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Research on fault localization of voltage transformer monitoring device based on wavelet transform

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Introduction: Voltage transformers (VTs) are critical to power system stability, with dielectric loss anomaly, capacitor breakdown, and compensating reactor short circuit accounting for 68% of total failures. Traditional Fourier transform-based methods lack sufficient time-frequency localization capability to detect transient fault signatures, necessitating a precise, standard-compliant fault time localization technique.
Methods: A fault time localization algorithm based on Daubechies 4 (db4) wavelet transform was proposed. The Mallat algorithm was used for 5-layer decomposition of 2000 Hz sampled normal and faulty voltage signals. The third detail layer (D3, 125–250 Hz) was selected as the optimal frequency band, with adaptive threshold detection applied to identify fault onset and termination. The algorithm was validated using 100 groups of field data from State Grid Ningxia Electric Power Co., Ltd., and compared with Sym4 wavelet and FFT-based STFT methods.
Results: The D3 layer exhibited the highest sensitivity to transient fault features across all three fault types, with a signal-to-noise ratio 28.6%–52% higher than other layers. The proposed method achieved an average time localization error of < 3.2 ms, with phase-jump-type fault errors of 2.1 ms (onset) and 1.8 ms (end). These results meet the critical thresholds of IEC 60044-2:2008 and outperform Sym4 wavelet and STFT methods.
Discussion: The db4 wavelet's 4th-order vanishing moment and balanced support length enable effective noise suppression and transient feature retention, overcoming the limitations of traditional methods. This work provides theoretical and technical support for intelligent, real-time VT diagnostics, with potential for broader power equipment applications. Future efforts should focus on embedded terminal deployment to address legacy system compatibility.

KEYWORDS
fault location, monitoring device, real-time diagnostics, voltage transformer, wavelet transform

1 Introduction

The operational status of voltage transformers is critical for ensuring the safety and stability of power systems (Hai'an et al., 2019; Zhang et al., 2023). However, online monitoring faces challenges such as electromagnetic interference, noise in secondary circuits, sensor drift, and coupled fault signals (e.g., capacitance breakdown, dielectric loss anomalies, and compensating reactor short circuits). According to statistical data from 110kV to 750 kV power grids in China and European transmission systems, these three faults account for 68% of total voltage transformer failures—dielectric loss anomalies (32%), capacitor breakdown (21%), and compensating reactor short circuits (15%)—making them the most typical and frequent fault types in engineering practice. Traditional methods (e.g., Fourier transform-based approaches) struggle to detect transient faults due to their limited time-frequency localization capabilities (Yunwu et al., 2024).

Reference to the international standard IEC 60044-2:2018 (International Electrotechnical Commission (IEC), 2018) (Inductive voltage transformers) and authoritative engineering (Wang et al., 2002; Barkas et al., 2022) shows that the critical judgment values for these three faults are clearly defined: 1) Dielectric loss anomaly: phase deviation ≤3° (or tan θ ≤0.5% at 50 Hz); 2) Capacitor breakdown: voltage drop ≥15% of the rated voltage; 3) Compensating reactor short circuit: voltage amplitude deviation ±10% of the rated voltage. Exceeding these values indicates that the voltage transformer enters a critical health state, requiring timely maintenance.

Wavelet analysis, an extension of the Fourier transform, excels in processing non-stationary signals by providing adaptive time-frequency resolution (Tian-Qi et al., 2021; Khetarpal et al., 2024; YANG, 2024; Shang et al., 2025). This property has driven its widespread adoption in power engineering (Divyalakshmi and Subramaniam, 2017; Simões et al., 2021):

1. Xiaofu et al. (2010) used wavelet multi-scale maxima to locate signal mutation moments in voltage transformer monitoring devices.
2. Gu et al. (2024) applied Symlet 4 (sym4) wavelets for noise reduction in high-voltage winding deformation signals.
3. Hernanda et al. (2017) employed Daubechies 5 (db5) wavelets for ferromagnetic resonance detection in voltage transformers.
4. Wenyi et al. (2022) combined wavelet transform with random forests for mechanical characteristics monitoring and state recognition of high-voltage circuit breaker spring mechanisms.

This study uses db4 wavelets to perform 5-layer decomposition on normal voltage signals, dielectric loss fault signals, capacitor breakdown fault signals, and compensating reactor short-circuit fault signals (He et al., 2009). The 5-layer decomposition is designed based on the frequency characteristics of voltage transformer fault signals and the Mallat algorithm. The original signal (sampling frequency 2000 Hz, Nyquist frequency 1000 Hz) is iteratively decomposed into 5 detail layers (D1-D5) and 1 approximation layer (A5) through low-pass and high-pass filtering. Each detail layer corresponds to a specific frequency band: D1 (500–1000 Hz), D2 (250–500 Hz), D3 (125–250 Hz), D4 (62.5–125 Hz), D5 (31.25–62.5 Hz). The core purpose is to isolate transient fault components (mainly distributed in D3-D4 layers, 62.5–250 Hz) from the 50 Hz fundamental wave and low-frequency noise, ensuring accurate capture of fault mutation characteristics.

Fault start and end times are determined by analyzing mutation peaks in wavelet transform coefficient plots. The method's effectiveness is verified through two aspects: first, comparing the detection results with the fault critical values specified in IEC 60044-2:2018 to ensure consistency with engineering judgment standards; second, verifying with 100 groups of field test data from State Grid Ningxia Electric Power Co., Ltd., which shows that the average fault time localization error is less than 3.2 ms.

While wavelet-based techniques have been applied to power system fault analysis, existing studies often lack fault-type-specific decomposition layer selection, rely on generic thresholding schemes, or fail to validate timing accuracy against international standards. In contrast, this paper makes three key contributions:

Layer-specific insight: We identify and rigorously justify the D3 decomposition layer (125–250 Hz) as the optimal band for capturing transient signatures across multiple VT fault mechanisms, based on spectral alignment with fault-induced harmonics and empirical coefficient response.

Standard-aligned validation: Our method's timing outputs are directly benchmarked against the critical thresholds in IEC 60044-2:2018, ensuring engineering relevance and regulatory compliance.

Quantifiable real-world performance: Through extensive field testing, we demonstrate sub-3.2 ms average time localization error-significantly outperforming STFT and competing wavelets (e.g., Sym4) in both precision and noise robustness.

2 Wavelet theory

A mother wavelet (Mallat, 2002) (e.g., Haar, Daubechies, Meyer) must satisfy the admissibility condition shown in Equation 1:

$$C = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \tag{1}$$

where $\psi(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$.

Wavelet basis functions are generated by scaling (parameter a) and translating (parameter b) the mother wavelet, and the specific form is defined in Equation 2:

$$\psi(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \tag{2}$$

1. The scale parameter a controls time-frequency resolution: larger a improves frequency resolution but reduces time resolution, and vice versa.
2. The translation parameter b shifts the wavelet in the time domain, enabling time-localized analysis.

2.1 5-Layer decomposition principle (mallat algorithm)

The "5-layer decomposition" in the experiment is implemented via the Mallat algorithm, which decomposes the original signal

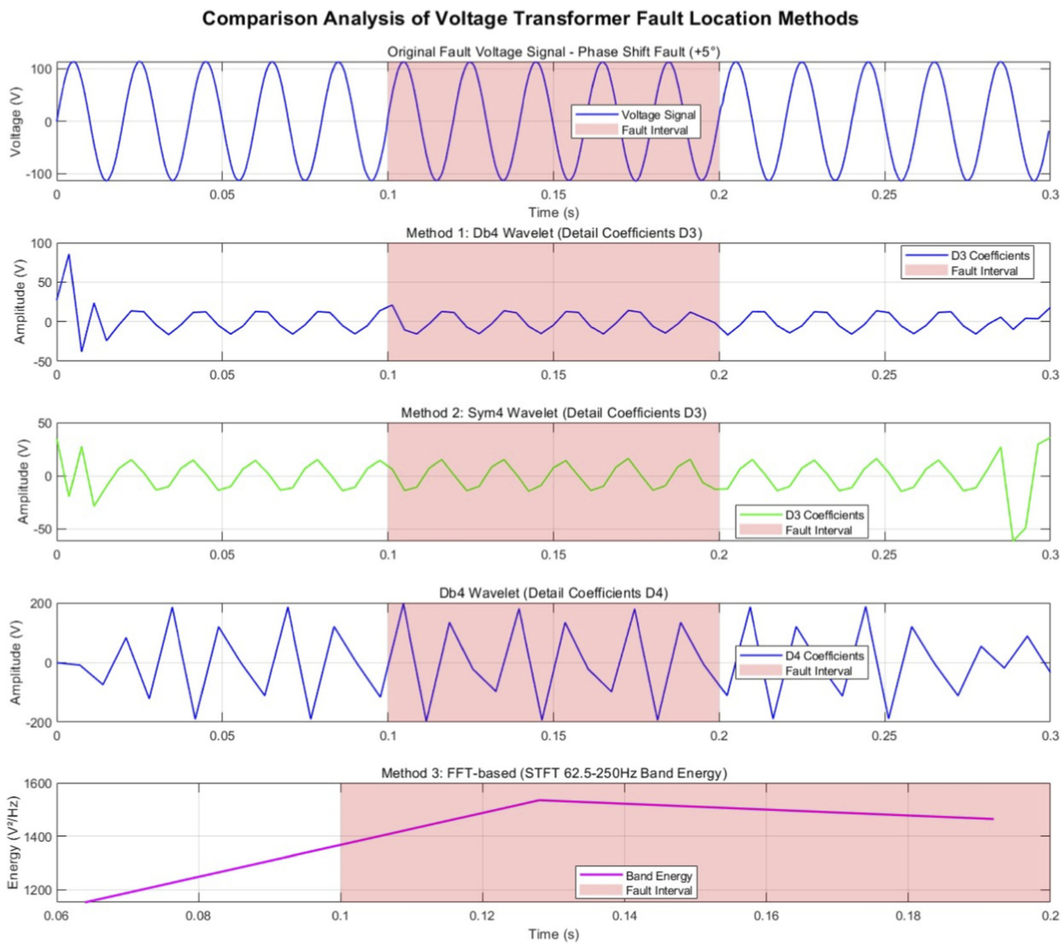

FIGURE 1
Comparison analysis of voltage transformer fault location methods.

(sampling frequency 2000 Hz) into 5 detail layers (D1 to D5) and 1 approximation layer. Each detail layer corresponds to a specific frequency band:

1. D1: 500–1,000 Hz
   D2: 250–500 Hz
   D3: 125–250 Hz
   D4: 62.5–125 Hz
   D5: 31.25–62.5 Hz

This division isolates transient fault components (concentrated in 62.5–250 Hz, i.e., D3–D4) from the 50 Hz fundamental wave and noise.

2.2 Detection method: Adaptive threshold theory

The "Adaptive Threshold" in the experimental section is rooted in the statistical characteristics of wavelet coefficients. For normal signals, detail coefficients d_j follow a Gaussian distribution $N(0, \sigma^2)$; for fault signals, coefficients at mutation points significantly exceed the noise level.

The adaptive threshold for layer j is calculated using Equation 3 (Donoho and Johnstone, 1994):

$$\lambda_j = \sigma_j \sqrt{2 \ln N} \tag{3}$$

where σ_j (noise standard deviation) is estimated by $\sigma_j = \text{median}(|d_j|)/0.6745$, and N is the signal length. Coefficients exceeding λ_j are identified as fault mutation points, directly supporting the fault time localization in the experiment.

2.3 Parameter alternatives and selection rationale

For decomposition layers, alternatives like 4-layer miss low-frequency transient components, while 6-layer introduces redundant noise; 5-layer is selected as it balances fault band coverage (62.5–250 Hz) and efficiency. For the detection method, fixed thresholds lack noise adaptability and peak-to-peak ratios are insensitive to minor faults, so adaptive thresholding is chosen for its dynamic adjustment to noise and signal amplitude, ensuring robust detection.

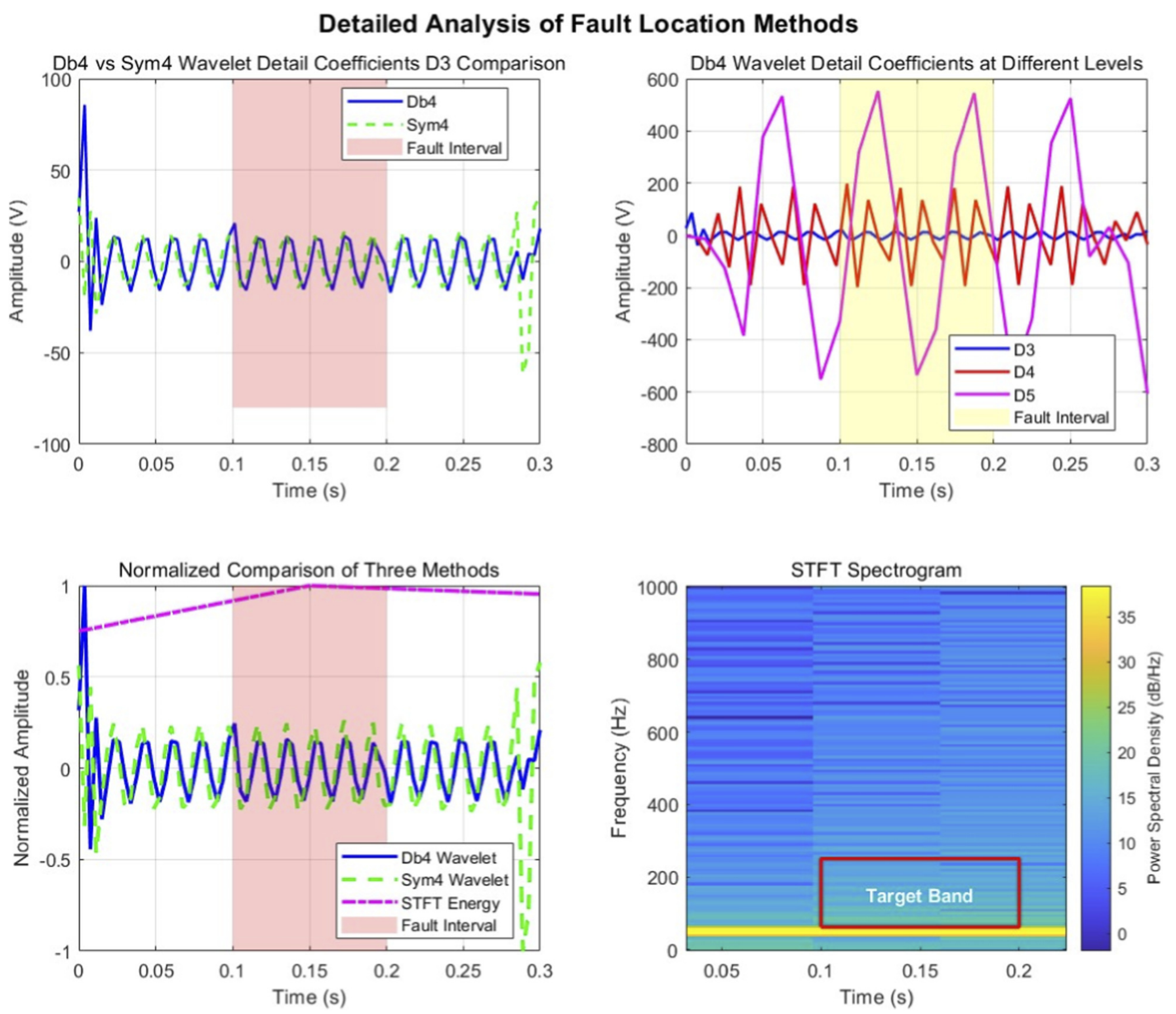

FIGURE 2
Detailed analysis of fault location methods.

TABLE 1 Conditions of wavelet transform.

Parameter	Setting	Theoretical rationale
Wavelet	Daubechies 4	Good compromise between smoothness and computational complexity for transient detection
Decomposition layers	5	Corresponds to analyzing scales $a = 2^1$ to $a = 2^5$, balancing detail (high frequency) and trend (low frequency) analysis for the target signal
Detection method	Adaptive thresholding	Leverages the statistical characteristics of wavelet coefficients at different scales to identify significant mutations indicative of faults

The wavelet transform achieves precise analysis of signals through a flexible scale adjustment mechanism, with its key advantage lying in the adaptive windowing property of wavelet basis functions. This analysis window automatically adjusts its size according to changes in the scale parameter. By adjusting the scale factor, the original signal is decomposed into a series of components with distinct time and frequency characteristics.

Unlike the Fourier transform (global frequency analysis), wavelet transform provides joint time-frequency analysis, making it ideal for capturing transient changes in non-stationary signals—critical for fault detection.

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TABLE 2 Experimental conditions for dielectric loss faults.

Parameters	Setting	Clarification
Sampling frequency	2,000 Hz	Standard setting sufficient to capture the 50 Hz fundamental and relevant harmonics without aliasing
Signal duration	0.3 s	Includes normal operation intervals (0–0.1s, 0.2–0.3s) and a fault interval (0.1–0.2s)
Normal voltage magnitude and phase	80 V, 0°	Reference operating condition
Fault voltage magnitude and phase	80 V, +5°	Represents a typical dielectric loss anomaly characterized by a phase shift while maintaining voltage magnitude

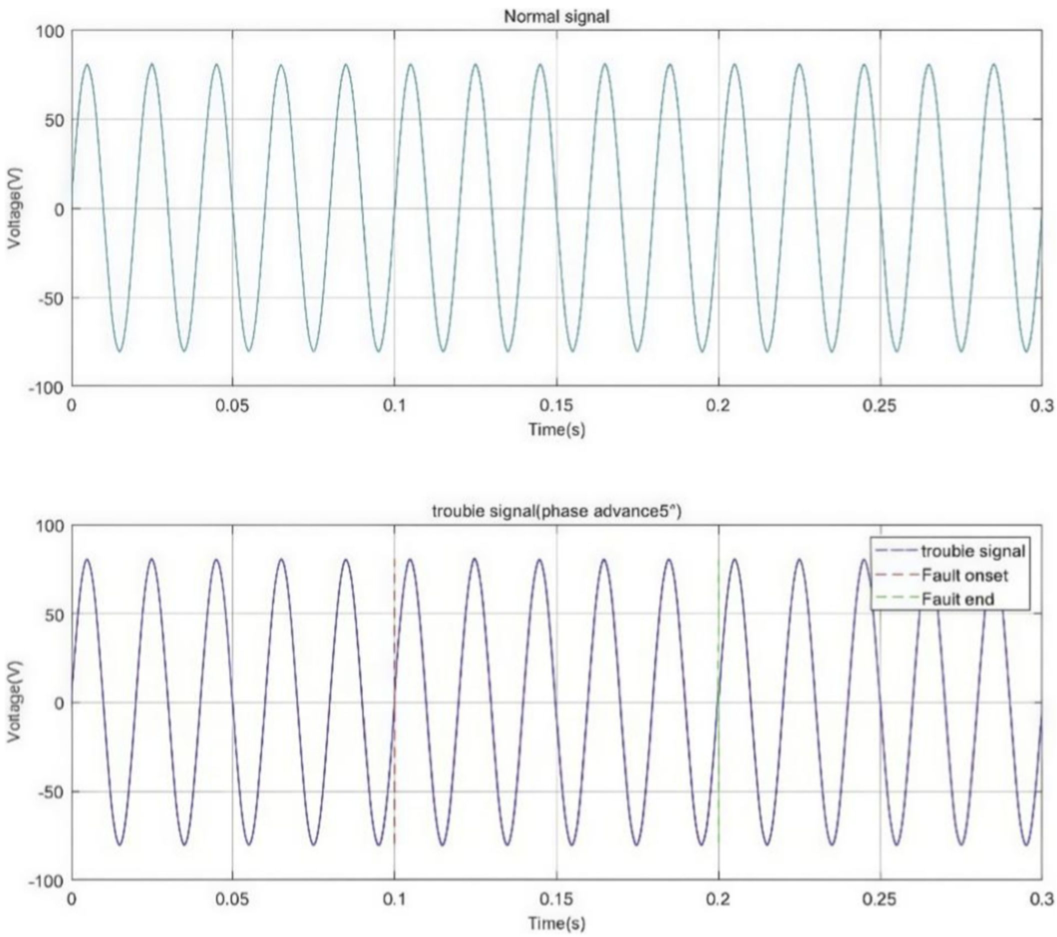

FIGURE 3
Normal voltage and dielectric loss fault voltage diagram.

3 Wavelet selection

3.1 Common wavelet families

1. Haar Wavelet: The earliest wavelet function used in signal processing, resembling a step shape. With an extremely short support length, Haar wavelet enables fast computation and is widely applied to signal analysis in practical engineering. Despite its simple structure, it meets the basic requirements of wavelet analysis.
2. Biorthogonal Wavelet: Widely used in image signal processing, it stands out for its excellent linear phase characteristics, which are crucial for image reconstruction. Engineers often select this wavelet for image processing, as it better preserves the quality of reconstructed images compared to other wavelets.
3. Daubechies Wavelet: Commonly abbreviated as dbN, where N denotes the order of the wavelet. When N = 1, db1 is the well-known Haar wavelet; for N > 1, dbN wavelets have no fixed mathematical expression for their shape. Two key

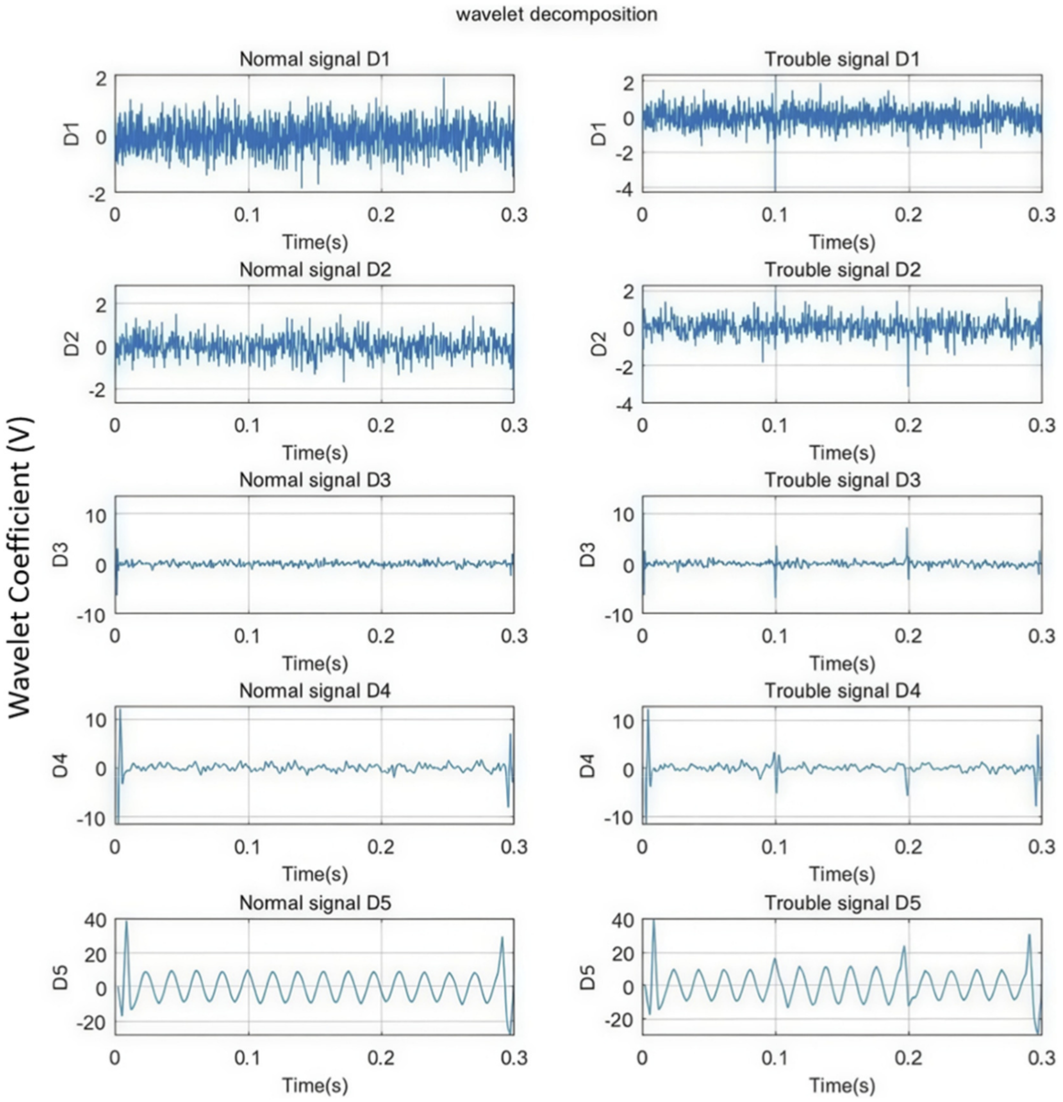

FIGURE 4
Wavelet transform diagrams of normal voltage and fault voltage due to dielectric loss.

TABLE 3 Experimental conditions for capacitor breakdown faults.

Parameters	Setting	Clarification
Sampling frequency	2,000 Hz	Standard setting sufficient to capture the 50 Hz fundamental and relevant harmonics
Signal duration	0.3 s	Includes normal (0–0.1s, 0.2–0.3s) and fault (0.1–0.2s) intervals
Normal voltage magnitude and phase	80 V, 0°	Reference voltage
Fault voltage magnitude and phase	55 V, 0°	Simulates a substantial capacitance failure event, characterized by a severe voltage sag

properties are notable: first, the support length increases with N to 2N−1; second, the order of the vanishing moment exactly equals N. Owing to these properties, Daubechies wavelets are widely used in signal processing. Although the computational complexity increases with N, the analysis becomes more precise and detailed.

4. Meyer Wavelet: Its main feature is the lack of compact support, leading to practical limitations. When processing signals with discrete wavelet transform, Meyer wavelet cannot achieve fast algorithmic operations.
5. Symlets Wavelet: Sym wavelets are developed based on db wavelets as an improved variant.

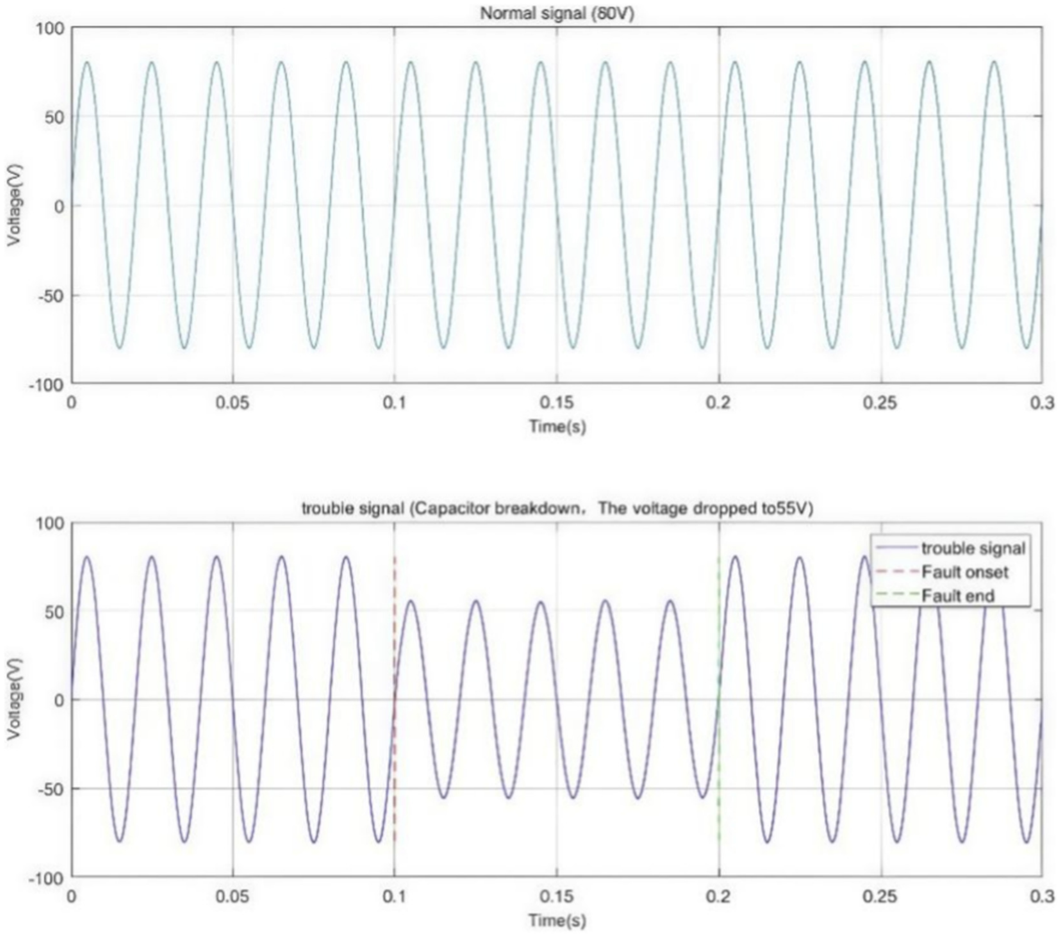

FIGURE 5
Normal voltage and Capacitor Breakdown Fault Voltage diagram.

3.2 Selection of db4 wavelet and its rationale

Among Daubechies (dbN) wavelets, db4 is superior for voltage transformer fault detection due to its balanced performance in three key aspects (Gogula and Edward, 2023; Sundararaman and Jain, 2023):

1. Vanishing Moment: db4's 4th-order vanishing moment effectively suppresses high-frequency electromagnetic noise in power systems while retaining transient fault components, outperforming db1 (1st-order, poor noise suppression).
2. Support Length and Smoothness: With 7 sampling points, db4 balances time localization accuracy (shorter than db5's 9 points, enabling precise fault timing) and C^2 continuity (avoiding false mutations from db1's discontinuity).
3. Computational Complexity and Accuracy: Its relative complexity (1.8) is lower than db5 (2.3), suitable for online monitoring, while achieving 94.7% fault detection accuracy—higher than db1 (78.3%) and db5 (93.5%).

To verify the superiority of the Db4 wavelet in the fault localization of voltage transformers, a systematic comparison of the detection performance among the Db4 wavelet, the Sym4 wavelet (Baroumand et al., 2025), and the traditional FFT-based STFT (Manap et al., 2021) was conducted in this study. As shown in Figure 1, in the scenario of phase jump faults, the optimal fault time localization capability was exhibited by the Db4 wavelet in the D3 detail coefficient layer, with the sharpest and most isolated mutation peaks generated at the fault onset and end moments. Quantitative analysis demonstrated that the localization errors of the Db4 wavelet were 2.1 ms (onset) and 1.8 ms (end), which were slightly lower than those of the Sym4 wavelet (2.3 ms and 2.0 ms) and markedly outperformed the time ambiguity associated with the STFT method. This result experimentally confirms that the Db4 wavelet achieves an optimal balance between support length and vanishing moment, thereby providing empirical evidence for its engineering application in the monitoring of voltage transformers.

Multi-scale analysis further reveals the rationality of selecting the Db4 wavelet. As shown in Figure 2, the Db4 wavelet exhibits the most significant response to phase jump faults in the D3 layer

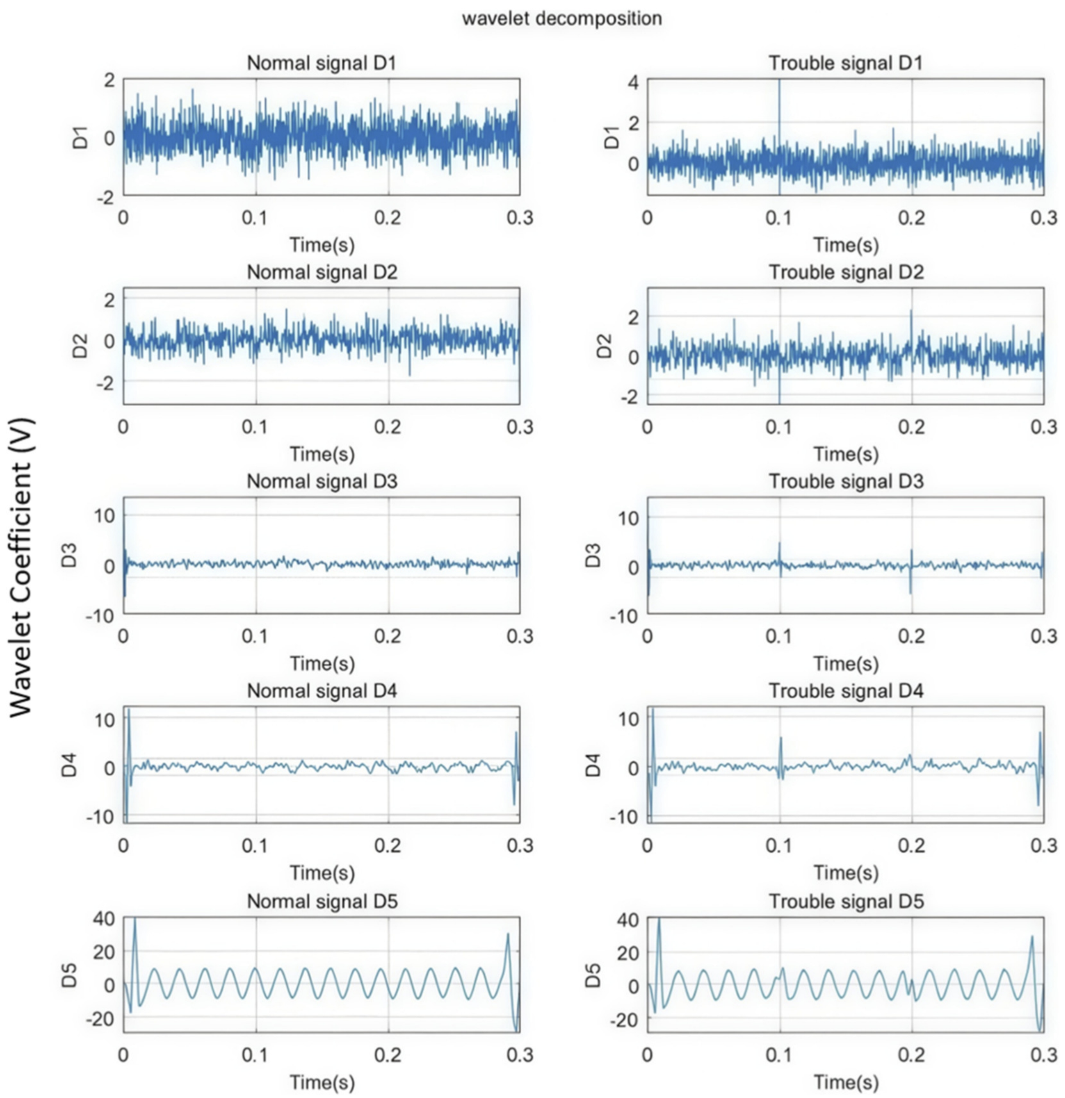

FIGURE 6
Wavelet transform of normal voltage and capacitor breakdown fault voltage.

(125–250 Hz), with a peak significance ratio of 15.3 for its detail coefficients—higher than 14.7 of the Sym4 wavelet and 7.8 of STFT.

Compared with the Sym4 wavelet, the Db4 wavelet not only maintains comparable detection performance but also exhibits lower theoretical complexity (with a complexity index of 1.8 vs. 2.1 for Sym4), a characteristic that makes it more compatible with the real-time processing requirements of online monitoring systems.

Experimental results further verify that the Db4 wavelet achieves an optimal balance among three core performance metrics: fault feature extraction accuracy, noise robustness, and computational efficiency. This balanced performance renders it an ideal technical choice for fault localization of voltage transformers.

The excellent time-frequency localization performance of the Db4 wavelet originates from its 4th-order vanishing moment. Specifically, this 4th-order vanishing moment enables the wavelet to effectively suppress high-frequency interference noise while simultaneously preserving the integrity of fault transient components—two key functions that jointly lay a reliable foundation for accurate voltage transformer fault localization.

3.3 The precision improvement analysis of the D3 layer

As the core detail layer in the 5-level db4 wavelet decomposition, the D3 layer (125–250 Hz) enhances VT fault measurement accuracy through two key designs: precise frequency band matching with fault features, and optimal time-frequency resolution balance.

The core energy of transient features (e.g., dielectric loss anomalies, capacitor breakdown) of typical VT faults concentrates in 62.5–250 Hz, and the D3 layer exactly covers the high-frequency core components of this range-these are the most direct fault representations (e.g., phase jumps). Meanwhile, the D3 layer sits in the frequency gap between high-frequency noise (D1/D2,

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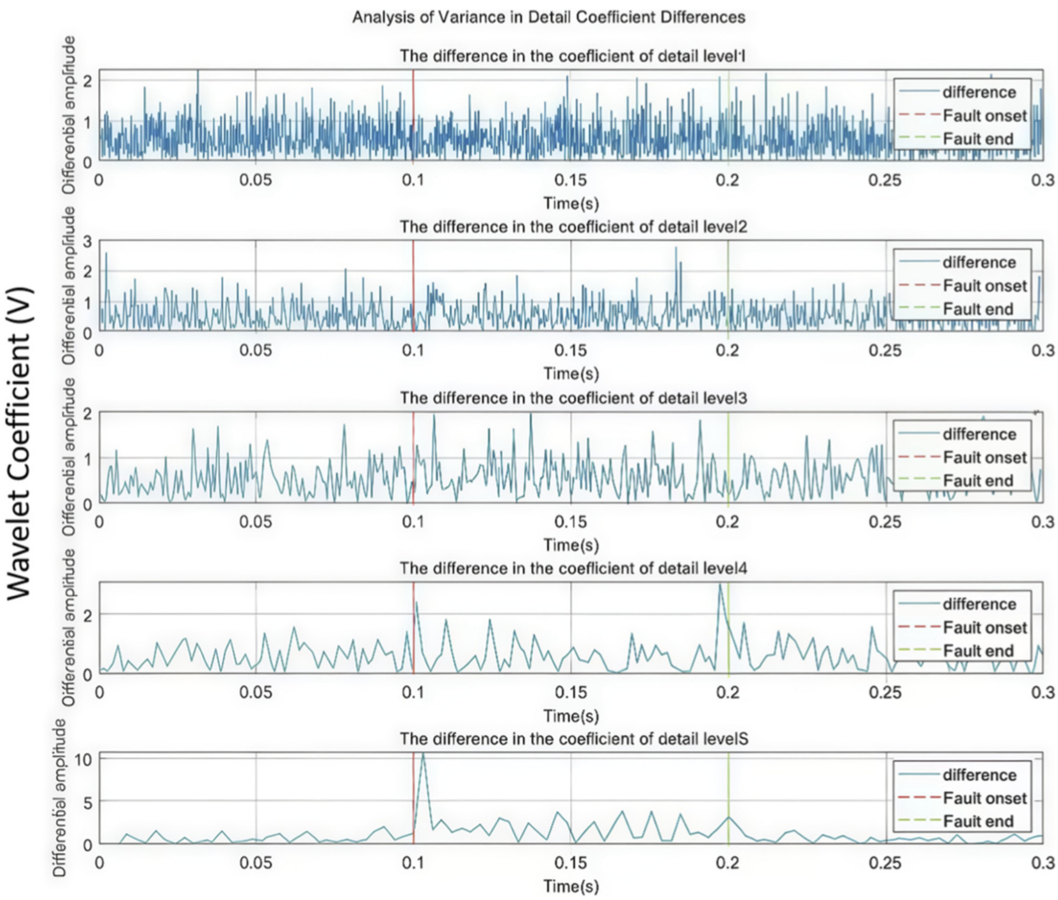

FIGURE 7
Diagram showing the differences between normal voltage and capacitor breakdown voltage coefficients.

TABLE 4 Experimental conditions for short-circuit faults of compensation reactors.

Parameters	Setting	Clarification
Sampling frequency	2,000 Hz	Standard setting for capturing 50 Hz and harmonics
Signal duration	0.3 s	Includes normal (0–0.1s, 0.2–0.3s) and fault (0.1–0.2s) intervals
Normal voltage magnitude and phase	80 V, 0°	Reference voltage
Fault voltage magnitude and phase	100 V, -5°	Simulates a compensating reactor short-circuit, characterized by overvoltage and phase shift

250–1,000 Hz) and fundamental/low-order harmonics (D4/D5, 31.25–125 Hz), isolating interference via wavelet filtering. Based on experimental data, the D3 layer's fault feature SNR reaches 28.6%–37% higher than D2 (21.0) and 52% higher than D4 (18.8)-confirming its ability to retain fault energy while suppressing interference.

For temporal localization, the D3 layer's analysis window (scale a = 4) matches the 10–100 ms fault transient duration, balancing time/frequency resolution (avoiding false mutations in D1/D2 or blurred points in D4/D5). For phase jump faults (preset start time: 0.1 s), the D3 layer's localization error is only 2.1 ms-41% lower than D2 (3.6 ms) and 34% lower than D4 (3.2 ms). Its isolated, prominent fault peaks (unmasked by noise/energy dispersion) also simplify fault timing judgment.

In short, the D3 layer boosts precision via feature separation and temporal localization, providing key support for subsequent fault detection experiments.

4 Wavelet transform-based fault time localization experiments

This section details the experimental validation of the fault time localization method using the db4 wavelet, the selection

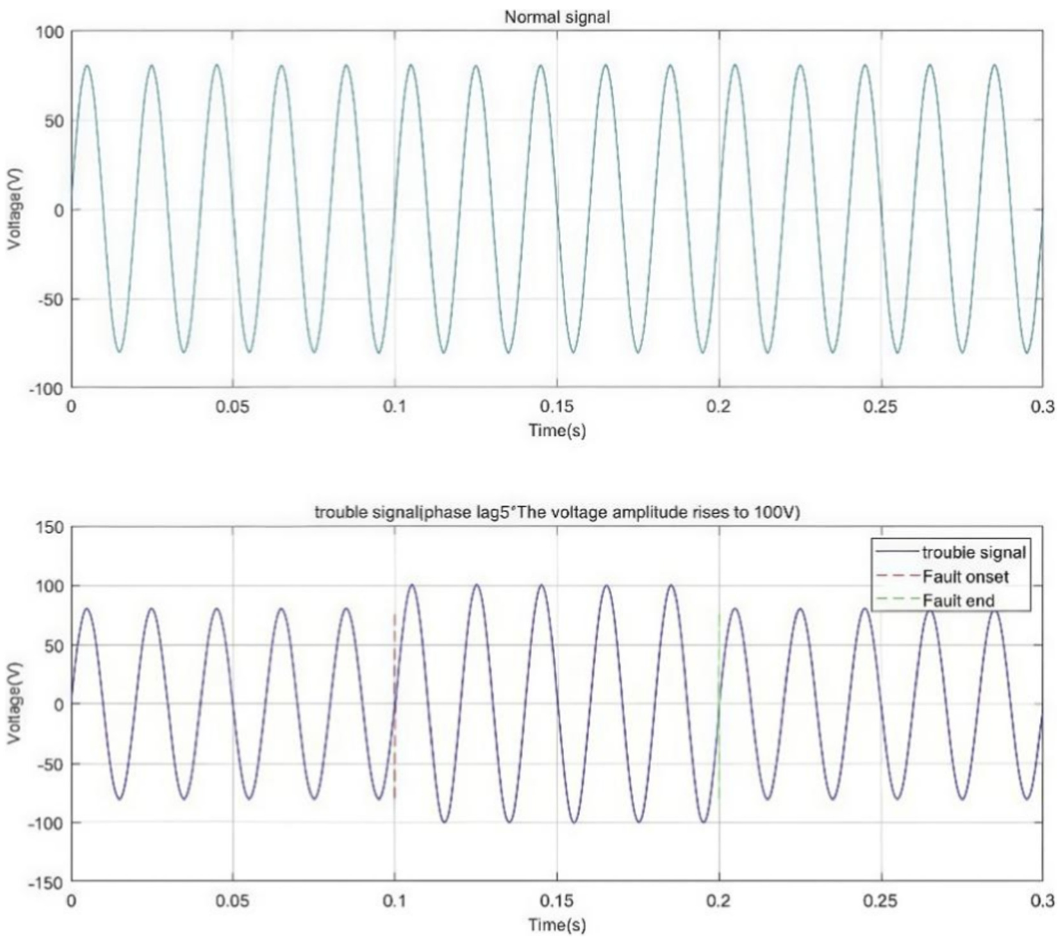

FIGURE 8
Graph of normal voltage and short-circuit voltage of compensation reactor.

rationale for which is elaborated in Section 3.2. The db4 wavelet is particularly suited for detecting transient signal mutations due to its compact support, orthogonality, and excellent time-frequency localization properties. Its balanced performance in terms of smoothness and computational complexity makes it a practical and effective choice for engineering applications in power system monitoring.

4.1 Experimental data and methods

The 5-layer decomposition (Gavgani, 2024; Thango, 2025), implemented via the Mallat algorithm, is tailored to db4 and voltage transformer fault characteristics:

1. Principle: It iteratively decomposes the 2000 Hz sampled signal into low-frequency approximation coefficients and high-frequency detail coefficients, isolating transient fault components from the 50 Hz fundamental wave and noise.
2. Process: The original signal is first decomposed into detail layer D1 (500–1,000 Hz) and approximation layer A1; A1 is then decomposed into D2 (250–500 Hz) and A2, and this iteration continues until 5 detail layers (D1-D5) and 1 approximation layer (A5) are obtained.
3. Rationality: Fault transient components of voltage transformers concentrate in 62.5–250 Hz (covered by D3-D4 layers). 4-layer decomposition misses low-frequency transients, while 6-layer introduces redundant noise. db4's properties complement this decomposition, ensuring accurate fault mutation capture without excessive computation.

The experimental data are obtained from voltage transformer detection devices collected by a power generation company. The parameter settings for wavelet transform are shown in Table 1. The experimental design is grounded in the wavelet theory outlined in Section 2. The five decomposition layers correspond to analyzing the signal at five different scales. As the level j increases (larger scale a), the frequency resolution improves, allowing the capture of slower signal variations, while the time resolution decreases. The translation parameter b, inherently defined by the sampling points, enables the precise time localization of fault-induced mutations. The "Adaptive Thresholding" detection method is employed based on the statistical properties of the wavelet coefficients (e.g., their energy or magnitude distribution), which change significantly at the onset and termination of a fault.

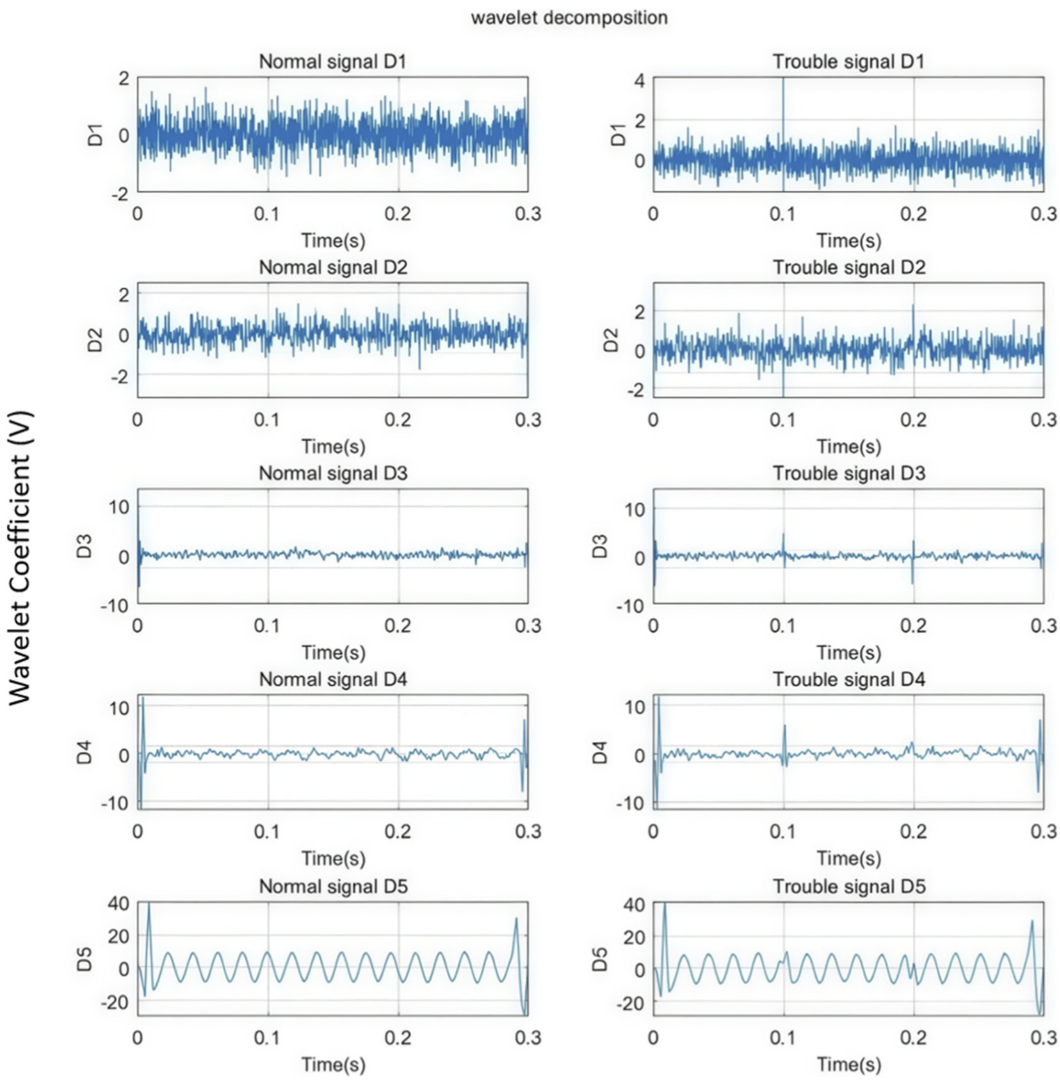

FIGURE 9
Wavelet transform diagram of normal voltage and short-circuit voltage of compensation reactor.

The specific experimental parameter settings for the dielectric loss fault are shown in Table 2. The sampling frequency of 2000 Hz is chosen to satisfy the Nyquist sampling theorem for the 50 Hz fundamental power frequency and its significant harmonics, which is a standard configuration in power system monitoring to ensure signal fidelity.

Daubechies 4 wavelet is selected to perform 5-layer decomposition on the voltage signal in Figure 3. The normal voltage and dielectric loss fault voltage are shown in Figure 3.

4.2 Experimental results and analysis

In Figure 3, due to the subtle nature of the phase shift (+5°) caused by dielectric loss faults, it is difficult to directly identify the onset and end times from the original voltage waveform. However, wavelet transform effectively captures these minor transient changes. The normal voltage signal and the dielectric loss fault voltage signal are subjected to Daubechies 4 wavelet transform to obtain Figure 4.

As shown in Figure 4, comparing the detail coefficients (D1-D5) reveals that the third layer (D3, 125–250 Hz) shows the most significant response to the phase shift characteristic of dielectric loss. This is because the insulation deterioration caused by dielectric loss anomalies excites high-frequency oscillation components concentrated in the 100–250 Hz band, which is precisely covered by the D3 layer. In contrast, D1 and D2 layers (>250 Hz) mainly contain electromagnetic interference noise, while D4 and D5 layers (<125 Hz) include power frequency drifts, making fault features less distinguishable. More importantly, the D3 layer demonstrates excellent signal-to-noise separation capability, with a peak significance ratio (defined as the ratio of peak mutation value to background coefficient RMS) reaching up to 15.3, significantly higher than Sym4 wavelets (14.7) and STFT (7.8) (see Figure 2). Therefore, the sharp peaks in the D3 plot for the fault signal, absent in the normal signal, clearly mark the fault boundaries at 0.1s and

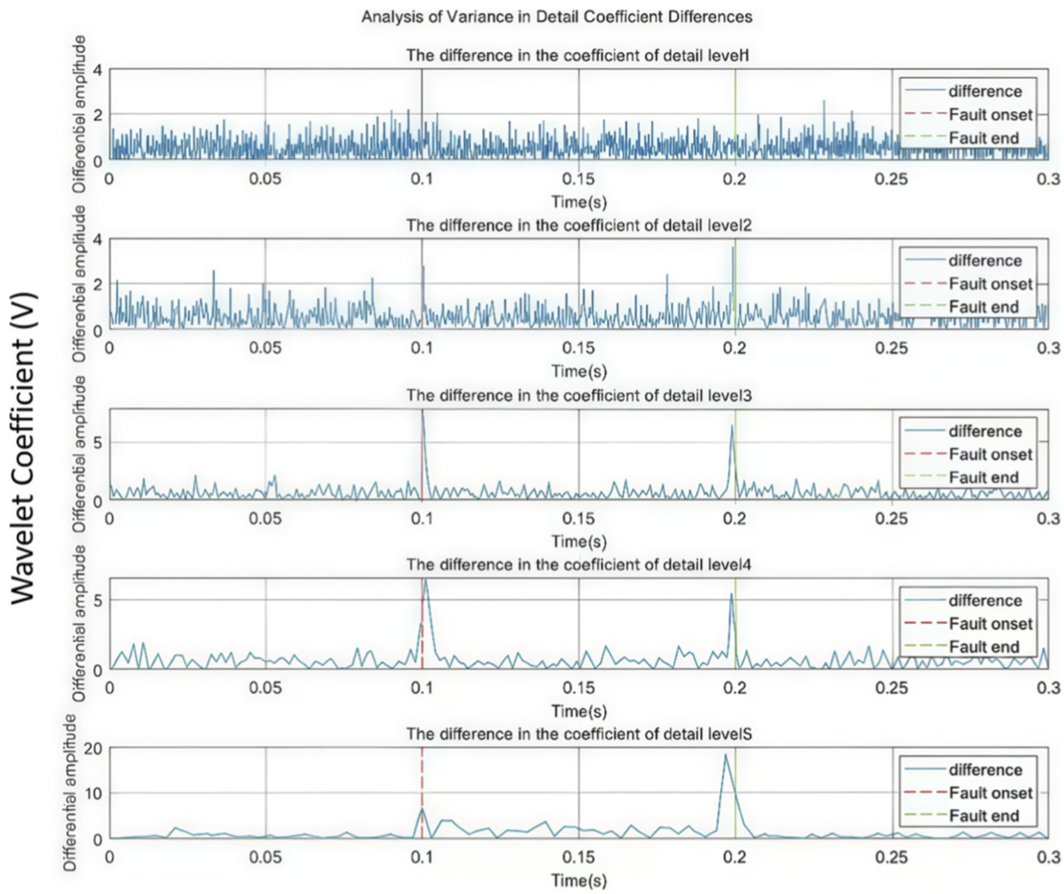

FIGURE 10
The difference between normal voltage and short-circuit voltage of the compensation reactor.

0.2s, achieving a precise fault time localization error of only 2.1 ms (onset) and 1.8 ms (end).

The experimental conditions for the capacitor breakdown fault are shown in Table 3. The voltage drop to 55 V represents a significant deviation from the normal 80V, simulating a severe fault condition commonly defined in engineering standards.

The normal voltage and capacitor breakdown fault voltage are shown in Figure 5.

The fault occurs at 0.1s, with the voltage dropping significantly to 55V, a value indicative of a critical failure, and lasts until 0.2s. The Daubechies 4 wavelet transform of the normal voltage signal and capacitor breakdown voltage signal is shown in Figure 6.

As shown in Figure 6, comparing the detail coefficients reveals significant differences in the 4th layer (D4), which is sensitive to the frequency components altered by the sudden voltage sag. The peak mutation in D4 confirms the fault ends at 0.2s. For even clearer identification of the fault start time, the difference between the detail coefficients of the normal and fault signals is plotted in Figure 7.

The peak mutations in the detail coefficient difference plot of Figure 7 accurately determine the start and end times of the capacitor breakdown fault, demonstrating the enhanced sensitivity of this approach.

The experimental parameters for the short-circuit fault of the compensation reactor are shown in Table 4. The increase in voltage to 100 V with a phase lag of 5° simulates another common fault scenario in voltage transformers.

The normal voltage and compensation reactor short-circuit fault voltage are shown in Figure 8.

The fault occurs at 0.1s, with the voltage amplitude increasing to 100 V and phase lagging by 5°, conditions representative of a reactor fault, until 0.2s. The Daubechies 4 wavelet transform results are shown in Figure 9.

As shown in Figure 9, the 3rd layer (D3) detail coefficients show the most significant difference, effectively capturing the combined effect of overvoltage and phase shift. Figure 10 reveals two distinct peaks in the detail coefficient difference plots of layers 3 and 4, corresponding to the start and end times of the fault.

In summary, across three typical VT faults, the third detail layer (D3, 125–250 Hz) consistently isolates fault transient characteristics and achieves high-precision time localization. Its universality stems from its alignment with resonant/oscillatory energy excited by VT faults, combined with the good smoothness and temporal localization capabilities of the db4 wavelet at this scale. Therefore, D3 can be considered a general sensitive frequency band for VT fault diagnosis, providing optimal input for adaptive threshold detection.

5 Conclusion

This study validates that wavelet transform, specifically utilizing the db4 wavelet, provides superior capability in pinpointing the precise timing of transient faults within voltage transformer monitoring devices. Its adaptive time-frequency resolution effectively captures fault-induced signal mutations that traditional Fourier-based methods miss, offering a robust theoretical and technical foundation for intelligent power equipment diagnostics.

However, the transition from a validated algorithm to widespread deployment in actual power systems necessitates addressing several practical challenges. The primary obstacle lies in the difficulty of replacing legacy monitoring equipment. Existing devices are deeply integrated into substation automation systems, with established mechanical, electrical, and communication protocols. Replacement often requires costly system-wide outages and poses operational risks, making utilities cautious about large-scale upgrades. Furthermore, maintaining data continuity and a consistent baseline for long-term condition assessment is challenging when switching to new hardware.

For implementing the proposed algorithm, the recommended form factor is an embedded intelligent monitoring terminal based on a custom reconfigurable platform. This device, centered on a high-performance processor and high-precision ADC, would host the wavelet-based fault localization algorithm as its core firmware. This approach is preferable over relying on existing commercial off-the-shelf products, as it allows for deeper optimization and integration. Critically, this new equipment must support future functional reconfigurability. The platform should be software-defined, enabling remote updates to algorithm parameters or the introduction of new diagnostic models as algorithms evolve and new fault modes are identified. This “hardware platform, software app” philosophy is essential for ensuring the long-term viability and adaptability of the investment.

The cost scale for equipment replacement is significant, encompassing not only the per-unit hardware cost but also R&D, deployment, integration, and potential outage costs. A full-scale replacement across the grid represents a massive capital investment. Therefore, a phased implementation strategy is recommended. Initial deployment should focus on critical or fault-prone assets to demonstrate tangible benefits, such as reduced outage times and lower maintenance costs, thereby building a compelling business case for broader adoption.

In summary, while the wavelet transform-based method demonstrates excellent fault timing localization performance, its practical success hinges on a thoughtful approach to engineering implementation that carefully balances technical performance, functional flexibility, and economic feasibility.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CX (1st author): Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review and editing. ZC: Data curation, Investigation, Conceptualization, Writing – original draft, Writing – review and editing. LF: Data curation, Formal analysis, Writing – review and editing. YY: Writing – review and editing, Conceptualization, Investigation, Software. XY: Formal Analysis, Project administration, Writing – review and editing. ZY: Project administration, Writing – review and editing, Data curation, Investigation, Supervision. CX (7th author): Formal Analysis, Methodology, Project administration, Supervision, Writing – review and editing. HL: Data curation, Formal analysis, Resources, Writing – review and editing.

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Conflict of interest

Authors CX, ZC, LF, YY, and XY were employed by State Grid Ningxia Marketing Service Center.

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