Computer Aided Identification of Inter-Layer Faults in Gas Insulated Capacitively Graded Bushing during Switching

M. Mohana Rao†, P.Dharani* and T. Prasad Rao*

Abstract – In a Gas Insulated Substation (GIS), Very Fast Transients (VFTs) are generated mainly due to switching operations. These transients may cause internal faults, i.e., layer-to-layer faults in a capacitively graded bushing as it is one of the most important terminal equipment for GIS. The healthiness of the bushing is generally verified by measuring its leakage current. However, the change in current magnitude / pattern is only marginal for different types of fault conditions. Leakage current monitoring (LCM) systems generate large amounts of data and computer aided interpretation of defects may be of great assistance when analyzing this data. In view of the above, ANN techniques have been used in this study for identification of these minor faults. A single layer perceptron network, a two layer feed-forward back propagation network and cascade correlation (CC) network models are used to identify interlayer faults in the bushing. The effectiveness of the CC network over perceptron and back propagation networks in identification of a fault has been analysed as part of the paper.

Keywords: ANN techniques, gas insulated capacitively graded bushing, leakage current patterns, success rate, and very fast transients (VFTs)

1. Introduction

SF_6 gas-to-air capacitively graded bushing is one of the most important modules of the Gas Insulated Substation (GIS). In this type of substation, two types of bushing are commonly used depending on the system voltage. The first is the non-condenser bushing. The second is the capacitively graded bushing. In non-condenser bushings, the electrical stress distribution is not uniform through insulation or along its surface. Concentration of stress in the insulation may give rise to partial discharge (PD) and may reduce its life. Furthermore, high axial stress may result in surface flashovers. To overcome the above problems, electrical stresses are generally controlled by means of capacitively graded principles. In this design, the insulation thickness is divided into a number of capacitors by using concentric conducting layers.

In a Gas Insulated Substation (GIS), Very Fast Transients (VFTs) are generated mainly due to switching operations. These transients are associated with frequency components in the order of a few hundred MHz. The VFTs generated internally by a GIS propagate partly to overhead transmission lines through a bushing. Thus, during switching operations, transient voltages coupled to overhead transmission lines may result in turn-to-turn or winding-to-winding breakdown in transformers or layer-to-layer breakdown in capacitively gradeed bushings connected to the GIS [1,4]. When the transient voltage encounters the grading structure (comprising of a large number of metallic layers insulated with polyethylene terephthalate (PET) film), the incident travelling wave divides among the concentric coaxial transmission lines formed by the foils [4]. For the high frequencies of VFTs, the voltage distribution across the layers of graded bushing may not be uniform. Furthermore, continuous application of these oscillating and aperiodic voltage transients to the capactively graded bushing may cause discharges inside the bushing. This phenomenon can progressively degrade the insulation strength of the bushing.

Leakage current monitoring (LCM) systems generate large amounts of data and computer aided interpretation of defects has been found to be effective in recent years. Interpretation is based on the analysis of statistical parameters extracted from the data, particularly those related to amplitude, repetition rate and frequency spectrum. Neural network (NN) techniques are found to be effective for applications such as leakage current pattern recognition. A neural network consists of layers of neurons which are interlinked by suitable weights. During system training using a database of leakage current patterns from known defect types, the weightages of neurons are strengthened or weakened on the basis of required output.

In this study, an equivalent electrical network of the 420kV SF_6 gas-to-air capacitively graded bushing is used to simulate the leakage current waveforms for different inter-layer faults of the bushing. Artificial Neural Network (ANN) techniques have been employed to identify such minor faults in the capacitively graded bushing during switching operations in GIS. The success rate of perceptron, feed-forward back propaga-

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tion and cascade correlation networks proposed in the study for identifying faults has been calculated. Finally, the variation of the success rate of these networks for different sets of training data has been analyzed as part of the study.

2. Modeling of the Bushing

420kV SF_6 gas-to-air capacitively graded bushings generally consist of 120 numbers of aluminium grading layers separated by PET film with a dielectric constant (ε_r) of 2.8. The basic structure of the capacitively graded bushing is shown in Fig. 1. The layers form a system of coaxial cylinders whose length increases from the outermost to the innermost one. The capacitance between the two adjacent layers is constant and is about 60nF. The outermost layer is connected to the external coaxial flange by means of a copper strip, which has an inductance (L_c) of about 0.2μH [4].

Fig. 2 shows the equivalent circuit of graded bushing. The capacitively graded layers are divided into a number of equivalent layers. The diameter of each equivalent layer is calculated in such a way that the capacitance between consecutive graded layers is constant. Each equivalent layer is divided into a number of sections depending on its length. Further, each section is represented by means of a Π-model (L-C network). Finally, the bushing model is formed like a cascade of Π sections. The total capacitance of the actual bushing, C_{tot}, must be shared among the N_{eq} equivalent layers. The section capacitance (C_m) is calculated by dividing the

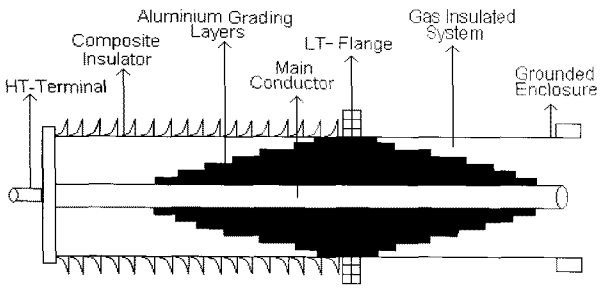


Fig. 1. Structure of 420 kV SF_6 gas-to-air capacitively graded bushing

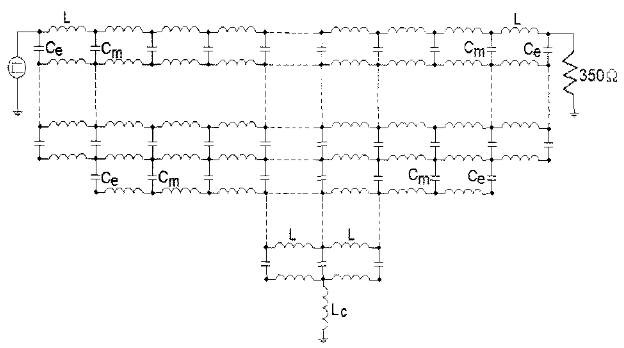


Fig. 2. Equivalent Electrical network of a graded bushing

layer capacitance (C_{lay}) with the number of sections. The end capacitance (C_e) of the section is equal to half of the middle or section capacitance. The inductance of each section (L) is calculated by dividing the inductance of the equivalent layer with the number of sections. To get a satisfactory compromise between modeling simplicity and accuracy, sixty equivalent co-axial layers have been considered to simulate the capacitively graded bushing, which was discussed in detail by authors at earlier work [5]. The PSPICE model developed based on the above equivalent circuit has been used to calculate the leakage current through a 420 kV graded bushing for high frequency transients which simulate VFTO. In this study, transient voltage is simulated by means of an impulse waveform of amplitude (420 kV*√2/√3) with a rise time 5 ns and a tail time of 1 μs. For this excitation of bushing, leakage current patterns are calculated by considering single equivalent-layer fault and double equivalent-layer fault at various layers of bushing.

3. Identification of Inter-layer Faults using ANN Techniques

In this study, identification of an inter-layer fault in a capacitively graded bushing is carried out using Artificial Neural Network (ANN) techniques [6]. The current through the copper strip inductance, i.e., the leakage current, is calculated for different types of inter-layer faults in the capacitively graded bushing. These current patterns are used as input to the ANN model for identification of faults. Fig. 3. illustrates the input and outputs of the ANN model proposed in the study.

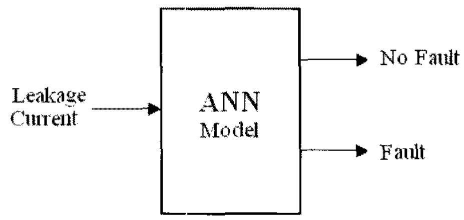


Fig. 3. Input and Outputs of the ANN Model

The leakage current pattern/waveform for each fault condition of the bushing is processed as a 1000x1 matrix and fed to a MATLAB based ANN model for training and testing purposes. The following steps are involved in the fault identification using NN Techniques:

1. Collection of the leakage current patterns with and without inter-layer faults in the bushing for transient voltage excitation.
2. Select the neural network model and target vectors.
3. Train the network for input vectors and the corresponding

target vectors until it can approximate a function.

4. Test the neural network model for new data and verify output of the network in terms of success rate.

Most of the training and testing data is obtained from the first 12 equivalent layers of the bushing model. This may be due to fact that the interlayer faults often occur near the HT conductor. Different equivalent layer faults, i.e., single equivalent-layer and double equivalent-layer faults, are considered. Since the change in magnitude and waveshape of the leakage current for these faults is only marginal, the authors developed perception, back propagation and cascade correlation network models for identification of a fault in a capacitively graded bushing [7]. The data manager screen of the ANN model in MATLAB is shown in Fig. 4.

3.1 Perceptron Network

The main feature of the perceptron network is that a weighted sum of input signals is compared to a threshold to determine the network output. When the sum is greater than or equal to the threshold, the output is 1. When the sum is less than the threshold, the output is 0. The perceptron model is a fast, reliable network and provides a good basis for understanding more complex problems. The architecture of the perceptron network is shown in Fig. 5. The output of the network is given as follows:

$$a = \text{hardlim}(Wp + b) \qquad (1)$$

where 'p' is an input to the network, 'W' is the weight of the perceptron layer, 'b' is the bias and 'a' is the output of the network. The objective is to reduce the error 'e', which is the difference between the network response 'a' and the target vector 't'. The perceptron learning rule 'learnp' calculates desired changes to the perceptron's weights and biases, for given input vector 'p' and the associated error 'e'. The target vector 't' contain values of either 0 or 1, because perceptron (with hardlim transfer functions) can only output these values. Fig. 6 shows the performance curve of the perceptron network.

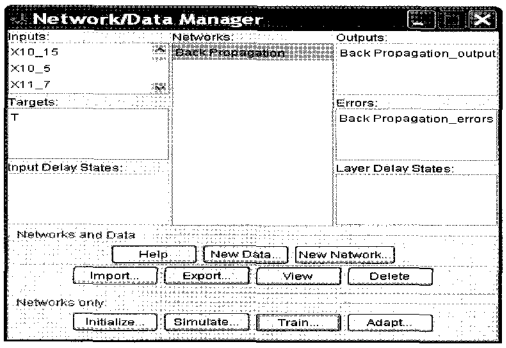


Fig. 4. Data Manger screen of ANN Model in MATLAB

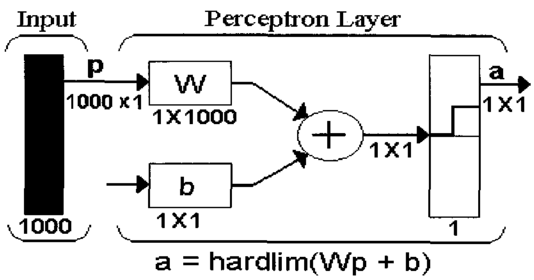


Fig. 5. Architecture of the Perceptron network

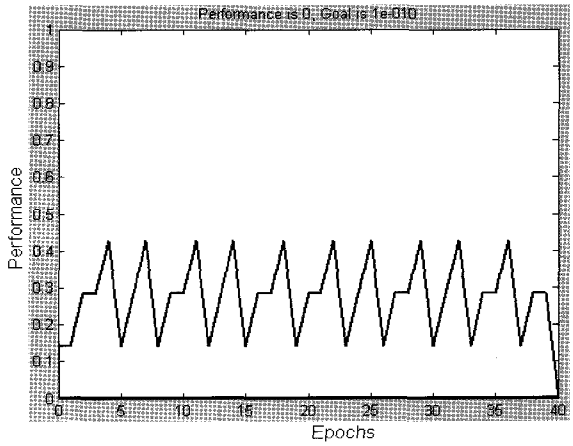


Fig. 6. Performance curve of the Perceptron network

3.2 Feed-Forward Back Propagation Network

A two layer feed-forward back propagation network has been used in the study to identify an interlayer fault in the bushing. In this network there is a hidden layer along with the input and output layers. The performance of the network is found to be a function of the number of neurons in the hidden layer. There are two neurons in the hidden layer and one neuron in the output layer. The transfer function being used in the first layer is tan-sigmoid, and in the output layer is a linear function. The output of the network is given as follows:

$$a_1 = \text{tansig}(IW_{1,1}p_1 + b_1) \qquad (2)$$

$$a_2 = \text{purelin}(IW_{2,1}a_1 + b_2) \qquad (3)$$

Where 'p_1' is the input vector. 'IW_1' and 'IW_2' are weights of the layer 1 and layer 2 respectively. 'b_1' and 'b_2' are the bias to layer 1 and layer 2 respectively. The parameters 'a_1' and 'a_2' are the outputs of the first and second layers respectively. 'a_2' is the output of the network. Fig. 7 shows the architecture of the two-layer feed-forward back propagation network. The performance curve of the feed-forward back propagation network is shown in Fig. 8. In the present study, number of neurons used in the hidden layer is varied from two to six. The number of epochs required for achieving the required accuracy in identification of a fault in the bushing depends on the number of neurons used in the hidden layer.

3.3 Cascade Correlation (CC) Network

Cascade-correlation (CC) is an architecture and supervised learning algorithm for artificial neural networks. A cascade-correlation network begins with a minimal network, then automatically trains and adds new hidden units one by one creating a multi-layered structure. The CC architecture has several advantages over existing algorithms such as it learns quickly, determines its own size and topology, retains the structure even if the training set changes and it does not require back propagation or error signals through the connections of the network. This network is very useful for incremental learning in which new information is added to the already trained network.

There are two stages in the execution of a CC algorithm. The first is the formation of the cascade architecture, in which hidden units are added only one at a time and do not change after they have been added. The second is the learning algorithm, which creates and installs the new hidden units. For each new hidden unit, the algorithm tries to maximize the magnitude of the correlation between the new unit's output and the residual error signal of the network. Fig. 9 shows the neural network trained with a cascade-correlation algorithm. In this study, a two-layer CC network has been found to be capable of identifying an interlayer fault in the bushing. In this network there is a hidden layer along with the input and output layers. The number of neurons required for the hidden layer of a CC network is found to be only 2. The number of epochs required for achieving the required accuracy is much less than that of a back propagation network even with two numbers of neurons in the hidden layer. The performance curve of the cascade correlation network is shown in Fig. 10.

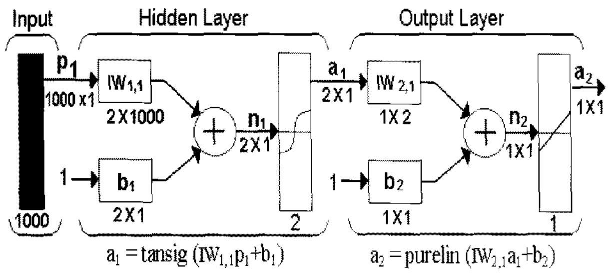


Fig. 7. Architecture of the back propagation network

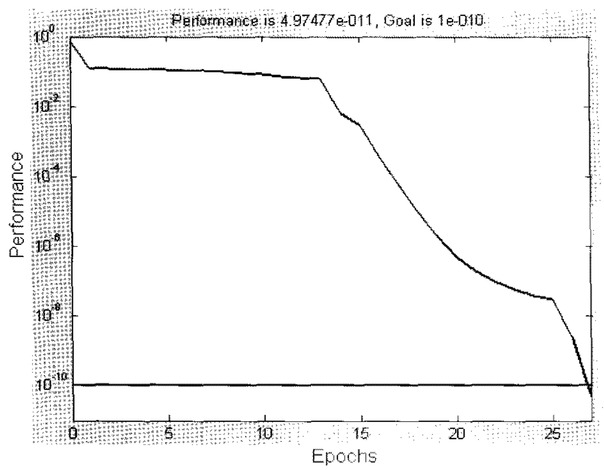


Fig. 8. Performance curve of back propagation network

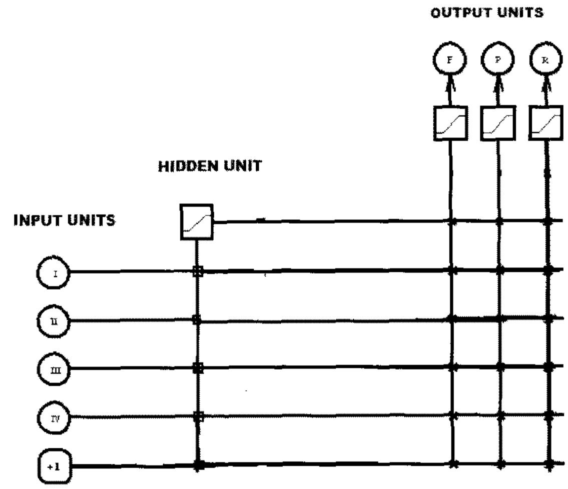


Fig. 9. A neural network trained with cascade correlation algorithm

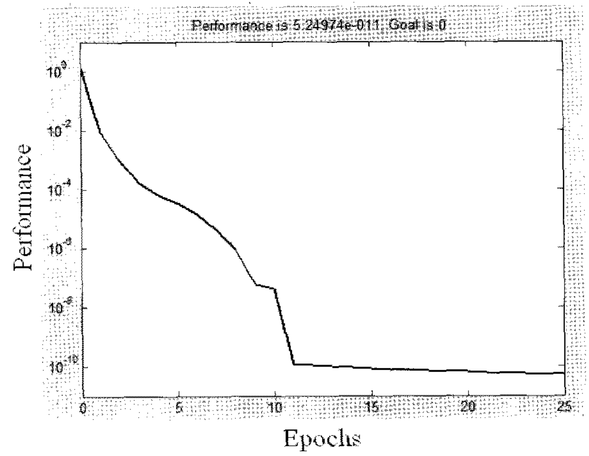
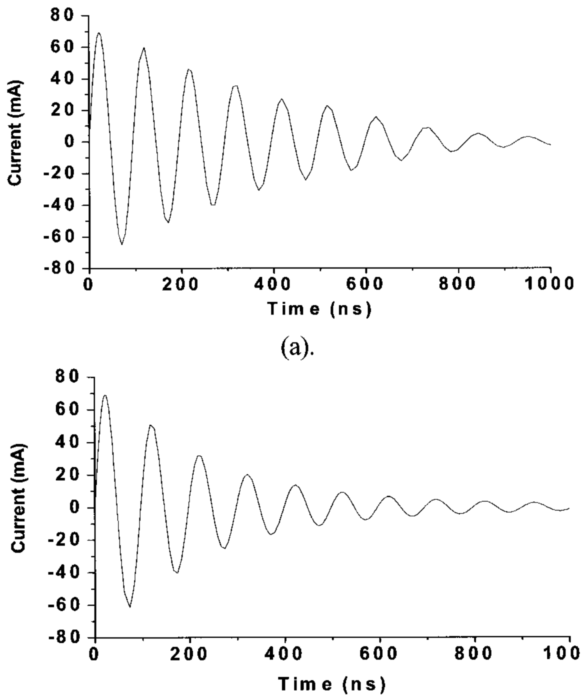


Fig. 10. Performance curve of CC network

4. Results and Discussions

The healthiness of the bushing is evaluated by measuring its leakage current during switching operations in GIS. This current is found to be sensitive to the interlayer faults that occur due to VFTs as they are associated with high frequency transients. Fig. 11 shows the leakage current calculated through a bushing with and without inter-layer fault. For this purpose, an impulse waveform of amplitude (420 kV*√2/√3) with a rise time of 5 ns is considered. From the results, it is seen that there is only a marginal change in the current waveform. Here, a single equivalent layer fault (in the first equivalent layer) is considered with a fault resistance of 0.1 Ω. Furthermore, it is noticed that the attenuation of the current magnitude with time is found to be a function of the type of abnormality, i.e., the type of inter-layer fault.

Leakage current patterns obtained for different types of fault conditions (single equivalent layer and double equivalent layer) in the bushing have been used for training the neural network models proposed in the study. A target matrix is set for training. In the target matrix, 0 is set for the without fault condition and 1 is set for the fault (i.e., single equivalent layer and double equivalent layer faults) condition. Table 1 shows different models considered for the study. The models are classified based on different percentages of training and testing data. The time taken to train a single layer perceptron network for one set of data is only in the order of fractions of seconds. Fig. 12 shows the output of the perceptron network for the leakage current patterns calculated from the equivalent circuit of the bushing. From this figure, it is seen that

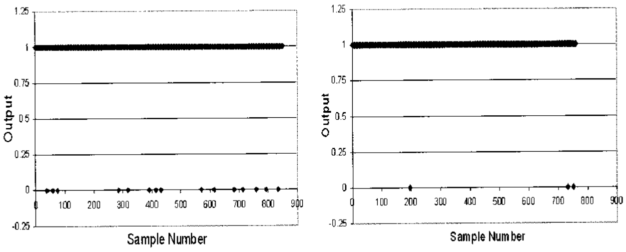


(b).

Fig. 11. Leakage current of the capacitively graded bushing. (a). without fault. (b). with inter-layer fault

Table 1. Different Models under study (N_{Tr} - Number of Training data and N_{Te} - Number of Testing data)

Eq. Layers	A		B		C		D		E	
	N_{Tr}	N_{Te}	N_{Tr}	N_{Te}	N_{Tr}	N_{Te}	N_{Tr}	N_{Te}	N_{Tr}	N_{Te}
1 – 6	32	292	64	260	97	227	128	196	162	162
7 – 12	25	227	50	202	75	177	101	151	126	126
13 – 18	9	81	18	72	27	63	35	55	45	45
19 – 24	6	48	11	43	16	38	21	33	27	27
25 – 30	4	32	7	29	10	26	14	22	18	18
31 – 36	4	32	7	29	10	26	14	22	18	18
37 – 42	4	32	7	29	10	26	14	22	18	18
43 – 51	6	54	12	48	18	42	24	36	30	30
52 – 60	6	54	12	48	18	42	24	36	30	30



(a). (b).

Fig. 12. Output of Perceptron network for (a). Model A (b). Model B

there is a significant increase in the success rate with an increase of training data from 10% (Model A) to 20% (Model B).

Similarly, a two-layer back propagation network is used with a different number of neurons in hidden layer for identification of a fault in the capacitively graded bushing. For this network also, a target matrix is set in which 0 is set for the without fault condition and 1 for the with fault condition. The time taken for the network to train the data depends on the error level and the number of neurons used in the hidden layer. Fig. 13 shows the output of the back propagation network for different models under study. From this figure, following observations have been made:

1. The output of the network does not necessarily have to be either 1 or 0. Thus a range has been set for identifying a fault.
2. As the percentage of training data increases, the output level approaches to target level.

The success rate of the above networks has been evaluated for different models and compared in Table 2. From the results, the following observations have been made:

1. The perceptron network and CC network are simple and effective for lower percentage of training data.
2. The time taken for CC network is in the same order of that of the back propagation network.

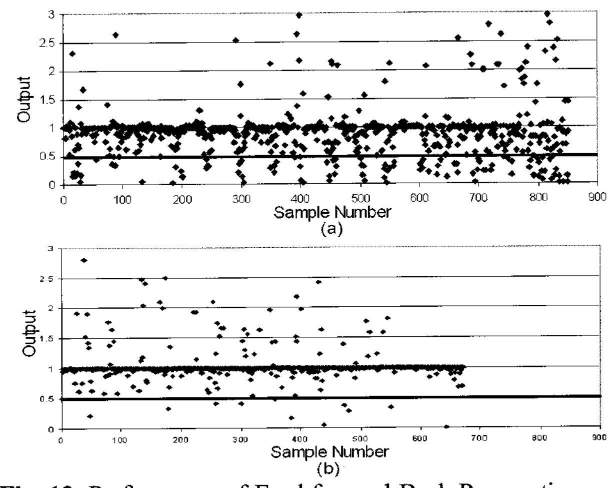


Fig. 13. Performance of Feed-forward Back-Propagation network for (a). Model A (b). Model B

3. The number of neurons required for hidden layer of CC network is much less than that of the back propagation network for a particular success rate.
4. CC network may be more effective to other networks, for new current data obtained from substation bushing during on-line monitoring.

In order to understand the effect of characteristics of hidden layer in feed-forward back propagation networks on success rate, different numbers of neurons have been employed in the hidden layer for the models under study (refer Table 3). From the results, it is clear that the success rate of the network increases with an increase of the number of neurons in the hidden layer. It is important to note that the time taken for the training of the back propagation network is very high compared to the perceptron network.

As the number of neurons in the hidden layer increases, the time taken for one epoch also increases. Even though the number of epochs decreases with an increase in the number of neurons, over all training time increases significantly. Thus, the time taken for the training of leakage current patterns depends on the accuracy at which the prediction of the interlayer fault is required for the reliable operation of the equipment. It may be noted that identification of fault alone may not be sufficient as part of the power equipment monitoring package. It is also important to know the type of abnormality before a bushing is said to require maintenance. In order to validate the capability of a perceptron network for the present application, different types of abnormalities (single-equivalent layer and double-equivalent layer) have been segregated, i.e., identified with the type of fault. A two layer feed-forward back propagation network is used with 4 numbers of neurons in hidden layer. Similarly, a cascade correlation network is used with two numbers of neurons in the hidden layer. The success rate of the above networks has been evaluated for different models and compared in Table 4. There is a significant increase in success rate with an increase of training data from 10% (Model A) to 50% (Model E). From the results, it is evident that, even though a perceptron network is simple, it is ineffective for the identification of types of abnormality. More clearly, the perceptron network is not sufficient enough for the identification of types of abnormality even for 50% of the training data (Model E). As the percentage of training data increases, the success rate of networks for this identification also improves significantly. Furthermore, the CC network is found to be superior compared to other networks, even for segregation of abnormalities, i.e., identification of fault with type.

Table 2. Success rate of the Perceptron and Feed-forward Back propagation Networks

Model	Perceptron Network (%)	Back Propagation Network (%)	CC Network (%)
A	98.23	89.62	98.69
B	99.61	96.19	99.72
C	99.85	98.36	100
D	100	99.31	100
E	100	99.38	100

Table 3. Success rate of the back propagation network for different number of neurons in the hidden layer

Model	Feed-forward Back propagation network (%)		
	2 Neurons	4 Neurons	6 Neurons
A	89.62	97.22	98.12
B	96.19	98.62	98.90
C	98.36	99.05	99.45
D	99.31	99.39	99.63
E	99.38	99.56	99.85

Table 4. Success rate of the Networks for identification of type of abnormality

Model	Perceptron network (%)	Back Propagation Network (%)	Cascade Correlation Network (%)
A	36.52	62.71	72.83
B	48.62	72.68	78.61
C	56.83	79.16	83.69
D	63.48	87.54	87.59
E	68.23	91.32	93.56

5. Conclusions

An optimal equivalent layers modeling circuit for a 420 kV SF_6 gas-to-air capacitively graded bushing has been used to simulate its behavior for very fast transients generated during switching operations in GIS. Since the change in leakage current with an interlayer fault in a bushing is only marginal, ANN techniques have been used for their identification. A single layer perceptron, two-layer feed-forward back propagation and cascade-correlated (CC) neural network models have been proposed in this study. For the identification of interlayer fault, a perception network is found to be superior to the feed-forward back propagation network. However, for identification of type of abnormality, a perceptron network is found to be ineffective even with an increased percentage of training data. For a particular success rate of the network, the number of neurons required for the hidden layer of the CC network is much less than that required for the back propagation network. The developed networks have been successfully tested for various leakage current patterns obtained from the bushing model.

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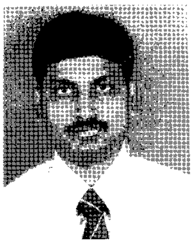

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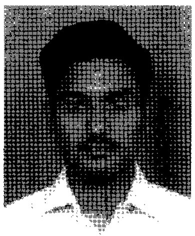

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