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POWER SYSTEM TRANSFORMERBOARD DEGRADATION DETECTION USING PROBABILISTIC NEURAL NETWORK

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ABSTRACT

The insulation condition monitoring of a power transformer has an important role for insulating materials which are subjected to extensive breakdown stress. In this study, a test setup has been constructed in order to simulate real world breakdown characteristics of transformerboards which are widely used as the insulating material. During the service life transformerboards may display undesired surface discharge damage due to increased rated voltages, which reduces the lifetime of transformerboards. The probabilistic neural network is used to detect the surface degradation of a transformerboard by analyzing electrical and ultrasound discharge data obtained from the test setup. The principle component analysis is employed to eliminate the messy matrix and vector calculations of the probabilistic neural network operations. Results of the classification procedure are given.

Keywords: *Transformerboard, Probabilistic Neural Network, Principle Component Analysis*

1. INTRODUCTION

The transformers together with generators are the major electrical system components and switchgear [1]. The operational reliability of a transformer mostly depends on the insulation system. The trend in the transformer insulation technology has been characterized by a continuous increase in the rated powers and voltages of power systems [2].

The damage observed on the transformerboards in service may cause malfunction or paralysis of an entire power system. In order to eliminate unexpected discharge patterns on the transformerboard an early failure detection method is proposed. There are a variety of traditional statistical classification algorithms in literature. Probabilistic neural networks (PNN) have similar beneficial properties compared to the other classification methods, such as simple structure, fast convergence and training and also rapid converge to Bayes optimal solution. However, PNN has some advantages in the sense of computational power and hence can tolerate outlier measurement values. There is neither iteration nor computation of weights in the PNN structure. In this study, PNN is used as the failure detection method of the monitoring system.

In general, PNN based algorithms have been used for many aspects of a variety of problems such as pattern classification, speaker identification purpose, and medical diagnosis systems [4-7]. In addition to PNN, PCA technique is also effectively employed to remove redundant information from the representative training set and the test set and get over the expensive higher dimension matrix computations.

The purpose of the test rig, used during the experiments, is to reproduce surface and sub-surface discharges discovered in transformerboards in active service. It is expected that such discharges may occur over time but may not be visible to the naked eye. So an effective detection method for discharges is required. Discharges within liquids can be detected as current pulses in a resistor placed in series with a discharging gap using oscilloscope. Also as an alternative a piezo-electric acoustic detector has been used to gather ultrasonic sounds during discharge on the transformerboard.

This paper is organized as follows. In section two, the test setup of the transformerboard degradation process is described. The next section provides the probabilistic neural network structure for the method and principle component analysis technique. Section four presents the test and

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classification results, and finally the conclusion is provided in section five.

2. TEST SETUP

Transformerboards may display unexpected internal and surface damage in their service life. A test rig has been constructed to reproduce these damages on a short time scale in the laboratory. The monitoring system analyses the discharge signal data in order to define the degradation level and early failure elimination [8]. All the boards used during the tests were cut into pieces with a dimension of 300*300*4mm and they are initially dried out and then soaked with oil under vacuum [3].

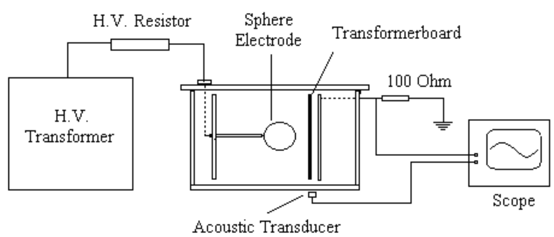

Fig.1. The test setup for transformerboard

A small and symmetrical model was used to simulate discharges observed in real transformers. In the model (Figure 1) a transformerboard was placed in a gap (5-400mm) between earthed plane and high-voltage electrode. In order to increase symmetry and electrode stresses, spherical electrode (representing coil) was used.

Applying 50kV voltage to the test cell produces stresses similar to those encountered full-scale 380kV transformer. Unexpected discharges and degradations on the boards are increased by raising the output voltage of the transformer up to %160. To simulate the degradation on the transformerboard 50kV, 60kV, 70kV and 80kV electrical stresses were applied to the test cell respectively.

The test cell was designed to withstand 100kV rms. applied voltage and contains transformer oil. The 100kV single phase H.V. transformer feeds the test cell spherical electrode via a 5MΩ high voltage (HV) resistor in order to limit the excessive current flow during the breakdown.

Surface and subsurface damage marks observed on the transformerboards are usually indicated by black spots. The most effective detection method of degradation on the boards seems continuous monitoring of discharge signal. In the test setup current pulse signal data (occurring on the 100Ω resistor) and also acoustic noise signal data (detected by using a piezo-electric transducer) were analyzed via a high speed oscilloscope.

3. PROBABILISTIC NEURAL NETWORK

In an electrical voltage monitoring systems, the imposed voltage levels can be determined and monitored by inspecting the distinctive features of breakdown patterns of the power system components, and also employing some efficient techniques such as the PNN. Donald Specht presented PNN as a kind of radial basis network in 1988 and since that time PNNs has been widely used for classification problems adequately [9]. PNN is based on Bayes decision rule and it uses Gaussian Parzen windows to yield outputs with Bayes posterior probabilities. Basically, three layers of PNN are given in Figure 2. The first layer determines the distances from the input vector to the training vectors. The second layer which is connected to the input layer sums all contributions for each class of inputs to find the vector of probabilities. The sum is scaled in this layer. The probability volume under the sum function is unity so that the sum forms a probability density function (pdf). The third layer is the last layer which is the competitive layer and chooses the maximum of the probabilities which are produced on the output of the second layer. Finally, the third layer produces a zero value for each class except for the winning class which has the maximum probability and at last has one value.

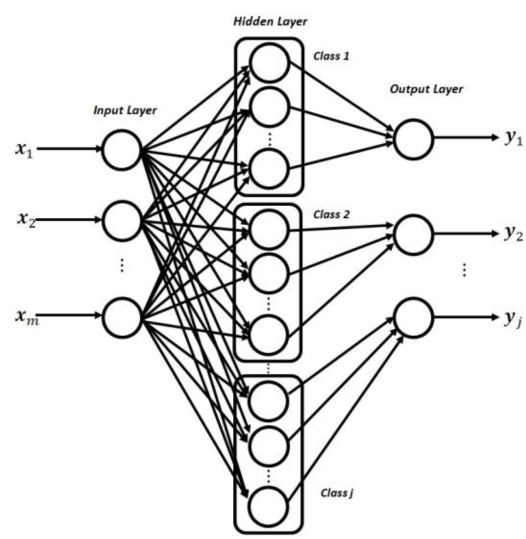

Fig. 2. Probabilistic neural network model

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The training data and the test data have been obtained by conducting the laboratory experiments for the proposed method. Electrical discharge signals and ultrasound discharge signals which cause of the degradation of the power system components have been recorded. Since for the selected gap 50kV did not cause considerable discharges, there are three voltage value classes of 60, 70 and 80 kV to be distinguished. The feature extraction step is applied to the raw data which have been provided by virtue of having some experiments. The electrical discharge signals transformed into feature vectors considering nine types of especially statistical characteristics. The feature extraction stage is followed by the PCA procedure to eliminate the redundant data and also to transform the possibly correlated variables into the uncorrelated variables namely principal components. PCA is a versatile tool for analyzing the obtained data, hence data be compressed by reducing the number of vector dimensions, without the expense of much loss of information. The decrease in dimension provides less computational load for matrix and vector calculations for the PNN. PCA technique has some advantageous properties based on the underlying mathematical foundation for the PNN procedure and pre-processing the feature vectors of the PNN.

Before Calculations the input feature vectors are first normalized so that they have zero mean and unity variance. The eigenvectors and eigenvalues of the covariance matrix are calculated after having the covariance matrix. The eigenvector with the highest eigenvalue is the principle component of the feature matrix. The eigenvalues are ordered in a decreasing order so, the first p components can be chosen from the whole covariance matrix.

If the observed signal matrix is defined by $s=[s_1,s_2,\ldots,s_k]^T$ where K is the number of classes, s1=[s(0), s(1),….,s(t)] and t=0,….,T. After having the feature extraction process, the obtained feature matrix is given by $x \in R^{KPxM}$, where P is the dimension of the training set for each class individually and M is the number of distinctive features and we have nine different features set. The total number of the feature vectors obtained from experimental setup is given by N=KP. The mean values of the data vectors have been subtracted from the feature vectors. Actually, PCA is defined as an orthogonal linear transformation that transforms the data to a new coordinate system. PCA procedure can be maintained by eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix. In our problem the data matrix is given by $x \in R^{KPxM}$.

The singular value decomposition of x is given by

$$x = UYV^T \tag{1}$$

where $U \in R^{MxM}$ is the orthogonal matrix of eigenvectors of xx^T. The matrix $Y \in R^{MxKP}$ is rectangular diagonal matrix with nonnegative real numbers on the diagonal, and the matrix $V \in R^{KPxKP}$ is the matrix of eigenvectors of x^Tx. The PCA procedure preserves the same number of principal components as in the original data set. Then transformation is given as follows,

$$y = x^T U = VY^T \tag{2}$$

y is the new representation of the data.

Obtained transformed matrix is fed into the PNN stage. The representation of the PNN is given in the Figure 2. There are three classes (K=3) of attributes to be distinguished. The input layer includes M number of nodes due to each node involves with one of the attributes of the feature vector. Input layer nodes connected to the each of the second (hidden) layer nodes so that all the hidden nodes receives the transformed feature vector y. The distance is computed from the input data to the other points, and a radial basis function (RBF) is applied to the distance to compute the weight for each point. The most common used RBF is the Gaussian function. The second layer nodes which correspond to a Gaussian function centered on its related feature vector are collected into clusters for each of the three classes [10].

The outputs of the hidden layer nodes are connected to the corresponding clusters therefore there are three output nodes at the output layer. All the Gaussian values are summed and the sum is scaled at the output layer. The k-th output node sums all the resultant values received from the second layer which is called Parzen windows in the k-th cluster. The PNNs are derived from Bayes' theory Parzen window estimation.

The Gaussian equation corresponding to the n-th feature vector of the k-th class of the input data y is given as,

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$$G_k(y) = \frac{1}{\sqrt{(2\pi\sigma^2)^m}} e\left\{-\left\|y - y^p{}_k\right\|^2 / (2\sigma^2)\right\} \quad (3)$$

where σ is the smoothing parameter. The smoothing parameter of the function determines the spread of the radial bases function and it determines the decline speed of the function as the distance increased from the input data. The maximum point of the radial basis function is centered on the point it is weighting. The larger σ values create more spread and therefore the distant input points can have greater influence on the output.

Although a variety of approaches are proposed for determining the σ parameter [11-12] the smoothing parameter is chosen empirically when it is common for all the classes. The smoothing parameter σ, values can be set as the one half of the average distance between the feature vectors. The k-th output node sums the values received from the hidden nodes in the k-th class, and the sum is given by,

$$S_k(y) = \frac{1}{\sqrt{(2\pi\sigma^2)^m}} \left(\frac{1}{p}\right) \sum_{p=0}^{p} e\left\{-\left\|y - y^p{}_k\right\|^2 / (2\sigma^2)\right\} \quad (4)$$

where y is one of the input feature vector. II . II denotes the Euclidean distance (square root of the sum of squared differences) between input feature vectors.

The maximum a posteriori (MAP) value of the sum functions $S_k(y)$, k=1,…, K in the output layer nodes determines the class of the any given input feature vector. The output nodes take the zero or one values in accordance with the following inequality,

$$\sum_p e\left\{-\left\|y - y^p{}_k\right\|^2 / (2\sigma^2)\right\} > \sum_l e\left\{-\left\|y - y^p{}_l\right\|^2 / (2\sigma^2)\right\} \quad (5)$$

One of the output nodes have value one due to the probability of being a member of p-th class is greater than other classes.

4. TEST AND CLASSIFICATION RESULTS

The test setup was constructed to obtain discharge signal data measured on the transformerboards. Tests were performed for different voltage levels (50kV, 60kV, 70kV and 80kV) which simulates different amount of degradation. For improved noise immunity all system has connected together to the same earth point. The test procedure is given in Figure 3.

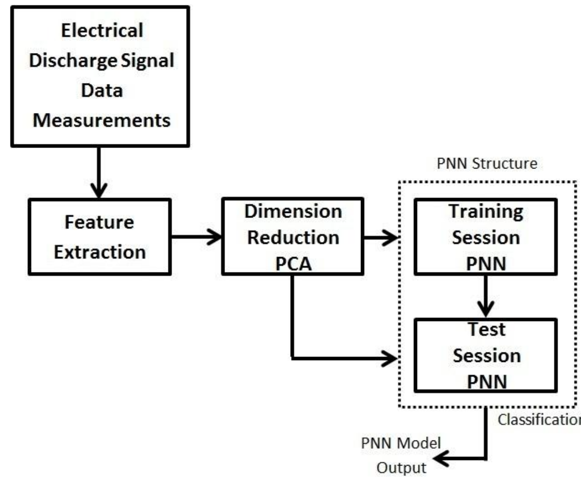

Fig.3. Proposed transformerboard degradation detection procedure

According to the test procedure electrical and ultrasound discharge signals are recorded and classified for training and test. There are 100 data sets for both test and training used. The electrical discharge signal training and test set samples are given in Figure 4 and 5.

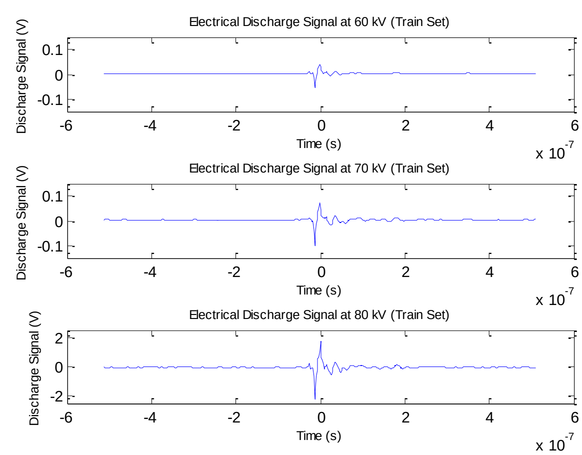

Fig.4. Electrical discharge signals training set for 60kV, 70kV and 80kV respectively

During the tests the discharge time is set to zero seconds. The valid discharge signal duration is measured as $2\text{x}10^{-7}$ seconds. The signal classification is fulfilled in this limited range.

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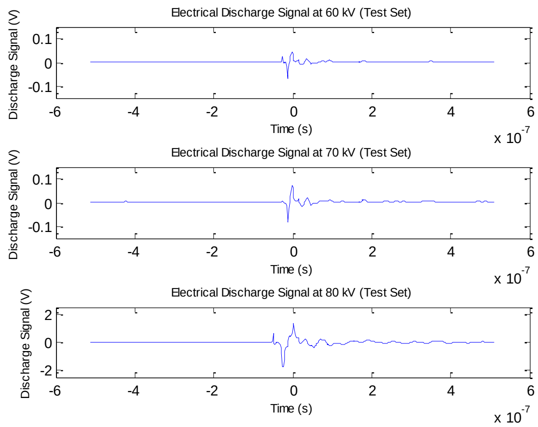

Fig.5. Electrical discharge signals test set for 60kV, 70kV and 80kV respectively

Also the ultrasound discharge noise signal training and test set samples are given in Figure 6 and 7.

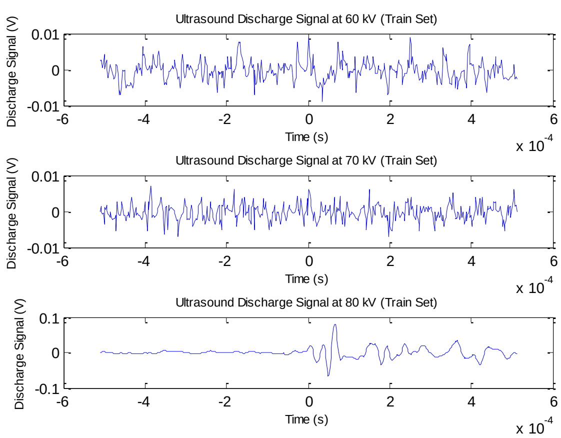

Fig.6. Ultrasound discharge signals training set for 60kV, 70kV and 80kV respectively

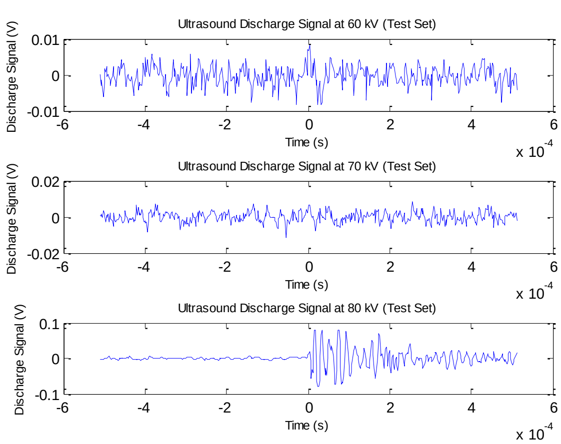

Fig. 7. Ultrasound discharge signals test set for 60kV, 70kV and 80kV respectively

During tests PNN performance was monitored for acoustic and electrical discharge with and without using PCA. For the feature extraction step the chosen feature vector contains mean, variance, median, interquartile range, skewness, kurtosis, discrete cosine transform and range features. The vector length is nine for feature set. In order to obtain satisfactory results algorithm was subjected to a number of tests and all the results are given in Table 1 and Table 2.

The electrical discharge classification performance alters depending on the smoothing parameter (σ) and test voltage. Empirically the best results were obtained by taking the smoothing parameter σ=0.40 and 80 kV. PCA reduces the dimensions and convergence time by eliminating redundant data hence it was preferred for the classification process.

Table 1. PNN performances for electrical discharge signals with and without PCA

Electrical Discharge	Classification Performance (for σ=0.40)	Classification Performance (for σ=0.55)	Classification Performance (for σ=0.90)
PNN(60kV)	%95	%93	%79
PNN with PCA(60kV)	%96	%94	%85
PNN(70kV)	%95	%95	%81
PNN with PCA(70kV)	%97	%96	%89
PNN(80kV)	%98	%97	%84
PNN with PCA(80kV)	%99	%97	%90

The ultrasound discharge classification performance is given in Table 2.

Table 2. PNN performances for ultrasound discharge signals with and without PCA

Ultrasound Discharge	Classification Performance (for σ=0.40)	Classification Performance (for σ=0.55)	Classification Performance (for σ=0.85)
PNN(60kV)	%80	%81	%94
PNN with PCA(60kV)	%84	%85	%95
PNN(70kV)	%84	%85	%95
PNN with PCA(70kV)	%88	%89	%95
PNN(80kV)	%88	%90	%96
PNN with PCA(80kV)	%93	%91	%97

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It is clear from the results that PNN performance is quite satisfactory under suitable conditions for the detection of degradation observed on transformerboards. In order to improve the performance of the system smoothing parameter should be chosen correctly. Although there are some algorithms to choose smoothing parameter, it can be defined empirically. The amplitudes of the discharge signals are quite small; hence there are little differences between feature sets of the signals. Therefore to fulfill satisfactory classification, optimum smoothing parameter may distinguish correct feature set. Increasing smoothing parameter may cause missing little details between feature sets. So defining smoothing parameter is vital for the classification performance of the algorithm. Also increasing voltage level improves the classification performance for both ultrasound and electrical signals by increasing amplitudes of the discharge signals.

5. CONLUSION

In this study the breakdown phenomena observed on a transformerboard under high stresses was investigated. Since the development of discharge tracks takes a long time in real life a simple test setup was built to produce discharge tracks and simulate the breakdown process. It was envisaged that a discharge detection algorithm for transformerboard might give a useful early warning and protection for the power system. To simulate discharge tracking phenomenon on a transformerboard HVAC current was applied and corresponding degradation data were obtained. For the comparison purpose electrical discharge and ultrasound discharge signals were monitored and classified. Inherited features of PNN are very compatible with the random discharge patterns of the transformerboard and hence it provides satisfying performance. The selection of the proper features in the feature extraction step defines the performance of the classification significantly. In order to, improve classification performance of the PNN, different feature vectors are employed in the training process. The smoothing parameter is a considerably vital factor for the performance of the network. PCA was also used to improve the performance and eliminate messy calculations and matrix computations. The satisfactory results for both electrical and ultrasound discharge signals were obtained by choosing optimum smoothing parameter and employing PCA. The proposed PNN algorithm with PCA is suitable for real time classification and detection of degradation of transformerboards where early warning may eliminate malfunction of a power system. Moreover, detecting electrical and ultrasound discharge signal at the same time may increase the performance and reduce the classification error rate.

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