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Evaluating Fault Detection Techniques in Real Electrical Transformers: A Comparative Case of Study

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Abstract Transformers are integral to the reliability of electrical networks, necessitating robust diagnostic methods for fault detection. This study conducts a comparative evaluation of three fault detection techniques using real-world data from distribution transformers. The methods analyzed include differential current analysis, correlation-based techniques, and flux linkage increments. Results demonstrate that differential current analysis exhibits the highest sensitivity (93.33%), detecting faults at 4.41% of the short-circuit current. Correlation-based methods follow with 86.67% sensitivity, while flux linkage increments offer lower sensitivity but robust performance at high current levels. This comparative analysis provides actionable insights for enhancing transformer reliability through effective monitoring strategies.

Keywords Electrical transformers, Fault detection, Voltage and current monitoring, Diagnostic techniques

AMS 2010 subject classifications: 90C90, 65C20, 94C12, 90B25.

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1. Introduction

Electrical transformers are critical components in the energy system infrastructure, playing a key role in ensuring the stability and reliability of the electrical grid [1]. Failure in these devices can disrupt the power supply, leading to significant consequences for both utility providers and end users, with technical, economic, and social repercussions.

Transformer failures can be broadly classified into two categories: developed failures, which result in immediate damage, and incipient failures, which gradually deteriorate over time [2]. The underlying causes of these failures can be further categorized as internal or external, including overheating [3], short circuits [4], winding failures [5], insulation degradation [6], and partial discharges [7], among others [8]. Recent studies have highlighted that the highest failure rates in transformers are predominantly linked to insulation issues, as illustrated in Figure 1, adapted from [8]. Additionally, a significant proportion of recurrent failures can be attributed to problems in the windings, referring to problems in the wire turns that make up the windings where the electrical current flows.

Timely identification and resolution of these issues are essential to prevent service interruptions and maintain the integrity of the power system. In recent years, advanced offline and online diagnostic methods have been developed for power transformers to facilitate the detection of potential faults. Offline diagnostic methods necessitate disconnecting the transformer from the electrical grid and are typically employed during scheduled maintenance

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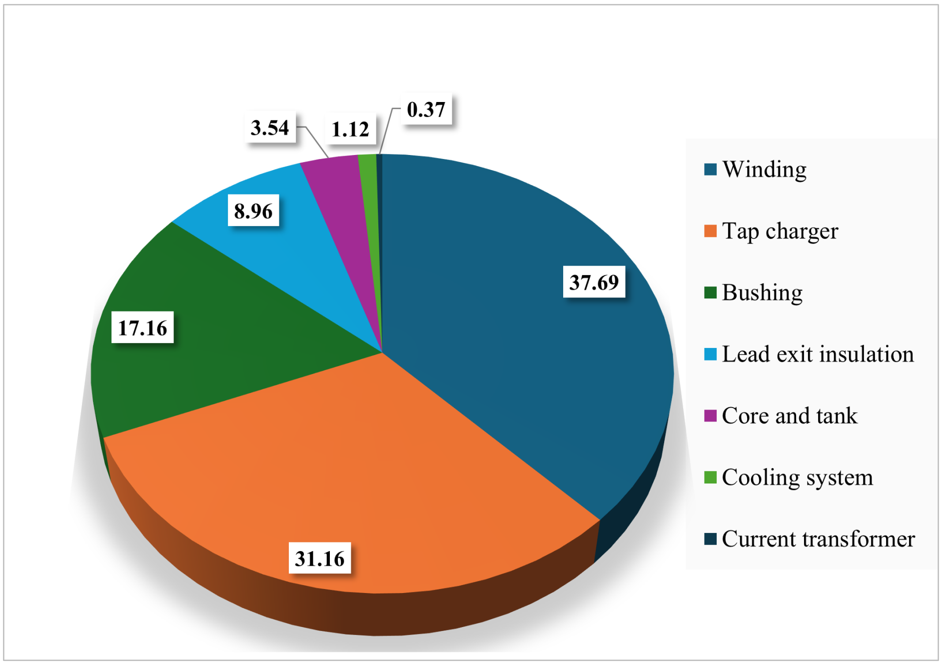

Figure 1. Transformers failures rates. Source: [8]

inspections or when there are indications of a potential malfunction. Conversely, online diagnostic techniques involve continuous monitoring during the transformer's operation, enabling the measurement and recording of critical parameters that may influence its service life. Automated analysis of this data enhances the ability to identify potential issues at an early stage.

Figure 2 presents a selection of the most used methods for fault diagnosing in electrical transformers, including Dissolved Gas Analysis (DGA), thermography, vibration analysis, and electrical variable monitoring, each offers distinct strengths and weaknesses in diagnosing faults.

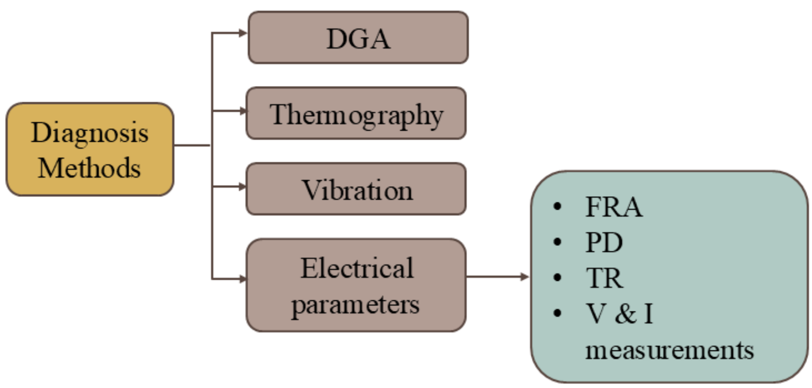

Figure 2. Classification of widely used methods for transformer fault diagnosis.

In recent years, the role of power transformers within asset-intensive infrastructures such as electrical networks has evolved from solely operational elements to strategic assets whose failure poses high operational and economic risks. This shift has emphasized the necessity of predictive and intelligent management strategies, particularly in response to major blackouts and system vulnerabilities observed in countries such as Spain or Portugal in 2025.

Within this framework, asset management practices have gained traction, aiming to balance cost, performance, and risk over the equipment's entire lifecycle [9]. Regulatory bodies, such as the *Comisión de Regulación de Energía y Gas (CREG)* in Colombia, now require utilities to adopt structured asset strategies, promoting reliability, life extension, and cost optimization. These strategies typically rely on real-time monitoring, condition-based assessments, and risk quantification to prioritize maintenance and capital investment decisions.

Health Index (HI)-based approaches have become important for transformer condition assessment [10, 11]. Unlike traditional maintenance practices, which focus on time-based or failure-based interventions, HI models allow for a comprehensive evaluation of transformer health using a combination of technical indicators such as dissolved gas analysis (DGA), insulation condition, thermal performance, and historical loading profiles. This highlights the need for advanced diagnostic methods that can operate continuously, adapt to real data equipment, and be integrated with intelligent management platforms to support more informed and proactive decision-making in utility environments.

DGA is a widely utilized technique for detecting incipient faults by analyzing gas concentrations dissolved in transformer oil. It is highly effective for early fault detection but requires manual sampling and laboratory analysis, which can delay fault identification [12]. Despite these limitations, advanced interpretation techniques, such as combining fuzzy logic with traditional DGA methods, can significantly improve accuracy. A study demonstrated a diagnostic accuracy of 99% for normal conditions and 98.76% for faulty conditions [13]. Additionally, AI-driven enhancements to traditional DGA methods further improve both accuracy and reliability in fault diagnosis [14].

Thermography offers real-time, non-invasive fault detection by visualizing thermal anomalies. This method provides real-time monitoring and non-invasive fault detection, but its accuracy can be affected by external environmental conditions [15]. Automatic diagnostic techniques using image processing and computational intelligence have been proposed to overcome the challenges of manual analysis, increasing reliability and efficiency [16].

Vibration analysis is particularly effective at identifying mechanical faults, such as imbalance or looseness, through continuous monitoring. This technique is advantageous for identifying mechanical faults without invasive procedures but requires complex signal processing and expertise, limiting its use for electrical faults [17]. Advanced techniques, including deep learning algorithms, enhance the robustness and accuracy of vibration-based fault detection. These methods are resilient to sensor misplacement and provide reliable predictions even under varying conditions [18].

Recent advancements in intelligent fault diagnosis have increasingly focused on leveraging vibration signals and deep learning architectures to overcome the limitations of conventional techniques. Li et al. [19] demonstrated that transformer faults could be effectively identified using an improved convolutional neural network (CNN) trained on vibration signals converted into time-frequency representations through continuous wavelet transform. Their method achieved a diagnostic accuracy of 99.95% on dry-type transformers. Similarly, Granados-Lieberman et al. [20] developed a hybrid framework combining short-time Fourier transform and wavelet denoising to detect short-circuited turns under both transient and steady-state regimes using vibration data. Their approach achieved a classification accuracy of up to 90%, confirming the feasibility of early detection through dynamic signal analysis. Shang et al. [21] proposed a fault diagnosis model for oil-immersed transformers based on multi-scale approximate entropy of dissolved gas components, processed by an optimized CNN via a sparrow search algorithm. Their model significantly reduced false positives while maintaining high classification performance across multiple fault types.

In parallel, hybrid deep-learning architectures are increasingly used to enhance diagnostic robustness. Ahmed and Nandi [22] introduced a convolutional-transformer model that captures both local and long-range dependencies in vibration signals, enabling highly accurate classification of bearing fault states with over 99% precision. Liu et al. [23] proposed an MSCViT-based framework combining signal denoising with transformer-based attention modules to extract deep fault features from noisy environments. Their method achieved over 99% accuracy across multiple datasets, highlighting its versatility. These emerging approaches reflect a broader shift toward data-driven, real-time monitoring systems that incorporate signal transformation, neural network optimization, and adaptive feature extraction. The present work builds upon these advances by comparatively analyzing voltage and current-based diagnostic techniques under real-world laboratory conditions, aiming to bridge the gap between method accuracy, implementation feasibility, and early-stage fault sensitivity in distribution transformers.

Each of the methods discussed has proven to be effective in detecting common faults; however, each faces specific challenges that limit its applicability in certain contexts. For instance, DGA is invasive, expensive, and not suitable for dry-type transformers or those using vegetable oil. Infrared thermography, while effective, can be costly and impractical as it necessitates field personnel for data collection. In contrast, vibration analysis provides valuable insights into the mechanical condition of the transformer but is heavily reliant on electrical variables, limiting its standalone diagnostic utility.

On the other hand, electrical variable monitoring involves tracking deviations in electrical parameters to detect potential issues. Some techniques in this category include frequency response analysis (FRA), partial discharge detection (PD), turn ratio testing (TR), and Voltage and Current Measurements (V and I). These methods offer early warnings without the need to disconnect the transformer; however, some may not be able to accurately identify the location or type of the fault without the use of additional diagnostic techniques [24].

Despite transformer fault diagnosis has progressed toward more advanced and effective methodologies, encompassing both online and offline techniques, implementing these methods in distribution transformers can be prohibitively expensive. Furthermore, certain techniques are unsuitable for dry-type transformers, while others may pose safety risks to testing personnel [8]. Concurrently, there has been notable growth in the development of online diagnostic strategies based on electrical variable monitoring. These approaches provide a cost-effective alternative to traditional methods and exhibit substantial potential for widespread adoption and future advancements [25].

In this context, Table 1 provides a comparative analysis of the various fault detection methods for transformers discussed above. It highlights that the V and I measurement approach offers significant cost, efficiency, and applicability advantages.

Table 1. Comparison of Different Fault Detection Methods in Transformers

Method	Application	Cost	Efficiency	Challenges
DGA	Oil-based transformers	High	High	Invasive, not applicable to dry/vegetable oil transformers
Thermography	All types	Moderate	Moderate	Requires field personnel, can be costly
Vibration Analysis	Mechanical faults	Moderate	High	Dependent on electrical variables
FRA	All types	Moderate	Low	Effective for early fault detection
TR		Low	High	
PD		Moderate	Moderate	
Voltage and Current Measurement		Low	High	

Based on the previous analysis, the V and I measurements techniques will be the focus of this article as it represents a fundamental method for early detection. This method utilizes the relationship between the incoming current to the transformer and the instantaneous voltage variation between the input and output of a specific phase, uniquely identifying the transformer condition [26]. Furthermore, it stands out for its ability to detect anomalies at early stages, offering significant advantages over the other methods described.

This article compares various V and I methods for fault detection by analyzing electrical signals applied to transformers. The comparison between techniques extends beyond their fault detection capabilities to encompass critical aspects such as detection sensitivity, implementation complexity, and the number of variables required for proper application. This comprehensive evaluation framework enables the assessment of each technique not only in terms of diagnostic accuracy but also in terms of practical feasibility in specific scenarios. Moreover, considering these factors facilitates the identification of relative strengths, limitations, and opportunities for optimization, ensuring their effective application in real-world environments. Such an approach is crucial for selecting the most appropriate methodology based on the system's requirements and operating conditions.

This study focuses on comparing fault detection methods based on voltage and current measurements, highlighting their relative performance, sensitivity, and feasibility. Unlike prior studies that rely on simulated data, this work evaluates real-world transformer data to ensure the practical applicability of findings. By assessing the strengths and limitations of these methods, the research aims to provide actionable insights for enhancing fault detection in distribution transformers. This study is limited to low-capacity single-phase distribution transformers tested under controlled laboratory conditions. The scope does not include three-phase transformers, high-capacity units, or fault types such as insulation breakdowns or partial discharges. Additionally, the analysis excludes real-world electrical grid dynamics such as load fluctuations, harmonic distortion, and transient phenomena. These constraints are intended to maintain methodological consistency and ensure the reproducibility of results.

The remainder of this document is structured as follows: Section 2 reviews the primary diagnostic methods for transformer fault detection. Section 3 details the selected techniques for comparative analysis. Section 4 describes the methodology and modeling assumptions. Results and discussions are presented in Section 5, while Section 6 concludes with key findings and future research directions.

2. Methods for Fault Diagnosis Using Electrical Variable Monitoring

Four primary techniques are recognized as key components of methods based on monitoring electrical variables: FRA, PD, TR, and V and I measurements.

FRA is a non-destructive diagnostic method used to measure the frequency response of a transformer across a broad range of frequencies. This technique is particularly effective for detecting deformations and displacements in transformer windings, issues that are challenging to identify using other methodologies such as DGA, PD, or thermography. Although effective, online measurement using the FRA technique can exhibit fluctuations in results due to factors such as electrical network conditions, the presence of additional loads, or load variations within the system. These external influences can alter the transformer's response, representing a significant limitation of the method as they may lead to inaccurate interpretations [8]. Moreover, current result interpretation methods are inefficient and lack standardization. To address these challenges, in [27] an interpretation technique was developed leveraging machine learning and numerical analysis has proven effective in enhancing fault detection and classification, providing an assessment of fault severity.

Online/offline PD testing evaluates the condition of electrical insulation through standardized procedures outlined in IEC 60270 [28]. This testing method measures PD pulses to assess the state of insulation, serving as a critical non-destructive high-voltage diagnostic tool for predicting system failures, particularly in routine maintenance applications [29]. Nevertheless, conventional electrical PD measurement, as defined by the standard, often encounters sensitivity challenges during on-site/online testing due to significant environmental interference. Non-conventional ultra-high frequency PD measurement techniques have emerged as a valuable alternative to address these limitations. These methods offer high sensitivity, as they are largely resistant to external disturbances, even in noisy environments. They are valuable complementary to other diagnostic techniques, such as acoustic PD localization [30].

The TR test to calculate the transformation ratio between the high and low voltage windings is critical for identifying potential short circuits or open circuits within the windings [8]. Discrepancies exceeding 5% in the transformation ratio, compared to a transformer in optimal condition, may indicate issues in the windings, which can be detected through tests using voltmeter-ammeters or measuring bridges. In online monitoring of this method, challenges may arise due to measurement errors from conventional potential and current transformers, as well as load variations. These limitations can be mitigated by employing inductive and capacitive couplings for voltage and current measurements, respectively, as outlined in [17].

Voltage and current measurement methods analyze the relationship between the current entering the transformer and the instantaneous voltage variation between the input and output of a specific phase [8]. Furthermore, these methods enable precise identification of the transformer's condition [26]. This analysis is considered a unique transformer identification, allowing anomalies to be detected from their early stages. In a healthy transformer, the graphical representation of a voltage variation ΔV against the current (ΔV-I) can serve as its identification under both sinusoidal and non-sinusoidal operating conditions. It can be constantly compared online to detect internal faults. The effectiveness of this method in online fault detection is evaluated through simulations and experiments, observing how different types and intensities of faults affect the ΔV-I graphical representation.

According to a study in [31], 19% of transformer faults occur in the windings. According to IEEE Standard C37.91-2000 [32], turn-to-turn faults can be detected when at least 10% of the transformer winding turns are shorted, producing a measurable change in the terminal current. However, for minor or incipient faults involving only a few shorted turns, the resulting change in terminal current becomes negligible, posing a significant challenge for detection.

Early detection of such faults has been explored in various approaches. The US patent in [33] outlines a method for assessing the condition of a transformer, specifically focusing on the winding condition between turns. This method utilizes an indicator derived from calculating and the effective turns ratio and the operating magnetizing current, both based on electrical parameters of the windings. Further details regarding the formulation of the algorithm developed for this method, along with its key results, are presented in [34].

In [35], a technique based on the analysis of current waveform correlation coefficients is proposed to detect an internal fault occurring in a three-phase transformer, as well as to distinguish it from external faults. The technique relies on changes in current waveforms that occur during faults. This method incorporates autocorrelation into cross-correlation, measuring how a current signal resembles itself at different times and how it relates to other current signals in the system. This enhances fault discrimination and increases the speed of fault detection in terms of time, with the proposed algorithm capable of detecting faults in less than 3 ms. The technique also overcomes the problem of current transformer saturation, one of the major issues in protection methods.

An algorithm for the identification of faulted phases and windings in two- and three-winding transformers, using six detectors and a rule based on the increments of flux linkages (IFLs), is presented in [36]. The ratio of the IFLs between the primary-secondary, primary-tertiary and secondary-tertiary windings, under normal, excessive magnetic inrush, and overexcitation conditions, corresponds to the respective turns ratio. However, during an internal fault, this ratio undergoes a change, enabling precise identification of the fault type and its location.

Asadi and Kelk [4] focus on the detection of turn-to-turn winding faults, which are particularly difficult to detect with conventional methods. They propose a new approach based on measuring the phase difference between the input voltages and the input currents in the transformer's primary windings. This approach is experimentally validated on a laboratory transformer, demonstrating its effectiveness even in the early stages of faults. The article concludes by highlighting the applicability and validity of the proposed method.

The paper [37] presents an online monitoring method based on electrical measurements for detecting inter-turn short circuits in transformers. By utilizing voltage and current measurements on both sides of the transformer, the method enables real-time classification of the transformer's health status and identification of faults during operation. Simulation and experimental results demonstrate that the method is capable of detecting short-circuit conditions of varying severities, with primary winding current serving as the key indicator. Additionally, the study analyzes the loop current generated by short circuits, highlighting its potential to cause damage due to high temperatures

3. Description of the methods selected for comparison

Among the fault detection proposals based on voltage and current measurements, three methods described in [34], [35] and [36] were selected for a comparative analysis. The goal is to evaluate their performance in terms of efficiency and applicability, ultimately determining the most effective method for early fault detection in distribution transformers, thereby enhancing reliability and monitoring capabilities.

3.1. Method 1: Fault detection method based on differential currents

The study in [34] presents an algorithm for the early detection of turn-to-turn faults in transformers based on differential current (I_{diff}) analysis. The algorithm uses voltage-current data monitored by the protection relay, eliminating the need for a physical short circuit. Its performance is evaluated using a 2D non-linear finite element model of a 10 MVA transformer and validated through fault simulations on a 5 kVA laboratory prototype. The turn-to-turn fault is simulated by connecting a rheostat between two turns, inducing a slight change in the winding insulation resistance. This, in turn, causes variations in the differential current. The proposed algorithm is straightforward and relies on the equivalent circuit representations of a transformer in both healthy and faulty conditions.

The methodology consists of two phases: one for calibration and another for monitoring. In the calibration phase, reference values of I_{diff} (in Equation 1) and the adequate turns ratio are established through current and voltage measurements at least on three different load points.

$$\frac{I_1}{I_2} = \frac{1}{I_2} I_{\text{diff}} + \frac{N_2}{N_1} \tag{1}$$

where, I_1,I_2, are phase currents on the primary and secondary side, and I_{diff} is the differential current.

Equation (1) is compared to the straight-line equation $y = mx + C$. During calibration, values for I_1 and I_2 are measured, which fit the straight-line equation. The slope (initial value of I_{diff}) and y-intercept (turn ratio) are identified. Once calibration is complete, the base value of I_{diff} and the adequate turns ratio are stored for monitoring mode.

During the monitoring phase, the real-time differential current I'_{diff} is calculated from baseline differential current I_{diff} and the turns ratio get in the calibration mode. Then, I'_{diff} is derived from equation (2).

$$I_{\text{diff}} + \frac{N_f}{N_1} I_f = I_1 - \left(\frac{N_2}{N_1}\right)_{\text{eff}} I_2 = I'_{\text{diff}} \tag{2}$$

If $I'_{diff} > I_{diff}$, an incipient winding fault is occurring. This approach detects small changes in winding insulation resistance, simulated through a rheostat between the turns. The simplicity and low implementation cost make this method a compelling option for online transformer monitoring.

3.2. Method 2: Fault detection method based on correlation coefficients of currents

The research in [35] presents a method based on the analysis of correlation coefficients of current waveforms to differentiate between internal and external faults in transformers, as well as to address current transformer saturation. The correlation coefficient, R, quantifies the degree of linear relationship between two variables. Its value ranges from -1 to $+1$, where $R = 0$ indicates no linear relationship, $R = +1$ signifies a perfect positive linear relationship, and $R = -1$ represents a perfect negative linear relationship. This metric provides a measure of the strength and direction of the linear association between the variables.

This method uses current measurements on both the primary and secondary sides of the transformer, calculates cross-correlation and autocorrelation coefficients using `MATLAB`, and identifies faults by evaluating the similarity between current signals, indicating deviations from expected patterns. Auto-correlation refers to the cross-correlation of a signal with itself. It measures the similarity between a signal's values at different points in time as a function of the time lag or shift between observations.

The methodology involves analyzing the correlation coefficients (R_{i12}) between primary and secondary currents, as well as negative sequence currents and their phase angles. The coefficients R_{i12} can be calculated by the equation (3).

$$R_{i12} = \frac{\sum_{k=1}^{m} i_1(k) i_2(k) - \frac{1}{m} \sum_{k=1}^{m} i_1(k) \sum_{k=1}^{m} i_2(k)}{\sqrt{\sum_{k=1}^{m} (i_1(k))^2 - \frac{1}{m}\left(\sum_{k=1}^{m} i_1(k)\right)^2} \times \sqrt{\sum_{k=1}^{m} (i_2(k))^2 - \frac{1}{m}\left(\sum_{k=1}^{m} i_2(k)\right)^2}} \tag{3}$$

where, R_{i12} is the cross-correlation coefficient between primary and secondary currents, I_1 and I_2, for each phase; m is the number of samples per window to correlate; $i_1(k)$ and $i_2(k)$ are the sampled current values at instant k on primary and secondary side.

When the currents show high correlation during saturation, the algorithm classifies it as an external fault and does not issue a trip or fault signal, allowing for fault condition identification.

The article presents a detailed methodology for processing and analyzing current data to identify the location and type of faults. It leverages specific mathematical models that establish correlations between current characteristics and potential internal or external faults. External faults are related to the saturation of current transformers.

3.3. Method 3: Fault detection method based on the increments of flux linkages

In [36], an algorithm is proposed for identifying faulted phases and windings in two- and three-winding transformers by analyzing increments of flux linkages (IFL). Under normal operating conditions, the ratio of IFLs between the primary-secondary, primary-tertiary, and secondary-tertiary windings matches the corresponding turns ratio. However, this ratio deviates in the presence of a fault, enabling fault detection.

The mathematical formulation is derived from the equations (4)-(6) governing the behavior of each winding under normal operating conditions.

$$\frac{d\lambda_1}{dt} = v_1 - R_1 i_1 - L_{l1}\frac{di_1}{dt} \tag{4}$$

$$\frac{d\lambda_2}{dt} = v_2 - R_2 i_2 - L_{l2}\frac{di_2}{dt} \tag{5}$$

$$\frac{d\lambda_3}{dt} = v_3 - R_3 i_3 - L_{l3}\frac{di_3}{dt} \tag{6}$$

where, R_1, R_2 and R_3 are the winding resistance; i_1, i_2 and i_3 are the phase currents; v_1, v_2 and v_3 are the phase voltages; L_{l1}, L_{l2} and L_{l3} are the leakage inductances; and λ_1, λ_2 and λ_3 are the flux linkages.

The ratio of increments of flux linkages (RIFL) between the windings are calculated using the expressions for the IFLs of the primary ($\Delta\lambda_1$), secondary ($\Delta\lambda_2$), and tertiary ($\Delta\lambda_3$) windings. These ratios are determined through equations (7)-(9), which are derived by integrating equations (4)-(6).

$$RIFL_{12} = \frac{\Delta\lambda_1}{\Delta\lambda_2} \tag{7}$$

$$RIFL_{13} = \frac{\Delta\lambda_1}{\Delta\lambda_3} \tag{8}$$

$$RIFL_{23} = \frac{\Delta\lambda_2}{\Delta\lambda_3} \tag{9}$$

Under normal and overexcitation conditions, the RIFL coincides with the nominal transformation ratio. However, in the event of a fault, the RIFL exhibits notable deviations from this expected ratio, enabling the detection and identification of system anomalies.

To identify such faults in a two-winding single-phase transformer, three detectors, defined by equations (10)-(12) are employed. These detectors analyze the IFL of the windings and trigger a fault signal if any exceeds a predefined threshold. The proposed algorithm not only detects internal faults but also accurately identifies the affected phase and winding.

$$Detector_{12} = \frac{\Delta\lambda_1 - (\frac{N_1}{N_2})\Delta\lambda_2}{\sqrt{2V_1} \cdot T} \times 100(\%) \tag{10}$$

$$Detector_{13} = \frac{\Delta\lambda_1 - (\frac{N_1}{N_3})\Delta\lambda_3}{\sqrt{2V_1} \cdot T} \times 100(\%) \tag{11}$$

$$Detector_{23} = \frac{\Delta\lambda_2 - (\frac{N_2}{N_3})\Delta\lambda_3}{\sqrt{2V_2} \cdot T} \times 100(\%) \tag{12}$$

where: V_1 and V_2 are the primary and secondary rated voltages; N_1, N_2 and N_3 are the number of turns of each windings; and T is the sampling interval.

The identification process employs three detectors combined with a set of logical rules to accurately determine the affected winding and phase. The robustness and precision of this method make it highly suitable for advanced real-time protection of distribution transformers.

The performance of the proposed algorithm was assessed using a three-phase Y-Y-D transformer model with three windings, implemented in the `EMTP` software. The model simulated ground-to-ground and turn-to-turn faults in the windings. Additionally, various operating conditions were evaluated, including magnetic inrush phenomena, internal winding faults, and overexcitation. The numerical integration of equations (4)-(6) was performed using the trapezoidal integration method.

Table 2. Comparison of Fault Detection Methods in Transformers

Feature	Method 1: Differential Current	Method 2: Current Correlation	Method 3: Flux Linkages
Theoretical Basis	Difference between primary and secondary currents; if it exceeds a threshold, a fault is detected.	Cross-correlation and autocorrelation between primary and secondary signals.	Relationship between magnetic flux increments in windings, sensitive to faults.
Detectable Fault Types	Internal faults, winding faults, and saturation under certain conditions.	Internal and external faults; distinguishes between them.	Internal faults, winding faults, and identification of affected phases.
Detection Mechanism	Fixed threshold of $I_{\text{diff}} > 0.2\,\text{A}$.	Correlation coefficient $R < 0.9$ indicates internal fault.	Variation of $\Delta\lambda_1/\Delta\lambda_2 > 5\%$.
Advantages	High sensitivity; simple implementation.	Discriminates internal/external faults; tolerant to saturation.	Does not require additional sensors; identifies faulted phase.
Disadvantages	False positives due to harmonics or transients; limited to single-phase transformers.	Does not identify faulted phase; requires more processing.	Cannot detect symmetric faults; complex implementation.

4. Methodology for compartive analysis

This research presents a comparative analysis of three methodologies based on electrical variables for detecting turn-to-turn faults in single-phase transformers. The comparison evaluates not only the fault detection capabilities of each method but also their detection sensitivity, implementation complexity, and the number of variables required for proper application. To ensure a consistent basis for evaluation, the alarm signals generated by each methodology are standardized within a common framework, using current (I) as the primary variable. This approach facilitates a direct comparison and detailed analysis of the results obtained by each method, allowing for the identification of their respective advantages and limitations.

4.1. Calibration of methods using transformer model

The methodology presented in [38] enables the modeling of a two-winding transformer by representing the primary and secondary sides with a single-phase equivalent circuit, as shown in Figure 3. This equivalent circuit simplifies the calculation of fundamental parameters for transformer analysis, such as the short-circuit current under symmetrical load conditions and nominal voltage. Additionally, it facilitates the representation of variations in the transformation ratio, allowing the modeling of transformer behavior with regulation taps or under fluctuations in nominal voltage caused by changes in demand or operating conditions

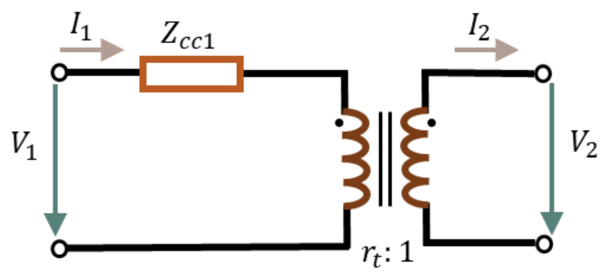

Figure 3. Equivalent circuit for two-winding transformers.

Based on Figure 3 and the nominal data provided, the equivalent circuit of a 5 kVA transformer is derived, from which the nominal currents in the primary (I_1) and secondary (I_2) windings are calculated using equations (13) and (14), respectively.

$$I_1 = \frac{S}{V_1} \tag{13}$$

$$I_2 = \frac{S}{V_2} \tag{14}$$

where, V_1 and V_2 are the rated nominal voltage on primary and secondary windings, and S is the rated nominal power.

Using the transformer's nominal currents, the short-circuit currents for both the primary ($I_{cc_{prim}}$) and secondary ($I_{cc_{sec}}$) windings are calculated based on the expressions in equations (15) and (16), where Z is the winding impedance.

$$I_{cc_{prim}} = \frac{I_1}{\frac{Z\%}{100}} \tag{15}$$

$$I_{cc_{sec}} = \frac{I_2}{\frac{Z\%}{100}} \tag{16}$$

4.2. Modeling assumptions

The evaluation of each method relies on specific thresholds to identify the presence of faults in the transformer. These thresholds are defined based on the characteristics and operational parameters of each approach. In the case of Method 1, a fault alarm is triggered when the difference between the differential currents, denoted as I_{diff} and I'_{diff}, exceeds 0.2 A. Method 2 determines faults by assessing the cross-correlation and autocorrelation coefficients of current signals, with a detection threshold set at 0.9. Method 3 employs a detector-based approach, where fault detection is initiated when the detector value surpasses a recommended operational threshold of 5%.

In Method 1, absolute current values are utilized for comparison, enabling either winding to serve as a reference without requiring specific prioritization or preference. This approach ensures flexibility in its application and facilitates straightforward analysis of current differentials.

The detection thresholds used in this study were directly adopted from the original proposals of each method, as established in their respective reference works. This methodological decision allows for a fair and consistent comparison among the three approaches, as it evaluates their performance under the same conditions for which they were designed. Modifying these thresholds would introduce bias by altering the baseline parameters that define their sensitivity and specificity.

4.3. Experimental Data

4.3.1. Test Methodology and Interval Selection To assess the performance of the proposed methods, three tests were designed based on controlled variations of current in the primary and secondary windings of the transformer. These tests simulated progressive operating conditions, using percentage increments relative to the short-circuit current ($I_{cc} = 694$ A) and the rated current ($I_n = 22.08$ A).

- **Test 1:** The primary current was kept at its rated value (I_n), while the secondary current was increased by 7% of I_{cc} (≈50 A) per interval, starting from I_n until reaching I_{cc}. Specific breakpoint values where each method detected a fault (e.g., 443.40 A at interval 11 for Method 3) were also included to capture nonlinear behavior.
- **Test 2:** Analogous to Test 1, but with roles inverted: the secondary current was fixed at I_n and the primary current was increased using the same intervals.
- **Test 3:** Both primary and secondary currents were simultaneously increased following the same increment scheme.

4.3.2. Database Composition The validation relied on two data sources:

1. **Historical data:** ≈1300 samples from routine tests conducted on similar transformers at Rymel's production plant, providing context under standard conditions.
2. **Experimental data:** Specific measurements from no-load tests applied to two transformers (repaired and new) at Rymel's laboratory under controlled conditions.

4.3.3. Limitations in Accessing External Data It was not possible to validate the proposed models with operational data from utility companies due to confidentiality and privacy policies of those organizations. The data used in this study comes exclusively from: Controlled laboratory tests on trial transformers and historical measurements from Rymel's production plant.

Commitment to Rigor: The methods were evaluated under reproducible conditions with calibrated instrumentation, ensuring their technical validity within the defined scope. Nevertheless, it is acknowledged that the inclusion of field data would enrich the study.

4.4. MATLAB Programming

The computational resources required for each method were evaluated on a system with an AMD Ryzen 7 4800H processor, 16 GB of RAM, and Windows 11 operating system. Method 1 (differential currents) and Method 2 (current correlation) exhibited execution times of 0.009 s and 0.014 s on average, respectively, making them suitable for real-time applications. In contrast, Method 3 (flux linkages) required 6.325 s, indicating higher computational load due to numerical integrations and vector operations. These times were averaged over 50 program runs. Moreover, this method demonstrated higher memory usage and implementation complexity, which may limit its applicability in embedded or online systems.

1. **Method 1: Differential Current Sensing [34]**
   This method is based on analyzing the differential current between the primary and secondary of the transformer. It consists of two stages:

   - *Calibration Mode:* Three current measurements in the primary (I_{1_cal}) and secondary (I_{2_cal}) are used to fit a polynomial model. This model allows calculation of:

   $$I_{diff} = I_1 - \left(\frac{N_2}{N_1}\right) I_2 \tag{17}$$

   where N_2/N_1 is the turns ratio.
   - *Monitoring Mode:* Measured currents (I_{1_m2}, I_{2_m2}) are compared with the calibration values. If the error exceeds:

   $$E_{allow} = 0.2 \tag{18}$$

   an alert is triggered.

2. **Method 2: Correlation-Based Current Estimation [35]**
   It uses correlation coefficients:

   - R_{11}, R_{22}: Autocorrelation of currents
   - R_{12}: Cross-correlation

   A fault condition occurs when:

   $$R_{12} < U \quad (\text{with } U = 0.9) \tag{19}$$

3. **Method 3: Increment of Flux Linkages [36]**
   This method analyzes changes in flux linkages (λ_1, λ_2), calculated as:

   $$\lambda_1 = \int (v_1 - R_1 i_1 - L_1)dt, \quad \lambda_2 = \int (v_2 - R_2 i_2 - L_2)dt \tag{20}$$

   Fault Detector: The ratio $RIFL_{12}$ and a detector ($Detector_{12}$) are calculated. If the latter exceeds a threshold ($Thr = 5\%$), an internal fault is identified.

5. Results and discussions

The evaluation of the fault detection methods utilized current data obtained from routine tests and no-load short-circuit tests performed on single-phase distribution transformers. These transformers had a capacity of 5 kVA and a nominal voltage of 7620/240 V. The tests were conducted at the laboratory facilities of Rymel S.A.S., a company based in Antioquia, Colombia, ensuring real-world applicability of the results. The fault detection methods described in Section 3 were implemented using `MATLAB` R2018a. The models were developed following the mathematical and logical frameworks detailed in the referenced studies, ensuring consistency and alignment with the theoretical basis of each method.

Performance evaluation was carried out through three tests, each comprising 15 samples. These tests introduced a controlled variation of 7% in the winding current to simulate fault conditions. For each test, the detection thresholds were assessed alongside the methods' consistency and sensitivity in identifying anomalous conditions. This approach facilitated a comprehensive analysis of the methods' effectiveness in detecting faults under varying operational scenarios.

5.1. Comparison of methods features

The qualitative evaluation of the three fault detection methods considers key aspects such as implementation complexity, transformer type, and the number of variables required for proper application. This analysis highlights the trade-offs and specific advantages of each approach, offering insights into their suitability for various scenarios and operational requirements. Table 3 summarizes the principal characteristics of each method as documented by their respective authors.

Methods 1 and 2 stand out for their simplicity and minimal variable requirements, making them relatively easy to implement. However, these methods are limited to single-phase transformer applications and cannot identify the specific phase involved in a fault. Despite these limitations, their straightforward nature makes them attractive for basic fault detection tasks.

In contrast, Method 3 demonstrates a broader diagnostic capability. It can diagnose faults in both single-phase and three-phase transformers, pinpoint faults at the phase level, and differentiate between internal and external faults. However, these enhanced features come with increased complexity, requiring a larger number of variables and more sophisticated implementation procedures. Additionally, the interpretation of results for Method 3 poses greater challenges compared to the other methods.

Table 3. Comparison of detecting fault methods features

Feature	**Method 1**	**Method 2**	**Method 3**
Differentiation between internal and external fault	No	Yes	Yes
Identify the phase faulted	No	No	Yes
Transformer type	Single phase	Single phase	Single and three phase
Variables needed	$I_{1,2}$, $N_{1,2}$, $V_{1,2}$	$I_{1,2}$,m	$I_{1,2}$,$V_{1,2}$, $v_{1,2}$, $R_{1,2}$, $L_{1,2}$, $N_{1,2}$
Data source	simulated/from tests	simulated/from tests	simulated/from tests
Easy implementation	Yes	Yes	No
Direct interpretation	Yes	Yes	No

5.2. Test 1: Sensitivity to secondary winding current changes

Test 1 evaluated the sensitivity of each method to variations in the secondary winding current. The secondary current was progressively increased by 7% of its nominal value at each interval, while the primary current remained constant at its nominal value. This test simulated conditions of progressive overload, providing insight into the fault detection thresholds of the methods.

Method 1 demonstrated high sensitivity, detecting faults as early as interval 2 when the secondary current reached 25.34 A. This rapid response highlights its capability to identify even minimal current increases. Fault detection was consistent across all subsequent intervals up to the short-circuit condition. In contrast, Method 2 began detecting faults at interval 3, corresponding to a secondary current of 42 A. This indicates a higher detection threshold than Method 1, albeit still effective in identifying faults under moderate overload conditions. Method 3 exhibited the lowest sensitivity, failing to detect faults until interval 11, where the secondary current reached 443.40 A. While its performance was limited under low current conditions, it maintained consistent fault detection from that point onward.

Figure 4 presents a graphical comparison of the fault detection performance of the three methods as a function of secondary winding current variations.

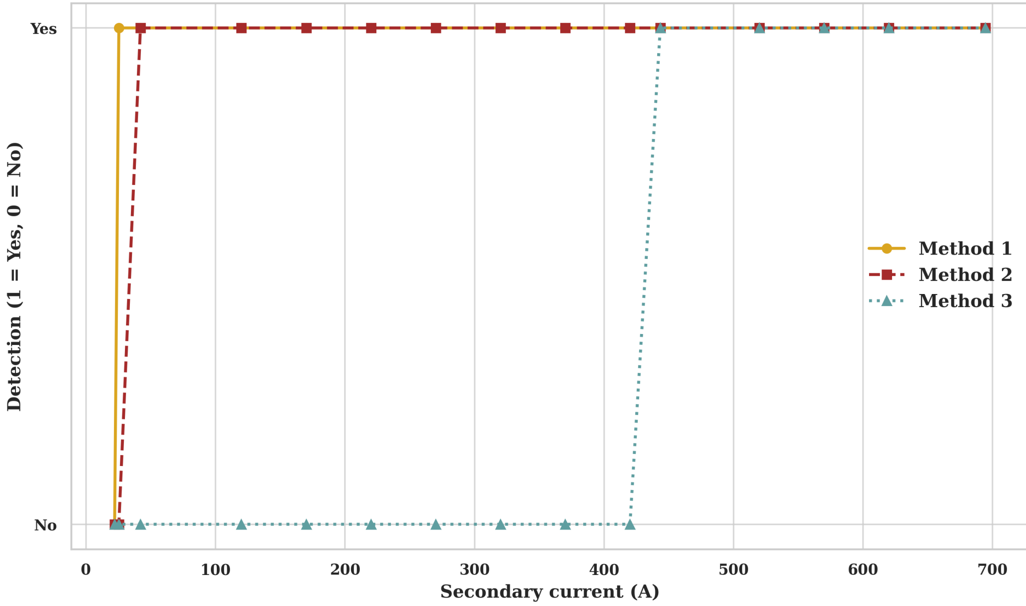

Figure 4. Fault detection versus secondary winding currents.

5.3. *Test 2: Sensitivity to primary winding current changes*

Test 2 assessed the sensitivity of the methods to variations in the primary winding current. The primary current was incremented by 7% of its nominal value at each interval, while the secondary current was maintained at its nominal value. This test aimed to analyze the fault detection thresholds and performance consistency under conditions of increasing primary current.

Method 1 exhibited high sensitivity, consistent with the results of Test 1, by detecting faults as early as interval 2 when the primary current reached 0.96 A. This early detection underscores its ability to respond effectively to even minor deviations in primary current. Method 2 began detecting faults at interval 3, corresponding to a primary current of 1.31 A. This behavior aligns with its performance in Test 1, reflecting a slightly higher detection threshold but stable fault identification once the threshold was crossed. Method 3 displayed similar results to those observed in Test 1, with fault detection commencing at interval 11 when the primary current reached 15.85 A. This higher threshold suggests that Method 3 is more suited to identifying faults under conditions of significant current deviations, albeit with reduced sensitivity to smaller changes.

Figure 5 provides a graphical representation of the fault detection performance of the three methods as a function of primary winding current variations.

5.4. *Test 3: Sensitivity to simultaneous changes in primary and secondary winding currents*

Test 3 evaluated the performance of the fault detection methods under conditions where both primary and secondary winding currents were simultaneously increased by 7% of their nominal values. This scenario aimed to simulate severe fault conditions and analyze the methods' ability to detect anomalies in a more complex operational environment.

Method 1 demonstrated fault detection beginning at interval 4, corresponding to a primary current of 5 A and a secondary current of 158.70 A. However, its overall performance in this test was less efficient compared to its performance in Tests 1 and 2, reflecting challenges in handling simultaneous variations in both windings. Method 2 also detected faults starting at interval 4, exhibiting similar sensitivity to Method 1. However, it encountered difficulties in accurately classifying faults under conditions of current transformer saturation, which affected

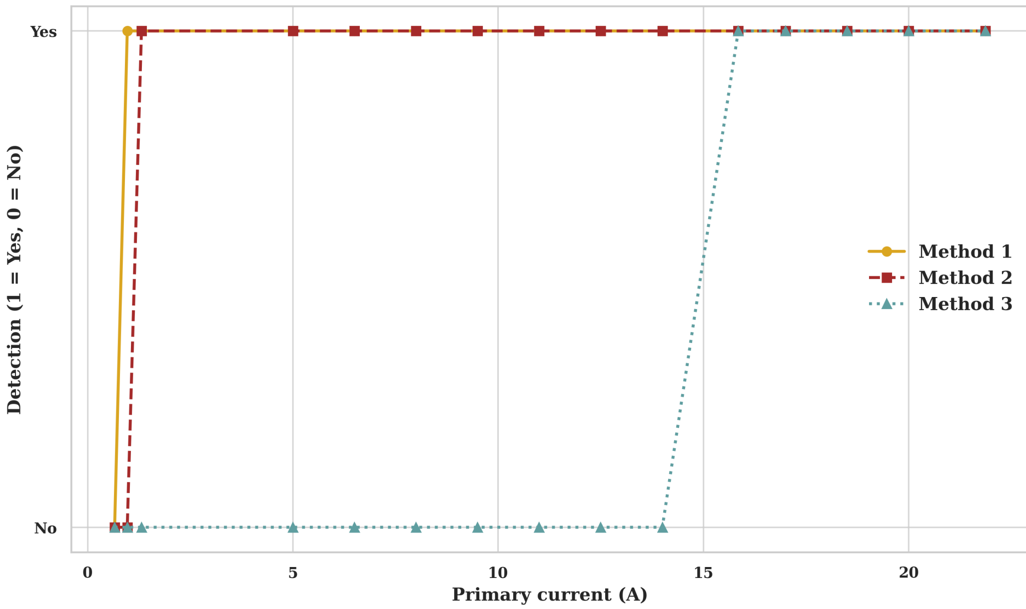

Figure 5. Fault detection versus primary winding currents.

its reliability in more severe scenarios. Method 3 did not detect faults at any interval during this test, even at current levels where the other methods were successful. This limitation can be attributed to its reliance on flux linkage-based fault detection. When proportional changes occur in both primary and secondary windings, the transformation ratio remains constant, preventing significant deviations in flux linkages and resulting in undetected faults.

Method 3, being based on the relationship of magnetic fluxes, requires asymmetric variations in the windings to detect faults, making it insensitive to incipient faults or balanced changes (as evidenced in Test 3), particularly when both currents vary simultaneously and the transformation ratio remains constant, thereby masking deviations in the fluxes. Furthermore, its reliance on precise parameters such as leakage inductances limits its applicability in transformers with incomplete nameplate data, which is a critical scenario in networks with dynamic loads or parallel faults, commonly found in industrial systems.

Figure 6 provides a graphical comparison of the fault detection performance of the three methods under simultaneous variations in primary and secondary winding currents.

5.5. *Discussion*

The results highlight significant differences in the performance of the three fault detection methods. Method 1 demonstrated exceptional sensitivity, capable of detecting incipient faults as small as 4.43% of the short-circuit current in the primary winding and 3.65% in the secondary winding. Across the 15 samples evaluated in each test, this method achieved a fault detection sensitivity of 93.33%, consistently identifying faults from their early stages. Its high sensitivity and low detection thresholds make it a reliable choice for early fault detection.

Method 2, which relies on correlation coefficient analysis to compare primary and secondary currents, achieved a fault detection sensitivity of 86.67%. Fault detection was initiated at 5.99% of the short-circuit current in the primary winding and 6.05% in the secondary winding. While effective, its performance was approximately 35% less sensitive than Method 1, resulting in slightly lower accuracy in identifying early-stage faults.

Method 3 exhibited the lowest sensitivity among the evaluated methods, detecting faults at 72.47% of the short-circuit current in the primary winding and 63.87% in the secondary winding, with an overall sensitivity of 33.33%. Despite its reduced effectiveness in detecting incipient faults, Method 3 demonstrated strong resistance to incorrect

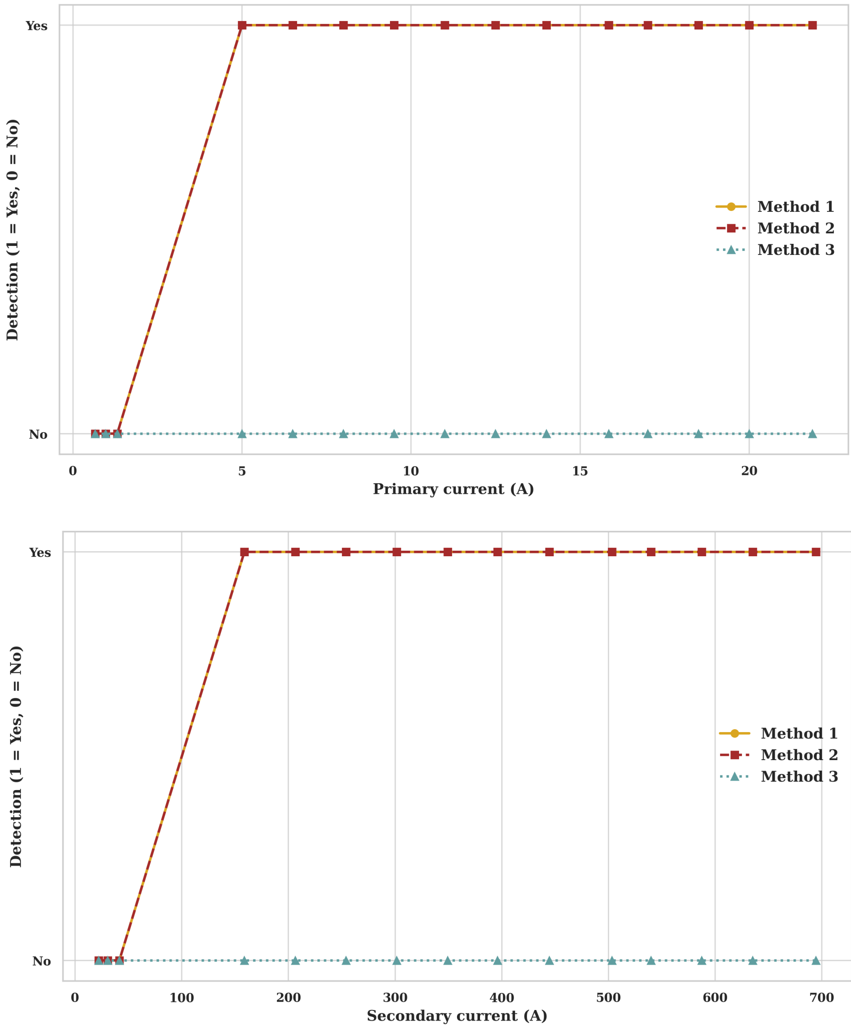

Figure 6. Fault detection versus primary and secondary winding currents.

fault detection, minimizing false alarms. Its robustness at high current levels suggests that it may be better suited for fault verification under advanced fault conditions rather than for early detection.

Table 4 provides a comprehensive comparison of the three methods, focusing on three critical parameters: the independent detection threshold, the percentage of the short-circuit current at which faults are detected, and overall sensitivity. The independent detection threshold indicates the current level at which each method begins to identify faults. The percentage relative to the short-circuit current quantifies the relationship between detection thresholds and nominal short-circuit currents, while sensitivity reflects the proportion of accurately detected faults.

In this analysis, Method 1 emerged as the most effective approach due to its minimal detection thresholds, low percentages relative to the short-circuit current, and high sensitivity. These characteristics make it particularly suitable for identifying incipient faults in both primary and secondary windings. Method 2 offered satisfactory performance with moderate detection thresholds and sensitivity, making it a reliable alternative for fault detection. Conversely, Method 3 displayed notable shortcomings due to its high detection thresholds and low sensitivity, limiting its utility for early fault detection. However, its robustness and resistance to false alarms may make it useful in specific scenarios requiring fault confirmation under severe conditions.

Detection Methods and Their Limitations

Scope: This study focuses on the experimental analysis of 5 kVA single-phase transformers with a voltage ratio of 7620/240 V under controlled laboratory conditions, using no-load tests based on discrete current increments (7% of I_{cc}). It does not consider transient or intermittent faults. The high-voltage winding was energized while the low-voltage winding was short-circuited, allowing a current equivalent to a percentage of the rated load to flow. This particular transformer had been repaired after a previous fault, adding relevance to the study since the results were compared against those of a new, optimally functioning unit subjected to the same tests. The test data were obtained in a controlled environment (temperature, humidity, and voltage stabilized), ensuring the reproducibility of results within these parameters. While extreme environmental conditions (e.g., significant thermal variations) could affect transformer performance in the field, their analysis lies outside the scope of this paper. The primary objective is to validate the evaluation methodology under standardized scenarios. For real-world operating contexts, additional adjustments based on high-voltage standards are recommended, although these would require a specific approach beyond the methodology applied here.

Limitations and Methodological Focus: It is important to note that the research is limited to low-capacity single-phase transformers (5 kVA), as Methods 1 and 2 are specifically designed for this configuration. Including three-phase or higher power transformers would require substantial technical adaptations of the methods and is not the aim of this study. Furthermore, the article does not address other types of faults (thermal, mechanical) or complex network dynamics (transients, harmonic distortion), as such phenomena would demand modifications to the testing protocols and employed methods. Nevertheless, the results provide a robust comparative basis for future studies that expand the analysis to those variables. Validation with operational data from utility companies was not feasible due to confidentiality restrictions. However, the experimental protocols implemented align with international standards, ensuring the relevance of the results. Future collaborations with industry stakeholders may help bridge this gap.

Method 1: False alarms may be triggered by abrupt load changes (e.g., motor startups or connection of non-linear loads), as these generate transient currents similar to those of incipient faults. Additionally, the presence of harmonics (generated by non-linear loads such as variable frequency drives) distorts the currents and affects the calculation of the differential current (I_{diff}), reducing the method's sensitivity to incipient faults.

The algorithm requires recalibration whenever the tap changer adjusts the transformer's turn ratio. If recalibration is not immediate or accurate, detection errors may occur during such events.

Method 2: This method is based on comparing the similarity of current waveforms. In networks with high harmonic distortion, waveforms lose their sinusoidal shape, which reduces the accuracy of correlation coefficients and may lead to:

- False alarms
- Undetected faults

Method 3: The method assumes that faults occur in only one winding at a time. If simultaneous faults occur in both the primary and secondary, the flux increments ($\Delta\lambda$) may cancel each other out, making it difficult to identify the affected winding.

In external faults with similar imbalances on both sides of the transformer, the IFLs may maintain the theoretical turns ratio (N_1/N_2), causing the method to fail to distinguish between:

- Normal operation
- Fault condition

5.5.1. Computational Load The computational resources required for each method were evaluated on a system with an AMD Ryzen 7 4800H processor, 16 GB of RAM, and Windows 11 operating system. Method 1 (differential currents) and Method 2 (current correlation) exhibited average execution times of 0.009 s and 0.014 s, respectively, making them suitable for real-time applications.

In contrast, Method 3 (flux linkages) required an average time of 6.325 s, reflecting a significantly higher computational load due to the use of numerical integrations and vector operations. These times were obtained from an average of 50 program executions. Moreover, this method shows greater memory usage and implementation complexity, which may limit its applicability in embedded or online systems.

Table 4. Comparison of the performance of three methods

Method	**Independented threshold**	**% of the short-circuit current**	**Sensitivity (%)**
1	$I_1 = 0.96A$	Primary: 4.41%	93.33%
1	$I_2 = 25.34A$	Secondary: 3.65%	93.33%
2	$I_1 = 1.31A$	Primary: 5.99%	86.67%
2	$I_2 = 42.00A$	Secondary: 6.05%	86.67%
3	$I_1 = 18.85A$	Primary: 72.47%	33.33%
3	$I_2 = 443.40A$	Secondary: 63.87%	33.33%

Figure 7 provides a visual representation of the sensitivity of the three fault detection methods based on the evaluation tests described in this study. Sensitivity serves as a key performance metric, capturing the effectiveness of each method in accurately identifying faults under the tested conditions.

As illustrated, Method 1 demonstrates the highest reliability, achieving a sensitivity of 93.33%. This result underscores its superior performance in detecting faults, particularly incipient ones, across a wide range of test scenarios. Method 2 follows with a sensitivity of 86.67%, showcasing stable and effective fault detection capabilities. In contrast, Method 3 exhibits significantly lower sensitivity, with a value of only 33.33%. This indicates its limited effectiveness, especially in scenarios where fault-induced current changes are minimal.

The comparative analysis reinforces Method 1's suitability for early fault detection while highlighting Method 3's constraints in applications requiring high sensitivity to minor anomalies.

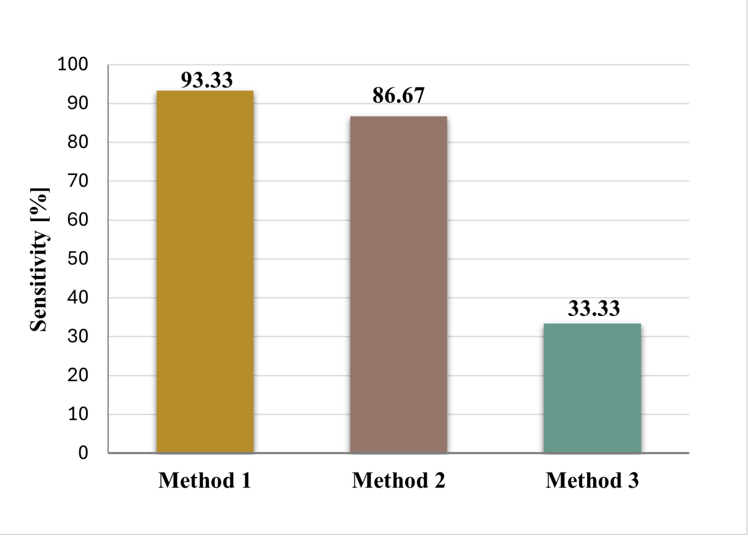

Figure 7. Sensitivity of the fault detection methods.

6. Conclusions and future work

This study presented a comparative evaluation of three fault detection methods for distribution transformers based on electrical variable monitoring. Each technique was implemented and tested using MATLAB R2018a, with experimental data obtained from both routine and no-load short-circuit tests conducted on real single-phase transformers at the Rymel S.A.S. laboratory in Antioquia, Colombia. This approach marked a significant departure from studies relying solely on simulated data, contributing to the results' methodological robustness and practical relevance.

The analysis revealed distinct performance profiles for each method:

- Method 1 exhibited the highest sensitivity, successfully identifying incipient faults at early stages. Its low implementation complexity and rapid response make it highly suitable for online monitoring systems, though its high sensitivity may lead to occasional false alarms if not combined with validation mechanisms.
- Method 2 demonstrated a balanced performance, capable of distinguishing between internal and external faults, and showed resilience to CT saturation. However, its effectiveness diminished under high-current fault conditions.
- Method 3, while less sensitive to early faults, proved to be highly robust and reliable for fault confirmation under severe conditions. Its complexity and higher computational demand limit its applicability in real-time or embedded systems but position it well for verification tasks.

The study contributes to the transformer diagnostics field by comparing fault detection approaches grounded in practical experimentation. It provides utility companies and equipment manufacturers with actionable insights for selecting and integrating monitoring strategies based on fault criticality, system constraints, and available infrastructure.

The findings also present the potential of combining methods to overcome individual limitations. The complementary nature of the evaluated techniques suggests that hybrid diagnostic systems could offer improved accuracy, reduced false positives, and broader operational applicability.

6.1. Future Work

Future research will focus on integrating some outstanding features of these fault detection methods into an adaptive, online monitoring system capable of providing early fault identification under various operating conditions. Such a system would enable rapid response actions and the prevention of further damage to distribution transformers, thereby enhancing system resilience and minimizing downtime. This approach aligns with ongoing efforts to develop real-time diagnostic tools that improve fault management in power distribution networks.

- Incorporation of additional variables: Future work will examine how external parameters such as temperature, humidity, or oil condition affect fault detection sensitivity. This may involve reformulating current models and validating hybrid approaches that combine electrical measurements with thermographic or environmental data.
- Extension to three-phase and high-capacity systems: To evaluate scalability, subsequent studies will address the application of the methods to three-phase transformers and higher-rated units. This includes accounting for operational conditions such as unbalanced loads, harmonic distortion, and mutual inductance effects.
- Optimization through advanced computational techniques: Research will explore machine learning approaches—such as classifiers and ensemble models—to optimize threshold selection and minimize false positives. This will require a large volume of labeled data from both normal and faulty conditions. Additionally, real-time implementation using platforms like LabVIEW or programmable logic controllers (PLCs) will be assessed, focusing on execution time, latency, and integration constraints.
- Development of a hybrid detection framework: A combined approach is proposed, leveraging the early fault detection capability of the differential current method and the robustness of the flux linkage method for fault confirmation. This hybrid model aims to improve reliability and reduce the likelihood of false alarms.

- Standardization and benchmarking: Future work will include performance benchmarking against established industry standards such as IEEE C37.91 and IEC 60270. This will provide a regulatory framework for validating detection thresholds and enable practical comparison with conventional diagnostic techniques such as dissolved gas analysis and partial discharge testing.

These initiatives will support the transition from theoretical modeling to deployable solutions in real-world distribution networks, positioning the proposed strategies as practical, scalable, and cost-effective tools for transformer fault management.

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Data availability Satatement

The original contributions presented in this study are included in the article. Additionally, the simulation code used for model implementation and testing has been made publicly available at the following GitHub repository: https://github.com/SantiagoGuzmanA/Fault-diagnosis-model-for-early-warnings-in-electrical-transformers.git. Further inquiries can be directed to the corresponding author.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve their writing. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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