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High Impedance Fault Detection and Classification in Distribution Networks Using Machine Learning Techniques

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Abstract
High-impedance faults (HIFs) in power distribution networks present significant challenges due to their low fault currents and intermittent nature, making them difficult to detect using conventional protection methods. These faults pose serious risks, including electrical hazards, wildfires, and system failures. This study explores the application of machine learning techniques, specifically Decision Trees (DT), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), to enhance the detection and classification of HIFs. A comprehensive model of the IEEE 14-bus distribution network was developed in MATLAB/Simulink. The Discrete Wavelet Transform (DWT) was employed to extract features from fault signals. Results indicate that ANN outperformed DT and SVM in terms of accuracy, precision, and recall, achieving an overall classification accuracy of 93.3%. This research introduces a novel, practical approach to improving fault-detection reliability in power systems.
Keywords: High Impedance Faults (HIF), Power Distribution, Machine Learning, Fault Classification, Discrete Wavelet Transform (DWT), Artificial Neural Networks (ANN).

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1.1 Motivation and survey study

Power distribution systems, by their very nature, are exposed to various environmental factors, rendering them susceptible to frequent faults and anomalies. Rainy conditions, for instance, can lead to short-circuit faults when objects come into contact with pole-mounted wires. While pole-mounted cables are more resilient to such issues, they remain vulnerable to instantaneous overvoltage's and significant current surges caused by lightning strikes. Furthermore, their connection points are at risk of various types of faults. In contrast, underground distribution lines are considered safer but incur higher maintenance costs in the event of faults because they require excavation for access. Consequently, distribution systems are engineered to mitigate the adverse effects of such disturbances. For example, the relay protection system is a critical component of this design, promptly detecting and mitigating faults by de-energizing the affected feeder. (Harish Kumar et al., 2021; Majeed Butt, Zulqarnain et Majeed Butt, 2021; Sharma et al., 2021; Zhang et al., 2022).

However, high-impedance faults (HIFs) are a unique kind of fault in power distribution systems. These faults exhibit a distinctive characteristic: they draw minimal current over time within the system's operational range. These faults, characterized by their intermittent nature and low fault currents, are exceptionally elusive and can lead to severe consequences if not promptly identified and addressed. (Ghaderi, Ginn and Mohammadpour, 2017; Baharozu, Ilhan and Soykan, 2023).

High Impedance Faults (HIFs) are a distinctive type of fault in power distribution systems, often occurring when an energized conductor of the primary network contacts a highly resistive surface, such as trees, grass, sand, roads, or construction materials. These faults are characterized by their low or similar current levels to the steady-state condition in PDSs (Lopes *et al.*, 2023). Consequently, conventional protective relays struggle to detect HIFs, posing risks such as electric shocks, wildfires, and equipment shutdowns that affect both human safety and power system reliability. (Dos Santos *et al.*, 2013).

Research indicates that HIFs account for 5-20% of faults in PDSs (Hossain, Zhu and Overbye, 2014), making them a significant concern for power utilities. These faults can cause unscheduled component shutdowns due to adverse electrical, mechanical, or thermal conditions, underscoring the urgency of their accurate detection and classification. (Dos Santos *et al.*, 2013).

Conventional fault detection methods, primarily reliant on relay protection systems, have shown limitations in effectively detecting HIFs (Aucoin and Jones, 1996; Dos Santos *et al.*, 2013; Sahoo and Baran, 2014), especially in real-world scenarios where multiple fault types coexist, including Line-to-Line (L-L), single-phase line-to-ground (L-G), phase-to-phase-to-ground (LLG), and three-phase faults. The transient nature of HIFs and their tendency to manifest as partial or intermittent faults often evade the detection capabilities of traditional protection schemes, giving rise to potential hazards such as threats to human safety, equipment damage, and power supply disruptions (Aucoin and Jones, 1996; Gadanayak, 2021; Lima *et al.*, 2021; Souza *et al.*, 2021).

To address this pressing issue, advancements in machine learning techniques have shown great promise in enhancing fault detection and classification capabilities in power systems. Machine learning algorithms, such as neural networks, support vector machines, and decision trees, have demonstrated the potential to analyze large datasets, extract complex patterns, and make accurate predictions. Applying machine learning techniques to HIF detection and classification in distribution networks offers a novel, sophisticated approach to overcoming the limitations of traditional methods. This paper identifies a research gap of particular significance in the integration, with a focus on impedance fault detection in distribution networks, that navigates into the intricacies of electrical power distribution and also incorporates challenges posed not only by faults but also by deployed machine learning techniques. This paper proposes a machine learning-based framework to detect and classify HIFs in distribution networks. The contributions of this work include:

i. Development of a dataset simulating various fault and non-fault scenarios.
ii. Feature extraction techniques capture key signal characteristics.
iii. Evaluation of several ML algorithms for detection and classification.
iv. Performance benchmarking under noisy and variable operating conditions.

1.2 Significance of the proposed study

Prior studies have explored HIF detection using rule-based and signal-processing techniques, such as wavelet transforms, harmonic analysis, and expert systems. However, these methods often struggle with generalization across different network conditions. Recent works incorporate ML methods, but insufficient datasets, a lack of real-time capabilities, or low fault classification accuracy limit many of them. This paper builds upon these efforts by integrating robust data preprocessing, advanced classification algorithms, and thorough validation.

High-impedance faults (HIFs) are common in power distribution systems and pose challenges for conventional protection devices due to their low current levels. (Wester, 1998; Gautam and Brahma, 2013; Nunes *et al.*, 2019; De Souza *et al.*, 2020; Gashteroodkhani, Majidi and Etezadi-Amoli, 2021; Akuru *et al.*, 2022). Many researchers have used known node/bus test feeders to simulate power distribution systems and study HIFs.

HIFs can arise from several sources, including pole-mounted wires coming into contact with trees, aging insulators degraded by factors like surface dust or humidity, and even bird carcasses, which are not uncommon in distribution systems. Human activities in rural areas, such as using utility poles to support small structures or hang clothes, poorly designed feeders near home walls, overextended feeders to accommodate more customers, and even electricity theft, can also contribute to HIFs. These diverse causes make HIFs relatively common in distribution networks. (Vico *et al.*, 2010; Theron, Pal and Varghese, 2018; Aljohani and Habiballah, 2020; Lopes *et al.*, 2023).

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1.3 Inspiration

High Impedance Faults (HIFs) remain one of the most elusive challenges in the protection of power distribution networks. Unlike low-impedance faults, HIFs produce fault currents that are too small to trigger conventional protective devices, yet they pose serious risks such as fires, electric shocks, and prolonged undetected outages. These faults typically occur when a live conductor makes unintended contact with high-resistance surfaces such as dry soil, concrete, tree branches, or asphalt, causing the current signature to blend in with normal load conditions.

The inspiration for this study stems from the growing inadequacy of traditional protection schemes in identifying such faults. As modern distribution networks become more complex due to increased electrification, aging infrastructure, and the integration of distributed energy resources, there is an urgent need for smarter, more adaptive fault-detection mechanisms.

Machine learning (ML) offers a promising solution by learning from historical and real-time data, detecting hidden patterns, and generalizing to unseen fault conditions. By leveraging advanced ML techniques, it is possible to distinguish between normal load variations, low-level disturbances, and actual high impedance fault events with high accuracy.

This research is driven by the hypothesis that combining time-frequency domain analysis (wavelet transforms) with supervised machine learning algorithms yields a robust, scalable framework for HIF detection and classification. The goal is to enable utility operators to move beyond threshold-based relay systems toward intelligent, data-driven protection solutions that enhance safety, reliability, and operational awareness in modern distribution networks.

1.4 Contribution

This paper advances intelligent fault detection systems in power distribution networks by addressing the longstanding challenge of accurately detecting and classifying High Impedance Faults (HIFs). Traditional protection devices often fail to identify HIFs due to their low current signatures and similarity to normal load variations. To overcome this, we propose a machine learning-based framework that combines signal processing with data-driven classification techniques to recognize and categorize HIFs across varying operating conditions effectively.

The core contributions of this research are summarized below:

(a) This study presents the design, development, and validation of a robust HIF detection model using machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees (DT), trained on a comprehensive dataset derived from simulated IEEE 14-bus distribution networks.

(b) A detailed feature extraction methodology using Discrete Wavelet Transform (DWT) is introduced to capture transient characteristics of voltage and current waveforms, improving the sensitivity of detection models to subtle fault signatures.

(c) A comparative analysis of different classifiers is conducted to evaluate accuracy, precision, recall, and fault classification effectiveness under various noise levels and load conditions.

(d) The study demonstrates that data-driven models, particularly ANN, outperform conventional rule-based or threshold-based systems in both fault detection and classification accuracy, even in high-resistance and nonlinear fault scenarios.

(e) The research provides a scalable and adaptable methodology that can be embedded into intelligent electronic devices (IEDs) or integrated into advanced distribution management systems (ADMS) for real-time monitoring and protection enhancement

2.1 Conventional Detection Techniques

Early HIF detection techniques relied on heuristic or rule-based methods. These included harmonic analysis, zero-sequence current monitoring, and arc signature recognition. Notably, Benner and Russell proposed one of the pioneering approaches to HIF detection using pattern recognition and signal features such as harmonic components, which are often present in arcing faults. However, these approaches were often sensitive to noise, system loading, and fault location.

2.2 Signal Processing-Based Methods

Signal processing methods such as the Fourier Transform, Short-Time Fourier Transform (STFT), and Wavelet Transform (WT) have been employed to extract time-frequency features from fault signals. Wavelet-based approaches, in particular, have shown promise due to their ability to capture transient characteristics of faults. Applied wavelet decomposition to detect HIFs and extracted statistical features from the transformed signals. Nevertheless, these methods require expert knowledge to design feature extraction pipelines and may not generalize well to unseen data.

2.3 Machine Learning-Based Approaches

With the advent of data-driven technologies, machine learning (ML) has emerged as a powerful tool for fault detection and classification. Supervised learning algorithms such as Decision Trees, Support Vector Machines (SVMs), and Random Forests have been applied to classify fault types using labeled datasets. These models offer improved detection performance compared to traditional methods, especially when combined with effective feature extraction techniques.

Recent studies have employed artificial neural networks (ANNs) and deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to learn fault signatures directly from raw or minimally processed signals [5]. These models exhibit superior performance in capturing nonlinearities and temporal dependencies inherent in HIF signals.

2.4 Limitations of Existing Work

Despite the promising results, most existing studies face several limitations:

- **Limited datasets**: Many works use simplified simulations with limited variation in fault conditions, leading to overfitting and poor generalization.
- **Lack of real-time validation**: Few studies address the computational efficiency and feasibility of deploying ML models in real-time systems.

- **Insufficient comparison**: Comparative evaluations of different ML techniques under consistent scenarios are often lacking.

This paper addresses these gaps by developing a comprehensive HIF detection and classification framework that leverages multiple ML models, extensive simulations across diverse conditions, and rigorous performance evaluation.

3. **Discrete wavelet transform (DWT)**

[24] proposed a wavelet transform-based approach to detect and classify different shunt faults that may occur in transmission lines. The algorithm primarily calculates the RMS values of the wavelet coefficients of the current signals at both ends of the transmission line, using a moving window of half a cycle.

(Chen *et al.*, no date; Bhalla and Saxena Larsen, 2012)also investigated the detection of HIFs using the discrete wavelet transform (DWT). DWT is a multi-resolution transform that provides high-frequency resolution for low frequencies and high time resolution for high frequencies. The DWT is a series of filtering and downsampling processes applied to the input signal. Scaling functions and wavelet functions are used to achieve this. Given a sampled signal s(n), the DWT decomposes it into several wavelet signals, including an approximation signal. The approximation coefficient, which represents the signal's low-frequency components, is obtained from a low-pass filter, and the detail coefficients, which represent the signal's high-frequency components, are obtained using the high-pass filter, as shown in Figure 1 b

Wavelet Decomposition (DWT): For a signal, $x(t)$

$$x(t) = A_j(t) + \sum_{i=1}^{j} D_i(t) \qquad (1)$$

Where is the approximation coefficient at level (representing the low-frequency components), and is the detail coefficient at level i (representing the high-frequency components at each level).

Multi-Level Decomposition: The DWT is applied iteratively at each level. For a four-level decomposition, it is expressed as:

$$x(t) = A_4(t) + D_1(t) + D_2(t) + D_3(t) + D_4(t) \qquad (2)$$

Where is the approximation coefficient at the fourth level (low-frequency components), and are the detail coefficients at levels 1, 2, 3, and 4, respectively, capturing progressively higher-frequency components.

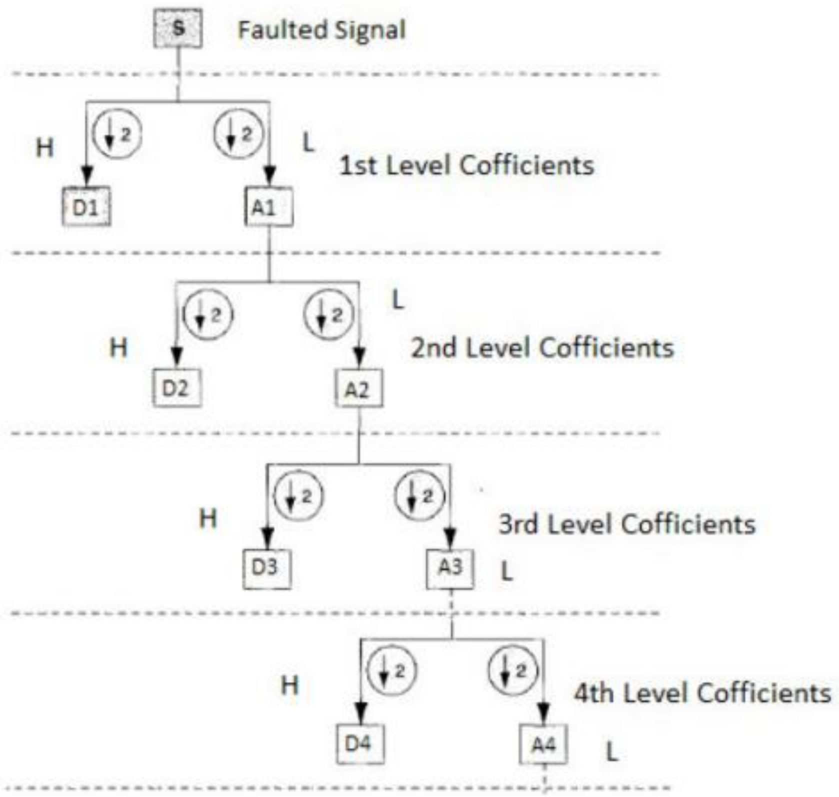

Figure 1 *Decomposition of the four-level discrete wavelet transform (Bhalla and Saxena Larsen, 2012)*

3.1. Support vector machine
The robust theoretical foundation and ease of implementation have made the SVM method one of the most popular classification methods. (Scholarship@western and Rai, 2021). Additionally, compared to the
In the ANN method, SVM has less tendency to overfit and provides more scattered responses. It is also independent of the input space. Therefore, this technique has been applied to many
classification problems and is much more practical for these problems.
Classification using SVM primarily involves training and testing, both of which consist of many components. In the training set, each sample includes several features and a target value called a class
or label. This method aims to generate a system that can successfully determine new data labels or test data consisting solely of features. Most algorithms of this method can only
divide the data between two classes, thus transforming it into a binary classification problem, as shown in Figure 2.

3.2 Decision Making and Classification

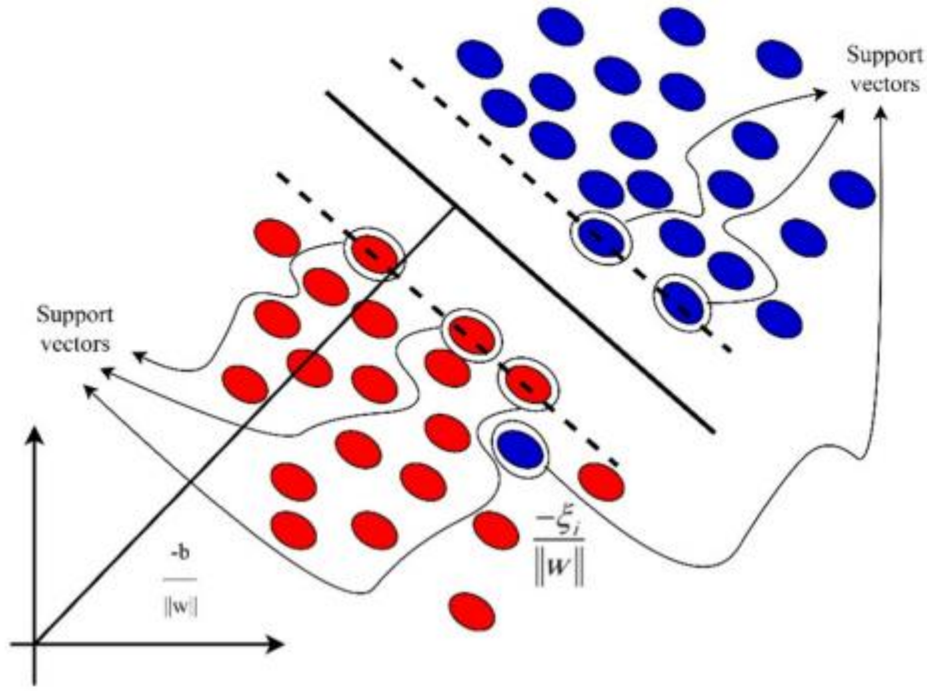

***Figure 2Classification of datasets using the SVM method** (Wang* et al.*, 2024)*

IV. Simulation Results

This section presents simulation results for both the IEEE Standard 14-Bus test system and the actual distribution network in Markazi Province. EMTP-RV software is used to assess the effectiveness of the proposed method. Moreover, MATLAB is used for feature extraction, and the Python programming language is used in Google Colab and Spyder environments to implement the SVM algorithm. The *Bus parameter for the IEEE 14-bus distribution system is given in **Table 1.***

Table 1: The Bus parameter for the IEEE 14-bus distribution system

fbus	tbus	r	x	b	rateA	rateB	rateC	ratio	angle	status
1	2	0.01938	0.05917	0.0528	0	0	0	0	0	1
1	5	0.05403	0.22304	0.0492	0	0	0	0	0	1
2	3	0.04699	0.19797	0.0438	0	0	0	0	0	1
2	4	0.05811	0.17632	0.034	0	0	0	0	0	1
2	5	0.05695	0.17388	0.0346	0	0	0	0	0	1
3	4	0.06701	0.17103	0.0128	0	0	0	0	0	1
4	5	0.01335	0.04211	0	0	0	0	0	0	1
4	7	0	0.20912	0	0	0	0	0.978	0	1
4	9	0	0.55618	0	0	0	0	0.969	0	1

5	6	0	0.25202	0	0	0	0	0.932	0	1
6	11	0.09498	0.1989	0	0	0	0	0	0	1
6	12	0.12291	0.25581	0	0	0	0	0	0	1
6	13	0.06615	0.13027	0	0	0	0	0	0	1

4.1 Results for IEEE 34-Bus Test System

4.1.1 Introduction of Network and Data Collection

The test network has a nominal voltage level of 24.9 kV and operates at a nominal frequency of 60 Hz. The main reasons for selecting this network are the proximity of the voltage level to
the real distribution network and the diversity in equipment, such as capacitor banks and various loads. These characteristics have made the 14-bus IEEE test network one of the most common test power networks for HIF detection studies. The single-line diagram of this network is presented in Figure 3. One of the most critical parts of data collection is accurate modeling of HIF. The HIF model should have specific general characteristics such as nonlinearity, asymmetry, and non-
stationarity. Therefore, the HIF model from (Hamatwi *et al.*, 2023)

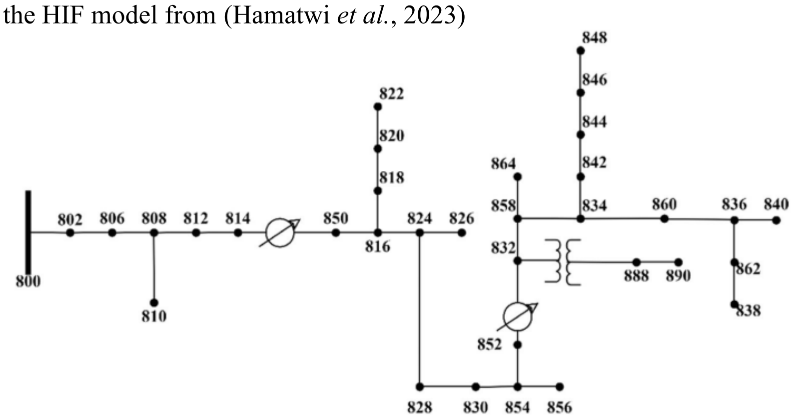

Figure 3Single-line diagram of the standard IEEE 14-bus network

4.1.2. Case Study: HIF Detection under Load and Environmental Variations

This case study demonstrates the initial performance of the proposed machine learning-based High Impedance Fault (HIF) detection framework under dynamic load and environmental conditions. Simulations were conducted using a custom-designed IEEE 14-bus distribution network in MATLAB/Simulink. To emulate real-world variability, load fluctuations and noise disturbances were introduced alongside simulated HIF and non-fault scenarios.

The figures (1-4) illustrate the three-phase voltage and current waveforms captured during a simulated High Impedance Fault (HIF) scenario in a distribution network. The waveform plots are shown over a time interval of 0 to 0.2 seconds. The top subplot displays the voltage waveforms, while the bottom subplot represents the corresponding current waveforms for phases A, B, and C.

In the voltage plot (top), the waveforms initially exhibit normal sinusoidal behavior, with uniform amplitude and phase separation. However, around 0.10 seconds, a noticeable distortion appears, particularly in the yellow waveform (Phase C), indicating a high-impedance fault. The oscillations increase in amplitude, and frequency modulation becomes evident, confirming the abnormal condition.

The current plot (bottom) reveals a more pronounced deviation from the steady-state condition. Initially, the currents maintain a balanced, sinusoidal shape. As the fault develops (also around 0.10 seconds), the phase currents, especially in the blue and yellow phases, experience a sudden decrease in amplitude and increased asymmetry. This reflects the erratic current signature typically associated with arcing or high-resistance faults, which are difficult to detect with conventional protection schemes.

These waveform changes serve as key indicators in the feature extraction process, particularly when applying the Discrete Wavelet Transform (DWT). By analyzing transient deviations such as those observed, the proposed machine learning model effectively distinguishes high-impedance faults from normal and other fault conditions.

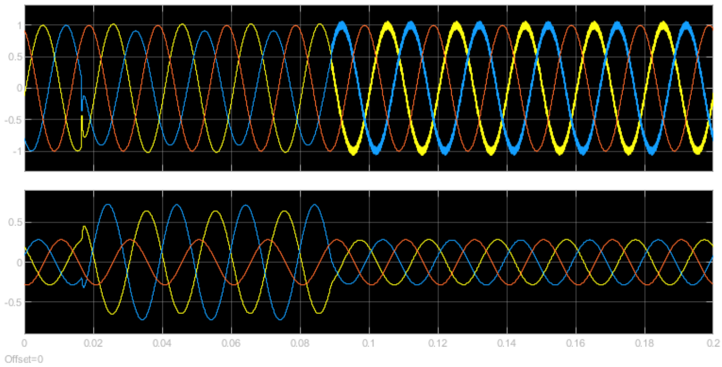

Figure 4: illustrates the voltage and current waveforms during a three-phase AB fault.

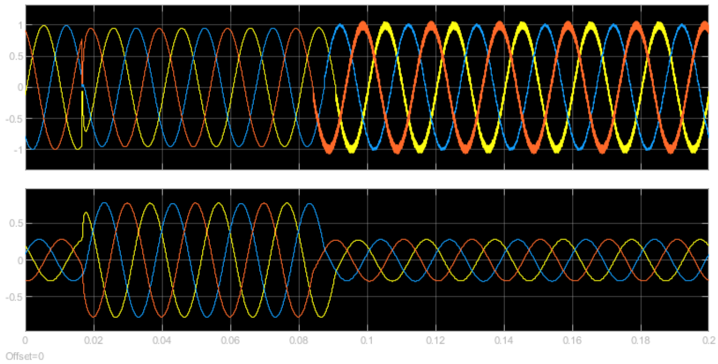

Figure 5: illustrates the voltage and current waveforms during a three-phase ABCG fault

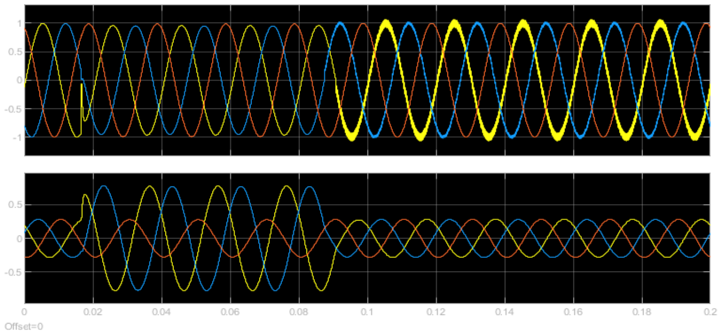

Figure 6:: illustrates the voltage and current waveforms during an AG fault voltage near zero

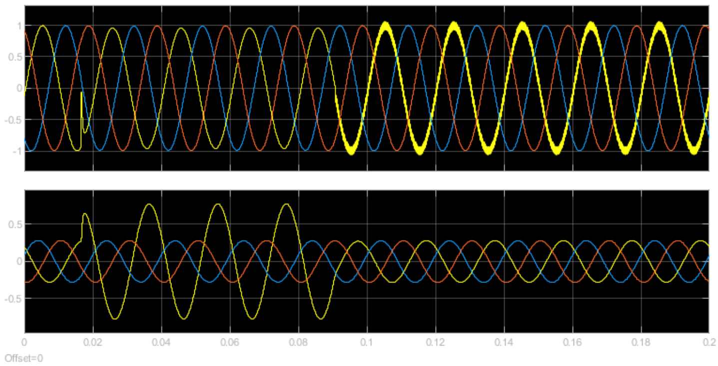

Figure 7: Depict a BG fault, the voltage and current waveforms during

VI. Conclusion

This study presents a robust, intelligent framework for detecting and classifying High Impedance Faults (HIFs) in distribution networks. The proposed method combines the Discrete Wavelet Transform (DWT) for feature extraction and machine learning algorithms, specifically the Support Vector Machine (SVM), for classification. A comprehensive dataset was generated through simulation, capturing various fault and non-fault conditions under realistic network scenarios.

Initially, the model was evaluated on the IEEE 14-bus test network, achieving a classification success rate of 99.58%. The system reliably distinguished between normal load variations and high-impedance fault conditions, with minimal false positives or negatives.

To further validate the method's generalizability and effectiveness, it was implemented on the model, which maintained a high detection accuracy of 97.94%, confirming its adaptability to practical network conditions, including noise, load diversity, and signal distortions.

The results confirm that integrating wavelet-based signal analysis with supervised machine learning provides a scalable and reliable solution for enhancing protection schemes in modern distribution networks. The proposed framework can be seamlessly integrated into Intelligent Electronic Devices (IEDs) and Advanced Distribution Management Systems (ADMS**)** to improve fault localization, reduce outage duration, and enhance grid resilience.

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