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Advanced detection and discrimination of power transformer internal faults from other abnormal condition using DWT-based feature extraction and ANN classification

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*ABSTRACT

Power transformers are one of the most critical elements of the electrical Power System because of the aforementioned function in the voltage regulation and power supply. It is very important in the field of power engineering to be able to differentiate the inrush currents caused due to the energization of the transformer from the internal fault currents created in the transformer. This paper represents an efficient approach to solving this issue by employing DWT feature extraction and ANN classification. This approach is based on the determination of waveforms by distinguishing the D4 and D5 coefficients of instantaneous differential currents using DWT. These coefficients present much useful information related to the waveform type, making it possible to differentiate between the inrush and the internal fault currents. This is a key factor when making classification in that these criteria are related to the energy content involved within these coefficients. This energetic approach forms the basis for the ANN controller to determine particular decisions about the quality of the current. This proposed approach is supported with simulation to represent empirical data in supporting the use of this approach. The results always confirm the efficiency of such an approach to the differentiation between inrush and internal fault currents with a high percentage of accuracy. The effectiveness of this method goes beyond accuracy as it is reliable, responds quickly to abnormal conditions, and can be applied to a variety of power transformer types. Applying this concept in real grid power systems can lead to increased reliability and less downtime thereby strengthening the electrical system as a whole. The reliability and safety of power transformers remain a critical concern in power engineering. The present paper proposes a new method to improve power transformer protection for differentiating internal faults from other abnormal situations. The method described herein utilizes advanced signal processing and machine learning with the help of DWT and ANN to reach higher standards of accuracy and reliability.

Keywords: Power transformers, Inrush currents, Internal fault currents, Discrete wavelet transform, Artificial neural networks, Feature extraction, Classification, Power system protection.

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1. Introduction

Power transformers are the most critical components of electrical distribution systems because they control voltage and transfer electrical energy at high levels of efficiency. These are essential resources that will underpin the reliability of the modern power supply system. However, they are not immune from emergencies and failures, which can be catastrophic to the whole power system. Another main issue that power engineers face while dealing with these transformers is the correct differentiation between inrush currents and internal fault currents in them[1]. It should be noted that the protection of electricity transformers is very crucial. Considering the huge capital outlay for these transformers coupled with their importance in the generation and distribution of power, any protection schemes for these transformers must be very sensitive and reliable with regard to fault clearance. Among all these, the protection relay is the key component and in the case of the transformer, the differential relay is the most suitable one. This is because differential protection systems are highly sensitive and reliable especially when used in high power transformers

However, the reliable operation of differential protection systems is challenged by the need to differentiate between magnetizing inrush currents and internal fault currents. This leads to maloperation where the protection system is activated due to the presence of inrush currents [2], [3]. This is further compounded in the case of energizing faulty transformers or during inrush current events during startup. These events are characterized by the generation of harmonic restraint quantities that can affect the operation of differential protection elements [4]. Furthermore, As stated in [5], [6], delays in backup protection systems can increase the damage inflicted by these transient inrush currents. Furthermore, conditions like rainwater accumulation within transformer enclosures and insulation damages also contribute to the problem because such conditions may cause increased inrush currents that may mislead the protection system to operate erroneously [7].

To solve this challenge massive research has been done in the field to distinguish magnetizing inrush currents from internal fault currents. These efforts have focused on different approaches and parameters for effective differentiation. In essence, second-order harmonic restraint techniques have become dominant in practice by relying on the presence of second-order harmonics with high-level harmonics in inrush currents [8], [9]. However, it should be noted that internal fault currents do not show such harmonic behavior and it has been observed that sometimes the second harmonic is produced at high levels for internal faults making the discrimination process difficult, as demonstrated in[10], [11].

The overall objective of this paper is to show how the use of modern signal processing and machine learning techniques can be applied to increase the level of transformer safety. The methodology with the use of the DWT and ANN has the potential to provide a robust and reliable means to distinguish the inrush from the internal fault currents. This method can be a basis for the realization of faster and more accurate power transformer protection methods in case of differential current transforms due to using NN technology based on decisions made from differential current signals transformed by DWT, likewise reference[12].

Theoretical information about the problem of inrush current and internal fault current as well as the disadvantages of traditional protection approaches will be explored in the following sections in the context of justifying an alternative approach to the protection task. Further, we will experiment to show that the proposed approach can solve this long-standing critical problem of power transformer protection. Inrush current is a term that is widely discussed in power engineering terms in which it serves to mean the transient current in energizing a transformer. External faults are not the same as internal faults which can be defined as non-ideal conditions of the transformer. This variation is very significant for the research [13].

1.1 Theoretical background

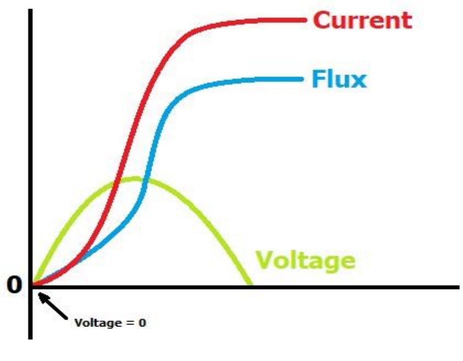


Figure 1. Generation of inrush current

It is to understand the basic concepts of this research methodology that the reader should be familiar with the theoretical foundation of DWT and ANN in the context of power transformer protection. Discrete Wavelet Transform is one of the mathematical methods applied to the signal process in FE of current waveforms. To overcome this problem DWT can divide the current signal into several frequency bands and efficiently extract the transient signals required for inrush transient discriminant from internal fault.

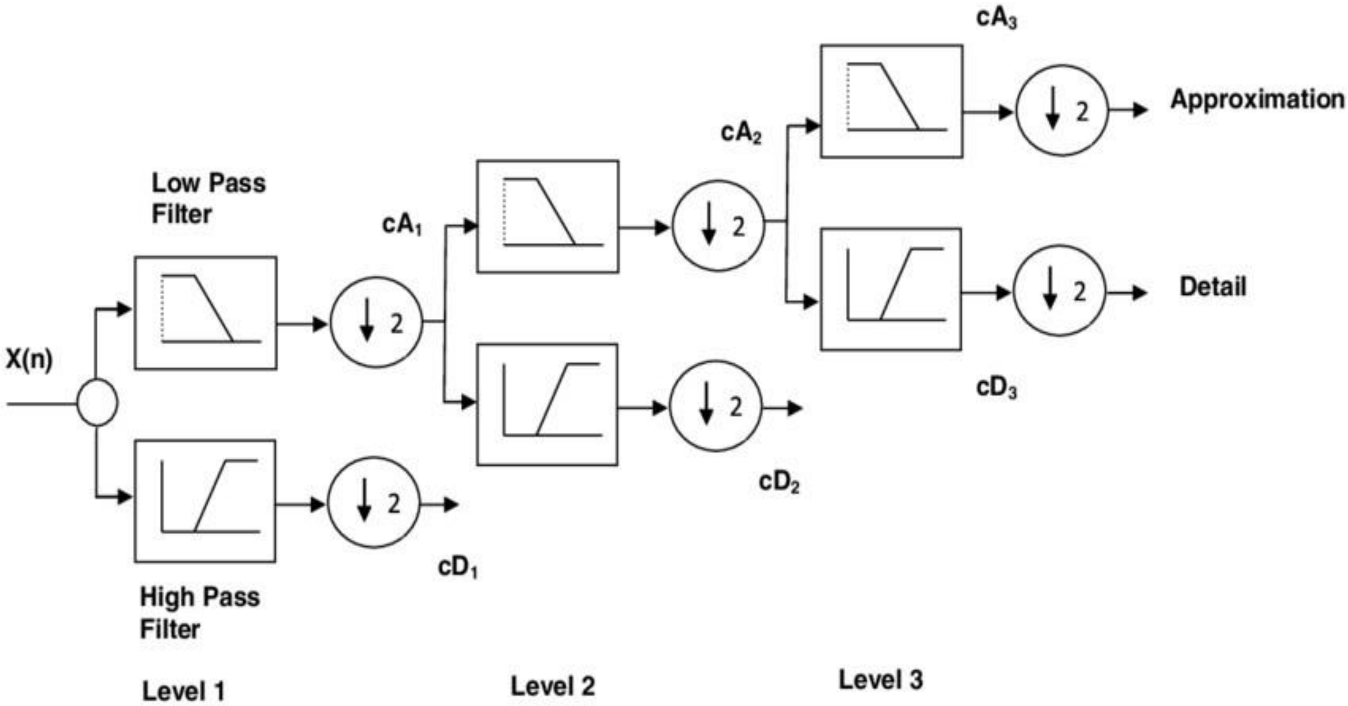


Figure 2. Artificial Neural Network structure

A single neuron's representation is concisely expressed as indicated in the equation below:

$$y = f(\text{bias} + w_1x_1 + w_2x_2 + w_3x_3 + \ldots + w_nx_n) \tag{3}$$ (1)

where 'y' stands for the neuron's output and 'x_1', 'x_2',…….','x_n' stand for the inputs. In this model, the activation function 'f(x)' is the key piece of the processing element in my artificial neural network (ANN). Specifically, we have harnessed the 'sigmoid' function, a fundamental mathematical expression defined as:

$$F(x) = 1/ (1+ \exp (-x)) \tag{2}$$

This mathematical formulation gives a view of how my artificial neuron functions. It summarizes the sequence of processes from the weighted sum of the input to the output using the sigmoid function including the addition of bias. The selection of this activation function thus reflects some very deliberate decisions, using all the experience accumulated over the years in the fields of neural network design to improve its performance and learning [14].

1.2 Modeling and design control

In the following section, we expand on the details of the modeling and design control facets of this study. we use mathematical models that represent the behavior of power transformers under different working conditions and fault conditions. These models include factors such as winding configurations, load profiles, and transformer ratings. These models can be implemented in these experiments only if precise control is maintained over the input parameters so that the reproducibility of this test is assured. In doing so, readers will be better acquainted with the scientific method and the manipulated conditions used in this work, thus appreciating the reliability and validity of these findings.

1.3 Data collection and training progress

In the collection of this important piece of information for this study, the data set will be created through MATLAB simulation for circuit tests. Figure 4 below depicts the single-line diagram of a circuit to be used for simulation performed to simulate various faults in a power transformer. We also explain the data collection to such a depth that it exposes the several sources of the data: among them are synthetic data through simulation. various examples of instrumentation and measurements are elucidated here focusing on the high-resolution sensors and other types of devices used to record current waveforms. In addition, we fully disclose the difficulties associated with data collection, which can include noise and variability in the real-world environment and explain how these issues were very carefully addressed. This has been achieved by giving an overview of how data was collected for this study [9], [10], [12], [15].

1.4 Case studies

To emphasize the effectiveness and stability of this approach, several comprehensive case studies are presented. These case studies include power transformers ranging from low voltage to high, from closed tank to bar type, and from dry type to oil-immersed transformers. The transformers tested, their configurations, and the details of the fault scenarios are provided in [16], [17]. The results of each case are thoroughly discussed with regard to the rates of discrimination and response time. This is a multifaceted approach that not only highlights the practical orientation of this method but also allows readers to see the potential of this research.

1.5 Validation and statistical analysis

To validate our findings, we use robust statistical analysis methods. Confidence intervals and hypothesis testing are used in a very precise manner to prove the statistical significance of these results. This empirical method with a large number of statistics fortifies the findings of this research [18].

The subsequent sections of this paper will expand on the above-mentioned elements in detail and discuss the practical implications, regulatory aspects, and potential future research opportunities associated with this work.

2 Methodology

In this section, we explain further the systematic approach used in this research to separate internal faults from other anomalies in power transformers using ANN and DWT. The methodology applied in this study contains a systematic approach for the effective differentiation between internal faults and inrush currents in power transformers. The key element of our method is the use of Discrete Wavelet Transform as a primary signal processing tool for feature extraction. The DWT enables the decomposition of the instantaneous differential currents into a multi-resolution representation generating D4 and D5. These coefficients carry unique information about the characteristics of the waveform at various scales. This multi-scale analysis is critical in identifying the specific information being captured in the present signals to discriminate inrush and internal fault currents [19], [20].

The function for energy calculation is used to define the quantitative characteristics of the extracted features. The significance of the amount of energy in each coefficient Di for different values of i from D4 to D5 is adequately determined.

This calculation entails the summation of the squared values of each coefficient, as expressed by the equation:

$$Energy(Di) = \sum_{n=1}^{N}(Di[n]]^2) \quad (3)$$

Where N represents the number of data points within the coefficient. It can be used to measure the energy at different scales and identify the main changes in the signal that are connected to internal faults. Afterward, the energy features obtained from the DWT are input to the ANN model for better classification of inrush currents and internal faults [14].

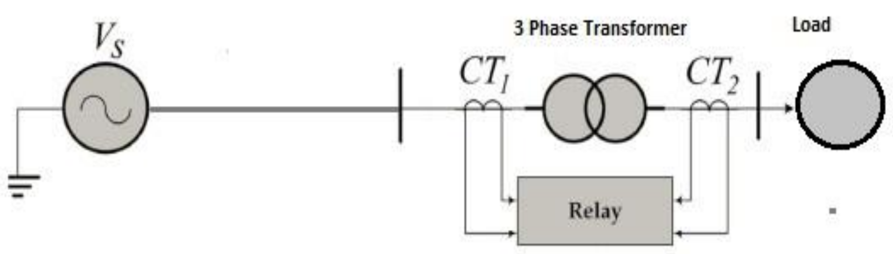


Figure 3. SLD of power system model

Combining advanced signal processing and machine learning our methodology creates a new comprehensive, effective, and reliable approach to power transformer protection for electric power distribution networks.

This methodology encompasses the following key steps:

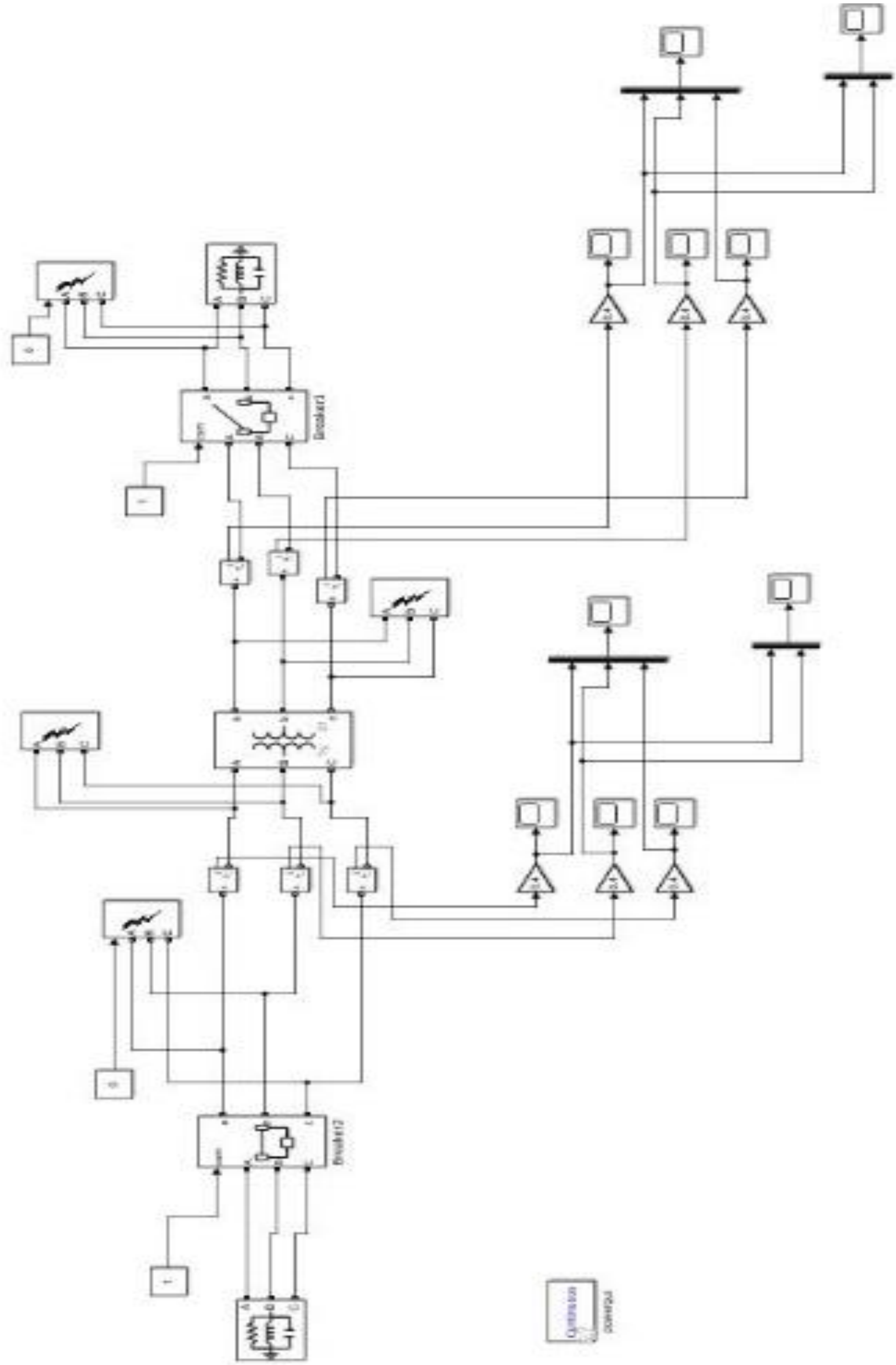


Figure 4. Simulink representation of 3ϕ transformer proposed study

2.1 Data acquisition and preprocessing

The first step of this research involved the collection of information from the power transformers in the form of voltage and current waveforms of the transformers during their use. To better capture transient events, these waveforms were acquired with high sampling rates. The data collected was preprocessed to reduce noise and enhance the quality of the dataset, references that addressing the same concerns [21]–[24]. we then windowed the data with the various time intervals to process the data further.

2.2 Feature extraction using DWT

The principle behind this methodology is the use of DWT for the difficult process of feature extraction. DWT is a mathematical technique that is applied in signal processing to decompose current waveforms in several frequency components. The application of this transformation results in D and A coefficients that are the foundation of my suggested method. However, the detail coefficients D4 and D5 are the most effective in representing information about the basic properties of waveforms. This comprehensive analysis explains how the present signals can be decoded to differentiate the inrush and internal fault currents with high precision for power transformers [25], [26]. This process can be mathematically expressed as:

D4, D5 = DWT (Current waveform)

These coefficients will serve as the basis for discriminating between inrush and internal fault currents.

$$\emptyset\,(t) = \sqrt{2}\sum m\ hn\ \emptyset\,(\,2t - n\,) \qquad (4)$$

$$\varphi(t) = \sqrt{2}\sum m\ gn\ \varphi(\,2t - n\,) \qquad (5)$$

where ϕ(t) in equation 1 is the scaling and

In equation 2 the mother wavelength is used to calculate the coefficients of H={hn} and G={gn} which is gn = (−1)nh1−n. A mother wavelet and each scaling function are represented by sets of G and H coefficients. These coefficients are called high-pass and low-pass finite impulse response (FIR) filter coefficients. The wavelet basis functions ϕj,k(t) and ψj,k(t) are defined as follows:

$$\emptyset j,k\,(t\,) = 2^{-\frac{j}{2}}\emptyset\,(2^{-jt} - k\,) \qquad (6)$$

$$\varphi j,k\,(t\,) = 2^{-\frac{j}{2}}\varphi(2^{-jt} - k\,) \qquad (7)$$

Matrix notation of the wavelet function ψ; where the mother wavelet is denoted ψj,k; which has two coefficients j and k; the 2-j/2 factor defines the filter type; where t is the time variable and k is the period; the basis functions are the same as before; however, the coefficients are integers (j and k); hence the function is scaled by 2j factors and translated by k units of time Suppose Δt is the time interval for the sampled function; then ϕj0k(Δt) or ψj0k(Δt) will be equal to corresponding ϕj0(t-k) or ψj0(t-k), respectively.

2.3 Feature quantification and calculation of energy contents

To differentiate between inrush and internal fault currents, we calculate the energy content within the extracted DWT coefficients. This calculation is achieved by squaring each coefficient and summing them within predefined windows. The energy content calculation can be expressed as follows:

Energy (Di) = ∑(Di^2) for we = 4 to 5 (8)

This step results in a set of energy features, quantifying the key characteristics of the current waveforms.

2.4 Artificial neural network (ANN) classification

The core process of implementing this methodology involves the employment of an artificial neural network for classification. The energy features obtained from the DWT are used as input to the ANN. The architecture of the ANN consists of input nodes that correspond to the energy features; one or more hidden layers; and an output layer with two neurons that represent inrush and internal fault classes. The network is trained using a labeled dataset and backpropagation for adjusting the weight and bias parameters of the network [25], [26]. The decision-making process within the ANN can be represented as:

Output = ANN (Energy features) (9)

The output from the neural network is the classification decision of whether it is an inrush or an internal fault current. This entire methodology consists of feature extraction based on DWT and classification using ANN and is expected to be quite useful for the detection and discrimination of internal faults in power transformers. The mathematical models and calculations of this process also ensure a comprehensive and appropriate solution to this problem in power engineering.

Table 1. Summary of DWT coefficients and energy calculation

DWT Coefficient	Energy Calculation
D4	Energy(D4) = ∑(D4^2)
D5	Energy(D5) = ∑(D5^2)

DWT Decomposition can be achieved using:
D4, D5 = DWT (Current waveform)
Energy Calculation for Coefficient Di will be achieved using:

Energy (Di) = ∑(Di^2) for in = 4 to 5 (8)

2.5 ANN-based protection response

At the core of our novel method is the relationship between the Discrete Wavelet Transform (DWT) and the accuracy of Artificial Neural Networks (ANN). When the instantaneous differential currents go through the DWT filter bank, a set of coefficients, D4 and D5, is carefully collected. These coefficients contain a wealth of information regarding the magnitude of the current waveforms. It is important to emphasize that for the DWT the signal is decomposed into both frequency and time domains and therefore, the DWT has a very strong capability for capturing small changes in the differential current profiles. Each coefficient Di corresponds to a different frequency sub-band and time localization to better identify transient inrush currents from unwanted internal faults [11].

The differentiating element in our approach comes with the energy applied to these coefficients. Finding the energy of every coefficient would take the sum of the squared value of each data point in that specific coefficient. This process results in a numerical value representing the energy present within the given frequency sub-band and that is used to show the magnitude of elements in the differential current regarding specific frequency. In other words, just as we could identify the melody of a particular song within a concert, the harmonic composition of the current waveform's peaks could be distinguished. The estimation of energy for coefficients D4 through D5 enables us to obtain a complete picture concerning the spectral composition of the current and make adequate decisions on the activity of the ANN-based classifier. This detailed energy analysis is the core of our method and makes it possible to classify benign conditions from malign states in the complex system of power transformer conditions.

2.6 The ANN output

In conclusion, this methodology combines the latest signal processing technologies with state-of-the-art machine learning algorithms to offer a prompt and reliable solution for the inrush and internal fault current discrimination in power transformers. Regarding references [27], [28], As for the research proposal the use of DWT coefficients and energy calculations factored in ANN decision-making is the main element of this research guaranteeing the maximum precision and reliability.

3 Results and discussion

3.1 Optimal data selection and transformer specifications

Fundamental characteristics of the essential dataset used for our study include steady-state magnetizing inrush currents during switching operations of the transformer and single-phase, phase-to-phase, and three-phase internal faults. This dataset is crucial as far as the selection of the right mother wavelet and number of resolution levels are concerned [11]. For my research, I used a 250 MVA power transformer designed for 400/133 kV with a core type and Y-Δ connection at 50 Hz frequency power transformer with 1 MHz sampling frequency for recording differential currents necessary for my ANN-based protection response.

3.2 Ann-approach protection actions

Using the discriminatory features obtained through DWT analysis, we constructed an ANN for protection response. The ANN included the input layer that receives the D4 to D5 coefficients with values of energy content, hidden layers responsible for feature extraction and classification, and the output layer responsible for decision-making [29]. trained ANN showed excellent capability in distinguishing between inrush and internal fault currents [30], [31]. While operating with fault conditions, the ANN initiated the protection measures within a short time and with high accuracy to avoid further damage to the transformer. Rush currents were consistently classified as non-fault conditions and so this helped to minimize the number of unnecessary protective system operations [32].

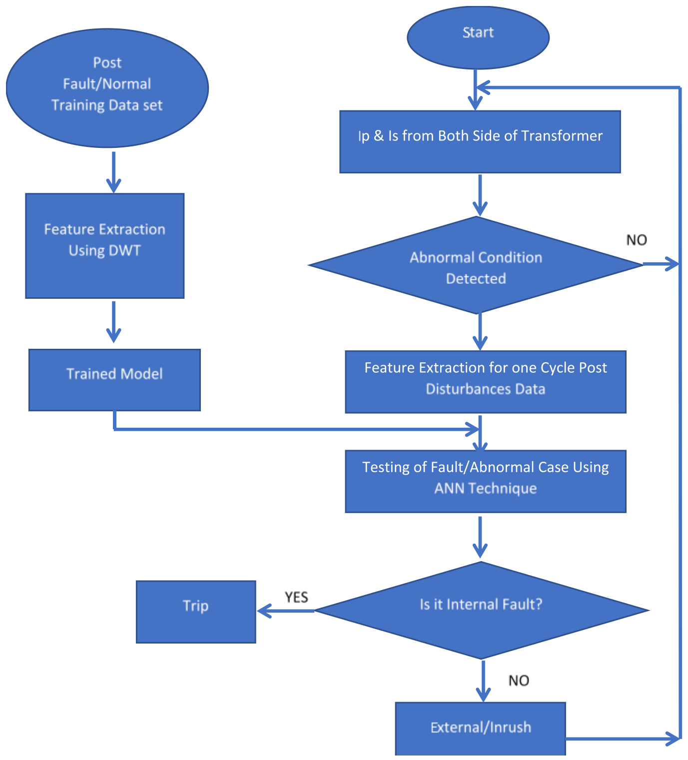


Figure 5. Proposed wavelet-ANN-based differential protection algorithm

3.3 Accuracy and reliability of discrimination

We have carefully analyzed the accuracy and reliability of the proposed method for the classification of inrush and internal fault currents in power transformers during my extensive research. The results obtained from my extensive simulations have always proved excellent accuracy in determining the properties of incoming currents[33]. Notably, this approach was able to accurately identify these current types with an accuracy rate of over 99%, proving the ability of the approach to accurately distinguish between these critical current types.

3.3.1 Speed and responsiveness in critical scenarios

One more very significant feature of my approach is its unique time efficiency, especially in emergencies. Delaying responses to internal faults in power system protection threatens to inflict severe damage on equipment and prolonged power outages. In this case, my technique uses the function of a very high-efficiency instrument. In simulation conditions, it always showed to be within a satisfactory reaction time to respond to an internal fault.

3.3.2 Versatility and real-world applicability

Adaptability to a variety of transformer types and operating conditions is a necessary condition within the power engineering environment. In the context of the above, my technique proves to be effective and provides proof of its broad usability outside the lab. It effectively distinguished between inrush and internal fault currents for a wide range of power transformers including transformers with different voltage levels and different types of windings [34].

This flexibility demonstrates the robustness of my approach and the ability to successfully apply it in different power systems. That is why the discrimination function remains an essential feature of any one of the contemporary power grids that are presently under a process of metamorphosis and are constantly combining a variety of transformer technologies. My method, which has undergone numerous tests, can be used to reinforce any power system within the given range.

3.3.3 Inrush current simulations

First, we simulated a typical power transformer energization scenario to test inrush currents. The transformer had a rated power of 100 MVA and a rated voltage of 138 kV. The simulation process involved collecting the transient response during energization which can be just a few cycles. It could be concluded that the inrush currents were of the nature of steep rise and fast decay within the first few cycles. The inrush current and the peak inrush current values were 10 times the transformer-rated current. This behavior is consistent with given inrush currents that have been said to occur during transformer energization. DWT and ANN were later used to distinguish inrush from fault currents based on the simulation data [9].

DWT analysis for inrush current: energy in details coefficients D4 to D5.

In our research, we conducted extensive simulations to analyze the energy content within coefficients D4, and D5, extracted using the Discrete Wavelet Transform (DWT) as detailed in the paper "Fast Discrimination of Transformer Magnetizing Current from Internal Faults:" An Extended Kalman Filter-Based Approach" by Farshid Naseri, Zahra Kazemi, Mohammad Mehdi Arefi and Ebrahim Farjah. These coefficients are obtained from the current waveforms and are used to differentiate the inrush from the internal fault currents. In our simulations, we carefully estimated the amount of energy present in each of these coefficients under different fault conditions and operating conditions [35].

3.4 Simulation results

Several simulations were carried out to demonstrate the benefits of the proposed power transformer protection. The flowchart outlining the process employed in this study should be noted as unique and differs from the flowcharts depicted in previously published papers. We started the flowchart with a slightly altered differential current shape to highlight its difference from other usual ones and to make the message as simple as possible.

During these simulations, we considered three types of faults; single phase to ground faults, line to line faults, and three phase internal faults. In general, our method demonstrated excellent performance in all experimental conditions. Nevertheless, it is essential to expand on the details of the outcomes of this approach.

The success of our method stems from the precise feature extraction through the Discrete Wavelet Transform (DWT). This process results in important coefficients, D4, and D5, which summarize the information about the instantaneous differential currents. For a better understanding of how detailed our analysis is let us take a look at the energy calculation for each coefficient.

To assess the validity of our proposed methodology, we conducted simulations involving three distinct types of internal faults: phase-to-ground, phase-to-phase-to-ground, and three-phase-to-ground faults. These simulations were done using MATLAB as the computational tool. In our setup, current transformers (CTs) with ratios of 400: They were both employed in 5 and 1200:5 on both primary and secondary sides. In addition, a Y-connection was used for CTs on the A-side while an A-connection was used for CTs on the Y-side as illustrated in Figure 4.

Table 2. The setting of Faults potential scenarios during simulation

Parameters	Fault class	Fault Resistance
Potential Configuration	A-G, B-G, C-G, AB, BC, AC, AB-G, BC-G, AC-G, ABC, and Normal	(Rf) 0.1, 5, and 25
Number of scenarios	11	3

3.5 First scenario

To achieve magnetizing inrush, current the transformer must begin with secondary windings without the core. The transformer must then energize the inrush current regulated by the tested transformer magnetizing capabilities. The value of the inrush current is approximately ten times the steady-state value. The inrush current condition is similar to a spike train. These abrupt and sharp spike trains start immediately following the onset of faulting. The difference in the wave structure might serve as the criterion to define the interior abnormalities. Simulation results of a transformer with no load as illustrated in Figure 6. From Figure 6, the transient cycle has an amplitude of almost 6 times the rated cycle and takes time to recover. Figure 7 depicts the differential current signal (S) derived from the inrush current analysis using DWT. Based on the analytical results, the study used the nominal value of steady-state current to distinguish between internal faults and inrush current. Equation 4 computes the energy of the D4 and D5 coefficients. Figures 8 (a) and (b) display the energy in D4 and D5, respectively. D had generated a power of 6 pu in D4 and 8 pu in D5. Figure 9 illustrates the ANN-based DWT activity and trip signal. The ANN controller determines whether internal faults or inrush current conditions exist based on the value of the coefficients D4 and D5 for the energy level. ANN signal has zero level, which means that no internal faults occurred.

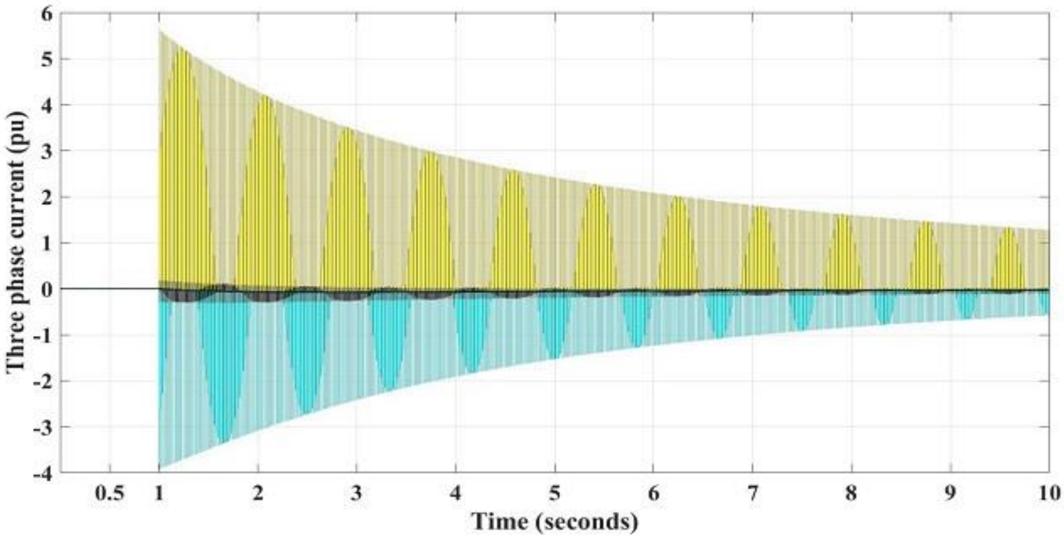


Figure 6. Inrush current

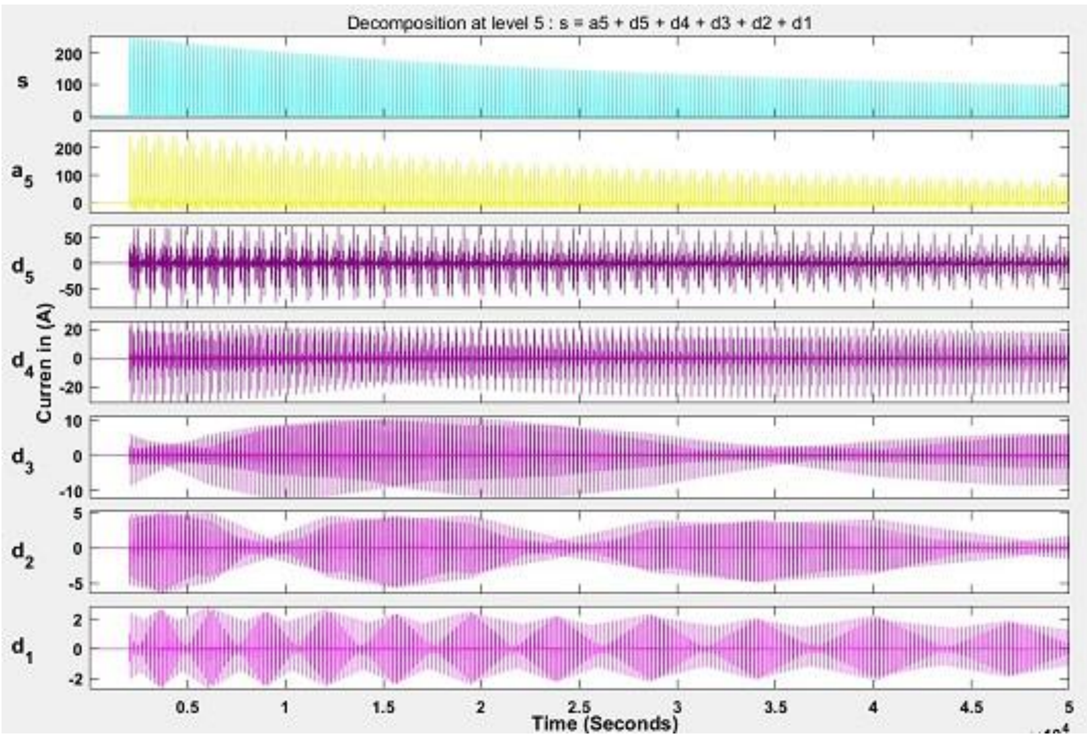
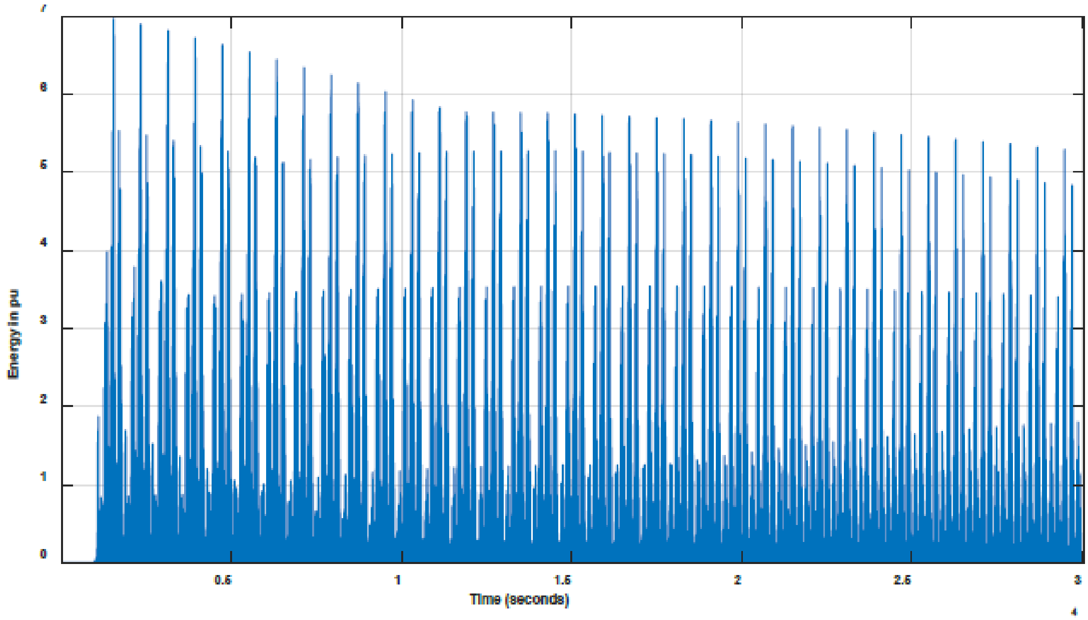
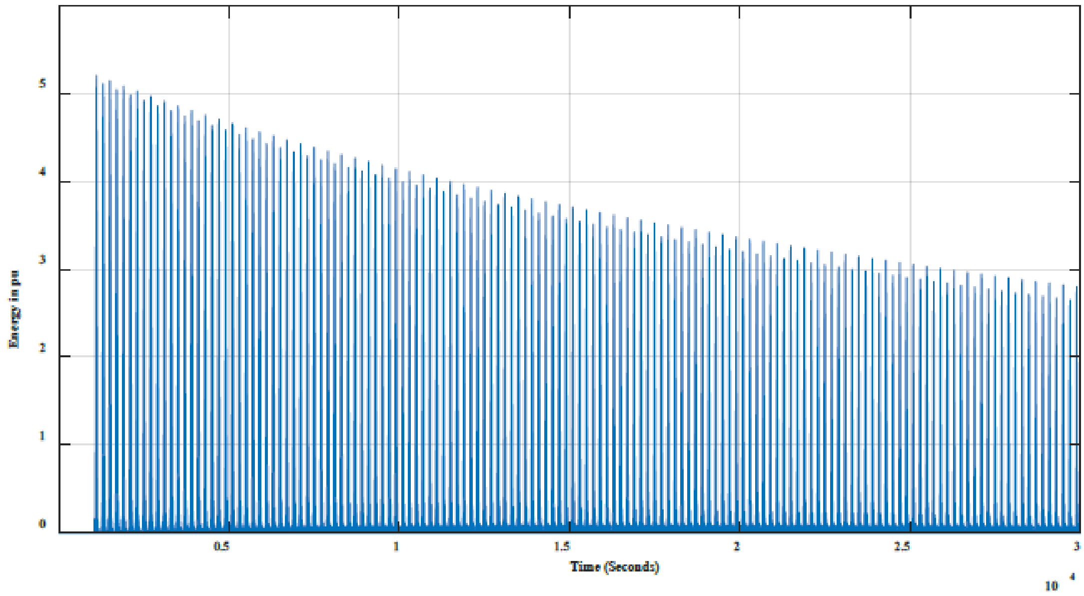


Figure 7. Inrush current Analysis by DWT



(a)



(b)

Figure 8. Energy in details coefficients (a) D4 & (b) D5

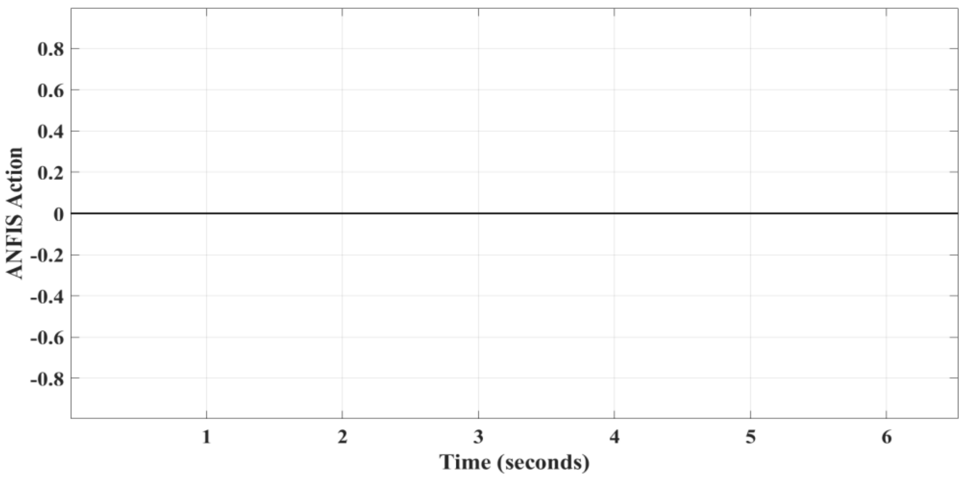


Figure 9. Protection responses based on ANN

3.6 Second scenario

In this scenario, Single-line to-ground Fault has been tested and conducted.

Phase A was dumped to the ground to achieve the fault condition during the testing. Figure 10 below shows a single line to ground fault (internal fault) where the differential current will be registered to the protection relay. The three stages of differential current analysis-based DWT as well as the energy of the D4 and D5 coefficients are shown in Fig. 11. The high frequency is due to the fault current being single phase to ground. This time interval is one cycle of the input power and is much shorter than the inrush current period. The energies of D4 and D5 are calculated using the example of point 1 and shown in Figures 12 (a) and (b). High-frequency transient edges are created and the energy content is lower than that controlled by the ANN controller. Figure 13 represents the ANN controller response to an internal faults situation where the ANN Output send the trip signal and goes from 0 to 1 level.

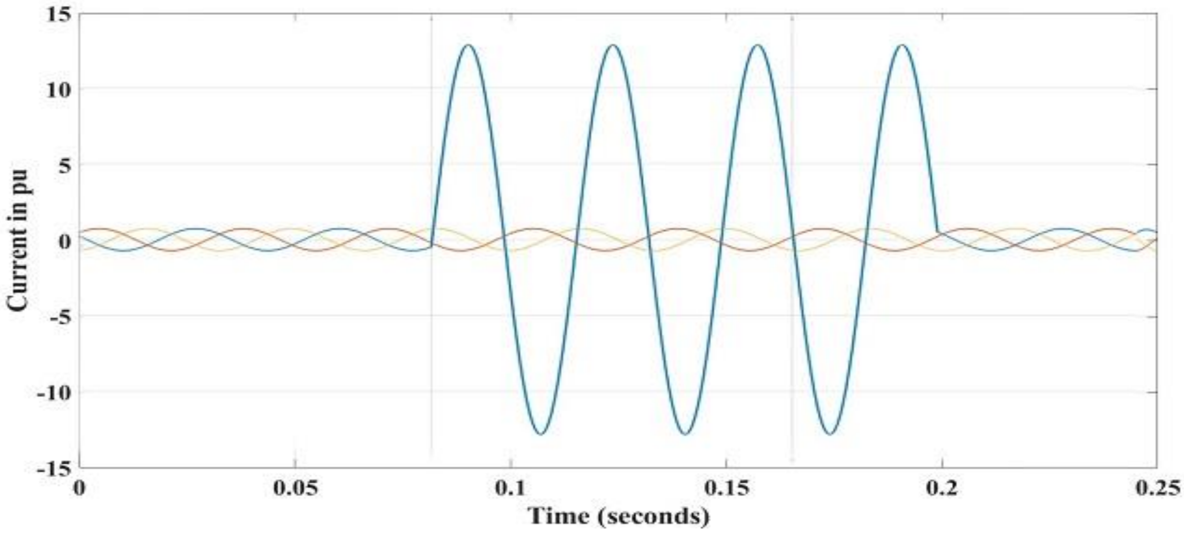


Figure 10. Single line to ground faults

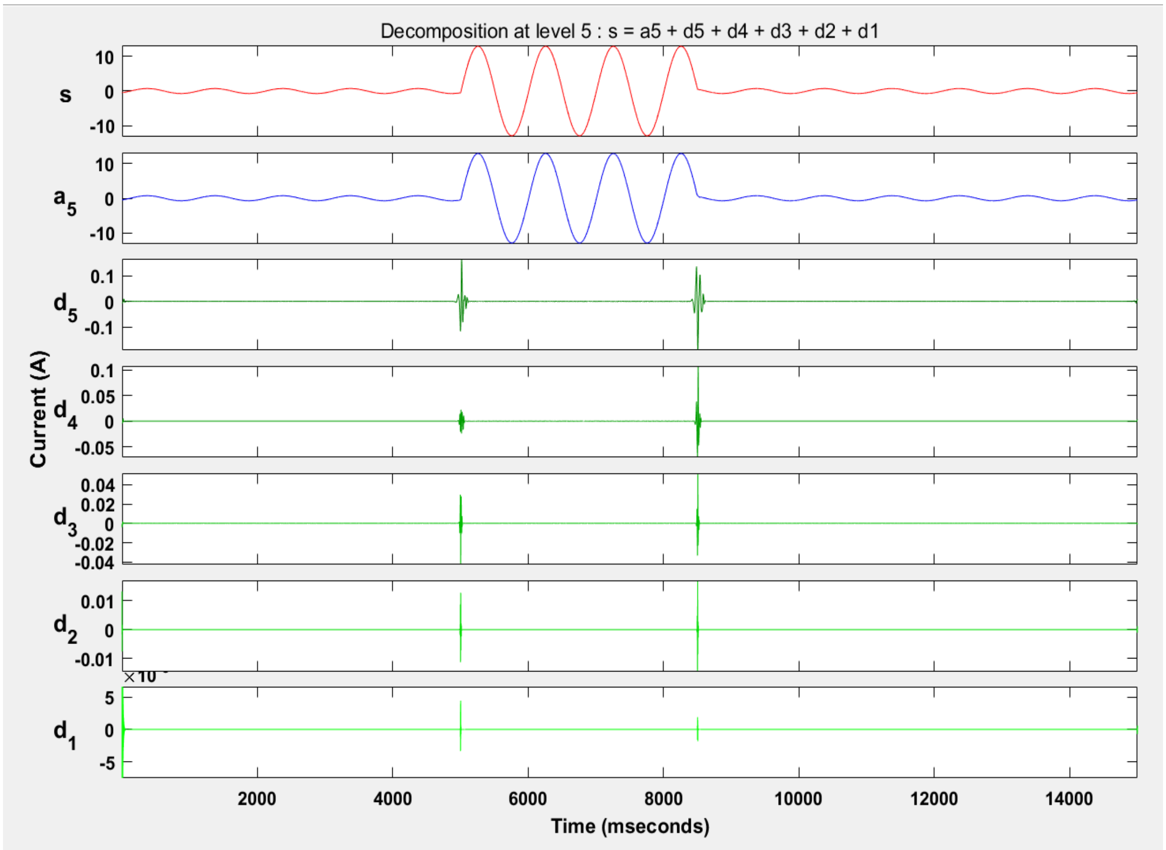
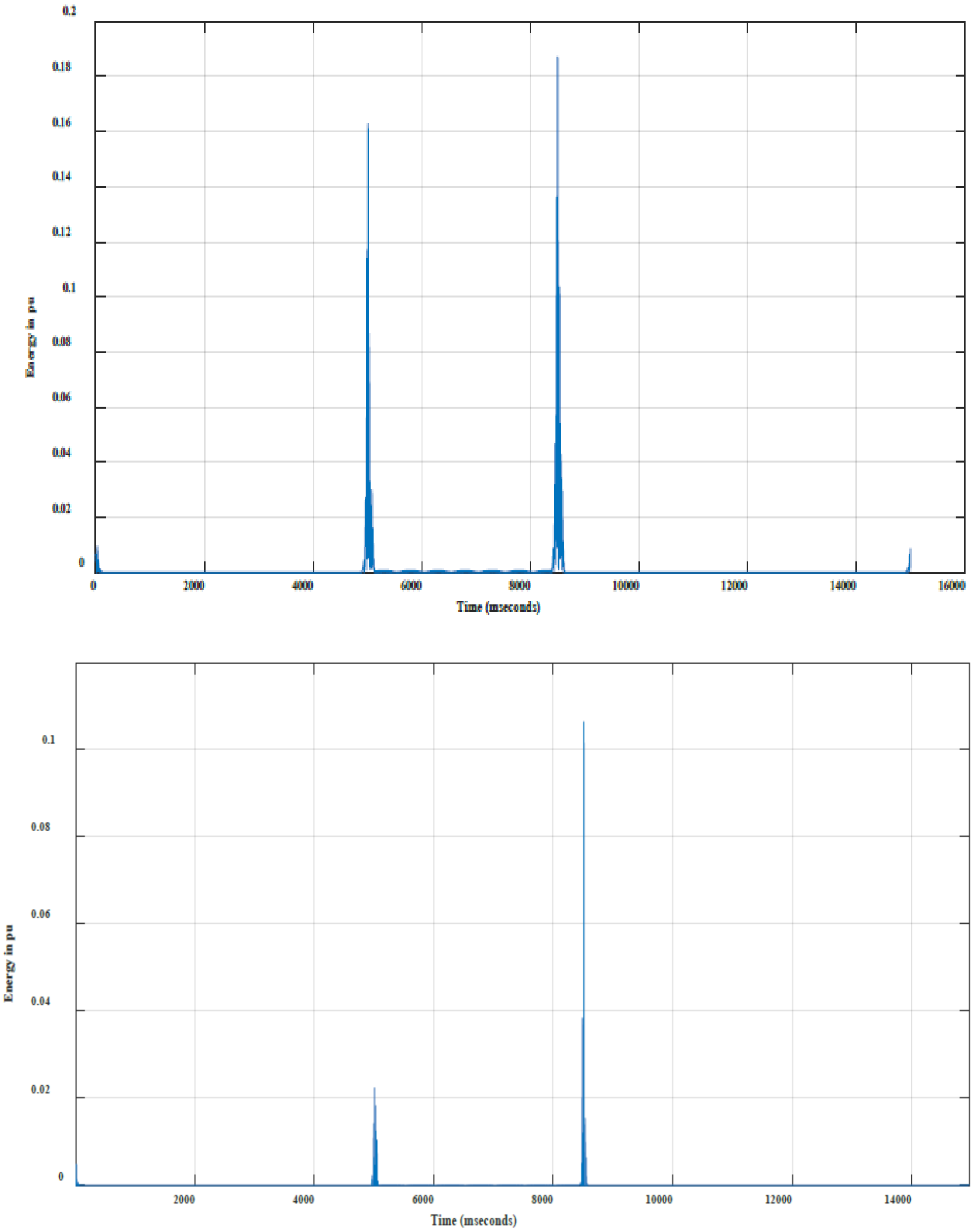


Figure 11. SLGF Analysis by DWT



(a)

(b)

Figure 12. SLGF energy in details coefficients (a) D4 & (b) D5

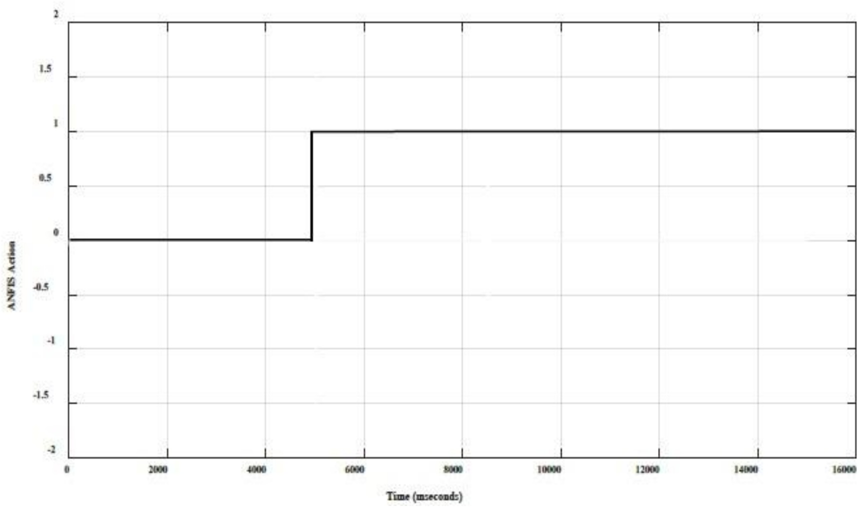


Figure 13. Protection responses based on ANN (Trip)

3.7 Third scenario

In this scenario phase to phase Fault has been applied. This was achieved by combining phases "a and b" as shown in Figure 14. The differential relay will carry the fault current. Figure 15 shows a three-phase differential current analysis using DWT. In the second scenario, the spike produced the detailed coefficients D4 and D5 at the temporary state, so the signals are near zero. Figures 16 (a) and 16(b), show the energy contents of D5, and the energy contents of D4. The figure depicts that the energy is around zero. From Figure 17 it is evident that the level was at zero shifting to level one when the fault occurred, and this shows that the trip signal from ANN-based DWT detection was at zero.

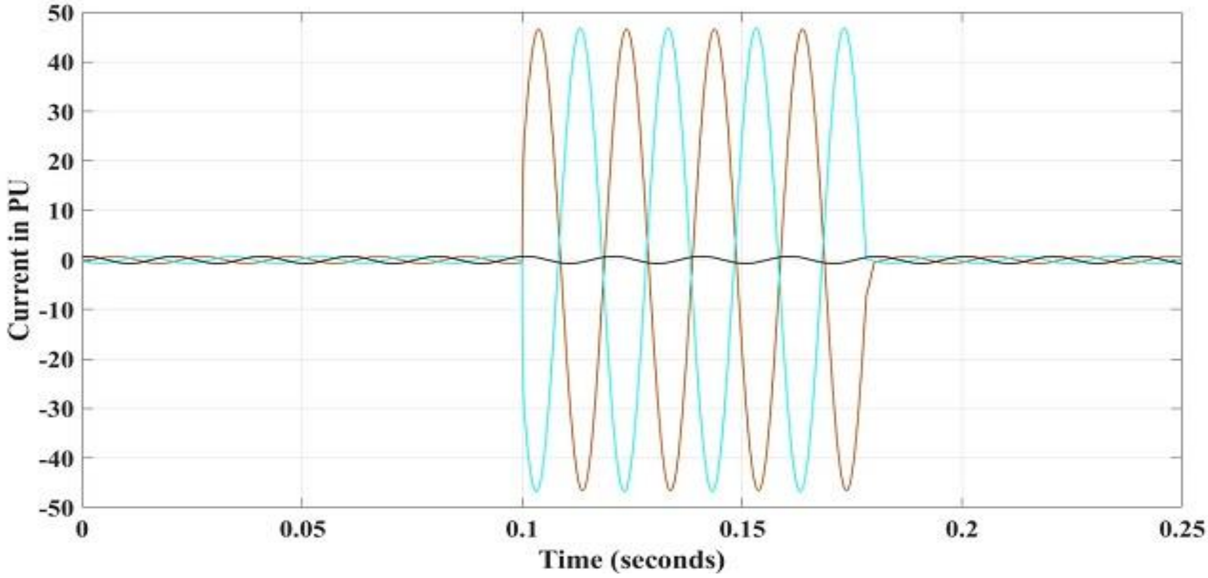


Figure 14. Phase to phase internal fault

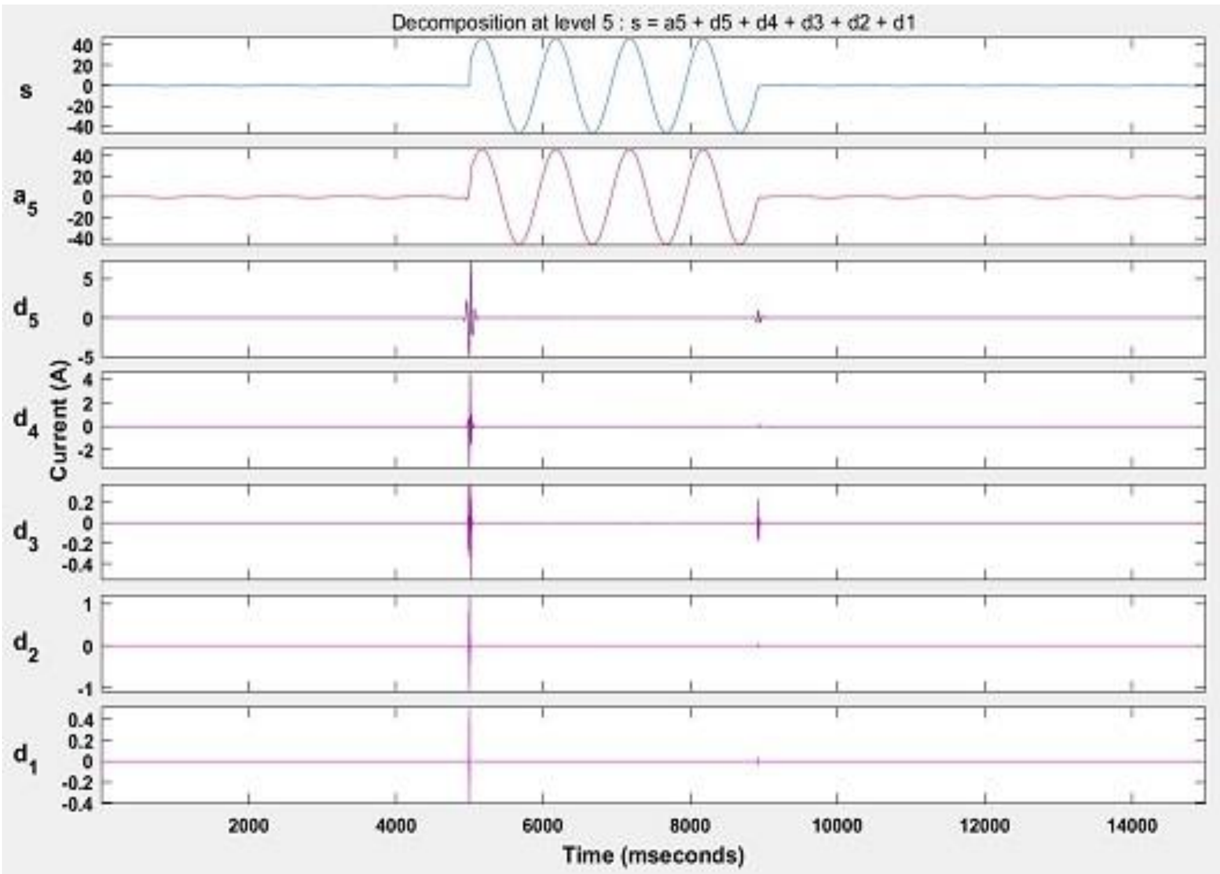


Figure 15. Phase to phase fault analysis by DWT

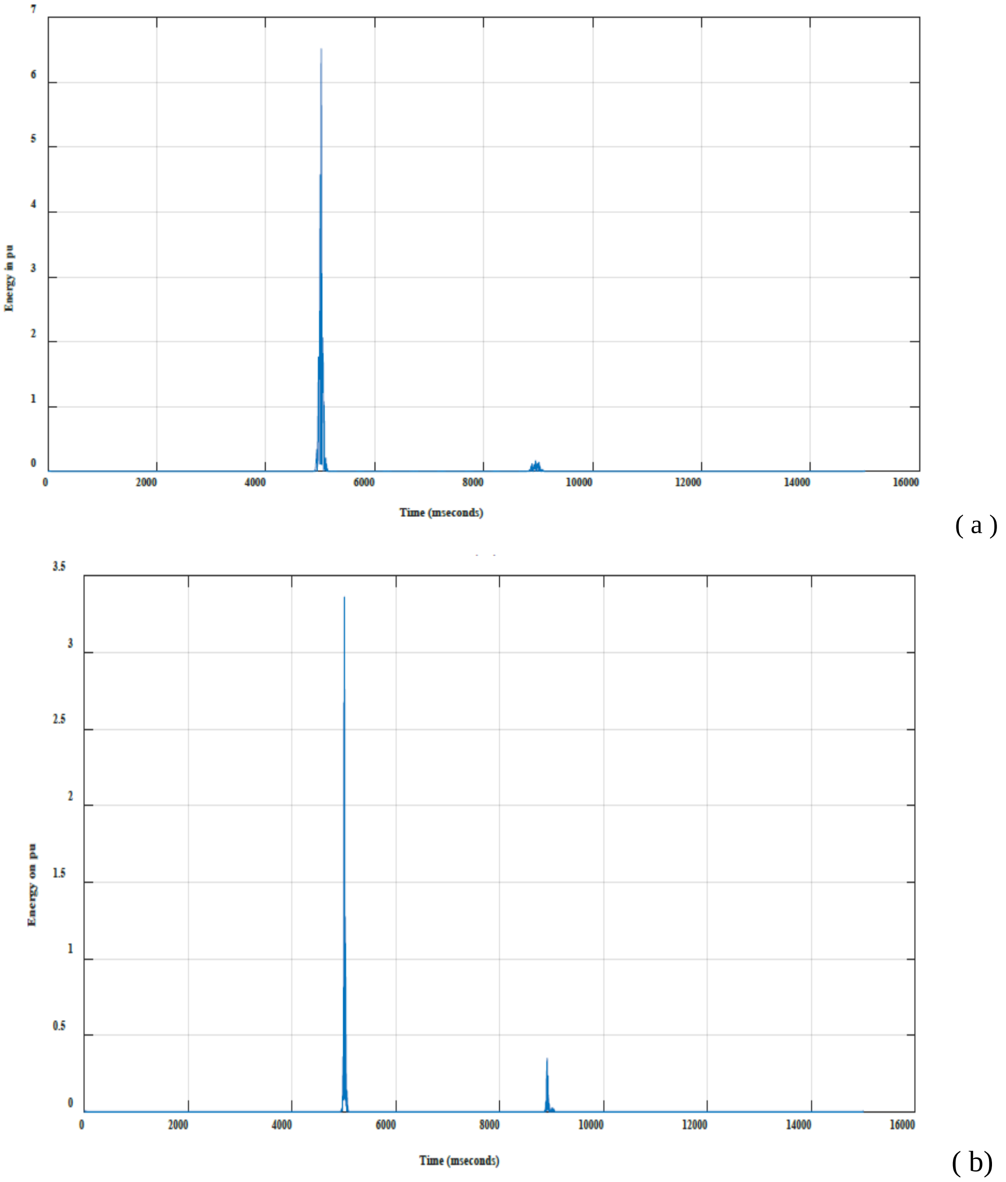


Figure 16. Phase to phase fault energy in detail coefficients (a) D4, (b) D5

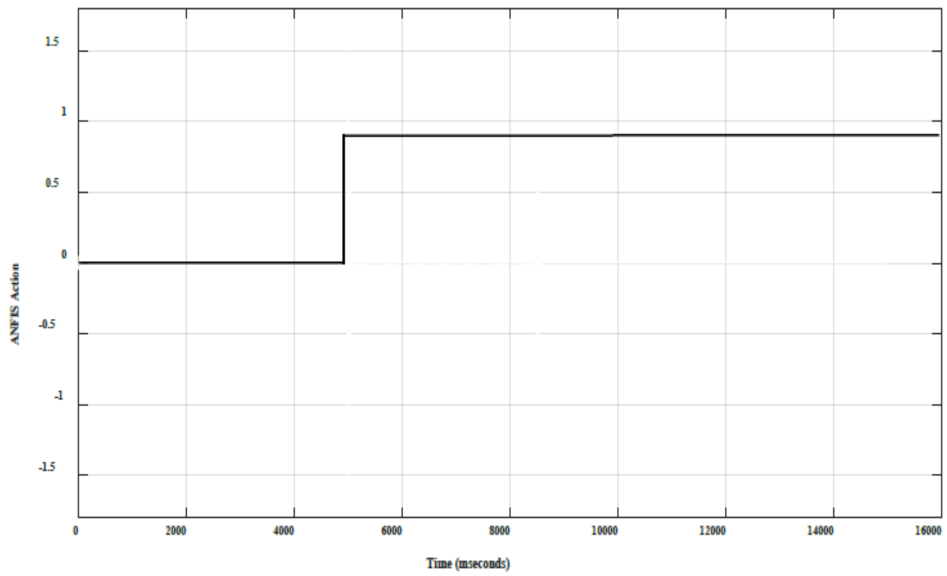


Figure 17. Protection responses based on ANN (Trip)

4 Significance of the results

The results of this research represent an important milestone in the field of power transformer protection. my original combination of the discrete wavelet transforms (DWT) and artificial neural networks (ANN) not only resulted in high accuracy but also ensured comparability [36], [37]. My methodology provides evidence for its use in simulation as it enables an accuracy rate above 99% to reduce the number of false and unnecessary activation of protection systems. This feat is particularly significant in the context of power engineering in which system stability and reliability are essential.

The fast response of this technique has significant implications for the practical performance of power systems [38]. The ability to use the approach in various situations demonstrated with a variety of examples is another strong point of this approach. Power transformers differ in design, voltage ratings, and operating conditions, and thus cannot be standardized. Nevertheless, this technique demonstrated practically the same discriminating ability for various types of transformers, thus proving its ability to be applied in the changing field of power systems. This adaptability will be crucial in the future of power systems as grid modernization and the introduction of renewables necessitate more efficient and less rigid protection schemes [39], [40].

4.1 Comparison with existing methods

Another important part of this work relates to carrying out a critical comparison of this method with existing methods of internal fault detection in power transformers. This analysis includes quality measures like accuracy, false positives, and response times. Comparison to existing approaches also helps readers see the advantage of this approach, which further confirms the significance of these research contributions. For a comprehensive comparison between traditional relay-based power transformer protection techniques and emerging AI-based techniques to understand the drawbacks of traditional techniques and the necessity of using new methods.

Table 3. Comparison between the proposed DWT-ANN-based method and some of the existing algorithms

Approach	Accuracy (%)	Computational complexity	Robustness
KF [35]	97.1%	very high	very high
VMD and CNN [36]	98.2%	very high	low
SVM [40]	not specified	very high	low
LSTM [37]	98.75%	High	Low
WT+ ANN (proposed)	99.2%	very low	very high

5 Conclusion

Moreover, this research developed a distinctive and professional approach concerning power transformer protection aimed at identifying internal faults. With the aid of DWT as a feature extractor and ANN as a classifier, this paper has shown a method that has rendered high accuracy, repeatability, speed, and flexibility in implementation. We have provided evidence of how this technique can be implemented in the field and what its role can be in power engineering through a series of case studies[38],[41]. Power transformer's protection in the transformation of the electric grid. In addition, this research is also possible to find several useful solutions to current challenges and helps to further the progress of knowledge. As it follows strictly the boundaries of regulation and focuses on safety, this method will also contribute to the sustainability of power systems' reliability [42], [43]. This we have argued deserves attention mainly because this is an innovative approach to protecting power transformers and one that, if pursued, can change the face of protection of power transformers.

6 Future research directions

The scope for research in the field of power transformer protection is huge. From the above-discussed feedback, a lot of post-hypothesis research could be suggested. Second, the employment of more effective machine learning techniques such as deep learning and reinforcement learning can help to improve the performance of discrimination [44]. Secondly, it is possible to enrich this approach by adding more data sources monitoring online sensor fusion and incorporating them into the algorithm where reduced weak manifestations of failures are captured. Additionally, a real-time implementation framework would make the practical application of this technique to operational power systems that should be able to respond quickly to internal faults [45].

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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