TRANSFORMER WINDING FAULTS - A NOVEL APPROACH OF RECOGNITION

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ABSTRACT

The purpose of lighting impulse test is to ascertain whether the transformer insulation can withstand the non-linear electric stresses without damage and test the dielectric integrity provided. A standard lightning impulse of standard wave shape 1.2/50µs is applied to the test transformer to check its dielectric integrity. This proposed method elucidates a novel approach of identifying the healthiness of insulation. The objective of this research is to provide information about the healthiness of the insulation to the test engineer during the process of LI test against faults such as inter turn and inter disc faults. The researchers have used the original version of Probabilistic Neural Network for obviating the need of experts for recognition of faults that has taken place. For this experimental test were carried out on a 315kVA, 11kV/433 V star /delta transformer. Tapping were provided on one HV winding for simulating various inter turn and inter disc faults. Several approaches were attempted and results observed were encouraging. It is argued by the authors in this paper that this approach can be effectively used for diagnosis against winding faults [08].

KEYWORDS: *Winding Fault diagnosis, Impulse Test, Probabilistic Neural Network (PNN).*

I. INTRODUCTION

The reliability of any power apparatus depends upon the performance of its insulation. Insulation failure is the root cause of total failure of power transformers. Several high voltage test like induced and applied over voltage test, partial discharge test and lightning impulse test are conducted on the completed transformer in order to assess the integrity of the winding. Lightning impulse tests are made using a standard 1.2/50µs wave shape with a tolerance of ±30% in front time and ±20% half value time on wave tail. The recording of the voltage wave shape and crest value of the impulse confirm to the relevant test specification and also serves to detect insulation failure [09]. An Artificial Neural Network based approach has been developed in order to find the deterioration of the insulation of the winding. This approach is applicable only to transformers of same capacity and ratings.

The fundamental principle behind impulse voltage test procedure is that to identity failure in an objective manner. As per standards, the objective is ensured by zero difference in waveforms recorded between reduced and full voltage. However when there is a difference, concrete decision cannot be arrived on the source of fault. This proposed approach provides knowledge on the windings faults if any and is also independent of the applied terminals [10].

Attempts by many researchers were made by comparing the neutral currents at reduced and full impulse voltage, approach of applying the FFT technique, swept frequency method and impulse frequency method etc. The results of the papers published are mainly based on simulation analysis [1].The researchers have also used effectively the Artificial Neural network as a tool to obviate the need of skilled experts to interpret faults based on the voltage waveforms obtained from the secondary side.

ANN is one of the non - parametric methods for pattern classification and it has the distinct advantage of being able to handle noisy and missing data. Its (ANN) feature of providing general solutions with good predictive accuracy made it highly accurate method for pattern classification. Beside this it has also the special capability to handle huge data. Hence, ANNs are programs designed to simulate the way a simple biological nervous system is believed to operate [11]. The network has the interpretation capability like human brain like the capability to run memorize and create relationship amongst data. Input layer, hidden layer (one or more) and output layer are the fundamental structure of ANN. The input layer may have several input neurons or processing elements and is driven by the data obtained. The hidden layer characterizes the typical structure of the ANN and differs diversely. The output layer is defined according to the user-anticipated parameters and can be one or more.

This paper reports on the effectiveness of Probabilistic Neural Network (PNN) which has been used for pattern classification purpose [12].

II. Probabilistic Neural Network – Concepts and Mathematical Aspects

The Probabilistic Neural Network (PNN) designed and developed by Specht. [4, 5, 6, 7] is a network formulation of "probability density estimation". They are models based on competitive learning with a "winner takes all attitude" and the core concept based on multivariate probability estimation. The PNN classifier has sometimes been accepted as belonging to the class of Radial Basis Function (RBF). Another school of thought prefers to associate RBF classifiers topologically with a feed forward network having only one hidden layer. PNN's have no feedback path. The feed forward networks learn from pattern statistics from a training set. Another distinction between BPA and PNN is that in the BPA feed forward network, the training is in terms of global basis function which are defined as non-linear (usually sigmoidal) functions of the distance of the pattern vectors from the hyper-plane, while in the PNN the training is in terms of local basis function which are exponential functions of the distance of pattern vectors from the hyper-plane [13]. The process-based classification that differentiates PNN from RBF is that PNN works on estimation of probability density function (pdf) while RBF works based on iterative function approximation. The strength of using local basis function stems from the fact that it is possible to train a network of local basis function in one pass through the data, by straightforwardly applying the principles of statistics.

The PNN is the classifier version obtained when the Baye's strategy for decision-making is combined with a non-parametric estimator for probability density function. The most important feature of PNN is the speed of training and the excellent generalization ability.

2.1. The Approach and Mathematical Aspects

In order to classify a feature pattern vector $X \in R^M$, that is to assign the pattern to one among K predefined classes, the conditional density $p(x|C_k)$ of each class Ck is estimated since it represents the uncertainty associated to class attribution. Then these estimates are combined by the rule of Baye's to yield a- posteriori class probabilities $p(C_k|x)$ that allow in making optimal decisions. In PNN, conditional density estimation is accomplished by implementing the Parzen window technique as explained earlier.

Another way of looking at this technique is to build a sphere of influence p(s,x) around each training (known) sample and to add them up from each of the k classes. In the Specht's implementation the basis functions usually used as a window are the Gaussian kernels as,

$$p(s,x) = \exp\left[\frac{-\left\|x - s^2\right\|}{2\sigma^2}\right] \tag{1}$$

where the only free parameter is the width or smoothing parameter (σ) of the Gaussian.

2.2. PNN Architecture

The PNN consists of an input layer, two hidden layers (exemplar and summation layers) and an output layer as illustrated in Figure 1 . The architecture of PNN is described below:

2.2.1. Input Unit and Input Layer

The input units are merely distribution units that supply the same input values to all the pattern units.

2.2.2. Pattern or Exemplar Layer

There is one pattern or exemplar node (unit) for each training example. Each pattern unit forms a dot product of the weight vector and the given example for classification, where the weights entering a node are from a particular example. After that it performs a non-linear operation on the dot product so obtained before sending its activation level to the summation unit. Instead of the sigmoidal activation function commonly used for back propagation based ANN, the non-linear operation used here is the exponential operator.

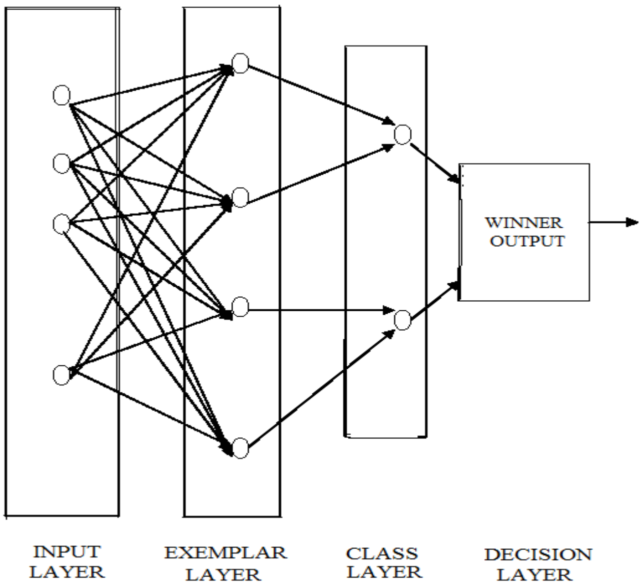

Figure 1 Architecture of Probabilistic Neural Network

2.2.3. Summation or Class Layer

This second hidden layer contains one summation unit for each class. Each summation unit (node) receives the output from the pattern nodes associated with a given class

$$\sum_{1}^{NK} I = \exp\left[\frac{\left(x^T w_{ki} - 1\right)}{\sigma^2}\right] \tag{2}$$

2.2.4. Output or Decision Layer

The output layer has as many neurons as the number of data classes considered. The output nodes are binary neurons that produce the classification decision

$$\sum_{1}^{NK} I = \exp\left[\frac{\left(x^T w_{ki} - 1\right)}{\sigma^2}\right] \quad > \sum_{1}^{NJ} I = \exp\left[\frac{\left(x^T w_{ki} - 1\right)}{\sigma^2}\right] \tag{3}$$

The PNN used for the classification task is explained in detail. The PNN program is encoded using MATLAB software. The training procedure and the observations of the testing are dealt in next section.

III. SIMULATION OF ARTIFICIAL FAULTS

Several papers have been made to present the different techniques for identifying different faults and its location in transformer windings [2,3] with different approaches in which simulation technique is the most common. An attempt is made here on 315kVA, 11kV/415V, Δ-Y, Dyn11 transformer. For this different tapping are brought out on the R phase winding of three phase distribution transformer at the different percentage of windings, 87.5%, 62.5%, 37.5% and12.5%.The transformer with tapped leads is shown in figure 2.

Figure 2 Transformer with tapped leads

For the actual classification task, 4 types of fault are simulated. During prolonged service of transformer, there are possibilities for the deterioration of insulation which eventually leads to inter turn or inter disc shorts. Various types of faults are simulated on one HV limb of the transformer with the aid of the tapping provided. Table 1 shows the different artificially created fault locations with the number and the type of waveform recorded with explanation [21].
Figure 2 gives the pictorial representation of the different tapping brought out from the transformer .Figure 3 gives the Diagrammatic representation of three-phase Transformer Winding.

Table 1 artificially created Faults and their description

Sl. No	Fault Type	No. of waveforms recorded	Naming of Individual Patterns
1	O- Impulse Voltage Patterns corresponding that no winding short has occurred	10	O1, O2, O3, O4, O5, O6, O7, O8, O9, O10
2	A-Short between the sections 100% - 87.5% (12.5% on the top section)	10	A1, A2, A3, A4, A5, A6, A7, A8, A9 &A10
3	B-Short between the sections 87.5%-62.5% (25% on the middle section)	10	B1, B2, B3, B4, B5, B6, B7, B8, B9 & B10
4	C- Short between the sections 62.5%-37.5%(25% on the bottom section)	10	C1, C2, C3, C4, C5, C6, C7, C8, C9 & C10
5	D- Short between the sections 37.5%-12.5% (25% on the bottom most section)	10	D1, D2, D3, D4, D5, D6, D7, D8,D9 &D10

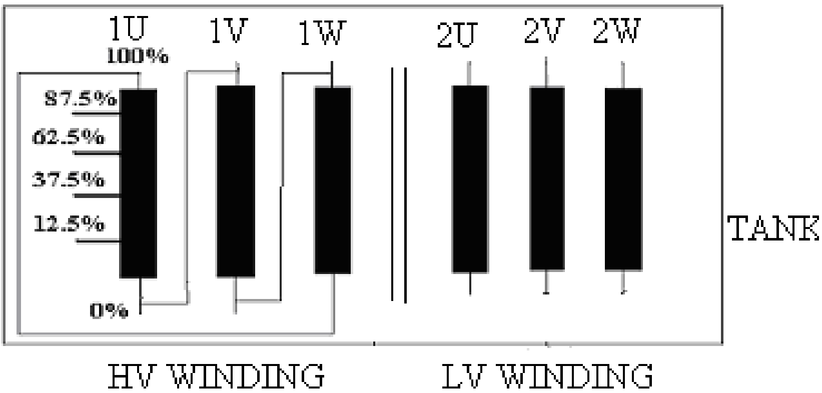

Figure 3 Diagrammatic representation of three-phase Transformer Winding.

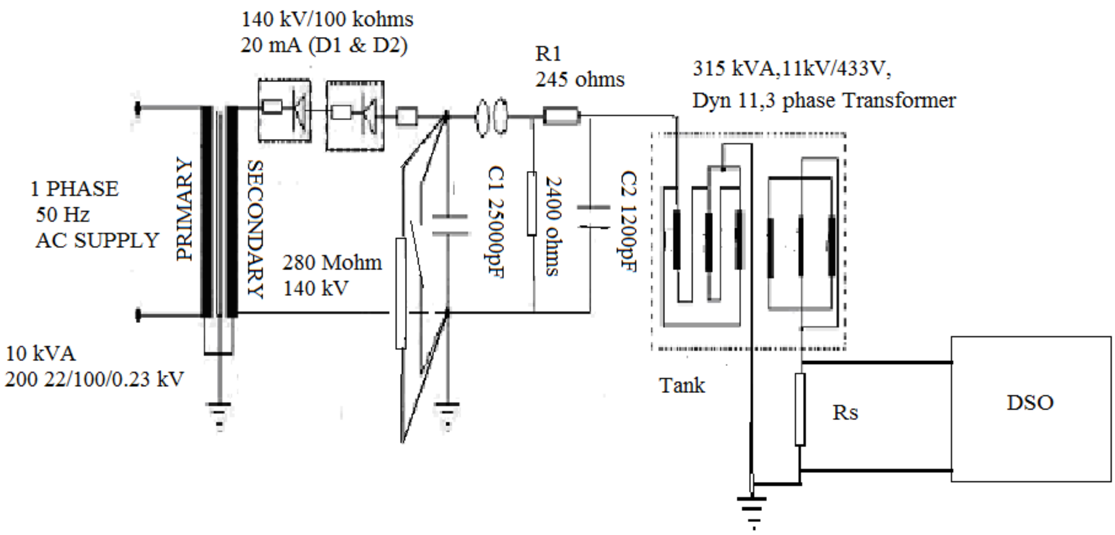

Figure 4 Electrical test set-up

IV. EXPERIMENTAL PROCEDURE AND FEATURE EXTRACTION

A standard lightning impulse voltage of waveshape 1.2/50 µs is generated with the Marx generator and is applied to the 'R' phase of the transformer winding while Y&B phase of the HV windings are short circuited and earthed along with tank [14]. The R, Y &B phase of the LV winding is short circuited and is earthed through a low value resistance (Figure 4). The voltage across the resistance is measured using a Digital Storage Oscilloscope. The impulse voltage is applied to the R phase and the voltage across the resistance connected in series with the LV arm is recorded using a DSO (Figure 5). Ten patterns were captured for each type of faults for the same magnitude of applied voltage. The number of finger prints in the database is 50 i.e. 10 for each type of fault [15].

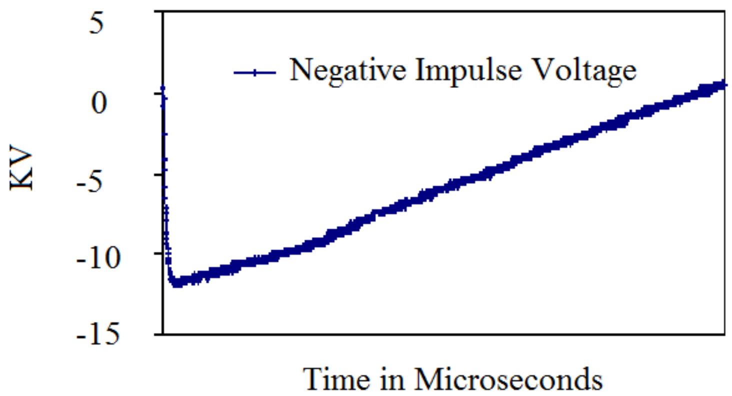

Figure 5 Lightning Impulse Voltage Waveform

Preliminary considerations involve two important stages. They are the features extraction and classification. The necessity of feature extraction is to capture the distinctive attributes that correlate to each discharge. Hence this step may be called a preprocessing step wherein an m- dimensional vector is mapped into a reduced n- dimensional feature vector where n is equal to the number of extracted features. The feature vector is applied to the ANN to perform the classification task. Thus the concept is that of defining the boundary surface that divides the feature space into a number of disjoint regions that represent the different classes. Thus the problem is now one of making a decision as to which side of the boundary the new input falls. In this case, the X and Y values of all the impulse voltage patterns captured using the DSO are extracted [16].

V. TRAINING AND TESTING –PROGRAM IMPLEMENTATION

The input data obtained from the computer aided measurement and acquisition system is provided to the ANN as input in the form necessary for feature extraction so as to capture the distinctive attributes that correlate to the discharge. Such preprocessed data input called the fingerprints now becomes the basis used for feature extraction [17]. Databank of such several faults extracted from the computer based measurement and acquisition system is now used as input. In this case database of 10 patterns of each fault is used. The training phase thus involves training from such a database, which now is preprocessed in the form of fingerprints for each type of pattern. In the test phase an unknown fault pattern is given as input, which is converted in the form of such fingerprints, and the classification is now reduced to one of matching to a particular class of fault / faultless [20].
The purpose of capturing 10 patterns on each category is that to train the neural network so that it can capture the inherent properties of the fault type.

Table 2 Patterns Available in the database

Faults Pertaining to Faults (impulse at R phase)*check				
Fault O	**Fault A**	**Fault B**	**Fault C**	**Fault D**
R01	RA01	RB01	RC01	RD01
R02	RA02	RB02	RC02	RD02
R03	RA03	RB03	RC03	RD03
R04	RA04	RB04	RC04	RD04
R05	RA05	RB05	RC05	RD05
R06	RA06	RB06	RC06	RD06
R07	RA07	RB07	RC07	RD07
R08	RA08	RB08	RC08	RD08
R09	RA09	RB09	RC09	RD09
R010	RA10	RB10	RC10	RD10

The total available fingerprints are shown on Table 2 .The PNN is trained with first 5 training exemplars of each class. The trained network is tested with all the fingerprints available in the database [18]. The test patterns include the training patterns also.
The following observations were inferred

- The classification rate is observed to be 98%. Only one pattern is found to be misclassified on fault D.
- The entire training pattern when presented as test input has been classified correctly.

The performance of the network was also validated using another set of five training exemplars (last five of each class) and was investigated.
The observations are

- The classification rate is observed only to be 92%. Four patterns are found to be misclassified. The patterns are R02 & R03 of fault O (no fault), RB01& RBO5 of fault B
- The entire training pattern when presented as test input has been classified correctly.

An attempt was also made to study the performance of the NN with increased training exemplars (first seven training exemplars)

- The classification rate is observed only to be 100%. No patterns are found to be misclassified.
- All the training patterns when presented as test input have been classified correctly.

The performance of the network was also validated using another set of seven training exemplars (last seven of each class) and was investigated. The observations are

- The classification rate is observed only to be 100%. No patterns are found to be misclassified.
- All the training patterns when presented as test input have been classified correctly.

Table 3 Patterns Available in the database

Faults Pertaining to Faults (impulse at Y phase)*check				
Fault O	**Fault A**	**Fault B**	**Fault C**	**Fault D**
Y01	YA01	YB01	YC01	YD01

Y02	YA02	YB02	YC02	YD02
Y03	YA03	YB03	YC03	YD03
Y04	YA04	YB04	YC04	YD04
Y05	YA05	YB05	YC05	YD05
Y06	YA06	YB06	YC06	YD06
Y07	YA07	YB07	YC07	YD07
Y08	YA08	YB08	YC08	YD08
Y09	YA09	YB09	YC09	YD09
Y010	YA10	YB10	YC10	YD10

The total available fingerprints are shown on table 3 .The PNN is trained with first 5 training exemplars of each class. The trained network is tested with all the fingerprints available in the database. The test patterns include the training patterns also.

The following observations were inferred

- The classification rate is observed to be 92%. Only four patterns are found to be misclassified on fault D.
- The entire training pattern when presented as test input has been classified correctly.

The performance of the network was also validated using another set of five training exemplars (last five of each class) and was investigated.

The observations are

- The classification rate is observed only to be 92%. Four patterns are found to be misclassified. The patterns are YB04, YB06, YB07 of fault B, YD01 of fault D
- Two training patterns when presented as test input has been misclassified (YB06 & YB07

An attempt was also made to study the performance of the NN with increased training exemplars (first seven training exemplars)

The observations are

- The classification rate is observed to be 96%. Only two patterns are found to be misclassified. Misclassified patterns are (YA09 & YD01)
- Only one training patterns when presented as test input have been misclassified (YD01).

The performance of the network was also validated using another set of seven training exemplars (last seven of each class) and was investigated.

The observations are

- The classification rate is observed only to be 96%. Two patterns are found to be misclassified (YB01 & YD01).
- Two of the training patterns when presented as test input have been misclassified (YB01 & YD01).

Table 4 Patterns Available in the database

Faults Pertaining to Faults (impulse at B phase)				
Fault O	**Fault A**	**Fault B**	**Fault C**	**Fault D**
B01	BA01	BB01	BC01	BD01
B02	BA02	BB02	BC02	BD02
B03	BA03	BB03	BC03	BD03
B04	BA04	BB04	BC04	BD04
B05	BA05	BB05	BC05	BD05
B06	BA06	BB06	BC06	BD06
B07	BA07	BB07	BC07	BD07
B08	BA08	BB08	BC08	BD08
B09	BA09	BB09	BC09	BD09
B010	BA10	BB10	BC10	BD10

The total available fingerprints are shown on table 4 .The PNN is trained with first 5 training exemplars of each class. The trained network is tested with all the fingerprints available in the database [19]. The test patterns include the training patterns also.

The following observations were inferred

- The classification rate is observed only to be 80%. Nine patterns are found to be misclassified (out of 50). The patterns are B004, BA02, BA06, BA07, BA08, BA09, BA10,& BD02..

- Three training patterns when presented as test input has been misclassified (B004, BA02 & BD02).
- The classification rate is observed only to be 64%. Seventeen patterns are found to be misclassified (out of 50). The patterns are B001, B002, B003, B004, B005, B006, BA01, BA10, BB01, BB02, BB07, BC07, BC08, BC09, and BC10.
- Seven training patterns when presented as test input has been misclassified (B006, BA10, BB07, BC07, BC08, BC09, and BC10).

An attempt was also made to study the performance of the NN with increased training exemplars (first seven training exemplars)

- The classification rate is observed only to be 96%. Two patterns are found to be misclassified (YA09).
- One training pattern when presented as test input has been misclassified (YD01).

The performance of the network was also validated using another set of seven training exemplars (last seven of each class) and was investigated.
The observations are

- The classification rate is observed only to be 80%. Ten patterns are found to be misclassified. Misclassified patterns are(BA01, BA02, BA03, BA04, BA05, BA06, BA07, BA08, BA09, BA10)
- Seven training patterns when presented as test input has been misclassified (BA01, BA02, BA03, BA05, BA06, BA07, and BA08).

VI. CONCLUSION

The major contributions of the research work based on exhaustive investigations are summarized as under:

- An approach for obtaining an accurate and reliable decision for the identification of defect classes has been proposed and implemented.
- Exhaustive literature surveys indicate that the innovative approach of using the Probabilistic Neural Network and its adaptive version, a simple and straightforward approach yet an effective technique, has enabled the task of training and testing the neural network for various patterns quickly yet effectively for the very first time in the history of winding fault diagnosis using neural network.
- The drawbacks in this approach is only that this technique can be adopted to transformers of same type and capacity. However on detailed investigation and novel approach of inputs to ANN can generalize it for any transformers and research leading to the same is under progress.

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