APPLICATION OF ARTIFICIAL NEURAL NETWORK (ANN) IN SF_6 BREAKDOWN STUDIES IN NON-UNIFORM FIELD GAPS

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ABSTRACT

In SF_6-filled electrical equipments, the electric field distribution is kept rather uniform. However in practice, the electric field in the gas gap is distorted by non-uniformities, For this reason, the inhomogeneous field breakdown in SF_6 has been extensively studied by various researchers and the breakdown characteristics of compressed SF_6 have been reported. Obtaining experimental data under all conditions is not possible. Therefore, an attempt has been made in the present work to apply an Artificial Neural Network (ANN) to obtain such data.

The Projection Pursuit Learning Network (PPLN) has been used as the ANN model. Breakdown data for four different voltage waveforms were used to train the network for SF_6 pressures of 1-5 bar and rod diameters of 1-12 mm in a rod-plane geometry. The ANN was first trained with these data so as to obtain a smooth regression surface interpolating the training data. The regression surface thus obtained, was thereafter used to generate the breakdown and corona inception voltages with in the range of gas pressures and non-uniformities studied, where no data is available.

1. Introduction

Sulphur hexafluoride (SF_6), a strongly electronegative gas is being increasingly used as an insulating medium in electrical power equipments. In SF6-filled electrical equipments, in practice, the electric field in the gas gap is distorted by field non-uniformities created by metallic particles present in the gas and surface protrusions on the electrodes. For this reason, the inhomogeneous field breakdown in SF_6 was extensively studied and in these studies the inhomogeneous field distribution has been simulated by rod-plane gaps, varying either the rod diameter or the gap spacing and the breakdown characteristics have been extensively reported[1,2,3].

In the absence of any mathematical model describing a relationship between the experimental parameters (gas pressure, rod diameter and gap spacing) and the corresponding breakdown voltages for a particular voltage waveform, an attempt has been made in the present work to apply an Artificial Neural Network (ANN) to obtain such a correlation. The Projection Pursuit Learning Network (PPLN) has been used as the ANN model. Breakdown data for four different voltage waveforms were used to train the network-DC (positive and negative polarity), AC, Standard LI (+1.2/50μs) and SI (+250/2500μs).

2. The Artificial Neural Network (ANN) model

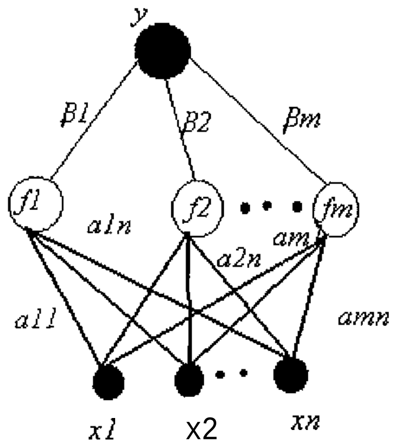

Figure 1: The PPL Network used in the present study

Fig 1. Shows the architecture of the Projection Pursuit Learning (PPL) network 1,2,3 used in the present stúdy[4,5]. The PPLN is a two-layer feed forward learning network whose trainable parameters are:

1. The hidden layer weights denoted by $\{\alpha_{kj}, j=1,\ldots,n\}$, connecting all the inputs units to the k_{th} hidden neuron.
2. The unknown (trainable) "smooth" activation functions denoted by $\{ f_k, k=1,\ldots,m \}$ of the k_{th} hidden neuron, which are hermite

$$f_k(z_k) = \sum_{r=l}^{R} c_{kr} h_r(z_k) \ldots(1)$$

functions defined as

where the c_{kr} s are the coefficients of the hermite functions h_r s, and ***R*** is called the order of the hermite function f_k, which is a constant set by the user. The hermite functions are orthonormal and defined by

$$h_r(z_k) = (r!)^{-1/2}\pi^{1/4}2^{-(r-1)/2}H_r(z_k)\phi(z_k) \quad \ldots(2)$$

where $H_r(z_k)$s are the hermite polynomials constructed in a recursive manner as

$$H_0(z_k) = 1 \quad \ldots(3)$$

$$H_1(z_k) = 2\, z_k \quad \ldots(4)$$

$$H_r(z_k) = 2[z_k H_{r-1}(z_k) - (r-1)H_{r-2}(z_k)] \quad \ldots(5)$$

$r = 2,3,4,\ldots$

and $\Phi(z_k)$ is the weighting function

$$\phi(z_k) = \frac{1}{\sqrt{2\pi}} e^{-z_k^2/2} \ldots(6)$$

3. The output layer weights are denoted by β_k connecting the k_{th} hidden

$$\hat{y}_l = \sum_{k=l}^{m} \beta_k f_k \Big(\sum_{j=1}^{n} \alpha_{kj} x_{jl}\Big) \ldots(7)$$

neuron to the output unit. The output of the network is mathematically expressed as

where $\hat{y}_l$ is the actual output of the network computed by the ANN for the l_{th} training pattern.

The training of all the weight parameters, β_k, $\{c_{kr}\}$ and $\{\alpha_{kj}\}$, is based on the criteria of minimizing the MSE(mean-square-error), or the so called L_2 loss function defined as

$$L_2 = \sum_{l=1}^{p} [y_l - \hat{y}_l]^2 \ldots(8)$$

$$= \sum_{l=1}^{p} [y_l - \sum_{k=l}^{m} \beta_k f_k(\alpha_k^T x_l)]^2 \ldots(9)$$

which is the sum squared error between the desired and the actual output over all the training patterns.

The characteristic features of the training process of the PPL network are as follows:

1. The network is built gradually, starting from a single hidden neuron; additional hidden units and weights are added subsequently during the training process till a minimum architecture is obtained which gives

a satisfactory solution for the given problem.

2. Instead of training the whole network after a new hidden unit is added, the PPL algorithm first trains only the new hidden unit. After the new hidden unit is trained, the parameters associated with the previously installed hidden units are updated one unit at a time. Thus the PPL network is trained in a neuron-by-neuron manner and not as a whole entity.
3. Further simplification is obtained by training a single hidden unit in a layer-by-layer manner. For this purpose, the parameters that have to he trained after adding the *k*th hidden unit are divided into three groups (α_k, c_k, and β_k). Each group is updated separately for that particular neuron.

3. Results and Discussion

For DC applied voltage (both polarities), the breakdown data[1] consisted of both the corona inception and breakdown voltage characteristics of rod-plane gaps. The field non-uniformity was varied by varying the rod diameter values in the range 1.0 to 6.3 mm for a fixed gap spacing of 20 mm. The gas pressure was varied in the range 1 to 5 bar. The breakdown voltage data were trained in the corona-stabilized region while the corona onset data were trained separately in the full pressure range. The ANN had two inputs, one corresponding to the pressure values, and the other to the rod diameter values. The maximum training error for both polarities was around 5% of the desired output value.

Similar breakdown data for AC applied voltage had a pressure range of 1 to *6* bar and rod diameter range of 1 to 10 mm for a fixed gap spacing of 60 mm[2]. The maximum training error was 5% of the desired output value, when this data was used for training. Using this, new data was generated for different values of the experimental parameters with 50 **Hz** ac voltages. Fig 2. shows both the sets of data.

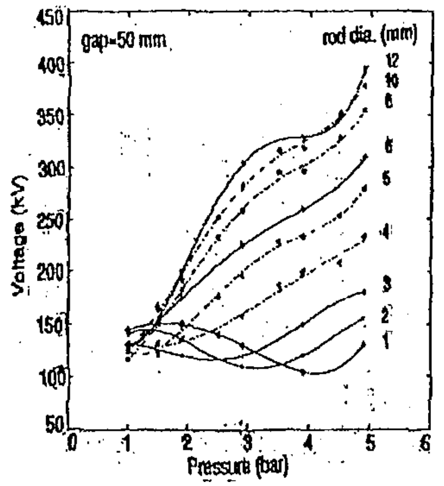

Fig 2 : SF_6 Breakdown Characteristics for positive LI (1.2μs/50μs) in a 50mm Rod Plane Gap. (The solid lines correspond to training breakdown voltage inputs and the broken lines to breakdown voltages computed by the ANN).

For impulse voltage waveforms, namely, standard LI (1.2/50 μs) and SI (250/2500μs)), the breakdown data used for training consisted of breakdown voltage values only. In this case, the field non-uniformity was varied by varying separately two experimental parameters - the rod diameter as well as the gap spacing. The ANN had three inputs, corresponding to pressure, rod diameter and gap spacing. The training data for types of impulse waveforms had pressure range of 1 to 5 bar, rod diameter range of 1 to 12 mm and gap spacing range of 10 to 100 mm. The maximum training error for both waveforms was around 10% of the desired output value. Using this, new data was generated for experimental parameters for which no data is available in the literature. Both the sets of data has shown in Fig. 3 (for standard LI voltage) for a gap spacing of 60 mm. Data at other gap spacings for LI and **SI** are not presented due to lack of space.

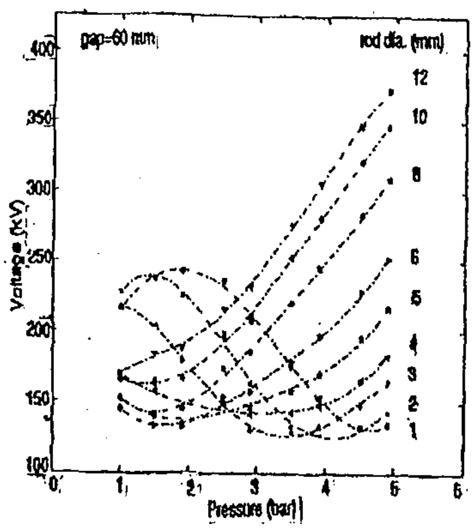

Fig 3: SF_6 Breakdown Characteristics for positive SI (250μs/2500μs) in a 60mm Rod Plane Gap. (The broken lines correspond to the breakdown voltages computed by the **ANN).**

The generalization of the network for all the applied voltage waveforms showed fairly good consistency with the general nature of the experimentally obtained breakdown voltage characteristics reported in the literature. For DC and **AC** voltages, the corona inception characteristics are linear while the breakdown voltage characteristics are non-linear and exhibit corona stabilization effect[1,3]. The corona stabilization effect was more pronounced with an increase in the field non-uniformity. Negative polarity DC had lower corona inception voltages but its breakdown voltage characteristics exhibited a more pronounced corona stabilization effect compared to the positive polarity voltages. The **SI** breakdown characteristics were similar to those of AC and DC voltages while in the case of LI breakdown characteristics. the corona stabilization effect was seen only for higher field non-uniformities.

The breakdown characteristics obtained by application of ANN show trends similar to those obtained experimentally with fair accuracy of about 5%. It appears to be a useful tool to generate breakdown data for a variety of conditions that exist in power apparatus.

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