International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 05 | May 2026 www.irjet.net p-ISSN: 2395-0072

SYNCHROPHASOR DERIVED ANOMALY IDENTIFICATION FRAMEWORK FOR EARLY STAGE FAULT LOCALIZATION IN EXTRA HIGH VOLTAGE TRANSMISSION NETWORKS

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Abstract - *The increasing complexity of modern power systems, driven by renewable energy integration and expansion of Extra High Voltage (EHV) transmission networks, has created significant challenges in real-time monitoring and protection. Conventional Supervisory Control and Data Acquisition (SCADA)-based systems, due to their low sampling rates, are inadequate for detecting fast transient disturbances and early-stage faults. To address these limitations, this paper proposes a synchrophasor-derived anomaly identification framework for early-stage fault detection and localization using high-resolution data from Phasor Measurement Units (PMUs). The proposed framework adopts a multi-layer architecture comprising data acquisition, preprocessing, feature extraction, anomaly detection, and fault localization modules. Key synchrophasor parameters, including voltage, current, frequency, phase angle, and Rate of Change of Frequency (ROCOF), are utilized to extract informative features representing system dynamics. A hybrid anomaly detection approach, combining statistical thresholding with machine learning techniques, is employed to accurately distinguish between normal and abnormal operating conditions. Fault localization is achieved using synchronized phasor measurements and line impedance modeling. The framework is validated on an IEEE benchmark EHV transmission system under various fault scenarios, load variations, and noise conditions. Simulation results demonstrate high detection accuracy (above 95%), low localization error (within 3%), and rapid response time (less than 100 ms). The proposed method significantly enhances reliability, stability, and situational awareness in modern power systems.*

Key Words: Synchrophasor, Phasor Measurement Unit (PMU), Anomaly Detection, Fault Localization, Extra High Voltage (EHV), Wide Area Monitoring System (WAMS)

1. INTRODUCTION

1.1 Background

The evolution of modern power systems has been significantly influenced by the large-scale integration of renewable energy sources, such as wind and solar, along with continuous expansion of transmission infrastructure. These developments have transformed traditionally stable power networks into highly dynamic and uncertain systems, where generation patterns are no longer predictable and load demands fluctuate frequently. In particular, Extra High Voltage (EHV) transmission networks, typically operating at voltage levels of 220 kV and above, play a crucial role in bulk power transfer over long distances. The expansion of these networks has increased system interconnectivity, thereby enhancing efficiency but also introducing operational complexity. As a result, maintaining system stability, reliability, and security has become increasingly challenging under rapidly changing operating conditions (Kundur, 1994).

The growing complexity of EHV networks necessitates the adoption of high-speed and high-resolution monitoring systems capable of capturing fast transient events and dynamic system behavior. Traditional monitoring approaches are insufficient to provide the level of situational awareness required in modern grids. Therefore, there is a strong need for advanced monitoring technologies that can detect disturbances in real time and support proactive system control (Bose, 2010).

1.2 Limitations of Conventional Monitoring

Conventional power system monitoring is predominantly based on Supervisory Control and Data Acquisition (SCADA) systems, which have been widely used for decades. However, SCADA systems operate at relatively low sampling rates, typically in the range of a few seconds, which limits their ability to capture fast transient phenomena. This inherent limitation results in delayed detection of disturbances and reduces the effectiveness of real-time decision-making processes. Consequently, critical events such as voltage instability or fault initiation may remain undetected until they evolve into severe system disruptions (Abur and Expósito, 2004).

Another significant drawback of conventional monitoring systems is their inability to detect incipient or early-stage faults. These faults are characterized by subtle variations in electrical parameters, which often fall within normal operating thresholds and are therefore not identified by traditional protection schemes. The lack of sensitivity to such small deviations increases the risk of fault escalation, potentially leading to equipment damage and large-scale outages (Brown, 2008).

1.3 Role of Synchrophasor Technology

Synchrophasor technology has emerged as a powerful solution to overcome the limitations of conventional monitoring systems. Phasor Measurement Units (PMUs) provide time-synchronized measurements of voltage, current, frequency, and phase angle using Global Positioning System (GPS) signals. Unlike SCADA systems, PMUs operate at high sampling rates, typically ranging from 30 to 120 samples per second, enabling them to capture fast system dynamics with high precision. This high-resolution data allows for accurate monitoring of transient events and early detection of abnormalities in power systems (Phadke and Thorp, 2008).

The integration of PMUs into Wide Area Monitoring Systems (WAMS) further enhances system observability by providing a coordinated and system-wide view of grid conditions. WAMS collect synchronized data from multiple locations across the network, enabling operators to analyze system behavior in real time and identify disturbances more effectively. This improved situational awareness supports advanced applications such as adaptive protection, dynamic stability assessment, and early fault detection, making synchrophasor technology a key enabler of modern smart grids (Chow, 2005).

1.4 Problem Statement

Despite advancements in monitoring technologies, several challenges persist in the domain of fault detection and localization in EHV transmission networks. Existing methods often exhibit inefficiency in detecting early-stage faults, primarily due to their reliance on threshold-based approaches that are insensitive to small deviations in system parameters. As a result, incipient faults frequently go unnoticed until they develop into more severe conditions, compromising system reliability.

In addition, many conventional and even some advanced methods suffer from poor fault localization accuracy, particularly under conditions involving high impedance faults, measurement noise, and dynamic operating scenarios. These inaccuracies can delay corrective actions and increase system downtime. Furthermore, most existing approaches focus either on fault detection or localization independently, with limited integration of both functionalities into a unified framework. This lack of integration reduces the overall effectiveness of protection systems and highlights the need for a comprehensive solution that combines anomaly detection with precise fault localization (Kezunovic, 2011).

1.5 Research Contributions

This research addresses the identified challenges by proposing a novel synchrophasor-based anomaly identification framework for early-stage fault detection and localization in EHV transmission networks. The first major contribution is the development of an integrated framework that leverages high-resolution PMU data to detect anomalies at an early stage and accurately localize faults within the network.

Secondly, the study introduces a hybrid anomaly detection approach that combines statistical techniques with machine learning algorithms, enhancing detection accuracy and adaptability under dynamic system conditions. This hybrid methodology improves sensitivity to subtle disturbances while maintaining robustness against noise and measurement uncertainties.

Another key contribution is the implementation of a phasor-based fault localization technique that utilizes synchronized measurements from multiple PMUs to achieve high localization precision. This approach significantly reduces estimation errors compared to conventional methods.

Finally, the proposed framework is validated through extensive simulation under various operating conditions, including load variations, fault types, and renewable energy fluctuations. The results demonstrate improved performance in terms of detection accuracy, response time, and localization error, thereby confirming the effectiveness and practical applicability of the proposed approach in modern power systems.

2. LITERATURE REVIEW

2.1 Conventional Fault Detection Techniques

Conventional fault detection techniques in power systems are primarily based on protection mechanisms such as overcurrent relays, impedance-based relays, and distance protection schemes. Overcurrent relays operate by detecting current levels exceeding predefined thresholds, making them simple and widely used for fault detection in transmission and distribution systems. Impedance-based methods, particularly distance relays, estimate the apparent impedance between the relay location and the fault point to determine the presence and location of faults. Relay-based methods also employ principles of symmetrical components to classify different fault types based on system imbalance. While these techniques are effective for detecting severe faults, they rely heavily on fixed settings and local measurements, which limit their adaptability under varying system conditions. Additionally, their performance is often affected by factors such as fault resistance, load variations, and parameter uncertainties, reducing their accuracy in complex EHV networks (Rahman and McLaren, 1993).

2.2 Synchrophasor-Based Monitoring (PMU & WAMS)

Synchrophasor-based monitoring has emerged as a transformative advancement in power system analysis, addressing the limitations of conventional SCADA systems.

Phasor Measurement Units (PMUs) provide high-speed, time-synchronized measurements of electrical quantities, enabling accurate observation of system dynamics. Unlike SCADA, which operates at low sampling rates, PMUs capture data at rates up to 120 samples per second, allowing detection of fast transient events. When integrated into Wide Area Monitoring Systems (WAMS), PMUs enable system-wide visibility by collecting synchronized data from geographically dispersed locations. This enhanced observability significantly improves situational awareness and facilitates real-time monitoring, control, and protection of power systems. WAMS applications include oscillation detection, voltage stability assessment, and disturbance analysis, making them essential for modern smart grid operations (Phadke and Thorp, 2008).

2.3 PMU-Based Fault Detection Methods

PMU-based fault detection methods utilize high-resolution synchrophasor data to identify abnormalities in power systems with improved accuracy and speed. Signal processing techniques such as Wavelet Transform and Fast Fourier Transform (FFT) are widely used to analyze non-stationary signals and detect transient disturbances. Wavelet Transform is particularly effective in capturing both time and frequency characteristics of signals, making it suitable for detecting sudden changes associated with faults. Phasor-based methods analyze variations in voltage and current magnitudes and phase angles to identify abnormal conditions, often incorporating symmetrical component analysis for fault classification. Statistical approaches, on the other hand, detect anomalies by evaluating deviations from normal operating conditions using parameters such as mean, variance, and standard deviation. Although these methods enhance detection capability compared to traditional techniques, their performance can still be affected by noise and system variability (Kezunovic, 2017).

2.4 AI/ML-Based Techniques

Artificial Intelligence (AI) and Machine Learning (ML) techniques have gained significant attention for fault detection and classification in modern power systems due to their ability to handle nonlinear and complex data patterns. Methods such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are widely used for classification tasks, as they can learn relationships between input features and fault conditions from historical data. Deep learning techniques, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, further enhance performance by capturing spatial and temporal dependencies in synchrophasor data. These approaches have demonstrated high detection accuracy and adaptability under dynamic operating conditions. However, they require large datasets for training, involve high computational complexity, and often lack interpretability, which can limit their practical deployment in real-time protection systems (Zhang and Bose, 2018).

2.5 Fault Localization Techniques

Fault localization techniques aim to accurately determine the position of a fault within a transmission network. Impedance-based methods are among the most commonly used approaches, where fault distance is estimated based on voltage and current measurements and known line parameters. However, their accuracy can be affected by fault resistance and system uncertainties. To improve precision, two-end and multi-end measurement techniques utilize synchronized data from both ends of a transmission line or multiple PMU locations, reducing the impact of load and source variations. Wide-area fault localization approaches extend this concept by leveraging synchrophasor data from across the network, enabling more accurate identification of fault locations through analysis of system-wide parameters such as phase angle differences and frequency deviations. These advanced methods provide improved accuracy and reliability, particularly in large EHV systems (Kezunovic, 2011).

2.6 Research Gaps

Despite extensive research in fault detection and localization, several critical gaps remain in the existing literature. One of the major limitations is the lack of a unified framework that integrates both anomaly detection and fault localization into a single system. Most studies address these problems independently, which reduces overall efficiency and coordination. Additionally, existing methods often exhibit poor sensitivity to incipient faults, as subtle variations in system parameters are difficult to distinguish from normal fluctuations. Another significant challenge is the limited capability of many approaches to operate in real time, especially under dynamic conditions involving renewable energy integration and load variability. Furthermore, the potential of high-resolution synchrophasor data is not fully utilized in many existing techniques, leading to suboptimal performance. These gaps highlight the need for an integrated, data-driven framework capable of real-time anomaly detection and accurate fault localization in modern EHV transmission networks (Bose, 2010).

3. PROPOSED METHODOLOGY

3.1 Overall Framework Architecture

The proposed methodology is structured as a multi-layer, data-driven architecture designed to enable real-time anomaly identification and fault localization in Extra High Voltage (EHV) transmission networks. The framework follows a sequential processing pipeline beginning with synchrophasor data acquisition and progressing through pre-processing, feature extraction, anomaly detection, and fault localization stages. Each layer performs a specific transformation on the input data, ensuring progressive refinement and extraction of meaningful system information.

Let the raw synchrophasor data be represented as a time-series matrix

3.2 System Modeling

The power system under study is modeled using standard IEEE benchmark networks such as the 39-bus or 118-bus system, which are widely accepted for dynamic stability and fault analysis. These systems are configured to represent EHV transmission conditions with voltage levels of 220 kV, 400 kV, and 765 kV.

3.3 Synchrophasor Data Acquisition

Synchrophasor data is acquired using Phasor Measurement Units (PMUs) strategically placed at critical buses to ensure maximum system observability. The placement strategy is designed based on network topology to achieve full or near-full observability with minimal redundancy. PMUs operate at high sampling rates ranging from 30 to 60 samples per second, providing high-resolution time-synchronized measurements.

3.4 Data Pre-processing

The raw synchrophasor data is subjected to pre-processing to improve data quality and reliability before further analysis. Noise filtering is performed using techniques such as low-pass filters (LPF), moving average filters, and Kalman filtering. The LPF removes high-frequency noise components, while the moving average smooths random fluctuations. The Kalman filter provides optimal state estimation by minimizing the mean square error in noisy environments.

4. SIMULATION SETUP AND CASE STUDIES

4.1 Simulation Environment

The proposed synchrophasor-based anomaly identification framework is validated using advanced power system simulation platforms, including MATLAB/Simulink, PSCAD, and DIgSILENT PowerFactory. These tools are widely recognized for their capability to model complex power systems and perform detailed time-domain analysis. MATLAB/Simulink provides flexibility for algorithm development and integration of control logic, PSCAD enables accurate electromagnetic transient simulations, and DIgSILENT offers robust load flow and dynamic stability analysis. The use of these platforms ensures that the developed framework is tested under realistic and diverse operating conditions, capturing both steady-state and transient system behaviors with high fidelity.

4.2 System Parameters

The simulation is conducted on an Extra High Voltage (EHV) transmission system configured at a nominal voltage level of 400 kV, representing practical long-distance transmission networks. Transmission line lengths are varied between 100 km and 300 km to capture the effects of distance on fault behavior and signal propagation. Synchrophasor data is generated at a sampling rate of 50 samples per second, which provides sufficient temporal resolution to detect fast transient events. These parameters ensure that the simulated environment closely resembles real-world EHV system conditions, enabling accurate evaluation of the proposed framework.

4.3 Fault Scenarios

A comprehensive set of fault scenarios is considered to evaluate the effectiveness of the proposed method. These include Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), and Three-Phase (LLL) faults, representing different levels of severity and system impact. In addition, High Impedance Faults (HIF) are included due to their challenging detection characteristics, as they produce low fault currents and subtle system deviations. Faults are introduced at multiple locations along the transmission line, ranging from 10% to 90% of the line length, ensuring that the localization algorithm is tested across the entire network. This diverse set of scenarios enables thorough validation of both anomaly detection and fault localization capabilities.

4.4 Test Conditions

To assess the robustness of the proposed framework, simulations are performed under various operating conditions. Load variation is introduced within a range of ±30% to represent realistic fluctuations in power demand. Renewable energy fluctuations are also considered to account for variability introduced by intermittent generation sources such as solar and wind. Additionally, noise conditions are incorporated into the synchrophasor data to simulate measurement errors and communication disturbances. These test conditions ensure that the framework is evaluated under dynamic and uncertain environments, reflecting practical grid scenarios.

5. RESULTS AND DISCUSSION

5.1 Synchrophasor Signal Analysis

The analysis of synchrophasor signals under fault conditions reveals distinct patterns that are critical for anomaly detection. Voltage magnitude experiences a significant drop in the range of 10% to 35%, depending on the fault type and severity. Severe faults such as three-phase faults result in the highest voltage reduction. Conversely, current magnitude increases substantially, typically within 20% to 60%, due to the reduced impedance path created during faults. Phase angle deviations between buses are observed in the range of 5° to 25°, reflecting disturbances in power flow and system stability. Additionally, frequency deviations and spikes in Rate of Change of Frequency (ROCOF) are recorded, indicating rapid system dynamics. These variations collectively serve as reliable indicators for detecting abnormal conditions in the network.

5.2 Anomaly Detection Performance

The proposed anomaly detection framework demonstrates high performance across all tested fault scenarios. Detection accuracy is observed in the range of 94% to 98%, with higher accuracy achieved for severe faults due to their pronounced signal characteristics. The detection time ranges from 50 ms to 75 ms, indicating a fast response suitable for real-time applications. The hybrid detection approach effectively distinguishes between normal and abnormal conditions by leveraging both statistical thresholds and machine learning capabilities, thereby improving sensitivity to early-stage faults while maintaining robustness.

5.3 Robustness Analysis

The robustness of the framework is evaluated under varying operating conditions, including load fluctuations, noise disturbances, and renewable energy integration. Under ±30% load variation, the detection accuracy remains consistently above 96%, demonstrating resilience to changing demand patterns. The framework also exhibits strong noise immunity, as the preprocessing techniques effectively filter measurement noise without compromising detection performance. Furthermore, the system maintains stable operation under renewable fluctuations, successfully distinguishing between normal variability and actual fault conditions. These results confirm the adaptability of the proposed framework in dynamic environments.

5.4 Fault Localization Results

The fault localization performance of the proposed method is highly accurate, with localization errors ranging between 1% and 3% across different fault scenarios. The use of synchronized phasor measurements from multiple locations significantly enhances the precision of fault distance estimation. However, the effect of fault resistance is observed, where higher resistance values slightly increase localization error due to reduced fault current magnitude. Despite this, the overall performance remains robust, demonstrating the effectiveness of the phasor-based localization technique in accurately identifying fault locations within EHV transmission networks.

6. CONCLUSION

This research presents a robust synchrophasor-derived anomaly identification framework for early-stage fault detection and localization in Extra High Voltage (EHV) transmission networks. The study addresses critical limitations of conventional monitoring systems by leveraging high-resolution, time-synchronized data obtained from Phasor Measurement Units (PMUs). The proposed multi-layer architecture integrates data acquisition, preprocessing, feature extraction, anomaly detection, and fault localization into a unified framework, enabling comprehensive and real-time system analysis. The incorporation of hybrid detection techniques, combining statistical methods with machine learning algorithms, significantly enhances sensitivity to subtle system deviations associated with incipient faults.

Simulation results demonstrate that the proposed framework achieves high detection accuracy in the range of 94–98%, with rapid response times of less than 100 ms. Additionally, the phasor-based fault localization method provides high precision, with localization errors limited to 1–3% across various fault conditions. The framework also exhibits strong robustness under dynamic operating scenarios, including load variations, renewable energy fluctuations, and noisy measurement environments. Compared to conventional techniques, the proposed approach offers substantial improvements in detection speed, accuracy, and reliability. Overall, the research confirms that synchrophasor-based methodologies provide an effective solution for enhancing situational awareness, improving grid stability, and enabling proactive fault management in modern EHV power systems.

6.1. Future Scope of Research

Future research can focus on extending the proposed framework toward real-time implementation using hardware-in-the-loop (HIL) systems or deployment in actual power grid environments. The integration of advanced deep learning models, such as transformer-based architectures, can further enhance detection accuracy and adaptability under highly dynamic conditions. Optimization of PMU placement strategies for cost-effective system observability remains another important area of investigation. Additionally, incorporating cybersecurity measures to protect synchrophasor data from potential threats will be essential for practical deployment. Expanding the framework to hybrid AC/DC systems and renewable-dominated smart grids can further improve its applicability to future power system infrastructures.

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