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Advanced Fault Detection in Power Systems Using Wavelet Transform: SIMULINK-Based Implementation and Analysis

Saiful Islam Tuhin[1*], Md. Al Araf[2], Faiyaj Ibna Zubayer[3], Md. Abu Al Mahtab[4], Md. Naeem[5]

[1,2,3,4,5]Department of Electrical & Electronic Engineering, Faculty of Engineering and Applied Sciences, Bangladesh University of Business & Technology (BUBT), Dhaka, Bangladesh.*

Email: [2]md.al.araf.2001@gmail.com, [3]faiyaj.zubayer@gmail.com, [4]a.al.mahtab.2000@gmail.com, [5]mdnaeem4261@gmail.com
Corresponding Email: [1]saifulislamtuhin15@gmail.com*

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***Abstract:** Traditional methods struggle to find faults in power transmission lines. This paper presents an approach for short transmission lines, leveraging the power of wavelet transforms. Traditional methods analyze time-domain signals, limiting their ability to differentiate fault transients. Wavelet transforms, offering a combined time-frequency analysis, provide a deeper understanding of these transients. A detailed short transmission line model is built in SIMULINK. Diverse fault scenarios are meticulously simulated, and current signals undergo wavelet transform analysis. Key features extracted from the wavelet coefficients act as fingerprints of potential faults. These features are then utilized to develop a robust fault detection algorithm specifically designed for short transmission lines. The proposed method promises enhanced fault detection capabilities compared to existing techniques in this domain. The results, presented in subsequent sections, will shed light on the effectiveness of wavelet transforms in empowering smarter and more reliable transmission line operations.*

***Keywords:** Fault Detection, Short Transmission Lines, Wavelet Transform, Simulink, Power System Protection, Transient Analysis.*

1. INTRODUCTION

Modern society thrives on a continuous and dependable supply of electricity. Disruptions caused by faults in power systems can have severe consequences, ranging from equipment damage and economic losses to widespread blackouts. Early and accurate fault detection is paramount for minimizing such negative impacts and ensuring a reliable power grid [1].

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1.1. Limitations of Traditional Fault Detection Methods

Conventional fault detection techniques primarily analyze current or voltage signals within the time domain. While effective in some scenarios, these methods encounter limitations when dealing with complex fault types or noisy environments in short transmission lines. Distinguishing between actual faults and transient disturbances becomes challenging, potentially leading to missed detections or false alarms.

1.2. Wavelet Transforms Analysis

The adoption of wavelet transform (WT) in real-world power system operations has attracted considerable interest. This signal processing method has found applications across various domains including image processing, load prediction, and power quality event categorization. WT proves to be a robust technique for breaking down a signal into its frequency constituents, enabling the concurrent examination of time and frequency aspects in transient signals. In contrast to Fourier analysis, which struggles with non-stationary signals, WT preserves temporal details, rendering it versatile for a multitude of tasks [2].
A wavelet has an average of 0 and is an integral of:

$$\int_{-\infty}^{+\infty} \varphi(x)dx = 0 \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (1)$$

In wavelet transform (WT), a pivotal element is the wavelet function, commonly known as the mother wavelet. Unlike Fourier analysis, which relies on fixed sinusoidal functions, WT employs wavelet functions with adjustable attributes like Daubechies, Haar, Coiflet, and Symlet, among others. The depiction of a signal in the time-frequency domain through functional representation is termed a WT.
Permanent Wavelet An explanation of a signal's transform is given as:

$$WT_{\varphi}\, Z(b,c) = \frac{1}{\sqrt{|b|}} \int_{-\infty}^{+\infty} z(x)\varphi_{m,n}\left(\frac{t-c}{b}\right)dx \quad \dots\dots\dots\dots\dots\dots\dots\dots. (2)$$

The Continuous Wavelet Transform (CWT) expresses a signal's transformation through an integral involving scale and translation parameters, as depicted in equation 2. To alleviate the computational complexity linked with CWT, the Discrete Wavelet Transform (DWT) was introduced. DWT operates with scale and position values that adhere to powers of two, enabling more efficient computation [3].
The discrete wavelet transform (DWT) simplifies the computational burden by utilizing scale and position values based on powers of two, also known as dyadic expansions and translations.

$$DWT_{(p,q)} = \int_{-\infty}^{+\infty} z(x)\ \varphi_{p,q}\,(x)dx \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (3)$$

$$\varphi_{p,q}(x) = a_1^{-\frac{p}{2}} \frac{(t - nb_1^p c_1)}{b_1^p} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Here, $a = b_1^p$ and $b = qb_1^p c_1$

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m and n, standing for frequency localization and temporal localization, respectively, are used to represent x in this situation. Multi-resolution analysis (MRA) is built on the couple orthogonal WT, which is typically produced when $p_2 = 2$ and $q_1 = 1$ [4]. In this study, a wavelet is employed to detect abnormalities in the three-phase compensation circuit. The Daubechies wavelet, specifically Db4, is utilized for fault identification due to its desirable characteristics such as low signal distortion and fast response. By using this approach, various faults, including line-to-ground (LG), line-to-line-ground (LLG), and three-phase faults, can be accurately detected. The results demonstrate the effectiveness, reliability, speed, and accuracy of the system.

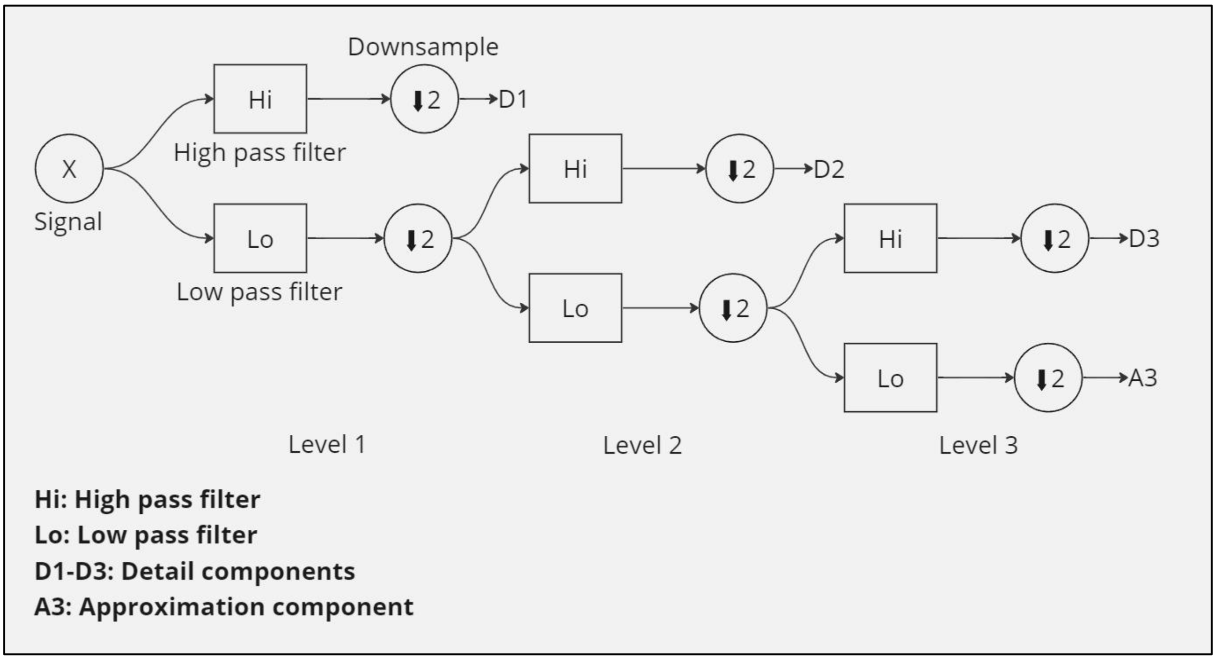

Fig. 1: Wavelet Multi-Resolution Analysis (MRA)

2. RELATED WORKS

Extensive research has been conducted on various fault detection methods in power systems, with a focus on improving their effectiveness, especially for short transmission lines. Here, we delve into some prominent approaches and their limitations:

Impedance-Based Techniques: These methods, such as those presented in analyzing changes in system impedance during fault conditions. While simple to implement, they struggle with differentiating between fault types in short transmission lines. The lower impedance changes in these lines compared to longer lines can lead to misinterpretations. Additionally, system parameter variations can further impact their accuracy. Synchronized Phasor Measurement (PMU) Based Techniques: PMUs provide high-resolution voltage and current phasor data, enabling fast and accurate fault detection, as demonstrated in. However, the cost and complexity of deploying PMUs limit their widespread application. This becomes particularly relevant for short transmission lines, where cost-effectiveness is often a primary concern [5]. Artificial Neural Networks (ANNs): ANNs offer a data-driven approach for fault detection,

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capable of learning complex patterns from historical data, as explored in. However, they require significant training data and computational resources. This can be a challenge for short transmission lines where data availability might be limited, especially for less frequent fault scenarios [6], [7]. Signal Processing Techniques: Recent research has explored the application of various signal processing techniques for fault detection in short transmission lines. These techniques aim to extract features from voltage and current signals that are indicative of faults. For instance, researchers in investigate the use of Discrete Fourier Transform (DFT) for fault classification. However, DFT offers limited time-frequency resolution, making it challenging to distinguish between fault transients and other system disturbances, particularly in short lines with fast transients [8].

Literature review: Kim et al. (2002) proposed a novel fault-detection technique for high-impedance faults in transmission lines using wavelet transform. Their method is robust to various fault conditions and achieves accurate detection through a combination of wavelet decomposition and fault criteria [9]. Dash et al. (2007) proposed a support vector machine (SVM) based method for fault classification and section identification in transmission lines with Thyristor-Controlled Series Compensator (TCSC). This method achieves fast and accurate classification using post-fault current samples and firing angle as input features [10]. Yadav and Dash (2014) reviewed various artificial neural network (ANN) techniques for fault detection, classification, location, and direction discrimination in transmission lines. Their survey can be a valuable resource for researchers interested in ANN-based transmission line protection techniques [11]. Jamil et al. 2015 proposed a neural network-based method for fault detection and classification in electrical power transmission lines. Their method achieved satisfactory performance using three-phase voltage and current data as inputs [12]. Flores et al. (2016) proposed a neural network-based fault diagnosis system for power systems. This modular approach assigns a neural network to each component (transmission line, bus, transformer) for fault detection and leverages various data sources like switch/relay states, voltage/current oscillograms, and frequency spectrums [13]. Ray and Mishra (2016) proposed a fault classification and location method for long transmission lines using support vector machines (SVM) with wavelet packet transform for feature extraction. Their method achieved high accuracy (over 98%) for fault type and distance estimation [14]. Ferdowsi et al. (2017) proposed a passive HIF detection method using Real-time Complexity Measurement (RCM) of load voltage data in a microgrid. This method offers easy implementation and avoids power quality issues [15]. Zormpas et al. (2018) investigated using Unmanned Aerial Vehicles (UAV) and basic image processing for power line inspection. Their method offers a cost-effective solution for transmission line inspection and fault detection [16]. Yetgin et al. (2019) proposed using convolutional neural networks (CNNs) for power line detection in aerial images. They achieved significant improvements by pre-training the CNN on the ImageNet dataset, demonstrating the effectiveness of pre-training for even basic image recognition tasks [17]. Tao et al. (2020) proposed a deep CNN cascade architecture for insulator defect detection in aerial images. Their method achieves high accuracy (precision 0.91, recall 0.96) and robustness to various conditions using data augmentation techniques [18]. Jiang (2020) proposed a data-driven fault location method for distribution systems with distributed generations (DGs) using smart meters and remote fault indicators. This method leverages outage reports and overcurrent notifications to pinpoint faulty line sections [19].

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Belagoune et al. (2021) proposed deep learning models using Long Short-Term Memory (LSTM) networks for fault detection, classification, and location in large power systems. Their approach utilizes pre- and post-fault data from PMUs to achieve high accuracy and robustness [20]. Jiang (2021) proposed a data-driven probabilistic fault location method for distribution systems that incorporates data uncertainties from various sources (relays, IEDs, SCADA, smart meters) to provide a list of potential fault locations with probabilities, aiding decision-making for faster fault isolation and restoration [21]. In a recent study by Ahmed et al. (2023), Discrete Wavelet Transform (DWT) was investigated for fault detection in overhead transmission lines. Their findings suggest that DWT combined with a classification algorithm can be a promising tool for real-time fault detection and classification [22]. Basher et al. (2024) proposed a fault classification and localization method for microgrids using Discrete Wavelet Transform (DWT) and multi-machine learning techniques with promising accuracy for advanced microgrid protection systems [23].

Background & Motivation

Reliable power delivery necessitates early fault detection. Traditional time-domain methods struggle with complex faults and noisy environments, especially in short transmission lines with fast transients. This can lead to missed detections or false alarms. This paper proposes a novel approach utilizing wavelet transforms for improved fault detection in short transmission lines. Wavelets offer combined time-frequency analysis, potentially overcoming the limitations of traditional methods.

Objectives

1. Develop a comprehensive short transmission line model in SIMULINK.
2. Simulate diverse fault scenarios.
3. Apply wavelet transform analysis to extract key features.
4. Develop a robust fault detection algorithm based on extracted features.

3. METHODOLOGY

The proposed methodology employs a multi-step approach, focusing on a short transmission line scenario and combining a simulated power system model with the power of wavelet transforms:

Power System Modeling in SIMULINK:

A detailed power system model is meticulously constructed in SIMULINK, specifically representing a short transmission line. This model incorporates various components like

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Generators, transformers, Three-Phase Series RLC Branch, and loads, ensuring it reflects the characteristics of a short transmission line system. The model parameters, including line length and voltage level, are chosen to be within the range typically considered for short transmission lines (generally less than 80 kilometers and voltage less than 20 kV). This ensures the study focuses on the behavior of faults in such systems. The frequency used in this model is 60 Hz.

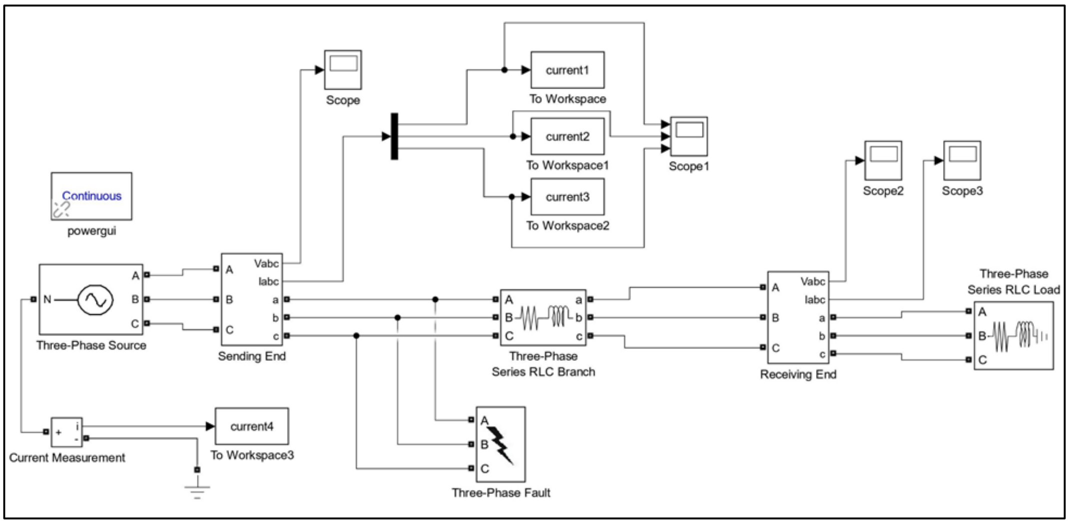

Fig. 2: Stimulated Model of Short Transmission Line using Wavelet Transform

Load Fault Detection and Measurement using Wavelet Transform Algorithm:
The MATLAB software, renowned for its effectiveness in power system analysis and simulation, serves as the foundation for implementing the algorithm [24]. Its versatility in signal processing and algorithmic development renders it an ideal choice for this particular research endeavor. Within MATLAB-Simulink, the simulation studies take place, allowing for the intricate modeling and simulation of power systems to be conducted with precision.
The wavelet transform algorithm dissects the load signal into distinct frequency bands, facilitating the scrutiny of localized alterations within the signal [25]. Through the analysis of wavelet coefficients' attributes, fault conditions such as voltage sags, swells, interruptions, and harmonics can be discerned and assessed. Additionally, the algorithm accommodates fluctuations in fault resistance and location, thereby augmenting the precision of fault detection and measurement processes.

The wavelet transform algorithm's effectiveness is evaluated through performance metrics including detection accuracy, false alarm rate, and computational efficiency. Testing is conducted on short transmission lines, a well-established benchmark system in power system analysis. Simulation outcomes vividly illustrate the algorithm's adeptness in precisely detecting and quantifying load faults across diverse operational scenarios.

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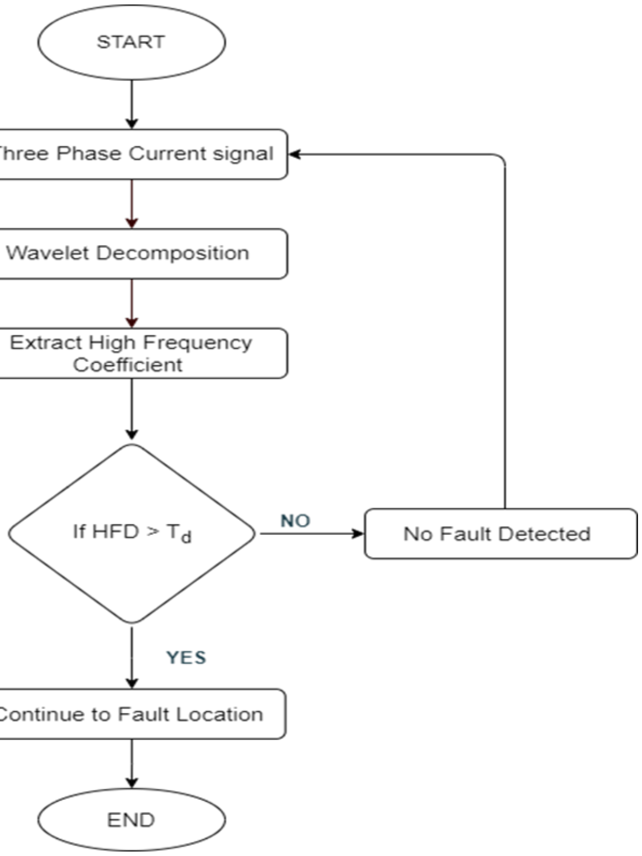
Fig. 3: Flow Chart for Fault Detection Procedure using Wavelet Transform



Fault Analysis:
After performing the process in Simulink using wavelet transform, we have obtained some data, which are given below**:**
The table displays the maximum values of detailed coefficients extracted from the wavelet decomposition of current signals for phases A, B, C, and the ground. Each row corresponds
To a specific fault scenario, including three-phase faults, double-line-to-ground faults, and single-line-to-ground faults in different phases, line-to-line faults, and a normal system. The maximum coefficient values provide crucial insights into the severity and type of faults present in the power system, aiding in fault diagnosis and mitigation strategies.

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Table 1: Maximum Value of Detailed Coefficients of all Phases and Ground Current for Different Faults

Type of Fault	Max. coefficient of Phase B Current	Max. coefficient of Phase B Current	Max. coefficient of Phase C Current	Max. coefficient of Ground Current
Three phase to ground Fault	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05
Three phase Fault	1.6097e+07	4.0725e+07	1.6097e+07	**0.0081**
Double Line to Ground Fault (AB-G)	1.0796e+07	2.1332e+07	**103.9772**	7.7574e+05
Double Line to Ground Fault (AC-G)	1.9807e+07	**103.9772**	8.6730e+06	1.9393e+06
Double Line to Ground Fault (BC-G)	**103.9784**	4.0725e+07	8.1478e+06	9.7619e+05
Line to Line (A-B) Fault	1.0794e+07	2.0363e+07	**103.9772**	**0.0087**
Line to Line (A-C) Fault	2.0363e+07	**103.9772**	8.6153e+06	**0.0204**
Line to Line (B-C) Fault	**103.9784**	4.0725e+07	7.2573e+06	**0.0100**
Single Line to Ground Fault (A-G)	1.3523e+06	**103.9772**	**103.9772**	1.6087e+06
Single Line to Ground Fault (B-G)	**103.9784**	3.7024e+06	**134.3960**	1.1253e+06
Single Line to Ground Fault (C-G)	**103.9784**	**103.9772**	1.4099e+06	3.7023e+06
System without Fault	**103.9784**	**103.9772**	**103.9772**	**7.1737e-10**

4. RESULTS AND DISCUSSION

The outcomes obtained from the SIMULINK simulations explore their significance for fault detection in short transmission lines using wavelet transforms.

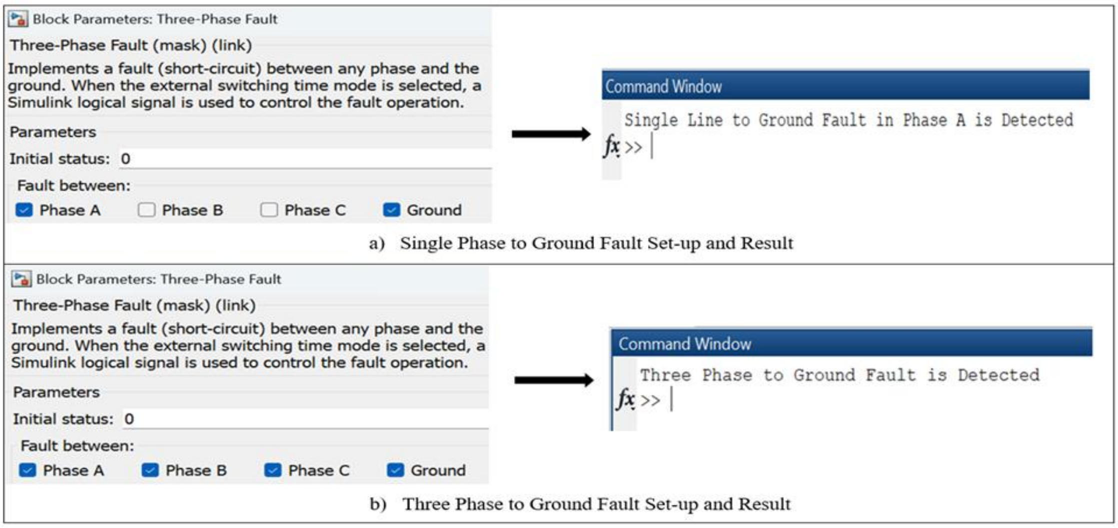

Fig. 4: Wavelet Transform Training Outcomes

Single-phase to ground (L – G) fault, commonly referred to as a single-phase to ground fault, typically arises from insulation failure between one of the phases and the earth within a

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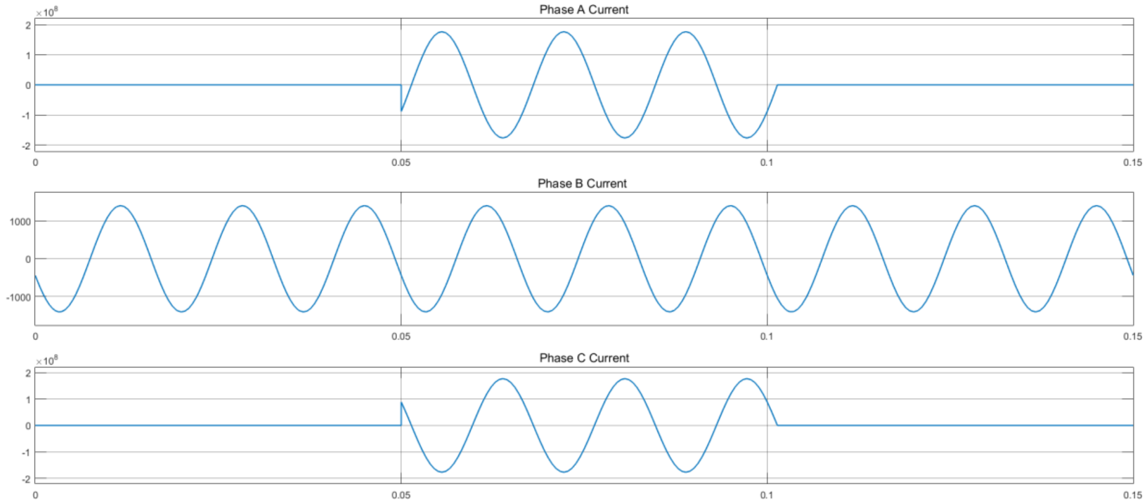
power system. This type of fault is prevalent, with a likelihood of occurrence ranging from 70% to 80%.

A. Single-phase to Ground (L – G) Fault:



B. Single-phase to Phase (L – L) Fault:

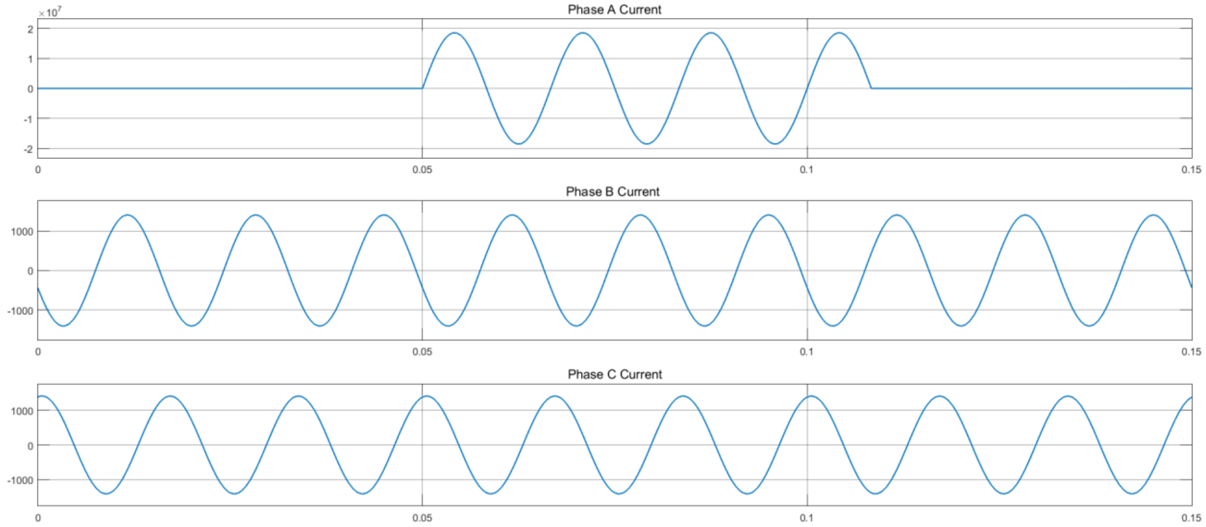


Fig. 6: Line to Line (L – L) Fault Graph

This fault is also known as a phase-to-phase fault, arising from the short-circuiting of two conductors within the system. Heavy winds are the primary catalyst for this fault, as they can cause line conductors to swing and potentially come into contact, leading to a short circuit. The probability of phase-to-phase faults occurring in power systems is estimated to be around 15% to 20%.

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C. Double-phase to Ground (L – L – G) Fault:

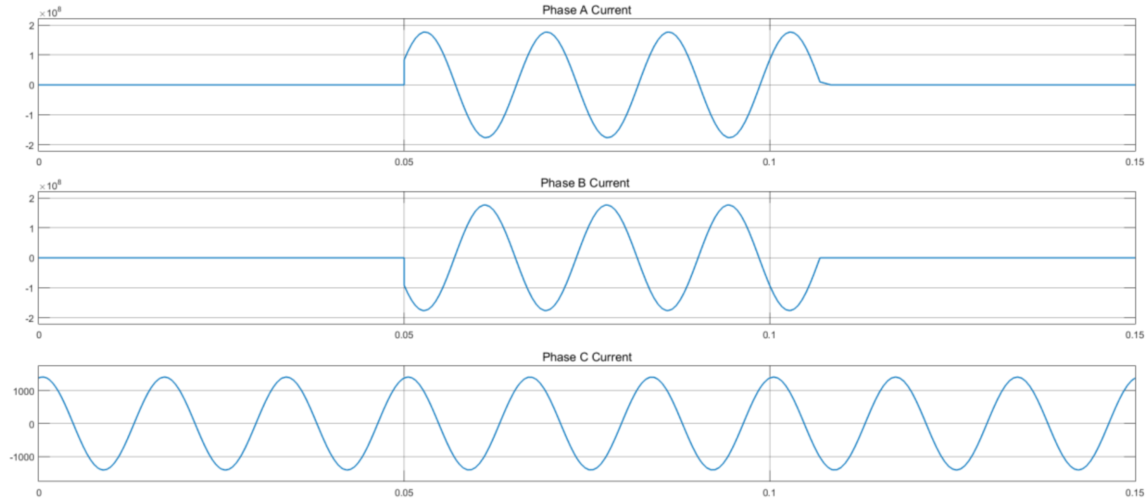

Fig. 7: Double Line to ground (L – L – G) Fault Graph

This fault involves insulation breakdown between two phases and the earth, alternatively known as a line-to-line-to-ground fault or a two-phase-to-ground fault. Although it is one of the more severe types of faults, it is infrequent in power systems. The likelihood of such faults occurring is approximately 10%.

D. Three-Phase Line (L – L – L) Fault:

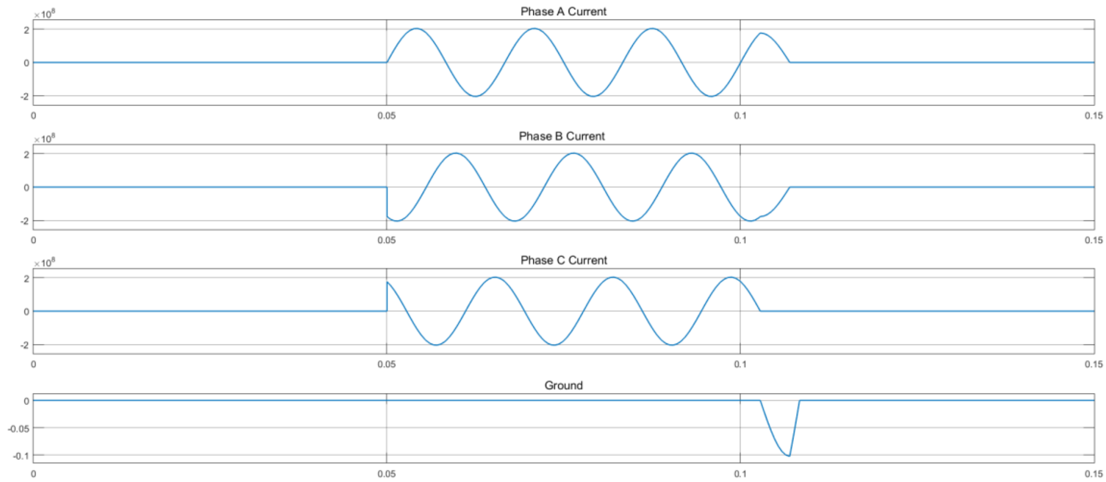

Fig. 8: Line to Line to Line (L – L – L) Fault Graph

This fault primarily arises from insulation failure across all three phases, constituting the most severe type of fault in power systems. Its occurrence rate is minimal, ranging from only 2% to 3%. However, it plays a crucial role in short circuit calculations, as it involves the largest short circuit current. Consequently, it is instrumental in determining the selection of protective devices and circuit breakers.

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E. Three-Phase to Ground (L – L – L – G) Fault:

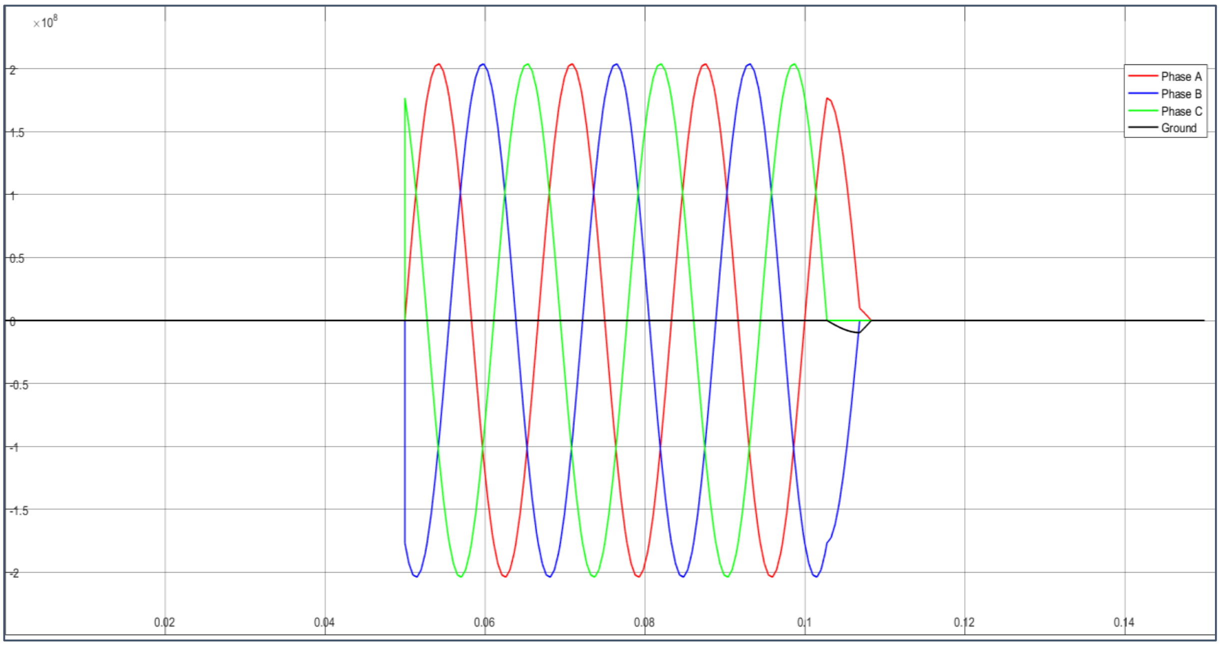

Fig. 9: Three-phase line to the ground (L – L – L – G) Fault Graph

This fault represents the most severe type and is exceedingly rare within power systems. It arises from insulation breakdown across all phases, including to the earth. Its occurrence rate within power systems is typically between 2% to 3%.

5. CONCLUSION

This study has explored the application of Wavelet Transform for fault detection in power systems using a SIMULINK-based implementation. The findings underscore the effectiveness of Wavelet Transform in accurately detecting various faults, highlighting its adaptability to non-stationary signals and robustness. These results contribute to the advancement of fault detection techniques in power systems, emphasizing the potential for improved reliability and operational integrity.

Declaration

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Competing Interests: The authors declare that they have no competing interests.
Ethics Approval: Not applicable
Consent for Publication: The authors declare that all authors consented to the publication of this research and the included data.
Data Availability: The data used in this study are available from the authors upon reasonable request.

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