ten voltage applications.

4. APPLICATION AND TEST RESULTS

The breakdown voltages of a mixture of 99.875%CO_2+0.125%SF_6 are measured and estimated using a rod-plane electrode system. The measured breakdown voltages is used to prepare the training data set of the FNN. For this purpose, the breakdown voltages measured from the experimental set-up are given within the range of 100-500 kPa with an increment of 100 kPa and this range is defined as the training data set of the FNN. After the training process with 50000 iterations to get the breakdown voltage estimations, the breakdown voltages within the range of 100-550 kPa with an increment of 50 kPa is asked to the FNN. Then interpolated and extrapolated values related to this given range are obtained with a high accuracy by means of the FNN. This second step is also defined as the recall process of the FNN. Therefore, combination of the training and the recall data sets for each gap spacing in the range of 5-15mm are given in Table 1.

Table 1. Measured (V_m) and estimated (V_{est}) values of breakdown voltages for different relative gas pressures.

Gas Pressure (kPa)	Breakdown Voltages (kVrms)					
	for a = 5 mm		for a = 10 mm		for a = 15 mm	
	V_m	V_{est}	V_m	V_{est}	V_m	V_{est}
100	9.00	9.09	14.50	14.62	21.50	21.55
150		11.27		19.08		29.51
200	13.00	12.76	24.00	23.82	33.00	32.84
250		13.71		27.79		33.28
300	14.50	14.81	31.00	31.12	34.00	34.22
350		16.40		34.11		37.15
400	18.50	18.28	36.67	36.78	41.80	41.66
450		19.79		39.04		45.41
500	20.50	20.65	41.00	40.80	47.25	47.32
550		21.05		42.07		48.08

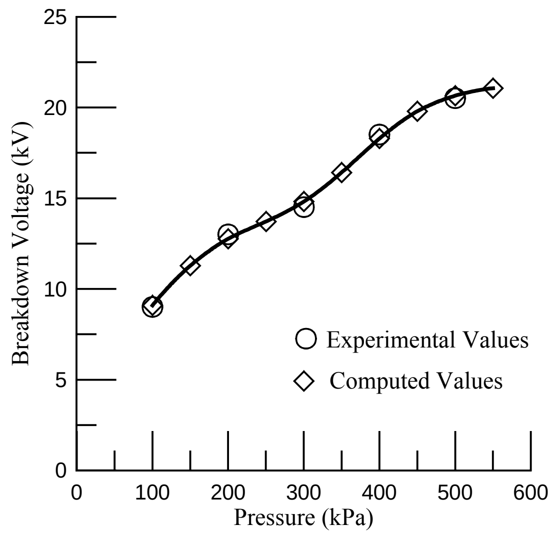

Figure 3. Variation of breakdown voltage with pressure in 99.875%CO_2+0.125%SF_6 for 5 mm gap spacing

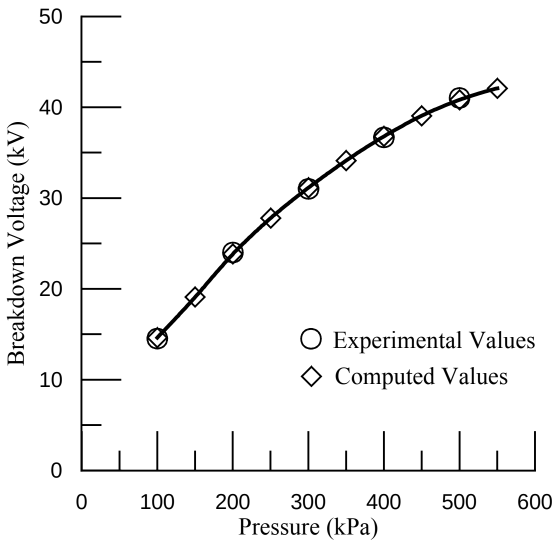

Figure 4. Variation of breakdown voltage with pressure in 99.875% CO_2+0.125% SF_6 for 10 mm gap spacing

Also to get more sensitive comparison, variations of the breakdown voltages versus to the pressure measurements for the different gap spacing values are shown in Fig. 3-5.

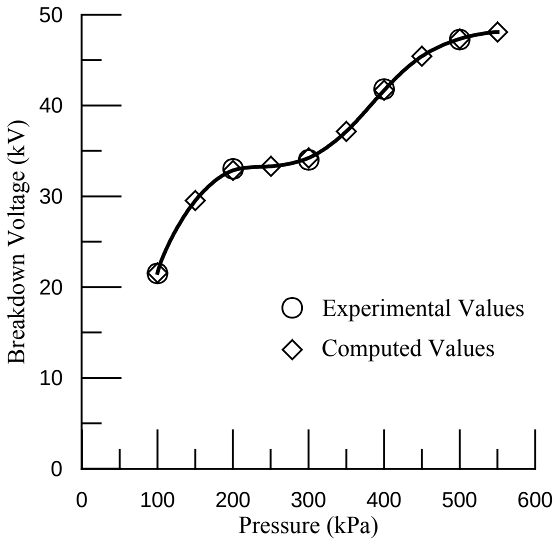

Figure 5. Variation of breakdown voltage with pressure in 99.875% CO_2+0.125% SF_6 for 15 mm gap spacing

5. CONCLUSIONS

Experimental measurements and estimated values of breakdown voltages using rod-plane gap indicate that there is a reasonably good degree of agreement between the measured and the estimated values for pressures of up to 550 kPa. Hence, Feedforward Neural Network architecture designed to estimate the breakdown voltages in the different experimental cases has shown a very good performance with an accuracy of 0.7% approximately. Therefore this approach can be accepted as a simple alternative tool to solve the difficulties in most experimental studies.

6. REFERENCES

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