Discrimination of Inter-turn Faults from Magnetizing Inrush Currents in Transformers: A Wavelet Transform Approach

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***Abstract*—** *Power transformers are designed to transmit and distribute electrical power. Depending on the size of a transformer, replacement costs can range from a few hundred dollars to millions of dollars. Performing invasive tests also add to the replacement cost. Hence, there is an increasing need to move from traditional schedule-based maintenance programs to condition-based maintenance. A focused approach is required for diagnostics. Considering the long service life of a power transformer and prevalent use of human judgment (expert), there is a need to develop a knowledge base expert system. This paper proposes a noninvasive approach, using digital signal processing wavelet-based artificial neural network technique for monitoring non stationary variations in order to distinguish between transformer inrush currents and transformer inter-turn faults. The performance of this algorithm is demonstrated on custom-built three-phase transform.*

Keywords*— *Transformer, Inrush, Interturn fault, Wavelet Transform, Artificial Neural Network.

1. INTRODUCTION

Monitoring and classifying power transformer inrush currents and transformer internal faults are still challenging problems for power system engineers because of the possibility of false tripping caused by the magnetizing effect of the inrush current. The second harmonic component of an inrush current is dominant among inrush current and may reach levels of 15 % or more of the fundamental. In recent years, improvements in core materials and design have resulted in inrush current with less distortion, with a second harmonic component being as low as 7%. Harmonics may appear during faults; however, they are generally small [1]. The 15 % second harmonic restraint criterion is used to prevent mal-operation of the differential relay in power transformers during external faults. However, some abnormal disturbances or operations still present a challenge when differential protection is based on a fast Fourier transform (FFT) [2], [3].

Different techniques have been proposed for overcoming relay mal-operation in the presence of inrush current or during transformer external faults. Yousef et al [4] suggested that the second harmonic component present in the magnetizing inrush current can be used to discriminate between faults and magnetizing inrush current. However, the second harmonic component may also be produced owing to the following reasons: internal faults, saturation of current transformer, parallel capacitances or the distributed capacitance of long EHV transmission lines. Moreover, modern transformers are designed in such a way that the magnitude of second harmonic component is quite less, hence the presence of second harmonic component in the magnetizing inrush current can no longer be used as a means to discriminate between magnetizing inrush current and internal fault. Wavelet analysis has emerged as a powerful tool for signal processing in different power system applications. A wavelet-based signal-processing technique is one of the effective tools for transient analysis and feature extraction. Butter-Pury and Bagriyanik [5] characterized inrush and internal faults using Discrete Wavelet Transform by visual pattern recognition. J. Faiz and S. Lotfifard [6] presented a new algorithm which discriminate between the inter-turn fault and magnetizing inrush current. The algorithm use wavelet coefficients as a discriminating function. Two peak values corresponding to the mod of d5 (|d5|) level following the fault instant is used to discriminate the cases studied. As the criterion compare the two peak values, hence no threshold settings are necessary in this algorithm, but it is observed that in noisy environment it is difficult to identify correct switching instant and there the strategy fails.

Saleh and Rahman [7], suggested wavelet packet transform technique for power transformer simulated using EMTP software. Artificial Neural Networks (ANNs) find its application for the classification of inrush current and fault with the help of features extracted through DWT. Various networks are tried by the researchers for this purpose, Mao and Agrawal (2001)[8], describe the technique for the faults on transformer, 27 spectral energy inputs computed in three time windows of d1–d3 levels are used to train feed-forward

ANN requiring more memory space and increased time of computation.

Jazebi, S.et. al [9] proposed a method to distinguish inrush current from internal fault currents in which an energy index is defined by calculation of 9-level frequency contours using S-transform. But the disadvantage of this method is determining the threshold value which can be different in transformers with different capacity and may change in noisy environment.

Manoj Tripathi, et.al [10] presented a scheme without application of any deterministic index, the logarithm values of models probabilities for different inrush and internal fault currents are sensitive to noise condition and discrimination accuracy is reduced. Intrinsic sensitivity of wavelet analysis to noise, finding suitable mother wavelet from different types of mother wavelet and preprocessing data using k-mean clustering algorithm increase the complexity of the algorithm encountering huge computational task.

In this paper, ANN has been proposed and has demonstrated to be an effective alternative for performing transformer fault detection while avoiding the need for a mathematical model. ANN can adapt itself to learn arbitrarily complicated continuous non-linear functions. In addition, the ANN can perform this function online through the use of inexpensive monitoring devices. These devices obtain the necessary measurements in a non-invasive manner. The main problems facing the use of ANN are the selection of the best inputs and the choice of ANN parameters making the structure compact, to create highly accurate networks. Many input features require a significant computational effort to calculate, and may result in a low success rate. This paper proposes an online algorithm, which uses the contained spectral energy in d3, d4 and d5 detail levels obtained from the DWT decomposition of differential current signal, as an input to FFANN to distinguish between inrush and internal fault.

2. Wavelet Transform

Wavelet analysis is about analyzing the signal with short duration finite energy functions which transform the considered signal into another useful form. This transformation is called Wavelet Transform (WT). Let us consider a signal *f*(t), which can be expressed as-

$$f(t) = \sum_{l} a_l \, \varphi_l(t) \qquad (1)$$

Where, *l* is an integer index for the finite or infinite sum. Symbol a_l are the real valued expansion coefficients, while $\boldsymbol{\varphi_l(t)}$ are the expansion set. If the expansion (1) is unique, the set is called a basis for the class of functions that can be so expressed. The bases are orthogonal if-

$$[\varphi_l(t), \varphi_k(t)] = \int \varphi_l(t)\, \varphi_k(t)\, dt = 0 \quad K \neq l \qquad (2)$$

Then coefficients can be calculated by the inner product as-

$$\langle f(t), \varphi_k(t) \rangle = \int f(t)\, \varphi_k(t)\, dt \qquad (3)$$

If the basis set is not orthogonal, then a dual basis set φ_k (t) exists such that using (3) with the dual basis gives the desired coefficients. For wavelet expansion, equation (1) becomes-

$$f(t) = \sum_{k} \sum_{j} a_{j,k} \, \varphi_{j,k}(t) \qquad (4)$$

In (4), j and k are both integer indices and $\boldsymbol{\varphi_{jk}}$ **(t)** are the wavelet expansion function that usually form an orthogonal basis. The set of expansion coefficients a_{jk} are called Discrete Wavelet Transform (DWT).

The DWT is implemented using a multiresolution signal decomposition algorithm to decompose a given signal into scales with different time and frequency resolution. The analysis filter bank divides the spectrum into octave bands. The cutoff frequency for a given level j is found by -

$$fc = \frac{fs}{2^{j+1}} \qquad (5)$$

Where *fs* is the sampling frequency.

3. Experimentation and Data Aquisition

To evaluate the developed algorithm, experimental tests were performed on a custom-built 440V/440V, 5KVA, 50 Hz star-star connected three-phase transformer with externally accessible taps on both primary and secondary to introduce inter-turn faults. Experimental set up is as shown in Fig1. Differential current of three phases Ia, Ib, and Ic are captured using the experimental setup.

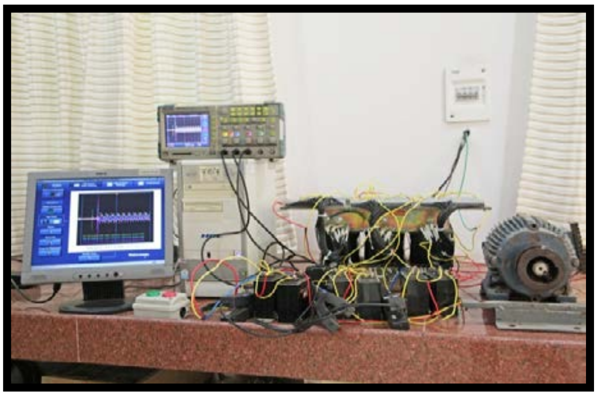


Fig.1: Experimental set up:

Tektronix DSO, TPS 2014 B series, with 100 MHz bandwidth and adjustable sampling rate of 1GHz, has been used, and current probes of rating 100 mV/A, input range of 0 to 70 Amps AC RMS, 100A peak and frequency range DC to 100KHz are used to capture the current signals. These signals are recorded at a sample rate of 10,000 samples/sec.

The transformer winding is designed with 415 turns per phase, external tapping's after every 20 turns are provided for creating inter-turn short circuit faults. Inrush current is captured keeping secondary winding open circuited and for inter-turn fault current, 20 turns on secondary are shorted.

4. FEATURE EXTRACTION

Analyzing all three phase voltages and current is quite tedious and time consuming; hence three phase differential currents are captured. The inrush and inter-turn fault events cannot be discriminated merely by observing the actual three phase differential current waveforms, hence processing of signal is necessary. Wavelets are mathematical tools for signal analysis. Wavelet analysis is particularly efficient where the signal being analyzed has transients or discontinuities, e.g., the post-fault voltage/current waveform. Compared to Fourier analysis, which relies on a single basis function, wavelet analysis uses basis functions of rather wide functional form. The basic concept of wavelet analysis is to select an appropriate wavelet function called "mother wavelet" and then perform analysis using shifted and dilated version of this wavelet. The advantage of wavelet analysis over short time Fourier analysis is that whereas the latter uses a single analysis window, the former use short windows at high frequencies and long windows at low frequencies.

For feature extraction, three differential currents are decomposed up to five detail level using Daubechies-4 (db-4) as a mother wavelet. An important step is the selection of mother wavelet to carry out the analysis. Several wavelets have been tried but db4 is found most suitable due to its compactness and localization properties in time frequency frame. The preserved transients in differential current signal can be extracted using wavelet transform, which provides time-frequency resolutions or localization of signal. Multi resolution analysis (MRA) technique of wavelet transform passes the signal through cascade of high and low pass filters providing the approximate and detailed level wavelet coefficients at different levels. In this paper the signal is sampled at a sampling frequency of 10 kHz.

When the transformer is energized a transient magnetizing inrush current flows in the primary side. This current may reach instantaneous peaks of 6–8 times full-load current because of the extreme saturation of the iron-core in the power transformer. Fig. 2 typifies the magnetizing inrush current waveforms corresponds to phase a, b, and c three phase differential currents and Fig. 3 typifies the interturn fault current waveforms corresponds to phase a, b, and c three phase differential currents. Differential current signals are passed through a DWT based structure using Daubechies wavelet (db4) as a mother wavelet. For brevity, only the DWT of 'a–phase' differential current is shown Fig.4, and Fig.5.

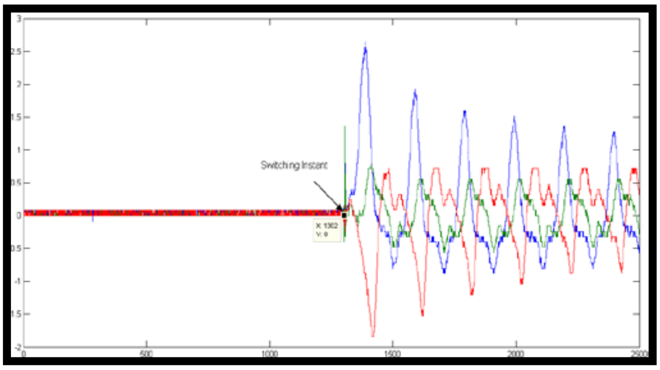


Fig.2. Three phase differential current for inrush

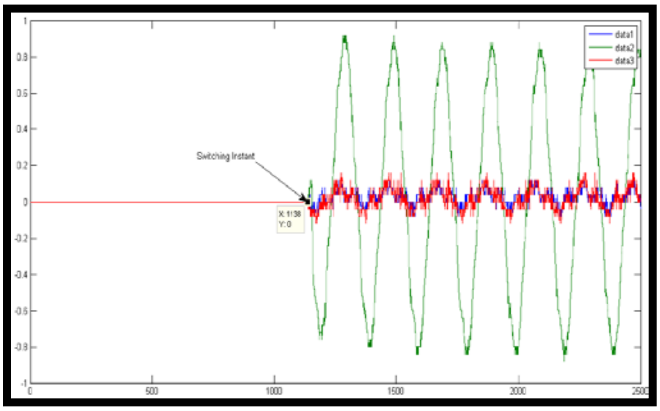


Fig.3 Three phase differential current for inter-turn fault

Fig.4 represents five level wavelet components of differential current signal for magnetizing inrush current and Fig.5 represents five level wavelet components of differential current signal for inter-turn fault current. From Fig. 4 it is observed that for inrush switching instant starts at sample number 1302 and for inter-turn fault switching starts at sample number 1138, and there is no discrimination between inrush and fault current wave form by visual inspection and from changes in the detailed and approximation coefficients for both cases. It is very difficult to draw any inference.

Hence processing of these signals is needed to extract distinguished features. The signals are operated upon by DWT using db4 to derive features capable of discriminating between inter-turn faults and magnetizing inrush current condition. From detail coefficient of decomposed level d1 to d5 in Fig.4 and Fig.5, the discrimination between inter-turn fault and magnetizing inrush is not possible. Therefore further processing of these wavelet coefficients is necessary to extract the some salient features. When DWT is applied to extract the scaling and wavelet coefficients from a transient signal, a large amount of information in terms of these coefficients is obtained. Although the information is useful, it is difficult for ANN to train /validate that large information. The detection/classification capability of any Artificial Intelligence technique primarily depends on the input given to it. It is observed that detection/classification becomes quite straightforward if features relevant to the specific event are extracted by appropriate pre-processing or post-processing technique. Extraction of relevant feature itself is a formidable task and it is the crux of all techniques.

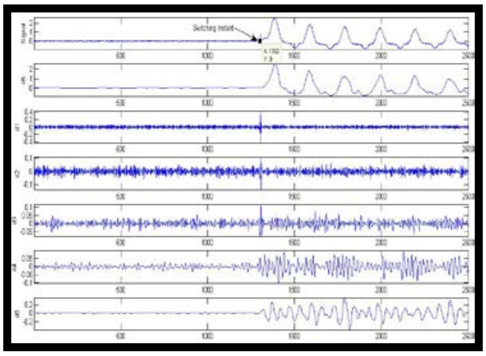


Fig.4 Wavelet decomposition of Inrush current.

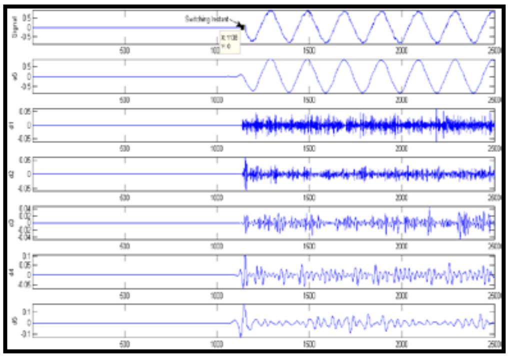


Fig. 5 Wavelet decomposition of inter-turn fault current.

Energy contained in the detail coefficient of transient signal is widely used as a distinguishing feature. It is given by Parseval's Theorem-

$$\int f(t)^2 dt = \sum_k C_j(k)^2 + \sum_{x=1:j} \sum_k dx(k)^2 \qquad (6)$$

Where $f(t)$ Signal to be decomposed using DWT, Cj Approximation of the DWT at level j, dx Detail number x of the DWT.

The general meaning of Parseval's theorem is that the energy contained in any signal is equal to the summation of the energy contained in the approximation and details at any DWT decomposition level (j).As only the transients are being focused so only the second part of above equation (6) is considered. The spectral energy of transient part (detail level) is given as an input to ANN for classification. In Fig. 2 and Fig.4 a transient at switching instant due to relay bouncing is observed in the decomposed level d1 and d2, therefore energy content in this levels are quite large which may cause error in the final classification. Hence while considering input to the neural network only energies of decomposed level d3, d4, and d5 are used in this paper.

5. Artificial Neural Network (ANN) as a Classifier

In the proposed strategy Back Propagation Feed Forward Multilayer Perceptron (MLP) Neural Network is used as a classifier and samples of only half cycle of three phase differential current for inrush and interturn fault conditions are decomposed up to the fifth level using db-4. Spectral energy of d3, d4, and d5 decomposed level is computed using equation (17) which is further used as an input to train the ANN to get the discrimination between inrush and inter-turn fault. This input dataset obtained through experiments on custom built transformer is found to be non-linear non-separable mixed data. ANN possesses ability to classify such mixed datasets and can be used effectively in obtaining the correct classifications of the events in transformer. For generalization, the randomized data is fed to the network and is trained for different hidden layers. The number of Processing Elements (PEs) in the hidden layer are varied to obtain minimum Mean Square

Table 1: Correct classification Accuracy for spectral energies

Spectral Energy of Detail level (Differential currents Ia,Ib,Ic)	Correct classification Accuracy
Only d3	83%
Only d4	82%
Only d5	97%
d3 & d4	89%
d3 & d5	100%
d4 & d5	100%

Error. It is found that the spectral energy content of different detail levels (i.e. 3, 4, 5 levels) has profound influence on the classification accuracy of ANN as shown in table 1.

It is thus seen that with spectral energy of only 5th level the correct classification accuracy is 97%. However, when spectral energy of 3rd and 4th level is used with 5th level the correct classification accuracy is 100%. Further it is also observed that with only 3rd or 4th level spectral energy the correct classification accuracy is 83%. When spectral energy of 3rd and 5th level is used the correct classification accuracy is 89%. Hence it is oblivious that the main distinguishing features are presented in the 5th level. The classification accuracy is maximized when spectral energy of 5th level component is used either with 3rd level or 4th level component.

Various training methods are used to train the network. For all training methods, the network is built with configuration as mention in Table2.

Table 2: Configuration of Artificial Neural Network

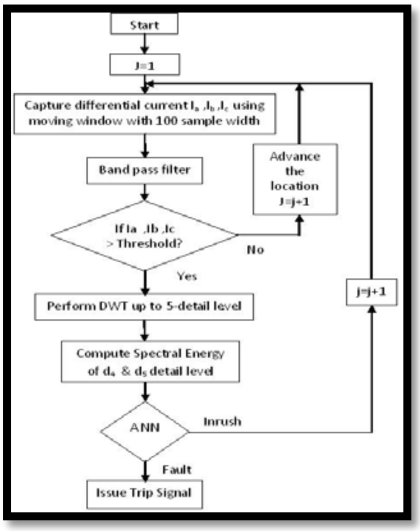
<table>
<tr><th>Layers</th><th>Number of Processing Elements</th><th>Learning Rate</th><th>Momentum</th><th>Training Data</th><th>Testing Data</th><th>Iterations</th><th>Transfer Function</th></tr>
<tr><td>Input</td><td>04</td><td rowspan="3">0.6</td><td rowspan="3">0.8</td><td rowspan="3">20%
(20 samples)</td><td rowspan="3">80%
(80 samples)</td><td rowspan="3">100</td><td rowspan="3">tan sig
moid</td></tr>
<tr><td>Hidden</td><td>01</td></tr>
<tr><td>Output</td><td>02</td></tr>
</table>

With this network the variation of average mean square error and correct percent accuracy for both Inrush and fault with respect to number of processing elements in the hidden layer is obtained. It is found that for training method of Levenberg- Marquardt for one hidden layer and only one processing element in the hidden layer the mean square error is minimum and correct classification accuracy is hundred percent.

6. Flow Chart For On line Decision Making Algorithm

The proposed relay logic for distinguishing an internal fault from a magnetizing inrush current by combining the wavelet transform with neural network is shown in Fig. 5. The wavelet transforms is applied to the windowed differential currents decomposing it up to five detailed levels, then the spectral energies are calculated. Obtained spectral energies of the wavelet signals are then used as an input to the ANN to carry on the discrimination between an internal fault and inrush current. If the internal fault is detected, a tripping signal will be issued, otherwise, the relay will be restrained. FFANN with one hidden layer and only one perceptron has shown the capability to discriminate the inrush current from internal fault current. Long term memory weights can then be used at the processor level to take decisions regarding the classification of inrush and fault current. The on-line discrimination process of inrush and fault current is illustrated in Figure 5. The step for carrying out the on-line detection scheme is presented as under-

1. Capture three phase differential current Ia, Ib and Ic by data acquisition system, using moving window (First In First Out technique) with 100samples(half cycle)
2. If value of any differential current Ia, Ib and Ic is less than threshold value (0.1 amps), go to step 1, otherwise go to step3.
3. Perform DWT up to five detail levels of all differential currents.
4. Obtain the energies of decomposed levels d4 and d5 using- $E = \sum_{i=1}^{n} x^2(i)$,
5. Where *'x (i)'* is discrete sequence representing a subset of detail coefficient sequences of d4 and d5.
6. The energy of decomposed levels d4 and d5 is given to ANN as input data to discriminate the fault and inrush.
7. If ANN output is discriminated as fault, then issue trip signal otherwise proceed further i.e. monitor the differential current (go to step1).



7. CONCLUSIONS

A novel method of discriminating magnetizing inrush current from inter-turn faults in a three phase transformer is presented in this paper. DWT with its inherent time frequency localization property is employed to extract discriminating features from the differential currents. The proposed algorithm sucessesfuly detect and classify the disturbance in to normal magnetizing current and inter-turn fault. The proposed DWT-FFANN based method can distinguish between magnetizing inrush and inter-turn faults efficiently and precisely in half cycle after their inception, even when only 5% (20 turns) of the winding turns are short-circuited to make inter-turn faults. The developed algorithm can be implemented in a digital relay for on line monitoring and protection of transformer.

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