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Fault Detection Using Artificial Neural Network and Wavelet Transforms for Power Transformer

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Abstract: The requirement for a stable supply of electrical energy to meet the needs of the modern world has expanded dramatically, necessitating near-faultless power system functioning. The main goal is to reduce the frequency and duration of undesired power transformer outages by imposing a high point demand that includes criteria for dependability (no false tripping) and operating speed (quick fault detection and clearance time). For many years, the second harmonic restraint concept has been widely applied in industrial applications. It employs the discrete Fourier transform (DFT) and frequently confronts issues like lengthy restrain times and the inability to distinguish internal defects from magnetizing inrush circumstances. As a result, artificial neural networks (ANNs), a strong tool for artificial intelligence (AI) that can imitate and automate information, have been suggested for defect identification and tracking in normal and inrush conditions. For the investigation of power transformer transient conditions under diverse settings, the wavelet transform (WT) is utilized, which has the capacity to extract information from transient signals in both the time and frequency domains at the same time. In the MATLAB/SIMULINK environment, all of the above-mentioned conditions of a power transformer to be investigated in a power system are modelled.
Keywords: Artificial Neural Network, Power Transformer, Differential Protection, Wavelet Transform.

I. INTRODUCTION

Transformers are necessary and vital components of power systems. Power transformer protection measures vary based on the situation due to their sizes and variety. High rupturing capacity (HRC) fuses will serve for small distribution transformers with less than 1.5 MVA. Overcurrent relays are used by others. Deferential protection based on the circulating current theory is frequently used for bigger power transformers. Differential protection compares primary and secondary currents by converting them to a common base. During normal operation, the difference between these currents is negligible. For external defects, the difference is also minimal, but it is bigger than for normal operating conditions. However, when a transformer experiences an internal fault, the difference becomes significant. For optimal operation, differential protection is predicated on matching the transformer's primary and secondary currents. When a transformer is turned off, it usually leaves some residual flux in its core. The core is likely to saturate when the transformer is re-energized later. The primary windings of a saturated transformer draw significant magnetizing currents from the power system. The differential protection relay is activated because of the significant differential current.

Significant efforts have been made to develop digital relaying algorithms due to the multiple benefits of digital relaying in terms of costs, performance, dependability, and flexibility. There have been several algorithms proposed for the deferential protection of power transformers [1], [2], and [3]. In general, an acceptable protection scheme has the following characteristics: dependability, cost, ease of use, and high speed of operation.

Traditional digital protective relays have several flaws. For example, they are typically based on algorithms that estimate the basic component of current and voltage signals while ignoring higher frequency transient components. Furthermore, phasor estimate necessitates a cycle's sliding window, which might result in a large delay. Furthermore, precision cannot be guaranteed. For examining the frequency content of stationary processes, the Fourier transform is quite useful. Other approaches for estimating the frequency content must be used when working with non-stationary systems.[4]

As a result, wavelet decomposition is suitable for analysing transitory signals and achieving significantly better current characterization and discrimination. Wavelets allow a signal to be decomposed into several levels of resolution (frequency octaves). Large windows are utilized to acquire the low frequency components of the signal, whereas tiny windows reflect discontinuities, because the basis function (Mother Wavelet) is dilated at low frequencies and compressed at high frequencies. [5].

II. MATHEMATICAL MODEL OF PROPOSED MODEL

Starting with the DT signal x[n] of length N, the first level m = 1 decomposition produces two sub band DT signals as

$$a^1[n] = \sum_{k=0}^{N-1} g[k]\, x[n-k]$$

$$d^1[n] = \sum_{k=0}^{N-1} h[k]\, x[n-k]$$

where a1[n] and d1[n] are the first-level approximations and the first level details respectively. k is a constant, and g[n] and h[n] are the low-pass filter and the high-pass filter respectively, which are associated with the used wavelet function. To increase the frequency resolution and ensuring the time localization of each frequency sub band, the outputs of both the filters i.e., Low Pass Filter (LPF) and High Pass Filter (HPF) are down sampled by two at the end of each stage of filtering. The second-level decomposition (m = 2) produces following four sub bands.

$$aa^2[n] = \sum_{k=0}^{\frac{N}{2}-1} g[k]\, a^2\left[\frac{N}{2}-1\right] \tag{3}$$

$$ad^2[n] = \sum_{k=0}^{\frac{N}{2}-1} h[k]\, a^2\left[\frac{N}{2}-1\right] \tag{4}$$

$$da^2[n] = \sum_{k=0}^{\frac{N}{2}-1} g[k]\, d^1\left[\frac{N}{2}-1\right] \tag{5}$$

$$dd^2[n] = \sum_{k=0}^{\frac{N}{2}-1} h[k]\, d^1\left[\frac{N}{2}-1\right] \tag{6}$$

Where, dd2[n] represents the highest frequency sub band of the second level of the WT decomposition equation 2 and 4. Fig. 1 shows Decomposing of a discrete signal x[n] using a two- level WT. The successive Low pass filtering (LPF) and High pass filtering (HPF) stages implement the WPT decomposition.

Wavelet Transform (WT) is generated by analysing the input current signal to a tree of low pass and high pass filtering operations as shown in figure 1. Down- sampling by 2 is taking place between any two successive levels. It is clear from the figure 1 that the frequency bandwidth of the levels band decreases with the growing of the level number, which means that the frequency resolution becomes higher by the increase of the level number.

However, the higher the number of the levels the higher the processing time of the signal. The increase of the processing time is a problem when the number of the levels needed is high.

It is obvious from the figure that by decomposing the signal f(n) the low and high frequencies, the low frequency of the first level is the approximation a1[n] of the signal and the high frequency is the details d1[n] of the input signal. Where the super fix 1 and 2 refers to the 1st and 2nd level of the wavelet decomposition respectively. Each part in the first level is also decomposed in the same manner into two parts of approximations and details. Therefore, it will produce four sub-bands by using the same filters used in the first level of decomposition.

These basis functions are generated from one base function called the mother wavelet. The first and second level sub-bands are obtained using two filters (low and high).

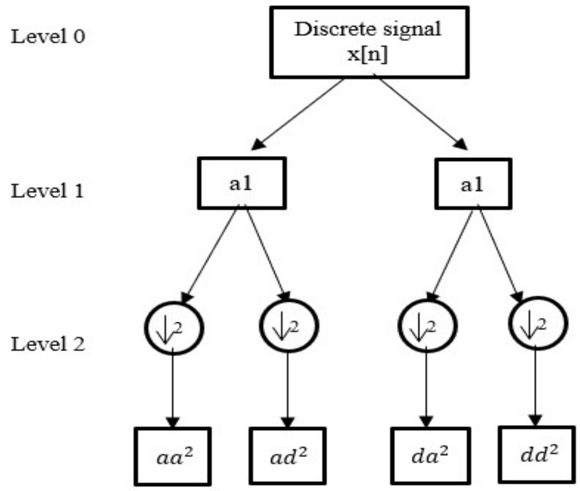

Figure 1: Decomposing of a discrete signal x[n] using a two- level WPT

In transmission lines, there are four basic types of faults that can develop.

1) SLG (single line to ground) is an asymmetrical fault characterized by a sharp increase in phase current and a sharp decrease in the faulted phase voltage. When compared to other forms of defects, it is the most common in transmission lines.
2) LLG (double line to ground): This is another unsymmetrical fault that has the same tendency as the LG fault in that it involves two faulted phases.
3) LL (Line to Line Fault): Unsymmetrical fault with a downward trend in phase voltage and a sudden rise in currents on all three phase voltages and currents that does not include a zero-sequence component.
4) LLL (Triple Line Fault): This is a symmetrical defect that causes all three phase voltages to collapse and all three phase currents to surge suddenly.

Wavelet transform is used to recognize inrush current and separate it from internal transformer faults utilizing an Artificial Neural Network (ANN) as a classifier, keeping the above points in mind. Figure 2 depicts a schematic representation of the planned work. Wavelet transform is used to extract valuable information from both defective and inrush generated transient current signals in the proposed technique. This data is subsequently utilized to train the ANN to distinguish between transients and relay malfunctions.

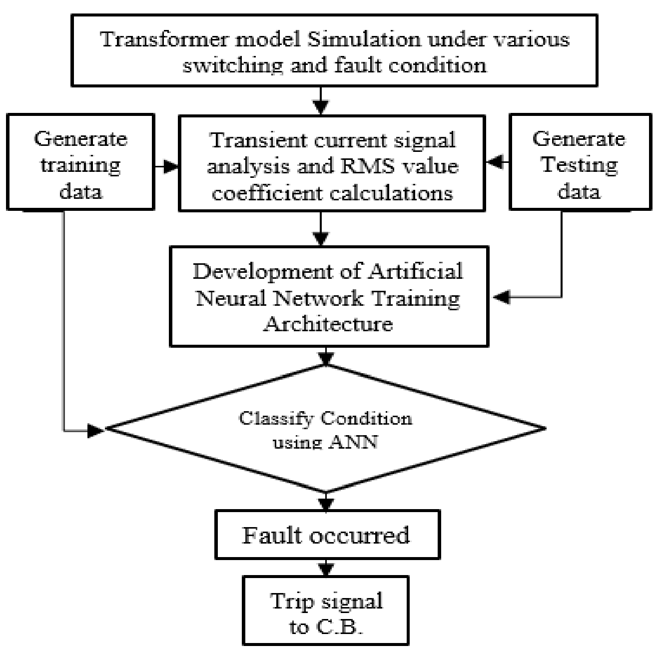

Figure 2: Proposed model flow chart

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III.RESULT

In the MATLAB environment, a power system network is simulated, as shown in Figure 3. Table 1 lists the power transformer's parameters. Current transformers are used to measure primary and secondary currents, and wavelet analysis is applied to signals collected under three different conditions: normal operation, magnetizing inrush, and internal fault. The simulation lasts 0.5 seconds, and the data is collected in two cycles with 130 samples each.

In this proposed method, wavelet transform is first applied to decompose the differential current signals of power transformer system into a series of wavelet components each of which covers a specific frequency band. Thus, the time and frequency domain features of the transients' signals are extracted for normal current, magnetizing inrush current, over excitation current, internal fault current. The sample of the differential current for 0.5 sec. is taken and is proceeded in MATLAB Wavelet Tool box. One of the most popular mother wavelets suitable for a wide range of applications is Daubechies's wavelet. In this work Db6 wavelet is used. The implementation procedure of Wavelet Transform, in which x[n] is the original signal obtained from workspace Current1, Current2 and Current3. At the first stage, an original signal Current1, Current2 and Current3 is divided into two halves of the frequency bandwidth and sent to both high-pass filter and low- pass filter. Then the output of low pass filter is further cut in half of the frequency bandwidth and sent to the second stage; this procedure is repeated until the signal is decomposed to a pre-defined certain level 6.

Transformer Rating	250 MVA
Transformer frequency	50 Hz
Transformer Winding Parameters	R = 0.002 pu, L = 0.08 pu
Magnetizing Resistance (Rm)	500 pu
Magnetizing Reactance (Rm)	500 pu

Table 1: Power transformer specification

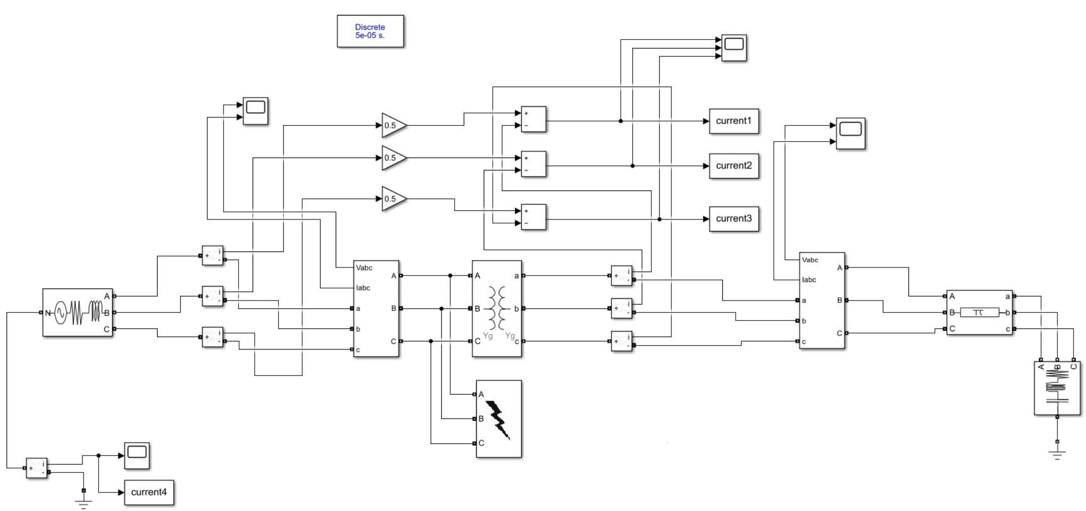

Figure 3: Simulink Model of Power Transformer Protection

The set of signals thus represent the same original signal, but all corresponding to different frequency bands. It is pointing out that the frequency band of each detail of the wavelet transform is directly related to the sampling rate of the original signal. If the original signal is being sampled Fs Hz, the highest frequency that the signal could contain, from Nyquist's theorem, would be Fs/2 Hz.

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This frequency would be seen at the output of the high frequency filter, which is the first detail. Thus, the band of frequencies between and would be captured in detail 1; similarly, the band of frequencies between and would be captured in detail 2, and so on. The WT is applied with four types of waveforms. These are normal condition, magnetizing inrush condition, over excitation condition and internal fault condition. WT coefficients for each condition obtained, for instance the average value, maximum value and normalization value can be calculated for these wavelets transform coefficients. The total number of the wavelet transform coefficients stays the same due to the nature of the discrete transform process. The mean values of d1 (first level), a1 (first level), the average value of d1 (first level), a1 (first level), and the normalization of d1 (first level), a1 (first level) are calculated and stored. Each of the values of every single coefficient is also a feature of the data. The signal data generated by Simulink in MATLAB. Signals are sampled at the sampling rate of 40 samples per cycle (over a data window of half cycle).
Different types of faults have been considered for the purpose of analysis. These faults are detected based on recognizing their wave shapes, more precisely, by differentiating their wave shapes from the fault current wave shapes using wavelet transform. These are as follows:

A. Normal Operating Condition

The normal operating current waveform for phase R, Y and B is shown in Figure 4. For the simulated transformer, the rated current is 50 A. Figure 5 depicts the wavelet decomposition of a normal condition with five levels of approximation and detailed coefficients. It is simulated using 1000 samples across two cycles (0.5 sec).

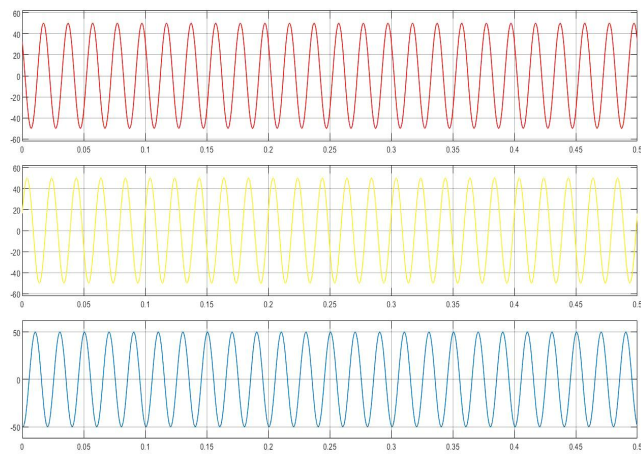


Fig 4: Normal operating current waveforms of phase RYB respectively.

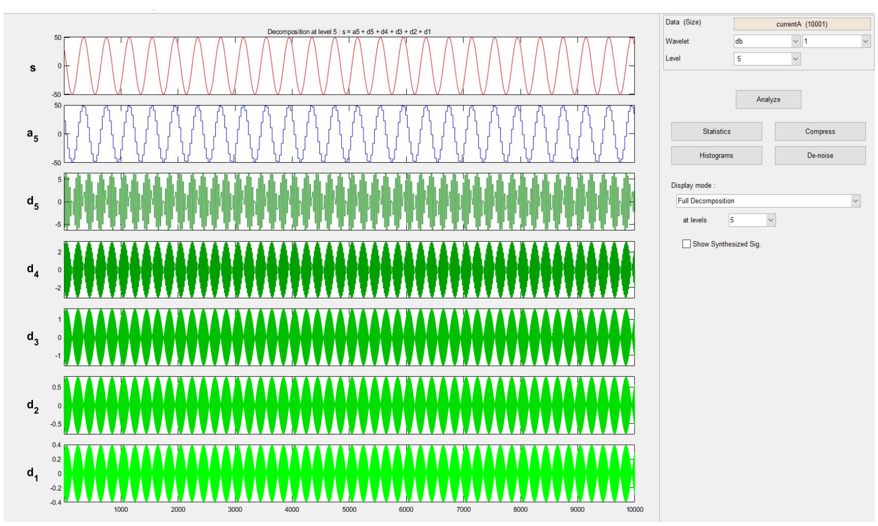


Fig 5: The wavelet decomposition of a normal condition

B. Line to Ground (LG) Fault Condition

The Line to Ground Fault Condition waveforms is shown in Fig 6. Fig 7 shows the wavelet decomposition of LG fault condition. Figure 6 illustrates a 0.2-second simulation of the LG fault waveform for phase A. Inrush current is 300 A, which is approximately three times the rated current. As a result, the differential relay perceives the excessive current as a fault and trips. In a transformer, flux is determined by residual flux, switching instant, and core magnetic characteristics.

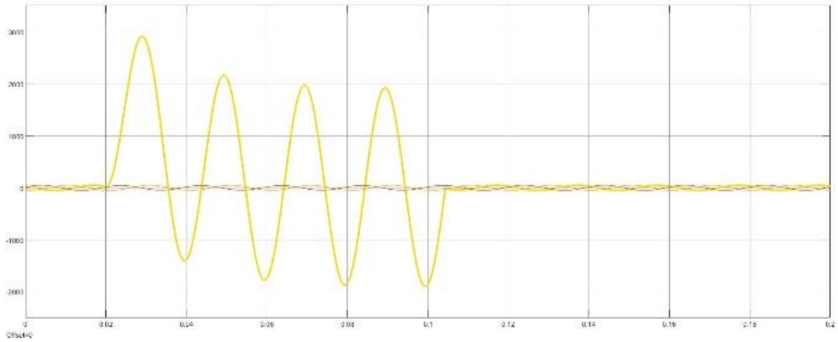


Fig 6: Line to Ground (LG) Fault Condition waveforms.

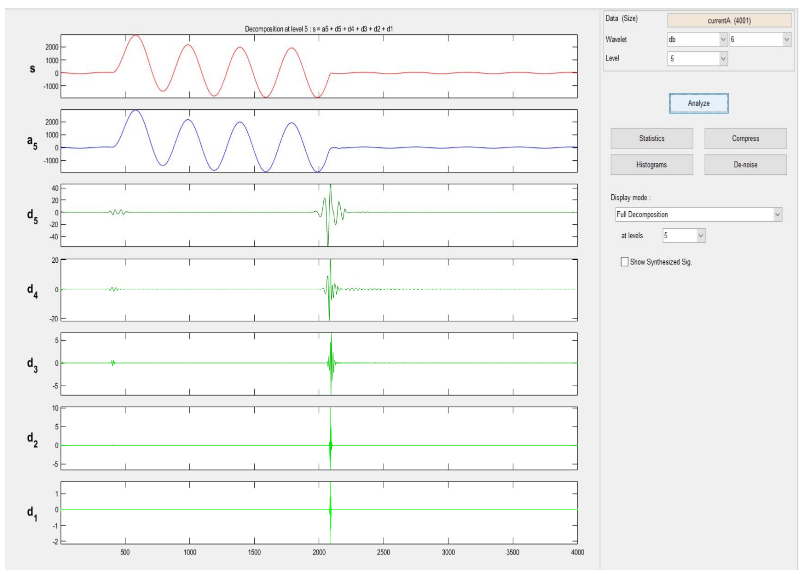


Fig 7: The wavelet decomposition of LG fault condition.

C. Double Line to Ground (LLG) fault condition

Fig 8 shows Double Line to Ground (LLG) Fault Condition waveforms as well as Fig 9 the wavelet decomposition of (LLG) fault condition. Wavelet analysis is performed using dB6 level 5 in this work. Figure 9 depicts the wavelet decomposition of the magnetizing inrush current in phase A, with approximate and detailed coefficients at five levels. It is simulated with 1000 samples for two cycles (0.2 sec).

Fig 8: Double Line to Ground (LLG) Fault Condition waveforms.

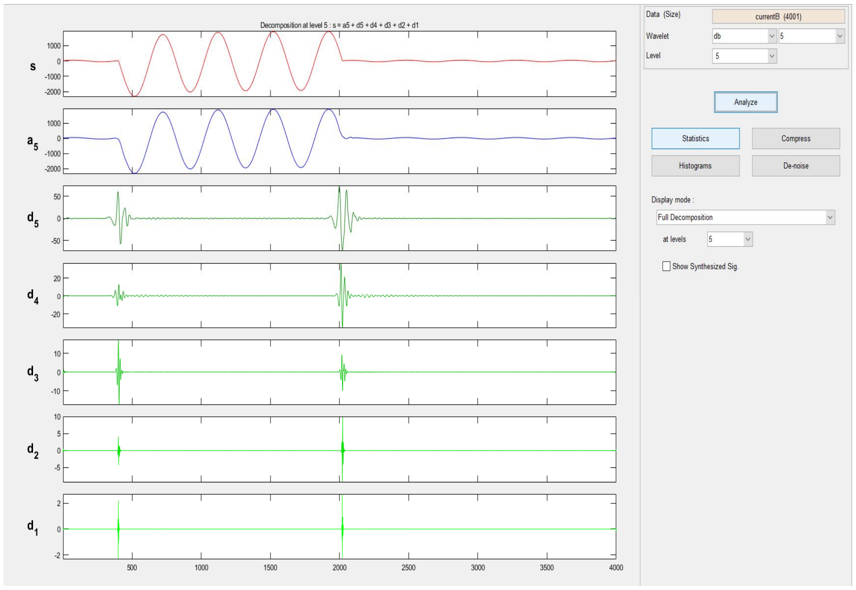


Fig 9: The wavelet decomposition of (LLG) fault condition.

D. Triple Line (LLL) Fault Condition

Fig 10 shows Triple Line (LLL) Fault Condition waveforms as well as Fig 11 The wavelet decomposition of (LLL) fault condition. Wavelet analysis is performed using dB6 level 5 in this work. Figure 11 depicts the wavelet decomposition of the magnetizing inrush current in phase A, with approximate and detailed coefficients at five levels. It is simulated with 1000 samples for two cycles (0.2 sec).

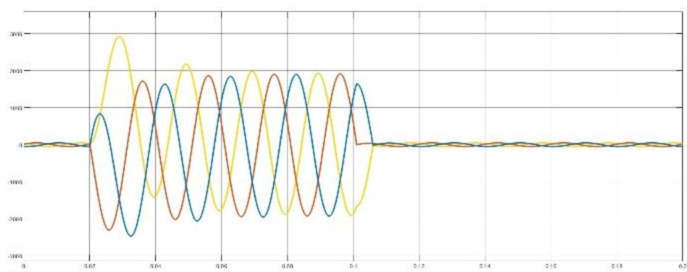


Fig 10: Triple Line (LLL) Fault Condition waveforms.

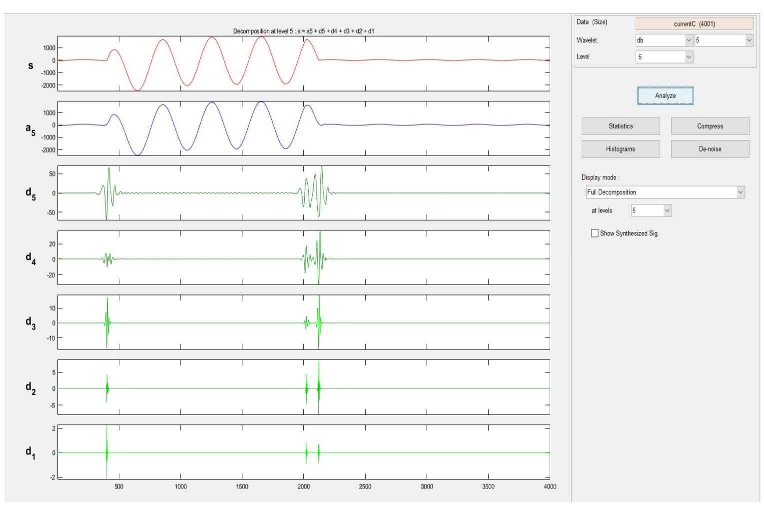


Fig 11: The wavelet decomposition of (LLL) fault condition.

E. Neural Network Analysis

The neural network is two-layered, with 4 neurons in the output layer; nevertheless, there are 10 hidden neurons and 4 inputs (detail and estimated coefficients) in the network. The Fig 12 shows Neural Network Architecture.

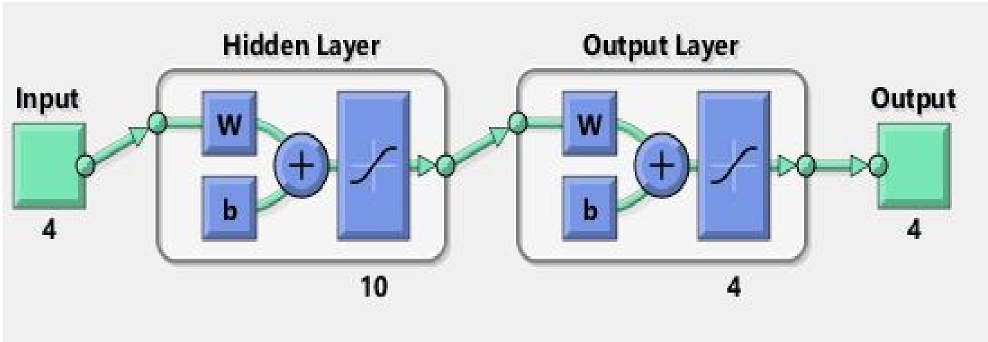


Fig 12: Neural Network Architecture

The Simulink generated 126 training sets of samples (100 sets for training and 26 sets for testing) in MATLAB. At a sampling rate of 40 samples per cycle, signals are captured (over a data window of half cycle). The transients in power transformers were analyzed using the Wavelet transform. The MATLAB (Wavelet Analysis) software is used to calculate the DWT coefficients of the signals using the data obtained from the simulations. This 100-coefficient training set has four different power transformer circumstances (normal, magnetizing inrush, overexcitation, and internal fault). Normal has 12 sets of coefficients, Line to Ground (LG) fault has 33 sets of coefficients, Double line to ground fault has 33 sets of coefficients, and Triple Line fault (LLL) as well as Triple line to ground fault (LLLG) has 11 sets each of coefficients.

After extensive testing, a hidden layer network with 10 neurons, 4 inputs, and 4 outputs was proven to be suitable for monitoring the various conditions of a power transformer. The network's outputs have a distinct set of values (for example, 0000 = normal, 1001/0101/0011 = Line to Ground fault, 1101/0111/1011 = Double line to ground fault, 1110 = Triple Line fault, 1111 = Triple line to ground fault). This network, which has four outputs, monitors all situations in the power transformer and only sends out a trip signal if there is an internal fault, which occurs when output is 0101. The training data of neural network is shown in table 2.

S. No.	Type of Fault	Maximum Coefficient of Phase current			
		Phase A	Phase B	Phase C	Ground
1	No Fault	0.2165	0.1703	0.0511	4.4114e-13
2	A-G Fault	3.7083	0.1703	0.0511	10.7322
3	B-G Fault	0.2165	4.9203	0.0511	11.0980
4	C-G Fault	0.2165	0.1703	1.2278	9.0851
5	AB-G Fault	3.2446	4.9203	0.0511	11.2850
6	BC-G Fault	0.2165	4.9209	2.4476	11.0412
7	AC-G Fault	3.2443	0.1703	0.6906	11.1381
8	ABC Fault	5.6040	4.9210	2.8130	0.0017
9	ABC-G Fault	2.7761	4.9210	1.6953	11.6952

Table 2: Training data for neural network.

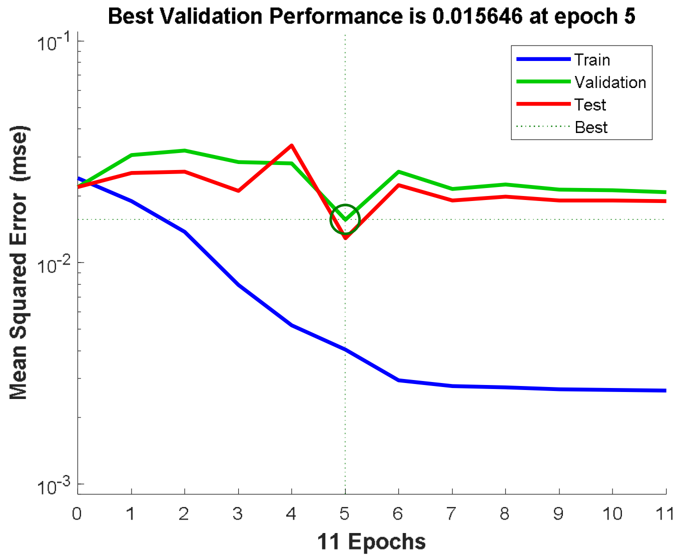


Fig 13: Neural Network training performance

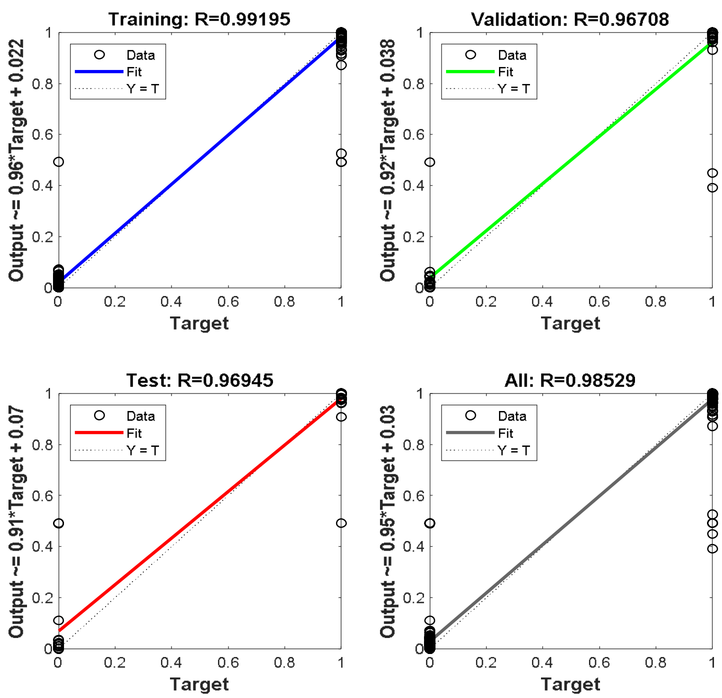


Fig 14: Neural Network training Regression

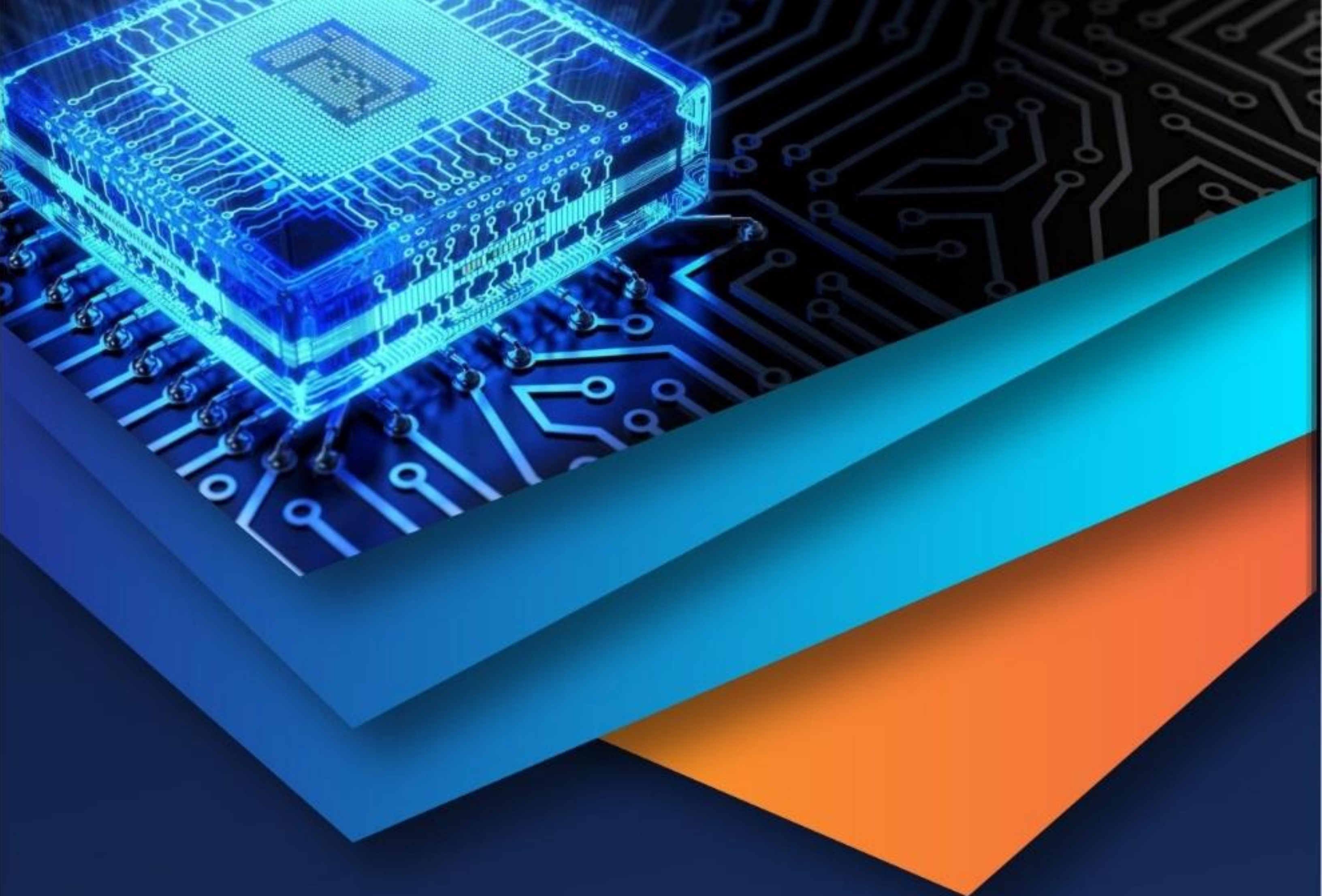
The number of inputs to the network and the number of neurons in the hidden layer were determined empirically when it came to the ANN construction. Experimenting with different network setups is a part of this process. The BP training approach has been discovered to perform satisfactorily with ANNs with fewer inputs and 10 neurons in the hidden layer. After 11 iterations, neural network training, the learning process was shut down. Also, Fig 13 which shows Neural Network training performance After 5 epochs, the suggested network's training error was 0.015646, which was within acceptable bounds. Also, in Fig 14 Neural Network training Regression the training R = 0.99195 which is best training regression as it is approximately 1. In all circumstances, the network performs admirably, properly distinguishing between normal, inrush, over-excitation, and internal fault currents. Here, we'll talk about the competitive model and how well it works.

IV. CONCLUSION

In this study, the Wavelet and Neural Network models for power transformer protection are discussed. The 4 input, 10 hidden layer, 4 output layer and 4 output architecture was capable of correctly distinguishing between various power transformer situations such as normal, magnetizing inrush over-excitation, and internal fault. The FFBP is effective at addressing classification problems, and a differential relay can be thought of as a classifier that determines what type of network event occurs. Neural Network training performance After 5 epochs, the suggested network's training error was 0.015646, which was within acceptable bounds. Also, Neural Network training Regression the training R = 0.99195. WNN was trained for all possible sets of simulated data under various transformer operating conditions. For power transformer differential relaying, WNN-based differential relaying shows promise in terms of security, accuracy, and speed. Within half of a cycle, the WNN effectively identifies and provides a trip signal, which is very quick.

REFERENCES

[1] M.A. Rahman, B. Jeyasurya, "A State-of-The-Art Review of Transformer Protection Algorithms", IEEE Transactions on Power Delivery, Vol. 3, No. 2, April 1988.
[2] M.A. Rahman, B. So, M. R. Zaman, M.A. Hoque, "Testing of Algorithms for A Stand-Alone Digital Relay for Power Transformers", IEEE Transactions on Power Delivery, Vol. 13, No. 2, April 1998.
[3] M. Habib, M.A. Marin, "A Comparative Analysis of Digital Relaying Algorithms for Differential Protection of Three Phase Transformers", IEEE Transactions on Power Systems, Vol. 3. No. 3, August 1988.
[4] M. Fancisco, A.A. Jose, "Wavelet Based ANN Approach for Transmission Line Protection", IEEE Power Engineering Review, 2003.
[5] G.-M. Moises, W.N. Denise, "A Wavelet-Based Differential Transformer Protection", IEEE Transactions on Power Delivery, Vol. 14, No. 4, October 1999.
[6] A. Guzman, S. Zocholl, G. Benmouyal, H. Altuve, "A current-based solution for transformer differential protection-part i: problem statement", IEEE Trans. Power Del. 16 (4) (2002).
[7] G. O. Rockerfeller, "Fault protection with digital computer", IEEE transactions on power apparatus and systems, vol. PAS-88, no 4, pp 438-461, 1969.
[8] J. C Maun, "Hardware and software design of a digital protection relay for power transformers", conference on computer relaying – future directions and impacts pp 1-19, 1988.
[9] M. M Saied, "A study on the inrush current phenomena in transformer power system protection and relay testing substations", IEEE Volume: 2, 30 Sept.-4 Oct. 2001 Pages: 1180 – 1187 vol.2.
[10] N. T Stringer, L. Lawhead, T. Wilkerson, J. Biggs, Rockefeller, "Testing and performance of transformer differential relays", IEEE, Volume: 3, Issue: 4, July-Aug. 1997 Pages: 36 – 420.
[11] N. T Stringer, L. Lawhead, T. Wilkerson, J. Biggs, Rockefeller, "Real-time transient testing and performance of transformer differential relays", IEEE Volume: 2, 8-12 Pages: 1142 - 1150 vol.2 U, Oct. 1995
[12] H. Bronzeado, R. Yacamini, R., "Phenomenon of sympathetic interaction between transformers caused by inrush transients", IEEE, Volume: 142, Issue: 4, Pages: 323 – 329 July 1995.
[13] K. Yabe, "Power differential method for discrimination between fault and magnetizing inrush current in transformers", IEEE Transactions on, Volume: 12, Issue: 3, Pages: 1109 - 1118July 1997.
[14] Hao Zhang a, Pei Liu a, O.P. Malik, "A new scheme for inrush identification in transformer protection", Electric Power Systems Research 63 (2002).
[15] H Kazemi Kargar, M Jabbari, and S Golmohammad-zadeh. "Inrush current identification based on wavelet transform and correlation factors". In IEEE Int. Conf. on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, volume 1, pages 50–53, 2009.
[16] B A1-Fakhri, I. Elagtal, "A Unique Current Differential Based Algorithm for Protection of Three -Winding Transformers and Busbars". IEEE 2001.
[17] K. K. Gupta and D. N. Vishwakarma, "Numerical Differential Protection of Power Transformer using Algorithm based on Fast Har Wavelet Transform" Indian Institute of Technology, Kharagpur 721302, December 27-29, 2002.
[18] T. Zheng, J. Gu, S. F. Huang, F. Guo and V. Terzija, "A New Algorithm to Avoid Maloperation of Transformer Differential Protection in Substations with an Inner Bridge Connection". IEEE Transaction on power delivery vol, no,3, 27, NO. 3, JULY 2012.
[19] K. Behrendt, N. Fischer, C. Labuschagne, "Considerations for using harmonic blocking and harmonic restraint techniques on transformer differential relays", Journal of Reliable Power 2 (3) (2011) 36–52.
[20] E. Alia, A. Helalb, H. Desoukib, K. Shebla, S. Abdelkadera, O.P. Malik "Power transformer differential protection using current and voltage ratios" Electric Power Systems Research 154 (2018) 140–150.
[21] Dmitry A. Etingov, Denis S. Fedosov "Development of Restraint Algorithm for Improvement of Reliability of Transformer Differential Protection During External Short Circuits" International Ural Conference on Electrical Power Engineering (UralCon), 2019.



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