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AN IMPROVED DECISION MAKING ALGORITHM FOR ON LINE DISCRIMINATION BETWEEN INRUSH AND FAULT CURRENT IN A TRANSFORMER: DWT APPROACH

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Abstract- Transformer protection is critical issue in power system and the issue lies in the accurate and rapid discrimination of magnetizing inrush current from internal fault current. This paper describes a new method to discriminate the magnetizing inrush current and inter-turn fault using the wavelet transform. This method is independent of setting any threshold for discrimination amongst these. A discriminating function and feature extraction is defined in terms of difference of two-peak amplitude of wavelet coefficients in a specific frequency band. Interturn faults were staged at various time instants and it was observed that the strategy holds good for all instants i.e. it is independent of instant of occurrence of fault also. This discrimination will aid in development of an automatic detection method and shall give information to predict the failure ahead of time so that the necessary corrective actions are taken to prevent outages and reduce down time. This paper also presents a comparison of two algorithms to discriminate magnetizing inrush current from interturn fault current, based on wavelet coefficients as a discriminating function, *A*) where two peak values corresponding to the $|d5|$ level following the fault instant is used as a discriminating feature, and *B*) where difference of two peak amplitude of wavelet coefficients of fast cross-correlated signal at $|d4|$ level is used as a discriminating feature. The performance of this algorithm is demonstrated on custom-built mains feed single-phase transformer, used in the laboratory to collect the data from controlled experiments. The proposed on line detection scheme is also discussed.

Keywords: Differential Protection, Discrete Wavelet Transform, Inrush Current, Internal Fault.

I. INTRODUCTION

Today, the world is gradually moving towards a deregulated power sector. The number of utilities supplying power is also increasing leading to a stiff competition. Owing to the challenging and competitive energy market, utilities tend to operate the transformers harder, longer and closer to their capabilities to reduce cost and generate more profit. Transformers are more likely to fail under such a stress besides regular ageing and insulation deteriorating processes. Therefore, utilities are calling for an economical yet reliable fault detection system to help in maintaining and extending the life of their existing assets and equipment to provide affordable and reliable electric power. The detection systems and diagnosis methods developed previously either require the transformers to be taken out of service, which means more operational cost to the utility, or are expensive to implement. Therefore, a low-cost, online, non-invasive fault diagnosis and detection system is highly demanded to provide immediate and accurate assessment of the conditions of the transformers in the field. Hence, in this scenario, minimization of frequency and duration of unwanted outages of distribution transformers is very important. For the modern power system, high-performance relays are required, especially in terms of operating speed. Magnetising inrush also exhibits a characteristic of peaked wave, which is caused by asymmetric saturation of transformer core. Identifying magnetising inrush by these characteristics opens a new avenue of research for improving the operating speed of relays.

A wavelet-based signal-processing technique is one of the effective tools for transient analysis and feature extraction. In [1] Inrush and internal faults are characterized using DWT by visual pattern recognition. The initial slopes of peaky magnetising inrush current characteristics and differential fault current are compared. In [2] for discrimination using DWT, whereas Mao and Agarwal [3] presented simple decision making logic for discrimination of fault and inrush using detailed coefficients of DWT. This method uses ratio change in maximum peak values of a-phase, b-phase and c-phase wavelet detail 1 coefficient and compares them with certain threshold for accurate classification.

In [4], the second harmonic component present in the magnetising inrush current is used to discriminate between faults and magnetising 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 magnetising inrush current can no longer be used as a means to discriminate between magnetising inrush current and internal fault.

In [5], for the simulated 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.

In [6] a new protection scheme is introduced to detect and identify transformer winding faults. The new approach is based on artificial neural networks (ANNs) using radial basis functions (RBFs) and the principal component analysis (PCA)[7]. The nonlinear system's input and output data is manipulated without considering any model of the system. This approach is used to *detect* and identify internal short circuit faults of a three phase custom built transformer. The suggested technique is also able to distinguish between the fault and magnetizing inrush current. The test studies carried out shows that the proposed method leads to satisfactory results in terms of detecting and isolating parameter faults taking place in non-linear dynamical systems.

In [8] the optimal probabilistic neural network (PNN) is proposed as the core classifier to discriminate between the magnetizing inrush and the internal fault of a power transformer. The particle swarm optimization is used to obtain an optimal smoothing factor of PNN which is a crucial parameter for PNN. An algorithm has been developed around the theme of the conventional differential protection of the transformer. It makes use of the ratio of voltage-to-frequency and amplitude of differential current for the determination of operating condition of the transformer.

The performance of the proposed heteroscedastic-type PNN is investigated with the conventional homoscedastic type PNN, feedforward back propagation (FFBP) neural network, and the conventional harmonic restraint method. To evaluate the developed algorithm, relaying signals for various operating condition of the transformer, including internal and external faults, are obtained by modeling the transformer in PSCAD/EMTDC.

In this paper a simple wavelet-based scheme is developed to identify inrush current and to distinguish it from internal faults. The novelty of proposed algorithm is that it does not require any threshold value of differential current, hence it is independent of transformer rating . The proposed method processes the samples corresponding to only one cycle thereby reducing the computational time.

A custom-built single-phase transformer was used in the laboratory to collect the data from controlled experiments. In these controlled experiments, a great variety of different fault scenarios on both primary and secondary windings of transformer were intentionally introduced. A schematic algorithm is developed for achieving the objective.

II. WAVELET TRANSFORM

The wavelet transforms associated with fast electromagnetic transients are typically non-periodic signals, which contain both high-frequency oscillations and localized impulses superimposed on the power frequency and its harmonics. If signals are altered in a localized time instant, the entire frequency spectrum can be affected. Figure 1 illustrates the implementation procedure of a Discrete WT (DWT), in which S is the original signal; LPF and HPF are the low-pass and high-pass filters respectively. At the first stage an original signal is divided in to two halves of the frequency bandwidth, and sent to both LPF and HPF. Then the output of LPF is further cut in half of the frequency bandwidth and then sent to the second stage, this procedure is repeated until the signal is decomposed to a pre-defined certain level. If the original signal were being sampled at Fs Hz, the highest frequency that the signal could contain, from Nyquist's theorem, would be Fs/2 Hz. This frequency would be seen at the output of the high pass filter, which is the first detail 1; similarly, the band of frequencies between Fs/4 and Fs/8 would be captured in detail 2, and so on. The sampling frequency in this paper is taken to be 10 kHz and Table 1 shows the frequency levels of the wavelet function coefficients.

Table 1. Frequency levels of Wavelet Functions Coefficients

Decomposition Level	Frequency Components (Hz)
d1	5000-2500
d2	2500-1250
d3	1250-625
d4	625-312.5
d5	312.5-156.25
a5	0-156.25

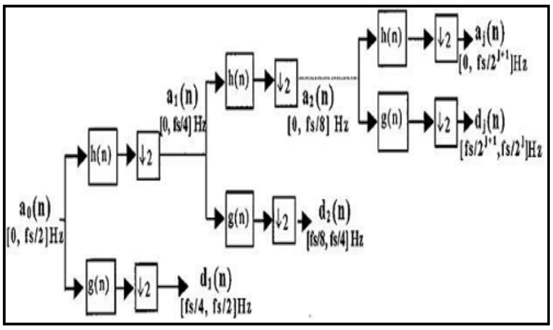

Figure 1. Multiresolution signal decomposition

III. FAST LINEAR CROSS CORRELATION

In signal processing, cross correlation is a measure of similarity of two waveforms as a function of a time-lag applied to one of them. This is also known as a sliding dot product or inner-product. It is commonly used to search a long duration signal for a shorter, known feature. It also has applications in pattern recognition, single particle analysis, electron tomographic averaging, cryptanalysis, and neurophysiology

With the use of zero padding, linear cross-correlation can be achieved using circular cross-correlation. Suppose $x(k)$ is an L-point signal and $y(k)$ is an M-point signal with $M \le L$. Let $x_z(k)$ be a zero padded version of $x(k)$

with $M+p$ zeros appended where $p \geq -1$. Similarly, let $y_z(k)$ be a zero padded version of $y(k)$ with $L+p$ zeros. Therefore, x_z and y_z are both signals of length $N = L+M+p$

$$x_z = [x(0),...,x(L-1),0,...,0]^{\mathrm{T}} \quad (1)$$

$$y_z = [y(0),...,y(M-1),0,...,0]^{\mathrm{T}} \quad (2)$$

Next, let y_{zp} be the periodic extension of $y_z(k)$, considering the circular cross-correlation of $x_z(k)$ with $y_z(k)$.

$$Cx_zy_z(k)=(1/N)\sum_{i=0}^{N-1} x_z(i)y_zp(i-k),\ 0 \leq k < N \quad (3)$$

If we restrict $Cx_z\,y_z(k)$ to $0 \leq k < L$, it can be shown to be proportional to the linear cross-correlation. In particular, recalling that $x(k)$ is an L-point signal ,we have

$$Cx_z\,y_z(k) = (1/N)\sum_{i=0}^{L-1} x_z(i)y_zp(i-k),\ 0 \leq k < L \quad (4)$$

Since $0 \leq k < L$, the minimum value for i-k is $(L-1)$. But $y_z(k)$ has $L+p$ zeros padded to the end of it. Therefore, $y_{zp}(k)$=0 for $0 \leq k < L+p$. It follows that, $y_{zp}(i\text{-}k)$ in equation (3) can be replaced by $y_z(i\text{-}k)$ as long as $p \geq$-1. The result is then the linear cross-correlation of $x_z(k)$ with $y_z(k)$.

But for $0 \leq k < L$, the linear cross correlation of $x(k)$ with $y(k)$, except for a scale factor of L/N. Consequently,

$$Cx_zy_z(k) = (L/N)r_{xy}(k),\ 0 \leq k < L \quad (5)$$

Thus linear cross-correlation can be achieved with circular cross-correlation using zero padding. Suppose we pick $p \geq$ -1, such that N=L+M+p is a power of two.

$$N = 2^{\text{ceil}\,[\log_2 (L+M-1)]} \quad (6)$$

From the above equations highly efficient version of linear cross correlation, called as fast linear cross-correlation can be obtained

$$R_{xy}(k) = IFFT\ \{X_Z(i)\ Y_Z^{*}(i)\}\ /\ L,\ 0 \leq k < L \quad (7)$$

A block diagram of the fast correlation operation is shown in Figure 2. Just as with the fast convolution; there is a value for L beyond which fast correlation is more efficient than the direct computation of cross-correlation.

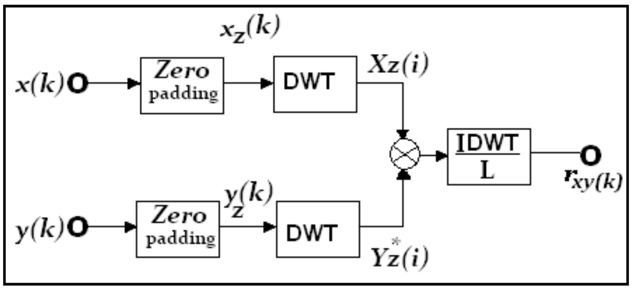

Figure 2. Fast linear cross-correlation

IV. EXPERIMENTATION & DATA COLLECTION

The setup for experiments has a custom built 220V/220V, 2KVA, and 50Hz single-phase transformer with externally accessible taps on both primary and secondary to introduce interturn faults. The primary winding and secondary winding has 272 turns respectively. The load on the secondary comprises of static and rotating elements. Data acquisition card by Tektronix Instruments was used to capture the voltage and current signals. These signals were recorded at a sample rate of 10,000 samples/sec. Different cases of inter turn short circuit are staged, considering the effect of number of turns shorted on primary, secondary and load condition. Experimental set up is shown in Figure 3.

Primary (I_p) and secondary (I_s) currents were captured using the experimental setup. The Tektronix DSO, TPS 2014 B, with 100 MHz bandwidth and adjustable sampling rate of 1GHz is used to capture the currents. The Tektronix 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. The captured current signals for inrush and faulted condition on mains feed custom built transformer were decomposed up to fifth level using wavelet db4 (Daubochies 4).

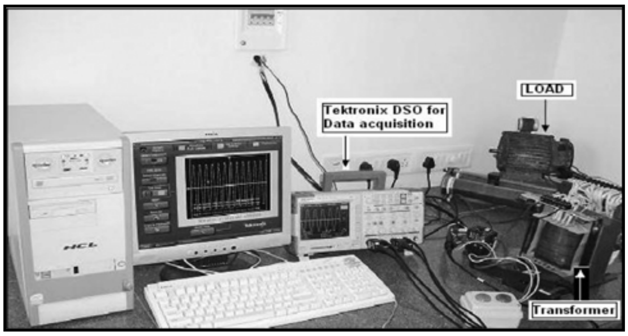

Figure 3. Experimental set up

V. ANALYSIS METHODS

A. Difference of Two-Peak Amplitude of Wavelet Coefficients

This method used wavelet coefficients as a discriminating function. Two peak values corresponding to the $|d5|$ level following the fault instant are used to discriminate the cases studied. As the criterion compare the two peak values, hence no threshold settings are necessary in this algorithm. Proposed technique is discussed in depth and validated through the practical results obtained on custom-built transformer.

In Figure 4, looking at the waveform of inrush differential current it is quite clear that its initial slope is less then it increases where as for fault differential current the initial slope is large and it start decreasing. A high value of slope indicates the presence of high frequency components. These features are independent of the connected power system and depend on the different nature of current and parameters of transformer.This significant marked difference between the initial slope of the differential current due to fault and that due to magnetizing inrush current has been used to discriminate between inter-urn fault and magnetizing inrush current.

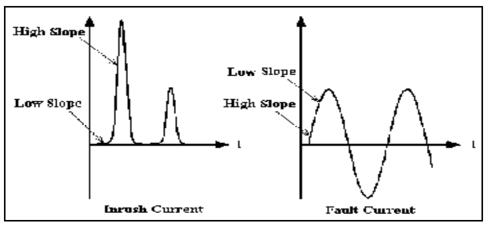

Figure 4. Different behavior of fault and inrush current

As per the proposed method for internal fault (in one case an inter-turn short circuit) the amplitude of high frequency is large initially and then it decreases. Hence high frequency components are captured in first two levels i.e. $d1$ and $d2$, as shown in Figure 5.

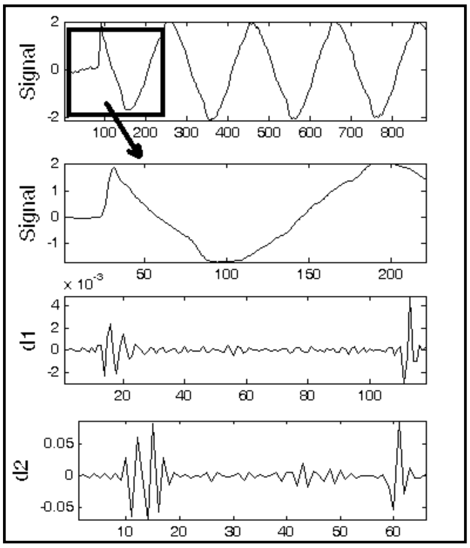

Figure 5. Illustration of Wavelet decomposition of fault current

Where as, in case of inrush current the amplitude of high frequency component initially is less and then increases.

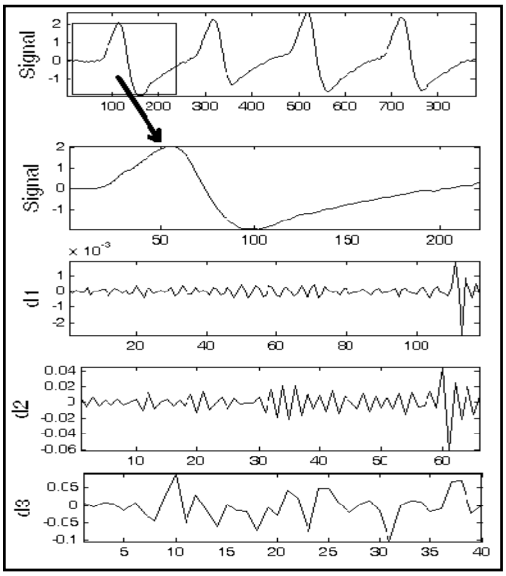

Figure 6. Illustration of wavelet decomposition of Inrush current

Here, the daub 4-mother wavelet is used to obtain the desired wavelet coefficients. In the Figure 7 $d1$-$d5$ represents detailed coefficients of decomposition levels 1 to 5 respectively against sample numbers, while $a5$ is approximate coefficients of level 5. At the bottom of this figure absolute value of $d5$ is given. The detailed description and interpretation of Figure 7 is given below. Original Differential current signal is captured with data acquisition system discussed previously, and represented as 'Signal' in the figure. The fault is initiated at sample number 39 (Approx.) and it is marked as 'x' in figure. First negative peak of differential current is observed at sample number 50, denoted by 'y' in figure.

In decomposition level '$d1$', peaking of wavelet coefficient is observed from sample number 39-64 approximately.

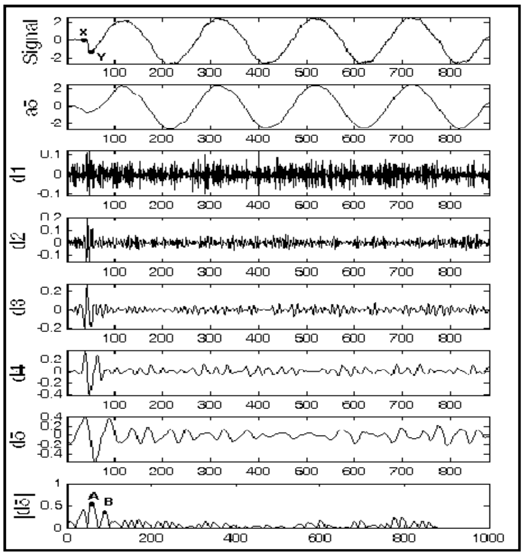

Figure 7. Wavelet decomposition of differential current for fault in primary winding

(a) In '$d2$' level, more clear vision of these abrupt changes in signal during samples 39-64 appears and maximum positive peak found at sample number 45.
(b) In '$d3$' level high frequency components present in d2 are filtered out. Here again, peak of waveform observed at sample number 45.
(c) In '$d4$' level, first peak positive peak appears at sample 39 with magnitude 0.3571 and first negative peak reproduced at sample 50 with magnitude –0.3651. This is the approximate reproduction of curve between 'x' and 'y'.
(d) In '$d5$' level, the first positive peak appears at sample 39 having magnitude 0.4041, while first negative peak appears at 59 with magnitude –0.5657. Therefore, the '$d5$' level represents precise measure for the slopes of fault and inrush currents.
(e) Hence, taking the absolute value of $|d5|$ as shown in figure, the first two consecutive peak values after the fault instant are the good approximations for the initial slope changes in the fault and inrush current. Therefore, the discrimination function for fault and inrush current can be chosen as

$$\Delta M\ \{d5\} = \{\text{First Peak after fault initiation}\} - \{\text{Second Peak after fault initiation}\} \tag{8}$$

$$\Delta M\ \{d5\} = A - B \tag{9}$$

Hence, for inrush current $\Delta M<0$ and for fault current $\Delta M>0$.

Figure 8 shows wavelet decomposition of differential current acquired during inter turn fault of 10 turns in secondary winding. Nearly, same high frequency components were observed in such faults like fault in primary winding.

The high frequency components were observed in decomposition level *d*1-*d*4 for high initial slope of fault current. As discussed previously, fault current starts with high initial slope and slope decreases as fault progresses. From time-frequency localization in *d*1-*d*3 levels, high frequency components with high amplitudes at instant of fault and with decaying trends afterwards are clearly visible. Filtration of this high frequency up to *d*5 level leads very interesting discriminating criterion of fault and inrush current. The absolute value of the coefficients of *d*5 waveform is shown at the bottom of this figure. In this, *A* and *B* are the amplitudes of first two peaks following the disturbance. From the Figure , It is seen that for inter-turn fault *A*>*B*. In the event of *A*>*B* trip command can be issued in quarter cycle. The features used for diagnosis normally are seen in the high frequency range and not in lower frequency. From figure, it is obvious that the amplitudes of wavelet coefficients in *d*5 are larger than that of *d*1-*d*4. Many wavelets were tried as an analyzing wavelet, but finally Daubochies 4 (db4) gave encouraging and distinguishing features**.** Here also, magnitude of two consecutive peaks *A* and *B*, follows the same relation i.e. *A*>*B*.

Inrush current exhibit different behavior or feature than the fault current, though their amplitude are comparable. Inrush current starts with low slope and increase rapidly afterwards.

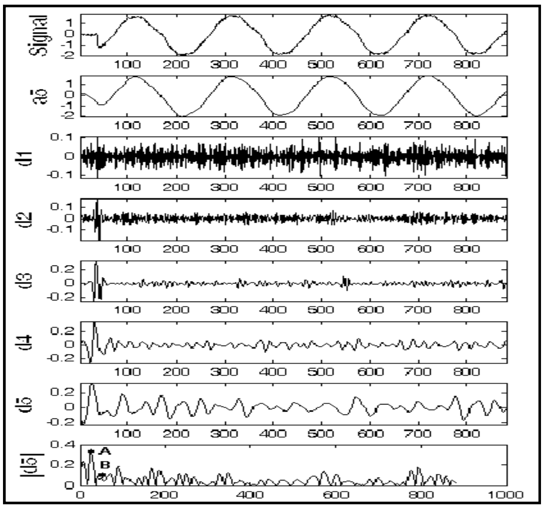

Figure 8. Wavelet decomposition of differential current for fault

This characteristic is demonstrated in Figure 9. The acquired inrush current signal is decomposed into five levels. No peaking was observed at the starting instant in *d*1-*d*2 level, as appeared in inter-turn fault. But high frequency oscillations can be noted in these levels, as high slope follows the low slope in inrush current. Therefore, repeated oscillations are reported in d4 level matching the high slope of inrush current, unlike the previous case. From the *d*5 and |*d*5|, the consecutive peaks *A* and *B* can be obtained and compared. For inrush, it can noted that *A*<*B*.

Following the previous discussion, proposed technique does not require any threshold value for discrimination amongst the magnetizing inrush and interturn faults in the transformer. Which is a significant achievement as setting a threshold value is quit difficult and is normaly influenced by the factors like rating and type of transformer.

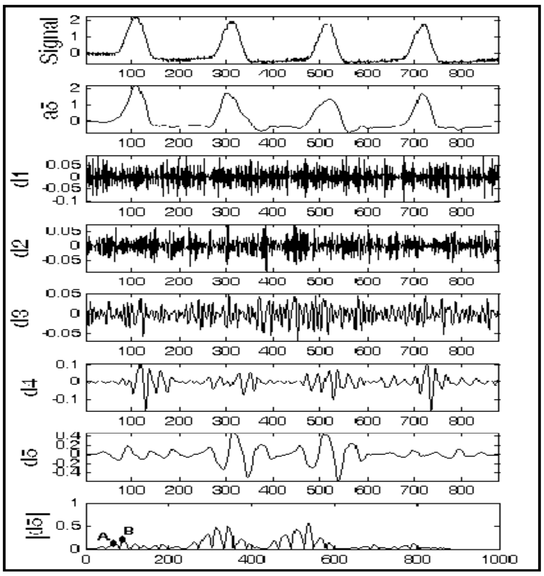

Figure 9. Wavelet decomposition of differential current during Inrush

The algorithm for the discrimination is presented below algorithm:

1. Capture the differential current with appropriate sampling frequency under the previously said conditions.
2. Apply MRA technique to obtain the discrete wavelet transform up to 5th decomposition level.
3. Obtain |*d*5|
4. Find the first two peak values *A* & *B* of |*d*5|
5. Calculate $\Delta M=A-B$
6. If $\Delta M<0$ then it is Inrush Current
7. If $\Delta M>0$ then it is Fault and provide trip signal or alarm

However this technique fails in noisy environment, as it is very difficult to pick up the switching instant and two consecutive peaks in noisy environment.

B. Difference of Two-Peak Amplitude of Wavelet Coefficients of Fast Linear Cross-Correlated Signal

When the algorithm used two peak values corresponding the |*d*5| level following the fault instant as a discriminating feature, the accuracy of discrimination is highly dependent on correct switching instant, and in noisy environment it is very difficult to identify the correct switching instant.

To overcome this difficulty the captured differential current signal is operated through fast linear cross-correlation technique, where the noise is suppressed or eliminated and then the difference of two peak amplitude of wavelet coefficients at *d*4 level is used as a discriminating feature. Figure 10 shows Wavelet decomposition of differential current during Inrush, where it is clearly observed that at *d*4 level *A* < *B*, which is discriminating criterion for Inrush behavior.

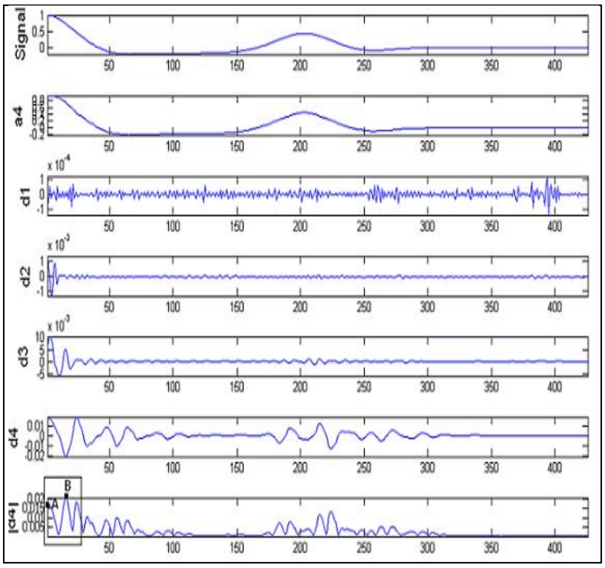

Figure 10. Wavelet decomposition of differential current during inrush

Similarly Figure 11 shows Wavelet decomposition of differential current for interurn faults, where it is clearly observed that at $d4$ level $A > B$, which is discriminating criterion for fault behavior.

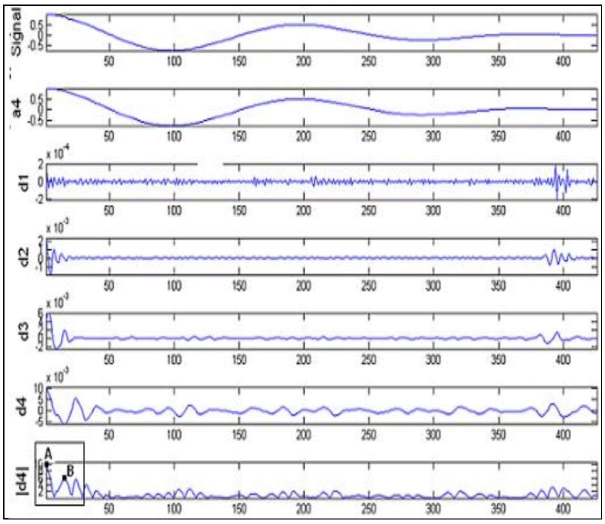

Figure 11.Wavelet decomposition of differential current for fault

The algorithm for the discrimination is presented below

1. Capture the differential current with appropriate sampling frequency under the previously said conditions.
2. Apply fast linear cross-correlation technique to eliminate noise from the signal.
3. Apply MRA technique to obtain the discrete wavelet transform up to 4th decomposition level.
4. Find the first two peak values A & B of $d4$
5. Calculate $\Delta M=A-B$
6. If $\Delta M<0$ then it is Inrush Current
7. If $\Delta M>0$ then it is Fault and provide trip signal or alarm.

V. RESULTS

The setup for experiments has a custom built 220V/220V, 2KVA, and 50Hz single-phase transformer with externally accessible taps on both primary and secondary to introduce interturn faults. Total 150 cases of inrush, inter turn short circuit on primary and secondary are staged. The captured differential current signals for inrush and faulted condition on mains feed custom built transformer were decomposed up to fifth level using wavelet db4, and then analyzed by the proposed algorithm. For normal operation, change in the loading condition and faults through very high impedance there will be no differential current hence algorithm capture next sample which avoids maloperation. The percentage of classification accuracy is tabulated in Table 2.

Table 2. Classification accuracy

S.N	EVENT	Identified Cases	Accuracy
1	Inrush	150	100%
2	Primary Interturn fault.	150	100%
3	Secondary Interturn fault	147	98%

VI. CONCLUSIONS

In this paper, an improved algorithm for transformer differential protection was presented. This method is based on the different behaviors of differential currents. A criterion function was defined using the difference of the amplitude of the WT over a particular frequency spectrum due to a interturn fault and inrush current. In addition to suitable accuracy, the proposed method can discriminate interturn fault from inrush current quickly, in less than quarter a cycle after the disturbance.

The proposed algorithm does not require choosing any threshold value of differential current, like the one mentioned in reference [2], hence it is independent of transformer rating which is main advantage of this method. For interturn fault only 10% turns are short circuited which is equivalent to an incipient fault, even then it is detected by this improved method. The main disadvantage of reference paper [2], that in noisy environment it is very difficult to identify the fault instant and therefore its strategy fails. That disadvantage is overcome by operating the signal through fast linear cross-correlation technique. The performance of this algorithm is demonstrated on custom-built mains feed single-phase transformer, used in the laboratory to collect the data from controlled experiments. The test results show that the proposed algorithm is quick and accurate.

APPENDIX

Transformer Parameter

Single phase: 2 KVA, 230 V / 230 V, 50 Hz
Primary winding: R = 0.0276 p.u., X = 0.02249 p.u.
Secondary winding: R = 0.0276 p.u., X= 0.02249 p.u.

REFERENCES

[1] K.L. Butterpury and M. Bagriyanik, "Characterization of Transients in Xmer Using DWT", IEEE Transactions on Power System, Vol. 18, No. 2, May 2003.

[2] J. Faiz, “A Novel Wavelet-Based Algorithm of Internal Faults from Magnetizing Inrush Currents in Power Transformers”, IEEE Transactions on Power Delivery, Vol. 21, No. 4, Oct. 2006.
[3] P.L. Mao and R.K. Agrawal, “A Wavelet Transform Based Logic Method for Discrimination between Internal Faults and Inrush Currents in Power Transformers”, Electrical Power and Energy System, Vol. 22, pp. 389-395, 2000.
[4] O.A.S. Yousef, “A Wavelet Based Technique for Discrimination between Faults and Magnetizing Inrush Currents in Transformer”, IEEE Transactions on Power Delivery, Vol. 18, No. 1, pp. 170-176, Jan. 2003.
[5] P.L. Mao and R.K. Agrawal, “A Novel Approach to the Classification of the Transient Phenomena’s in Power Transformers Using Combine Wavelet Transform and Neural Network“, IEEE Transactions on Power Delivery, Vol. 16, No. 4, pp. 654-660, Oct. 2001.
[6] A.K. Al-Othman and K.M. El-Naggar, “A New Digital Dynamic Algorithm for Detection of Magnetizing Inrush Current in Transformers ”, Electric Power Components and Systems, Vol. 37, Issue 4, pp. 355-372, April 2009.
[7] E. Kilic, O. Ozgonenel, O. Usta and D. Thomas, “PCA Based Protection Algorithm for Transformer Internal Faults”, Turk Journal of Electrical Engineering & Computer Science, TUBITAK, Vol. 17, No. 2, 2009.
[8] M. Tripathy, R. Prakash Maheshwari and H.K. Verma, “Power Transformer Differential Protection Based On Optimal Probabilistic Neural Network”, IEEE Transactions on Power Delivery, Vol. 25, No. 1, January 2010.

BIOGRAPHIES

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