Fault Detection and Classification in Power Systems Using Wavelet Transform

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Abstract — Power system faults can lead to significant disruptions, economic losses, and safety hazards. Accurate and timely fault detection and classification are crucial for maintaining system reliability and security. This paper proposes a novel approach utilizing Wavelet Transform (WT) for effective fault detection and classification in power systems. WT, with its ability to provide time-frequency analysis, is well-suited to capture the transient characteristics of fault signals. By decomposing the fault signals into different frequency components, WT enables the extraction of relevant features for fault identification. The proposed method involves applying WT to the post-fault voltage and current signals to obtain wavelet coefficients. These coefficients are then analyzed to identify specific patterns associated with different fault types, such as single-line-to-ground, double-line-to-ground, and three-phase faults. Simulation results demonstrate the effectiveness of the proposed method in accurately detecting and classifying various fault scenarios.

Keywords: Fault Detection, Type of Fault, Location Identification Wavelet Transform

I. INTRODUCTION

Power system faults are unavoidable events that can disrupt power supply and cause significant economic losses.Prompt detection and accurate classification of faults are essential for rapid fault clearance and system restoration. Traditional fault detection techniques, such as impedance-based methods, often face challenges in handling complex fault scenarios and noise interference[1]. Wavelet Transform (WT) offers a powerful tool for analyzing non-stationary signals, making it suiTable for fault diagnosis in power systems[2]. The study of wavelet transform-based fault classification and compensation using Dynamic Voltage Restorers (DVRs) involves a multi-step process. Firstly, voltage and current signals within the power system are continuously monitored and captured at high speeds to capture transient events[3]. These acquired signals are then pre-processed using wavelet transforms, a mathematical tool that decomposes signals into different frequency components. The choice of mother wavelet is crucial and depends on the specific characteristics of the signals obtained from sensors[4]. The wavelet coefficients obtained from the decomposition process are further processed by normalizing them using z-score normalization to extract features related to fault conditions[5]. These features are then classified as either normal or faulty based on predefined thresholds. The classification process can be implemented using machine learning algorithms such as Support Vector Machines (SVMs) or Neural Networks, depending on the specific fault type[6]. Once a fault is detected and classified, the DVR is activated to mitigate the voltage anomaly. The DVR's control algorithms determine the appropriate voltage magnitude to be injected into the power system using energy storage devices like capacitors or batteries[7]. This stored energy is then converted into the necessary compensating voltage by a Voltage Source Converter (VSC), which injects the voltage into the power line to stabilize the voltage[8]. In addition to voltage compensation, the DVR also functions as an active filter, capable of reducing harmonic distortions present in the power supply[9]. This ensures a clean and sTable power supply for sensitive loads. This integrated fault management approach, combining wavelet transform-based fault detection and classification with DVR compensation, significantly reduces the time required to detect, classify, and mitigate faults. This ultimately leads to improved power system reliability and quality[10].

II. IMPLEMENTATION OF WAVELET TRANSFORM

The core idea behind the wavelet transform is to use a set of wavelet functions to decompose a signal into distinct sizes and locations. These wavelet functions are typically small, localized oscillatory functions that can be scaled and shifted to analyze different frequency components of the signal at various time scales. The wavelet transform enables the understanding of a signal's frequency content at different time intervals. The implemented algorithm is illustrated in the Figure 1

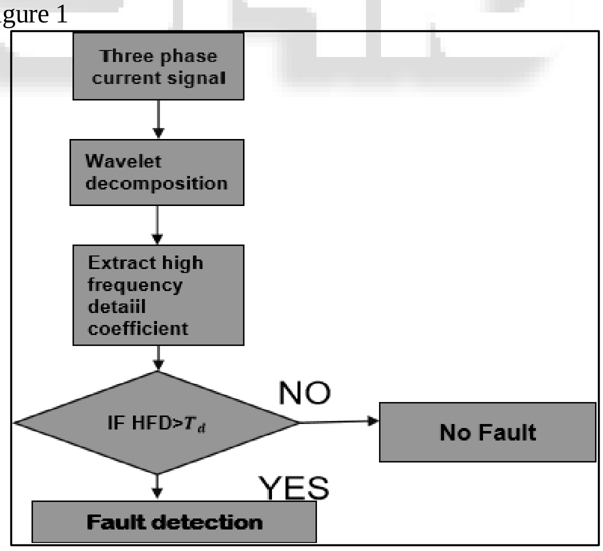

Fig. 1: Block diagram of fault detection algorithm

A. *Continuous Wavelet Transform*

The Continuous Wavelet Transform (CWT) is a continuous-domain transformation that involves convolving the input signal with a continuous wavelet function. The wavelet function is essentially a small, localized waveform, often resembling a "mother wavelet." The CWT provides a time-scale representation, meaning it can show how different frequency components of a signal change over time. Mathematically, the CWT of a continuous signal f(t) with respect to a wavelet function ψ(x, t) is given by:

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$$CWT(x,y) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{x_\varphi}}\left(\frac{t-y}{x}\right)dt$$

Where:
- 'x' is the scale parameter, and it controls the width of the wavelet function. Changing allows you to analyze the signal at different scales or frequencies.
- 'y' is the translation parameter, and it shifts the wavelet function along the time axis. This parameter allows you to analyze the signal at different time positions.
- Ψ (x, t) represents the wavelet function. The wavelet function is a waveform that is localized in both time and frequency. It is often chosen based on the specific characteristics of the signal that are analyzing.

B. *Discrete Wavelet Transform*

In the Discrete Wavelet Transform (DWT), a low-pass filter (approximation filter) and a high-pass filter (detail filter) are employed to convolve with the signal, followed by downsampling, resulting in coefficients at various scales and positions.

The DWT can be stated mathematically as:

$$A\ p, q = \sum m\ f[m] \cdot h\ [m-2pq]$$
$$D\ p, q = \sum m\ f[m] \cdot g\ [m-2pq]$$

Where:
- A p, q and D p, q are the approximation and detail coefficients at scale p and position q, respectively.
- h [m] and g[m] are the low-pass and high-pass filters, respectively.

C. *Signal Passes Through Filter Bank*

When a fault occurs, the proposed logic utilizes the wavelet transform to extract hidden information from the current waveform. This information is then processed to extract fault signatures, enabling accurate fault characterization and localization. The Daubechies 4 (db4) wavelet, known for its good time and frequency localization properties, is applied to the pre-processed signal. The decomposition level in the wavedec function should be carefully chosen based on the signal characteristics and the frequency content of the faults of interest

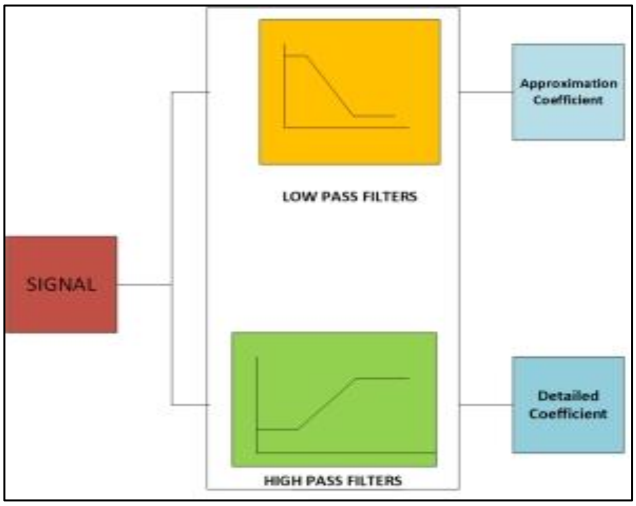

Fig. 2: Signal flow through Filter Bank

The wavelet transform, a versatile tool for analyzing transient and non-stationary signals, is widely used in various engineering fields, including electrical systems. Its ability to provide both time and frequency information makes it ideal for detecting and classifying faults in power systems. By decomposing signals into different scales, wavelet transform can identify irregularities that might indicate faults. The Daubechies 4 (db4) wavelet, known for its good time-frequency localization properties, is commonly used to analyze power system signals. This wavelet-based approach helps in accurately detecting and classifying faults, improving overall system reliability.
- Pre-processing the Signal: This step typically involves noise reduction, normalization, and possibly filtering to prepare the signal for wavelet analysis. Pre-processing ensures that the extracted features are representative of the actual faults without being distorted by noise or other irrelevant components.
- Selecting the Decomposition Level: The decomposition level in the wavelet transform determines the level of detail in the signal analysis. A higher decomposition level provides more detailed frequency information, crucial for identifying and classifying faults. However, increasing the decomposition level also increases computational complexity.
- Applying the Daubechies 4 (db4) Wavelet Transform: The Daubechies 4 (db4) wavelet is chosen for its excellent time-frequency localization properties, making it suiTable for analyzing transient and non-stationary signals. Using a wavelet transform function like wavedec, the signal is decomposed into different frequency components. By examining the wavelet coefficients, patterns or anomalies indicative of faults can be identified. Further processing, such as thresholding and feature extraction, can then be applied to accurately classify these faults.

III. CASE STUDY FOR FAULT DETECTION

This research investigates the application of wavelet transform for fault detection and classification in a short transmission line used as a load. The transmission line, with its inherent electrical properties of resistance, inductance, capacitance, and conductance, exhibits complex behavior under various operating conditions. Wavelet transform, a powerful signal processing technique, is employed to analyze fault signals in both time and frequency domains. By decomposing the signals into different frequency components, the wavelet transform enables the identification of transient fault characteristics. The maximum values of wavelet coefficients are then extracted and compared to predefined thresholds to classify fault types, such as line-to-ground, line-to-line, and three-phase faults. This approach enhances fault detection and classification accuracy, leading to faster fault identification and localization. Ultimately, this leads to improved power system reliability, reduced downtime, and enhanced system stability.

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IV. RESULT AND DISCUSSIONS

A. Normal System Current Analysis Using Wavelet Transform

This section analyzes normal (no-fault) current conditions in a short transmission line used as a load within a system. By comparing normal and fault current waveforms using wavelet transforms, we demonstrate the effectiveness of this method in detecting and classifying faults.

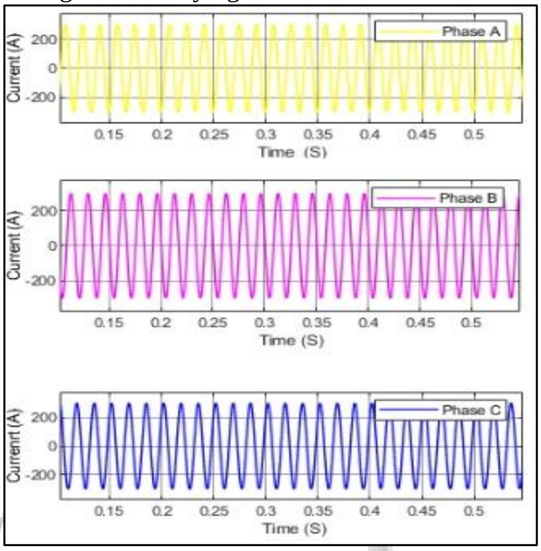

Fig. 3: Normal System Current or No-Fault Current

The above results show the current waveforms in all three phases during normal (no-fault) conditions:

1) Phase A Current:

Observation: The current in Phase A remains steady and sinusoidal, indicating no fault.

Discussion: The sTable waveform of Phase A reflects normal operation without any disturbances or faults. The amplitude is consistent, and the waveform shows no significant fluctuations.

2) Phase B Current:

Observation: Similar to Phase A, the current in Phase B also exhibits a steady and sinusoidal pattern.

Discussion: The sinusoidal waveform of Phase B indicates that the system is operating normally. The absence of irregularities confirms that there are no faults in this phase.

3) Phase C Current:

Observation: The current in Phase C maintains a steady and sinusoidal form as well.

B. Fault Current Analysis in double line to ground configuration using wavelet transform.

The results of the fault analysis using the wavelet transform were visualized through various MATLAB SIMULINK graphs. These graphs illustrate the system's behavior under different fault conditions, demonstrating the effectiveness of the wavelet transform in identifying and classifying faults.

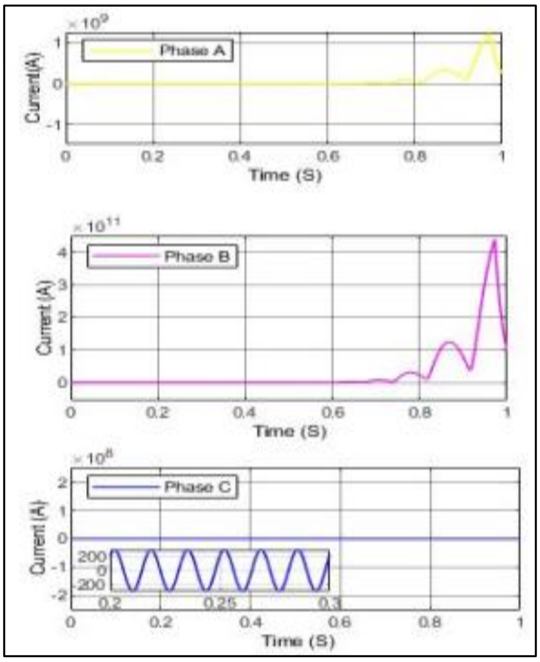

Fig. 4: Fault Current in Double Line-to-Ground Configuration

The above result show the current waveforms in the affected phases (Phase A and Phase B) and an unaffected phase (Phase C) during a DLG fault condition.

1) Phase A Current:

Observation: The current in Phase A shows a significant rise around the 0.9-second mark, indicating the occurrence of a fault.

Discussion: The sharp increase in current magnitude in Phase A suggests that it is involved in the DLG fault. The waveform is relatively sTable until the fault occurs, highlighting the transient nature of the fault.

2) Phase B Current:

Observation: Similar to Phase A, the current in Phase B also exhibits a substantial increase at the 0.9-second mark.

Discussion: The behavior of the current in Phase B corroborates the presence of a DLG fault involving both Phase A and Phase B. The significant rise in current is a clear indication of the fault's impact on this phase.

3) Phase C Current:

Observation: The current in Phase C remains relatively unaffected throughout the fault event, showing minor fluctuations but no significant increase.

Discussion: The sTable current in Phase C confirms that this phase is not involved in the DLG fault. This observation helps isolate the fault to Phases A and B configuration in a short transmission line used as a load. The wavelet transform is employed to detect and classify faults by examining the fault current waveforms and their wavelet coefficients. The results, visualized through MATLAB SIMULINK, demonstrate the effectiveness of this method in fault detection and localization.

C. Fault Classification

The fault classification system operates based on a threshold value of 200 for the coefficient values obtained from simulations. These coefficients, indicative of fault presence or absence in different phases, exhibit significant variation across fault types. In normal operation, without any faults, the

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coefficient values remain relatively low, not exceeding 134.4171 in the observed case. A coefficient value exceeding 200 is considered a strong indicator of a fault in the corresponding phase, while values below 200 suggest normal operation. This classification method effectively distinguishes between normal and faulty conditions, enabling prompt identification of potential issues and facilitating proactive maintenance to minimize system disruptions.

Max. Coefficient of Phase A	1.6097e+07	Three phase to ground fault detected
Max. Coefficient of Phase B	4.0725e+07	
Max. Coefficient of Phase C	1.6097e+07	
Max. Coefficient of Ground	7.1824e+05	

Table 1.1: Type Of Fault: Three Phase to Ground

Max. Coefficient of Phase A	1.6097e+07	Three phase fault detected
Max. Coefficient of Phase B	4.0725e+07	
Max. Coefficient of Phase C	1.6097e+07	
Max. Coefficient of Ground	0.0081	

Table 1.2: Type Of Fault: Three Phase Fault

Max. Coefficient of Phase A	1.0667e+07	Double Line to Ground Fault (AB-G) Detected
Max. Coefficient of Phase B	2.1332e+07	
Max. Coefficient of Phase C	119.5264	
Max. Coefficient of Ground	7.7120e+05	

Table 1.3: Type Of Fault: Double Line to Ground Fault (Ab-G)

Max. Coefficient of Phase A	1.9807e+07	Double Line to Ground Fault (AC-G) Detected
Max. Coefficient of Phase B	116.5351	
Max. Coefficient of Phase C	9.0563e+06	
Max. Coefficient of Ground	1.9393e+06	

Table 1.4: type of fault: double line to ground fault (ac-g)

Max. Coefficient of Phase A	1.0802e+07	Line to Line Fault Between Phase A and B is Detected
Max. Coefficient of Phase B	2.0363e+07	
Max. Coefficient of Phase C	119.5264	
Max Coefficient of Ground	0.0087	

Table 1.5: type of fault: double line to ground fault (bc –g)

Max. Coefficient of Phase A	2.0363e+07	Line to Line Fault Between Phase A and C is Detected
Max. Coefficient of Phase B	104.6242	
Max. Coefficient of Phase C	8.6274e+06	
Max. Coefficient of Ground	0.0204	

Table 1.6: type of fault: line to line (A-C) fault

Max. Coefficient of Phase A	103.9857	Line to Line Fault Between Phase B and C is Detected
Max. Coefficient of Phase B	4.0725e+07	
Max. Coefficient of Phase C	7.3446e+06	
Max. Coefficient of Ground	0.0100	

Table 1.7: type of fault: line to line (b-c) fault

Max. Coefficient of Phase A	1.0802e+07	Line to Line Fault Between Phase A and B is Detected
Max. Coefficient of Phase B	2.0363e+07	
Max. Coefficient of Phase C	119.5264	
Max Coefficient of Ground	0.0087	

Table 1.8: type of fault: line to line (A-B) FAULT

Max. Coefficient of Phase A	1.3523e+06	Single Line to Ground Fault in Phase A is Detected
Max. Coefficient of Phase B	103.9844	
Max. Coefficient of Phase C	119.5264	
Max. Coefficient of Ground	1.6087e+06	

Table 1.9: type of fault: single line to ground (a-g)

Max. Coefficient of Phase A	103.9857	Single Line to Ground Fault in Phase B is Detected
Max. Coefficient of Phase B	3.7024e+06	
Max. Coefficient of Phase C	134.4171	
Max. Coefficient of Ground	1.1253e+06	

Table 1.10: type of fault: single line to ground (b-g)

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Max. Coefficient of Phase A	103.9857	Single Line to Ground Fault in Phase C is Detected
Max. Coefficient of Phase B	103.9844	
Max. Coefficient of Phase C	1.4099e+06	
Max. Coefficient of Ground	3.7023e+06	

Table 1.11: type of fault: single line to ground (c-g)

Max. Coefficient of Phase A	103.9857	No Fault is Detected. System is Normal
Max. Coefficient of Phase B	103.9844	
Max. Coefficient of Phase C	119.5264	
Max. Coefficient of Ground	7.1791e-10	

Table 3.12: type of fault: system without fault

V. CONCLUSIONS

Moreover, wavelet-based fault detection techniques have proven their efficacy in various industrial applications within power engineering. Results from these methods demonstrate their ability to deliver reliable fault detection outcomes, supporting proactive maintenance strategies and reducing downtime due to unexpected failures. In conclusion, wavelet analysis with a multistage filter bank is a robust tool in modern power system diagnostics. Its ability to provide detailed time-frequency insights into power signals empowers engineers to enhance system reliability, accurately diagnose faults, and improve the overall performance of electrical networks and equipment.

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