International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Mapping the Research Landscape of PMU-Based Fault Detection, Classification, and Localization in Power Systems

Dr. Jatinkumar J. Patel

Submitted: 05/09/2023 **Revised:** 10/10/2023 **Accepted:** 20/10/2023

Abstract: The rising complexity of the modern power systems and the transition towards smart grids have made the development of rapid and reliable fault detection techniques a need. The Phasor Measurement Unit (PMU) has emerged as a crucial enabler for real-time monitoring and security of power networks with its capabilities to provide time-synchronized high-resolution measurements. We propose a systematic and bibliometric review of PMU-based fault detection, classification and localization algorithms in power systems for the period 2014–2023, based on a comprehensive dataset of 162 research articles. The surveyed literature is divided into five primary categories, including signal processing-based methods, model-based approaches, machine learning techniques, deep learning frameworks and hybrid intelligent methods. The extensive examination of these categories shows the transition from conventional signal processing methods to data-driven and deep learning based approaches, driven by the rising availability of PMU data. From the bibliometric data, it is clear that the number of publications has increased substantially after 2018 indicating a strong trend towards artificial intelligence based solutions. On comparing the existing approaches, it is found that the traditional methods are simple and respond quickly but are not flexible enough to be used in dynamically changing operational situations. On the other hand, machine learning and deep learning methods show more accuracy and robustness but require large data sets and computer resources. Despite considerable progress, there are still a number of hurdles, including communication delays, data quality, cybersecurity, and limited real-time deployment in practical systems. This review emphasizes significant research gaps and future initiatives such as integration of edge computing, development of cyber resilient frameworks, and use of advanced deep learning models for real-time fault analysis. The results of this study give a systematic insight into the available methodologies and represent an essential reference for researchers and practitioners in the future of PMU-based power system protection.

Keywords: *Phasor Measurement Unit; Fault Detection; Fault Classification; Fault Localization; Power Systems*

1. Introduction

The modern electric power system is undergoing a considerable transformation driven by the integration of renewable energy sources, growing load demand and the rapid development of smart grid technology. These changes have brought new operational problems, especially in maintaining system stability, reliability and security. One of the most important tasks in power system operation is the timely detection, categorization and localization of faults, since failure to do so may lead to severe repercussions, such as equipment damage, cascading outages and large-scale blackouts [1–237].

Traditional defect detection methods are mostly focused on local measurements and protection schemes. These methods frequently have limited observability and slow response under dynamic operating situations. As power networks become more and more linked and sophisticated, there is a demand for better monitoring and protection methods that provide online system-wide information. In this regard, the PMU has been recognized as a critical enabling technology for modern power systems [24], [148]. PMUs are

Professor, Department of Electrical Engineering, Vadodara Institute of Education and Research, Vadodara-391510, India. Email: jjpatelgcet@gmail.com

devices that offer high resolution, time synchronized measurements of voltage and current phasors utilizing Global Positioning System (GPS) signals. This enables accurate monitoring of system dynamics at geographically scattered locations.

The availability of synchronized phasor data has boosted the capability of Wide Area Monitoring, Protection and Control (WAMPAC) systems greatly. In particular, PMU-based fault detection schemes have received much interest because of their capability of fast and precise disturbance detection under wide-area situations [24], [148]. Over the past decade, various methodologies have been proposed including signal processing based approaches, model based analytical techniques and more recently, data driven approaches such as machine learning and deep learning [14], [105], [24], [63], [72], [83].

The recent literature reviewed comprehensively suggests a marked methodological shift. Early research mainly concentrated on signal processing techniques such as Fourier transform, wavelet transform and Hilbert–Huang transform, which are effective for transient analysis but limited in dealing with nonlinear and noisy situations [105], [63], [72], [88]. Later, model based approaches, such as impedance based fault location and state estimate methods, have been proposed to increase interpretability, although they are still affected by system parameter uncertainties [148], [54], [79]. Recently, the availability of large-scale PMU datasets increased, which has allowed the use of machine learning and deep learning approaches, which give more adaptability and accuracy in the tasks of fault detection and classification [14], [24], [83], [97], [118].

While research in this area is growing rapidly, the literature is still scattered, with individual studies focused on specific approaches, system configurations, or application scenarios. Moreover, although some review articles have been published, most of them focus on limited aspects, e.g., communication infrastructure, islanding detection or power quality analysis, instead of providing a comprehensive and unified framework for PMU-based fault detection [13], [14], [105], [148]. Moreover, the current advances in deep learning, hybrid approaches and real-time implementation issues have not been systematically included in the prior reviews [24], [118], [141].

Driven by these restrictions, this paper offers a systematic and bibliometric review of fault detection, classification and localization strategies based on PMU in power systems spanning the period 2014–2023, using a comprehensive dataset of 162 research papers. The research shows the progression of methodology from traditional analytical approaches to sophisticated intelligent systems and gives quantitative information on research directions and progress.

The primary contributions of this study are summarized as follows:

- Development of a comprehensive taxonomy of PMU-based fault detection techniques, including signal processing, model-based, machine learning, deep learning, and hybrid approaches
- Presentation of a bibliometric and trend analysis highlighting the evolution of research between 2014 and 2023
- A detailed comparative evaluation of different methodologies in terms of accuracy, computational complexity, and real-time applicability
- Identification of key research challenges and emerging directions, including real-time implementation, cybersecurity, and intelligent protection systems

The rest of this paper is organized as follows. Section 2 shows the identification of a literature review and important research gaps in the existing PMU-based fault detection studies. Section 3 explains the research methodology including systematic literature review approach, data gathering plan and selection criteria. In Section 4, a bibliometric analysis of the selected literature is performed, including publication trends, prominent journals, keyword distributions and regional research contributions. Section 5 describes the methodological frameworks of PMU-based protection, namely signal processing, model-based, machine learning, deep learning and hybrid techniques and their comparative evaluation. Section 6 covers the evolution of methodology, performance trade-offs of techniques, practical implementation issues and upcoming research prospects. Finally, Section 7 ends the work and discusses the future research directions of PMU-based intelligent protection systems.

outperform in detecting nonlinear patterns and enhancing the accuracy of fault classification.

In addition, hybrid methods that merge signal processing with artificial intelligence and optimization methods, have been attracting attention because to their greater resilience and adaptability. This development is indicative of a clear trend away from the classic deterministic methodologies towards intelligent, data-driven frameworks for problem identification in modern power systems.

2. Literature Review and Research Gap

This section includes a comprehensive evaluation of literature on PMU-based applications for power systems, with a special focus on techniques for fault detection, classification and localization. The analysis identifies major research gaps, therefore establishing the motivation and novelty of the present study.

2.1 Overview of PMU-Based Fault Detection Studies

Traditional electricity systems are being transformed into highly linked, data-driven smart grids, which has dramatically raised the requirement for real-time monitoring and protection. In this context, the PMU has arisen as a key technology to provide time-synchronized high precision measurements of electrical quantities. PMUs enable dynamic observability of the grid and can be used for advanced applications like as fault detection, classification, and localization, unlike traditional SCADA systems.

In the past decade (2014–2023), research on PMU-based fault detection has been growing significantly. The early works focused on signal processing methods like Fourier transform, wavelet transform and Prony analysis to extract the fault associated features from synchrophasor data. These approaches offered fast reaction and ease of implementation but showed limits in treating noise, non-stationary signals and complicated system dynamics.

Later improvements included model-based and analytical techniques such as impedance-based fault location and state estimation methods which increased interpretability, but still suffered from system parameter uncertainties and modeling errors. With the availability of large-scale PMU datasets, the research has gradually moved towards data-driven methodologies, particularly machine learning techniques such as support vector machines and artificial neural networks. Recently deep learning approaches, such as convolutional and recurrent neural networks, have been shown to

2.2 Review of Existing Studies

Various review studies have been conducted on different areas of PMU applications, synchrophasor technology and fault detection in power systems. These studies offer useful insights, but are generally limited in scope and depth.

Several review studies have studied different elements of synchrophasor technologies and PMU applications in power systems. However, there is a major difference in terms of scope, technique and focal areas in these research. Table 1 presents a comparative summary of the most important review publications reviewed in this investigation.

Authors in [13] provide a complete study of synchrophasor communication systems, with a primary focus on communication technologies, protocols, and architectures that support Wide Area Monitoring System (WAMS). Though throughout the study, the relevance of communication infrastructure for reliable PMU operation is highlighted, the study mainly focuses on communication issues rather than fault detection approaches. In [14], the authors study PMU-based data analytics and islanding detection approaches for distribution systems. The paper categorizes islanding detection techniques into communication-based, active and passive methods and highlights the importance of data analytics. However, it is mainly concerned with islanding cases and does not offer a generic framework for problem detection and classification. A study of PMU applications in real-time grid monitoring and protection, including WAMS architecture, state estimates, and load shedding methods, is presented in [24].

Table 1. Summary of Existing Review Studies on PMU-Based Applications

Ref. No.	Objective / Scope	Methodology	Key Focus Areas	Major Findings / Contributions	Research Gaps Identified
13	Review of synchrophasor communication systems, technologies, standards, and WAMS applications	Literature review and classification of communication technologies and architectures	Synchrophasor Communication System (SPCS); communication technologies; IEEE standards; WAMS; network architectures	Identifies communication system as backbone of WAMS; classifies wired/wireless technologies; discusses IEEE C37.118 standards; highlights role in real-time monitoring	Limited research on SPCS; lack of practical validation; insufficient reliability analysis; limited work on optimal placement; need for co-simulation; under-explored SDN applications
14	Review of PMU-based data analytics and islanding detection in distribution systems	Literature review of islanding detection techniques and PMU data analytics methods	Islanding detection (active, passive, communication-based); PMU data analytics; WAMS; frequency and phase-based methods	Classifies islanding detection methods; integrates PMU data analytics; highlights role in real-time monitoring and grid reliability	Difficulty distinguishing islanding vs faults; threshold selection issues; high computational complexity; missing PMU data; limited real-time implementation
24	Review of PMU applications in real-time monitoring, protection, and WAMS-based systems	Systematic review of PMU applications and protection schemes	PMU; WAMS; state estimation; fault detection; load shedding; communication systems	Highlights PMU advantages in real-time monitoring; discusses WAMS architecture; enables advanced protection and load shedding schemes	Optimal PMU placement challenges; communication delays; cybersecurity issues; high cost; lack of standardization; limited real-time validation
105	Review of power quality disturbance (PQD) characterization using signal processing and pattern recognition	Classification-based review of feature extraction, selection, and classification techniques	PQ disturbances; signal processing (FT, WT, HHT); pattern recognition; machine learning; PMU-based monitoring	Provides taxonomy of PQD techniques; compares signal processing and AI-based methods; highlights transition toward intelligent approaches	Limited real-time implementation; sensitivity to noise; lack of hybrid models; insufficient PMU integration; computational complexity issues
148	Review of synchrophasor technology, PMU architecture, placement, and applications in transmission and distribution systems	Comprehensive literature review of ST architecture, standards, placement, and applications	PMU architecture; WAMS; optimal PMU placement; fault detection; state estimation; smart grid applications	Provides detailed ST architecture; classifies applications in transmission and distribution; highlights advantages over SCADA; discusses IEEE standards	Lack of scalable PMU placement solutions; communication latency; cybersecurity issues; limited AI integration; challenges in distribution systems

Although the review gives an overall picture of PMU applications, it does not provide thorough classification and comparison of fault detection methods. In [105], authors focus on power quality disturbance characterisation by employing signal processing and pattern recognition techniques. This paper includes a complete taxonomy of feature extraction, selection and classification algorithms but is limited to power quality analysis and does not provide a comprehensive overview of PMU-based fault detection and localization. Authors in [148] present a comprehensive assessment of synchrophasor technologies covering PMU architecture, optimal positioning and applications in transmission and distribution systems. The study includes a variety of applications such as monitoring, state estimation and protection, but, it does not provide a structured taxonomy or comparative analysis of defect detection techniques.

Existing review studies, in general, deal on some areas such as communication systems, islanding detection, power quality analysis or general PMU applications. None of these studies present a unified and systematic picture of the PMU-based fault detection.

2.3 Research Gap

Based on the critical analysis of existing review articles, many key research gaps are identified:

- Lack of standardized taxonomy: The literature available does not offer a complete classification structure that unifies signal processing, model-based, machine learning, deep learning, and hybrid techniques for PMU-based fault detection.

- Limited attention on fault detection as a main theme: A majority of the research focus on broader PMU applications (e.g., communication systems, WAMS, power quality) rather than particularly addressing fault detection, classification and location in an integrated manner.

- Limited coverage of current developments: current advances in machine learning and deep learning approaches, especially after 2018, are not thoroughly addressed in previous review articles.

- Lack of bibliometric and trend analysis: Previous studies do not provide quantitative information such as publishing trends, evolution of research, and change of methods over time. No comparative evaluation: There is no extensive comparison of alternative strategies in terms of accuracy, computational complexity, robustness and real-time applicability.

- Limited explanation of practical implementation challenges: Critical issues like as communication latency, data loss, cybersecurity threats, and real-time deployment limits are not fully discussed.

2.4 Contribution of the Present Study

To bridge the mentioned gaps, this work provides a comprehensive and bibliometric review of PMU based fault detection, classification and localization algorithms in power systems for the years 2014-2023. In total, 162 research publications are examined to provide:

- A detailed taxonomy of strategies for fault detection

- Trend analysis showing the transition from traditional to intelligent approaches

- Comparison of methodologies

- Determined the key obstacles and potential research directions

This paper provides a systematic and up-to-date knowledge of PMU-based fault detection systems. Therefore, it might be a valuable reference for researchers and practitioners working in the power system protection field.

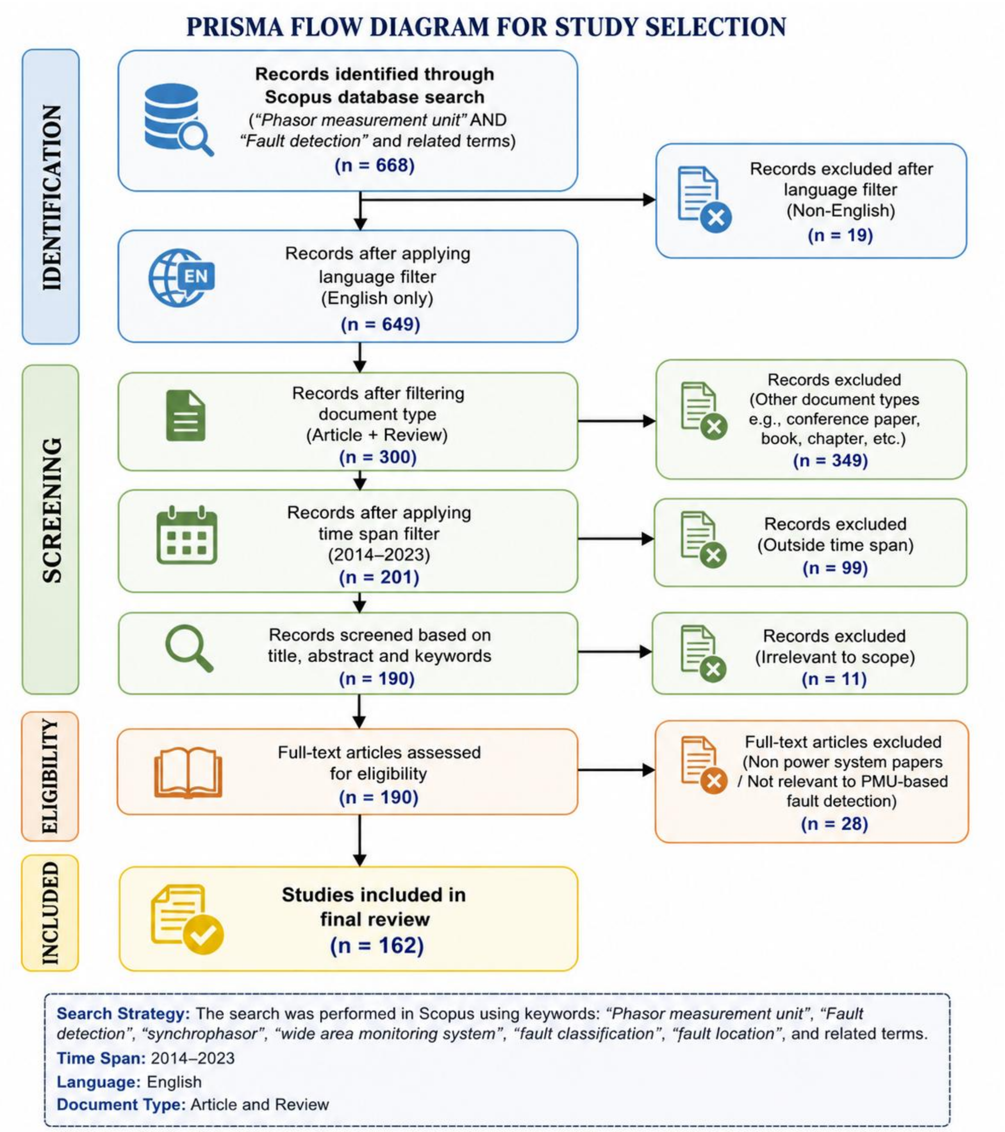


Figure 1. PRISMA Flow Diagram for Literature Screening and Selection (2014–2023)

3. Research Methodology

This section describes the systematic review structure, including the selection of data sources, the screening method, inclusion-exclusion criteria and the classification strategy used to analyze the 162 selected research papers.

3.1 Research Design

This present work uses a Systematic Literature Review (SLR) method to conduct a complete review of the development of PMU application for power system protection in the last decade. The systematic design guarantees a visible, rigorous and reproducible technique. This technique mitigates selection bias through a systematic review process and offers a credible synthesis of methodological shifts, prevalent optimization algorithms, and testing settings that define contemporary fault detection and location strategies.

3.2 Data Source and Search Strategy

The Scopus database was selected as the major data source for the aggregation of peer-reviewed literature. It was chosen to assure high quality aggregation as it covers a large number of high-impact electrical and power engineering publications. A targeted Boolean search string was developed to cover essential technological domain. Main search phrase was: ("Phasor measurement unit" OR "PMU") AND ("Fault detection" OR "Fault location") The initial search in document titles, abstracts and author keywords revealed a preliminary total of 668 documents.

3.3 Inclusion and Exclusion Criteria

To refine the initial results into a highly relevant dataset focusing on grid safety and optimization, strong inclusion and exclusion criteria were defined:

- Language: Only documents written in the English language were included to maintain accuracy during qualitative analysis.

- Document Type: The search was strictly limited to peer-reviewed "Articles" and "Reviews." Conference proceedings, book chapters, and short surveys were excluded to uphold a high standard of validated empirical and theoretical research.

- Timeline: A definitive observation window from 2014 to 2023 was applied. This timeframe captures the most critical era of growth, mirroring the transition from traditional analytical models to advanced data-driven grid monitoring.

- Scope Relevancy: Papers that referenced PMUs but were disconnected from core protection mechanisms—such as those lacking focus on fault diagnostics or coordination—were systematically excluded.

3.4 Study Selection Process

The application of inclusion and exclusion criteria was done using a multi-stage filtering cascade, following the PRISMA structure as shown in Figure 1, which led to the final database used in this review:

1. Initial Identification: The baseline keyword search across the Scopus database returned 668 papers.

2. Language Filter: Applying the English-language-only restriction removed 19 non-English documents, leaving 649 papers.

3. Document Type Filter: Restricting the results strictly to full-length journal articles and comprehensive reviews reduced the dataset to 300 papers.

4. Temporal Filter: Applying the 2014–2023 publication timeline narrowed the pool to 201 papers.

5. Primary Screening (Title/Abstract/Keyword): A manual review of the titles, abstracts, and keywords was conducted to eliminate false positives and off-topic studies, resulting in 190 relevant papers.

6. Secondary Screening (Full-Text Review): A rigorous full-text screening was performed on the remaining documents to ensure methodological alignment with core power system protection goals. This final step yielded the definitive dataset of 162 core papers.

3.5 Data Extraction and Classification

The selected 162 publications were assembled in a structured database for more detailed quantitative and qualitative analysis. The theme review was driven by the separation of data extraction into three major categorization vectors:

- Bibliometric and Temporal Data: Extraction of publication years, source journals, and authorship networks to map the chronological growth of the research.

- Algorithmic and Methodological Classification: Papers were categorized by their core analytical approaches. This includes tracking the utilization of advanced metaheuristic algorithms, the integration of distributed generation impacts, and the notable shift toward machine learning techniques for fault diagnosis.

Validation frameworks and coordination strategies: The studies were also categorized based on their simulation environment (e.g., MATLAB, RTDS) and specific applications in grid security, including the investigation of PMU data usage for optimizing relay coordination operating times and enhancing directional overcurrent relay performance in complex networks.

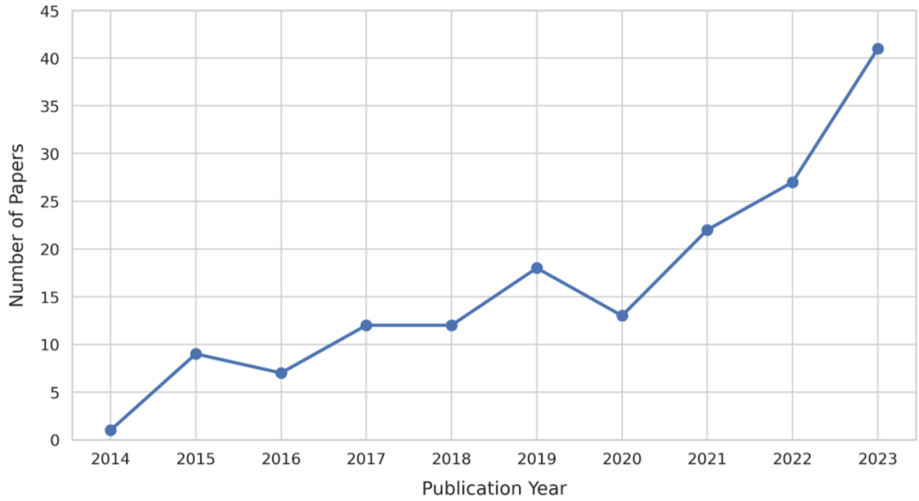


Figure 2. Annual publication trend of PMU-based fault detection research (2014–2023).

4. Bibliometric Analysis

A bibliometric analysis was undertaken on the final set of 162 selected papers to map the basic landscape of the current research. This quantitative study offers critical insights into the development of the discipline, the main academic venues that influence the discourse, and the changing thematic interests of scholars over the last 10 years.

4.1 Publication Trends and Growth Trajectory

The examination of the time distribution of the selected literature demonstrates a clear exponential increase of research interest in PMU-driven fault detection.

The decade started with little attention, with only one very relevant paper in 2014, as can be shown in Figure 2. However, there was a continuous increase between 2017 and 2019 reflecting the initial proliferation of Wide-Area Monitoring Systems (WAMS). The largest rise is seen in the latter three years of the data, where it rises from 13 publications in 2020 to a peak of 41 papers in 2023. This recent surge in the volume of published work is strongly associated with the increasing complexity of modern power grids, increasing penetration of distributed energy resources (DERs), and the pressing need for high-speed, data-driven protection schemes capable of dealing with bidirectional power flows.

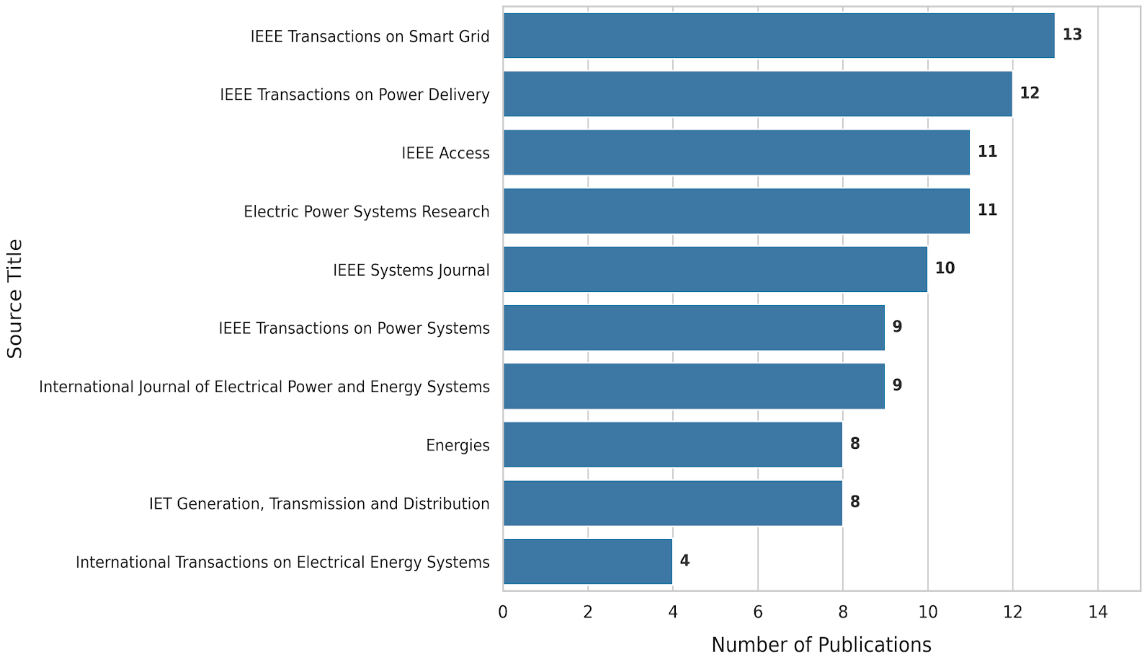


Figure 3. Top 10 publication venues contributing to PMU-based fault detection research (2014–2023)

4.2 Leading Venues and Academic Impact

Analysis of the source titles of the collected literature indicates that research on PMU-based fault detection is highly focused in top-tier, high-impact engineering publications. The main publication sites are described in Figure 3. The most influential journal is IEEE Transactions on Smart Grid (13 publications), followed by IEEE Transactions on Power Delivery (12 publications), IEEE Access (11 publications), and Electric Power Systems Research (11 publications). The dominance of these rigorous IEEE transactions and top-quartile energy journals indicates the technological maturity of the area. This also means that the suggested fault detection algorithms and relay coordination mechanisms are being put through the wringer of peer review and validation at the highest levels.

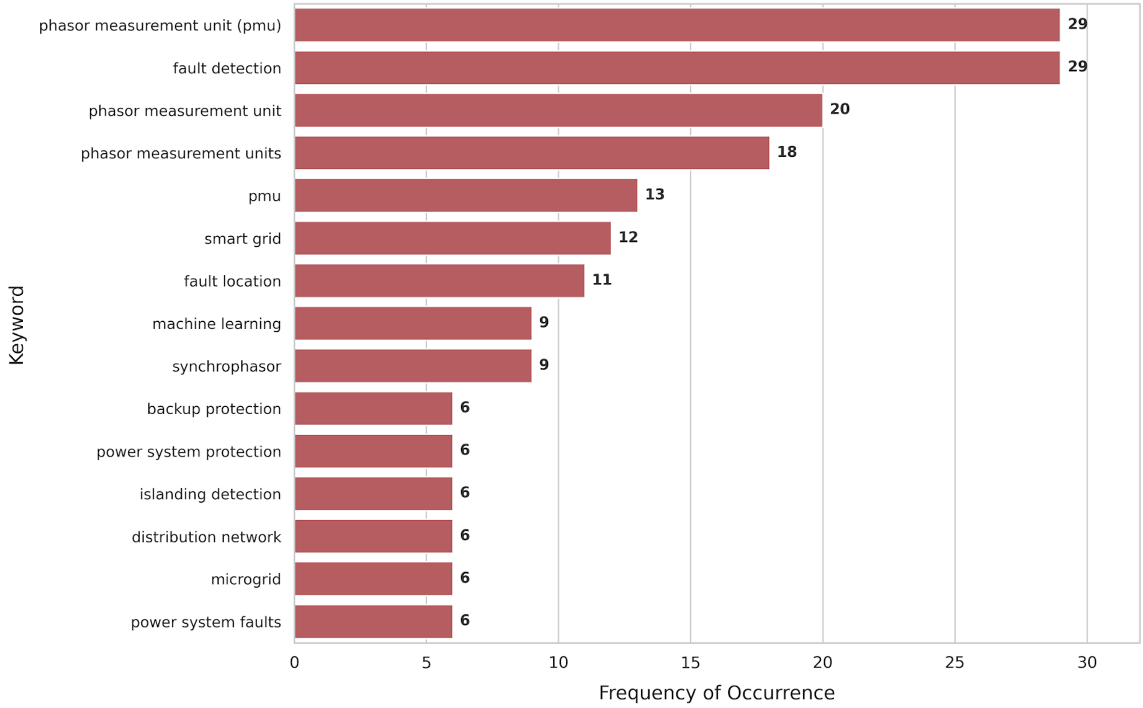


Figure 4. Frequency of the top 15 author keywords identified in the selected literature (2014–2023)

4.3 Keyword Analysis and Thematic Focus

Naturally, the main search parameters made keywords such as "phasor measurement unit" and "fault detection" stand out. However, a look at the secondary author keywords shows the specific application fields and methodological changes driving the current study. As illustrated in Figure 4, the prevalence of secondary keywords shows three different topic pillars in the recent literature:

1. *Application Environments:* Keywords such as Smart Grid (12 occurrences), Distribution Network (6 occurrences), and Microgrid (6 occurrences) indicate a strong shift from traditional transmission line protection toward complex, decentralized network topologies.

2. *Protection Mechanisms:* Terms like Backup Protection (6 occurrences) and Islanding Detection (6 occurrences) reveal that PMU data is not just being used for general monitoring, but is being actively integrated to optimize specific, critical relay coordination tasks.

3. *Algorithmic Evolution:* The prominence of Machine Learning (9 occurrences) as a leading keyword visually confirms the methodological pivot identified during the abstract screening. Researchers are increasingly moving beyond traditional metaheuristic mathematical models, leveraging artificial intelligence to process massive streams of synchrophasor data for rapid fault classification.

4.4 Geographical Distribution of Research

Figure 5 presents a high concentration of research in some areas of the world in terms of authors' affiliations for the 162 selected papers. Phasor Measurement Units (PMUs) are being used globally, however the intellectual output is dominated by a few significant countries:

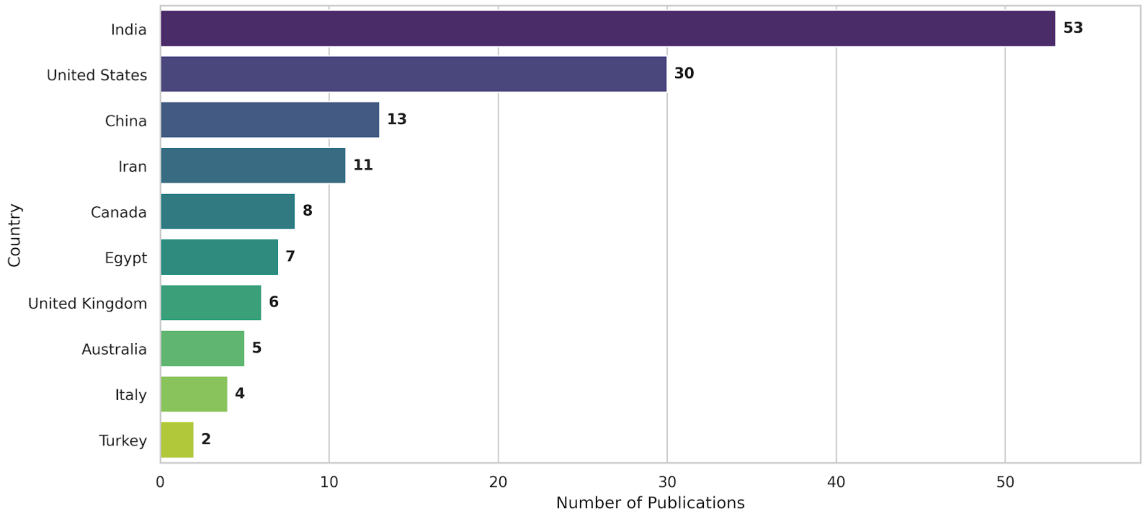


Figure 5. Geographical Distribution of Research (Top 10 Countries)

- *India:* Leading the global research output, India accounts for 53 publications. This significant contribution likely stems from the country's aggressive modernization of its national grid and the integration of WAMS to manage its vast and complex electrical infrastructure.

- *United States:* Ranked second with 30 publications, the U.S. continues to be a major hub for PMU innovation, driven by early adoption of synchrophasor technology and extensive research into grid resilience and cyber-physical security.

- *China:* With 13 publications, China represents a significant force in the field, focusing on high-speed fault detection for its extensive ultra-high voltage (UHV) transmission networks.

- *Other Key Contributors:* Iran (11 papers), Canada (8 papers), and Egypt (7 papers) also show a consistent research presence, indicating that PMU-based fault detection is a priority for nations managing both expanding grids and the integration of renewable energy sources.

Thematic Significance: This geographical clustering indicates that the research on PMU-based fault detection is concentrated in areas experiencing particular grid issues such as large-scale geographic coverage, the shift towards smart grids, and the requirement for decentralized protection in microgrids. The data suggests that countries with a strategic interest in autonomous, high-speed grid self-healing are driving the technology conversation.

4.5 Document Profile and Accessibility (Updated)

Finally, the bibliometric analysis investigates the characteristics of the publications and their availability. This assessment guarantees that the review is anchored in original empirical data and is consistent with current trends in academic publishing models.

4.5.1 Distribution of Document Types

As shown in Figure 6 (left), the dataset consists almost entirely of original research:

- *Articles (157 papers):* The overwhelming majority of the selected literature comprises original research articles. This ensures that the findings of this review are based on primary experimental data, novel algorithmic developments, and rigorous mathematical modeling.

- *Reviews (5 papers):* A small fraction of the dataset consists of high-level review papers. These provide valuable secondary perspectives on the overarching challenges and historical development of PMU technology.

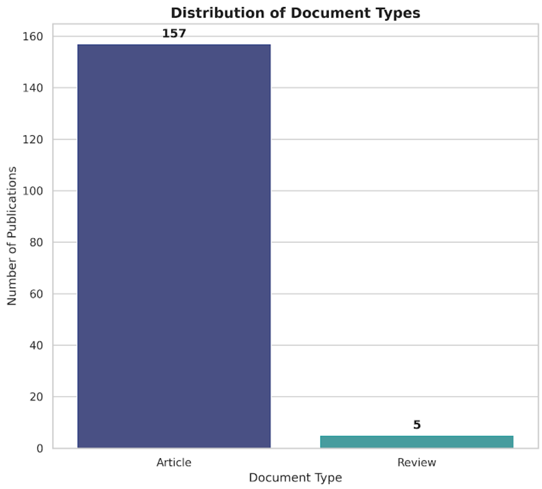
The high article-to-review ratio suggests the active phase of the technological innovation and empirical validation in the field of PMU-based fault detection.

4.5.2 Subscription vs. Open Access Trends

Accessibility is an important measure of research diffusion. The data shows a distinct division between open access synchrophasor research and research that is behind a paywall:

- *Subscription-Based (50.0%):* Exactly half of the identified literature (81 papers) is published under traditional subscription models. These often require institutional access or individual purchase, representing research that may not be fully accessible to all global stakeholders without specific credentials.
- *Gold Open Access (32.7%):* Approximately one-third of the papers are available via Gold Open Access, where the final version of record is immediately and permanently free to read.
- *Green Open Access (13.0%):* A notable portion is available through self-archiving in institutional or subject repositories.
- *Bronze Open Access (4.3%):* A smaller segment is made free to read on the publisher's website without a formal open license.

The fact that 50% of the literature is open access indicates a strong willingness of the power engineering community to communicate crucial developments in the field of grid protection world-wide, whilst the other 50% is behind traditional subscription walls.



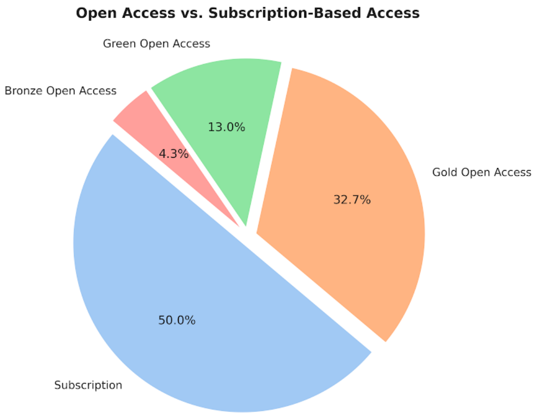


Figure 6. Distribution of document types (left) and accessibility status (right).

5. Methodological Frameworks for PMU-Based Protection

This section includes a detailed classification and technical review of PMU-based defect detection techniques covering signal processing, model-based, machine learning, deep learning and hybrid techniques.

5.1 Overview of Classification Framework

The 162 selected research publications were carefully classified into five separate methodological frameworks based on the basic algorithmic methodology used, so as to give a structured technical review. This classification offers a clear understanding of the history of strategies for defect detection based on PMUs and allows for a comparative comparison of different methodologies.

The categories identified are [24], [105], [148]: (i) model-based methods, (ii) machine learning approaches, (iii) deep learning techniques, (iv) signal processing-based methods, and (v) hybrid approaches. The categories reflect the trend of research shifting from traditional physics-based and mathematical models towards data-driven and intelligent frameworks. Model-based techniques (25 publications) use power system topology and physical equations to find and locate failures. They are good in interpretability but weak in adaptability under dynamic settings [148]. Machine learning techniques (19 articles) such as support vector machines and artificial neural networks use statistical learning to find patterns and get better categorization results [14]. Deep learning methods (5 publications) such as convolutional and recurrent neural network further improve the performance of defect detection by automatically extracting complicated features from large-scale PMU datasets [24].

Transient feature extraction is based on signal processing techniques (3 publications), e.g. wavelet transform and Hilbert–Huang transform, which can achieve quick responses but limited robustness in complicated circumstances [105]. Hybrid techniques (34 publications) integrate several frameworks, leveraging the characteristics of signal processing and artificial intelligence to provide better accuracy, robustness, and real-time applicability [14], [24].

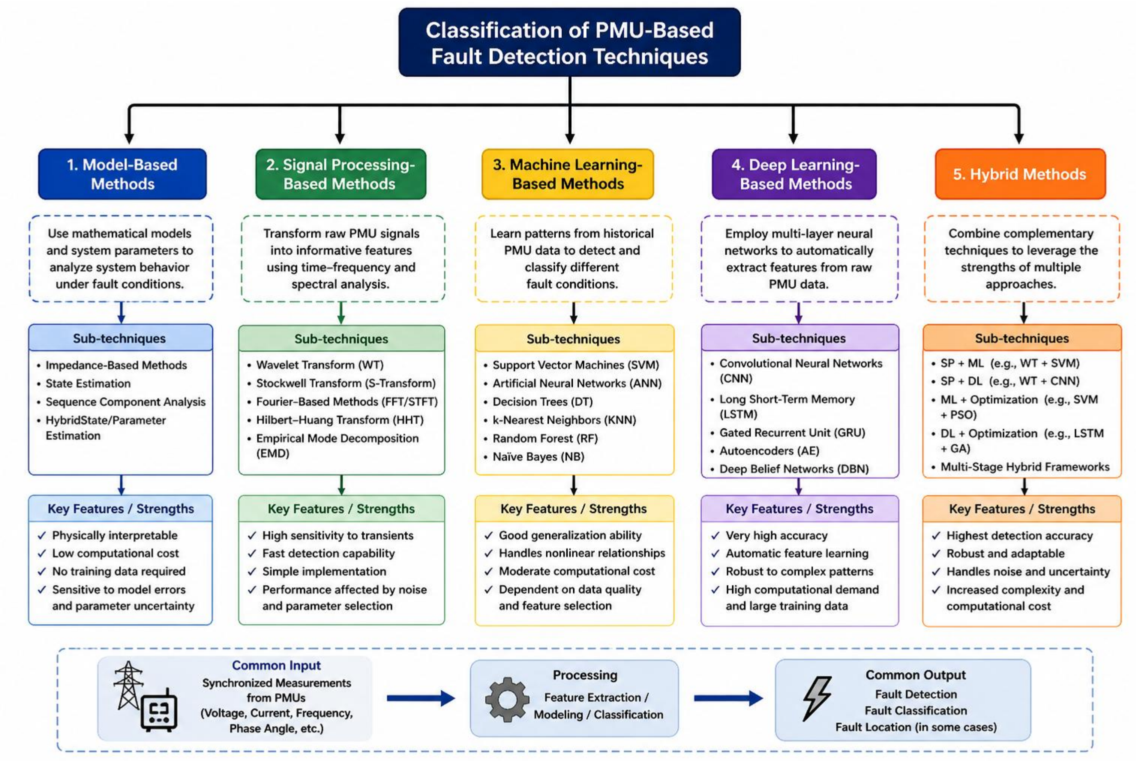


Figure 7. Classification of PMU-Based Fault Detection Techniques [1-237]

This classification shows in general a strong tendency in research towards hybrid and intelligent approaches due to the growing availability of high-resolution data from Phasor Measurement Unit (PMUs) and the improvement of computing tools [24], [148]. The taxonomy of PMU-based fault detection strategies is shown in Figure 7, where the available techniques are classified into model-based, signal processing, machine learning, deep learning and hybrid approaches.

5.2 Signal Processing-Based Methods

Synchrophasor data are pre-processed with signal processing (SP) algorithms that convert raw voltage and current measurements into meaningful feature vectors for defect identification [24], [105]. These methods are well adapted to treat the non-stationary nature of power system disruptions, where the properties of the signal can change rapidly with time. SP methods can identify flaws at an early stage by using transient behaviors based on the data of the PMU[105], [148].

5.2.1 Core Techniques

Some of the signal processing techniques generally applied for defect detection in PMUs include:

- Wavelet Transform (WT): Wavelet transform is generally employed for multi-resolution analysis that permits the decomposition of data into various frequency bands. This capacity is very successful for the detection of quick transient events and sudden variations related to the commencement of a defect [105], [72], [88].

- Stockwell Transform (S-Transform): The S-transform provides frequency-dependent resolution directly related to the Fourier spectrum. It provides better time-frequency localization and has been frequently used for assessing various fault scenarios in power systems [105], [91].

- Fourier-based methods (FFT/STFT) : Basic tools for harmonic analysis and steady-state phasor estimate are Fourier transform techniques such as Fast Fourier Transform (FFT) and Short-Time Fourier Transform (STFT). But the performance of their system in dynamic settings suffers from problems like spectral leakage and fixed resolution [105], [63].

5.2.2 Technical Evaluation for Signal Processing Methods

Signal processing-based methods have various advantages such as computational economy and fast responsiveness. They are very effective for detection of high frequency components and accurate fault initiation time detection that is crucial for protection systems [105], [72].

But these methods also have considerable shortcomings. They are sensitive to measurement noise which may have a considerable effect on the feature extraction accuracy. Moreover, appropriate selection of parameters, e.g. analysis window size, decomposition level and transform functions, is crucial to prevent distortion of the signal [105, 88]. These difficulties degrade robustness in complex and highly dynamic contexts of power systems.

In general, signal processing techniques provide a good basis for fault identification, but their limitations have resulted in the use of data-driven and hybrid strategies in recent studies [14], [24].

5.3 Model-Based Methods

Model-based solutions represent the traditional backbone of power system protection, utilizing mathematical formulations and physical concepts to detect and find defects [148], [24]. These methods study the system behavior under fault scenarios by using system parameters, network topology and electrical principles. More accurate and wide-area fault analysis has been achieved by combining synchronized measurements from PMUs with model-based approaches [24], [13].

5.3.1 Core Techniques

The analyzed studies in this category primarily employ impedance-based measurements and state estimation algorithms:

- *Impedance-Based Methods:* These methods estimate the apparent impedance between the measurement location and the fault point. By comparing calculated impedance values with predefined thresholds, faults can be detected and localized along transmission lines [148], [54], [79].

- *State Estimation Techniques:* State estimation approaches use PMU data to determine system states such as voltage magnitude and phase angles. Fault conditions are identified by detecting deviations between measured and estimated system states [24], [61].

- *Sequence Component Analysis:* For fault classification and localization, positive-sequence components are typically used for balanced faults, while sequence-component analysis (positive, negative, and zero sequences) is applied for asymmetrical faults [148], [66].

5.3.2 Technical Evaluation

Model-based approaches have many advantages, among them strong physical interpretability as they are based on well-established electrical principles [148]. Moreover, the proposed methodologies do not require huge training data sets and may be applied to systems with limited history data.

However, their success heavily depends on the accuracy of the system parameters and the network models. Both differences in topology, parameter estimation or measurement synchronization can have a non-negligible impact on the accuracy of fault detection [24], [13]. Moreover, these approaches are less flexible to dynamic and nonlinear situations which are more widespread in modern power systems with high renewable energy penetration [148, 79].

In summary, although model-based approaches are still dependable and widely used, the limits of these methods have caused a transition to data-driven and hybrid approaches for better performance and flexibility [14], [24].

5.4 Machine Learning-Based Methods

ML-based techniques consider power system safety as a pattern recognition problem, in which models are trained on historical data to understand the signatures of different fault types [14], [24]. These methods can find intricate links between system variables and fault circumstances and thus improve the detection and classification performance by using synchronized measurements from PMU [24], [148].

5.4.1 Dominant Architectures

The analyzed studies highlight several widely adopted ML techniques:

- *Support Vector Machines (SVM):* SVMs are extensively used for fault classification and islanding detection due to their ability to achieve high accuracy in high-dimensional feature spaces [14], [83], [97]. Their strong generalization capability makes them suitable for distinguishing between multiple fault conditions.

- *Artificial Neural Networks (ANN):* ANN models mimic biological neural systems and are capable of approximating nonlinear mappings between input phasor measurements and fault categories. They have been widely applied for capturing complex system behaviors [24], [76], [102].

- *Decision Trees (DT):* Decision tree-based methods are particularly suitable for real-time applications, as they can be translated into simple "if–then" rules that are easy to interpret and validate by system operators [14], [69].

5.4.2 Technical Evaluation for ML Methods

Machine learning-based approaches have the advantage of better generalization ability and effectiveness in the presence of nonlinear interactions inherent in power system dynamics [24], [83]. These methods are suitable for large scale processing of PMU data and enhance classification accuracy greatly over older methods.

However, their effectiveness depends heavily on the quality and labeling of the training dataset. Poor performance and reliability of the model can be due to inaccurate or incomplete training data [14], [97]. Furthermore, feature selection and pre-processing are still necessary processes requiring domain knowledge, and wrong handling may influence the accuracy of the model [24, 76].

In summary, machine learning approaches have boosted the capability of PMU-based fault detection systems, but their dependence on data quality has led to the development of more sophisticated deep learning and hybrid algorithms [24], [148].

5.5 Deep Learning-Based Methods

Deep learning-based methods represent the state of the art in PMU-based fault detection and protection. They employ multi-layered neural architectures to automatically extract characteristics from raw data streams [24], [148]. Deep learning models, as opposed to traditional machine learning methods, do not require manual feature engineering, instead learning hierarchical representations directly from synchronized measurements received using PMU [24]. This capacity makes them particularly convenient for dealing with complicated, nonlinear and high dimensional data in current power systems.

5.5.1 Specialized Applications

Recent studies have explored several deep learning architectures for fault detection and related applications:

- *Convolutional Neural Networks (CNN):* CNNs are widely used by transforming one-dimensional synchrophasor data into two-dimensional time–frequency representations. This enables the model to capture complex spatial patterns, making it highly effective for fault classification and emerging applications such as cyber-physical security, including detection of data-manipulation and false data injection attacks [105], [118], [126].

- *Long Short-Term Memory (LSTM) Networks:* LSTM networks, a specialized form of recurrent neural networks (RNNs), are designed to process temporal sequences and retain long-term dependencies. This makes them particularly suitable for analyzing time-varying synchrophasor data and monitoring gradual system changes, such as drifting signals during slow-moving instabilities or evolving fault conditions [24], [121].

5.5.2 Technical Evaluation for DL Methods

Deep learning approaches have a few benefits, namely the capacity to learn complicated features automatically from raw PMU data without the need for manual preprocessing [24], [118]. These methods provide great accuracy and robustness, particularly in detecting complex fault signatures and nonlinear system behaviors.

Yet these advantages are not without disadvantages. Deep learning models carry a substantial computational load, demanding high processing power and huge training data set [148], [126]. Furthermore, they are often not physically interpretable, which complicates the explanation of decision-making processes compared to typical model-based methods [24]. This is difficult to accomplish for important power system applications that require transparency and reliability.

In general, deep learning algorithms provide powerful tools for improved fault identification and monitoring, but their actual application needs careful consideration of the computational resources and system constraints [24], [148].

5.6 Hybrid Methods

Hybrid methods constitute the largest category in the analyzed dataset (36 papers), reflecting the growing emphasis on combining multiple techniques to enhance the robustness and accuracy of PMU-based fault detection systems [14], [24]. These approaches integrate the strengths of signal processing, machine learning, and optimization techniques to overcome the limitations of individual methods.

5.6.1 Hybrid Mechanism

Typically, hybrid techniques work via a simple two-step procedure. In the first stage, a signal processing method, for example wavelet transform or Hilbert–Huang transform, is applied to extract significant features from synchrophasor data acquired from PMUs [105], [72], [88]. These properties generally contain the energy content, frequency components and transient characteristics associated with fault episodes. In the second stage, the recovered characteristics are inputted to a machine learning based classifier such as support vector machines or fuzzy logic systems to obtain fault detection and classification [14, 83, 97]. This combination provides efficient feature extraction and accurate and adaptable decision making.

5.6.2 Optimization Strategies

In many hybrid techniques, metaheuristic optimization algorithms are combined further to improve the system performance. The optimum parameters such as PMU location, feature selection and relay thresholds are selected using certain popular techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [148], [134], [141]. These optimization solutions can increase the detection accuracy, lower the computational complexity, and provide higher flexibility under different operating situations. Besides, they are of great importance for solving practical problems, e.g. optimal placement of sensors and modifying parameters of the protective system.

5.6.3 Technical Evaluation for hybrid methods

Hybrid methods provide various advantages over stand-alone methods, such as increased accuracy, robustness and adaptability [24], [141]. Complementary approaches are used to deal efficiently with non-linearities, noise and complicated dynamics of the systems. Also, the use of optimization methods improves the system efficiency and performance. However, these approaches also bring more system complexity and processing overhead. Combining several strategies needs careful design and adjustment of parameters, which can limit the real-time implementation in large-scale systems [148], [134]. In general, hybrid approaches are a promising avenue for PMU-based fault detection since they can balance the strengths of traditional and data-driven approaches while addressing their particular shortcomings [14], [24].

Table 2. Comparative Analysis of PMU-Based Fault Detection Techniques

Methodology	Accuracy	Processing Speed	Real-Time Feasibility	Complexity
Model-Based	Moderate	High	Excellent	Low
Signal Processing	High (Transients)	High	Good	Moderate
Machine Learning	High	Moderate	Good	Moderate
Deep Learning	Very High	Low	Moderate	High
Hybrid Methods	Highest	Moderate	Excellent	High

5.7 Comparative Analysis of Methodologies

A comparison of the performance of different PMU-based fault detection systems is presented to evaluate their performance taking into account some important factors including accuracy, processing speed, real-time feasibility, and computational complexity [24], [148]. The summary of this comparison is shown in Table 2. Figure 8 shows visual comparison of accuracy, processing speed, real-time feasibility and computational complexity of several defect detection approaches. Table 2 shows that each category of fault detection techniques has its own advantages and disadvantages. Model-based approaches are of good real-time practicality and low computing cost which are ideal for practical deployment, but their accuracy is limited in dynamic settings [148], [24]. Signal processing approaches provide good accuracy for transient detection and fast reaction, but the performance is subject to noise and parameter selection [105], [72].

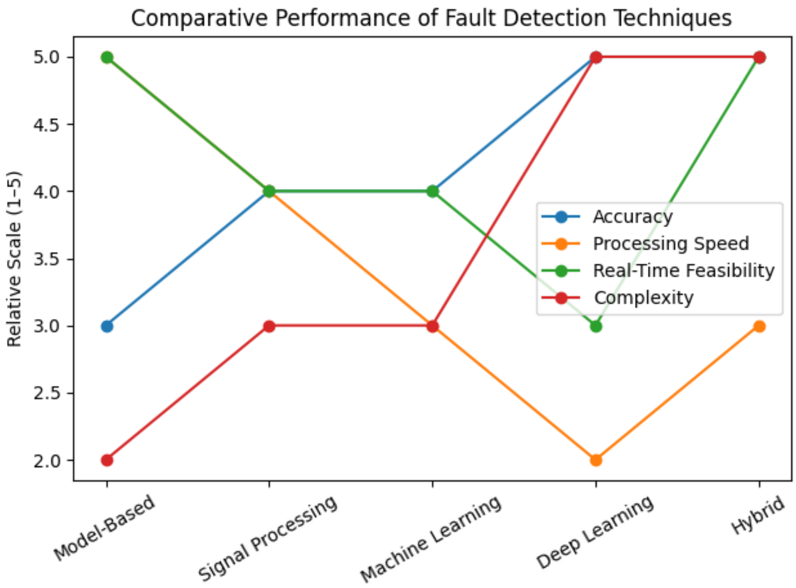


Figure 8. Comparative Performance of PMU-Based Fault Detection Techniques

Machine learning methods increase the classification accuracy and adaptability but they need modest processing time and depend on the data quality [14], [83]. Deep learning based approaches can attain the best accuracy by capturing complicated nonlinear patterns, however the high computing requirements of deep learning approaches limit their use in real-time in large-scale systems [24], [126]. Hybrid methods that combine the advantages of numerous approaches and reach the maximum accuracy and good real-time feasibility [14], [24], [141] are the best overall performance. They are more sophisticated, but they are the most promising approach for future PMU-based fault detection systems.

6. Discussion

A comprehensive review of 162 research articles demonstrates a clear progression of PMU-based fault detection systems from traditional analytical approaches to more sophisticated data-driven and hybrid schemes. The rising complexity of modern power systems, the widespread installation of PMUs and the increasing availability of high-resolution synchrophasor data [24], [148] are the main reasons for this trend.

6.1 Evolution of Methodologies

The results show that the early studies (2014-2017) were dominated by signal processing and model-based methods that provided fast response and ease of implementation but were limited in dealing with nonlinearities and uncertainties [105], [148]. However, with the evolution of power systems towards more dynamic and distributed architectures these traditional methodologies were insufficient to capture complex fault patterns. Since 2018, there is a clear shift towards the use of machine learning and deep learning techniques, as can be seen in the growth trends of the publications. The machine learning techniques raised classification accuracy and flexibility by using the historical PMU data. The deep learning techniques advanced the performance further by autonomous feature extraction and nonlinear modeling capabilities [24], [14]. This change signifies a paradigm shift from deterministic models to data-driven intelligence in power system protection.

6.2 Performance Trade-offs Across Techniques

The comparative analysis presented in Section 5.7 demonstrates that no single methodology satisfies all performance requirements simultaneously. Model based methods still have advantages in terms of interpretability and real-time practicality which makes them appropriate for actual deployment in conventional systems [148]. However, their performance is limited due to the need of accurate system parameters, especially under uncertain and fast time-varying settings.

Signal processing approaches are highly sensitive to transitory events and have quick detection, but are highly impacted by noise and parameter adjustment [105]. Machine learning algorithms provide better generalization and classification accuracy but their performance is highly dependent on the availability of quality labeled datasets [14].

Deep learning approaches offer the best accuracy in defect identification and classification because of their ability to capture complicated nonlinear interactions. However, their high computing costs and lack of interpretability are problems for real-time implementation and operator trust [24], [148]. The hybrid approaches, which incorporate signal processing, machine learning and optimization methodologies, show the most balanced performance, achieving high accuracy, resilience and real-time feasibility [14], [24].

6.3 Practical Implementation Challenges

Despite the huge progress, the application of PMU-based fault detection systems in practical power systems is limited due to many obstacles. One of the primary concerns is the communication latency and data loss, which affect the reliability of Wide Area Monitoring Systems (WAMS) [13], [24]. In addition, model-based and data-driven methods might be affected by synchronization issues and missing data. Another big concern is cyber security since the PMU-based systems are susceptible to cyber physical attacks such as fake data injection which may affect the accuracy of fault detection [24], [148]. Moreover, the application of sophisticated machine learning and deep learning algorithms to present protection systems requires significant computing power and infrastructure changes.

Further, the application of these techniques in practice is inhibited by the lack of defined frameworks regarding the location of PMUs, data handling and real-time processing. These problems underscore the gap between theoretical progress and practical application.

6.4 Emerging Research Directions

The review of the chosen literature suggests that the research on PMU-based fault detection is progressing fast in the direction of intelligent, adaptive and real-time protection schemes. Several prospective research directions stemming from the identified research gaps and recent technological advancements can guide future progress. One of the most important new topics is the integration of edge computing and distributed intelligence into PMU-based protection systems. Edge-based designs allow processing of synchrophasor data closer to the measurement source, therefore considerably reducing communication latency, bandwidth needs and computational overhead, and enabling speedier real-time fault detection in large-scale smart grids. Another promising research avenue is the development of cyber-resilient and safe protection mechanisms. With an increasing number of networked PMU-based WAMS, the susceptibility to cyber-physical risks such as fake data injection attacks, communication failures and synchronization issues is also increased . Hence, future study should emphasize on secure communication protocols, anomaly detection schemes, and resilient fault diagnosis systems.

Recent advances in deep learning and cognitive analytics also provide great prospects for improving the performance of defect detection. Hybrid CNN-LSTM architectures, transformer-based models, and attention mechanisms have demonstrated great potential in modeling complicated spatial and temporal interactions in synchrophasor data. Moreover, the application of Explainable Artificial Intelligence (XAI) approaches can improve the model interpretability and boost the trust of the operator in the AI-driven protection systems. The increasing penetration of renewable energy sources and distributed generation also forces to design adaptive and self-learning protection systems, which can react dynamically to the continuously changing operational conditions. Future intelligent protection schemes are projected to use online learning, predictive analytics and autonomous decision making skills to enhance grid resilience and operational flexibility. Moreover, the integration of digital twin technology, real-time simulation platforms, and cloud-assisted monitoring frameworks may present novel prospects for predictive fault diagnosis and proactive grid management. These technologies can be used for continuous monitoring of the system, virtual testing, and intelligent coordination of protection devices.

Finally, further study is necessary in the fields of standards, interoperability and practical application. To enable large-scale real-world deployment of PMU-based intelligent protection systems, challenges such as optimal PMU location, synchronization reliability, communication infrastructure, and hardware deployment limits need to be addressed.

7. Conclusion

This report provides an extensive systematic and bibliometric overview of PMU-based strategies for fault detection, classification and localization in power systems from 2014 to 2023 based on an in-depth examination of 162 academic articles. The study presented a systematic taxonomy of existing methodologies, classifying them into signal processing-based methods, model-based approaches, machine learning techniques, deep learning frameworks, and hybrid methods. This classification provides a comprehensive view on the development of the defect detection techniques in modern power systems.

The results show a significant shift from conventional analytical and signal processing methods towards data-driven and intelligent procedures, due to the increased availability of high-resolution synchrophasor data and the advances in computer technologies. Traditional approaches are still valuable because of their simplicity, interpretability and applicability in real-time, however, it suffers from the limits of non-linearity and dynamic grid conditions. On the contrary, machine learning and deep learning approaches are more accurate and flexible but require huge datasets, computational resources, and robust training frameworks. The comparative research reveals that the hybrid methods are the most promising answer, integrating the qualities of numerous methodologies, and attaining enhanced accuracy, resilience and real-time feasibility. However, their rising complexity and implementation issues demonstrate the need for streamlined and scalable frameworks for real application.

This is a great progress, but some key issues remain. These are communication delay, data quality problems, cybersecurity concerns, and lack of defined frameworks for PMU deployment and data processing. Moreover, the gap between theoretical study and practical application is a big concern especially in large scale and highly dynamic power systems. In summary, this work gives a detailed and systematic knowledge of the methodologies for PMU-based fault detection and illustrates the current transition to intelligent and adaptive protection systems. The insights offered in this paper serve as a significant reference for researchers and practitioners developing next-generation smart grid protection systems.

Declaration on the Use of Artificial Intelligence Tools

The authors used AI-assisted technology only for language refinement and grammatical correction during manuscript preparation. All scientific content, interpretations, and conclusions are the sole responsibility of the authors.

References

[1] Abasi, M., et al. (2021) 'Fault classification and fault area detection in GUPFC-compensated double-circuit transmission lines based on the analysis of active and reactive powers measured by PMUs', Measurement: Journal of the International Measurement Confederation, Vol. 169, No., https://doi.org/10.1016/j.measurement.2020.108499

[2] Abd el-Ghany, H.A., Soliman, I.A. and Elgebaly, A.E. (2022) 'An advanced wide-area fault detection and location technique for transmission lines considering optimal phasor measurement units allocation', Alexandria Engineering Journal, Vol. 61, No. 5, pp.3971-3984, https://doi.org/10.1016/j.aej.2021.09.022

[3] Afrasiabi, S., et al. (2020) 'Fault localisation and diagnosis in transmission networks based on robust deep Gabor convolutional neural network and PMU measurements', IET Generation, Transmission and Distribution, Vol. 14, No. 26, pp.6484-6492, https://doi.org/10.1049/iet-gtd.2020.0856

[4] Agustoni, M., et al. (2023) 'Time Synchronization Sensitivity in SV-based PMU Consistency Assessment', Metrology, Vol. 3, No. 1, pp.99-112, https://doi.org/10.3390/metrology3010006

[5] Ahmed, A., et al. (2019) 'Cyber Physical Security Analytics for Anomalies in Transmission Protection Systems', IEEE Transactions on Industry Applications, Vol. 55, No. 6, pp.6313-6323, https://doi.org/10.1109/TIA.2019.2928500

[6] Ahmed, A., et al. (2021) 'Anomaly Detection, Localization and Classification Using Drifting Synchrophasor Data Streams', IEEE Transactions on Smart Grid, Vol. 12, No. 4, pp.3570-3580, https://doi.org/10.1109/TSG.2021.3054375

[7] Almutairi, A., et al. (2022) 'A blockchain-enabled secured fault allocation in smart grids based on μPMUs and UT', IET Renewable Power Generation, Vol. 16, No. 16, pp.3496-3506, https://doi.org/10.1049/rpg2.12332

[8] Alqudah, M., Kezunovic, M. and Obradovic, Z. (2023) 'Automated Power System Fault Prediction and Precursor Discovery Using Multi-Modal Data', IEEE Access, Vol. 11, No., pp.7283-7296, https://doi.org/10.1109/ACCESS.2022.3233219

[9] Alqudah, M., et al. (2022) 'Fault Detection Utilizing Convolution Neural Network on Timeseries Synchrophasor Data From Phasor Measurement Units', IEEE Transactions on Power Systems, Vol. 37, No. 5, pp.3434-3442, https://doi.org/10.1109/TPWRS.2021.3135336

[10] Al-Shamaain, Z.S., Al-Majali, H.D. and Al-Majali, B.H. (2023) 'Out-of-Step Detection based on Phasor Measurement Unit', WSEAS Transactions on Power Systems, Vol. 18, No., pp.354-363, https://doi.org/10.37394/232016.2023.18.36

[11] Amutha, A.L., et al. (2023) 'Anomaly Detection and Classification in Streaming PMU Data in Smart Grids', Computer Systems Science and Engineering, Vol. 46, No. 3, pp.3387-3401, https://doi.org/10.32604/csse.2023.029904

[12] Anguswamy, M.P., et al. (2022) 'Optimal Micro-PMU Placement in Distribution Networks Considering Usable Zero-Injection Phase Strings', IEEE Transactions on Smart Grid, Vol. 13, No. 5, pp.3662-3675, https://doi.org/10.1109/TSG.2022.3174917

[13] Appasani, B. and Mohanta, D.K. (2018) 'A review on synchrophasor communication system: communication technologies, standards and applications', Protection and Control of Modern Power Systems, Vol. 3, No. 1, https://doi.org/10.1186/s41601-018-0110-4

[14] Arefin, A.A., et al. (2022) 'Review of the Techniques of the Data Analytics and Islanding Detection of Distribution Systems Using Phasor Measurement Unit Data', Electronics (Switzerland), Vol. 11, No. 18, https://doi.org/10.3390/electronics11182967

[15] Arefin, A.A., et al. (2021) 'A novel island detection threshold setting using phasor measurement unit voltage angle in a distribution network', Energies, Vol. 14, No. 16, https://doi.org/10.3390/en14164877

[16] Asgharigoavr, S. and Seyedi, H. (2017) 'Development of PMU-based backup wide area protection for power systems considering HIF detection', Turkish Journal of Electrical Engineering and Computer Sciences, Vol. 25, No. 4, pp.2846-2859, https://doi.org/10.3906/elk-1605-200

[17] Babu, N.V.P., et al. (2023) 'A Synchrophasor-Based Line Protection for Single Phase-Ground Faults', Journal of Electrical Engineering and Technology, Vol. 18, No. 3, pp.1693-1704, https://doi.org/10.1007/s42835-022-01312-y

[18] Bakdi, A., et al. (2021) 'Real-time fault detection in PV systems under MPPT using PMU and high-frequency multi-sensor data through online PCA-KDE-based multivariate KL divergence', International Journal of Electrical Power and Energy Systems, Vol. 125, No., https://doi.org/10.1016/j.ijepes.2020.106457

[19] Banna, H.U., et al. (2023) 'Proactive anomaly source identification using novel ensemble learning with adaptive mitigation measures for microgrids', Electric Power Systems Research, Vol. 218, No., https://doi.org/10.1016/j.epsr.2023.109157

[20] Bansal, Y. and Sodhi, R. (2022) 'A novel μPMUs assisted loss-of-mains detection technique for active distribution systems', Electric Power Systems Research, Vol. 202, No., https://doi.org/10.1016/j.epsr.2021.107578

[21] Barreto, N.E.M., et al. (2021) 'Artificial Neural Network Approach for Fault Detection and Identification in Power Systems with Wide Area Measurement Systems', Journal of Control, Automation and Electrical Systems, Vol. 32, No. 6, pp.1617-1626, https://doi.org/10.1007/s40313-021-00785-y

[22] Basumallik, S., Ma, R. and Eftekharnejad, S. (2019) 'Packet-data anomaly detection in PMU-

based state estimator using convolutional neural network', International Journal of Electrical Power and Energy Systems, Vol. 107, No., pp.690-702, https://doi.org/10.1016/j.ijepes.2018.11.013

[23] Belagoune, S., et al. (2021) 'Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems', Measurement: Journal of the International Measurement Confederation, Vol. 177, No., https://doi.org/10.1016/j.measurement.2021.109330

[24] Biswal, C., et al. (2023) 'Real-Time Grid Monitoring and Protection: A Comprehensive Survey on the Advantages of Phasor Measurement Units', Energies, Vol. 16, No. 10, https://doi.org/10.3390/en16104054

[25] Biswal, M., Brahma, S.M. and Cao, H. (2016) 'Supervisory Protection and Automated Event Diagnosis Using PMU Data', IEEE Transactions on Power Delivery, Vol. 31, No. 4, pp.1855-1863, https://doi.org/10.1109/TPWRD.2016.2520958

[26] Chatterjee, S., et al. (2023) 'Adaptive Divided Difference Filter for Power Systems Dynamic State Estimation With Outliers and Unknown Noise Covariance', IEEE Transactions on Industry Applications, Vol. 59, No. 6, pp.7529-7544, https://doi.org/10.1109/TIA.2023.3296576

[27] Chawla, A., et al. (2023) 'Deep-learning-based data-manipulation attack resilient supervisory backup protection of transmission lines', Neural Computing and Applications, Vol. 35, No. 7, pp.4835-4854, https://doi.org/10.1007/s00521-021-06106-3

[28] Chawla, A., et al. (2022) 'Denial-of-Service Attacks Pre-Emptive and Detection Framework for Synchrophasor Based Wide Area Protection Applications', IEEE Systems Journal, Vol. 16, No. 1, pp.1570-1581, https://doi.org/10.1109/JSYST.2021.3093494

[29] Chen, L., et al. (2020) 'Harmonic Phasor Estimator for P-Class Phasor Measurement Units', IEEE Transactions on Instrumentation and Measurement, Vol. 69, No. 4, pp.1556-1565, https://doi.org/10.1109/TIM.2019.2916961

[30] Chen, L., et al. (2021) 'Harmonic Phasor Estimation Based on Frequency-Domain Sampling Theorem', IEEE Transactions on Instrumentation and Measurement, Vol. 70, No., https://doi.org/10.1109/TIM.2020.3039618

[31] Chintakindi, R. and Mitra, A. (2022) 'WAMS challenges and limitations in load modeling, voltage stability improvement, and controlled island protection—A review', Energy Reports, Vol. 8, No., pp.699-709, https://doi.org/10.1016/j.egyr.2021.11.217

[32] Chougule, M. and Soman, S.A. (2020) 'Real-Time data-Assisted replay attack detection in wide-Area protection system', IET Generation, Transmission and Distribution, Vol. 14, No. 19, pp.4021-4032, https://doi.org/10.1049/iet-gtd.2020.0215

[33] Ciancetta, F., et al. (2023) 'Micro Phasor Measurement Units: a Review from the Prosumer Point of View', Renewable Energy and Power Quality Journal, Vol. 21, No., pp.303-308, https://doi.org/10.24084/repqj21.307

[34] Čišija-Kobilica, N., et al. (2019) 'A new approach for the fault identification, localization, and classification in the power system', Journal of Engineering Research (Kuwait), Vol. 7, No. 2, pp.259-280,

[35] Das, S., Singh, S.P. and Panigrahi, B.K. (2017) 'Transmission line fault detection and location using Wide Area Measurements', Electric Power Systems Research, Vol. 151, No., pp.96-105, https://doi.org/10.1016/j.epsr.2017.05.025

[36] Desai, J.P. and Makwana, V.H. (2021) 'Phasor Measurement Unit Incorporated Adaptive Out-of-step Protection of Synchronous Generator', Journal of Modern Power Systems and Clean Energy, Vol. 9, No. 5, pp.1032-1042, https://doi.org/10.35833/MPCE.2020.000277

[37] Dua, G.S., Tyagi, B. and Kumar, V. (2023) 'Fault Detection Technique for Distribution Networks and Microgrids Using Synchrophasor Data', IEEE Transactions on Industry Applications, Vol. 59, No. 6, pp.7368-7381, https://doi.org/10.1109/TIA.2023.3305362

[38] Dua, G.S., Tyagi, B. and Kumar, V. (2023) 'Microgrid Differential Protection Based on Superimposed Current Angle Employing Synchrophasors', IEEE Transactions on Industrial Informatics, Vol. 19, No. 8, pp.8775-8783, https://doi.org/10.1109/TII.2022.3222319

[39] Dubey, R., et al. (2016) 'Data-mining model based adaptive protection scheme to enhance distance relay performance during power swing', International Journal of Electrical Power and Energy Systems, Vol. 81, No., pp.361-370, https://doi.org/10.1016/j.ijepes.2016.02.014

[40] Dubey, R., et al. (2018) 'Koopman analysis based wide-area back-up protection and faulted line identification for series-compensated power network', IEEE Systems Journal, Vol. 12, No. 3, pp.2634-2644, https://doi.org/10.1109/JSYST.2016.2615898

[41] Ebrahim, M.A., Wadie, F. and Abd-Allah, M.A. (2019) 'Integrated fault detection algorithm for transmission, distribution, and microgrid networks', IET Energy Systems Integration, Vol. 1, No. 2, pp.104-113, https://doi.org/10.1049/iet-esi.2019.0002

[42] Ebrahim, M.A., Wadie, F. and Abd-Allah, M.A. (2020) 'An Algorithm for Detection of Fault, Islanding, and Power Swings in DG-Equipped Radial Distribution Networks', IEEE Systems Journal, Vol. 14, No. 3, pp.3893-3903, https://doi.org/10.1109/JSYST.2019.2944870

[43] El Mrabet, Z., et al. (2022) 'Random Forest Regressor-Based Approach for Detecting Fault Location and Duration in Power Systems', Sensors, Vol. 22, No. 2, https://doi.org/10.3390/s22020458

[44] Elghazaly, H., Emam, A. and Saber, A. (2017) 'A backup wide-area protection technique for power transmission network', IEEJ Transactions on Electrical and Electronic Engineering, Vol. 12, No. 5, pp.702-709, https://doi.org/10.1002/tee.22456

[45] Elhabashy, M.M., Sharaf, H.M. and Ibrahim, D.K. (2023) 'Reliable protection for static synchronous series compensated double-circuit transmission lines based on positive sequence active power calculations using PMUs', Electric Power Systems Research, Vol. 223, No., https://doi.org/10.1016/j.epsr.2023.109695

[46] Esmaeilian, A. and Kezunovic, M. (2016) 'Fault Location Using Sparse Synchrophasor Measurement of Electromechanical-Wave Oscillations', IEEE Transactions on Power Delivery, Vol. 31, No. 4, pp.1787-1796, https://doi.org/10.1109/TPWRD.2015.2510585

[47] Gharavi, H. and Hu, B. (2018) 'Space-Time Approach for Disturbance Detection and Classification', IEEE Transactions on Smart Grid, Vol. 9, No. 5, pp.5132-5140, https://doi.org/10.1109/TSG.2017.2680742

[48] Gholami, A., Srivastava, A.K. and Pandey, S. (2019) 'Data-driven failure diagnosis in transmission protection system with multiple events and data anomalies', Journal of Modern Power Systems and Clean Energy, Vol. 7, No. 4, pp.767-778, https://doi.org/10.1007/s40565-019-0541-6

[49] Gholami, M., et al. (2020) 'Detecting the Location of Short-Circuit Faults in Active Distribution Network Using PMU-Based State Estimation', IEEE Transactions on Smart Grid, Vol. 11, No. 2, pp.1396-1406, https://doi.org/10.1109/TSG.2019.2937944

[50] Gilanifar, M., et al. (2020) 'Multi-Task Logistic Low-Ranked Dirty Model for Fault Detection in Power Distribution System', IEEE Transactions on Smart Grid, Vol. 11, No. 1, pp.786-796, https://doi.org/10.1109/TSG.2019.2938989

[51] Gopakumar, P., et al. (2018) 'Remote monitoring system for real time detection and classification of transmission line faults in a power grid using PMU measurements', Protection and Control of Modern Power Systems, Vol. 3, No. 1, https://doi.org/10.1186/s41601-018-0089-x

[52] Gopakumar, P., Reddy, M.J.B. and Mohanta, D.K. (2015) 'Fault Detection and Localization Methodology for Self-healing in Smart Power Grids Incorporating Phasor Measurement Units', Electric Power Components and Systems, Vol. 43, No. 6, pp.695-710, https://doi.org/10.1080/15325008.2014.995839

[53] Gopakumar, P., Reddy, M.J.B. and Mohanta, D.K. (2015) 'Transmission line fault detection and localisation methodology using PMU measurements', IET Generation, Transmission and Distribution, Vol. 9, No. 11, pp.1033-1042, https://doi.org/10.1049/iet-gtd.2014.0788

[54] Gopakumar, P., Reddy, M.J.B. and Mohanta, D.K. (2015) 'Adaptive fault identification and classification methodology for smart power grids using synchronous phasor angle measurements', IET Generation, Transmission and Distribution, Vol. 9, No. 2, pp.133-145, https://doi.org/10.1049/iet-gtd.2014.0024

[55] Granados-Lieberman, D., et al. (2021) 'Harmonic PMU and Fuzzy Logic for Online

Detection of Short-Circuited Turns in Transformers', Electric Power Systems Research, Vol. 190, No., https://doi.org/10.1016/j.epsr.2020.106862

[56] Guo, L., et al. (2022) 'Data-Driven Cyber-Attack Detection for PV Farms via Time-Frequency Domain Features', IEEE Transactions on Smart Grid, Vol. 13, No. 2, pp.1582-1597, https://doi.org/10.1109/TSG.2021.3136559

[57] Guo, Y., et al. (2015) 'Synchrophasor-Based Islanding Detection for Distributed Generation Systems Using Systematic Principal Component Analysis Approaches', IEEE Transactions on Power Delivery, Vol. 30, No. 6, pp.2544-2552, https://doi.org/10.1109/TPWRD.2015.2435158

[58] Hai, A.A., et al. (2021) 'Transfer Learning for Event Detection from PMU Measurements with Scarce Labels', IEEE Access, Vol. 9, No., pp.127420-127432, https://doi.org/10.1109/ACCESS.2021.3111727

[59] Hajnorouzi, A.A. and Shayanfar, H.A. (2019) 'A response-based approach to online prediction of generating unit angular stability', Scientia Iranica, Vol. 26, No. 6, pp.3592-3605, https://doi.org/10.24200/sci.2019.53966.3517

[60] Harish, A., Asok, P. and Jayan, M.V. (2023) 'A comparative evaluation of Stacked Auto-Encoder neural network and Multi-Layer Extreme Learning Machine for detection and classification of faults in transmission lines using WAMS data', Energy and AI, Vol. 14, No., https://doi.org/10.1016/j.egyai.2023.100301

[61] Harish, A., Prince, A. and Jayan, M.V. (2022) 'Fault Detection and Classification for Wide Area Backup Protection of Power Transmission Lines Using Weighted Extreme Learning Machine', IEEE Access, Vol. 10, No., pp.82407-82417, https://doi.org/10.1109/ACCESS.2022.3196769

[62] Hatata, A.Y., Essa, M.A. and Sedhom, B.E. (2022) 'Implementation and Design of FREEDM System Differential Protection Method Based on Internet of Things', Energies, Vol. 15, No. 15, https://doi.org/10.3390/en15155754

[63] Hu, C., Yan, J. and Liu, X. (2023) 'Reinforcement Learning-Based Adaptive Feature Boosting for Smart Grid Intrusion Detection', IEEE Transactions on Smart Grid, Vol. 14, No. 4, pp.3150-3163, https://doi.org/10.1109/TSG.2022.3230730

[64] Iqbal, A. and Jain, T. (2022) 'Real-Time Event Detection Based on Weibull Distribution Using Synchrophasor Measurements for Enhanced Situational Awareness', IEEE Transactions on Power Systems, Vol. 37, No. 2, pp.1425-1436, https://doi.org/10.1109/TPWRS.2021.3108481

[65] Jafarzadeh, S. and Genc, V.M.I. (2021) 'Real-time transient stability prediction of power systems based on the energy of signals obtained from PMUs', Electric Power Systems Research, Vol. 192, No., https://doi.org/10.1016/j.epsr.2020.107005

[66] Jena, M.K. and Panigrahi, B.K. (2019) 'Transient Potential Power Based Supervisory Zone-1 Operation during Unstable Power Swing', IEEE Systems Journal, Vol. 13, No. 2, pp.1823-1830, https://doi.org/10.1109/JSYST.2018.2820013

[67] Jena, M.K., Samantaray, S.R. and Panigrahi, B.K. (2018) 'A New Decentralized Approach to Wide-Area Back-Up Protection of Transmission Lines', IEEE Systems Journal, Vol. 12, No. 4, pp.3161-3168, https://doi.org/10.1109/JSYST.2017.2694453

[68] Jiang, H., et al. (2016) 'Spatial-Temporal Synchrophasor Data Characterization and Analytics in Smart Grid Fault Detection, Identification, and Impact Causal Analysis', IEEE Transactions on Smart Grid, Vol. 7, No. 5, pp.2525-2536, https://doi.org/10.1109/TSG.2016.2552229

[69] Jiang, Y. and Srivastava, A.K. (2020) 'Data-Driven Event Diagnosis in Transmission Systems with Incomplete and Conflicting Alarms Given Sensor Malfunctions', IEEE Transactions on Power Delivery, Vol. 35, No. 1, pp.214-225, https://doi.org/10.1109/TPWRD.2019.2947671

[70] Jin, Z., et al. (2021) 'An improved algorithm for cubature Kalman filter based forecasting-aided state estimation and anomaly detection', International Transactions on Electrical Energy Systems, Vol. 31, No. 5, https://doi.org/10.1002/2050-7038.12714

[71] Kabra, P., Lalitha, S.V.N.L. and Donepudi, S.R. (2023) 'Bad data analysis and detection using PMU with UPQC integration to grid during fault conditions', International Journal of Power Electronics and Drive Systems, Vol. 14, No. 1,

pp.256-265, https://doi.org/10.11591/ijpeds.v14.i1.pp256-265

[72] Khan, I. and Centeno, V. (2023) 'Realtime Detection of PMU Bad Data and Sequential Bad Data Classifications in Cyber-Physical Testbed', IEEE Access, Vol. 11, No., pp.71235-71249, https://doi.org/10.1109/ACCESS.2023.3292059

[73] Killi, V., P, R. and Mp, S. (2023) 'Detection and isolation of faulty line in an active distribution network using intelligent numerical relay', Electric Power Systems Research, Vol. 214, No., https://doi.org/10.1016/j.epsr.2022.108921

[74] Kiruthika, M. and Bindu, S. (2023) 'A security enabled real time fault detection and classification of power system conditions', International Journal of Advanced Technology and Engineering Exploration, Vol. 10, No. 107, pp.1260-1278, https://doi.org/10.19101/IJATEE.2022.10100425

[75] Krishnan, K. and Iyengar, S. (2022) 'Fault detection in an interconnected power system using optimal number of phasor measurement unit', International Journal of Power Electronics and Drive Systems, Vol. 13, No. 4, pp.2109-2119, https://doi.org/10.11591/ijpeds.v13.i4.pp2109-2119

[76] Kumar, B., Yadav, A. and Pazoki, M. (2019) 'Impedance differential plane for fault detection and faulty phase identification of FACTS compensated transmission line', International Transactions on Electrical Energy Systems, Vol. 29, No. 4, https://doi.org/10.1002/etep.2804

[77] Kumar, G.P. and Jena, P. (2021) 'Pearson's Correlation Coefficient for Islanding Detection Using Micro-PMU Measurements', IEEE Systems Journal, Vol. 15, No. 4, pp.5078-5089, https://doi.org/10.1109/JSYST.2020.3021922

[78] Kumar, M. and Kumar, J. (2023) 'A Solution to Islanding Event Detection Using Superimposed Negative Sequence Components-Based Scheme', Arabian Journal for Science and Engineering, Vol. 48, No. 11, pp.14639-14653, https://doi.org/10.1007/s13369-023-07787-9

[79] Kundu, P. and Pradhan, A.K. (2014) 'Synchrophasor-assisted zone 3 operation', IEEE Transactions on Power Delivery, Vol. 29, No. 2, pp.660-667, https://doi.org/10.1109/TPWRD.2013.2276071

[80] Kundu, P. and Pradhan, A.K. (2019) 'Supervisory protection of islanded network using synchrophasor data', IEEE Transactions on Smart Grid, Vol. 10, No. 2, pp.1772-1780, https://doi.org/10.1109/TSG.2017.2777873

[81] Lal, M.D. and Varadarajan, R. (2023) 'A Review of Machine Learning Approaches in Synchrophasor Technology', IEEE Access, Vol. 11, No., pp.33520-33541, https://doi.org/10.1109/ACCESS.2023.3263547

[82] Lam, H.A. and Dong, Z.Y. (2021) 'Transfer learning based dynamic security assessment', IET Generation, Transmission and Distribution, Vol. 15, No. 16, pp.2333-2343, https://doi.org/10.1049/gtd2.12181

[83] Laverty, D.M., Best, R.J. and Morrow, D.J. (2015) 'Loss-of-mains protection system by application of phasor measurement unit technology with experimentally assessed threshold settings', IET Generation, Transmission and Distribution, Vol. 9, No. 2, pp.146-153, https://doi.org/10.1049/iet-gtd.2014.0106

[84] Le Roux, P.F. and Bansal, R.C. (2017) 'Detection of Network Instability using Area-Based Centre of Inertia-Referred Frame', Technology and Economics of Smart Grids and Sustainable Energy, Vol. 2, No. 1, https://doi.org/10.1007/s40866-017-0037-2

[85] Lee, J.W., et al. (2016) 'Fault area estimation using traveling wave for wide area protection', Journal of Modern Power Systems and Clean Energy, Vol. 4, No. 3, pp.478-486, https://doi.org/10.1007/s40565-016-0222-7

[86] Li, B., et al. (2023) 'Coordinated Cloud-Edge Anomaly Identification for Active Distribution Networks', IEEE Transactions on Cloud Computing, Vol. 11, No. 2, pp.1204-1216, https://doi.org/10.1109/TCC.2022.3155441

[87] Li, W.T., et al. (2016) 'Location identification of power line outages using PMU measurements with bad data', IEEE Transactions on Power Systems, Vol. 31, No. 5, pp.3624-3635, https://doi.org/10.1109/TPWRS.2015.2495214

[88] Liang, X., Wallace, S.A. and Nguyen, D. (2017) 'Rule-Based Data-Driven Analytics for Wide-Area Fault Detection Using Synchrophasor Data', IEEE Transactions on Industry Applications, Vol. 53, No. 3, pp.1789-1798, https://doi.org/10.1109/TIA.2016.2644621

[89] Liu, G., et al. (2017) 'Low-Complexity Nonlinear Analysis of Synchrophasor Measurements for Events Detection and Localization', IEEE Access, Vol. 6, No., pp.4982-4993, https://doi.org/10.1109/ACCESS.2017.2772287

[90] Liu, G., et al. (2022) 'Hessian Locally Linear Embedding of PMU Data for Efficient Fault Detection in Power Systems', IEEE Transactions on Instrumentation and Measurement, Vol. 71, No., https://doi.org/10.1109/TIM.2022.3146905

[91] Livanos, N.A.I., et al. (2023) 'OpenEdgePMU: An Open PMU Architecture with Edge Processing for Future Resilient Smart Grids', Energies, Vol. 16, No. 6, https://doi.org/10.3390/en16062756

[92] Ma, H., et al. (2023) 'Deep-Learning Based Power System Events Detection Technology Using Spatio-Temporal and Frequency Information', IEEE Journal on Emerging and Selected Topics in Circuits and Systems, Vol. 13, No. 2, pp.545-556, https://doi.org/10.1109/JETCAS.2023.3252667

[93] Mahdi, M. and Genc, V.M.I. (2018) 'Post-fault prediction of transient instabilities using stacked sparse autoencoder', Electric Power Systems Research, Vol. 164, No., pp.243-252, https://doi.org/10.1016/j.epsr.2018.08.009

[94] Manoharan, H., et al. (2023) 'Application of solar cells and wireless system for detecting faults in phasor measurement units using non-linear optimization', Energy Exploration and Exploitation, Vol. 41, No. 1, pp.210-223, https://doi.org/10.1177/01445987221113122

[95] Mazhari, S.M., et al. (2018) 'A Hybrid Fault Cluster and Thévenin Equivalent Based Framework for Rotor Angle Stability Prediction', IEEE Transactions on Power Systems, Vol. 33, No. 5, pp.5594-5603, https://doi.org/10.1109/TPWRS.2018.2823690

[96] Mingotti, A., Peretto, L. and Tinarelli, R. (2021) 'Low-impact current-based distributed monitoring system for medium voltage networks', Energies, Vol. 14, No. 17, https://doi.org/10.3390/en14175308

[97] Mirshekali, H., et al. (2022) 'Machine Learning-Based Fault Location for Smart Distribution Networks Equipped with Micro-PMU', Sensors, Vol. 22, No. 3, https://doi.org/10.3390/s22030945

[98] Mnyanghwalo, D., et al. (2020) 'Deep learning approaches for fault detection and classifications in the electrical secondary distribution network: Methods comparison and recurrent neural network accuracy comparison', Cogent Engineering, Vol. 7, No. 1, https://doi.org/10.1080/23311916.2020.1857500

[99] Mohsenian-Rad, H. and Xu, W. (2023) 'Synchro-Waveforms: A Window to the Future of Power Systems Data Analytics', IEEE Power and Energy Magazine, Vol. 21, No. 5, pp.68-77, https://doi.org/10.1109/MPE.2023.3288583

[100] Na, S., et al. (2019) 'Detecting instant of multiple faults on the transmission line and its types using time-frequency analysis', IET Generation, Transmission and Distribution, Vol. 13, No. 22, pp.5248-5256, https://doi.org/10.1049/iet-gtd.2018.5572

[101] Nagananda, K.G., Kishore, S. and Blum, R.S. (2015) 'A PMU Scheduling Scheme for Transmission of Synchrophasor Data in Electric Power Systems', IEEE Transactions on Smart Grid, Vol. 6, No. 5, pp.2519-2528, https://doi.org/10.1109/TSG.2014.2388238

[102] Najafzadeh, M., et al. (2023) 'A New Method for Fault Detection and Location in a Low-Resistance Grounded Power Distribution Network Using Voltage Phasor of D-PMUs Data', International Transactions on Electrical Energy Systems, Vol. 2023, No., https://doi.org/10.1155/2023/1754305

[103] Nale, R., Verma, H. and Biswal, M. (2021) 'An Enhanced Fuzzy Rule Based Protection Scheme for TCSC Compensated Double Circuit Transmission System', International Journal of Modelling and Simulation, Vol. 41, No. 2, pp.120-130, https://doi.org/10.1080/02286203.2019.1692299

[104] Nguyen, B.L.H., et al. (2023) 'Spatial-Temporal Recurrent Graph Neural Networks for Fault Diagnostics in Power Distribution Systems', IEEE Access, Vol. 11, No., pp.46039-46050, https://doi.org/10.1109/ACCESS.2023.3273292

[105] Oubrahim, Z., et al. (2023) 'Power Quality Disturbances Characterization Using Signal Processing and Pattern Recognition Techniques: A Comprehensive Review', Energies, Vol. 16, No. 6, https://doi.org/10.3390/en16062685

[106] Palepu, S.B. and Reddy, M.D. (2022) 'Binary spider monkey algorithm approach for optimal siting of the phasor measurement for power system state estimation', IAES International Journal of Artificial Intelligence, Vol. 11, No. 3, pp.1033-1040, https://doi.org/10.11591/ijai.v11.i3.pp1033-1040

[107] Pignati, M., et al. (2017) 'Fault Detection and Faulted Line Identification in Active Distribution Networks Using Synchrophasors-Based Real-Time State Estimation', IEEE Transactions on Power Delivery, Vol. 32, No. 1, pp.381-392, https://doi.org/10.1109/TPWRD.2016.2545923

[108] Pourramezan, R., Karimi, H. and Mahseredjian, J. (2023) 'Synchrophasor network-based detection and classification of power system events: A singular value decomposition approach', Electric Power Systems Research, Vol. 223, No., https://doi.org/10.1016/j.epsr.2023.109645

[109] Prada Hurtado, A.A., et al. (2022) 'Application of IIA Method and Virtual Bus Theory for Backup Protection of a Zone Using PMU Data in a WAMPAC System', Energies, Vol. 15, No. 9, https://doi.org/10.3390/en15093470

[110] Qasim Khan, M., Mohamud Ahmed, M. and Haidar, A.M.A. (2022) 'An accurate algorithm of PMU-based wide area measurements for fault detection using positive-sequence voltage and unwrapped dynamic angles', Measurement: Journal of the International Measurement Confederation, Vol. 192, No., https://doi.org/10.1016/j.measurement.2022.110906

[111] Radhakrishnan, R.M., Sankar, A. and Rajan, S. (2020) 'Synchrophasor based islanding detection for microgrids using moving window principal component analysis and extended mathematical morphology', IET Renewable Power Generation, Vol. 14, No. 12, pp.2089-2099, https://doi.org/10.1049/iet-rpg.2019.1240

[112] Radhakrishnan, R.M., Sankar, A. and Rajan, S. (2020) 'A combined islanding detection algorithm for grid connected multiple microgrids for enhanced microgrid utilisation', International Transactions on Electrical Energy Systems, Vol. 30, No. 2, https://doi.org/10.1002/2050-7038.12232

[113] Rajaraman, P., et al. (2018) 'Robust fault analysis in transmission lines using Synchrophasor measurements', Protection and Control of Modern Power Systems, Vol. 3, No. 1, https://doi.org/10.1186/s41601-018-0082-4

[114] Rajeev, A. and Binu Ben Jose, D.R. (2017) 'Identifying the fault location in distribution feeders with optimally placed PMU'S', Journal of Electrical Engineering, Vol. 17, No. 2, pp.1-8,

[115] Rajpoot, S.C., et al. (2021) 'A Dynamic-SUGPDS Model for Faults Detection and Isolation of Underground Power Cable Based on Detection and Isolation Algorithm and Smart Sensors', Journal of Electrical Engineering and Technology, Vol. 16, No. 4, pp.1799-1819, https://doi.org/10.1007/s42835-021-00715-7

[116] Rao, A.V.K., et al. (2022) 'A Faulty Line Detection Technique for Series Compensated Line using Synchrophasor Data', Journal of The Institution of Engineers (India): Series B, Vol. 103, No. 5, pp.1407-1413, https://doi.org/10.1007/s40031-022-00736-4

[117] Rao, J.T., et al. (2022) 'Synchrophasor Assisted Power Swing Detection Scheme for Wind Integrated Transmission Network', IEEE Transactions on Power Delivery, Vol. 37, No. 3, pp.1952-1962, https://doi.org/10.1109/TPWRD.2021.3101846

[118] Rezaeian Koochi, M.H., Dehghanian, P. and Esmaeili, S. (2020) 'PMU Placement with Channel Limitation for Faulty Line Detection in Transmission Systems', IEEE Transactions on Power Delivery, Vol. 35, No. 2, pp.819-827, https://doi.org/10.1109/TPWRD.2019.2929097

[119] Rezaeieh, M.R.H., Bolandi, T.G. and Jalalat, S.M. (2023) 'A novel approach for resilient protection of AC microgrid based on differential phase angle of superimposed complex power', Sustainable Energy, Grids and Networks, Vol. 34, No., https://doi.org/10.1016/j.segan.2023.101024

[120] Rinaldi, G., et al. (2021) 'Adaptive dual-layer super-twisting sliding mode observers to reconstruct and mitigate disturbances and communication attacks in power networks', Automatica, Vol. 129, No., https://doi.org/10.1016/j.automatica.2021.109656

[121] Rizvi, S.M.H., Sadanandan, S.K. and Srivastava, A.K. (2021) 'Data-Driven Short-Term Voltage Stability Assessment Using Convolutional Neural Networks Considering Data Anomalies and Localization', IEEE Access, Vol. 9, No.,

pp.128345-128358, https://doi.org/10.1109/ACCESS.2021.3107248

[122] Rovatsos, G., et al. (2017) 'Statistical Power System Line Outage Detection Under Transient Dynamics', IEEE Transactions on Signal Processing, Vol. 65, No. 11, pp.2787-2797, https://doi.org/10.1109/TSP.2017.2673802

[123] Saha Roy, B.K., et al. (2017) 'Faulty Line Identification Algorithm for Secured Backup Protection Using PMUs', Electric Power Components and Systems, Vol. 45, No. 5, pp.491-504, https://doi.org/10.1080/15325008.2016.1266417

[124] Saifuddin, M.R.B.M., et al. (2019) 'Apprehending Fault Crises for an Autogenous Nanogrid System: Sustainable Buildings', IEEE Systems Journal, Vol. 13, No. 3, pp.3254-3265, https://doi.org/10.1109/JSYST.2018.2853078

[125] Samantaray, S.R. and Kamwa, I. (2022) 'A Missing Data Tolerant Wide-Area Back-Up Protection Scheme for Transmission Network', IEEE Access, Vol. 10, No., pp.88001-88011, https://doi.org/10.1109/ACCESS.2022.3200549

[126] Seyedi, Y. and Karimi, H. (2018) 'Coordinated protection and control based on synchrophasor data processing in smart distribution networks', IEEE Transactions on Power Systems, Vol. 33, No. 1, pp.634-645, https://doi.org/10.1109/TPWRS.2017.2708662

[127] Seyedi, Y., Karimi, H. and Grijalva, S. (2017) 'Distributed generation monitoring for hierarchical control applications in smart microgrids', IEEE Transactions on Power Systems, Vol. 32, No. 3, pp.2305-2314, https://doi.org/10.1109/TPWRS.2016.2610322

[128] Seyedi, Y., et al. (2022) 'A Supervised Learning Approach for Centralized Fault Localization in Smart Microgrids', IEEE Systems Journal, Vol. 16, No. 3, pp.4060-4070, https://doi.org/10.1109/JSYST.2021.3112710

[129] Seyedi, Y., et al. (2020) 'A New Approach to Reliability Assessment and Improvement of Synchrophasor Communications in Smart Grids', IEEE Transactions on Smart Grid, Vol. 11, No. 5, pp.4415-4426, https://doi.org/10.1109/TSG.2020.2993944

[130] Shabani, H.R., Kalantar, M. and Hajizadeh, A. (2022) 'Real-Time Transient Instability Detection in the Power System With High DFIG-Wind Turbine Penetration via Transient Energy', IEEE Systems Journal, Vol. 16, No. 2, pp.3013-3024, https://doi.org/10.1109/JSYST.2021.3079253

[131] Shadi, M.R., Ameli, M.T. and Azad, S. (2022) 'A real-time hierarchical framework for fault detection, classification, and location in power systems using PMUs data and deep learning', International Journal of Electrical Power and Energy Systems, Vol. 134, No., https://doi.org/10.1016/j.ijepes.2021.107399

[132] Shafiei Chafi, S.C., Afrakhte, H. and Borghetti, A. (2023) 'μPMU-based islanding detection method in power distribution systems', International Journal of Electrical Power and Energy Systems, Vol. 151, No., https://doi.org/10.1016/j.ijepes.2023.109102

[133] Shanmugapriya, J. and Baskaran, K. (2023) 'Rapid Fault Analysis by Deep Learning-Based PMU for Smart Grid System', Intelligent Automation and Soft Computing, Vol. 35, No. 2, pp.1581-1594, https://doi.org/10.32604/iasc.2023.024514

[134] Sharma, N.K. and Samantaray, S.R. (2019) 'Assessment of PMU-based wide-area angle criterion for fault detection in microgrid', IET Generation, Transmission and Distribution, Vol. 13, No. 19, pp.4301-4310, https://doi.org/10.1049/iet-gtd.2019.0027

[135] Sharma, N.K. and Samantaray, S.R. (2020) 'PMU Assisted Integrated Impedance Angle-Based Microgrid Protection Scheme', IEEE Transactions on Power Delivery, Vol. 35, No. 1, pp.183-193, https://doi.org/10.1109/TPWRD.2019.2925887

[136] Sharma, P. and Saxena, A. (2017) 'Critical investigations on performance of ANN and wavelet fault classifiers', Cogent Engineering, Vol. 4, No. 1, https://doi.org/10.1080/23311916.2017.1286730

[137] Shazdeh, S., Golpîra, H. and Bevrani, H. (2023) 'A PMU-based back-up protection scheme for fault detection considering uncertainties', International Journal of Electrical Power and Energy Systems, Vol. 145, No., https://doi.org/10.1016/j.ijepes.2022.108592

[138] Sheta, A.N., Abdulsalam, G.M. and Eladl, A.A. (2021) 'Online tracking of fault location in distribution systems based on PMUs data and iterative support detection', International Journal of

Electrical Power and Energy Systems, Vol. 128, No., https://doi.org/10.1016/j.ijepes.2021.106793

[139] Sodin, D., et al. (2021) 'Advanced edge-cloud computing framework for automated PMU-based fault localization in distribution networks', Applied Sciences (Switzerland), Vol. 11, No. 7, https://doi.org/10.3390/app11073100

[140] Soni, B.P., et al. (2018) 'Identification of generator criticality and transient instability by supervising real-time rotor angle trajectories employing RBFNN', ISA Transactions, Vol. 83, No., pp.66-88, https://doi.org/10.1016/j.isatra.2018.08.008

[141] Sreelekha, V. and Prince, A. (2023) 'ANFIS-Based Fault Distance Locator With Active Power Differential-Based Faulty Line Identification Algorithm for Shunt and Series Compensated Transmission Line Using WAMS', IEEE Access, Vol. 11, No., pp.91500-91510, https://doi.org/10.1109/ACCESS.2023.3307466

[142] Srivastava, A. and Parida, S.K. (2022) 'Data driven approach for fault detection and Gaussian process regression based location prognosis in smart AC microgrid', Electric Power Systems Research, Vol. 208, No., https://doi.org/10.1016/j.epsr.2022.107889

[143] Srivastava, A., et al. (2023) 'Transmission Line Protection Using Dynamic State Estimation and Advanced Sensors: Experimental Validation', IEEE Transactions on Power Delivery, Vol. 38, No. 1, pp.162-176, https://doi.org/10.1109/TPWRD.2022.3184479

[144] Su, H.Y. and Liu, T.Y. (2018) 'Enhanced-online-random-forest model for static voltage stability assessment using wide area measurements', IEEE Transactions on Power Systems, Vol. 33, No. 6, pp.6696-6704, https://doi.org/10.1109/TPWRS.2018.2849717

[145] Sun, D., et al. (2023) 'Development of Synchronized Waveform Measurement and Its Application on Fault Detection', IEEE Transactions on Instrumentation and Measurement, Vol. 72, No., https://doi.org/10.1109/TIM.2023.3315390

[146] Swain, K., et al. (2015) 'IoT Based Transmission Line Fault Classification Using Regularized RBF-ELM and Virtual PMU in a Smart Grid', CMES - Computer Modeling in Engineering and Sciences, Vol. 145, No. 2, pp.1993-2015,

[147] Swain, K.B., Mahato, S.S. and Cherukuri, M. (2019) 'Expeditious situational awareness-based transmission line fault classification and prediction using synchronized phasor measurements', IEEE Access, Vol. 7, No., pp.168187-168200, https://doi.org/10.1109/ACCESS.2019.2954337

[148] Usman, M.U. and Faruque, M.O. (2019) 'Applications of synchrophasor technologies in power systems', Journal of Modern Power Systems and Clean Energy, Vol. 7, No. 2, pp.211-226, https://doi.org/10.1007/s40565-018-0455-8

[149] Veerakumar, N., et al. (2023) 'PMU-based Real-time Distribution System State Estimation Considering Anomaly Detection, Discrimination and Identification', International Journal of Electrical Power and Energy Systems, Vol. 148, No., https://doi.org/10.1016/j.ijepes.2022.108916

[150] Velpula, R., et al. (2023) 'A simple approach for the protection of EHV transmission lines', Electric Power Systems Research, Vol. 224, No., https://doi.org/10.1016/j.epsr.2023.109744

[151] Vosughi, A., Sadanandan, S.K. and Srivastava, A.K. (2022) 'Synchrophasor-Based Event Detection, Classification, and Localization Using Koopman, Transient Energy Matrix, Best Worth Method, and Dynamic Graph', IEEE Transactions on Power Delivery, Vol. 37, No. 3, pp.1986-1996, https://doi.org/10.1109/TPWRD.2021.3102148

[152] Wang, C., et al. (2021) 'MILP-Based Fault Diagnosis Model in Active Power Distribution Networks', IEEE Transactions on Smart Grid, Vol. 12, No. 5, pp.3847-3857, https://doi.org/10.1109/TSG.2021.3071871

[153] Wang, C. and Zhang, Y. (2015) 'Fault correspondence analysis in complex electric power systems', Advances in Electrical and Computer Engineering, Vol. 15, No. 1, pp.11-16, https://doi.org/10.4316/AECE.2015.01002

[154] Wu, X., et al. (2019) 'A Genetic-Algorithm Support Vector Machine and D-S Evidence Theory Based Fault Diagnostic Model for Transmission Line', IEEE Transactions on Power Systems, Vol. 34, No. 6, pp.4186-4194, https://doi.org/10.1109/TPWRS.2019.2922734

[155] Xing, J. and Mu, L. (2023) 'A Novel Islanding Detection Method for Distributed PV System Based on μpMUs', IEEE Transactions on Smart Grid, Vol. 14, No. 5, pp.3696-3706, https://doi.org/10.1109/TSG.2023.3236790

[156] Yang, B., et al. (2018) 'Cost-Efficient Low Latency Communication Infrastructure for Synchrophasor Applications in Smart Grids', IEEE Systems Journal, Vol. 12, No. 1, pp.948-958, https://doi.org/10.1109/JSYST.2016.2556420

[157] Yang, D., et al. (2019) 'Fault Diagnosis for Energy Internet Using Correlation Processing-Based Convolutional Neural Networks', IEEE Transactions on Systems, Man, and Cybernetics: Systems, Vol. 49, No. 8, pp.1739-1748, https://doi.org/10.1109/TSMC.2019.2919940

[158] Yang, F., et al. (2019) 'Detection and analysis of multiple events based on high-dimensional factor models in power grid', Energies, Vol. 12, No. 7, https://doi.org/10.3390/en12071360

[159] Yu, F., et al. (2019) 'Wide-area backup protection and protection performance analysis scheme using PMU data', International Journal of Electrical Power and Energy Systems, Vol. 110, No., pp.630-641, https://doi.org/10.1016/j.ijepes.2019.03.060

[160] Yu, S., et al. (2016) 'State Estimation of Doubly Fed Induction Generator Wind Turbine in Complex Power Systems', IEEE Transactions on Power Systems, Vol. 31, No. 6, pp.4935-4944, https://doi.org/10.1109/TPWRS.2015.2507620

[161] Zare, J., Aminifar, F. and Sanaye-Pasand, M. (2015) 'Synchrophasor-based wide-area backup protection scheme with data requirement analysis', IEEE Transactions on Power Delivery, Vol. 30, No. 3, pp.1410-1419, https://doi.org/10.1109/TPWRD.2014.2377202

[162] Zhang, T., et al. (2023) 'Fault diagnosis and protection strategy based on spatio-temporal multi-agent reinforcement learning for active distribution system using phasor measurement units', Measurement: Journal of the International Measurement Confederation, Vol. 220, No., https://doi.org/10.1016/j.measurement.2023.113291