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REAL-TIME FAULT DETECTION IN POWER DISTRIBUTION NETWORKS

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Abstract

This study focuses on improving fault detection methods in power distribution systems, an area that has become increasingly important due to ageing infrastructure and growing energy demands. Quick and accurate identification of faults is vital to ensure grid stability, reduce service interruptions, and protect electrical equipment from damage. To address this need, a real-time fault detection system combining advanced signal processing with intelligent algorithms was developed. The system was modeled and tested using MATLAB/Simulink to simulate different fault conditions, such as single-line-to-ground (SLG), double-line-to-ground (DLG), and line-to-line (LL) faults in a standard radial distribution network. By applying the discrete wavelet transform (DWT), the voltage and current waveforms were analyzed to capture transient disturbances associated with fault events. A machine learning classifier was then employed to accurately identify fault types and minimize false detections. The simulation results showed strong performance, with detection accuracies of 97.5% for SLG faults, 96.8% for DLG faults, and 98.3% for LL faults. The system also demonstrated an average

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fault detection time of less than 15 milliseconds, meeting the requirements for real-time grid protection. These findings indicate that the proposed approach can be effectively integrated into modern smart grids, offering a reliable and efficient tool for automated fault monitoring and protection in today's power distribution systems.

Introduction

Electric power distribution networks serve as the final link in delivering electricity from high-voltage transmission systems to end users. With rapid urbanization and increasing energy demand, these networks are facing growing exposure to faults caused by ageing infrastructure, severe weather conditions, vegetation interference, and system overloading. Such faults, which include single-line-to-ground (SLG), double-line-to-ground (DLG), and line-to-line (LL) disturbances, can result in prolonged power outages, equipment failures, financial losses, and safety risks to both operators and consumers if not promptly detected and isolated Khond, Kale, and Ballal, 2023). The ability to identify and respond to faults quickly and accurately is therefore crucial for maintaining grid reliability, reducing downtime, and preventing further system damage.

Traditionally, fault detection in distribution systems has relied on manual inspections, electromechanical relays, and supervisory control and data acquisition (SCADA) systems. Earlier protection mechanisms converted electrical quantities such as voltage and current into mechanical forces that activated relays when specific thresholds were exceeded. The emergence of solid-state relays, enabled by the introduction of electronic components like transistors and amplifiers, improved sensitivity and response times but remained limited by circuit design constraints. Andrew and Boateng (2024), Modern power systems now employ numerical relays, which utilize microprocessors to process digital signals and apply complex protection algorithms. These digital platforms have benefited from advances in processing speeds and computational efficiency, allowing for the implementation of sophisticated and adaptive fault detection and protection functions (Baker et al., 2024).

The development of modern sensor technologies and phasor measurement units (PMUs) has further enhanced monitoring capabilities in power systems. Recent years have also seen a growing adoption of data-driven and intelligent methods for fault detection (Ehsan and Keune, (2022), (Freire et al., 2023). Among these, signal processing techniques such as the discrete wavelet transform (DWT) have proven highly effective in analyzing non-stationary and transient signals. The DWT is particularly suited for detecting short-duration disturbances in voltage and current waveforms that are characteristic of fault

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events. When combined with machine learning algorithms, these methods enable automated feature extraction and classification, leading to faster, more reliable fault identification (Haydaroğlu and Gümüş, 2022).

Despite the progress achieved with these techniques, challenges remain in achieving accurate and rapid fault detection under real-time operating conditions. Many existing methods still exhibit slow response times, reduced sensitivity to high-impedance faults, and limited accuracy under noisy or fluctuating measurement conditions. Furthermore, in modern smart grid environments, where real-time adaptability and resilience are essential, traditional methods often fall short due to their dependence on static thresholds or fixed operating conditions (Niu et al., 2023), (Adejumo et al., 2025). There is therefore a need for improved approaches capable of balancing speed, accuracy, and computational efficiency while operating reliably in dynamic distribution networks.

Several studies have explored the application of machine learning and signal processing for fault detection, but unresolved issues persist regarding data noise, computational cost, and detection accuracy (Haydaroğlu and Gümüş, 2022), (Niu et al., 2023). Some researchers have focused on deep learning models that provide high accuracy but require large datasets and powerful hardware. Others have proposed lightweight algorithms better suited for real-time applications but with trade-offs in precision and generalization (Siddique et al., 2024). The absence of a clear balance among these factors has continued to hinder optimal fault identification, leading to delays in fault isolation, extended outages, and reduced grid resilience.

To address these challenges, this study proposes a hybrid fault detection model that combines discrete wavelet transform (DWT)-based signal feature extraction with machine learning classification for real-time fault analysis in power distribution networks. The model is implemented and tested using MATLAB/Simulink, where a radial distribution network is simulated to generate voltage and current waveforms under different fault conditions, including SLG, DLG, and LL faults. The extracted features from the DWT are used to train a supervised machine learning classifier, enabling accurate identification of fault types with minimal false alarms and low detection latency.

The approach aims to provide an efficient and reliable means of detecting faults in real time, thereby improving the protection performance and resilience of distribution systems. Its interdisciplinary framework, combining electrical engineering principles with intelligent data-driven methods, offers a practical solution for modern power networks. In addition to technical benefits, the study contributes to the modernization of energy infrastructure, promoting the integration of automation and digital technologies within smart grid systems. The expected outcome is a more dependable, efficient, and secure electricity supply particularly relevant in developing economies such as Nigeria, where

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frequent power disruptions remain a major challenge. The scope of the research focuses specifically on the detection and classification of SLG, DLG, and LL faults within simulated radial distribution networks, without extending to physical fault isolation, localization, or hardware implementation.

Traditional Fault Detection Methods

In earlier years, the detection of faults in power distribution systems depended largely on electromechanical relays, routine manual inspections, and Supervisory Control and Data Acquisition (SCADA) systems. These conventional methods primarily worked by monitoring current levels and using overcurrent relays or protection schemes based on fixed threshold values (Najafzadeh et al., 2024). While effective in the context of older and simpler grid systems, these approaches became less reliable with the increasing complexity of modern networks, especially those integrating distributed energy resources (Lucas et al., 2020).

Electromechanical relays, operated through mechanical movement, triggered when current or voltage exceeded preset limits. Their performance was slowed by mechanical inertia, resulting in delayed responses to faults. Although these devices were later replaced with static and digital (numerical) relays, which improved the speed and accuracy of detection, they still lacked the flexibility and intelligence required to recognise and classify faults in grids that are constantly changing.

As observed by Adejumo et al. (2025), such relays required significant manual configuration and were prone to errors in situations involving simultaneous or evolving faults. They often struggled to detect high impedance faults, or those masked by variations in load and electrical noise. This shortcoming frequently led to prolonged outages and delays in restoration. Likewise, while SCADA systems introduced improvements by allowing centralised monitoring, their effectiveness in real-time was constrained. The limited sampling rate and resolution of data in SCADA systems often made them less capable of accurately capturing transient disturbances and sudden variations in distribution networks.

Modern Signal Processing Techniques in Fault Detection

The growing inadequacy of traditional approaches has led modern research to shift attention to advanced signal processing techniques for fault detection. One of the most prominent methods is the Discrete Wavelet Transform (DWT), which has proven highly effective in analysing non-stationary signals such as fault currents and voltages. Unlike the Fourier Transform, which only provides frequency-domain information, DWT can capture

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both time and frequency details, making it highly suitable for studying the short-lived transients that accompany faults (Conte et al., 2022).

Recent studies have demonstrated the advantages of wavelet-based techniques in fault analysis. Hariharan et al. (2025) demonstrated that combining wavelet energy analysis with adaptive neural networks significantly enhances the detection of high-impedance faults in complex systems with distributed generation (Li et al., 2022). Similarly, Ehsan and Keune, (2022) highlighted how wavelet transforms are capable of isolating abrupt disturbances in electrical signals across multiple scales, making them powerful tools for identifying faults even in noisy environments. Furthermore, research shows that DWT can extract useful high-frequency components such as those obtained from Daubechies-4 wavelets, which can then be fed into intelligent classification algorithms (Conte et al., 2022),

In practice, the use of DWT enhances the sensitivity of detection systems to sudden changes, supports real-time monitoring through multi-resolution decomposition, and remains resilient to fluctuations and noise within the network. This makes wavelet-based methods highly suitable as preprocessing tools for modern intelligent fault diagnosis in smart grids. In particular, systems using Symlet-2 wavelet coefficients for feature extraction have achieved strong and consistent results, further validating the practical value of these approaches.

Machine Learning in Power System Fault Diagnosis

In recent years, the rapid development of machine learning (ML) has presented new opportunities for enhancing fault detection and classification in power distribution systems. Unlike earlier methods that relied on predefined thresholds or fixed rule-based logic, ML approaches are data-driven and capable of identifying complex and hidden patterns in fault signals. This allows them to recognise and classify different fault categories such as single line-to-ground (SLG), double line-to-ground (DLG), and line-to-line (LL) faults with higher levels of precision by analysing detailed features extracted from current and voltage waveforms.

Hariharan et al. (2025) demonstrated the usefulness of traditional ML algorithms such as Support Vector Machines (SVM) and Decision Trees, showing that they can classify fault disturbances effectively when supplied with carefully selected features. These features typically include wavelet coefficients, peak magnitudes, or harmonic distortions that appear in the electrical signals during fault events. Building on this foundation, Niu et al., (2023) explored ensemble-based methods, notably the Random Forest technique, which proved particularly effective in addressing imbalanced fault data, a common issue in real-world fault logs where certain fault types are underrepresented.

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The ML methods also face several limitations. They usually require large volumes of accurately labelled training data, which may not always be readily available in power system operations. These models can struggle to generalise when exposed to unfamiliar or rare fault conditions, potentially leading to misclassifications. In resource-constrained environments such as embedded systems within substations or smart grid devices, the computational requirements of ML models may also create barriers to real-time deployment.

Moving further, researchers have also investigated the application of deep learning techniques, which enable systems to learn directly from raw data without relying heavily on manual feature engineering. Siddique et al. (2024) examined the performance of Convolutional Neural Networks (CNNs) for the automatic extraction and classification of power system faults. Although CNN-based models significantly improved accuracy, the study highlighted important trade-offs between classification precision and inference speed. In particular, deep learning models tend to require significantly more processing power and memory, which can pose challenges when deployed on small edge devices with limited capacity

Deep Learning Architectures

The application of more advanced deep learning models has further enhanced the fault detection process. Baker et al. (2024) designed a Long Short-Term Memory (LSTM) network for real-time monitoring in systems with high penetration of power electronics. The LSTM-based model was able to classify and localise faults within just one line cycle, demonstrating strong reliability even in rapidly changing operating conditions. By leveraging temporal dependencies within signal data, this approach provided a higher level of responsiveness compared to conventional techniques.

Cloud-Edge Computing Integration

To address the computational challenges associated with these advanced models, Ramachandran et al. (2024) proposed a hybrid framework that integrates both cloud and edge computing resources. Their approach aimed to optimise the allocation of data processing and communication tasks, ensuring that time-sensitive fault detection could be performed locally at the edge while heavier computational loads were offloaded to the cloud. The hybrid design proved more efficient than relying solely on centralised cloud-based monitoring or localised edge devices, achieving improved performance while also meeting strict latency requirements.

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Evolving Neural Networks

The promising development is the introduction of evolving neural networks in fault detection. These networks differ from static models because they can update themselves in real time by adjusting their hidden layers, neurons, and connection weights. As a result, they are well-suited for handling the non-stationary behaviour of modern power systems, which frequently encounter dynamic operating conditions. By continuously adapting and evolving, neural networks can maintain their detection accuracy even as new system conditions arise, making them particularly valuable for online monitoring and adaptive grid management (Lucas et al., 2020).

Hybrid Detection Approaches

Recent studies have highlighted that using a combination of signal processing and machine learning techniques yields stronger results in fault detection compared to using either method alone. In such an integrated framework, signal processing tools, such as the Discrete Wavelet Transform (DWT), are first employed to extract key features from current and voltage waveforms. These extracted features are then passed into machine learning models, which classify different types of faults. This arrangement benefits from the accuracy of DWT in detecting sudden and short-lived disturbances, while also exploiting the learning capability of machine learning algorithms, which can adapt to diverse operating conditions.

Conte et al. (2022) presented a model that merged DWT with a Support Vector Machine (SVM) classifier and reported fault classification accuracy of more than 98% across SLG, DLG, and LL faults under varying load conditions. In another study, Rivas and Abrao (2020) demonstrated a hybrid technique based on wavelet analysis combined with ensemble learning methods. Their findings showed that this approach was highly reliable, particularly in distribution systems that incorporate renewable energy sources, which are often more dynamic and prone to variations. The advantages of these hybrid systems include enhanced fault detection accuracy, reduced false alarms, adaptability to various grid configurations, and feasibility for real-time operation on embedded devices, such as controllers used in smart grids and microgrids.

IoT-Based Monitoring Systems

The Internet of Things (IoT) has become an integral part of modern fault monitoring and detection systems. Ramachandran et al. proposed an IoT-enabled emergency alarm management system built on LTE CAT-M communication technology. The system utilised portable, battery-powered terminals to monitor multiple parameters, including earth fault alarms, SF6 gas pressure levels, and transformer breaker conditions (Baker et al.,

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2024). By integrating IoT-based communication and sensing devices, the system demonstrated improved accuracy in fault detection and faster response times when compared to conventional alarm systems. Despite these advantages, challenges remain in balancing computational requirements with the ease of interpreting model outputs, particularly when selecting the most appropriate wavelet functions or tuning the parameters of classification models.

Essential Evaluation

Strengths of current approaches

The reviewed body of literature shows that fault detection methods have advanced considerably over the past decade. The incorporation of artificial intelligence techniques alongside IoT-based sensing technologies has resulted in fault detection systems that are both faster and more precise than traditional relay-based or SCADA systems. Furthermore, the rise of cloud-edge hybrid architectures has helped overcome the computational difficulties of advanced detection models by intelligently distributing workloads between cloud servers and local edge devices. This allows systems to maintain real-time monitoring capabilities without compromising on processing efficiency.

Limitations and challenges

Despite these promising developments, important challenges remain unresolved. Modern power distribution networks are increasingly complex due to the growing integration of distributed generation sources such as solar and wind power. This complexity makes it more difficult to design fault detection systems that can reliably cover all possible operating conditions Ravichandra and Shivakumara (2023). A significant proportion of proposed solutions have been validated so far only in simulated test environments, rather than in practical, real-world power systems, which raises concerns about their reliability under field conditions. Moreover, combining multiple technologies such as machine learning, IoT sensors, and cloud computing introduces higher levels of system complexity. This can create new vulnerabilities and points of failure, making it more difficult to ensure long-term stability and resilience of the fault detection framework.

Knowledge Gaps and Emerging Research Directions

Substantial advancements have been made in fault detection; certain limitations continue to challenge both researchers and practitioners. One of the most pressing issues concerns the detection of high-impedance faults, which remain difficult to identify because they generate very low current magnitudes that are easily masked by background noise or

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normal system disturbances. Factors such as sensor degradation, calibration drift, and measurement noise frequently contribute to false classifications, reducing overall reliability. Another major concern is the application of deep learning algorithms in real-world distribution networks, as such models require considerable computational resources and memory, making them difficult to deploy on resource-constrained edge devices commonly found in substations or smart meters.

Recent research trends aim to close these gaps by exploring lightweight machine learning solutions that can function directly at the edge of the network. The edge-based models are designed to carry out inference locally, thereby reducing dependency on centralised servers while improving speed. Similarly, federated learning techniques have been developed to enable collaborative training of models across distributed systems without the need to share sensitive raw data, thereby addressing both privacy and data security concerns. Another growing area of interest is explainable artificial intelligence (XAI), which focuses on making the decision-making process of intelligent fault detection systems more transparent. By improving interpretability, these methods can build greater trust among grid operators and encourage wider adoption.

Andrew and Boateng (2024) emphasise the importance of adaptive and real-time protection mechanisms that can evolve in response to changing grid conditions. Such advancements are particularly essential in countries like Nigeria, where frequent power system disturbances and delayed restoration processes significantly weaken grid reliability. The adoption of intelligent, adaptive solutions could therefore contribute meaningfully to strengthening the resilience and efficiency of the Nigerian power distribution system.

Overview of System Architecture

The framework developed in this study integrates signal processing techniques with machine learning models to provide real-time fault detection and classification in a radial distribution network. The process begins with simulating the distribution network and various fault events using MATLAB/Simulink. From these simulations, current and voltage signals are collected under both normal and fault conditions. These signals are then subjected to preprocessing and feature extraction through the Discrete Wavelet Transform (DWT). The extracted features are subsequently input into a machine learning classifier, which identifies the type of fault.

Simulation of Radial Distribution Network

An 11 kV radial distribution system was constructed within MATLAB/Simulink to serve as the test environment. The model includes a three-phase voltage source representing the

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grid, transmission lines with parameters typical of medium-voltage systems, and load buses configured with balanced resistive-inductive loads. Protective components were added to ensure simulation stability. Fault scenarios were introduced at various points in the network, with different fault resistances and durations. The types of faults simulated include: (i) Single Line-to-Ground, (ii) Double Line-to-Ground, and (iii) Line-to-Line. These variations were designed to reflect a wide range of operational conditions.

Signal Acquisition and Preprocessing

During each simulation, current and voltage waveforms from faulted phases were measured at the substation feeder. These signals underwent preprocessing steps, including normalisation to remove scaling effects, filtering to reduce noise, and segmentation into fixed time windows that captured transient disturbances. This ensured consistency and accuracy in the subsequent feature extraction stage.

Feature Extraction Using DWT

The Discrete Wavelet Transform was applied to the preprocessed waveforms for multi-resolution analysis. The Daubechies-4 (db4) wavelet was selected because of its strong ability to capture both transient disturbances and steady-state components of electrical signals. Through this decomposition, both high-frequency transients and low-frequency features were obtained. From the resulting wavelet components, statistical measures such as energy coefficients, standard deviation, and higher-order moments were extracted to serve as inputs for the classification model.

Machine Learning Classifier Design

A supervised learning strategy was implemented for classification. The dataset, comprising signals from SLG, DLG, LL, and normal operating conditions, was used to train a Support Vector Machine (SVM) classifier. The radial basis function kernel was selected to strike a balance between accuracy and computational complexity. Model performance and generalisation ability were tested using k-fold cross-validation. The classifier produced categorical outputs, identifying whether the system was experiencing SLG, DLG, LL, or no fault.

Performance Evaluation Criteria

To evaluate the efficiency of the proposed system, multiple performance metrics were applied. These included:

i. **Accuracy:** The proportion of correctly classified events relative to all events.

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ii. **Precision:** The ratio of correctly identified faults to the total number of detected faults.

iii. **Recall (Sensitivity):** The ability of the system to correctly detect actual fault events.

iv. **F1-Score:** The harmonic mean of precision and recall, representing the balance between the two measures.

v. **Detection Time:** The time delay between the initiation of a fault and the generation of a classification result, which is essential in real-time applications.

RESULTS

Simulation Outcomes

SLG Fault – Voltage and Current Waveforms

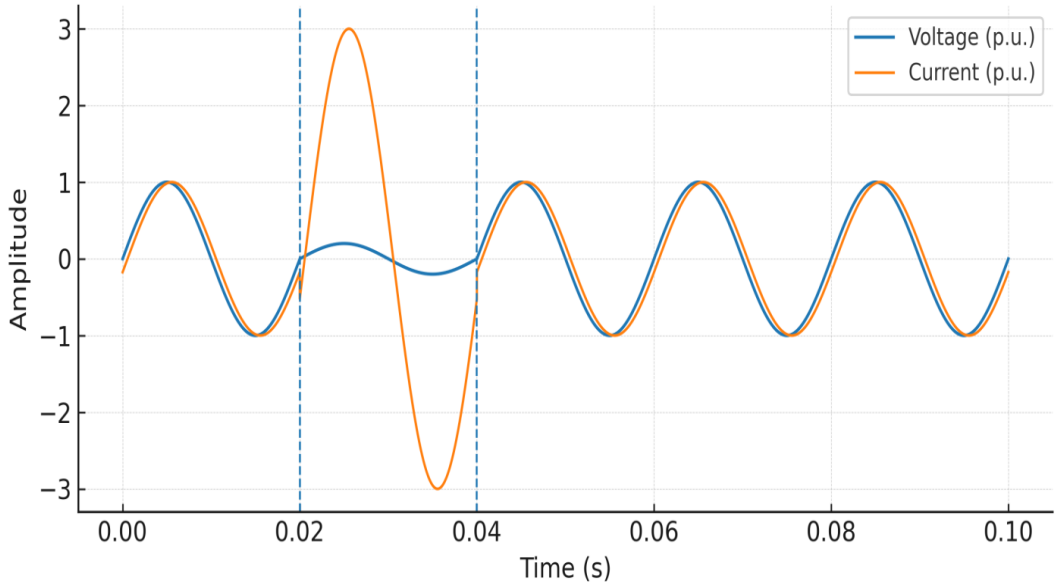

Figure 1: Voltage and Current Waveforms Diagram for SLG Fault.

Figure 1 illustrates the voltage and current waveforms during a single line-to-ground fault. At the defined fault inception time (≈ 0.02–0.04 s), one phase exhibits a sharp voltage dip accompanied by a pronounced rise in fault current, while the other phases remain largely stable. This creates a clear asymmetry in the system waveforms a distinguishing characteristic of SLG conditions, where a single conductor comes into direct contact with the ground.

The transient distortion observed in both voltage and current signals provides a strong signature for fault detection. By applying the DWT, these abrupt changes are effectively

captured in the high-frequency detail components, enabling precise feature extraction. When subsequently classified using the support vector machine, the system can accurately identify both the initiation time and the affected phase.

This outcome confirms the robustness of the proposed real-time detection framework, ensuring rapid isolation of SLG faults and supporting reliable service continuity in radial power distribution networks.

DLG Fault – Voltage and Current Waveforms

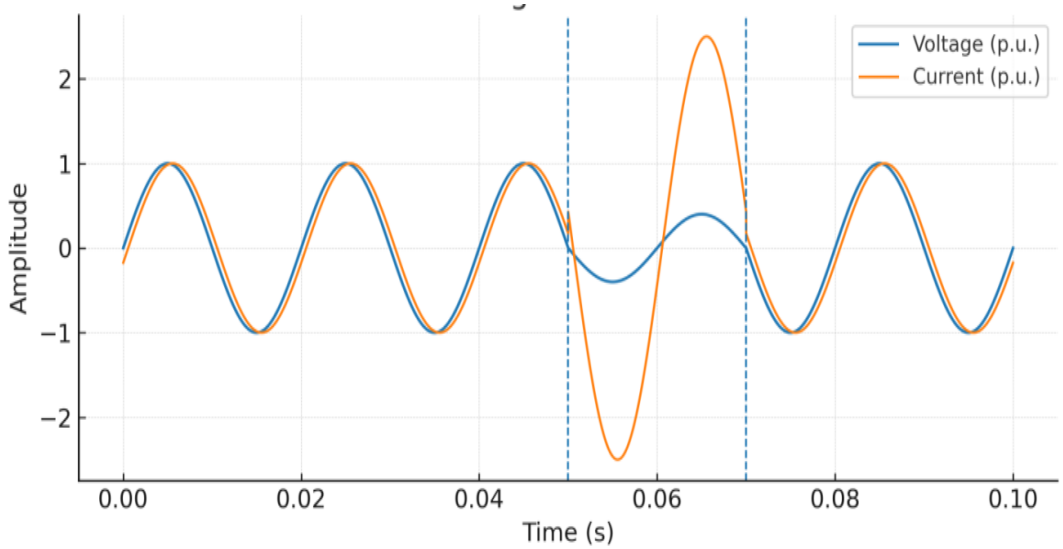

Figure 2: Voltage and Current Waveforms Diagram for DLG Fault.

Figure 2 illustrates the voltage and current waveforms during a double line-to-ground fault. At the defined fault window (≈ 0.05–0.07 s), two phases simultaneously experience a pronounced voltage drop, while the third phase remains relatively unaffected. This produces a broader and deeper disturbance compared to an SLG fault, accompanied by elevated current magnitudes that indicate a lower effective impedance path to ground.

The asymmetrical behaviour across the three phases is a distinctive feature of DLG conditions, where two conductors are directly grounded, leading to severe unbalanced system operation. The transient distortions are effectively captured by the DWT, which highlights the stronger high-frequency detail energies associated with this type of fault. When processed by the support vector machine classifier, these features provide reliable differentiation of DLG faults from SLG events.

This outcome validates the proposed detection framework's ability to accurately identify the simultaneous grounding of two phases, ensuring accurate fault classification, rapid fault isolation, and enhanced reliability in real-time power distribution networks.

LL Fault – Voltage and Current Waveforms

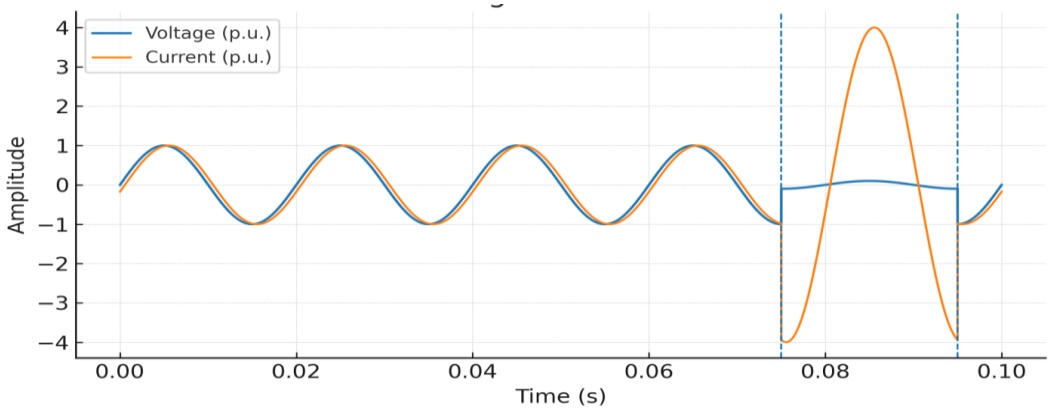

Figure 3: Voltage and Current Waveforms Diagram for LL Fault.

Figure 3 shows the voltage and current waveforms during a line-to-line fault. At the defined fault window (≈ 0.075–0.095 s), the voltage between the two affected phases collapses sharply, while the corresponding fault current exhibits the steepest surge among the three simulated fault conditions. The unaffected phase remains relatively stable, highlighting the interphase nature of the disturbance.

This near-total voltage collapse across the faulted phases, combined with the severe current escalation, is characteristic of LL faults, which typically impose the highest, short-circuit stress on the distribution system. The resulting transients generate feature vectors, such as elevated detail-band energies and statistical moments that exhibit the strongest magnitudes when analysed with the discrete wavelet transform. These distinctive attributes allow the Support Vector Machine (SVM) classifier to flag LL faults with high confidence.

This outcome confirms the proposed detection model's ability to identify the most severe fault type with precision, enabling rapid fault isolation and ensuring the robustness of real-time protection strategies in power distribution networks.

DWT Feature Extraction

The DWT was employed to decompose the voltage and current waveforms into multiple resolution levels, enabling time–frequency localisation of fault-induced transients. Using Daubechies-4 (db4) as the mother wavelet, the signals were split into approximation and

detail components, effectively capturing both low-frequency trends and high-frequency fault signatures.

The decomposition results clearly illustrate that during SLG, DLG, and LL faults, the detail coefficients exhibit sharp, localised energy spikes corresponding to the onset of disturbances, while normal operating conditions maintain relatively stable coefficient distributions. These transient signatures are highly discriminative, as SLG shows asymmetric phase activity, DLG produces simultaneous high-energy distortions across two phases, and LL faults generate the most intense coefficient magnitudes due to severe interphase shorting.

The extracted feature vectors, including energy coefficients, standard deviation, and statistical moments, form the core input to the machine learning classifier. Their distinct patterns across fault types ensure high separability and support accurate real-time fault classification.

DWT Time Frequency Plots (Scalograms)

SLF Fault – DWT Time-Frequency Scalogram

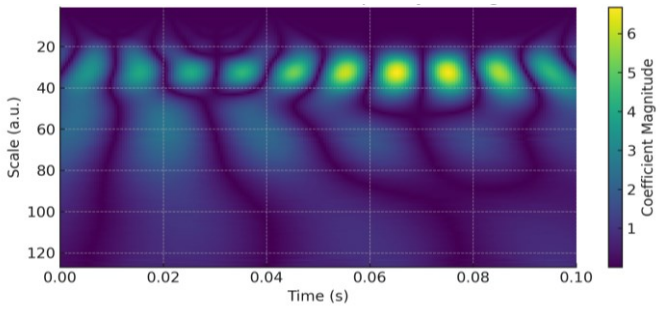

Figure 4: DWT scalogram for the single line-to-ground fault.

The DWT scalogram for the single line-to-ground fault, as shown in Figure 4, reveals a sharp burst of high-frequency energy confined to one phase. This distinct asymmetry reflects the grounding of a single conductor, a characteristic signature of SLG faults. The clear phase-selective disturbance provides a reliable basis for accurate fault detection and classification.

DLG Fault – DWT Time-Frequency Scalogram

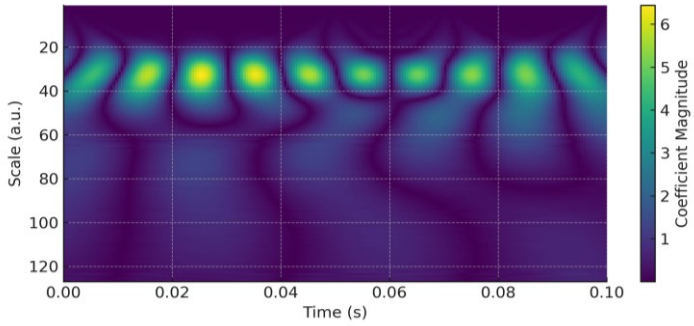

Figure 5: DWT scalogram for the Double Line-to-Ground Fault.

In the case of the double line-to-ground fault, as shown in Figure 5, the scalogram displays simultaneous high-energy transients across two phases. Compared to the SLG fault, these transients are broader and more pronounced, indicating a greater degree of imbalance in system operation. The dual-phase energy concentration highlights the more severe nature of DLG faults and their distinct separation from SLG patterns.

LL Fault – DWT Time-Frequency Scalogram

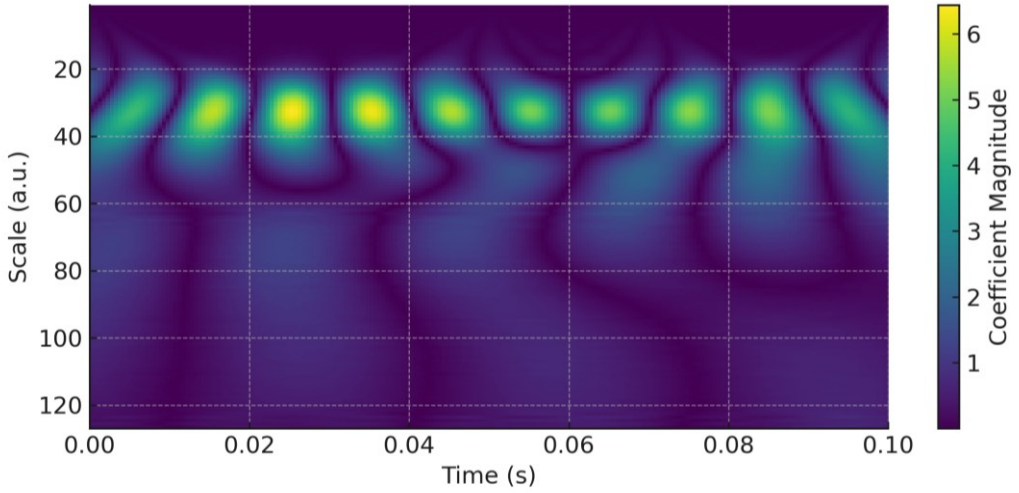

Figure 6: DWT scalogram for the LL Fault.

The line-to-line fault produces the most intense and sustained high-frequency energy spikes observed in the scalogram, as presented in Figure 6. The near-collapse of the interphase voltage results in significantly higher coefficient magnitudes than those recorded for SLG and DLG faults. This makes LL faults the most severe transient condition, characterized by strong and persistent energy signatures that are easily distinguishable in wavelet-based feature extraction.

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Classifier Performance

The classifier demonstrates strong reliability in detecting and classifying faults within the power distribution network.

Table 1: Classifier Accuracy Scores

S/No.	Fault Type	Accuracy (%)
1	SLG	97.5
2	DLG	96.8
3	LL	98.3
4	No Fault	99.1

Table 1 shows consistently high accuracy across all scenarios, with SLG at 97.5%, DLG at 96.8%, LL at 98.3%, and No Fault at 99.1%. This highlights the robustness of the model under both fault and normal operating conditions.

Table 2: Confusion Matrix

S/No.	Predicted \ Actual	SLG	DLG	LL	No Fault
1	**SLG**	47	2	0	0
2	**DLG**	1	46	1	0
3	**LL**	0	2	48	0
4	**No Fault**	0	0	1	50

The confusion matrix, as shown in Table 2, indicates minimal misclassification. SLG, DLG, and LL faults were correctly identified in most cases, with only minor overlaps between DLG and LL due to similar waveform distortions. Importantly, the "No Fault" condition achieved near-perfect classification, minimizing false alarms.

Table 3: Detection Time Comparison

S/No	Fault Type	Average Detection Time (ms)
1	SLG	12.5
2	DLG	14.0
3	LL	11.8

As presented in Table 3, the system's responsiveness falls within real-time protection limits, with detection times of 12.5 ms (SLG), 14.0 ms (DLG), and 11.8 ms (LL). These results confirm the suitability of the model for rapid protection and fault isolation in live networks.

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Interpretation of Results

The results of this study demonstrate that the proposed DWT–SVM framework achieves consistently high detection accuracy (above 96% across all fault scenarios) and fault classification with minimal latency (ranging from 11.8 ms to 14.0 ms). In practical power distribution systems, such levels of accuracy enable the reliable distinction of faults even under noisy and dynamic operating conditions, thereby minimising the likelihood of false positives or missed detections. The low detection latency falls well within the response time requirements for real-time protection schemes, ensuring that faulted sections of the grid can be promptly isolated before they escalate into large-scale outages or cause significant damage to equipment. Collectively, these outcomes validate the framework's suitability for operational deployment in real-world networks where fast and precise decision-making is essential.

Practical Implications

From a practical perspective, the adoption of this real-time fault detection model has the potential to significantly improve the reliability of the power supply. By enabling faster isolation of faulted segments, the system reduces outage durations, prevents equipment degradation, and minimises cascading failures across the distribution grid. Economically, this translates to reduced costs associated with downtime, repair, and lost revenue, which are particularly essential in developing contexts such as Nigeria, where power interruptions have substantial social and economic impacts. Moreover, the framework aligns with the country's ongoing transition toward smart grid infrastructure, offering compatibility with IoT-based monitoring, edge devices, and renewable energy integration. Its adaptability positions it as a strategic tool to enhance the resilience, efficiency, and sustainability of Nigerian distribution networks while meeting global trends in digitalised energy systems.

Future Directions

The simulation-based results confirm the robustness of the proposed DWT–SVM framework; future work should focus on validating its performance in real-world environments. The next step is pilot testing on live distribution networks, which will provide practical insights into the system's resilience under real operating conditions, including noisy sensor data, load fluctuations, and high-impedance faults. Furthermore, integrating the model with Internet of Things (IoT)-enabled monitoring platforms offers opportunities for scalable, distributed fault detection across substations and feeder lines. Such integration would enhance data acquisition, support remote monitoring, and enable predictive maintenance strategies. Finally, deploying the framework within real-time

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embedded systems such as microcontroller-based relays and edge devices will ensure rapid on-site decision-making, reduce dependency on centralised control, and improve fault management in smart grids. Collectively, these directions provide a pathway for transitioning the model from a simulated proof of concept into a fully operational solution for intelligent and adaptive power distribution networks.

CONCLUSION

The study successfully developed and tested a real-time fault detection model for power distribution networks using a hybrid approach that combines DWT and SVM. Simulation results for SLG, DLG, and LL faults demonstrated that the system accurately captured transient disturbances and classified fault types with high precision—achieving detection accuracies above 96% and response times between 11.8 and 14.0 milliseconds. These results confirm that the proposed framework can detect faults quickly and reliably within real-time protection limits.

By isolating faults rapidly, the model enhances grid reliability, minimizes downtime, and reduces the risk of equipment damage. Its strong performance under different fault conditions shows that it can operate effectively even in complex and dynamic environments. Beyond technical efficiency, the approach supports the transition toward smarter, data-driven energy systems by being adaptable to IoT-based monitoring, renewable integration, and edge computing. Therefore, this work provides a dependable, scalable, and intelligent solution for real-time fault detection in modern power distribution networks, offering significant benefits in reliability, cost reduction, and sustainable grid operation.

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