Faults in Transformer Winding and Probing their Occurrence by S-Transform and RBF Neural Network Technique

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Abstract

Now a days significant enhancement of certainty, reliability and economics of the power transformer is an important topic in power system engineering because among all equipment as for expedition used in electrical systems power transformer is one of the most costly piece of equipment. So that accurate diagnosis of fault has been always been a major issue. Simulation studies based on transient model of transformer winding enhance understanding of surge voltage and fault current waveforms. Those are non-stationary in nature. The non -stationary nature of current waveforms inside the transformer winding requires the model parameter to be both time and frequency dependent. it will help to detect type of fault as well as location of occurrence using simulation studies. This paper aims to present a technique for diagnosis of the type of the fault and location of occurrence. . The proposed method is based on a transient model based transformer under impulse test and S-Transform with good time frequency resolution for all frequencies (multi resolution). S-Transform is used to produce a stock well coefficient vector which utilized as inputs testing set to a Radial Basis Function Neural Network (RBF). The fault conditions are simulated by the variation of fault location according to inter turn winding of power transformer or disc. The training is conducted by programming in MATLAB. The robustness of the proposed scheme is investigated by synthetically polluting the simulated voltage signals with White Gaussian Noise. The suggested method has produced fast and accurate results. Estimation of fault location is intended to be conducted in future.
Keywords: EMTP, S-transformation, TRF Time frequency response, Stock well Coefficient, RBF, transient model of transformer

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I. INTRODUCTION

Today transformers constitute the major portion of the capital equipment of the power utilities all over the world and the reliable power supply depend heavily on the fault free operation of the transformer. Power rating of the transformer varies from few tens of KVA to several hundred of MVA and as same as the cost of replacing transformer is varies from a few hundred dollars to several million dollars. Failure of transformer while in service usually lead to significant revenue loss to the utility, potential environment damage, explosion and fire hazard, and expensive repairing and replacement cost. Hence it is desirable that the transformer should be utilized to the maximum extent consistent with adequate service life. A failure of transformer is defined as either any forced outage of the transformer due to its failure in service or trouble which requires extensive field repair. Insulation breakdown means winding failure which may lead to complete failure of transformer. Transformer failure can be broadly classified as electrical, mechanical and thermal. The failure may be also classified in a different manner as external and internal. Failure due to external degradation, increased moisture content, over heating winding resonance etc, Fall under the internal category whereas the fault due to lightning strikes ,switching over voltage ,system fault ,system overload etc, fall under the external category. So according to classification there are various reason behind insulation failure[1-2]. Mainly insulation of transformer windings can be broken down by impulse voltages of high amplitude produced by lightning or switching transients. This reduces the average expected life of the transformer, and increases the maintenance and operation cost. A fault occurring in a transformer can develop breakdowns, resulting in very expensive repairs. Therefore monitoring of types of winding fault and detection of particular location of fault occurrence to provide appropriate maintenance schedule is of considerable interest among utilities. An early and periodic detection of changes in the transformer windings will predict the transformer condition and will provide proper maintenance. . Finally, the procedure should be such that data may be obtained by varying a readily measurable parameter and the data would make it possible to interpret the results obtained by test. Since fault detection is essential, new signature methods were being continually discovered. With availability of fast digital recorders and personal computers, these waveforms were stored digitally, leading to their analysis rather than just visual observation. Primarily, differences in waveforms were amplified and compared [3-4].

II. PROPOSED APPROACHES

Step 1: Simulation of fault in transformer model

Step 2: Features Extraction from simulated fault current waveform (Time-domain)

Step 3: Fed Extracted features to the S-transformation (Time-frequency)

Step 4: Training with suitable advance signal processing method RBF

Step 5: Identification the occurrence of fault

III. CASE STUDY

A. Impulse Testing Methode

The conventional method for evaluating the transformer transfer function uses an impulse signal as the input stimulus and FFT as the frequency response analysis. One of the disadvantages of the impulse testing method is that the input signal does not provide adequate excitation across the span of the pass band of the transformer. This problem could be alleviated with broadband signals designed to have almost equal energy across a wide range of frequencies The impulse testing is used to determine the ability of the insulation of the transformers to withstand the transient voltages. The voltage distribution along the transformer winding will not be uniform, as the transients are impulses of short rise time. If an impulse wave is applied to such a network, the voltage distribution along its element will be not even, as well as oscillations will be sent in producing voltages much higher than applied voltage [7]. The impulse test is normally done with impulse voltages, having standard wave shape of 1.2/50 µsec as per IEC 60076-4, as stated earlier [8].The routine impulse test normally consists of one reduced and one full-wave impulse, or two full-wave impulses, with the standard wave shape of 1.2/50 µsec as per IEC. The full-wave impulses are of a crest value equal to the rated BIL of the terminal being tested. These standard wave shapes are impressed on one side of the transformer winding, while keeping other end of the winding and tank to ground through a low resistance (called tank current method). The winding currents are recorded by measuring the voltage across the standard or known low resistance shunt. These currents are analyzed in order to find. The faults within the transformer winding. For Impulse testing of a three-phase winding, the impulse voltage is applied at one terminal at a time. The other two terminals are shorted at that time and grounded through a resistance equal to the surge impedance of the line. The standard impulse wave can be represented as double exponential waves defined by the equation.

$$V = V_0 (e^{-\alpha t} - e^{-\beta t})$$

Where, V0 in kilovolt, α and β are constants. The above equation represents a unidirectional wave which usually has a rapid rise to the peak value and slowly falls to zero value. Hence, the standard 1.2/50 µsec, 150 kV wave represents an impulse voltage wave with a front time of 1.2µs , falling time to 50 % peak value in 50 µs , and a peak value of 290 KV. The standard 1.2/50 µs 290KV impulse voltage will be used next in the case study, as shown in Fig.1.

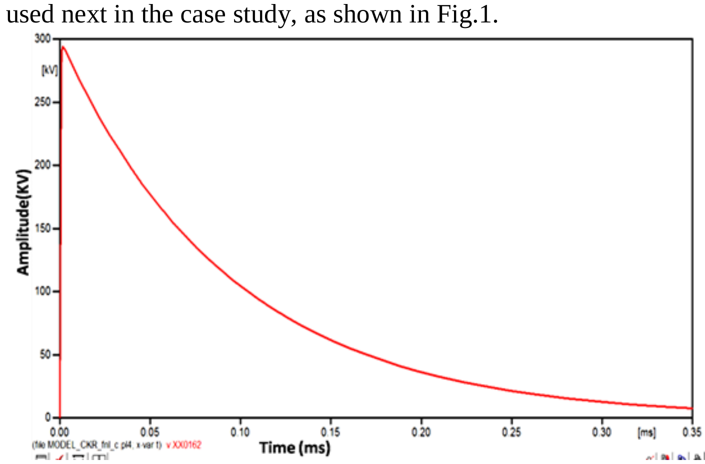

Fig.1: The Standard 1.2/50 µsec 290KV impulse voltage.

B. Tank Current Method

The routine impulse test normally consists of one reduced and one full-wave impulse, or two full-wave impulses, with the standard wave shape of 1.2/50 µsec The full-wave impulses are of a crest value equal to the rated BIL of the terminal being tested. These standard wave shapes are impressed on one side of the transformer winding, while keeping other end of the winding and tank to ground through a low resistance (called tank current method. So that the earth end and transformer winding connected to ground through a low resistance which is known as tank resistance? The winding currents are recorded by measuring the voltage across the standard or known low resistance shunt. These currents are analysed in order to find the faults within the transformer winding.

1) Step 1: EMTP Model of Transformer

Electromagnetic Transient Program (EMTP) is computer simulation software which is designed to study power system transient phenomena for different systems, including single-phase or multiphase systems, electromagnetic phenomena ,electromechanical phenomena, balanced or unbalanced circuits, power system control, etc. An EMTP based model of the transformer is used for the present study . In the present study, EMTP, which proved to be an efficient tool for transformer having voltage rating of 33/11 KV design with 80 discs has been employed for simulating the lumped parameter model of a transformer. The lumped parameter network represents the delta connected disc winding of the HV side of the transformer .The design parameters of this lumped network are either calculated using the formulae presented in [9].

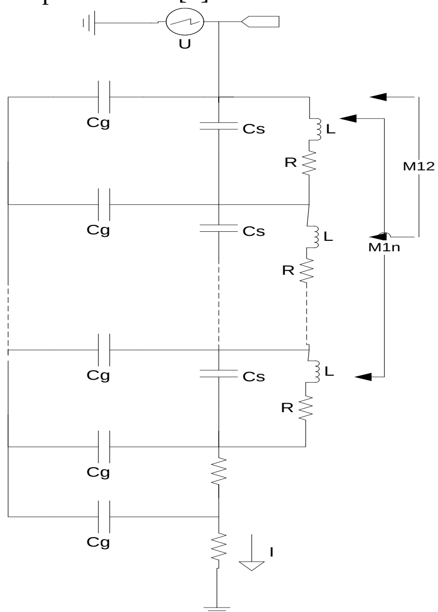

Fig. 2: EMTP model of The Transformer

In the present study, EMTP, which proved to be an efficient tool for transformer design has been employed for simulating the lumped parameter model of a transformer. In order to demonstrate the parameters of the transient model of transformer model were taken from test which has been already done [8].The parameters of the transformer are shown in below Table.1.

Table - 1
Parameters Value

S. NO	*EMTP Model*	
	Parameters	*Value*
1.	*Cg*	*0.08 pF*
2.	*Cs*	*2.1 pF*
3.	*L*	*0.16 mh*
4.	*R*	*1.4 Ω*

The parameters are presented in Table 2. Since the transformer has a unique set of ground capacitance (Cg), series capacitance (Cs) and inductance (L) hence is found to have its own natural frequency of oscillation that ultimately portrays its impulse response. In the present case, the winding responses to faults are observed by neutral current method. As mentioned earlier, this current is measured both at full and reduced impulse voltages and any difference in the current signatures, if observed, is interpreted as a fault. The currents are recorded under the application of a lightning impulse of 1.2/50 µsec of positive polarity.

Table - 2
Simulation Parameters

S.NO	*Transformer Parameters (EMTP Model)*	
	Parameters	*Notation*
1.	*Ground Capacitance*	*Cg*
2.	*Series Capacitance*	*Cs*
3.	*Line Inductance*	*L*
4.	*Line resistance*	*R*
5.	*Impulse Voltage*	*U*
6.	*Mutual Inductance*	*M*

The concept of the case study is as follows: a standard voltage impulse 1.2/50 μsec 290KV is injected into the high voltage winding of the transformer and by simulation different faults are artificially generated at each and every disc of high voltage side of the transformer winding. Different Fault currents are recorded across tank for further analysis. Those user interference generated faults may be shunt or series type likewise Series fault represents fault between windings or disc Whereas shunt fault stand in between winding to ground or disk to the core of transformer which is having ground potential

2) Step 2: Simulation of Fault Current and the Cor-Responding Obseravtions using Emtp-Model of Transformer

The transformer designed here contains 80 discs. During fresh or no faulty condition the current across tank resistance is shown below.

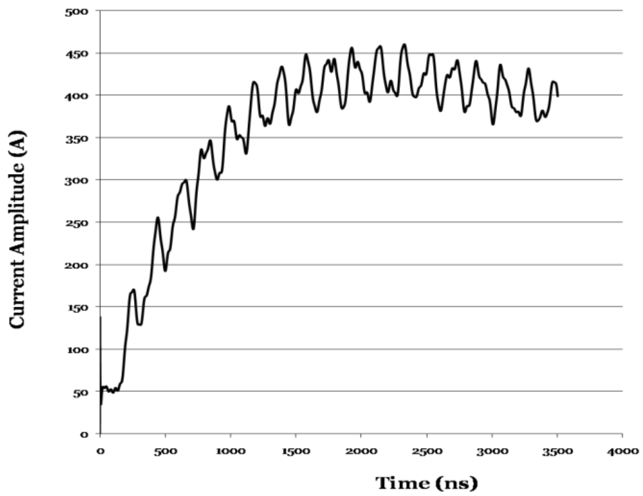

Fig. 3: No-Fault current

Insulation failure may occur at any disc due to impulse voltage. The failures considered in the present case are series faults caused due to the inter-disc or inter-turn insulation failure. Whereas Shunt fault caused when the insulation between the winding and the earthed components has failed. . Different Fault currents are recorded across tank for further analysis. Now those user interference generated fault is shunt. Here following fingerprints shunt current observations are given below.

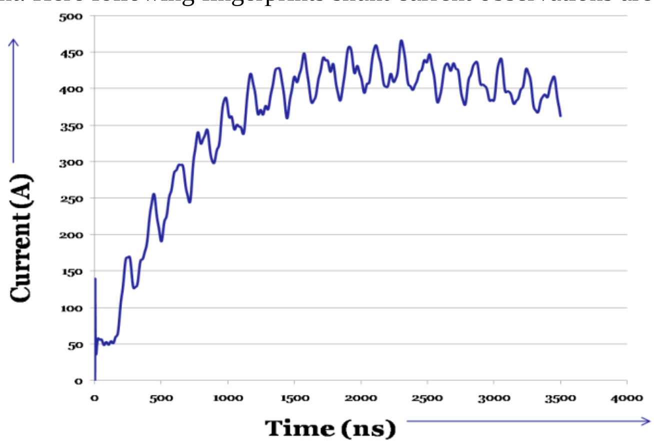

Fig. 4: Series Fault current waveform on first disc

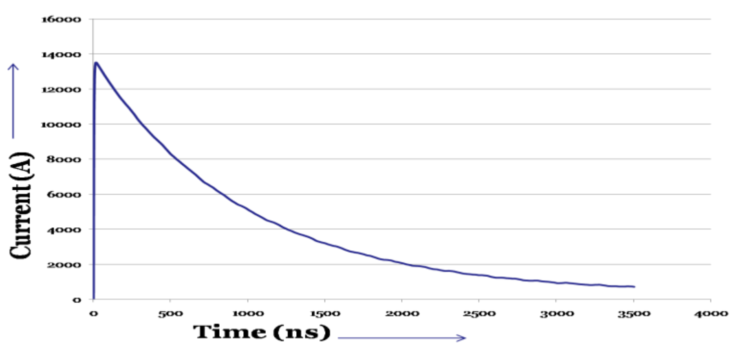

Fig. 5: Shunt fault current waveform on first disc.

3) Step 3: Feed Extracted Features Of The S-Transformation Time-Frequency Representation

a) Feature Extraction Methodologies:

There are many different techniques available for detecting and/or locating these kinds of faults such as: off-line techniques, high frequency analysis, Frequency Response Analysis (FRA) , Artificial Neural Networks (ANNs) and winding transfer functions, finite element analysis, online diagnostics techniques park vector approach combination of discrete\ wavelet transforms and back propagation neural networks , experimental studies . The field of time frequency analysis got an impetus with the development of the Short Time Fourier Transform (STFT). The STFT is a localized time frequency representation of a time series. It uses a windowing function to localize the time and the Fourier transform to localize the frequency. On account of the fixed width of the window function used, STFT has poor time frequency resolution. The Wavelet Transform (WT) on the other hand uses a basis function which dilates and contracts with frequency. The WT does not retain the absolute phase information and the visual analysis of the time scale plots that are produced by the WT is intricate. A time frequency representation developed by Stock well, which combines the good features of STFT and WT is called the S transform. It can be viewed as a frequency dependent STFT or a phase corrected Wavelet transform. So in this paper we are proposing S-Transformation for the feature extraction and for the classification we are using PNN method because it is having some features like fast training process ,inherently parallel process & training samples can be easily added and removes without any extensive retraining as compare to other methods like back propagation method etc.

b) S-TRANSFORMATION:

The problem of impulse fault current analysis using modern machine intelligence tools may be addressed in two stages: extraction of suitable features from the fault current waveforms. Classification of the features for proper fault identification with suitable classification algorithm .Most of the signals present in time domain .Time domain information is not enough able to analyze the signals. To obtain further more information from that signal mathematical transformations are applied. So we need to do S-Transformation of time-domain signal. The ST provides the time-frequency Spectrum. Advancement of Fourier transforms (FT). The -transform is becoming popular for time-frequency analysis and data-adaptive filtering. It is well-known Fourier frequency analysis decomposes a signal into its frequency components it does not tell anything about the time distribution of each component. The step to solve these problems was made with the S-transformation.

$$S(t, f) = \int_{-\infty}^{\infty} u(t) w(\tau - t, f) e^{-i2\pi ft} dt$$

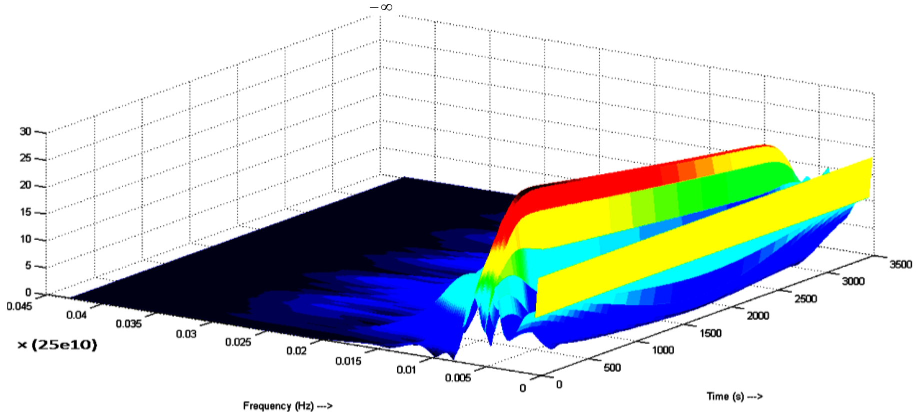

Fig. 6: 3D surface plotting in s-transform (Due to series fault on 80th disc)

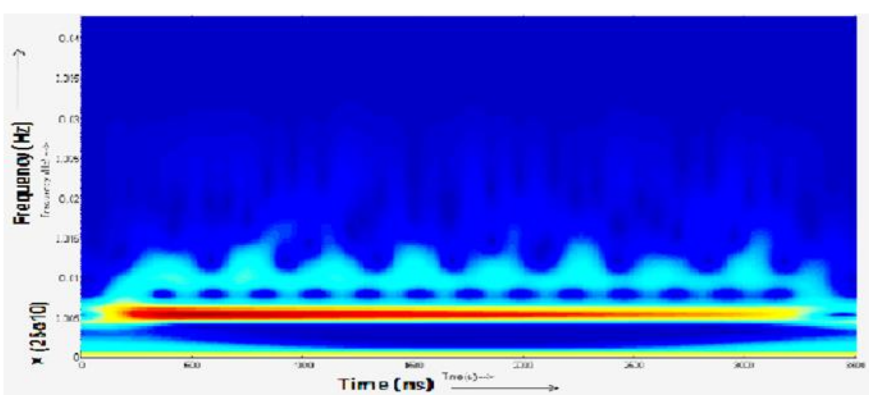

Fig. 7: 2D surface plotting of s-transform (series fault on 80th Disc).

$$w(\tau - t, f) = \frac{|f|}{k\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{f(\tau - t)}{k}\right)^2} \quad \forall k \rangle 0$$

Where is the frequency, is the time, is the delay, and is the scaling factor which controls the time-frequency resolution. It is important to emphasize that in order to have an invertible S-transform, any window used must be normalized, so that The S-transform can also be computed directly from, the Fourier transform of u(t). To do so, first (1) has to be rewritten as a convolution.

$$S(\tau, f) = u(t)e^{-i2\pi ft} * w(t, f)$$

From the results of S-Transform surface plotting presented in this paper we are concluded that in the case of series fault a low frequency noise has distorted the current waveform and in the case of shunt fault the same has been corrupted by a high frequency noise. On the basis of the information delivered by 3D surface plotting of current waveforms using stock well transformation.

4) Step 4: Training With Suitable Advance Signal Processing Method Rbf(Radial Basis Function)

a) Radial Basis Functional Link Network (RBFLN):

The radial basis function neural networks (RBFNNs) train rapidly, is robust and based on elegant concepts. The radial functions (RBFs) originated in 1964 as potential functions, but were first used for nonlinear regression. The architecture and training algorithms for RBFNNs are simple and they train more quickly than do multiple perceptron (MLP) networks. Unlike MLPs, they allow somewhat for explanation when interpreted as fuzzy rule-based systems. We use RBFs with the random vector functional link nets (RVFLNs) to obtain the powerful radial basis functional link nets (RBFLNs). As RBFNN represents a nonlinear model while the RBFLN includes that nonlinear model as well as a linear model (the direct lines from the input to output nodes) so that the linear parts of a mapping do not need to be approximated by the nonlinear model. Thus the RBFLN is a more complete model of a general nonlinear mapping. Both MLPs and RBFNNs are universal approximate, and thus RBFLNs are also universal approximates because they are more general and include RBFNNs. The radial basis net is a variant of the functional link net or the radial basis function neural network. It is more general than the RBF neural network because it consists of nonlinear and linear links. In the following section a new algorithm has been presented to train the radial basis RBFLN for pattern recognition of non- stationary power signal database. The RBFLN shown in Fig. has an input layer of M units, a hidden layer consisting of Gaussian node functions of m units, a set of weights W, to connect the hidden layer and output layer. Let x be the input vector

$X = (x_1, x_2, \ldots\ldots\ldots x_M)^T$

where M represents input dimension. The output vector $O = (o_1, o_2, \ldots\ldots\ldots o_N)^T$

For an input vector tx)(, the output of j th output node produced by an RBF is given $O_i(t) = \sum_{i=1}^{m} W_{ij}\phi_i(t) + \sum_{n=1}^{m} W_{ij} X_n(t)$

If output of the hidden neurons, by vector notation $\phi = (\phi_1(t), \phi_2(t) \ldots\ldots\ldots \ldots \phi_{tot}(t))$

and weight vector for the hidden RBF units $W_j = (W_{1j}, W_{2j}, \ldots\ldots. W_{mj})$

the weight vector for the linear units $W'_j = (W'_{1j}, W'_{2j}, \ldots\ldots. W'_{mj})$

RBFLN output can be written as $O_j = W_j \phi^T + W'_j$

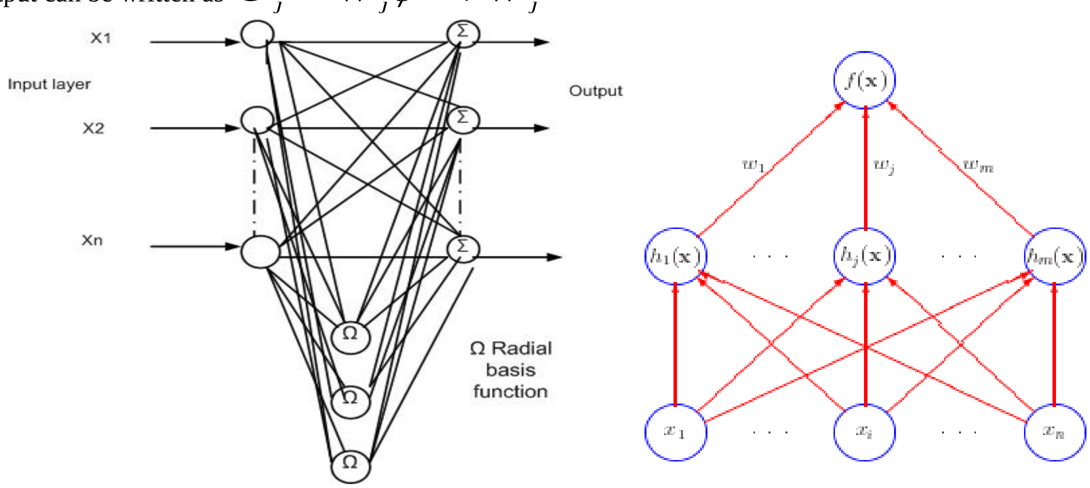

Fig. 8 & 9: Radio Basis Functional Link Network (RBF Network)

5) Step 5: Identification of the Occurrence of Faul: Results of Simulation and RBF Classifier

The RBFLN is a special type of neural network that is widely used in the classification applications [10]. In this work, the RBF is used to find out the exact occurrence of fault on disc. Fault identification using RBF is formed from three steps: in the first step measurements should be carried out to acquire TFs needed which we have got from S-transform The second step is related to feature extraction, in which the most proper features found for classification by PCA principle component analysis . In the third step, using extracted features in previous items are used for training RBF. After training, the obtained data from S-transformers and PCA are applied to the RBF as a testing input for prediction of fault location. The RBF response to these test data are shown in Tables 3. A close observation of these tables shows that the PNN is able to identify the fault location correctly in most of the cases. In order to prove the capabilities of the proposed method, Tables3 shows the accuracy of RBF in the detection of fault location is much better than previously proposed methods. This table contains RBF analysis for 80 discs of winding over which 33.7% part of the total disc considered under the live end, middle end and ground end of the winding. Here for the PNN analysis we are considering random set of test set from to 26 pattern set of discs S-coefficient matrix as well simulation result of the RBF neural network coding result shown below in the table.

S. No	*Output After Optimization of Radial Basis Functional Link Network (Neural Network)*				
	Transformer Winding Section	*Spread Value of Activation Function*	*Number of correct prediction*	*Number of wrong prediction*	*% Percentage Accuracy*
1	*Live End of Winding (33.7%)*	*0.5*	*25*	*1*	*96.15*
2	*Middle Section of the winding (33.7%)*	*0.5*	*27*	*0*	*100*
3	*Ground End of (33.7%)*	*0.5*	*27*	*1*	*96.29*

IV. CONCLUSIONS

Use The feature extraction from the current signals is the most important part in fault detection using signal processing analysis. In this paper the occurrence of fault detected by combination of S-Transformation and the new approach presented here as RBF. The features can be conveniently obtained from the absolute value of the Stock well coefficient matrix by programming of S-Transform based processed signal data in MATLAB. The type of fault and the affected disc can be accurately identified using the proposed classification scheme. The technique has been proposed to fault on transformer winding contains 80 discs in which the accuracy of fault detection of occurrence is all and average 97.48%. Different methods of diagnostics and fault detection on transformer winding have been already proposed apart from RBF which are employed in practice DGA Doernenburg ration analysis , FRA Frequency response analysis , Wavelet, RVM Reverse voltage measurement , Park negative sequence method likewise, But the proposed methods are The S-transform which has a progressive time-frequency resolution, so it could describe the non-steady signals effectively and RBF would have been comparatively more percentage accuracy (PA),robust ,have fast training and learning, and it can be deal with the complex situations such as missing data even if the large number of data is required for training of neurons , On the other hand, involvement of neural network would only require a change in the set of training features for every new system.

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