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TRANSFORMER PROTECTION USING ARTIFICIAL NEURAL NETWORK

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Abstract*—*This paper gives idea about use of artificial neural network to the protection of power transformer. The high pointed demand includes the requirements of dependability associated with no false tripping and operating speed with short fault detection and clearing time. By use of the second harmonic restrain and using discrete Fourier transform (DFT) problems such as long restrain time and inability to discriminate internal fault from magnetizing inrush condition. So, artificial neural network (ANN), a helping tool for artificial intelligence (AI), The wavelet transform(WT) which has the ability to extract information from transient signals in both time and frequency domain simultaneously is used for the analysis of power transformer The ANN is tested by varying the hidden layers, number of nodes in the hidden layer, learning rate and momentum factor, and the suitable architecture of ANN is selected having least mean square error during observations.

I. INTRODUCTION

Protection of large power transformers is a big problem in power system relaying. The protective system include devices that recognize the existence of a fault, indicates its location and class, detect some other abnormal fault like operating conditions and starts the inceptive steps of opening of circuit breakers to disconnect the faulty equipment of the power system. Since the transformer inrush current is rich in second harmonic component therefore to avoid the needless trip by inrush current harmonic restraint logic together with differential logic is used in most of the fault detection algorithm in the digital differential protection of power transformer.

Altitude of second harmonic and fundamental are computed by discrete Fourier transform (DFT) and the ratio is used to judge whether the current is inrush or internal fault one. 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 but does not give information in the time domain. While DFT assumes a periodic signal, inrush current and fault currents are nonstationary signals.Artificial Neural Networks (ANN) is extremely used particularly in the field of power system protection since 1994 as this problem is subclass of pattern recognition of current waveforms. It is to be noted that ANNs were primarily used in different areas such as pattern recognition, image processing, load forecasting, power quality analysis, and data compression. The main advantage of the ANN method over the conventional method is the non-algorithmic parallel distributed architecture for information processing and inherent ability to take intelligent decision. In recent years, few works which investigate the feasibility of using ANN for power transfordifferential protection has also been reported However, the ANNs in these existing studies are specific to particular transformer systems, and would have to be retrained again for other systems. Moreover, the employed feature extraction techniques are based on either time or frequency domain signals, or not both time and frequency features of the signal; this is very important for accurately distinguishing between an internal fault and inrush current.Recently, the wavelet transforms have been applied to analyse the power system transients , power quality as well as fault location and detection problems . In reference the wavelet transform for analysing the transient phenomena in a power transformer under conditions of faults and magnetizing inrush currents was presented, and simulated results have shown that it is possible to use certain wavelet components to discriminate between internal faults and magnetizing inrush currents.

II. TRANSFORMER PROTECTION AND INRUSH CURRENT

Transformer switching phenomenon being random makes the magnetizing inrush also random. During energisation large magnitudes of currents flow into the primary winding of a transformer while no currents flow out of the secondary winding. This is similar to the conditions occurring during internal faults. Hence there arises a chance of incorrect tripping of the circuit breaker. Therefore it is necessary to distinguish between an internal fault and a magnetizing inrush current condition

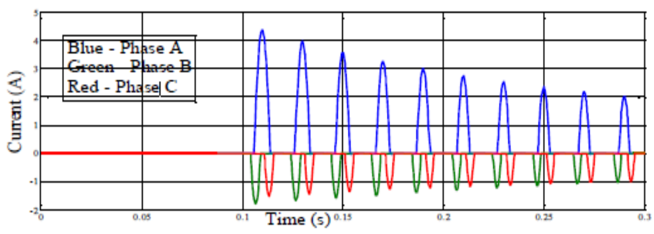


Fig.1 Differential inrush current of all the three phases of a power transformer

III. ARTIFICIAL NEURAL NETWORKS AND WAVELET TRANSFORM

Neural network or artificial neural network (ANN), as the name indicates, is the interconnection of artificial neurons that tends to simulate the nervous system of a human brain. It is also defined in a literature as a neurocomputer or a connectionist system.Neurocomputing is a more generic form of artificial intelligence than expert system and fuzzy logic. The Fourier transform is a useful tool to analyse the frequency components of the signal. But Fourier transform is silent about the instant at which a particular frequency appears. Short-time Fourier transform (STFT) uses a sliding window to find spectrogram, which gives the information of both time and frequency. But in case of STFT the length of window is fixed for all frequency. The ability of wavelet transform (WT) to focus on short time intervals for high-frequency components and long intervals for low-frequency components improves the analysis of signals with localised impulses and oscillations.

A. DWT AND FILTER BANKS

The signal resolution is determined by the filtering operations and is a measure of the amount of detail information in the signal whereas the scale is determined by up sampling and down sampling operations. Down sampling a signal corresponds to reducing the sampling and up sampling a signal corresponds to increasing the sampling rate.The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal in one algorithm called the Mallat algorithm or Mallat-tree decomposition given in Fig 3.5. Initially an original signal is divided into two halves of the frequency bandwidth and given to high pass (H0) and low pass (G0) filter. Then the output of the low pass filter is again half the frequency bandwidth and fed to second stage. This procedure is repeated until the filter length becomes equal to length of the signal.

COMPARISON OF DWT WITH OTHER TRANSFORMS

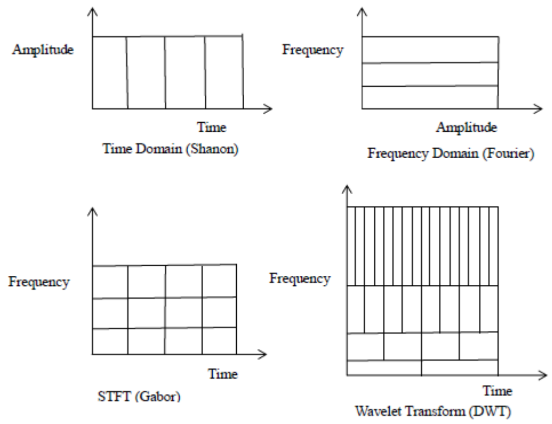


Fig.2 Comparison of DWT with other transforms

IV. DFT ANALYSIS AND SIMULATED TRANSIENT SIGNALS

The DFT of the simulated transient current signals obtained for various conditions of a power transformer (star-star) connected to a power system are obtained using fast Fourier transform (FFT) algorithm. The objective of this analysis is to show the harmonic content during the transient period. The conventional differential protection scheme that are based upon second harmonic restrain assume that only inrush current is reach in second harmonic component.Fig 3 shows R phase current under normal operating condition.

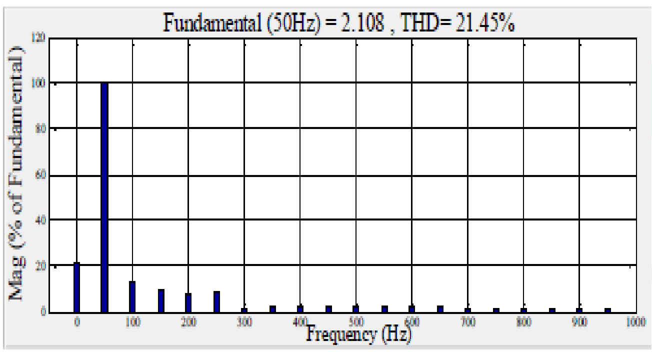


Fig.3 R phase differential current

The above FFT plots shows that during normal case the percentage of second harmonic current is very less in comparison to fundamental and in this case there is no problem with the conventional relay. Those relays will remain dormant in this case as the ratio of inrush to fundamental is negligible and that matches with their algorithm. The relays can only issue a trip command to the circuit breaker if the ratio exceeds a predefined limit which is formed by taking the inrush current case as the base or reference. Fig.4 showing the R,Y,B phase current under inrush condition.

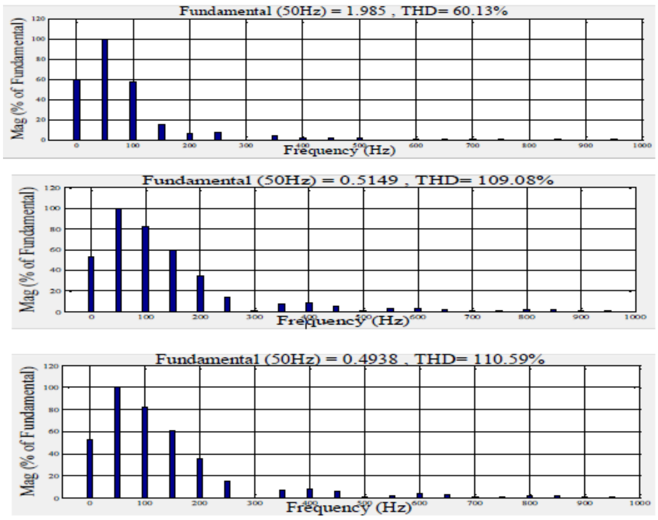


Fig.4 R,Y,B phase cuurent under inrush condition.

During the FFT analysis of inrush case transient currents for one cycle it is seen that the percentage of second harmonic content is different for the three phases. The percentage second harmonic content is of significant amount. The conventional relay will work in this case but the detection and algorithm will fail if the relay operating time will be taken less than a cycle and also if the transient phenomena lasts for less than a cycle. The conventional algorithm starts the FFT window from the starting of the event resulting less percentage of second harmonic content. But the analysis of the transient current signal for less than a cycle also predicts a large mismatch among the three phase contents as far as second harmonic factor is considered. Fig.5 showing the R,Y,B phase diffential current under LLLG fault condition

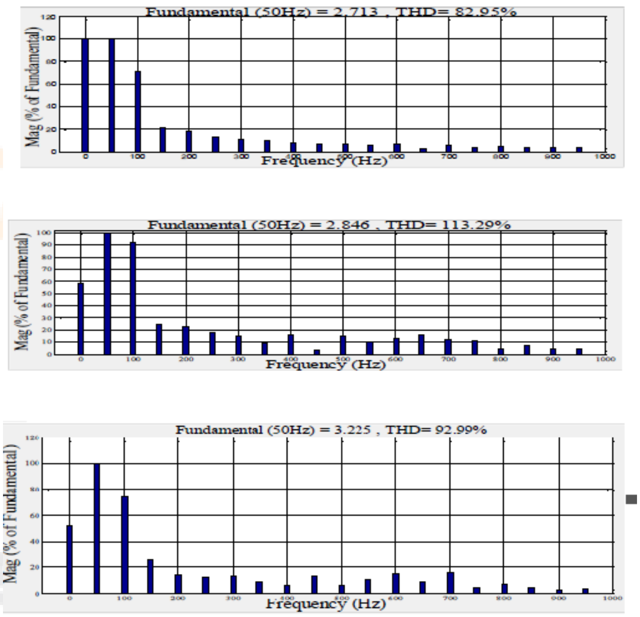


Fig.5 R,Y,B phase diffential current under LLLG fault condition

TABLE 1- PERCENTAGE OF SECOND HARMONIC CONTENT IN THE DIFFERENTIAL CURRENT IN VARIOUS CONDITIONS IN CASE OF STAR-STAR TRANSFORMER

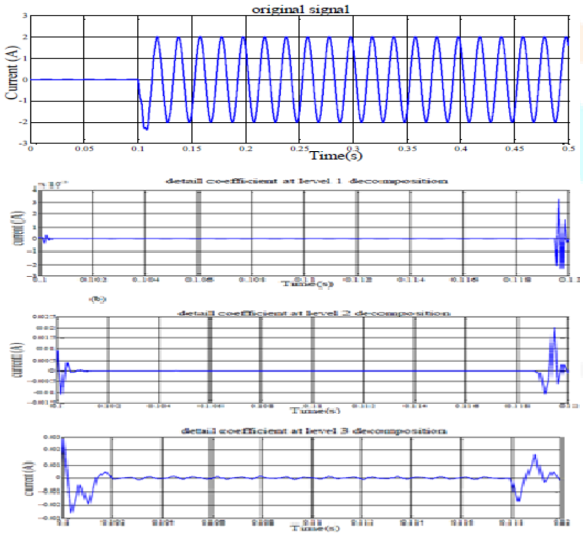
Type of condition	Phase A	Phase B	Phase C
Normal	14.23	5.76	17.26
Inrush	55.69	86.67	78.47
L-G fault	70.85	0.81	1.08
L-L-G fault	79.52	92.53	0.81

L-L-L-G fault	71.25	91.23	75.24
L-L fault	61.31	74.36	0.71
L-L-L fault	81.23	90.35	86.23
External fault	24.89	25.31	41.2
Over excitation	16.89	11.95	17.12

The percentage of second harmonic component is not same for the three phases in a particular case. As conventional relays are not provided with artificial intelligence (AI) therefore they are not efficient in fuzzy situations like how much less or how much more. Secondly due to different methods adopted to mitigate the inrush current in power transformer itself decrease the second harmonic component in the magnetizing inrush 30 currents in modern day power system by the use of advanced core materials. Thirdly as the frequency content of the transient current signals is different in comparison to steady portion so the transient current is aperiodic and non-stationary during transient period. Hence the traditional DFT based algorithm is not a strong protective measure for smart power system if the interest is efficient performance of the protective relay within a cycle i.e. 20 m sec. This opens window for different advanced signal processing techniques and AI based classifier to meet the requisite demand.

V. WAVELET ANALYSIS OF THE TRANSIENT CURRENT SIGNALS

Wavelet analysis for normal operating case at the instant when switching takes place at zero degree angle of the source voltage is shown in Figures. The Fig 6 represents the original signal. In this chapter only phase A differential current is selected for the analysis. Analyses of other phases are not represented graphically. The analysis of all the three phases is performed and the data obtained from the detail coefficients in different levels are used for training of ANN. As the detail level increases the frequency of the signal content in that decreases and the time for which that is analysed increases. The frequency decrease by a factor of two and the time increase by a factor of two. The Fig 6.1 represent the decomposed detail coefficient signals in different levels.



A.WAVELET ANALYSIS IN INRUSH CASE

Wavelet analysis for inrush case at the instant when switching takes place at zero degree angle of the source voltage is shown. The Fig) represents the original current signal of phase R. It is seen that the current waveform is distorted in shape. Gaps appear over the times of inrush current. It is seen that the magnitude of inrush current changed from nearly zero value to a significant value at the edges of the gaps. This sudden change from one state to other should produce small ripples. But these ripples are not visible in the time domain representation.. The Fig represent the decomposed detail coefficient signals in different levels. From the figures of details it is clear that there are a number of sharp spikes during the period of the inrush current transient. High frequency component is located better in time domain and low frequency component is located better in frequency domain. Details 1 to 3 are located better in time domain as they contains high frequency components and detail 4 to 5 are located better in frequency domain as they contains low frequency components.

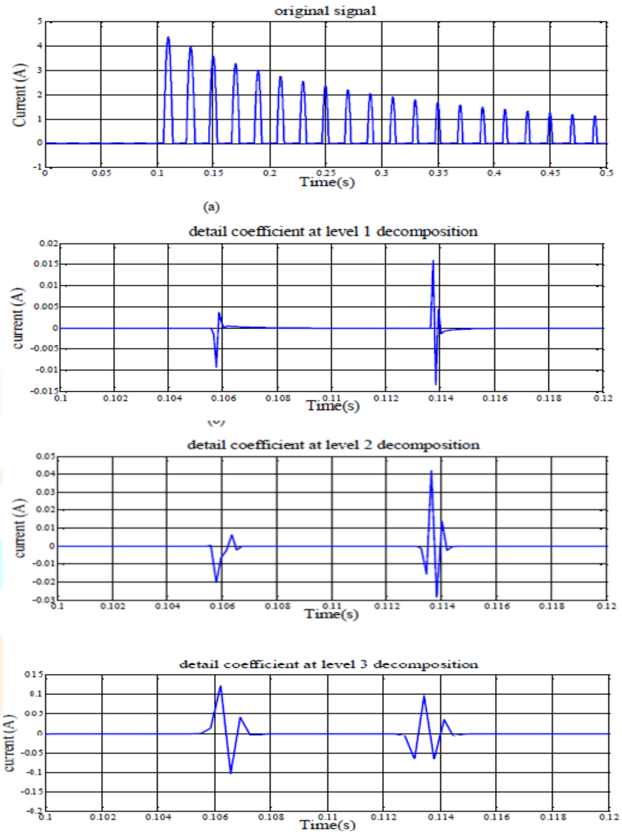
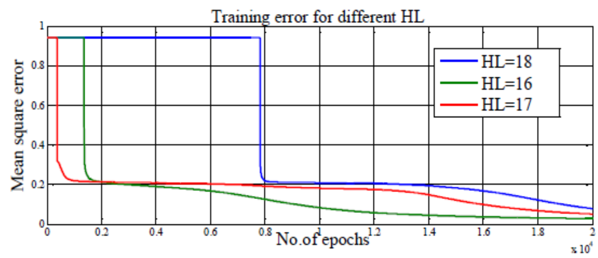


Fig.6 Wavelet analysis of phase R differential current for inrush case.

VI. PERFORMANCE OF ANN

The ANN is trained and tested for each level decompose detail coefficients i.e. for high frequency and low frequency constituents and the detail comparison is given in Table.for star-star and delta-star transformer respectively. The architecture of the ANN having one hidden layer, 16 nodes in hidden layer, 9 nodes in input layer and 9 nodes in output layer is the best out of all the tested architecture as the mean square error in this type is least during training. The learning rate suitable for that network having least error is 0.2 and the momentum factor 0.9 in the same network gives the least error. The performance of ANN by varying the hidden layer nodes, learning rate and momentum factor are given in terms of mean square error in table respectively. The weights of the ANN after training using each level detail coefficient data are given for each level.

PERFORMANCE OF ANN USING D1 LEVEL DATA FOR STAR-STAR TRANSFORMER



The learning rate (n) and the momentum factor (m) are kept constant when the performance of ANN is checked for different hidden nodes (HL) in the hidden layer at 0.2 and 0.9 respectively. The least error is for HL=16.

TABLE: 6.1 COMPARISON OF ERRORS OF ANN FOR DIFFERENT HIDDEN LAYERS

MOMENTUM FACTOR (M)	MEAN SQUARE ERROR DURING TRAINING AFTER 20000 ITERATIONS
0.7	0.1671
0.8	0.0377
0.9	0.0288

VII. CONCLUSIONS

The current signals for different cases for a power transformer are obtained using MATLAB. These waveforms are analysed using wavelet transform for extraction of feature vector (containing statistical data) to train the ANN. The performance of trained ANN is tested successfully for the classification of various cases. ANN is implemented in the LabVIEW environment for real time application. From the study and analysis carried out in this dissertation, the performance of neural networks has been found to surpass the performance of conventional methods, which need accurate sensing devices, costly equipment and an expert operator or engineer. The classification ability of the ANN in combination with advanced signal processing technique opens the door for smart relays for power transformer protection with very less operating time and with desirable accuracy.

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