

Article

Low-Level Inter-Turn Fault Detection Algorithm for Transformer Differential Protection

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Abstract

This paper presents a novel hybrid protection scheme based on Maximal Overlapped Discrete Wavelet Transform (MODWT) energy and a specialized difference function (DF) to accurately detect low-level inter-turn short-circuit faults in power transformers while maintaining high-selectivity features against transient conditions. Low-level inter-turn short-circuit faults (LIFs) in power transformers start at a low level and gradually spread to other windings. It is crucial to detect the fault in early stages and prevent further damage by disconnecting the faulty transformer immediately. A wavelet transform and difference function-based Transformer Differential Protection (TDP) algorithm is proposed in this paper. A differential protection scheme consists of two stages: feature extraction and fault detection. Maximum Overlapped Discrete Wavelet Transform (MODWT) energy and a difference function are used for feature extraction and an analytical logic is used for fault detection. It is also shown that this combination provides more reliable differential protection scheme than TDP with the wavelet transform only or TDP with a difference function (DF) alone. The method is assessed with experimental datasets collected from a laboratory-based, custom-built transformer which is specifically designed for validating the methods to detect LIFs. The method is evaluated according to a confusion matrix method with accuracy, dependability and sensitivity indices. The proposed TDP method detected all LIF cases, representing less than 2% of total windings. Therefore, the proposed hybrid algorithm represents an innovative step in applied system monitoring by providing a high-precision, software-based solution that enhances the operational reliability and resilience of existing TDP systems without requiring additional hardware.

Keywords: power system protection; power transformers; relays; signal resolution; discrete wavelet transforms; inter-turn short-circuit; inrush current; fault detection



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1. Introduction

Reliable transformer protection is vital for power networks due to the critical locations of power transformers and their high cost. Undetected internal faults may cause irreversible damage. On the other hand, any unnecessary blackouts in power networks due to transformer transients, such as inrush current, may result in long-term service interruptions in the related zone [1].

The differential protection scheme is the preferred protection method for power transformers over 10 MVA, which compares terminal currents of related zones or devices.

This protection scheme is standardized as 87T-phase current and 87Q-Negative Sequence Current (NSC) TDP functions [2,3].

TDP relays may malfunction due to the nonlinear behaviors of transformers, such as magnetizing inrush current, resulting in unwarranted service disruptions. The magnetizing inrush current is a transient difference between the transformer's terminal currents, and mostly appears during energization when the residual flux and the instantaneous steady-state core flux overlap. Traditional Harmonic Restraints and Blocking (HRB) methods are used to improve selectivity, and thus the reliability, of differential protection algorithms. These methods are typically based on the ratio of the 2nd harmonic to the fundamental component of the inrush current. The minimum value of this ratio is calculated as 17.1% for a traditional HRB method [4]. However, state-of-the-art core materials are capable of keeping less residual flux, resulting in fewer harmonics in the inrush current [5]. Furthermore, traditional HRB methods are based on the idea of blocking or restraining the trip signal when the inrush current appears. This leaves the transformer without protection against internal faults for a while, decreasing the reliability of the method [6]. Therefore, there is a need to establish more reliable methods to eliminate the blind side of TDP relays.

Inter-turn faults in power transformers start at a low level and increase gradually for such reasons as moisture, overloading, high temperature, and insulation failure. These faults cannot be detected by traditional TDP algorithms until about 14% of the windings are affected by the internal fault [7], because the inter-turn faults initially have little direct impact on the terminal currents. However, a short-circuited winding's current flow is far more than its rated value, causing incremental damage [8,9]. Therefore, it is an important task to detect internal faults at an early stage. Many studies have focused on methods other than Transformer Differential Protection as researchers have become convinced that traditional TDP methods are ineffective against LIFs [9–14]. Numerous scholars choose to start afresh and pursue the route of transformer remodeling. In ref. [9], a magnetic field circuit-coupled 3-D model is simulated using the Finite Element Analysis (FEA) approach. As the most significant change is seen in the power loss rate, an improved online monitoring method is established to estimate and prevent possible inter-turn faults by observing the change in power loss rate due to the insulation resistance variation. Lu et al. improved Tellegen's quasi-power theorem-based solution to detect and monitor LIFs [10]. Moradzadeh et al. propose a Frequency Response Analysis (FRA) approach with isometric feature mapping to locate inter-turn faults in transformer windings [11]. Another FRA-based online monitoring method suggests estimating possible fault locations by calculating the series and shunt capacitance of each winding in healthy and faulty conditions. This method requires a look-up table to store the values in healthy condition [12]. A complex online monitoring approach combines three methods for feature extraction, the $\Delta V-I$ locus, FRA and IV methods [13]. In ref. [14], an online monitoring method is presented to detect cumulative deformation effects in power transformers using an additional fiber Bragg grating sensor. The aforementioned techniques for detecting LIFs are difficult to implement into existing transformer protection applications because they require additional software and hardware components. Meanwhile, Farzin et al. proved that TDP approaches can still be used as the main fault-detection algorithm for LIFs thanks to NSC Component calculations. They enhanced an analytical, signal-processing-based, fault-related incremental current TDP approach to detect LIFs by observing changes in NSC before and after a fault occurs [15]. The Power System Relaying and Control Committee of the IEEE Power and Energy Society reported that sudden pressure relays were too slow to detect LIFs and confirmed that NSC-based TDP methods are promising approaches to mitigating the disruption of transformer winding symmetry during LIFs [16]. This idea

is further supported by a study that combines the NSC-based TDP approach with the magnetic equivalent circuit of faulty transformers in [17].

The two stages of the TDP method are feature extraction and fault detection. To improve the reliability of TDP relays, model-based, data-driven and signal-processing-based approaches have been proposed to date. However, hybrid methods have become more common because these techniques can be utilized in both the feature extraction and fault detection stages. For instance, Jiao et al. propose a hybrid approach that uses a hysteresis curve-based model to produce the necessary data for the data-driven approach based on support vector machine to instantly determine the transformer state [18].

A variety of model-based TDP methods have been proposed, such as using FEA to model magnetizing currents [19], calculating differential power data using an electrical dynamic model [20], developing a centralized protection model using different magnetic models of core materials [21], and online monitoring of differential magnetizing admittance [22]. However, due to the nonlinear characteristics of the core material, model-based TDP techniques suffer from parameter dependence. Moreover, the susceptibility of the TDP scheme increases because of the additional computational complexity required to deal with parameter variations.

Data-driven TDP methods have recently evolved into deep learning-based TDP approaches. Convolutional Neural Networks (CNNs) have been studied in various forms. Li et al. divided the differential current fault component into saturated and unsaturated forms. The unsaturated fault component is used as the feature extraction input to a source CNN unit, and the output of this unit is used in the target CNN unit to distinguish between inrush current and internal faults [23]. Afrasiabi et al. used an accelerated CNN to discriminate between inrush current and internal fault and combined both the feature extraction and fault detection steps into one single CNN unit [24]. However, deep learning and ANN-based TDP methods exhibit significant drawbacks, such as the need for an extensive amount of training data, considerable engineering time, and high computational cost. Additionally, inter-turn faults are unstable as they start at a low-level and spread gradually, prohibiting training data collection. Consequently, some extra strategies are needed to lower the required data for data-driven methods [25].

Signal-processing-based TDP approaches also have some disadvantages, like the need for thresholds and setting arrangements. However, they are still preferred for their promising performance, parameter independence and relatively low computational cost. Some researchers choose to refine traditional HRB methods [26], while others seek alternative analytical solutions like TDP using superimposed differential current data in sliding windows [27], a second-order difference function-based TDP [28], a second central moment-based TDP [29], a Kullback–Leibler divergence-based TDP [30], and DC decay NSC-based TDP [31]. Time–frequency decomposition-based TDP methods also exist. Bhalja et al. improved a TDP method that harvests meaningful signals for discriminating between internal faults and transients by calculating the sum of the mean absolute value derived from the significant mode function of each phase terminal current [32]. Shahbazi et al. introduced a hyperbolic S-transform-based feature extraction block, which consists of a discrete Fourier transform and a wavelet transform with a hyperbolic (frequency-dependent) window [33]. In [34], the MODWT energy resolution method is combined with a difference function for LIF detection. Another method combines decision tree and Artificial Neural Networks (ANNs) in a fault detection scheme [35]. A similar study used MODWT energy with a Clarke transform [36].

Our comparative analysis of various research works already reported in the literature, highlighting their respective advantages and disadvantages in transformer protection, is summarized in Table 1.

Table 1. Comparison of various transformer protection methods reported in the literature.

Methodology	Domain	Detection Speed	LIF Sensitivity	Inrush Immunity	Feature Extraction
Traditional (HRB)	Time	Moderate (1.5–2 cyc)	Low	Moderate	2nd Harmonics
Data-Driven (ANN)	Data	Slow (Training)	High	High	Black-box
Standard DWT	Time–Freq	Moderate (<1 cyc)	Moderate	Moderate	Wavelet Coeff.
Model-Based	Time	Moderate	Moderate	Low	Parameters

In this paper, a MODWT energy and difference function-based TDP approach is proposed to enhance reliability under LIF conditions. The method is embedded in both 87T phase current and 87Q NSC TDP functions and is verified using experimental data collected from a specifically produced transformer for testing algorithms for LIF conditions. The experimental dataset involves data for the inrush current only, for the inrush current and internal fault together, and for primary/secondary-side LIFs only and the sympathetic inrush. The confusion matrix evaluation method is used with accuracy (A), dependability (Dp) and selectivity (S) indices. The remainder of the paper is structured as follows: We introduce the proposed TDP scheme, the experimental set-up and the experimental data. Then, the validation process is thoroughly explained, and the results are discussed in the conclusion.

2. Differential Protection Algorithm for Power Transformers

Traditional 87T phase current and 87Q NSC algorithms are employed as the differential protection scheme in this study. The 87Q NSC function for three-phase transformers with an A-B-C phase sequence is formulated as below [3]:

$$i_1(k) = \frac{1}{3} \left(i_{1a}(k) + i_{1b}(k + \frac{f_s}{3f}) + i_{1c}(k + \frac{2f_s}{3f}) \right) \quad (1)$$

$$i_2(k) = \frac{1}{3} \left(i_{2a}(k) + i_{2b}(k + \frac{f_s}{3f}) + i_{2c}(k + \frac{2f_s}{3f}) \right) \quad (2)$$

where i_{1abc} and i_{2abc} represent the primary and secondary abc phase currents, respectively, and f and f_s represent the power system and sampling frequencies.

The instant differential current i_d and restraint current i_R are calculated according to (3) and (4) [37]. k_1 is the adjusting parameter, mostly defined as 0.5.

$$i_R(k) = k_1(|i_1(k)| + |i_2(k)|) \quad (3)$$

$$i_d(k) = |i_1(k) + i_2(k)| \quad (4)$$

Th is the first threshold value calculated using Chi^2 distribution. This is an instant value and surrounds the main signal (i_d and its wavelet coefficients in this study). μ represents mean value and σ denotes standard deviation.

$$Th(k) = |\mu_{i_d}(k) + 2\sigma_{i_d}(k)| \quad (5)$$

$$D = \begin{cases} 1 & i_d > i_0 + k_2 i_R \\ 0 & i_d \leq i_0 + k_2 i_R \end{cases} \quad (6)$$

2.1. Difference Function

Sudden variations in differential current are an indicator of abnormal or unusual operation. The first-level difference function in (7) is used for feature extraction to detect any sudden variations, and a sliding-window algorithm is employed at each step [28,38].

$$d_1(k) = Th(k) - Th(k - 1) \quad (7)$$

2.2. Wavelet Transform

The Maximum Overlapped Discrete Wavelet Transform (MODWT) is a multi-resolution tool for feature extraction. Instant wavelet $w_{d,R}$ and scaling $s_{d,R}$ coefficients of i_d and i_R currents are calculated as follows:

$$w_{d,R}(k) = \frac{1}{\sqrt{2}} \sum_{n=1}^L h(n) \times i_{d,R}(k+n-L) \quad (8)$$

$$s_{d,R}(k) = \frac{1}{\sqrt{2}} \sum_{n=1}^L g(n) \times i_{d,R}(k+n-L) \quad (9)$$

where $h(n)$ and $g(n)$ represent the filters of the chosen mother wavelet family (Daubechies 4 in this study), and L is the length of the filters. Wavelet transform is used for feature extraction.

The MODWT energy $\varepsilon_{d,R}$ represents energy signals of fifth-level wavelet coefficients in one sliding window, calculated as below:

$$\varepsilon_{d,R}(k) = \sum_{n=k-\Delta k+1}^k w_{d,R}^2(n) \quad (10)$$

where Δk represents the length of one sliding window, which is one period long—40 samples in this paper.

The second threshold, Th_{w5} , is defined for the MODWT energy-based TDP method and calculated with Chi^2 distribution of the fifth level w_d .

$$Th_{w5}(k) = |\mu w_d(k) + 2\sigma w_d(k)| \quad (11)$$

2.3. Fault Detection

Analytical fault detection algorithms are defined for both the difference function and MODWT energy function. D_w and D_d are defined as the fault signals for the MODWT energy and the difference functions. D is the overall fault signal defined using a logical AND for D_w and D_d .

$$Dd = \begin{cases} 1 & \sum_{n=k-\Delta k+1}^k Th(n-1) \leq k_2 \sum_{n=k-\Delta k+1}^k Th(n) \\ 0 & \sum_{n=k-\Delta k+1}^k Th(n-1) > k_2 \sum_{n=k-\Delta k+1}^k Th(n) \end{cases} \quad (12)$$

where D_d is defined based on the sum of Th values within one sliding window. The fault detection parameter k_2 is set to 1.1 in this study.

$$Dw = \begin{cases} 1 \text{ (LIF)} & E_{Ra5} > E_{da5} > Th_{w5} \\ 0 \text{ (Inrush)} & \begin{cases} E_{da5} > E_{Ra5} > Th_{w5} \\ E_{Ra5} > E_{da5} > Th_{w5} \wedge d_{1,ERa5} < k_3 \end{cases} \\ 0 \text{ (Regular)} & E_{Ra5} > Th_{w5} > E_{da5} \end{cases} \quad (13)$$

$d_{1,ERa5}$ is a difference function inserted into wavelet-based TDP to see the sudden variation in E_{Ra} , and k_3 is defined as fault detection threshold parameter.

3. Evaluation

3.1. The Experimental Setup and Data

A laboratory-based transformer, shown in Figure 1, is used for practical testing. The three-phase 1 KVA, 400 V, 1:1, Y-Y-connected transformer is custom-built for eval-

uating LIF detection algorithms. Some of the windings on both the primary and secondary sides were taken out to imitate low-level short-circuits.

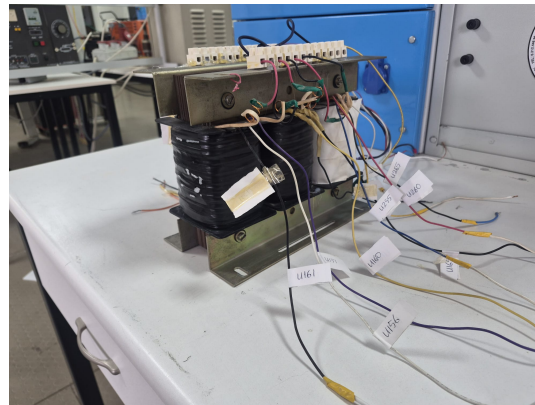


Figure 1. Customized Transformer.

Figure 2 illustrates the transformer in the experimental setup, and Figure 3 shows a single-line diagram. Solid state buttons were used to short-circuit the windings numbered 151 to 156 on the primary side and 143 to 148 on the secondary side (representing less than 2% of the total windings). The data was captured from each phase using 5/1 current transformers and recorded using a National Instruments (NI) USB 6210 multifunction DAQ device [39].

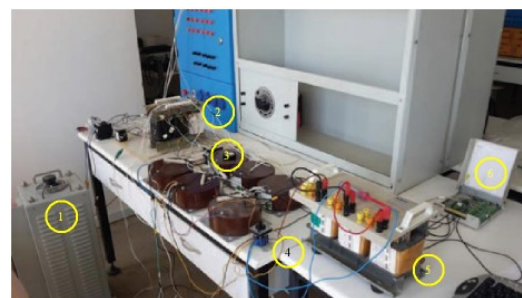


Figure 2. Experimental set-up: 1. Auto-transformer for power supply. 2. Tested transformer. 3. Current transformers (x6). 4. Parallel transformer for sympathetic inrush tests. 5. the external transformer for sympathetic inrush current data acquisition. 6. NI DAQ device.

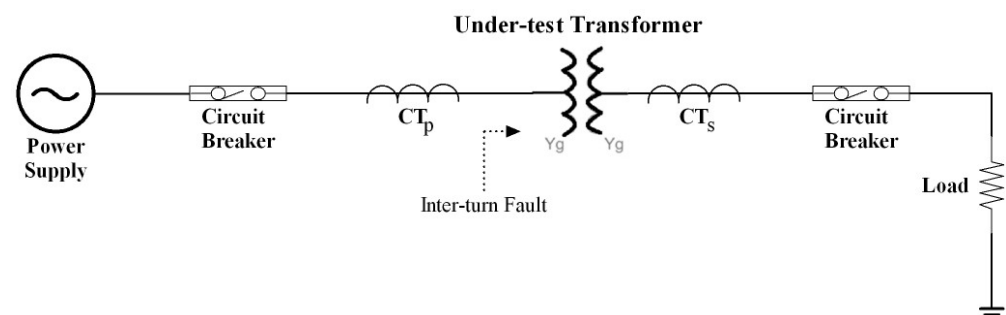


Figure 3. TDP single-line diagram.

The experimental setup was used to gather 81 distinct 2-s-long datasets at a 2 kHz sampling frequency. As illustrated in Table 2, these datasets represent a comprehensive range of operational scenarios. The load resistance values (ranging from 1 k Ω to 7 k Ω) were specifically selected to simulate different loading levels of the power transformer, ensuring the algorithm's robustness under varying power demands. For transient conditions such as sympathetic inrush, specific switching sequences were applied to capture the complex interaction between transformers. Each category in Table 2 represents a unique physical

state, providing a diverse training and testing environment for the proposed MODWT–DF scheme. The data was converted to the IEEE C37.111 COMTRADE format to ensure compatibility with industrial TDP relay testing standards.

Table 2. Experimental Data.

Data Content	Number of Data	Load Resistance
Inrush current	10	1 K Ω
Regular operation	14	1 to 7 K Ω
Inrush current + primary-side internal fault	12	1 K Ω
Inrush current + secondary-side internal fault	10	1 K Ω
Primary-side internal fault	12	2 to 7 K Ω
Secondary-side internal fault	12	1 K Ω
Sympathetic inrush current	11	1 K Ω

3.1.1. Experimental Constraints

Each data point is 2 s long and sampled with a 2 kHz sampling frequency. The number of samples per cycle is 40. During the experimental tests, phase displacement of around 12 to 20° was observed between the primary- and secondary-side currents, despite the Y–Y connection of the transformer in Figure 4a. This discrepancy, attributed to the inherent characteristics of the current transformers used for measuring, non-synchronized sampling or leakage impedance in Figure 4b, was effectively mitigated using a software-based phase alignment technique with Fast Fourier Transform (FFT) and interpolation. This ensures that the differential current remains below the threshold during regular operation, as shown in Figure 4c,d.

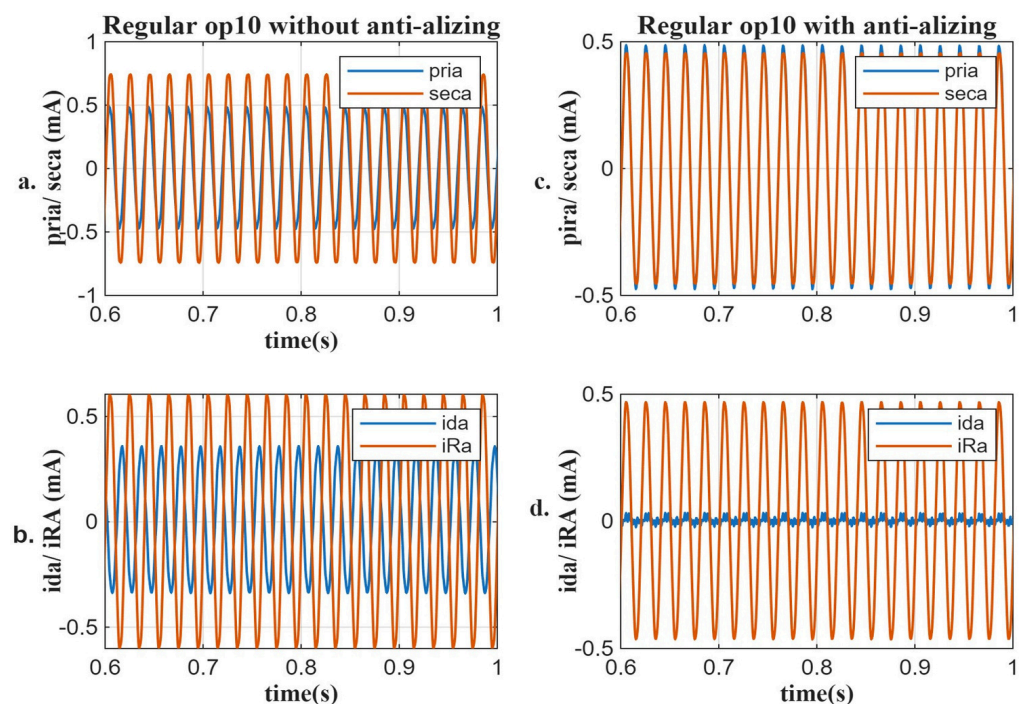


Figure 4. Regular operation data (a,b) without and (c,d) with phase alignment technique.

3.1.2. Real Time Operation

The proposed TDP method is enhanced with a sliding-window approach for real-time operation, which will then be applied to industrial differential relays [40]. As shown in

Figure 5, the length of a single sliding window is one cycle (20 ms for 50 Hz), and sequential windows slide one sample length for each step (0.5 ms for a 2000 kHz sampling frequency f_s). Only one MODWT energy coefficient is calculated with (10) for each window.

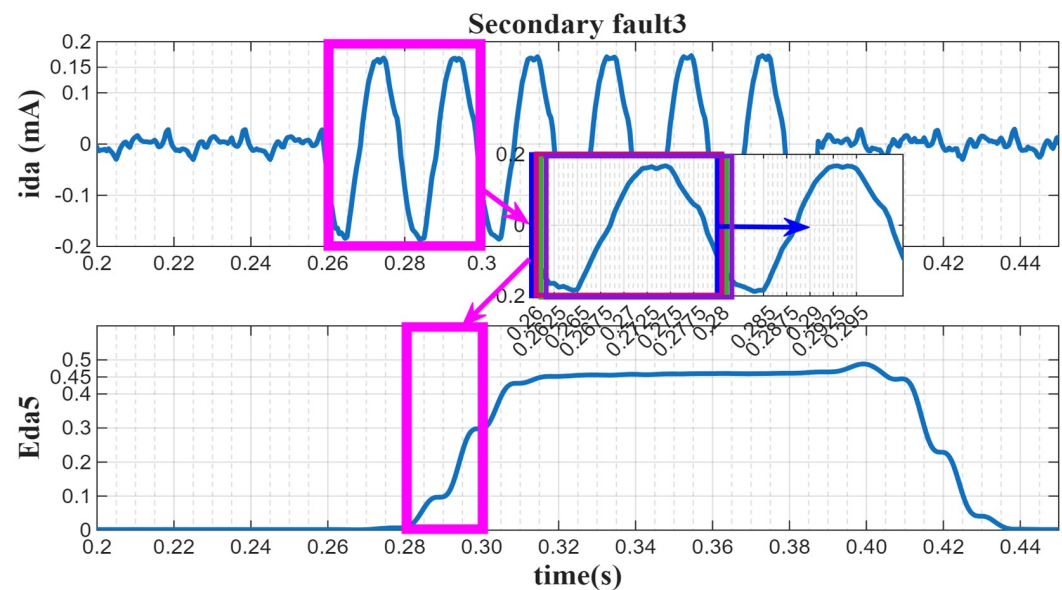


Figure 5. Sliding window process for real-time operation.

3.1.3. Methodological Constraints: Parameter Selection and Sensitivity Adjustments

The proposed method is classified as a signal-processing-based TDP algorithm. The need to define thresholds is a fundamental drawback of this type of method. However, signal-processing-based TDP methods are still preferred due to their high reliability, lower complexity and quick response. A few thresholds are defined in this method both for the feature extraction and fault detection steps demonstrated in the flow chart in Figure 6. i_0 is defined for the minimum current value to commence the whole TDP procedure. Th is calculated with the Chi^2 function to trace the envelope of the differential current i_{da} , used as the feature extraction threshold of the difference function. This approach transforms the instantaneous sinusoidal current waveforms into a stable magnitude envelope for each period. By doing so, the algorithm can effectively track abrupt variations in signal that occur during fault conditions, without being hindered by the zero-crossings of the AC cycle. This ensures that the instantaneous threshold levels remain sensitive to genuine fault signatures while providing a robust baseline for energy-based comparison. The purpose of Th_{w5} is to identify any unusual operation of the wavelet transform-based TDP function. k_2 and k_3 are the fault detection thresholds of the difference function and wavelet transform-based function, respectively.

The performance of the proposed hybrid method depends on four key parameters: k_2, k_3 (weighting factors), and Th, Th_{w5} (decision thresholds). These parameters are not arbitrary; they are derived from the statistical distribution of energy signals under extreme non-fault conditions. Specifically, Th is defined as $Th = (1 + \alpha) \cdot E_{max, inrush}$, where $E_{max, inrush}$ is the maximum normalized energy during inrush and α is a security margin (set to 0.15 in this study). A sensitivity analysis was performed by varying the thresholds by $\pm 20\%$. The results indicated that increasing the thresholds enhances security against noise but introduces a slight delay (up to 5 ms) in detection time. Conversely, lowering the thresholds improves sensitivity to extremely low-level faults but requires a more stable sensing environment. The study demonstrates that the proposed values offer an optimal trade-off for most industrial transformer configurations.

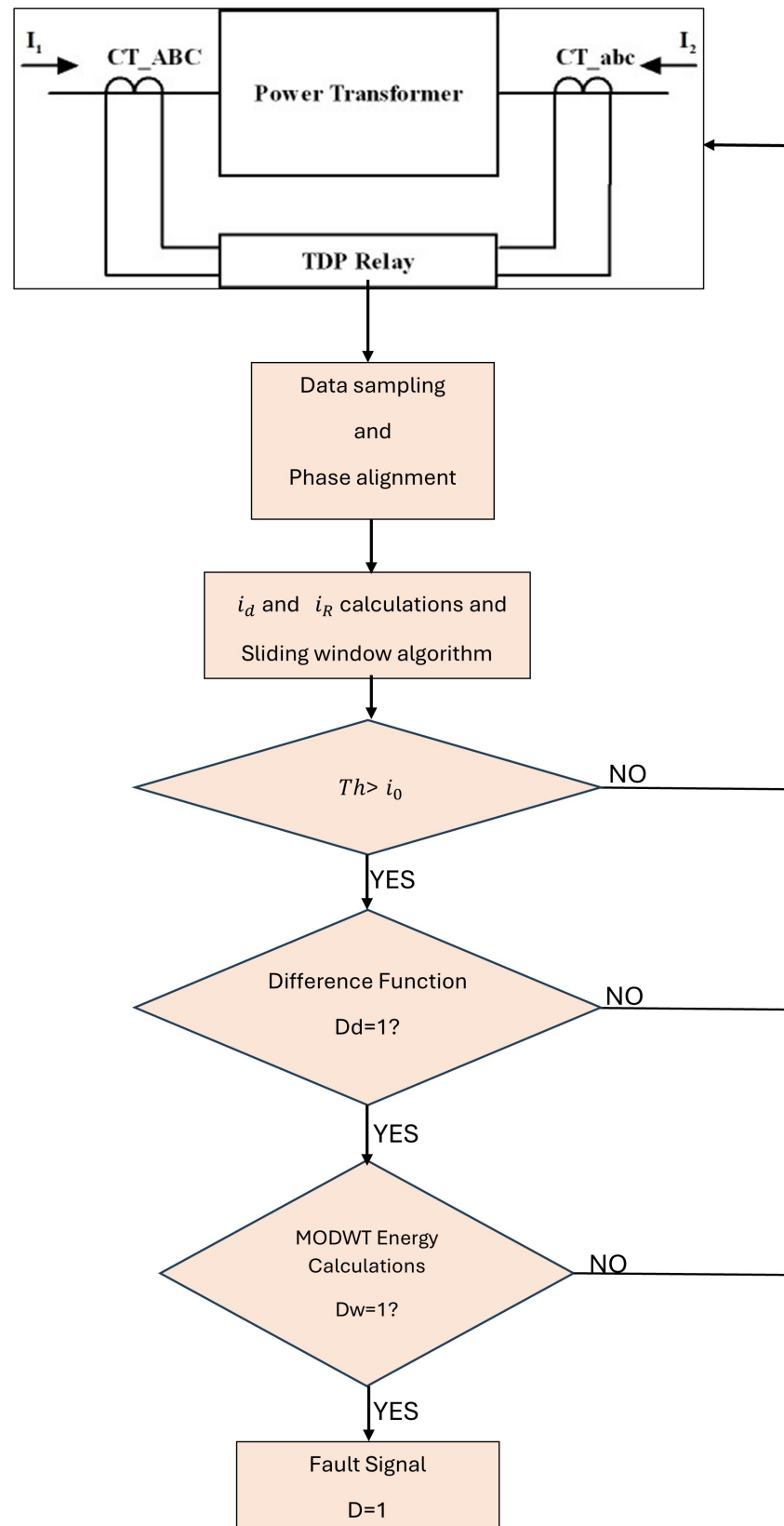


Figure 6. A flow chart of the proposed method.

3.2. Proposed TDP Method Validation

This paper proposes and validates a TDP method based on MODWT energy and the difference function under a variety of fault and transient conditions. The proposed method is implemented in both 87T phase current and 87Q NSC TDP algorithms. Since it

may reveal any asymmetrical fluctuations in the terminal currents, 87Q NSC-based TDP methods are widely recognized in the literature for their sensitivity to LIF conditions [15–17]. Nevertheless, as shown in Figure 7, the experimental data in this study indicate a key reliability bottleneck: faded-out LIFs in the inrush current. The method's reliability is reduced by the inrush current's masking effect on the LIF in the NSC component. Therefore, the preference for 87T phase percentage current analysis over NSC is due to the inherent 'masking effect' observed during simultaneous inrush and fault events. Physically, the NSC transformation involves the vectorial summation of phase currents, which can cause the subtle signatures of a low-level inter-turn fault (LIF) to be canceled out or obscured by the dominant unbalanced components of the inrush current, thereby reducing the reliability of NSC-based detection.

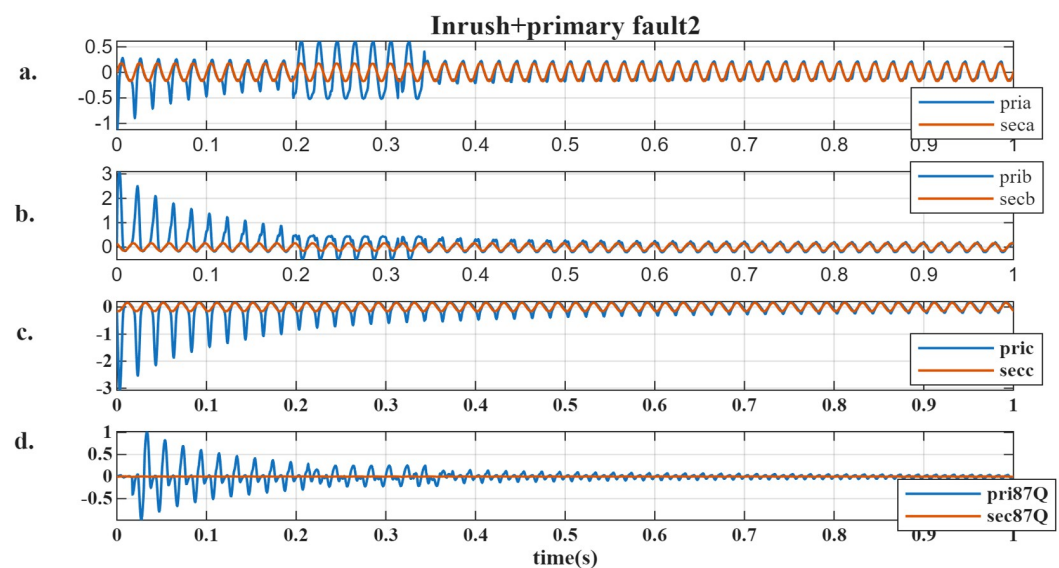


Figure 7. The primary and secondary currents of (a) Phase A; (b) Phase B; (c) Phase C; (d) NSC component when LIF and inrush current are present simultaneously.

The proposed method is tested using a variety of datasets, which are listed in Table 2. High reliability is shown for inrush current only, for primary and secondary LIF conditions, and for inrush current and LIF together and regular operation cases. As shown in Figure 8, the method does not generate any fault signals during regular operation because E_{da5} is smaller than Th_{w5} . The method functioned correctly in inrush-current-only cases and did not generate any fault signals, waiting for the transient case to be completed, as seen in Figure 9, while fault signals were generated for all LIF-only data, as demonstrated in Figure 10. The condition of inrush current and LIF together is validated for both transient operation and faulty condition responses. Overall, the method is supposed to stay silent during transient cases and to generate a fault signal under LIF conditions, proving its ability to pick out faulty cases correctly, as seen in Figure 11.

The proposed method is assessed using a confusion matrix evaluation [41]. Each actual data point, including faulty, transient or healthy conditions, is classified into one of four categories [24,42], derived from the classifier/confusion matrix represented in Equation (14): CF (correctly detected faults), WF (undetected faulty conditions), CT (transient conditions that do not activate the differential relay) and WT (transient conditions that mistakenly trigger the differential relay).

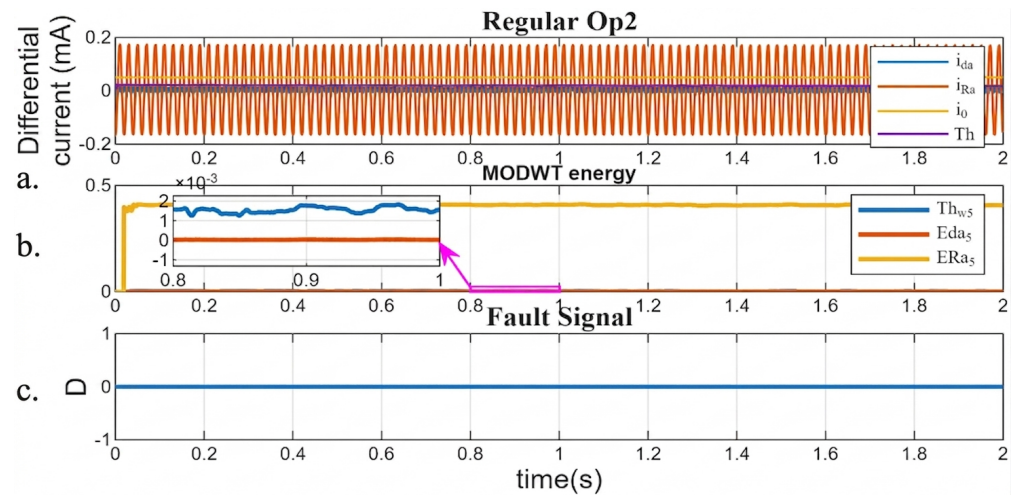


Figure 8. Regular operation: (a) differential current; (b) MODWT energy; (c) Fault Detection Response.

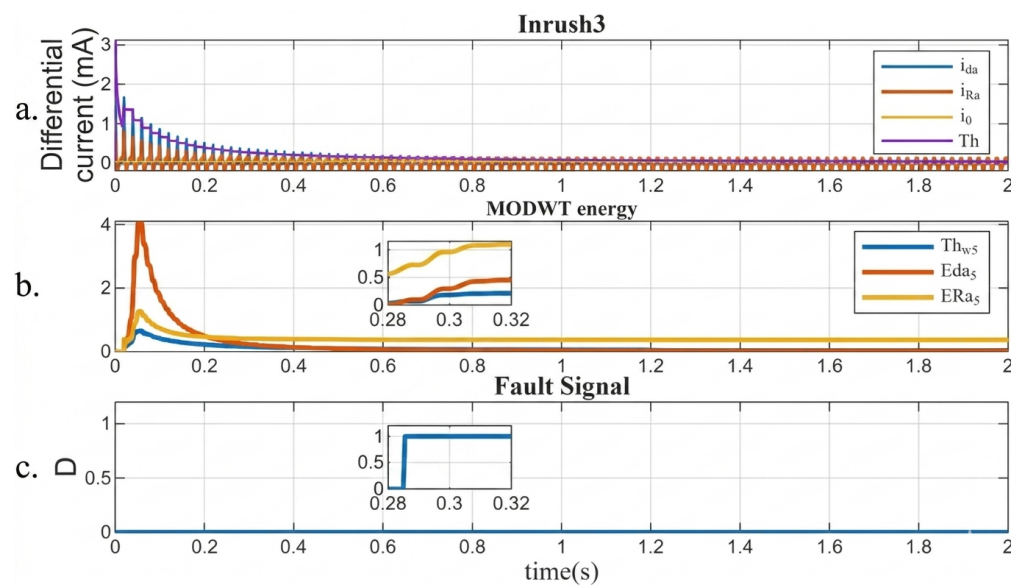


Figure 9. Inrush current: (a) differential current; (b) MODWT energy; (c) Fault Detection Response.

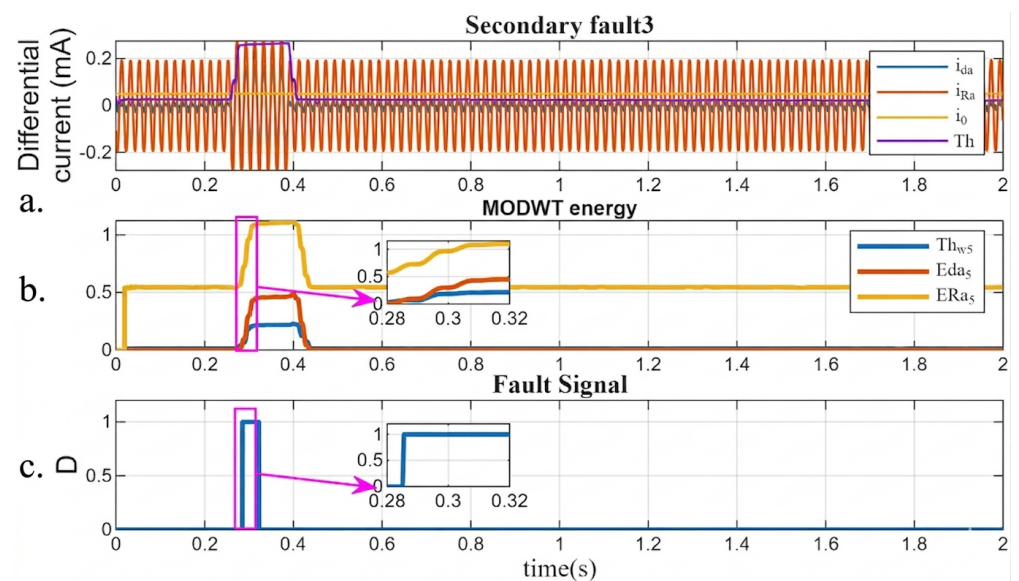


Figure 10. LIF conditions: (a) differential current; (b) MODWT energy; (c) Fault Detection Response.

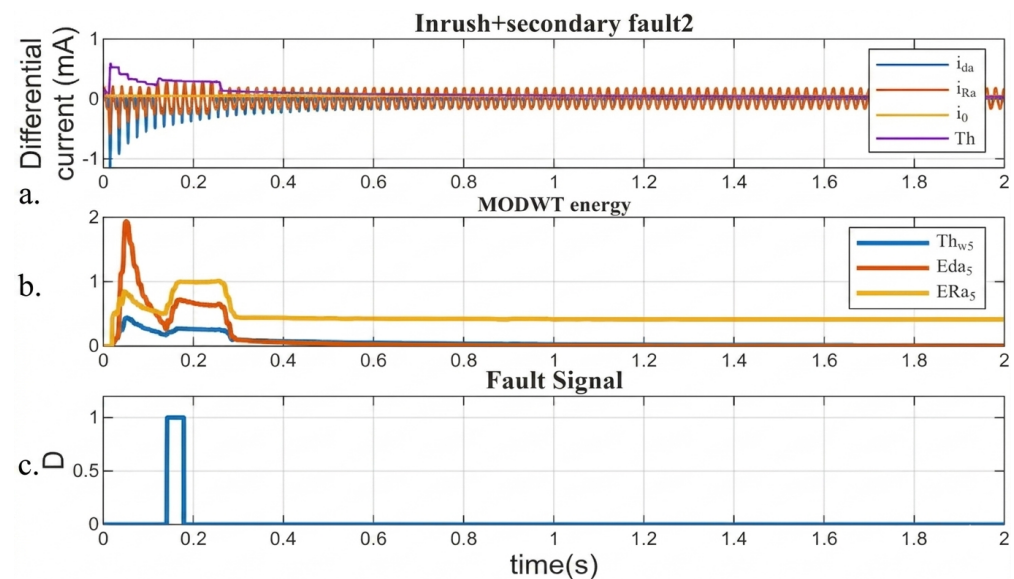


Figure 11. Inrush current and LIF together: (a) differential current; (b) MODWT energy; (c) Fault Detection Response.

$$C = \begin{bmatrix} CF & WF \\ CT & WT \end{bmatrix} \rightarrow \begin{matrix} \text{Faulty conditions} \\ \text{Transient conditions} \end{matrix} \quad (14)$$

Three indices are specified to verify the reliability of any TDP approach: accuracy (A) is for validating how accurately the method responds in all cases, dependability (Dp) is the success rate for detecting all faulty cases correctly, and selectivity (S) shows the capability of distinguishing inrush current and LIF conditions. The indices are formulated in Equation (15).

$$\begin{aligned} Dp &= \frac{CF}{CF + WF} \% \\ S &= \frac{CF}{CF + WT} \% \\ A &= \frac{CF + CT}{CF + CT + WF + WT} \% \end{aligned} \quad (15)$$

4. Results and Discussion

The suggested LIF detection algorithm was experimentally validated using a custom-designed 1 kVA laboratory-scale transformer. While laboratory settings are carefully regulated, this physical arrangement was deliberately chosen above purely numerical simulations to assure the utmost integrity in capturing complicated magnetic interactions. LIF conditions involve highly nonlinear phenomena like as local magnetic saturation and localized leakage flux variations, which are frequently oversimplified by lumped-parameter models found in common transient modeling tools like PSCAD. This work uses a physical transformer with internal taps to capture real-world transients and physical noise, which are critical for developing a robust protection strategy. Furthermore, to address the transition from laboratory-scale results to industrial-scale power systems and to overcome generalizability limitations, the proposed algorithm employs *normalized MODWT energy signals* rather than absolute current magnitudes. This normalization process ensures that the algorithm captures the fundamental physical characteristics of LIF conditions, which remain consistent across different transformer scales, rather than being tuned to the specific electrical parameters of the 1 kVA laboratory unit. Thus, the mathematical framework focuses on relative spectral shifts and energy distribution patterns, ensuring that the fundamental fault indicators identified at 1 kVA remain scalable and applicable to larger units.

On the other hand, the data acquisition technique used in this research is consistent with established practices in the current literature [13], where physical experimental modeling remains the preferred and most reliable data acquisition path for internal transformer faults due to the scarcity of high-resolution field data in a *diverse range of scenarios*, including fault locations, impedance, and non-fault transients (e.g., inrush, sympathetic inrush). This variation assures that the procedure is resistant against specific experimental conditions while focusing on the underlying fault dynamics.

The suggested hybrid MODWT energy/DF-based TDP method was developed by assessing the limitations of two previously stated approaches in the literature [3,28]. While the MODWT energy-based approach [3] has great spectral sensitivity for fault feature extraction, its application alone may sometimes result in a lack of fault identification during complicated transients. The difference function-based technique [28] responds quickly to sudden variations in the time domain of the differential current, but it may lack the robustness required to discriminate LIF conditions from external disturbances like a sympathetic inrush current. To validate the superiority of the proposed method, these approaches were evaluated and compared using the confusion matrix method, with the experimental results summarized in Table 3. This comparative analysis reveals that the hybrid method significantly improves overall accuracy by achieving a near-perfect classification of internal faults and inrush currents. Specifically, the hybrid approach maintains the Fast detection speed of the difference function while incorporating the ‘Excellent’ sensitivity of MODWT energy signals, effectively eliminating the malfunctions observed in the isolated methodologies. These results demonstrate that the combined spectral and temporal analysis provides a more reliable protection scheme for LIF conditions and various cases. Furthermore, the 100% dependability rate observed in the experimental results is consistent with the fundamental quality standards required for industrial transformer protection. In the field of power system protection, absolute reliability is a prerequisite rather than an optimistic target, as even a 1% failure rate in a differential relay could lead to catastrophic damage to high-value power transformers and grid stability. This high level of performance is attributed to the hybrid physical logic of the MODWT energy and DF, which is designed to capture universal electromagnetic deviations. The comprehensive comparative analysis presented in Table 4 further situates the proposed combined MODWT energy–DF method within the broader landscape of TDP methods. Unlike traditional harmonic restraint methods (HRB), which often struggle with sensitivity during low-level inter-turn faults due to overlapping harmonic signatures, the proposed method utilizes normalized energy features to ensure reliable detection even at minimal fault levels. Furthermore, while AI and deep learning-based approaches offer high accuracy, they typically require significant computational resources and extensive training datasets, which may limit their real-time applicability in standard relay hardware. In contrast, the proposed hybrid logic achieves ‘Very Fast’ detection speeds without the need for intensive training, providing a computationally efficient alternative that does not compromise on robustness. The ‘Excellent’ rating in LIF sensitivity specifically underscores the advantage of combining spectral depth with temporal derivatives, confirming that the hybrid approach offers a superior trade-off between complexity and performance compared to existing state-of-the-art solutions.

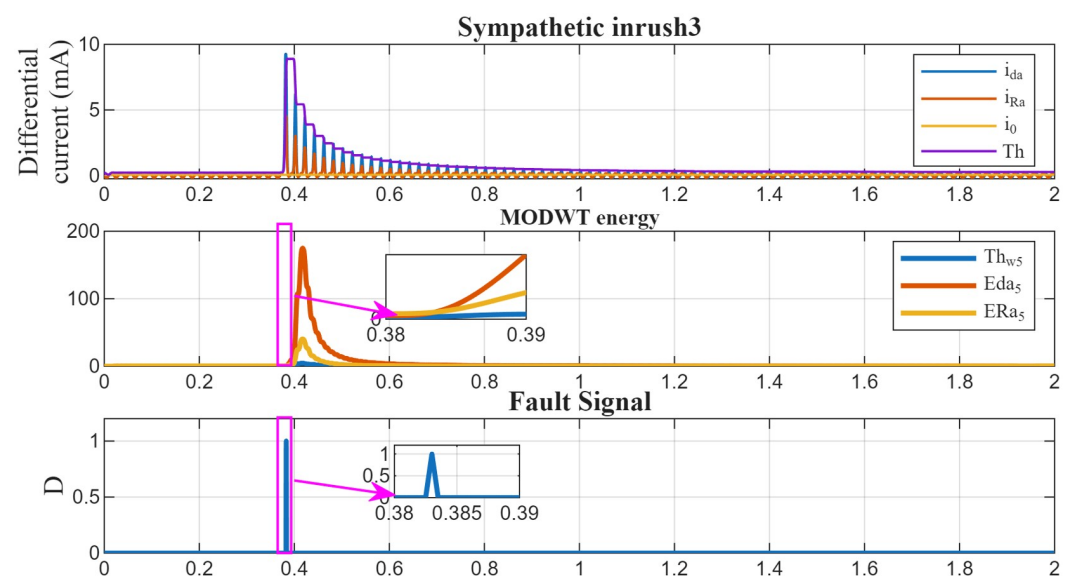
Table 3. TDP evaluation with experimental data.

	A (%)	Dp (%)	S (%)
Difference function-based TDP	90	100	85
Wavelet transform-based TDP	91	100	82
TDP with wavelet transform and difference function	95	100	89.6

Table 4. Comparative analysis of the proposed hybrid method and state-of-the-art techniques .

Methodology	Domain	Speed	Sensitivity to LIF (<5%)	Robustness	Feature Extraction
Traditional HRB	Time	Moderate	Low	Moderate	Harmonics
ANN/Deep Learning	Data	Slow (Training req.)	High	High	Black-box
Standard DWT	Time–Freq	Moderate	Moderate	Moderate	Wavelet Coefficients
Proposed Hybrid	Time–Freq	Very Fast	Excellent	Very High	Normalized Energy/DF

Table 3 shows that with the sensitivity index degradation, while the proposed hybrid MODWT–DF method demonstrates high robustness, the phenomenon of sympathetic inrush current represents a complex operational challenge that warrants deeper analysis. Sympathetic inrush occurs when the energization of a transformer causes a neighboring, already connected transformer to enter a period of saturation, leading to prolonged and distorted current waveforms. In the experimental observations in this research, demonstrated in Table 3, slight performance degradation was noted during such events. This is primarily because the spectral features of sympathetic inrush can partially overlap with LIF conditions in the very beginning of the sympathetic inrush phenomena. The E_{da5} and E_{Ra5} elements are situated just like during the LIF condition before they reach their inherent levels during the sympathetic inrush current, as shown in Figure 12. As the abrupt changes happen simultaneously, both MODWT energy and DFs may result in fault signals. Regarding the potential for mis-operation, this could theoretically be mitigated by introducing a time-restricting logic. However, such a precaution would inevitably result in a delay in fault detection across all scenarios. Therefore, the proposed TDP algorithm is not interfered with at this stage, as the overall system response and dependability indices were already found to be satisfactory under the evaluated conditions. However, the integration of the DF acts as a critical safeguard here; by monitoring the rate of change in the time domain, the algorithm mostly prevents ‘false trips’—maintaining security at the expense of a marginal increase in operating time.

**Figure 12.** Sympathetic inrush malfunction.

From a practical implementation perspective, the introduction of a fixed time delay or a traditional second-harmonic restraint was considered to mitigate these false detections. However, such interventions were intentionally excluded for two primary reasons: Prioritization of Sensitivity: Introducing a time delay would inherently compromise the detection speed for actual LIF conditions, which is a critical priority for transformer protection. Lack of Distinctive Markers: As stated in the Introduction, traditional harmonics often fail to

provide a reliable distinction for modern transformers. At this stage of the research, a consistent and unique energy-based ‘marker’ that differentiates sympathetic inrush from a 1% LIF has not been isolated. Consequently, the algorithm is presented in its raw form to maintain maximum dependability. Future work could focus on developing an adaptive thresholding mechanism that dynamically adjusts sensitivity only when a sympathetic transient is detected, provided that a reliable distinguishing feature can be identified in the signal energy domain. By documenting these occurrences via the confusion matrix, this study provides a transparent roadmap for the next generation of adaptive protection relays.

The proposed hybrid MODWT–DF algorithm is designed for seamless integration into real-time industrial protection relays. Compared to data-driven (AI-based) methods that require multi-layer weight updates or model-based approaches that necessitate real-time parameter optimization for changing physical conditions (e.g., temperature and moisture), the signal-processing-based nature of this method ensures a significantly lower computational burden. In this study, a sampling frequency of 2 kHz was utilized, providing 40 samples per cycle at a 50 Hz fundamental frequency. The execution of the MODWT energy and difference function logic within a sliding-window framework exhibits linear computational complexity relative to the number of input channels. Modern Digital Signal Processor (DSP) or Field Programmable Gate Array (FPGA) architectures can handle these calculations in parallel. Consequently, extending the method to multi-winding transformers (e.g., 6-channel monitoring) would linearly increase memory utilization while the total decision delay remains effectively constant. Given that the execution time for a single processing step is substantially shorter than the 0.5 ms sampling interval, the method is highly suitable for real-time substation environments without requiring specialized high-performance hardware.

5. Conclusions

In this study, a Transformer Differential Protection (TDP) method has been developed to provide instantaneous and accurate responses under both transient and LIF conditions without the necessity for additional hardware. The NSC function is utilized to detect inherent asymmetries in the primary and secondary three-phase currents during the initial stages of LIFs. However, 87T phase current TDP is preferred due to the fading out of the NSC component during simultaneous inrush current and LIF cases. Feature extraction is performed by applying MODWT energy and DF, while analytical fault detection algorithms are defined for both components. Furthermore, a sliding-window algorithm is implemented to provide real-time protection throughout the entire process.

The performance of the proposed method is validated using datasets collected from a laboratory-based 1 kVA Y–Y connected transformer, which was specifically designed to imitate the early stages of LIFs. The method’s effectiveness is assessed using three indices: accuracy (A), dependability (Dp), and selectivity (S). Despite the requirement for threshold identification and specific settings—consistent with all signal-processing-based TDP approaches—solid performance is achieved across a wide variety of data. All LIF cases were detected with 100% dependability. Selectivity performance of 97% was achieved when sympathetic inrush current data was excluded. Although sympathetic inrush current cases caused momentary malfunctions due to rapid changes in E_{da5} and E_{Ra5} values—resulting in a decrease in the S index to 89.6%—the overall accuracy remains approximately 95%.

In alignment with the objectives of applied systems innovations, it is demonstrated that integrating multi-resolution wavelet analysis with an analytical difference function creates a robust framework for early-stage fault detection, offering a scalable and efficient advancement for modern power transformer protection architectures.

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Abbreviations

The following abbreviations are used in this manuscript:

TDP	Transformer Differential Protection
LIF	Low-Level Inter-Turn Fault
HRB	Harmonic Restraints and Blocking
MODWT	Maximum Overlapped Discrete Wavelet Transform
DF	Difference Function
NSC	Negative Sequence Current
87T	Phase Current TDP Standard
87Q	NSC TDP Standard
NI	National Instruments
DAQ	Data Acquisition
A	Accuracy
Dp	Dependability
S	Selectivity
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
FEA	Finite Element Analysis
FRA	Frequency Response Analysis

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