Virtual Instrument based Fault Classification in Power Transformers using Artificial Neural Networks

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***Abstract*— Inrush currents in power transformers are detected based on magnitude of second harmonic component. To avoid the harmful effects of inrush, amorphous core is widely used in recent days. Transformers with amorphous core cause low magnitude inrush current and hence the second harmonic of inrush current is comparable with that during internal faults. This increases the chances for relay mal operation when classical techniques of discriminating inrush from other faults are used. To overcome this, advanced signal processing techniques like wavelets, S-transform, H-transform and pattern recognition tools like fuzzy logic, neural network, support vector machine etc. are being used in recent days. A combination of wavelets and neural network is found to give satisfactory solution to the above problem. In this paper, a comparative study using different mother wavelets along with different activation function is made to enhance the performance. Virtual instrument is used to demonstrate the method of fault classification.**

***Keywords*— wavelets; neural network; virtual instrument; faults; power transformer**

I. Introduction

Power transformers are a class of very expensive and vital components of electric power systems. The crucial objective to mitigate the frequency and duration of unwanted outages related to power transformer puts a high pointed demand on power transformer protective relays to operate immaculately and capriciously. One of the major problems associated with the power transformer relay is the false tripping during magnetizing inrush current. It is found that the ratio of second harmonic to fundamental component is more in the case of inrush than other faults [1-2]. Considering this ratio, a method known as harmonic restraint differential protection scheme was developed to judge whether the current is inrush or due to internal fault. Traditionally, frequency analysis of the currents was performed using discrete Fourier transform (DFT). But it is well known that DFT is not accurate if the current is contaminated by harmonics that are not integer multiples of the fundamental, especially when the computation window is very short and DFT only accounts for frequency analysis and provides no information in the time domain [3]. DFT assumes the inrush and fault currents as periodic signal, whereas inrush and fault currents are non-stationary and non-periodic containing both high frequency oscillations and localized impulses superimposed on the power frequency and its harmonics [4].

The first few cycles of inrush current consists of high magnitude peaks that cause huge mechanical forces in transformer windings [4]. Also the presence of large quantity of harmonics in the inrush current can cause damage to power factor correction capacitor by exciting resonant overvoltage [5]. Hence steps are taken to mitigate the transformer inrush current by controlled switching and use of low loss amorphous core materials in modern power transformer [5]. The inrush current of these transformers produce low second harmonic that is comparable with that of fault currents. Hence the traditional methods are not reliable. New algorithm based on advanced digital signal processing techniques like discrete wavelet transform (DWT), wavelet packet transform (WPT), S-transform, H-transform etc. are being implemented for power transformer protection [4-8]. Different pattern recognition tools like fuzzy logic, artificial neural network (ANN), principal component analysis, support vector machine (SVM) etc. are also being used in recent days as classifiers to classify inrush current from faults current [9-14].

Instead of using DWT and ANN separately to distinguish between inrush and fault currents, the algorithm that uses combination of both is proven to be more efficient than other methods [1]. However, the procedure used in [1] is complex as it involves four layered ANN and data extraction based on Parseval's theorem. In this paper, a simplified method is proposed by using statistical data extraction and two layered feed forward ANN. This method requires less number of iterations for training and found to classify inrush current accurately.

II. Simulation of Faults and Inrush Currents

A. Power System Studied

A simple block diagram model of the power system [1] as shown in Fig. 1 is considered for study. The model consists of 3ϕ components with ratings as shown in Table I. The power system model with star-star transformer is simulated in MATLAB/SIMULINK environment separately for normal operation, internal faults (I), external faults (E) and inrush.

It is assumed that the power system model is not energized at time $t = 0^+$. To simulate different cases required for ANN training, the instance of switching is varied so that initial angle of voltage changes. To simulate different over excitation cases, increased load is considered for study. To simulate internal and external fault patterns, the fault resistance is varied from 0.1 Ω to 100 Ω in multiples of 10. To simulate inrush, secondary is kept open and switching instances are varied.

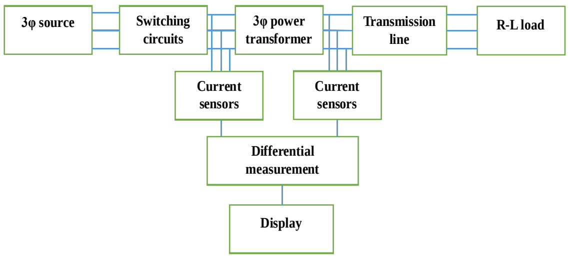


Fig. 1. Power system model

TABLE I. DETAILS OF POWER SYSTEM COMPONENTS

3 ϕ Component	Rating
Power Supply (Y connected)	230 kV, 50Hz, source resistance 0.8929 Ω source inductance 16.58 mH
Transformer (Y-Y connected)	450 MVA, 230 kV/500 kV, 50 Hz Winding resistance 0.02 pu Winding reactance 0.08 pu (for both Secondary and Primary) Saturable core with no residual flux
Transmission Line	100 Km Resistance 0.01273×10^{-3} Ω/m, Inductance 0.9337×10^{-6} H/m Capacitance 12.04×10^{-6} F/m
R-L Load (Y connected)	450 MW, 530 MVAR
Current transformers (Δ connected)	3000/5 (LV side), 800/5 (HV side)

Initially, differential current measured during normal operating condition, inrush and fault conditions are simulated by closing the switches at 0.1 s, 0.1s and 0.05 s respectively. The three phase current signals coming from the differential measurement during normal operating condition and inrush are shown in Fig. 2 and Fig. 3 respectively. Finite current observed during normal condition is due to the difference in the current transformer (CT) ratio.

Although different fault conditions (internal and external faults) are considered for different patterns, only the severe fault (L-L-L-G and L-L-L) currents are shown in Fig. 4, Fig. 5 and Fig. 6.

III. WAVELET ANALYSIS

The transient currents during fault, inrush and over excitation conditions are fast decaying, oscillating and consists of high frequency, so Daubichies's wavelet of level 6 (db6) suits best for the analysis purpose. The performance of different mother wavelets is given in Table V.

As the sampling frequency is 20 kHz, the highest frequency that the signal could contain will be 10 kHz. This frequency is observed at the output of high frequency filter which gives the first Detail. Thus, the band frequencies between 10 kHz to 5 kHz are captured in Detail-1. Similarly the band frequencies are captured for other Details as given in Table II. The wavelet analysis using db6 as the mother wavelet is performed up to Detail 5 level for the differential current signals of all the cases to extract the Detail coefficients. The analysis is carried out for 20 ms during 0.1 s to 0.12 s.

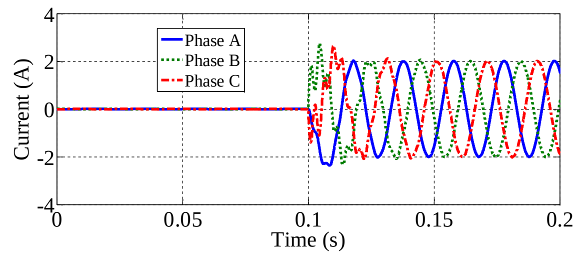


Fig. 2. Differential current during normal operation

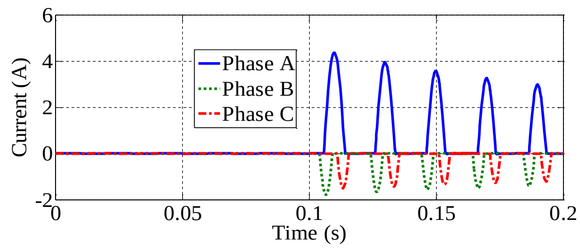


Fig. 3. Differential inrush current of a three phase power transformer

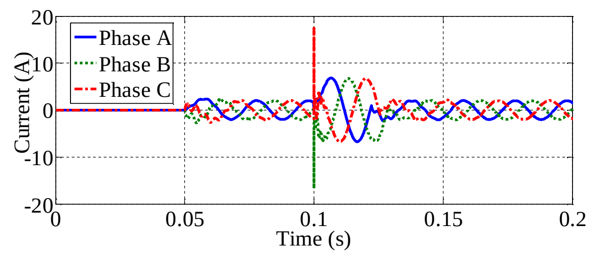


Fig. 4. Differential current during internal L-L-L-G fault

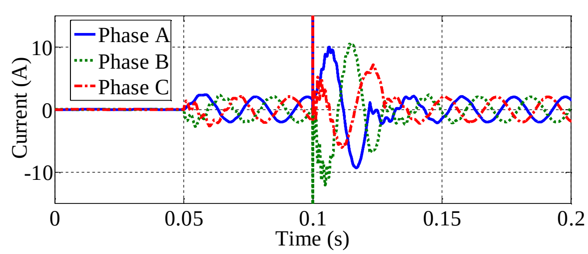


Fig. 5. Differential current during internal L-L-L fault

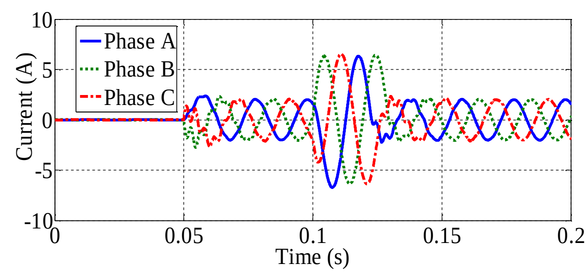
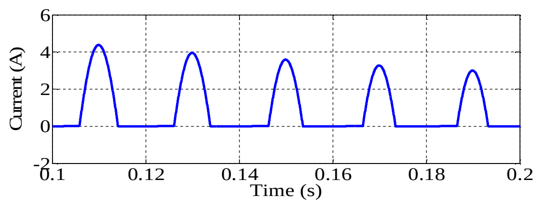


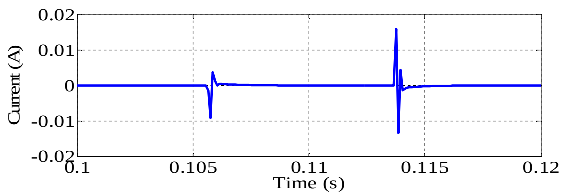
Fig. 6. Differential current during external L-L-L-G fault

A. Wavelet Analysis in Inrush Case

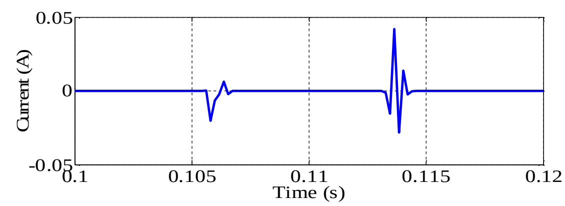
Wavelet analysis for inrush case at the instant when switching takes place at 0^0 angle of the source voltage is shown in Fig. 7. Fig. 7(a) represents the original current signal of phase A. It is seen that the current waveform is distorted in shape. Abrupt changes in the slope of inrush current are observed at the edges of the gaps. These sudden changes are visible as ripples in the wavelet plots shown in Fig. 7(b) - 7(f). These ripples of significant magnitude are the major characteristics of inrush current.



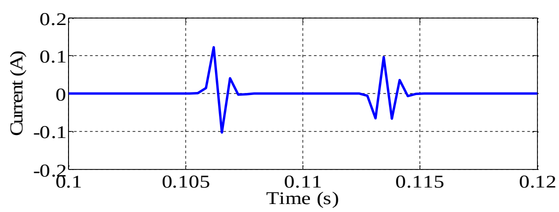
(a) Original current signal



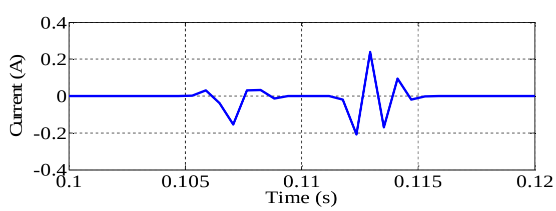
(b) Detail coefficient at level 1 decomposition.



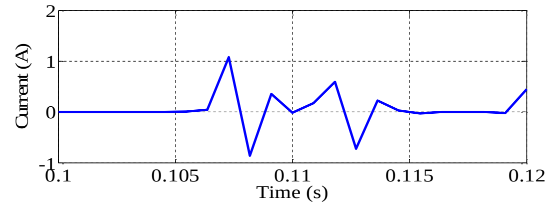
(c) Detail coefficient at level 2 decomposition.



(d) Detail coefficient at level 3 decomposition.



(e) Detail coefficient at level 4 decomposition.



(f) Detail coefficient at level 5 decomposition.

Fig. 7. Wavelet analysis of phase-A differential current for inrush

B. Wavelet Analysis in Internal Fault Case

The power system is energized at 0.05s and fault is created at 0.1s in the secondary side of the power transformer and lasts for one cycle. Wavelet analysis for internal fault case at the instant when switching takes place at 0^0 angle of the source voltage and fault resistance 100 Ω for the time 0.1s to 0.12 s is shown in Fig. 8. Fig. 8(a) represents the original current signal of phase-A during L-G fault. The fault occurs on the high voltage side of power transformer between phase-A and ground. A high frequency distortion is observed in the fault current waveforms as shown in Fig. 8(a). This distortion is the consequence of the effects of distributed inductance and capacitance of the transmission line. This distributed inductance and capacitance lead to significant second harmonic in the internal fault during the transient period. Hence the distributed inductance and capacitance poses difficulty in an accurate discrimination between magnetizing inrush current and internal fault currents by the conventional protection method based on DFT.

From the Detail coefficients (1 to 5) shown in Fig. 8 (b)-(f), it is observed that there are several spikes immediately after fault inception time in L-G fault. One important observation to distinguish between the inrush and internal fault is that the ripples during inrush sustain over long time than the case of internal fault.

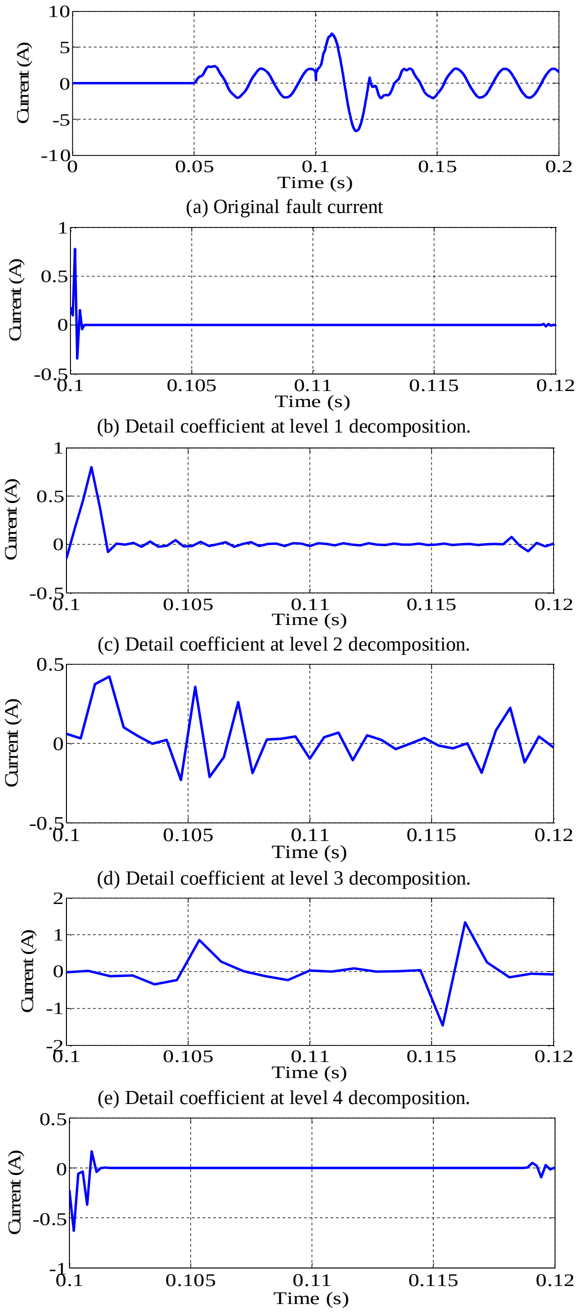
Similarly other internal fault situations like L-L-G fault, three phase symmetrical line to ground and line to line fault and external fault are simulated by creating those in the secondary side of the power transformer for the time same as that of L-G fault.

TABLE II. FREQUENCY BAND OF DIFFERENT DETAIL COEFFICIENTS

Level of Detail coefficient	Frequency band
d1	5 kHz-2.5 kHz
d2	2.5 kHz-1.25 kHz
d3	1.25 kHz-0.625 kHz
d4	0.625 kHz - 0.3125 kHz
d5	0.3125 kHz-0.15625 kHz

IV. PERFORMANCE OF ANN AND IMPLEMENTATION IN LABVIEW

The statistical data obtained from the decomposed signals of wavelet analysis at level 1 to 5 are used to train and test the ANN. The ANN consists of three layers with 9 nodes in the input layer, 9 nodes in the output layer. The nodes of the hidden layer are varied for optimization. Back propagation algorithm is used to train the ANN. The activation function used in the ANN is of sigmoid type. The training and testing data are statistical features obtained for the three phases. The mean, standard deviation and norm (root mean square value) of the decomposed Detail coefficients for the three phases are used as input data as these statistical variables are distinct and significant as observed from the analysis and acts like principal components.



(a) Original fault current

(b) Detail coefficient at level 1 decomposition.

(c) Detail coefficient at level 2 decomposition.

(d) Detail coefficient at level 3 decomposition.

(e) Detail coefficient at level 4 decomposition.

(f) Detail coefficient at level 5 decomposition.

Fig. 8. Wavelet analysis of phase-A differential current for L-G fault

The output data is unity for the condition represented by the input and zero for others. Table III shows the different nodes representing the different conditions. The input data are normalized before training or testing by dividing the maximum value of data of a row with other data.

Neural network training and testing programs are written and simulated in Matlab. After performing analysis for obtaining the optimal values for neural network it is found that, learning rate of 0.2, the momentum factor of 0.9 and 16 nodes in hidden layer gives least error and faster convergence. The ANN is trained with 108 patterns and tested with 72 patterns for each Detail coefficients separately. Percentage accuracy with which ANN is able to classify the different cases during testing is given in Table IV. From the table, Detail-3 (1.25 kHz-0.625 kHz) is found give better classification. This indicates that for the above configuration of ANN, input and output patterns formed using Detail-3 is well suited for discrimination of inrush from faults.

The weights obtained after training with Detail-3 input and output pattern are used to construct a virtual instrument ANN using LabVIEW. The fault waveforms and inrush waveforms are fed as inputs to virtual instrument. To indicate type of fault, LED indicators are used on the front panel. After testing with several input waveforms, the virtual instrument is found to classify the waveforms as expected. Fig. 9 shows the front panel of virtual instrument with input data of inrush and a glowing LED corresponding to inrush.

TABLE III. TARGET DATA SET OF THE ANN

Name of the event	**Target value of the i^{th} nodes (N_i)**								
	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8	N_9
Normal	**1**	0	0	0	0	0	0	0	0
Inrush	0	**1**	0	0	0	0	0	0	0
L-G fault (I)	0	0	**1**	0	0	0	0	0	0
L-L-G fault (I)	0	0	0	**1**	0	0	0	0	0
L-L-L-G fault (I)	0	0	0	0	**1**	0	0	0	0
L-L fault (I)	0	0	0	0	0	**1**	0	0	0
L-L-L fault (I)	0	0	0	0	0	0	**1**	0	0
L-L-L-G fault (E)	0	0	0	0	0	0	0	**1**	0
Over excitation	0	0	0	0	0	0	0	0	**1**

TABLE IV. COMPARISON OF TEST RESULTS OF ANN FOR DIFFERENT WAVELET DECOMPOSITION LEVEL

Name of the event	**% of correct discrimination using different wavelet decomposition level data**				
	d1	d2	d3	d4	d5
Normal	75	**100**	**100**	**100**	50
Inrush	**100**	50	**100**	75	50
L-G fault (I)	**100**	**100**	**100**	**100**	**100**
L-L-G fault (I)	**100**	**100**	**100**	**100**	**100**
L-L-L-G fault (I)	**100**	**100**	**100**	50	**100**
L-L fault (I)	**100**	**100**	**100**	50	75
L-L-L fault (I)	75	50	75	75	75
L-L-L-G fault (E)	75	75	**100**	**100**	75
Over excitation	**100**	**100**	**100**	**100**	**100**

The detail analysis of all the cases are carried out for different mother wavelets and statistical data obtained after the analysis are used to train and test the ANN. The performance of ANN for different mother wavelets is given in Table V. From Table V it is clear that Daubichies mother wavelet when used for analysis of the transient signals give high efficiency in discrimination of simulated cases. The Haar wavelet gives the least efficiency whereas Symlet and Coiflet wavelets performance are better than Haar but not as good as Daubichies.

TABLE V. COMPARISON OF TEST RESULTS OF ANN FOR DIFFERENT MOTHER WAVELETS

Name of the event	**% of correct discrimination using different mother wavelets**			
	Haar	Coiflet	Symlet	Daubichies
Normal	69.44	86.11	90.27	**100**
Inrush	72.22	84.72	91.66	**100**
L-G fault (I)	73.61	87.5	90.27	**100**
L-L-G fault (I)	69.44	84.72	93.05	**100**
L-L-L-G fault (I)	69.44	86.11	88.88	**100**
L-L fault (I)	72.22	83.33	87.5	**100**
L-L-L fault (I)	69.44	87.5	88.88	**75**
L-L-L-G fault (E)	70.83	86.11	86.11	**100**
Over excitation	72.22	84.72	88.88	**100**

V. CONCLUSIONS

It is possible to distinguish between inrush currents and fault currents by analyzing the ripple patterns obtained from wavelet transforms. ANN with sigmoid activation function is found to classify better with Detail-3 data. To show the real time application of this method a virtual instrument in LabVIEW is developed. The performance of trained ANN is tested successfully for the classification of various cases. The classification ability of the ANN in combination with advanced signal processing technique opens the door for smart relays power transformer protection with very less operating time and with desirable accuracy.

Fig. 9. Front panel of virtual instrument

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