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Transformer Differential Protection Based on Wavelet and Neural Network

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Abstract

This paper presents a novel power transformer differential protection scheme by using combined Wavelet Transform and Artificial Neural Network which provide the means to enhance the classical protection principles and facilitate faster, more secure and dependable differential protection for power transformer. Wavelet transform is used to extract the feature from transient signal and the neural network is trained by the extracted features of the transient signal to accurately discriminate between the internal fault and magnetizing inrush current. The wavelet transform is firstly applied to decompose the differential current of power transformer in to a series of detailed wavelet components and then the spectral energies of the detailed wavelet components are calculated. The obtained spectral energies are employed to train the Optimal Feed Forward Back propagation Neural Network (OFFBNN). A three phase 315 MVA, 220/400 kV, 50Hz, power transformer is modelled in PSCAD/EMTDC software and the algorithm is evaluated in MATLAB. The results clearly shows that the proposed scheme is reliable, accurate and fast than the conventional differential protection scheme.

Keywords. Differential Protection, Power Transformers, Wavelet Transforms (WT), Discrete Wavelet Transform (DWT), Optimal Feed Forward Back Propagation Neural Networks (OFFBNN).

1. Introduction

Power transformers are an important and vital components of the power systems networks whose protection needs to be addressed so as to ascertain the stability and reliability of the system network. Tremendous amount of electricity usage in the present scenario of rapid industrialization have triggered the need to install equipment with higher ratings and sizes. Although protection is ensured in the form of minimum usage of circuit breakers, relays and other protective devices but since then the abnormal conditions and faults cannot be avoided. Such a situation requires the digital relays as protection measures which employs software algorithm relying on advanced logics to ensure a higher degree of protection.

Recently, researchers have been formulating protection algorithms for power transformer differential protection using intelligent techniques like artificial neural networks, fuzzy logic, phase angle difference method, harmonic restraint method etc. [4, 8-10, 11, 13]. These techniques are proving to be the most suitable for classifying various operating conditions of transformer, the abnormal condition or the fault classification. Moreover, techniques like Fourier transform, wavelet transform, wavelet packet etc. have been employed by the researchers in their studies for analyzing the transient signals in power system under faulted condition in time domain, frequency domain or both and thereby for feature extraction to discriminate between healthy and unhealthy condition is wavelet transform is very useful tool [5-7, 14].

This paper presents a novel power transformer differential protection algorithm by using combined wavelet transform and Artificial Neural Network (ANN) which provide the means to enhance the classical protection principles and facilitate faster, more secure and dependable protection for power transformers. Wavelet transform is used to extract the feature from transient signal and the neural network is trained by the extracted features of the transient signal to discriminate between the internal fault and magnetizing inrush current. The wavelet transform is firstly applied to decompose the differential current of power transformer in to a series of detailed wavelet components and then the spectral energies of the detailed wavelet components are calculated. The obtained spectral energies are employed to train the Optimal Feed Forward Neural Network (OFFNN). The proposed technique being pattern recognition based will be able to maintain relay stability even during sympathetic inrush and external fault condition.

2. Simulation and training cases

During the operation of power transformer following conditions are encountered:

- Normal condition
- Magnetization inrush /or sympathetic inrush condition
- Over-excitation condition
- External fault
- Internal fault

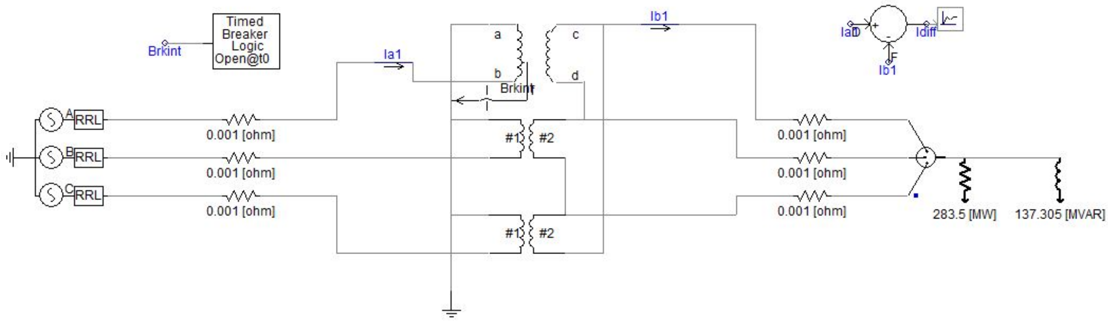


Fig 1: Internal fault (LG fault) condition of power transformer

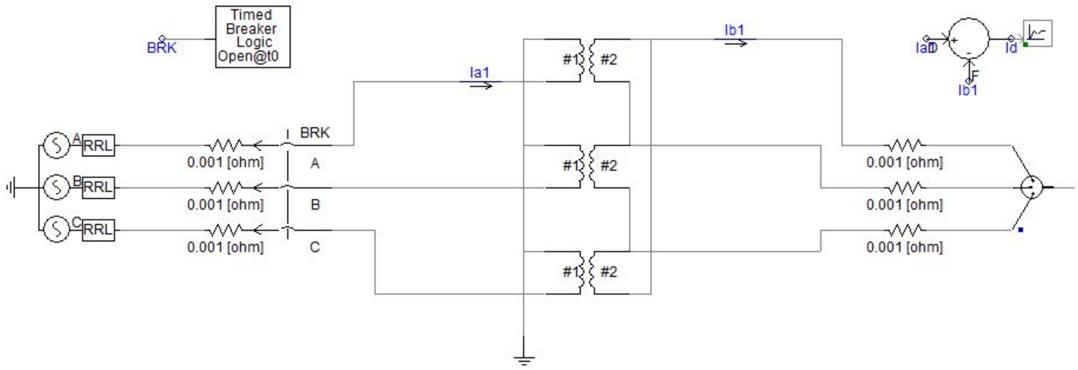


Fig 2: Magnetizing Inrush condition of power transformer

As shown in figs. 1-3, PSCAD/EMTD software is used for simulation of aforementioned operating conditions of a three phase 315 MVA, 220/400 kV, 50Hz power transformer so that the differential relaying signal can be obtained obtain testing and training data signals. It is assumed that the ideal CTs of 1200/5A and 2400/5A respectively on primary and secondary side of the transformer are connected to compensate the phase angle created by the power transformer.

As the magnitude and wave shape of magnetizing inrush current depends on the switching-in angles, remenant flux, the variation in switching-in angle, remanence flux are considered to obtain data of inrush. Energisation angle is varied from 0^0 to 360^0 with the tolerance of remanence flux variation from 0% to 80% of the peak value of the flux at rated voltage with the load conditions being considered at full load and no load, thereby, obtaining a total of 794 cases. For generating data signal of the internal fault, winding of one phase is short-circuited with another for phase by varying the turns of the phase windings from 5% to 95% of the total winding, hence, obtaining a total of 440 cases. Figure 1-3 show the implementation of power transformer differential relaying system in PSCAD/EMTDC. Simulation is performed at a sampling frequency of 600 Hz i.e. 12 samples per power frequency cycle of 50 Hz supply. Figures 4-8 illustrates the differential current of power transformer during normal, magnetizing inrush, over-excitation, external fault and internal fault conditions respectively. Internal fault is made to occur at 0.2 sec. as demonstrated in fig.8. Hence, the relay detects it and calls for the breaker to operate just after the fault has taken place which can be observed in fig.9.

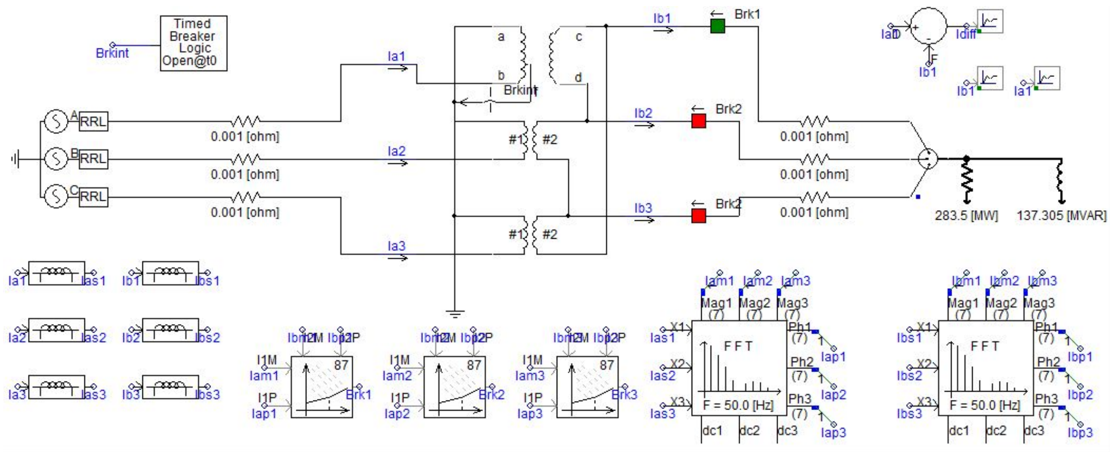


Fig 3: Implementation of differential relay for internal fault (LG fault) condition of transformer in PSCAD/EMTDC

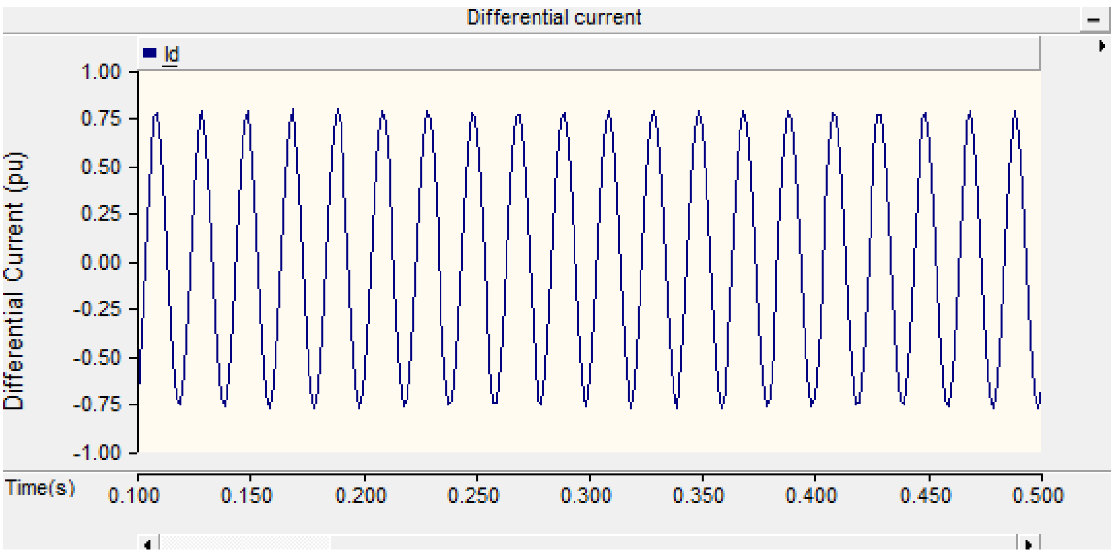


Fig 4: Normal Operation differential current

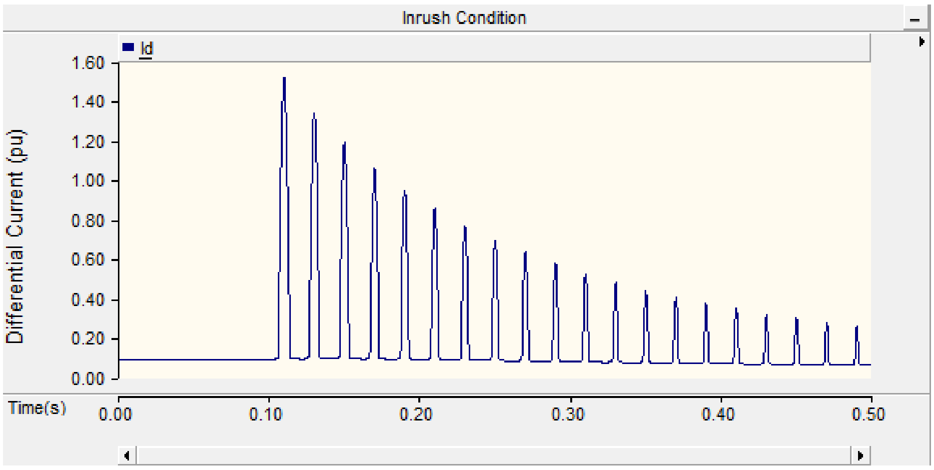


Fig 5: Magnetizing Inrush differential current

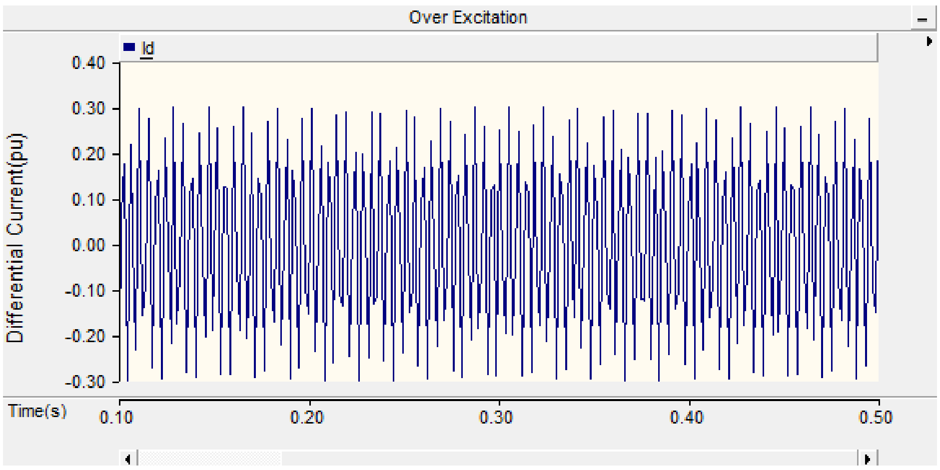


Fig 6: Differential current under Over-excitation condition

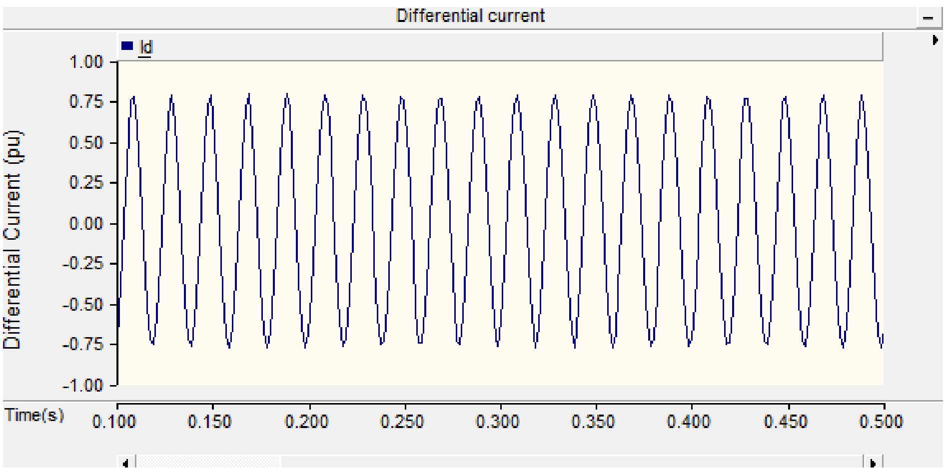


Fig 7: External fault differential current

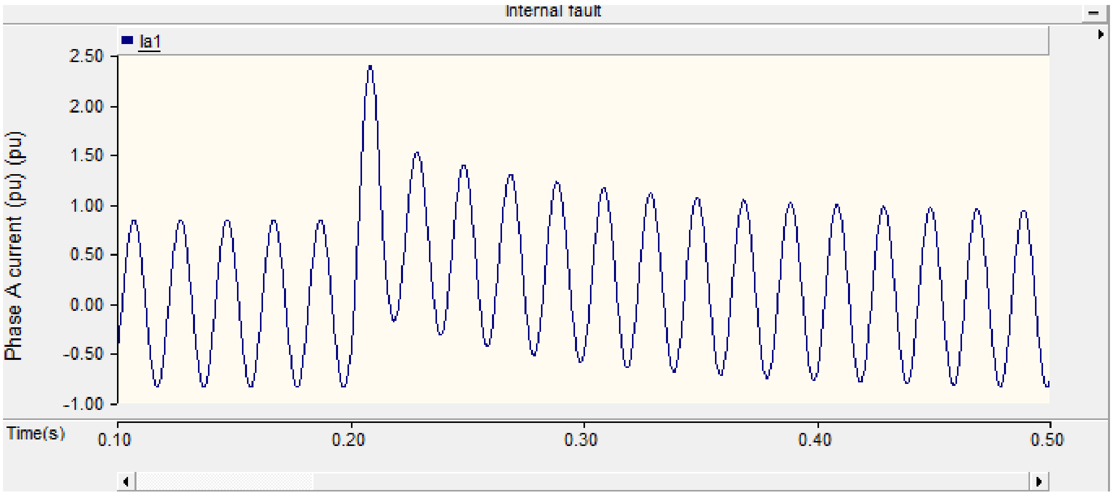


Fig 8: Differential current during internal fault condition

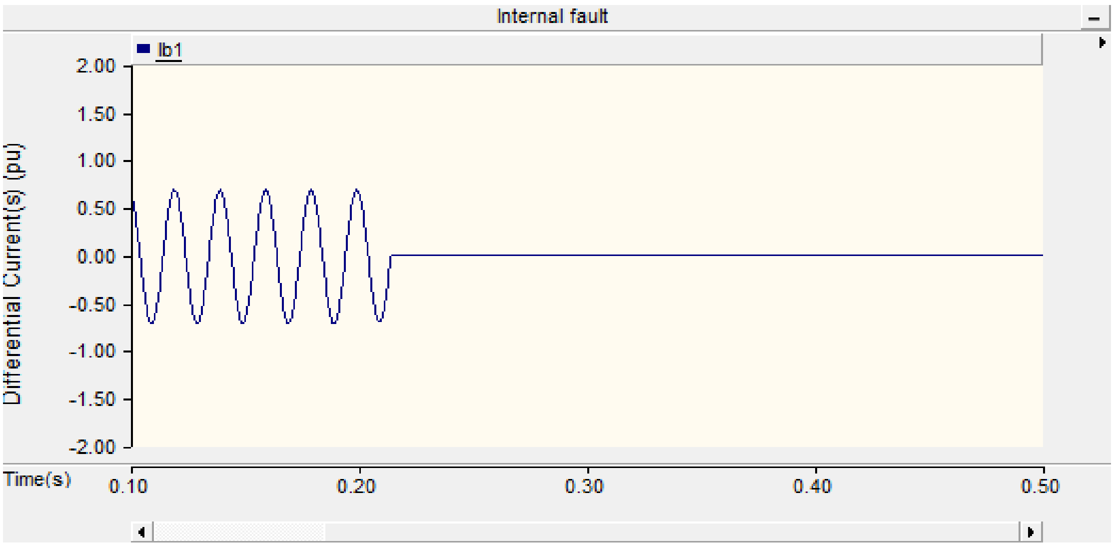


Fig 9: Secondary Phase Current after breaker operation

3. Implementation of combined wavelet and neural networks

A. Input selection of neural network and wavelet transform

The input data-set for the neural network is the pattern waveform of the wavelet energy obtained from the detailed and approximate coefficients (by eq.(1)) at five different levels and been summed to form the signature waveform of the spectral energy, for both inrush condition as well as internal fault cases. It is not feasible to use wavelet coefficients as the inputs to the neural networks, since it may amount to a large number of inputs which may lead to difficulty in convergence of ANN. Also, the extracted information from the energy waveform is able to discriminate between internal fault and inrush condition more reliably.

The signal is sampled at 600 Hz frequency i.e. 12 samples per power frequency cycle of 50 Hz. The total length of the energy signal is taken to be two power frequency cycles, i.e. 40ms and a total of 24 samples.

A five-level decomposition with sym2 as the mother wavelet is selected to develop the proposed algorithm. Sym2 belongs to the symmlet wavelet families. If the original signal is sampled at Fs Hz, then by Nyquist theorem the highest frequency that a signal could contain would be Fs/2 Hz. The sampling frequency taken in this paper is 600 Hz.

$$E_w = \sum_{j=1}^{N} |C_j|^2, \; i = 1, 2, 3, 4, 5 \tag{1}$$

Where, C denotes the coefficient value, i is the level number and j is the count of sample points.

B. Neural Network Architecture

Neural networks can be formulated in a different number of ways, each network with its own characteristics, features, advantages and disadvantages. For performing this scheme, feed-forward network is employed.

Since the number of inputs to the neural network is 24, the number of output neurons is 2 such that the target 0 represents internal fault and 1 represents inrush condition. Selection of hidden layer neurons is performed by testing various architectures and choosing the most optimal neural network. The number of hidden layer neurons is varied from 5 to 16 and searched for lowest mean squared error and comparison between their performance plots is satisfied. Optimal neural network architecture includes:

- small mean squared error
- no significant overfitting
- test and validation set errors should have similar characteristics

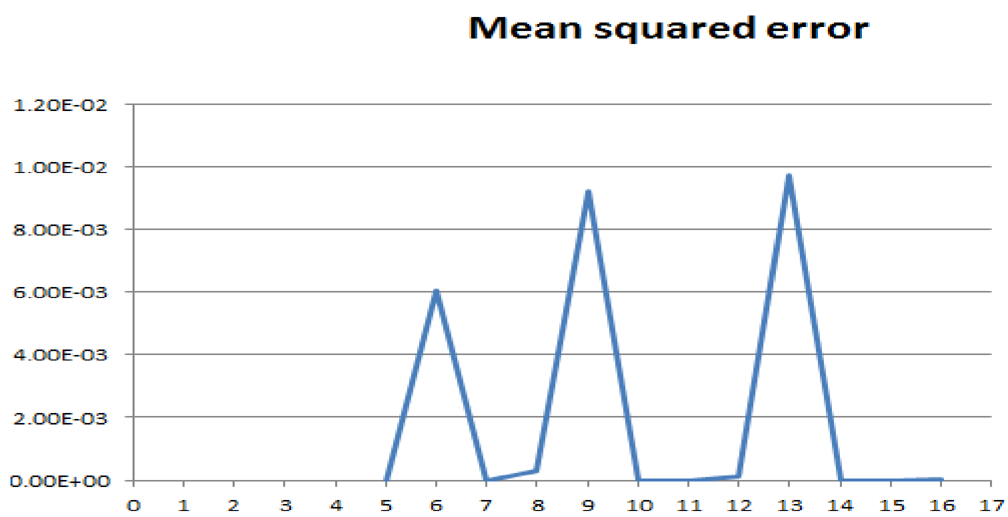


Fig. 10: Typical variation of errors for different number of hidden neurons

From the fig. 10, it is found that among the various architectures tested, the most optimal neural network architecture been employed has 10 hidden neurons with scaled conjugate gradient training function and therefore it is adopted to perform the proposed application. Feed forward network is used with log-sigmoid activation function in the hidden and output layer respectively.

C. Combined wavelet and neural networks protection scheme

Fig.11 clearly demonstrates all the steps of the proposed transformer differential protection scheme. The normal operating condition is discriminated by measuring the peak-to-peak value of the differential current whereas the over-excitation condition is found by the using voltage to frequency ratio of differential current. If these conditions are not valid than DWT is used to find the detailed and approximation coefficients of relaying signal and the energy of these coefficients are calculated by using eq. (1). The wavelet energy signal for magnetizing inrush and internal fault condition is shown in fig. 12. Moving window concept is applied to train the neural network. In this work one full power frequency cycle, i.e. 20ms is considered for moving window. The energy pattern obtained is fed to the OFFBNN (24-10-2) to discriminate between the magnetizing inrush and internal fault condition. If internal fault condition is found then a differential relay issue a trip signal.

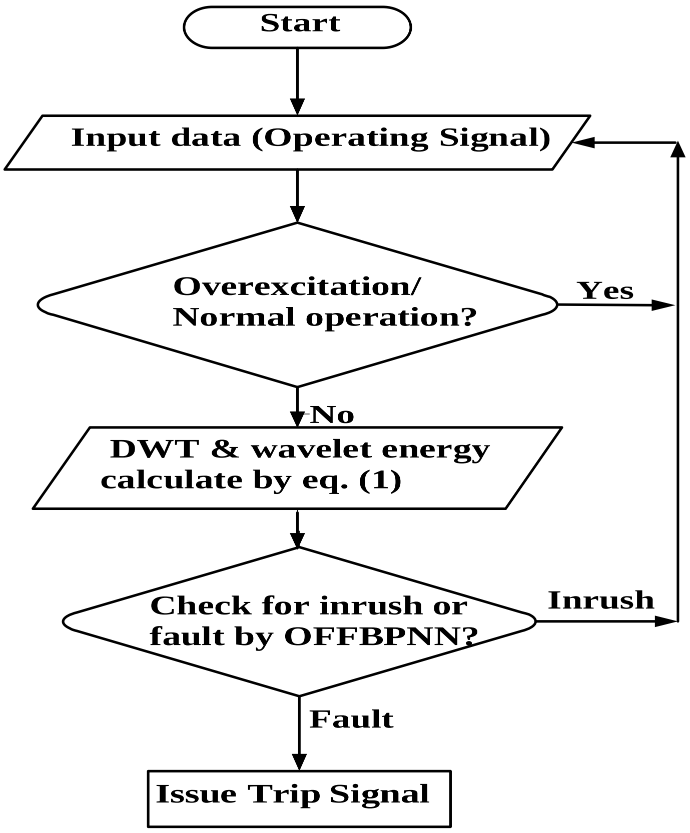
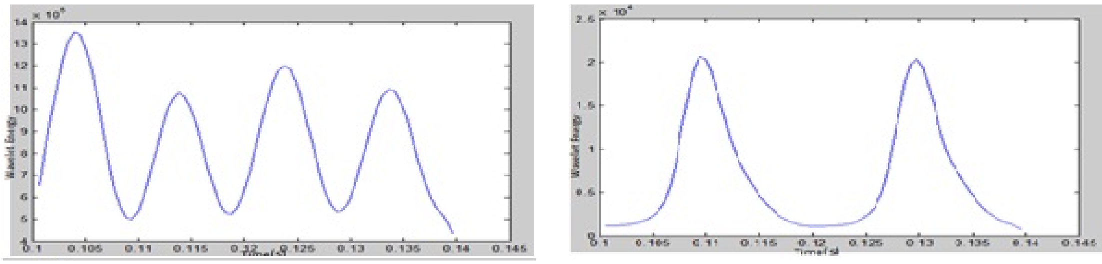


Fig.11: Flow char of the proposed Scheme



a b

Fig. 12: Waveform of wavelet energy for (a) inrush condition, (b) Internal fault

D. Performance evaluation

A total of 1234 data cases have been simulated using the PSCAD/EMTDC software for different operating conditions of power transformer. Out of 1234 patterns, 794 patterns are simulated for magnetizing inrush and/or sympathetic inrush conditions, and 440 patterns are generated for internal fault cases including phase-to-ground, phase-to-phase, and turn-to-turn faults respectively. Out of these 1234 patterns, 1086 patterns have been used to construct the OFFBNN. The rest 148 cases have been used to test the generalization ability of the neural network. These 148 test patterns are other than those been used to train the OFFBNN. Fig.13 shows the performance plot of training, validation and test errors and reasonability can be observed since:

- The final mean squared error is very small.
- Test and validation set errors have similar characteristics.
- No significant over fitting has occurred.

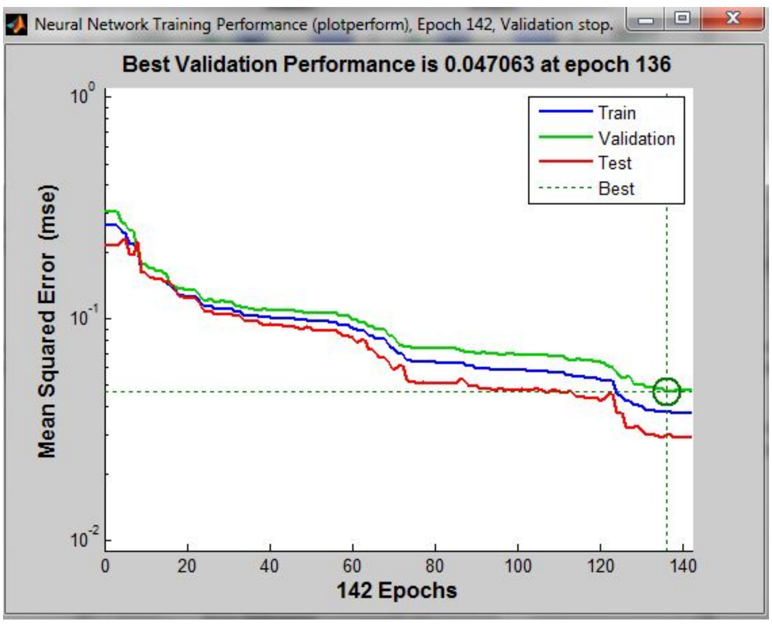


Fig. 13: Typical performance of the OFFBNN

$$Classification\ Error\ \% = \frac{Number\ of\ false\ detections}{Total\ number\ of\ test\ cases}\ X\ 100\% \tag{2}$$

$$Classification\ Accuracy\ \% = 100 - Error\ \% \tag{3}$$

Performance of the proposed scheme is evaluated by calculating the classification error by using eq. (2 and 3) and the accuracy of the proposed scheme is 94.6%. The proposed differential relay is stable in case of external fault and over-excitation conditions. Moreover, this scheme does not require any threshold index to discriminate between the internal fault and inrush condition and it is also free from the harmonic contain of differential current like conventional differential relay.

4. Conclusion

This paper presents a novel power transformer differential protection scheme by using combined Wavelet Transform and Artificial Neural Network which is faster, stable and accurate. Wavelet transform is used for the feature extraction from the differential relaying signal. Dead angle detection in wavelet energy of signal has an advantage that that it will always lie in the first quadrant, as the wavelet energy is always a positive value, thereby making algorithm simpler. The proposed scheme does not require any threshold index to discriminate between the internal fault and inrush condition. The proposed digital differential protection scheme is an intelligent technique based scheme and can be used as effective approach for modern power transformer protection.

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