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Recognition of Power Transformer faults using Wavelet based Neural Networks

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Abstract- Recognition of Power-Transformer Protection is a veryimportant task for the power system operation. In this work, a hybrid of wavelet transform and neural network (WNN) approach is introduced for PTP (Power-Transformer Protection) events classification.The PT(Power Transformer) waveform is first decomposed by four levels Daubechies-4(db4) waveletanalysis and the decomposed waveforms then be processed by the NN for PTP event classification. (4) By utilizing the WNN, the PTP event recognition system can be implemented with minimum neurons and produces maximum attainment. Furthermore, this technique can accommodate maximum training patterns automaticallyreconsider the ANN system. The proposed approach is implemented in a simulation program to verify the validation and classification accuracy.

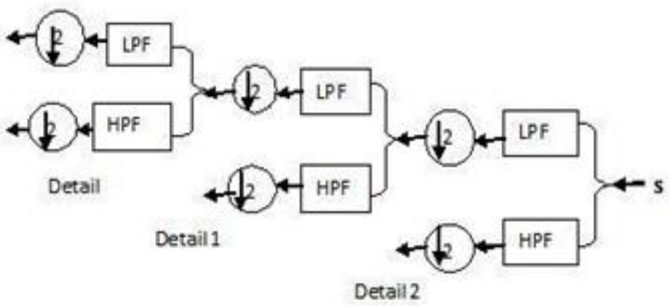
Keywords*-WNN, Power transformer protection, Wavelet Transform, Inrush Current, Internal Fault*

I. INTRODUCTION

Power transformers are devices that need to uniquepreservationdue to their essentially required to the electricalSystem toconnected. Generally,Differential relays are used for the primary protectionof large transformers. Some ofThe situations appear during transformer energisation (inrush currents), CT (currenttransformer) saturation, among others, which canresult in an incorrect trip [4]. The correct and fastdetection ofdifferent faults from the power transformers protection. Regarding therecognition of transformer faults as opposed tomagnetizing inrushcurrents, the approach traditionally used is theaforementioned differential combined technique withharmonic restraint. In this method, transformer inrushCurrent due to energisation is recognized on the basisof second harmonic components Obtained by filters. In this work, we proposed a PTP event classification approach that combined wavelet transform and neural network [4]. There are two main types of features for detecting PT disturbances, which are frequency domain features and time domain features. Wavelet transform method provides time-frequency information simultaneously. Therefore, we utilized wavelet transform method to preprocess the PT data. Then the preprocessed WT data are feed into the neural network for classification. During the training process, the neural network can automatically reconfigure the network structure to improve the classification performance of the system. Therefore, we can obtain a high efficiencyat low neurons, which also intimate lowcompetitioncomplication. This paper is organized as follows: Section II introduces wavelet transform method and its implementation technique. Section II provides briefly introduction of Standard deviation. Section III provides briefly introduction of neural network. Section IV presents the pattern recognition and Transformer faults classification system. Section V provides the experimental results of the proposed approach, and the conclusions are discussed in the last section.Powertransformer faults can deal with complex frequency signals, where in non- uniform bandwidths, can be employed [4]. The applications of wavelet analysis in Power transformer include analysis and detection of electromagnetic transients and fault detection [6]. Among the various applications of the wavelet analysis, current differential relay and linearly divided frequencies are of importance[8].The wavelet families are further classified.Daubieches, Coiflet, Symlet and Meyer are examples of orthogonal wavelet families, while B-Spline is an example of orthogonal wavelet families. Morlet, Gaussian and Mexican Hat are examples of the non orthogonal wavelet families[13], [20]. Appropriate selection of the mother wavelet for signal representation can maximize the advantages of this technique.Moreover, thewavelet transform will be interpreted in termsof the required number of levels of analysis [14], [21]–[23]. This paper proposes a new algorithm based on the wavelet transform and neural network (WNN)) to diagnose magnetizing inrush and internal faults currents in three-phase power transformer. TheWNNdemonstrate reliable and fast responses to fault currents without depending on transformer parameters, loadingconditions and grounding.The results demonstrate the stable, reliable and fast discrimination between the prominent events of magnetizing inrush current and internal faults.

II. WAVELET TRANSFORM

Wavelet transform is used for decomposition of transformer current signals forAnalysis of a various faults. Wavelet analysis is suitable for analysis of transient signal [26]. The WT is an efficient signal processing tool used in power system analysis [26]–[15]. The WT and STFT allow different frequency components to be time localized, with fixed window width function as in STFT.[26].This analyse the frequency and time resolution. However the WT using wavelets as the analyzing function have a self-adjusting capability to the time and frequency relation to thereby creating a opposite matched frequency / width wavelet, i.egreater frequency - narrow width and vice versa.Transients create higher frequency components and have shorter time intervals, in contrast to lower frequency components and higher time intervals. WT has the inherent advantage of focusing on shorter time intervals, thereby picking transients for analysis and discrimination based on current characteristics. [15].



1 Implementation of DWT

Fig. 1 illustrates the implementation Discrete WT (DWT), S - original signal, LPF and HPF: low-pass and high-pass filters respectively. The analysis is done by successive decomposition of the signal i.e. the signal is bifurcated and the two components passed through HPF and LPF. The output of the LPF is again bifurcated and sent through HPF and LPF and this process is repeated up to a predetermined level of decomposition. According to Nyquist's theorem.

III. ARTIFICIAL NEURAL NETWORKS

In many real world applications, the computers have to perform complex pattern recognition problems. Since the conventional computers are obviously not suited to this type problem, the features from the physiology of the brain is borrowed for the basis for the new processing models. Hence, the technology has come to be known as Artificial Neural Networks (ANN). [26]The ANN is an exact simulation of a real nervous system. It can be used to solve complex pattern-matching problems.[26].A Feed Forward Neural Network (FFNN) consists of layers of processing units, where each layer feeds input to the next layer in a feed forward manner through a set of connection strengths or weights. By a suitable choice of architecture for a feed forward network, it is possible to perform several pattern recognition tasks. The constraint on the number of input patterns is overcome by using a two layer feed forward network with nonlinear processing units in the output layer. This modification automatically leads to the consideration of pattern classification problems.[26] While this modification overcomes the constraints of number and linear independence on the input patterns, it introduces the limitations of linear separability of the functional relation between input and output patterns. Classification problems which are not linearly separable are hard problems. In order to overcome the constraint of linear separability for pattern classification problems, a multilayer feed forward network with nonlinear processing units in all the intermediate hidden layers and in the output layer is proposed. While a multilayer feed forward architecture could solve representation of the hard problems in the network, it introduces the problem of hard learning i.e., the difficulty in adjusting the weights of the network to capture the implied functional relationship between the given input-output pattern pairs. The hard learning problem is solved by using the back propagation learning algorithm. The resulting network provides a solution to the pattern mapping problems. The generalization i.e., ability to learn a mapping function of a multi-layer feed forward network with the back propagation learning law depends on several factors such as the architectural details of the network, the learning rate parameter of the training process and the training samples themselves. An ANN performs in two different modes: training and testing. During training, testing is simply an adaptive process during the weights associated the change in order to provide the best possible response to all the signals. Neural networks have reached the desired performance, the learning stage is over and the associated weights are frozen. The final state of the network is preserved and it can be used to classify present, old hidden inputs. At the testing stage, the network receives an input signal and processes it to produce an output. If the network has perfectlydigest, it should be accomplished to conclude, and the original outputformed by the network should be near to as good as the ones produced in the learning stage for similar inputs.

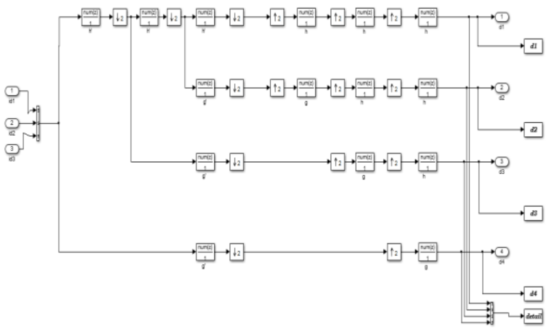


Fig.2 Wavelet Decomposition

The flowchart of the algorithm for WPT based relaying is shown in Figure 5 and is explained in steps.**Step 1**: The current and voltage signals are obtained from the three phase transformer using MATLAB /SIMULINK software for different types of fault and no fault conditions.
Step 2: The differential current for the various cases are calculated.
Step 3: The differential current after the occurrence of the fault or no fault condition are fed to ANN and trained after taking the 500 samples. The output of the fault samples are assigned '1' and the output of the no fault samples are assigned '0'.
Step 4: Next, the ANN classify the internal faults like L-G, LL-G and LLL-G.

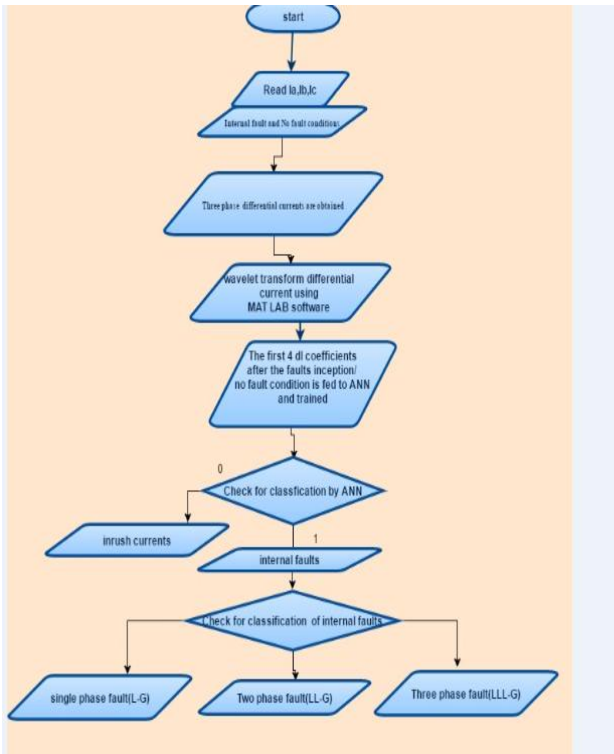


Fig.3Flowchart of the algorithm for WNN

IV. SIMULATION RESULTS

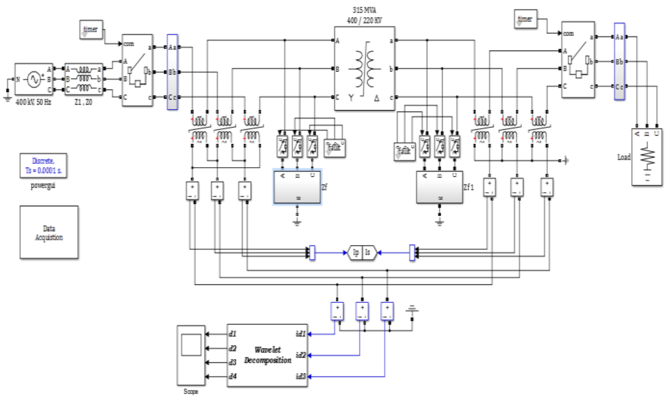


Fig. 4 Configuration OfPower Transformer

The proposed technique is tested on the model of a 3-Φ, 315-MVA, 400/220-kV, 50-Hz core-type Y-Δ power transformer [20]. The 400kVA power transformer is configured as a step-down transformer; its configuration is shown in Fig. 6. In this work, the grounding is Implemented using a resistance RG = 20Ω and leakage inductance 0.6mH. The ground resistance RG connects the neutral point of the Secondary windings with the ground. The experimental setup used for online tests of both power transformers is shown in Fig.7. Two sets of 3 identical CTs, one each on primary and secondary are employed and the methods used to simulate the various faults, was explained earlier.

Case 1: Magnetizing Inrush Current:

For tested power transformer, in most cases, the magnetizing inrush current had a high magnitude with longer time to decay. The WNNbased WT trip signal remained low, indicating that the detected magnetizing inrush current was classified as non fault condition. The simulation results for the case of magnetizing inrush current without a load are shown in Fig.5.

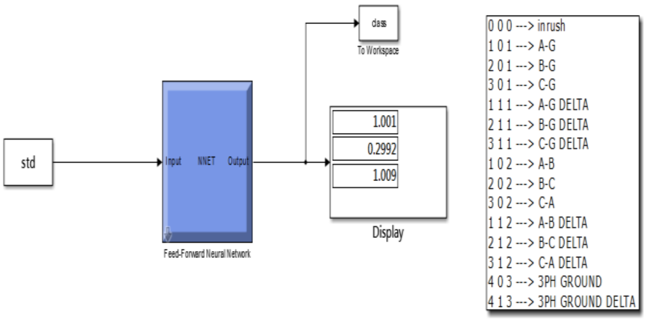


Fig.5 Ann Patter Recognition

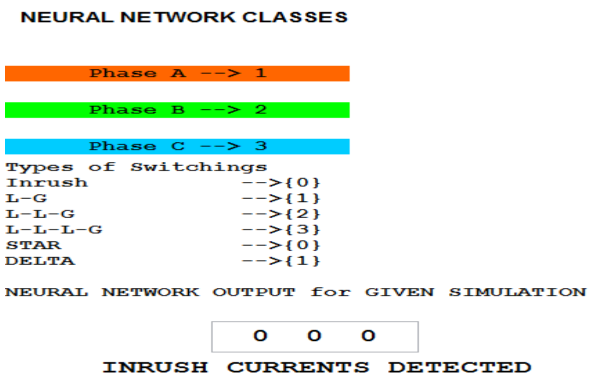


Fig.6 Ann Classes

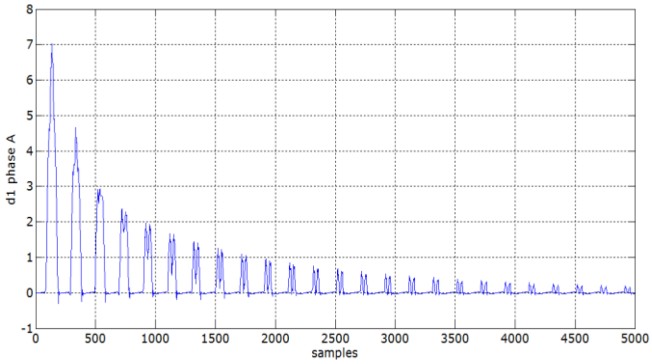


Fig.7 Inrush Current For Phase-A

On WT, there are a number of sharp spikes during the period of inrush current transient. Several sharp spikes occur immediately following the fault inception time, these sharp spikes rapidly decay near zero within ten cycles, whereas those spikes associated with inrush current, are attenuated at the most during a 10 cycle period for small transformers, lasting for 1 min for large units. This difference can be effectively used as a key feature to discriminate an internal fault current from magnetizing inrush current.

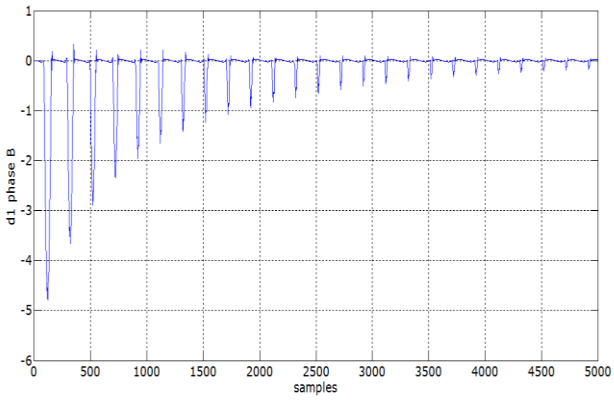


Fig.8 Inrush Current For Phase-B

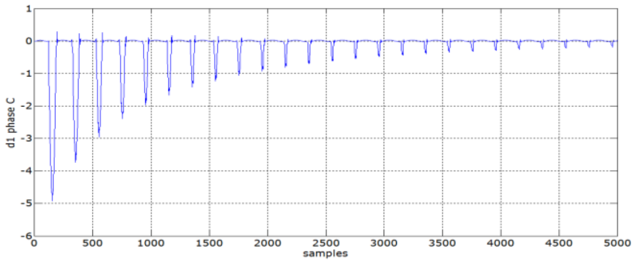


Fig.9 Inrush Current For Phase-C

Fig.7, 8 and 9shows the WT Analysis of the three phases of the inrush current when an unloaded transformer is energized at 0.025Sec with a voltage closing angle of 45 degrees.The normalized amplitudes with d2 coefficients are plotted on X axis and Y axis respectively. d2 transient spikes occur at the start of the inrush current with a slow decay in a time interval of 10 cycles.

Case 2: Single Phase-to-Ground Fault Current

The test for this fault was carried out through connecting phase A to the ground. Fig. 10 depicts the three phase differential currents and the WNN based WT response.It clearly shows that the WNN based WT classify the faults from low to high indicating that an internal fault has been detected in less than five cycles.

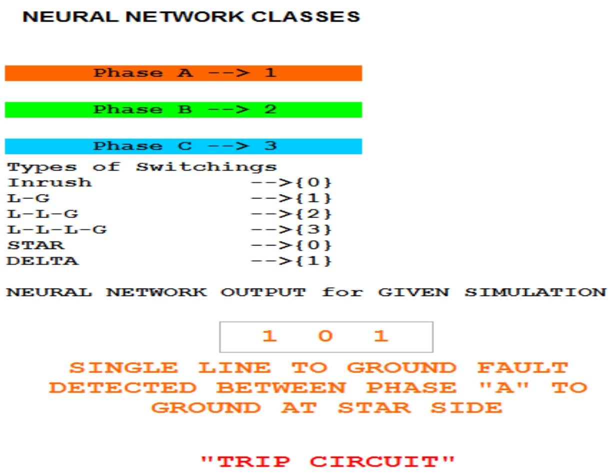


Fig.10 Single Phase-to-Ground Fault.

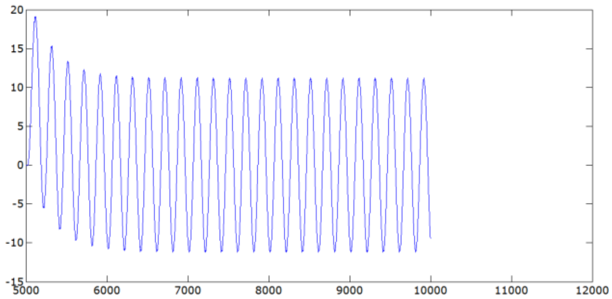


Fig.11 Internal FaultFor Phase-A

Single phase A to Ground (A-G) internal fault with fault resistance of 20 ohms at 0.5 sec for duration of 0.5 sec is simulated and the DWT analysis of differential current for all the three phases are shown in the Fig.11. During internal fault, transients of high frequency are generated in the current. It is observed that the occurrence of transient spike and subsequent decay occur within three cycle.

Case 3: Line-to-Line Fault Current

The test for this fault was carried out through connecting phase A and phase B. Fig.12.Represents the three phase currents and the WNN including WT response of the trip signal. It clearly shows that the WNN based WT trip signal changed its status from low to high indicating that an internal fault has been detected in less than five cycles.

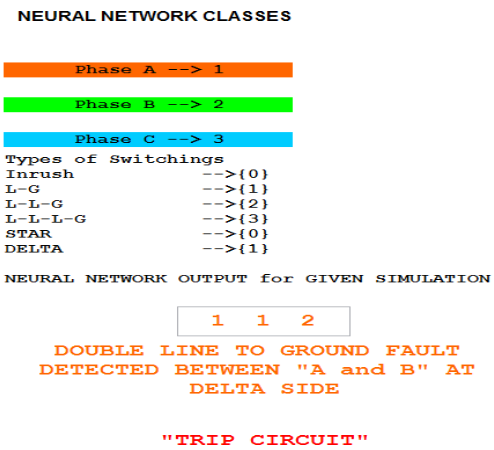


Fig.12Double Line to ground Fault.

Double Line to ground (AB-G) internal fault with fault resistance of 20 ohms at 0.5 sec for duration of 0.5 sec is simulated and the DWT analysis of differential current for all the three phases are shown in the Figure 12.

Case 4: three phase Fault Current

Three Phase Fault Current the test for this fault was carried out through connecting phase A, B and phase C. three phase differential currents are represented in Fig. 12 and Fig.13. It clearly shows that the WNNbased WT signal changed its status from low to high indicating that an internal fault has been detected in less than five cycles.

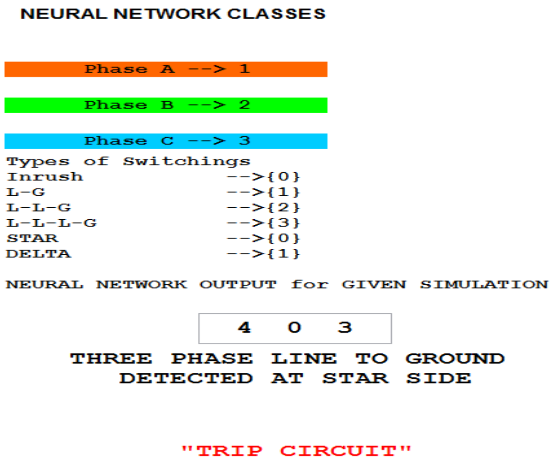


Fig.12 Three Phase Ground Fault.

TEST RESULTS FOR ANN (86.66%)

S.NO	TYPE OF FAULT		TARGET	OUTPUT	FAULT NAME	RECOGNITION
1	Inrush		000	000	inrush	YES
2	A-G	STAR	101	101	A to ground fault	YES
3	B-G		201	201	B to ground fault	YES
4	C-G		301	301	C to ground fault	YES
5	A-G	DELTA	111	101	A to ground fault	FALSE
6	B-G		211	211	B to ground fault	YES
7	C-G		311	311	C to ground fault	YES
8	AB-G	STAR	102	112	AB to ground fault	YES
9	BC-G		202	202	BC to ground fault	YES
10	CA-G		302	302	CA to ground fault	YES
11	AB-G	DELTA	112	112	AB to ground fault	YES
12	BC-G		212	212	BC to ground fault	YES
13	CA-G		312	312	CA to ground fault	YES
14	ABC-G	STAR	403	403	ABC to ground fault	YES
15	ABC-G	DELTA	413	413	ABC to ground fault	YES

Fig.14 Recognition of Ali Fault

In the above table out of 15 test results 13 faults are exactly recognised remaining two faults are not able to recognised so that ANN pattern recognition capacity is 86.6 % in this case only.

V. CONCLUSIONS

In this proposed work tested 15 cases of pattern recognition of power transformer faults. Out of 15 test results 13 faults are exactly recognised remaining two faults are not able to recognise so that ANN pattern recognition capacity is 86.6 % in this case only.

REFERENCES

[1] X. Hao and S. Cai-xin, "Artificial immune network classification algorithm for fault diagnosis of power transformer," IEEE Trans. Power Del., vol. 22, no. 2, pp. 930–935, Apr. 2007.

[2] M. A. Zaman, M. A. Hoque, and M. A. Rahman, "On-line implementation of the artificial neural network based protection for power transformers," in Proc. NECEC, St. John's, NL, Canada, 1996, pp. 5–11.

[3] M. R. Zaman, "Artificial Neural Network Based Protection of Power Transformer," Ph.D. dissertation, Memorial Univ. Newfoundland, St. John's, NL, Canada, 1996.

[4] Chen Xin-gang**,** Zhao Yangyang**,** Zhang Chaofeng and Tian Xiaoxiao'**"**Partial Discharge Pattern Recognition of power transformer by UsingInformation Fusion"Applied Mechanics and Materials Vols 128-129 (2012) pp 933-937 .

[5] S. A. SalehandM. A. Rahman, "Modeling and protection of a three-phase power transformer using wavelet packet transform," IEEE Trans. Power Del., vol. 20, no. 2, pp. 1273–1282, Apr. 2005.

[6] T. S. Sidhu and M. S. Sachdev, "On-line identification of magnetizing inrush and internal faults in three-phase transformers," IEEE Trans. Power Del., vol. 7, no. 4, pp. 1885–1891, Oct. 1992.

[7] P. E. Sutherland, "Application of transformer ground differential protection relays," IEEE Trans. Ind. Appl., vol. 36, no. 1, pp. 16–21, Jan./Feb. 2000.

[8] X. Dong and S. Shi, "Identifying single-phase-to-ground fault feeder in neutral noneffectively grounded distribution system using wavelet transform," IEEE Trans. Power Del., vol. 23, no. 4, pp. 1829–1837, Oct. 2008.

[9] S. A. Saleh and M. A. Rahman, "Testing of a wavelet packet transformbased differential protection for resistance-grounded three-phase transformers," in Conf. Rec. IEEE IAS Annu. Meeting, Hong Kong, Oct. 2005, vol. 2, pp. 852–859.

[10] R. Naresh, V. Sharma, and M. Vashisth, "An integrated neural fuzzy approach for fault diagnosis of transformers," IEEE Trans. Power Del., vol. 23, no. 4, pp. 2017–2024, Oct. 2008.

[11] Ying-Tung Hsiao*, Cheng-Long Chuang*, and Joe-Air Jiang "Recognition of Power Quality Events Using

[12] Wavelet-based Dynamic Structural Neural Networks",

[13] 0-7803-8834-8/05/$20.00 ©2005 IEEE.

[14] Y. T. Hsiao, C. L. Chuang, C. C. Chien, "Novel dynamic structure neural network for optical character recognition," Proceedings of the 4th IEEEInternational Symposium on Signal Processing and Information Technology, Rome, Italy, Dec. 2004.

[15] G. Zheng, M.X. Shi, D. Liu, J. Yao, Z.M. Miao, "Power quality disturbance classification based on rule-based and wavelet-multi-resolution decomposition," Proceedings of 2002 International Conference on MachineLearning and Cybernetics, vol. 4, 4-5 Nov. 2002, pp. 2137-2141.

[16] S. A. Saleh, "AWavelet Packet Transform-Based Differential Protection of Three-Phase Power Transformers," Master's Thesis, Memorial Univ.f Newfoundland, St. John's, NF, Canada, 2003.transformers," IEEE Trans. Power Del., vol. 22, no. 4, pp. 2126–2131, Oct. 2007.

[17] T. S. Sidhu, M. S. Sachdev, H. C. Wood, and M. Nagpal, "Design, implementation, and testing of a micro-processor based high speed relay for detecting transformer winding faults," IEEE Trans. Power Del., vol. 7, no. 1, pp. 108–117, Jan. 1992.

[18] S. K. Pandy and L. Satish, "Multiresolution signal decomposition: A new tool for fault detection in power transformers during impulse tests," IEEE Trans. Power Del., vol. 13, no. 4, pp. 1194–1200, Nov. 1998.

[19] C. K.Wang, C.W. Lam, K. C. Lei, and Y. D. Han, "A novel wavelet approach to current differential pilot protection," IEEE Trans. Power Del., vol. 18, no. 1, pp. 20–25, Jan. 2003.

[20] E. Y. Hamid and Z. I. Kawasaki, "Wavelet-based data compressionfor power disturbances using minimum description length data," IEEE Trans. Power Del., vol. 17, no. 2, pp. 460–466, Apr. 2002.

[21] M. G. Morante and D. W. Nicoletti, "A wavelet-based differential transformer protection," IEEE Trans. Power Del., vol. 14, no. 4, pp. 1351–1358, Nov. 1999.

[22] O. S. Youssef, "A wavelet-based technique for discrimination between faults and inrush currents in transformers," IEEE Trans. Power Del., vol. 18, no. 1, pp. 170–176, Jan. 2003.

[23] C. K. Chui, Wavelets: A Mathematical Tool for Signal Processing. Philadelphia, PA: SIAM, 1997.

[24] Matlab: Wavelet Tool Box, 1995. Mathworks, Ver. 6.1.

[25] G. Stang and T. Nguyen, Wavelets and Wavelet Filter Banks. Wellesley, MA: Wellesley-Cambridge, 1996.

[26] Applied Protective Relaying,Westinghouse Elect. Co., Newark, NJ, 1976.

[27] T. S. Sidhu, J. Burnworth, A. Darlington, B. Kasztenny, Y. Liao, P. G. McLaren, M. Nagpal, M. S. Sachdev, M. M. Saha, M. Swanson, and P. B. Winston, "Bibliography of relay literature, 2006 IEEE Committee Report," IEEE Trans. Power Del., vol. 23, no. 4, pp. 1864–1875, Oct. 2008.

[28] SuribabuMiriyala ,Dr.Sanker Ram,"Fuzzy Logic Techniques and Wavelet Transform Based Differential Protection for Power Transformer",International Journal of Innovative Research in Science, Engineering and Technology(IJIRSET),Vol. 5, Issue 12, December 2016

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