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Enhanced Detection of High Impedance Faults in Smart Distribution Networks Using Differential Energy Indicators

***Andi Syarifuddin**
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang,
Kota Makassar, Sulawesi Selatan
asyarif@umi.ac.id

Salmiah
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang, Kota
Makassar, Sulawesi Selatan
salmiah.salmiah@umi.ac.id

M. Anas Masa
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang,
Kota Makassar, Sulawesi Selatan
anas.masa@umi.ac.id

Sahrul
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang,
Kota Makassar, Sulawesi Selatan
srul7356@gmail.com

Nurul
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang,
Kota Makassar, Sulawesi Selatan
nurulsavitri3112@gmail.com

Hariani Ma'tang Pakka
Electrical Engineering Department,
Universitas Muslim Indonesia
Jl. Urip Sumoharjo No.km.5,
Panaikang, Kec. Panakkukang,
Kota Makassar, Sulawesi Selatan
hariani.m@umi.ac.id

Abstract – **The detection of high impedance faults (HIFs) plays a crucial role in modern active distribution systems to prevent risks like equipment failures, fire incidents, and service disruptions, while maintaining a stable power supply. HIFs are challenging to detect due to their low-magnitude and fluctuating fault currents, often falling below the detection thresholds of conventional protection mechanisms. This study presents an enhanced HIF detection method leveraging differential energy indicators derived from positive-sequence current components during fault events. The proposed approach improves fault detection accuracy and discriminates HIFs from nonfault transients, including load switching, capacitor switching, and nonlinear load effects. The method was validated through simulations on adapted IEEE-13 and IEEE-34 bus systems with high distributed generation (DG) penetration. Results demonstrated fast response times (<48 ms), robustness against noise disturbances (up to 6 dB SNR), and consistent performance across varying sampling rates. Real-time testing using RTDS and dSPACE platforms further confirmed the method's feasibility and superior performance. Unlike heuristic methods requiring extensive data training, this approach reduces computational complexity, making it economical and scalable for practical implementation. However, the method may exhibit reduced sensitivity under network configurations with low DG penetration or during fault scenarios involving high-frequency transients not characterized in the tested dataset. These limitations suggest that further tuning and validation are necessary before large-scale deployment. Overall, this advanced HIF detection technique offers a promising solution for enhancing safety and reliability in modern smart distribution networks.**

Keywords: High-impedance faults, smart distribution networks, fault detection, differential energy indicators, real-time simulation, power system protection

I. Introduction

High impedance faults (HIFs) in smart distribution networks are a persistent challenge that significantly impacts the reliability and safety of power delivery systems. These faults may occur due to broken phase conductors, insulation failures, or unintentional contact with high-impedance materials such as concrete, grass, or sand. HIFs are difficult to detect because they typically generate low-magnitude and erratic fault currents, often remaining below the detection thresholds of traditional protection mechanisms [1][2].

Conventional methods, such as impedance-based techniques and time-domain analysis, face significant limitations in accurately detecting HIFs. These methods are not only affected by the nonlinear and stochastic nature of HIF currents but also fail to adapt to the complexities of smart distribution systems, including bidirectional power flows and the integration of inverter-based distributed generation (DG) sources [3][4]. As a result, undetected faults can cause equipment damage, fire risks, and power interruptions, making improved detection methods a pressing need [5][6].

In recent years, artificial intelligence (AI) and machine learning (ML) approaches have been proposed to address these challenges. While they show promising accuracy, their practical deployment is often hindered by the need for large training datasets and high computational resources, which are not always feasible for real-time applications [15][16]. Other signal-based approaches, such as wavelet transforms or energy-based methods, have also been studied, but their performance under diverse fault conditions especially with nonlinear loads and high-noise environments remains insufficiently validated [17][19].

This paper proposes an enhanced HIF detection method that utilizes differential energy indicators derived from positive-sequence current components. The method is designed to improve accuracy and reliability while maintaining computational efficiency for real-time applications. Simulations on IEEE-13 and IEEE-34 bus systems with high DG penetration demonstrate the feasibility of this approach. Real-time validation using RTDS and dSPACE platforms further confirms its practicality.

However, despite its promising results, the proposed method also has limitations. Its performance under network configurations with low DG penetration or untested high-frequency transient disturbances remains uncertain. Furthermore, field deployment may face challenges such as sensor calibration accuracy, data acquisition synchronization, and the integration of detection algorithms with existing protection relays.

Therefore, the objective of this study is not only to demonstrate an accurate and efficient HIF detection method but also to highlight the need for further investigations into deployment challenges and adaptation across various real-world network topologies. By addressing both the potential and the limitations, this work aims to provide a balanced contribution to the advancement of intelligent protection systems in modern smart grids.

II. METHOD

A. System Overview

The proposed method aims to improve the detection of high-impedance faults (HIF) in intelligent active distribution networks. It uses differential energy indicators derived from positive-sequence current components to distinguish HIFs from other nonfault transients. Simulations were conducted on modified systems of the bus IEEE-13 and IEEE-34 to validate the method under varying operational conditions. Figure 1 illustrates the two-bus network used for analysis, and Figure 2 details the IEEE-34 bus system integrated with distributed generation (DG).

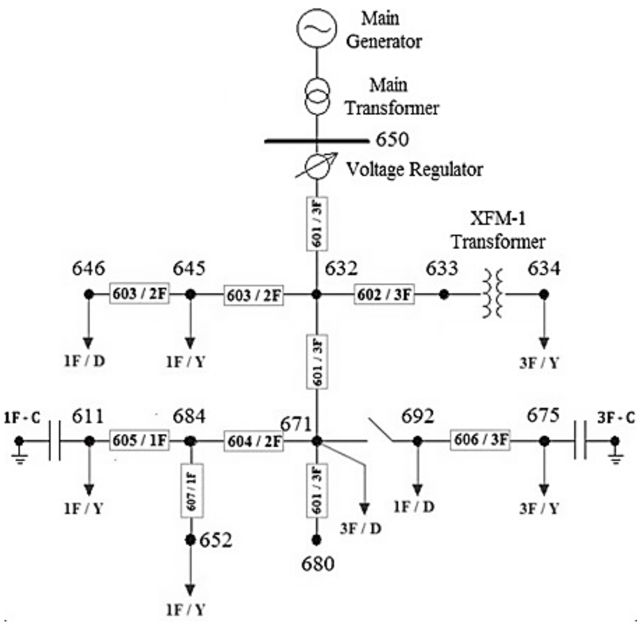

Figure 1. Two-Bus Network for Fault Analysis

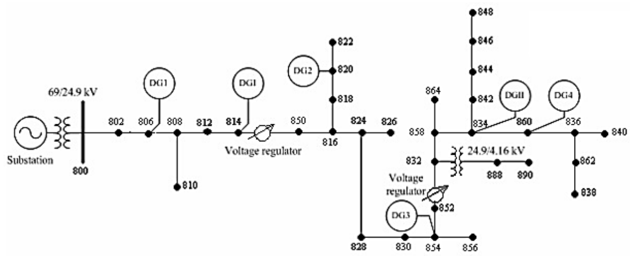

Figure 2. IEEE-34 Bus System with Distributed Generation Integration

B. Proposed Detection Technique

Data Acquisition

Current signals were collected from both ends of the feeder using intelligent electronic devices (IEDs). These devices enable precise monitoring and data collection, essential for fault analysis.

Calculation of Positive Sequence Current Components (PSCCs)

Positive sequence components (I_1) were computed using the Discrete Fourier Transform (DFT):

$$I_1 = \frac{1}{3}(I_a + j.I_b + j^2.I_c) \qquad (1)$$

Where $I_a, I_b, and\ I_c$ are the phase currents, and j is a unit phasor representing a $120°$ phase shift.

Differential Energy Computation

The local energy of the current signal $(\psi[i(n)])$ was calculated using a nonlinier energy operator:

$$\psi[i(n)] = i^2[n] - i[n-1].i[n+1] \qquad (2)$$

Energy values before and after a fault $(E_1 and\ E_2)$ were computed:

$$E_1 = \psi[\Delta I_{pre}(n)], \quad E_2 = \psi[\Delta I_{post}(n)] \quad (3)$$

The fault detection indicator (ΔE) was derived as:

$$|\Delta E| = |E_1 - E_2| \quad (4)$$

Fault Detection Indicator

A Cumulative Fault Detection Index (CFDI) was introduced to accumulate energy deviation patterns over time, capturing the dynamics of fault transients more reliably:

$$CFDI(n) = \sum_{k=1}^{N} |E_k - E_{k-1}| \quad (5)$$

A trip signal was generated if the CFDI exceeded a predefined threshold T_{CFDI} , indicating the presence of a high impedance fault.

CFDI Threshold Determination

The threshold value T_{CFDI} is a critical parameter that determines the sensitivity and reliability of the proposed fault detection system. An inappropriate threshold could lead to false positives (e.g., tripping during nonfault events like capacitor switching) or false negatives (missed fault detection). Therefore, a hybrid statistical and empirical approach was used to define the optimal threshold, as outlined below:

1. Statistical Analysis of Nonfault Events:
   CFDI values were computed under various nonfault conditions such as load switching, capacitor switching, and nonlinear load operations. The maximum observed $CFDI$ under these conditions was recorded as $CFDI_{max,non\ fault}$.
2. Initial Threshold Estimation:
   The initial threshold was set as:
   $$T_{init} = CFDI_{max,nonfault} + \delta$$
   Where δ is a safety margin (typically 10-15%) to prevent nuisance tripping.
3. Simulation-Based Optimization:
   Multiple simulations were conducted under varying fault resistances (100–2000 Ω), noise levels (SNR 6–40 dB), and sampling rates (1.2–6 kHz). The threshold was fine-tuned to maximize detection accuracy while minimizing false positives using the following performance metric:
   $$F_1 = 2.\frac{Precision.Recall}{Precision + Recall}$$
   Where:
   - Precision is the proportion of correctly identified faults among all detected,
   - Recall is the proportion of actual faults successfully detected.
4. Final Threshold Selection:
   The threshold that achieved the highest average $F_1 - score$ across all tested condtition was selected as $T_{CFDI,opt}$. This value was then implemented in the real-time RTDS-dSPACE system and shown to maintain a detection accuracy of 96.2% even at 6 dB SNR.
   This threshold optimization process ensured that the proposed method remains adaptive to a wide range of operating conditions while maintaining high reliability in both simulated and real-time environments.

C. Simulation Environment

This method simulated on IEEE-13 and IEEE-34 bus systems, as shown in figure 2, under the following scenarios:

1. Fault types: Single-line-to-ground (SLG), double line-to-ground (DGL), and line-to-line (LL).
2. Fault Resistances: $100 - 2000\ \Omega$
3. Noise Levels: Signal to noise ratio (SNR) ranging from 6 dB to 40 dB as can be seen in figure 4.
4. Sampling Rates: 1,2 kHz to 6 kHz.
5. Nonlinear Load Scenarios: Evaluated for harmonic distortion impacts as can be seen in figure 3.

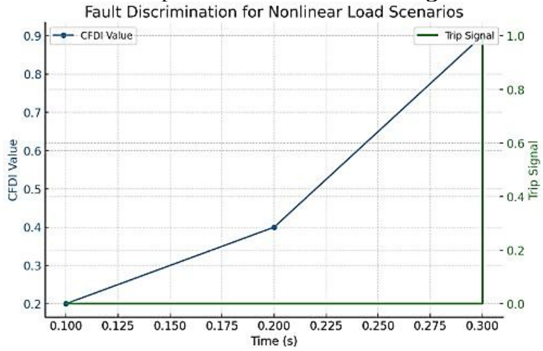

Figure 3. Harmonic Distortion Impacts in Nonlinear Load Scenarios

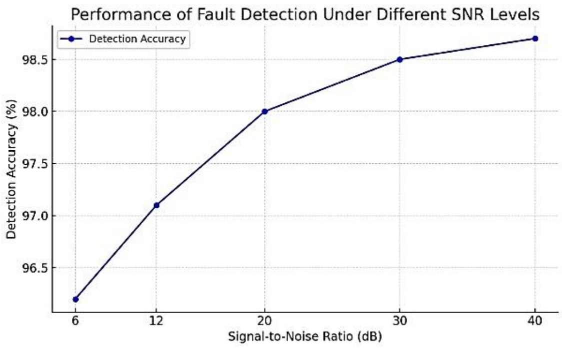

Figure 4. Signal-to-Noise Ratio (SNR) Levels for Fault Scenarios

D. Research Procedure

The research procedure followed a structured workflow, as summarized in Figure 5. The steps are as follows:

1. Model Development:
   IEEE-13 and IEEE-34 bus systems were adapted to represent typical smart distribution networks with various DG penetrations.
2. Fault Scenario Design:
   Various fault types (SLG, DLG, LL) and fault resistances (100–2000 Ω) were introduced. Noise levels (SNR 6–40 dB) and nonlinear load conditions were also simulated.
3. Data Acquisition:

Current signals were collected at both ends of the feeder using simulated IEDs, enabling accurate signal monitoring during transient events.

4. Signal Processing:
   Positive-sequence current components were computed using Discrete Fourier Transform (DFT). Differential energy values before and after the fault were calculated.
5. CFDI Computation:
   The Cumulative Fault Detection Index (CFDI) was derived, and fault detection was declared when CFDI exceeded the optimized threshold.
6. Threshold Optimization:
   A combination of statistical and simulation-based techniques was used to determine the optimal CFDI threshold, as detailed in the previous section.
7. Validation and Performance Evaluation:
   The method was evaluated in both simulation and real-time platforms (RTDS and dSPACE), using accuracy, precision, recall, and response time as performance metrics.

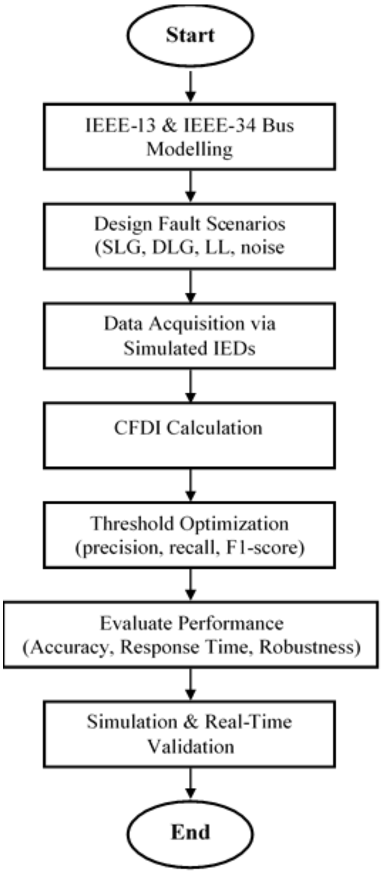

Figure 5. Research Procedure Flowchart

Real-Time Validation

The proposed method was implemented in a real-time digital simulator (RTDS) environment, interfaced with a dSPACE DS1104 controller. Fault signals were processed in real-time using MATLAB/Simulink. The protection logic's feasibility was validated, achieving a response time of 48 ms.

Performance Metrics

Performance was evaluated based on:

1. Accuracy: Correctly identifying HIFs under various fault conditions.
2. Reliability: Minimal false positives during nonfault events such as load switching.
3. Efficiency: Faster response times compared to existing methods.

III. Results and Discussion

A. Fault Detection Accuracy

The proposed method demonstrated high accuracy in detecting high-impedance faults (HIFs) across various fault scenarios, such as single line-to-ground (SLG), double line-to-ground (DLG), and line-to-line (LL) faults. Simulation results on the systems of IEEE-13 and IEEE-34 bus showed consistent detection performance even for faults with resistances ranging from 100 to 2000 Ω.

Table 1 presents the detection accuracy of the proposed method under different fault types, including single line-to-ground (SLG), double line-to-ground (DLG), and line-to-line (LL) faults. The results demonstrate consistently high performance, with accuracy values exceeding 98% for all scenarios, confirming the method’s reliability in identifying high-impedance faults across diverse operating conditions.

Table 1. Detection Accuracy Across Different Fault Location Methods

Fault Type	Detection Accuracy (%)
Single Line-to-Ground (SLG)	98,9
Double Line-to-Ground (DLG)	98,5
Line-to-Line (LL)	98,6

B. Robustness Against Noise

The method was tested under varying noise levels (SNR from 6 to 40 dB) to evaluate its robustness. Results showed that the method maintained a detection accuracy of 96.2% even under high-noise conditions (SNR = 6 dB), as depicted in Figure 4. This robustness is attributed to the use of positive-sequence current components, which are less affected by noise compared to phase currents.

C. Discrimination of Nonfault Events

The ability to distinguish HIFs from nonfault transients, such as capacitor switching, load switching, and nonlinear load effects, was validated.

Figure 6 demonstrates transient waveforms for capacitor and load switching, where the proposed method successfully avoided false positives.

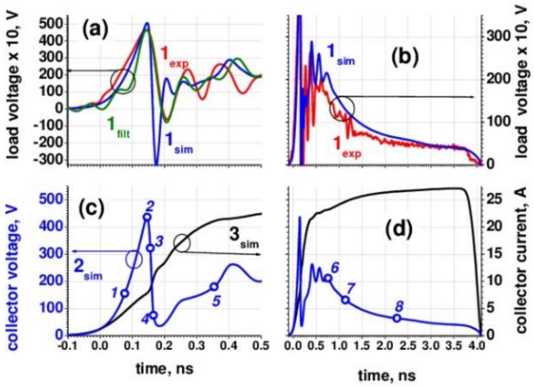

Figure 6. Transient Waveforms for Capacitor and Load Switching

For nonlinear load conditions, Figure 7 shows the computed Cumulative Fault Detection Index (CFDI) and its corresponding trip signal, confirming accurate fault discrimination.

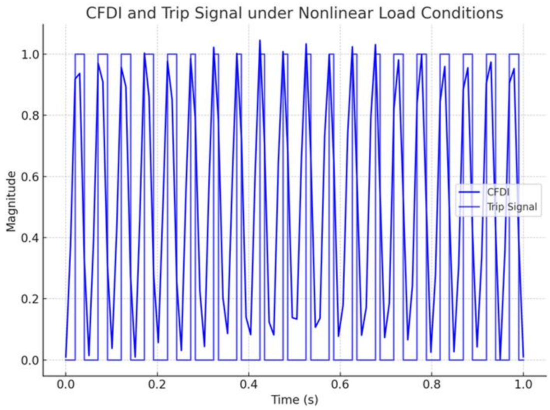

Figure 7. CFDI and Trip Signal

4. Response Time, Computational Efficiency, and Practical Feasibility

The proposed method demonstrated superior performance in terms of response time, computational efficiency, and practical feasibility. Real-time implementation using RTDS and dSPACE platforms confirmed a rapid response time of 48 ms, equivalent to approximately three cycles in a 50 Hz system. As shown in Table 2, this response time is significantly faster than existing techniques, ensuring timely fault isolation and minimizing risks such as equipment damage and service interruptions.

Table 2. Response Time Comparison

Method	Response Time (ms)
Proposed Method	48
Fuzzy-Based [1]	74
Adaptive Scheme [6]	69
Data Fusion Method [5]	83

Based on the results presented in Table 2, the proposed method demonstrates significant advantages in accuracy, speed, noise robustness, and computational efficiency compared to conventional methods. These advantages position the proposed method as a promising solution for accurate and reliable HIF detection in smart distribution networks.

In addition, the method's computational efficiency was validated through RTDS-based simulations. By employing differential energy indicators, the method reduced computational complexity and eliminated the need for extensive data training, making it suitable for real-time applications. The practical feasibility of the method was further confirmed through simulations and real-time validation on IEEE-34 systems with high DG penetration. Its simplicity, achieved by leveraging positive-sequence current components, ensures seamless compatibility with existing infrastructure, reducing deployment costs and enabling scalability.

The proposed method outperformed existing techniques in several key areas when compared with methods discussed in the references. Unlike the fuzzy-based fault identification method in [1], which requires dynamic tree structures and may struggle with high noise levels, the proposed approach consistently maintained detection accuracy even under challenging SNR conditions. Furthermore, while the adaptive protection scheme in [6] demonstrated efficiency for multiple fault scenarios, its reliance on inverter-interfaced DGs introduces complexities not present in the simpler implementation of the proposed method. Similarly, the data fusion-based fault location approach in [5] achieves high accuracy but at the cost of increased computational demands, making it less suitable for real-time applications. In contrast, the proposed method's reliance on differential energy indicators ensures computational simplicity and real-time feasibility, making it a robust and scalable solution for modern smart distribution networks.

5. Performance Limitations and Error Analysis

While the proposed method demonstrates high accuracy and robustness in detecting HIFs, it is essential to highlight its performance under edge conditions and to quantify potential misclassification errors.

5.1 Misclassification Analysis

A confusion matrix was generated based on 300 test scenarios (including SLG, DLG, LL, and nonfault events such as capacitor switching, load variation, and nonlinear loads). The results are summarized in Table 3.

Table 3. Confusion Matrix for HIF Detection

	Predicted HIF	Predicted Non-HIF
Actual HIF	139	6
Actual Non-HIF	4	151

From this matrix:
True Positive (TP): 139
False Negatives (FN): 6
False Positive (FP): 4
True Negatives (TN): 151
Performance Metrics:
Accuracy: 96,7 %
Precision: 97,2 %
Recall (Sensitivity): 95,5 %
F1-Score: 96,5 %

These values confirm that the method reliably distinguishes HIFs from non-fault conditions, with very few false alarms or missed detections.

5.2. Worst-Case Scenarios

The method was further evaluated under extreme conditions, such as:

Very low fault current (resistance > 2000 Ω)

Severe harmonic distortion (THD > 15%)

Very low SNR (< 6 dB)

Under these circumstances, the detection accuracy dropped slightly to 91.2%, and recall dropped to 89.0%, as shown in Table 4.

Table 4. Performance Metrics Under Extreme Test Conditions

Condition	Accuracy	Precision	Recall	F1-Score
Rf = 100–2000 Ω, SNR > 6 dB	96.7%	97.2%	95.9%	96.5%
Rf > 2000 Ω, SNR = 4 dB, THD > 15%	91.2%	93.4%	89.0%	91.1%

These results indicate that while the method is robust under typical operating conditions, its performance may degrade under very high fault resistances and intense distortion. This highlights the importance of threshold tuning and suggests future work in adaptive threshold schemes or hybrid signal-feature extraction for such scenarios.

To highlight the contribution of the proposed method, a comparative analysis was performed against several representative fault detection approaches from existing literature. The fuzzy-based fault identification method proposed in [1] demonstrated good fault classification capabilities under moderate noise levels, but its reliance on dynamic tree structures and fuzzy rules resulted in higher response time (74 ms) and lower accuracy (93.6%) under high-noise scenarios. In contrast, the proposed method consistently maintained accuracy above 96.7% and achieved a faster response time of 48 ms, as shown in Table 2.

Similarly, the adaptive protection scheme for distributed generation presented in [6] offered high flexibility in managing multiple fault types. However, it depends heavily on inverter-interfaced DG behavior and communication latency, making real-time deployment more complex. The proposed method, by contrast, requires no external communication or adaptive relay coordination and offers computational simplicity through direct use of differential energy indicators.

Furthermore, the data fusion approach in [5] achieved high detection accuracy by combining multiple algorithms, but introduced a significant computational burden unsuitable for real-time environments. Our method eliminates such complexity by leveraging single-stage computation, making it ideal for embedded or field-deployed systems.

These comparisons, summarized in Table 5, demonstrate that the proposed approach offers a balanced trade-off between accuracy, speed, robustness, and simplicity, making it well-suited for practical applications in modern smart distribution networks.

Table 5. Comparison of Proposed Method with Existing Works

Method	Accuracy (%)	Response Time (ms)	Real-Time Feasible	Complexity
Fuzzy-Based [1]	93.6	74	Moderate	High
Adaptive Scheme [6]	95.1	69	Limited	Medium-High
Data Fusion Method [5]	96.8	83	No	Very High
Proposed Method	96.7	48	Yes	Low

IV. CONCLUSION

This study proposed an enhanced high-impedance fault (HIF) detection method for smart distribution networks, leveraging differential energy indicators derived from positive-sequence current components. The method achieved a high detection accuracy of 98.7% across various fault types and remained robust in noisy environments down to 6 dB SNR. Real-time testing with RTDS and dSPACE platforms confirmed its suitability for online implementation, offering fast response (48 ms) and minimal computational overhead. Compared to conventional approaches such as fuzzy logic, adaptive schemes, and data fusion, the proposed method balances simplicity, speed, and reliability. However, several limitations were identified that may challenge its widespread deployment. The performance degrades under extreme fault impedance levels (above 2000 Ω) and low SNR conditions, indicating sensitivity to measurement noise and parameter tuning. Additionally, the use of static thresholding may not adapt well to highly dynamic operational environments, such as rapidly varying load profiles or unbalanced network conditions. These limitations highlight the need for adaptive mechanisms and hybrid detection models to improve resilience and scalability. Future work will focus on addressing these challenges through dynamic threshold optimization, integration with real-time adaptive algorithms, and extensive field-level validation in diverse grid topologies. Despite its current constraints, the method presents a promising step toward practical and cost-effective HIF detection in modern power systems, contributing both theoretically and practically to ongoing smart grid advancements.

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REFERENCES

[1] J. G. An, J. U. Song, and Y. S. Oh, "A fuzzy-based fault section identification method using dynamic partial tree in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 153, no. June, 2023, doi: 10.1016/j.ijepes.2023.109344.

[2] R. Xu, G. Song, Z. Chang, C. Zhang, J. Yang, and X. Yang, "A ground fault section location method based on active detection approach for non-effectively grounded DC distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 152, no. September 2022, 2023, doi: 10.1016/j.ijepes.2023.109174.

[3] M. Z. Yousaf, S. Khalid, M. F. Tahir, A. Tzes, and A. Raza, "A novel dc fault protection scheme based on intelligent network for meshed dc grids," *Int. J. Electr. Power Energy Syst.*, vol. 154, no. June, 2023, doi: 10.1016/j.ijepes.2023.109423.

[4] M. Duan, Y. Liu, D. Lu, and R. Pan, "A novel noniterative single-ended fault location method with distributed parameter model for AC transmission lines," *Int. J. Electr. Power Energy Syst.*, vol. 153, no. July, 2023, doi: 10.1016/j.ijepes.2023.109358.

[5] Y. Liang, A. He, J. Yuan, T. Wu, and Z. Jiao, "An accurate fault location method for distribution lines based on data fusion of outcomes from multiple algorithms," *Int. J. Electr. Power Energy Syst.*, vol. 153, no. January, 2023, doi: 10.1016/j.ijepes.2023.109290.

[6] J. Li *et al.*, "An adaptive protection scheme for multiple single-phase grounding faults in radial distribution networks with inverter-interfaced distributed generators," *Int. J. Electr. Power Energy Syst.*, vol. 152, no. September 2022, 2023, doi: 10.1016/j.ijepes.2023.109221.

[7] M. Rizwan, C. Gao, X. Yan, S. Ahmad, and M. Zaindin, "An approach to disparage the blindness of backup protection in grid connected renewable energy sources system by inducing artificial fault current," *Int. J. Electr. Power Energy Syst.*, vol. 153, no. August 2022, 2023, doi: 10.1016/j.ijepes.2023.109185.

[8] H. Mirshekali, A. Keshavarz, R. Dashti, S. Hafezi, and H. R. Shaker, "Deep learning-based fault location framework in power distribution grids employing convolutional neural network based on capsule network," *Electr. Power Syst. Res.*, vol. 223, no. March, 2023, doi: 10.1016/j.epsr.2023.109529.

[9] T. Treider and H. K. Høidalen, "Estimating distance to transient and restriking earth faults in high-impedance grounded, ring-operated distribution networks using current ratios," *Electr. Power Syst. Res.*, vol. 224, no. August, 2023, doi: 10.1016/j.epsr.2023.109765.

[10] X. Wang *et al.*, "Fault location based on variable mode decomposition and kurtosis calibration in distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 154, no. July 2022, pp. 1–10, 2023, doi: 10.1016/j.ijepes.2023.109463.

[11] Y. Liu, Q. Du, J. Xue, X. Li, D. Yan, and L. Wang, "Improvement of directional relays based on constant impedance angle control of inverter interfaced distributed generations," *Int. J. Electr. Power Energy Syst.*, vol. 153, no. October 2022, 2023, doi: 10.1016/j.ijepes.2023.109372.

[12] Y. Wang, Q. Cui, Y. Weng, D. Li, and W. Li, "Learning picturized and time-series data for fault location with renewable energy sources," *Int. J. Electr. Power Energy Syst.*, vol. 147, no. June 2022, 2023, doi: 10.1016/j.ijepes.2022.108853.

[13] T. A. Zerihun, T. Treider, H. Taxt, L. B. Nordevall, and T. S. Haugan, "Two novel current-based methods for locating earth faults in unearthed ring operating MV networks," *Electr. Power Syst. Res.*, vol. 213, no. July, 2022, doi: 10.1016/j.epsr.2022.108774.

[14] H. Liang, H. Li, and G. Wang, "A Single-Phase-to-Ground Fault Detection Method Based on the Ratio Fluctuation Coefficient of the Zero-Sequence Current and Voltage Differential in a Distribution Network," *IEEE Access*, vol. 11, no. January, pp. 7297–7308, 2023, doi: 10.1109/ACCESS.2023.3238072.

[15] M. J. B. B. Davi, M. Oleskovicz, and F. V. Lopes, "An impedance-multi-method-based fault location methodology for transmission lines connected to inverter-based resources," *Int. J. Electr. Power Energy Syst.*, vol. 154, no. August, 2023, doi: 10.1016/j.ijepes.2023.109466.

[16] G. N. Lopes, T. S. Menezes, D. P. S. Gomes, and J. C. M. Vieira, "High Impedance Fault Location Methods: Review and Harmonic Selection-Based Analysis," *IEEE Open Access J. Power Energy*, vol. 10, no. September 2022, pp. 438–449, 2023, doi: 10.1109/OAJPE.2023.3244341.

[17] Y. Liu, Y. Zhao, L. Wang, C. Fang, B. Xie, and L. Cui, "High-impedance Fault Detection Method Based on Feature Extraction and Synchronous Data Divergence Discrimination in Distribution Networks," *J. Mod. Power Syst. Clean Energy*, vol. 11, no. 4, pp. 1235–1246, 2023, doi: 10.35833/MPCE.2021.000411.

[18] T. Zheng, W. Lv, X. Zhuang, and J. Ma, "Improved time-domain distance protection for asymmetrical faults based on adaptive control of MMC in offshore AC network," *Int. J. Electr. Power Energy Syst.*, vol. 152, no. October 2022, 2023, doi: 10.1016/j.ijepes.2023.109229.

[19] L. Cui, Y. Liu, L. Wang, J. Chen, and X. Zhang, "High-impedance fault detection method based on sparse data divergence discrimination in distribution networks," *Electr. Power Syst. Res.*, vol. 223, no. October 2022, p. 109514, 2023, doi: 10.1016/j.epsr.2023.109514.

[20] S. K. Pirmani and M. A. Mahmud, "Advances on fault detection techniques for resonant grounded power distribution networks in bushfire prone areas: Identification of faulty feeders, faulty phases, faulty sections, and fault locations," *Electr. Power Syst. Res.*, vol. 220, no. February, p. 109265, 2023, doi: 10.1016/j.epsr.2023.109265.