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PMU-data assisted state estimation of distribution network with integrated renewables: a comprehensive review

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ABSTRACT

The variability and distributed nature of renewable energy sources (RES) pose challenges to real-time monitoring and control in distribution networks. Phasor measurement units (PMUs) provide high-precision, time-synchronized measurements, significantly improving state estimation (SE) accuracy in complex grids. This paper reviews SE in distribution systems using PMU data, focusing on challenges introduced by high-RES integration. Traditional techniques, such as weighted least squares (WLS), are analyzed, revealing limitations like reduced observability and accuracy due to RES intermittency. To address these challenges, advanced methods such as robust optimization, dynamic network reconfiguration, and decentralized control are explored, showing improved network reliability and adaptability under RES variability. Furthermore, innovative approaches like Bayesian non-parametric modelling are discussed, offering solutions to mitigate uncertainties and enhance grid flexibility. Case studies highlight the scalability and effectiveness of PMUs in extensive networks, showcasing their role in improving both SE precision and system stability. These findings underline the critical need for precise and integrated SE techniques to develop resilient, adaptable smart grids capable of accommodating the increasing penetration of RES, setting a foundation for future technological advancements.

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1. INTRODUCTION

The integration of renewable energy sources (RES), such as wind and solar photovoltaics (PV), into modern distribution networks presents significant challenges to grid efficiency, stability, and reliability [1]. RES variability and intermittency due to changing weather patterns make managing power flows and voltage stability more complex than with traditional generation, intensifying real-time monitoring difficulties for distribution network operators (DNOs) [2]. The general layout of a distribution grid with integrated renewables is shown in Figure 1 [3]. State estimation (SE), a key tool in transmission systems for optimizing grid performance, faces new challenges in distribution networks due to their radial topology, low X/R ratios, and high load variability, particularly with integrated RES. Traditional SE techniques, like the weighted least squares (WLS) method, often fall short in this context, as real-time estimation is hindered by a lack of wide-scale, high-resolution measurement data. Phasor measurement units (PMUs) offer a potential solution by providing high-frequency, synchronized voltage and current phasor data, significantly enhancing SE resolution [4]. However, logistical and financial challenges limit PMU deployment at the distribution level, requiring optimized placement strategies and hybrid approaches that integrate PMU and SCADA data. This review provides a comprehensive examination of SE in distribution networks with integrated renewables, focusing on PMU-assisted methods. It evaluates PMU integration efficacy, identifies shortcomings in existing SE approaches, and explores advanced techniques, such as machine learning, to address the unique challenges posed by modern RES-integrated grids.

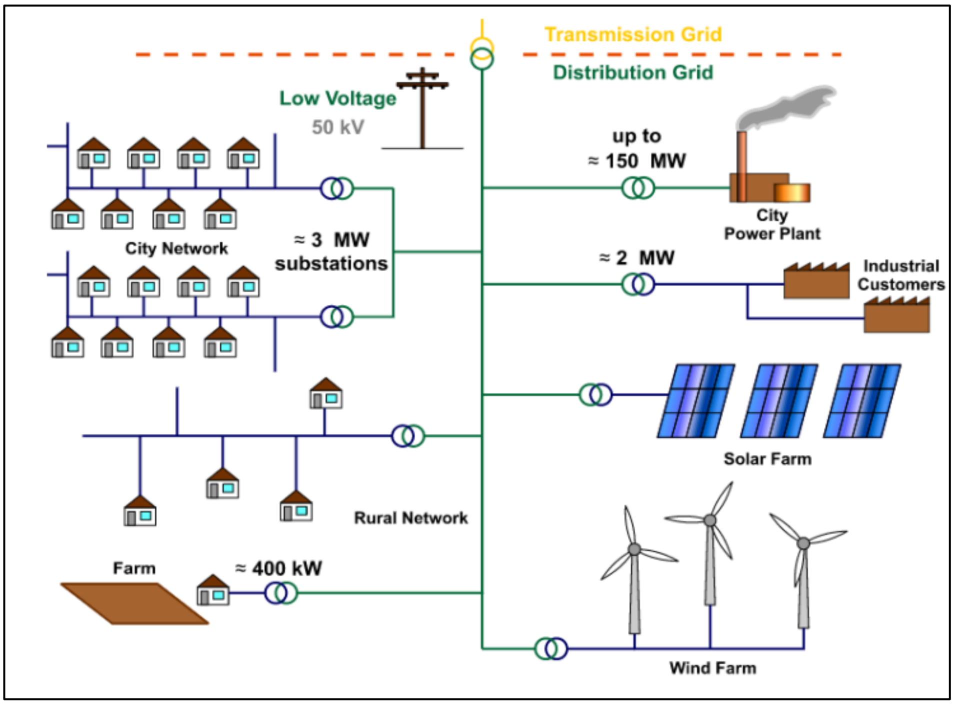


Figure 1. General layout of distribution grid with integrated renewables [3]

SE is critical for maintaining reliability in distribution networks with increasing RES integration, such wind and PV [5]. PMUs significantly enhance SE capabilities with high-precision, real-time data, but the integration of distributed generation (DG) and RES introduces challenges like data uncertainty, network observability, and measurement synchronization. Several works address these challenges by improving SE methods. For instance, [6] proposed a joint topology and SE approach using Bayesian non-parametric modeling to enhance accuracy and adaptability in dynamic grids. Another study [7] applied deep neural networks for topology and SE in RES systems, although real-time large-scale deployment poses challenges due to computational demands. Other studies [8], [9] highlight PMU-based SE benefits, improving fault detection, situational awareness, and grid stability in high-RES systems.

To further improve SE in RES-integrated systems, optimization strategies and sophisticated algorithms are investigated. For example, [10] proposed a cost-effective PMU placement framework, while [11] suggested L-1 regularized forecasting-aided SE to minimize errors in high-RES systems. Another study [12] incorporated multi-source data, addressing topology errors and outage detection in SE frameworks. Research also focuses on multi-source data integration, such as PMUs, μPMUs, and smart meters, to manage uncertainty in distribution networks [13]. Methods that model non-Gaussian uncertainties in measurements, like [14], have improved SE accuracy but face challenges in real-time anomaly detection. In contrast [15], used GMM-PSEs and KL divergence to address dynamic topology and DG uncertainties. Other advanced techniques include multi-area state estimation (MASE) frameworks [16] and SE performance in complex and unbalanced systems is greatly enhanced by Chen *et al.* [17], who offers a more realistic depiction of DG variability. An additional study [18] underlined the necessity of precise synchronization of various data sources, including SCADA and PMU, and suggested a delay estimation technique to address synchronization problems, thereby improving the multi-source SE's reliability. Pseudo-measurement modeling is crucial for SE in RES-integrated networks, as demonstrated by [19], which used entropy-weighted support vector machines (SVM) to model DG uncertainties. However, managing high uncertainty levels remains difficult. Robust interval state estimation (ISE) methods, like in [20], address these uncertainties by providing tight bounds on state variables.

PMU integration has been thoroughly explored for enhancing observability in SE frameworks. For example [21], proposed a robust PMU placement strategy for ensuring system observability while minimizing PMU deployment costs. Similarly, another study [22] concentrated on DGs, zero injection buses (ZIBs), and network reconfigurations while optimizing D-PMU placement to guarantee system observability. Machine learning techniques are increasingly integrated into SE frameworks, such as in [23], which used synchrophasors for topology identification and SE. Hybrid optimization techniques have also been applied, such as [24], which developed a robust PSOS-CGSA method for SE in unbalanced networks. Other studies focus on real-time SE frameworks for managing voltage stability in DG-heavy networks [25]. Although SE processes have improved, challenges remain, such as managing inaccurate measurement data and system errors, addressed by techniques like the extended Kalman filter in [26] and augmented SE in [27].

Despite these advancements, several research gaps remain. Scalability challenges persist when applying SE frameworks to large, dynamic networks with high DG penetration. Managing uncertainties from DG remains a significant obstacle, particularly in networks with varying observability levels. Synchronizing data from multiple sources remains another critical issue, necessitating further optimization in PMU placement strategies.

This review addresses these challenges by providing a comprehensive examination of SE in distribution networks with integrated renewables, focusing on PMU-assisted methods. It evaluates PMU integration efficacy, identifies shortcomings in existing SE approaches, and explores advanced techniques, such as machine learning, robust optimization, and hybrid algorithms, to address the unique challenges posed by modern RES-integrated grids.

The main contributions of this review include:

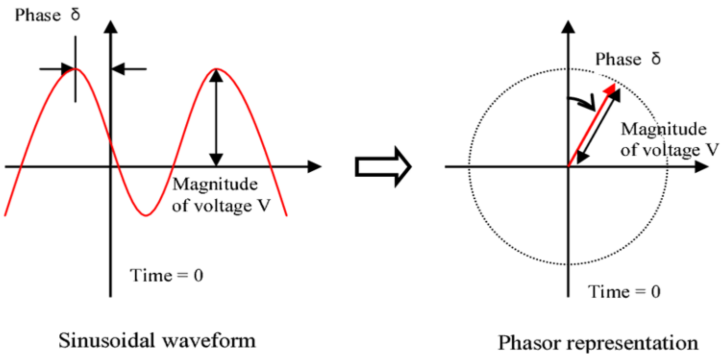
- A critical analysis of the methodologies and advancements in PMU-assisted SE frameworks for distribution networks with integrated renewables.
- A detailed comparison of traditional and modern SE techniques, including WLS and PMU-based approaches, highlighting improvements in accuracy and non-linearity reduction.
- A focus on challenges such as renewable variability, data synchronization, and DG uncertainties, with potential solutions for improving SE in distribution networks.
- Suggestions for future research directions, including cybersecurity risks in PMU data integration and real-time SE in renewable-heavy grids.

The paper is structured as follows: section 2 outlines the strategy for PMU deployment in distribution networks. Section 3 presents the SE methodology, detailing its formulation and integration. Section 4 offers a comparative evaluation of conventional and proposed approaches. Section 5 critically examines recent advancements in SE techniques tailored for distribution systems with high renewable energy source (RES) integration. Finally, Section 6 concludes the study by highlighting the pivotal role of PMU-assisted SE in improving the observability, accuracy, and stability of modern RES-integrated distribution networks.

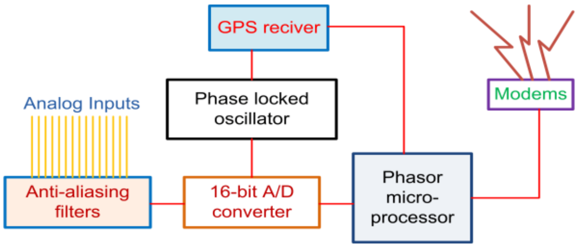
2. PHASOR MEASUREMENT UNIT

IEEE standards include detailed descriptions of synchronized phasor technology. A PMU is an instrument that can measure waveforms of voltage and/or current and calculate their frequency, synchrophasors, and rate of change of frequency (ROCOF, also known as df/dt) concerning a single coordinated universal time (UTC). After PMUs are installed at a substation, standard instrument transformers are frequently used to link them to the electrical grid. A synchrophasor is an absolute measurement of the phase angle and magnitude at a specific point in time. A sine wave's representation and its phasor representation are shown in Figure 2(a).

The general block diagram of the PMU is displayed in Figure 2(b). Wherein the voltage and current inputs to a PMU are obtained directly from the current transformer (CT) and the potential transformer (PT), respectively. A predetermined sample rate is used when utilizing a synchronized GPS clock. Power grids use the GPS signal, just like other commercial (non-military) uses. The central frequency of this signal is 1575.42 MHz, and its bandwidth is 2.046 MTz. It is available to all users. GPS can be advantageous for electricity grids because of its high degree of timing precision, free availability, and global coverage. Still, spoofing is possible. Another application for a phase-locked oscillator in the second is time tag generation (output with phasors). After passing via a filter and an analog-to-digital converter, the analog voltage and current signals are time-tagged. PMU then uses the digital data to calculate the frequency, ROCOF, voltage and current phasors, and binary information. This data is typically located at primary substations and sent to phase data concentrators (PDCs) within frames to store it for later offline assessments or online system health monitoring.



(a)



(b)

Figure 2. A comparative visualization of phasor measurement concepts; (a) A sine wave representation versus its corresponding phasor form and (b) general block diagram illustrating the functional components of a PMU

2.1. Phasor measurement unit installation in distribution networks

Early in the 1980s, Virginia Tech's Power System Research Laboratory produced the first PMU prototype. Many companies soon started working on synchrophasor technology. PMUs are crucial to the control and monitoring of power systems. They provide synchronized voltage and current phasor readings across the entire network. PMUs significantly enhance the observability, fault detection, and grid stability of distribution networks (DNs). Analysis of PMU deployment procedures in distribution networks evaluates different strategies for setting up and utilizing PMUs to monitor grid condition effectively [28]. The optimal deployment strategy depends on several factors, such as the network configuration, the monitoring objectives, the resources that are available, and any applicable laws. By creating effective strategy for PMU deployment utilities and grid operators can enhance their capacity for distribution network grid monitoring and control. Installing PMUs at key nodes in the distribution network, like substations or centralized control centers, is known as centralized deployment. On the other hand, distributed deployment enables wider coverage by positioning PMUs at different points in the grid, such as distribution feeders, distributed energy resource (DER) interconnection points, and critical nodes. PMUs are positioned both centrally and dispersedly across the network for improved observability in a hybrid deployment, which blends centralized and distributed techniques. By dynamically placing PMUs based on grid conditions and particular monitoring objectives, adaptive deployment adopts a more flexible approach and ensures responsive coverage to shifting system dynamics. Lastly, to achieve efficient deployment, cost-optimized deployment balances network topology, monitoring requirements, and budgetary constraints to determine the most cost-effective PMU locations using optimization algorithms [29]. Consequently, distribution network PMU adoption necessitates meticulous analysis of network dynamics, integration of RES, and communication infrastructure. Grid operation must strike a balance between observability, redundancy, and precision to be durable and efficient.

3. METHOD

Figure 3 shows the methodology used for this review. This paper conducts a critical review of SE of distribution networks with integrated renewables aided by PMU data that has been published in the last six years, up until 2024 (2019–2024). Preferred reporting items for systematic reviews and meta-analysis (PRISMA) [30] were used to guide the selection of the articles. This review's methodology is set up to ensure a thorough, in-depth, and consistent analysis of the field. An organized methodology was used, starting with a thorough search of the literature through several of the most well-known scientific databases, such as IEEE Xplore, ScienceDirect, Google Scholar, and Web of Science. To pertinent studies, search terms like "PMU-assisted SE," "renewable energy integration," "distribution network monitoring," "PMU placement optimization," and "cybersecurity in smart grids" were used. These topics included PMU placement optimization, the integration of renewable energy, and SE techniques. The title and keywords were used to filter the search results. After removing duplicates, 106 articles remained from the 180 that were gathered after the search. The conclusions and abstracts of the chosen papers were carefully examined to ascertain their applicability to the particular goals of the investigation. Two impartial reviewers were tasked with evaluating each paper during this screening phase, guaranteeing a thorough and objective evaluation procedure. Fifty-five articles were deemed eligible for additional examination after this screening process. Following selection, the full text of these articles was subjected to a thorough review process by three impartial reviewers, who assessed the methodology, results, discussions, and conclusions. After that, the reviewers contrasted their analyses until they came to a mutual understanding. Ultimately, only 37 publications were chosen for critical review after being judged pertinent.

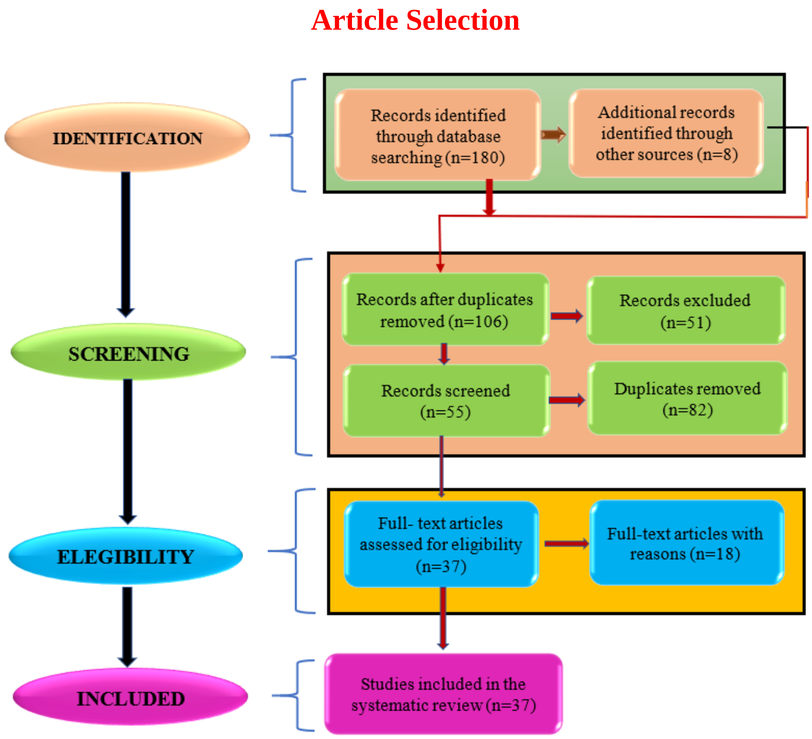


Figure 3. Review methodology

3.1. Mathematical formulation of state estimation in distribution networks: traditional vs novel methods

SE in distribution networks involves determining the voltage magnitude and angle at different nodes or buses, along with the overall electrical state of the power system. Accurate SE is essential for real-time monitoring, control, and optimization, particularly in networks integrating RES and advanced technologies like PMUs [31].

3.1.1. Traditional method for state estimation

The conventional SE approach in power systems is based on the WLS method [32]. This method relies on traditional measurements such as power injections, active and reactive power flows, and bus voltage magnitudes. Below is a detailed explanation of its components:

a. State variables (X)

Determining the system's state, which normally consists of voltage magnitude ($|V_i|$) and voltage angle (θ) at each bus i, is the main goal of SE. In a system with N buses, the state vector is:

$$X = [|V_1|\ |V_2| \dots\dots |V_N|\ \theta_1\ \theta_2 \dots\dots \theta_N]^T \tag{1}$$

b. Measurement vector (Z)

The available measurements can include: bus voltage magnitudes V_i; active power flows P_{ij}; reactive power flows Q_{ij}; power injections P_i, Q_i; m represents the number of measurements. Now measurement vector is:

$$z = [z_1\ z_2\ \ldots .\ z_m]^T \tag{2}$$

c. Measurement model

A non-linear function h(x) defines the relationship between the measurements (z) and the state variables (x), where:

$$Z = h(x) + e \tag{3}$$

Here: the non-linear measurement function h(x) is used to map the measurements to the state vector. The measurement error, or noise, is represented by the symbol e. It is commonly assumed to be Gaussian with zero mean and covariance coefficient R.
The following model represents the active power flow P_{ij} between two buses, i and j:

$$P_{ij} = |V_i||V_j|\ (G_{ij}\cos(\theta_i - \theta_j) +\ G_{ij}\sin(\theta_i - \theta_j)) \tag{4}$$

where the conductance and susceptance of the line are denoted by G_{ij} and B_{ij}.

d. WLS formulation

SE is formulated as an optimization problem to minimize the difference between the measured values (z) and the estimated values (h(x)):

$$J(x) = (z - h(x))^T R^{-1}(z - h(x)) \tag{5}$$

where R represents the measurement noise covariance matrix.
The non-linear optimization problem is solved by the WLS method through an iterative technique, typically Newton-Raphson. Every iteration, k, updates the state vector as (6):

$$x^{k+1} = x^k + \Delta\, x \tag{6}$$

In this case, the correction term Δx is computed as (7):

$$\Delta\, x = (H^T R^{-1} H)^{-1} H^T R^{-1}(z - h(x^k)) \tag{7}$$

The measurement function's partial derivatives with respect to the state variables are contained in the Jacobian matrix, or H.

$$H = \frac{\partial h(x)}{\partial x} \tag{8}$$

This iterative process keeps going until the correction term Δx gets small enough, or until the state estimates converge.

e. Observability

Observability ensures that the available measurements are sufficient to uniquely determine the state variables. Traditional methods use numerical or topological observability analysis to verify system observability before estimation.

3.1.2. Novel method for state estimation: phasor measurement unit-assisted state estimation

Modern SE techniques leverage PMU to improve accuracy and reduce dependency on conventional measurements.

a. PMU-based measurement

PMUs measure voltage and current phasors in real time, providing direct measurements of both magnitude and angle. Compared to conventional SCADA-based measurements, these measurements are more accurate and simplify SE [33].
The PMU measurement model is easier and linear.

$$z_{PMU} = h_{PMU}(x) + e_{PMU} \tag{9}$$

Here the voltages and currents are directly measured in $h_{PMU}(x)$. In iterative techniques such as Newton-Raphson, the reduced non-linearity greatly accelerates convergence. SE process changes the structure of the problem:

- Linear PMU measurements

Since PMUs measure voltage magnitudes and angle directly, the need for extensive non-linear transformation is reduced. This speed up calculations.

- Hybrid measurement model

Traditional SCADA and PMU data are now combined in the SE problem. After combination, the measurement vector becomes:

$$z = \begin{bmatrix} z_{SCADA} \\ z_{PMU} \end{bmatrix} \tag{10}$$

The measurement function which corresponds to this is (11):

$$h(x) = \begin{bmatrix} h_{SCADA}(x) \\ h_{PMU}(x) \end{bmatrix} \tag{11}$$

The WLS objective function remains the same, but the addition of linear PMU measurements improves performance:

$$J(x) = (z - h(x))^T R^{-1}(z - h(x)) \tag{12}$$

b. Observability

PMU measurements greatly improve the accuracy and robustness of SE in the WLS framework, especially in complex networks with high integration of renewable energy. The deployment of PMUs enhances system observability by providing additional measurements, even in low-measurement scenarios. Hybrid models address observability gaps, ensuring reliable SE in modern, renewable-rich networks.

While traditional SE methods based on WLS have served power systems well, the integration of PMUs marks a significant leap forward. By combining SCADA and PMU data, hybrid approaches offer improved accuracy, faster convergence, and enhanced observability, making them indispensable for active distribution networks with renewable energy integration.

3.1.3. Renewable energy sources integration

Integrating RES into distribution networks poses several challenges due to their intermittent and variable nature, as well as their impact on grid stability, power quality, and overall network reliability [34]. These challenges are driven by the characteristics of RES such as solar and wind, which vary depending on environmental conditions. The following are some of the key challenges and their potential solutions.

a. Key challenges in RES integration

The integration of RES into distribution networks poses several significant challenges (as illustrated in Figure 4) [35]. One of the most significant issues is the intermittent and variable nature of RES, such as solar and wind power, which can cause fluctuations in power generation and complicate grid stability and reliability.

The distributed nature of RES, which is often located at the grid's edges, complicates voltage control, power flow management, and protection coordination. The limited observability of traditional distribution networks, which were not designed for high levels of distributed generation, causes these issues, making it difficult to monitor and manage RES' dynamic behavior. Furthermore, the uncertainty in RES power output makes it difficult to accurately forecast generation and balance supply and demand. This can strain grid operations and increase reliance on ancillary services to keep the system stable.

The seamless integration of RES is further hindered by inadequate grid infrastructure and investments in smart technologies, such as sophisticated metering systems and communication networks. In conclusion, the adoption of the technologies and practices required for RES integration may be hindered by regulatory and market barriers, such as out-of-date policies and a lack of financial incentives. Figure 4 shows the key challenges in RES integration in distribution network.

b. Potential solutions for RES integration

To effectively integrate RES into distribution networks, innovative approaches are essential to manage the inherent variability and uncertainty. Advanced SE techniques, such as those utilizing PMUs, provide precise real-time monitoring and forecasting, which enhances grid observability and control. These techniques, in combination with traditional SCADA systems, allow grid operators to make accurate, timely decisions and better handle the intermittent nature of RES. Alongside SE, robust optimization and forecasting models are crucial for predicting generation patterns and managing load demand. These models, enhanced by artificial intelligence (AI), offer improved accuracy and help optimize grid operations, ensuring stability even under unpredictable conditions [36].

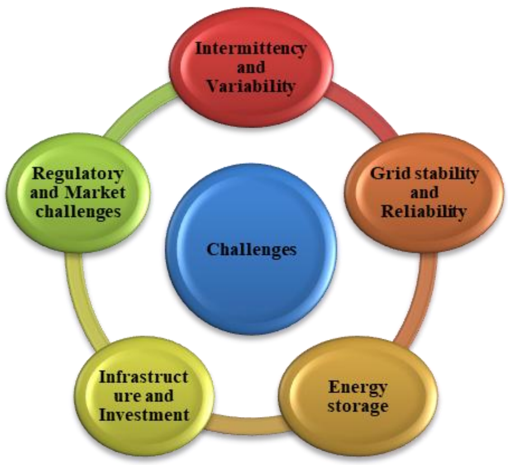


Figure 4. Key challenges in RES integration

Dynamic network reconfiguration is another key solution, enabling real-time adjustments to the grid’s topology, rerouting power flows to prevent overload and congestion during high renewable output. This flexibility enhances the grid's resilience, particularly in handling localized fluctuations in energy production. Decentralized and multi-area control further strengthens this approach by distributing control responsibilities, allowing more localized and efficient grid management. By enabling peer-to-peer energy trading and more granular control over DER, decentralized control improves energy efficiency and scalability.

c. Incorporating cybersecurity in PMU-assisted SE frameworks

The reliance on real-time data acquisition and communication in PMU-based systems exposes distribution networks to potential cyber threats, including data spoofing, denial of service (DoS) attacks, and unauthorized access to sensitive system parameters. These vulnerabilities can compromise SE accuracy, grid stability, and overall reliability.

To mitigate these risks, robust cybersecurity measures are imperative:

- Encryption and authentication protocols: implementing advanced encryption standards (AES) and multi-factor authentication ensures secure communication between PMUs and control centers, preventing unauthorized access.
- Intrusion detection systems (IDS): deploying machine learning-based IDS can identify and respond to anomalous behavior in data transmission, enhancing network resilience.
- Blockchain technology: incorporating blockchain for data validation creates a tamper-proof ledger, ensuring data integrity across decentralized networks.
- Redundancy and backup systems: establishing redundant communication paths and real-time backup mechanisms mitigates the risk of data loss or corruption during attacks.
- Regular security audits: routine penetration testing and software updates ensure that vulnerabilities are identified and patched proactively.

Future research should explore integrating these cybersecurity measures with advanced PMU-based SE frameworks, balancing real-time performance with robust security. Additionally, a focus on scalable, lightweight security algorithms can address computational constraints in large, dynamic networks with high renewable penetration.

3.1.4. Enhanced observability with phasor measurement units and renewable energy sources

PMU provides real-time, synchronized data at multiple network points, significantly enhancing network observability. Compared to a traditional SCADA system, fewer PMUs are needed to make a system observable. Traditional SCADA-based methods, which mainly rely on non-linear are models and a large number of measurements, have been replaced by novel PMU-assisted methods that offer faster convergence, better observability, and increased robustness in the mathematical formulation of SE [37], [38]. The new techniques better meet the requirements of contemporary distribution networks integrating distributed generation and renewable energy since they make use of robust optimization and linear measurement functions. The general network configuration is depicted in Figure 5. The network topology and the electrical characteristics of the power system components make up the network model. PMUs supply the voltage, current, and angle needed to estimate the unknown states of the system. Direct angle measurements are included for SE using PMU measurements in addition to the classical measurement set. The WLS state estimate and PMU measurements must be modelled as a linear measurement set to improve the output. A model demonstrates how measurements, system variables, and measurement noise are correlated [39].

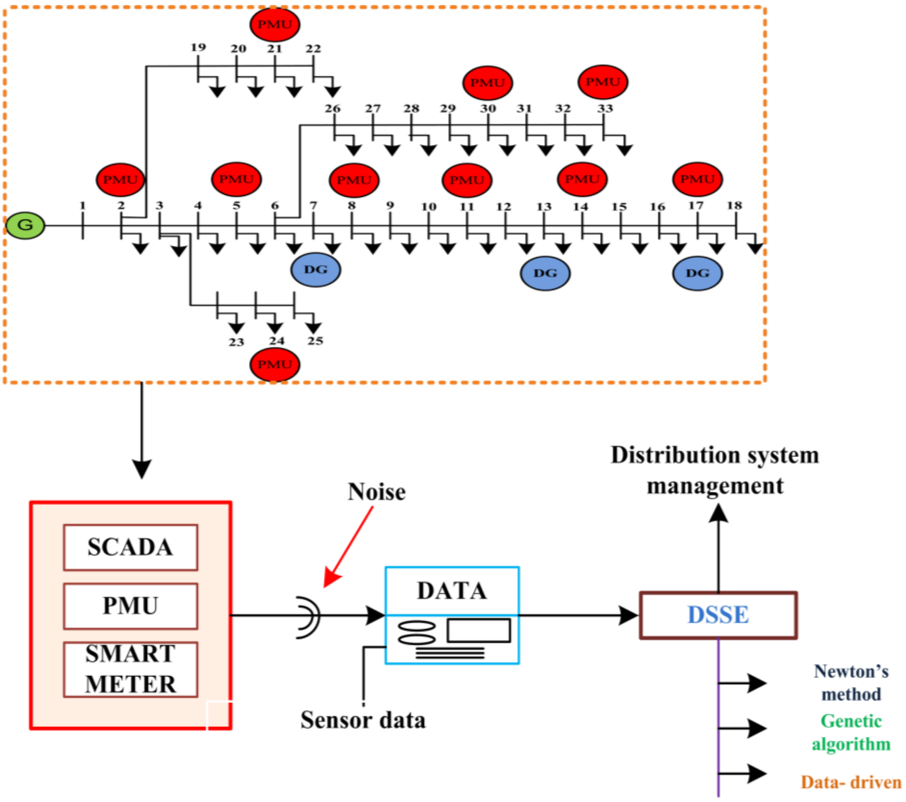


Figure 5. Network configuration for SE

4. RESULTS

4.1. Comparison of traditional and novel method of state estimation

The study of distribution network SE has undergone substantial development, with conventional techniques providing the foundation for preserving grid stability, particularly in simpler, more predictable systems. Nonetheless, new approaches have been developed as a result of the growing integration of RES and the growing complexity of contemporary distribution networks. These more recent methods take advantage of cutting-edge technologies like PMUs, optimization algorithms, and machine learning to tackle issues like unobservability, dynamic topology changes, and real-time performance. A comparative analysis is performed to assess the advantages and disadvantages of both traditional and innovative approaches. Important factors like measurement type, function, convergence speed, observability criteria, robustness, and optimization are the main subjects of the analysis. Table 1 provides an overview of the key differences between innovative and traditional SE techniques, as well as an understanding of the benefits and drawbacks of each [40], [41].

The primary functions of SCADA systems in conventional SE techniques are the collection of voltage magnitudes and active/reactive power flows. Due to the non-linear nature of these measurements, the estimation process converges more slowly. Furthermore, traditional approaches are typically less resilient to noise and uncertainties and suffer from low observability, necessitating a high number of measurements to fully monitor the network. These methods' optimization techniques, such as WLS, have limited robustness. However, new PMU-assisted techniques make use of PMUs, which offer linear or hybrid measurement functions and provide both voltage and current phasors, including magnitude and angle.

Table 1. Comparative analysis between traditional and novel method

Aspect	Traditional method	Novel method (PMU-assisted)
Measurement type	SCADA: Voltage magnitudes, active/reactive power flows	PMU: Voltage and current phasors (magnitude and angle)
Measurement function	Non-linear	Linear (for PMUs) or hybrid
Convergence speed	Slower (due to non-linearity)	Faster speed (due to linearity)
Observability	Low observable (limited measurement)	Enhanced due to PMU
Robustness	Less robust due to noise and uncertainties	More robust
Optimization	Traditional WLS and LAV	Advanced approach, ML based, and hybrid approach

This greatly improves observability and accelerates convergence, enabling thorough monitoring with fewer devices. PMU-assisted approaches further enhance performance in modern-day distribution networks by being more resilient, better able to manage uncertainty, especially from RES, and by making use of cutting-edge optimization techniques like robust and multi-objective frameworks.

4.2. Review and comparison of existing studies

To maintain grid stability and reliability, the increasing integration of RES into modern distribution networks has made SE technique advancements necessary. Several studies have put forward various approaches to deal with issues like fault detection, network observability, and the dynamic nature of RES. A comparative analysis has been carried out to gain a deeper understanding of the contributions made by these studies which includes different type of SE techniques, the extent of RES integration, and the primary conclusions put forth by each study are important factors that are taken into account. Table 2 (see Appendix) [8]-[10], [15], [22]-[27], [41]-[53] provides a systematic comparison of these studies, emphasizing the different approaches used for SE in RES-integrated distribution networks, along with their applications, limitations, and methodology.

5. DISCUSSION

Table 2 (see Appendix) provides a comprehensive overview of recent studies on SE methodologies in distribution networks integrated with RES. These studies highlight various approaches and innovations aimed at improving the accuracy, robustness, and adaptability of SE in dynamic and RES-rich environments. One notable approach is the use of Bayesian non-parametric modelling, which enhances SE accuracy and adaptability, especially in dynamic networks. Another study explores the application of deep neural networks (DNNs) for both state and topology estimation, improving accuracy in unobservable systems, which is crucial for networks with high-RES penetration. Additionally, several studies emphasize the role of PMUs in fault detection, noting improvements in fault localization within active distribution networks incorporating RES. Research on high PV penetration emphasizes its effect on grid stability and the need for advanced SE techniques to manage the complexity introduced by renewable sources. To optimize system observability while reducing costs, a cost-effective framework for PMU placement has been proposed, ensuring efficient deployment of PMUs in large-scale networks. Other studies investigate advanced forecasting techniques such as L-1 regularization, which helps to reduce estimation errors, while the integration of multi-source measurements enhances the robustness of SE. Real-time applications of SE, including micro-PMUs and smart meter data, are also explored for improved topology detection in RES-integrated systems. Additionally, advanced modelling techniques addressing non-Gaussian uncertainties and dynamic topologies are discussed, allowing for more accurate and adaptive SE in systems with high-RES variability. Augmented SE techniques are considered to address computational complexity, improving efficiency in real-time applications. Research also focuses on voltage issues and error estimation in multiterminal DC networks, which present unique challenges in comparison to AC systems. The introduction of a virtual reference for three-phase estimation and adaptive dynamic SE using interacting multiple model approaches further enhances the accuracy of SE in complex networks. Despite the advancements, several practical challenges persist. A major issue is the dependency on high-quality measurement data, as factors like noise, synchronization errors, and device calibration problems can degrade estimation accuracy. To address this, robust error-handling mechanisms and improvements in device reliability are necessary. The high cost of deploying PMUs also remains a challenge, particularly in large networks. While PMUs provide accurate and real-time data, their installation and maintenance can be expensive, so optimizing their placement is essential to reduce costs while maintaining system observability. Additionally, integrating PMUs with existing legacy systems is difficult because many traditional networks are not designed to handle the high-frequency data generated by PMUs, requiring significant hardware and software upgrades for seamless integration. Cybersecurity also emerges as a critical concern, particularly with the increased reliance on real-time data communication and PMU integration. The risk of cyberattacks, such as false data injection, can compromise the accuracy of SE, leading to erroneous operational decisions. Robust encryption, authentication protocols, and enhanced cybersecurity measures, including firewalls and IDS, are crucial to safeguarding data integrity. The literature also highlights several directions for future research. Studies on MASE frameworks are needed to address the complexities of large, interconnected distribution networks. Further advancements in load and PV estimation methods will be vital for accurately predicting the behaviour of renewable sources in distribution networks. Additionally, optimization of PMU placement through hybrid methods and pseudo-measurement strategies could improve the overall performance of SE systems. In conclusion, the body of research presented in Table 2 (see Appendix) illustrates significant advancements in SE for RES-integrated distribution networks, with improvements in accuracy, robustness, and adaptability. However, addressing the practical challenges of data quality, cost, integration, and cybersecurity remains critical to realizing the full potential of these methods in real-world applications.

6. CONCLUSION

This comprehensive review of PMU-data-assisted SE for distribution networks with integrated renewables demonstrates PMUs' transformative potential in improving grid observability, accuracy, and resilience. The integration of RES poses significant challenges, including uncertainty, variability, and the requirement for real-time monitoring and control. PMUs, with their ability to provide high-resolution, time-synchronized measurements, have emerged as an important tool for dealing with these issues. Researchers have shown that advanced methodologies such as robust optimization, machine learning, and adaptive SE frameworks improve SE accuracy, fault detection, and overall grid stability in active distribution networks. There are still a number of drawbacks, mainly with regard to the cost of deployment, computational complexity, and scalability to more expanding distribution networks. For wider adoption, it is imperative to address communication delays, implement cost-effective PMU placement strategies, and synchronize with other data sources like SCADA and smart meters. Additionally, more research is needed to find real-time solutions that can adapt to changing grid conditions due to the complexity of modern distribution networks, which have dynamic topologies and a variety of DERs.

Future efforts need to focus on overcoming these limitations by increasing the computational efficiency of SE algorithms, optimizing PMU placement for cost and coverage, and developing scalable solutions that can be applied to increasingly complex distribution networks. By overcoming these challenges, PMU-assisted SE will play a critical role in enabling the reliable integration of renewable energy into modern distribution networks, ensuring grid stability, and furthering the vision of smart, sustainable power systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Nida Khanam	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓
Mohd. Rihan					✓	✓				✓	✓	✓	✓	
Salman Hameed					✓	✓				✓	✓	✓	✓	

C	:	**C**onceptualization	I	:	**I**nvestigation	Vi :	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su :	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P :	**P**roject administration
Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu :	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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APPENDIX

Table 2. Existing literature in summerized form

References	SE	RES integration	Main findings
[8]	Bayesian non-parametric modelling combined with joint topology and SE	Yes	enhances estimation accuracy and adaptability to changes in the network.
[9]	State and topology estimation using deep neural networks	Suitable for RES-integrated unobservable systems	Improves estimation accuracy in unobservable systems using machine learning techniques.
[10]	PMU-based SE for fault detection	Active distribution networks with RES	Improves fault detection and localization in RES-integrated active distribution networks.
[15]	Real-time topology detection and SE using μPMU and smart meter data	Active distribution networks with RES and microgrids	Enhances real-time grid observability and reliability using μPMU and smart meter data for topology detection.
[22]	SE with non-Gaussian measurement uncertainty modelling	Applicable to RES and active distribution networks	Models non-Gaussian uncertainties to improve estimation accuracy in active distribution systems.
[23]	SE considering dynamic topology and distributed generation uncertainties	DG uncertainties and active distribution networks	Improves topology awareness and SE accuracy under dynamic DG uncertainties using GMM-PSEs and KL divergence.
[24]	Augmented SE for estimating line parameters	Active power distribution systems with RES	Improves line parameter estimation accuracy in active distribution networks with PMU data integration.
[25]	Computational complexity analysis for SE methods	Not explicitly focused on RES	Provides detailed computational complexity analysis to optimize SE performance.
[26]	SE with sensitivity analysis to solve voltage and congestion issues	Active distribution networks with DG	Proposes methods for addressing voltage problems and congestion in active networks using SE.
[27]	SE for multiterminal DC networks	Not directly focused on RES	Proposes an error estimation method for small-signal models, improving SE accuracy in DC distribution networks.
[41]	Three-phase SE for unbalanced distribution networks	Applicable to RES systems in unbalanced networks	Introduces a virtual reference for more accurate three-phase SE.
[42]	Adaptive dynamic SE for networks with changing conditions	Active distribution networks with RES	Improves DSSE accuracy in dynamically changing networks using interacting multiple model approach.
[43]	Forecasting-aided MASE	Unbalanced distribution networks with DG	Enhances SE accuracy by integrating forecasting models in multi-area unbalanced networks.
[44]	Multi-area framework with DG modelling and pseudo-measurements	DG integration	Proposes a multi-area framework for unbalanced active distribution networks, with innovative DG modelling and pseudo-measurements for unmonitored DGs.
[45]	Load/PV estimation and topology estimation using Gaussian mixture model (GMM)	Load and PV integration	Improves accuracy and reduces uncertainty in topology estimation by integrating load/PV estimation using GMM.
[46]	Robust measurement placement considering network reconfiguration	DG integration	Uses measurement saturation analysis and heuristic algorithm to propose a robust measurement placement method for active distribution systems with DG.
[47]	ISE considering multiple uncertainties	DG integration	Proposes a fast ISE algorithm addressing imprecise line parameters, measurement noise, and uncertain DG outputs, offering tight bounds on state variables.

Table 2. Existing literature in summerized form *(continued)*

References	SE	RES integration	Main findings
[48]	Voltage profile estimation considering line X/R ratios and laterals	DG integration	Proposes a method for estimating voltage profiles in smart distribution networks with DG, facilitating online voltage control.
[49]	Hybrid PSO and CGSA optimization for SE	DG integration	Proposes a hybrid optimization method for improved SE in three-phase unbalanced DG-integrated distribution systems.
[50]	Pseudo-measurement modeling using entropy-weighted SVM	DG integration	Proposes a strategy that optimizes pseudo-measurement selection to improve SE effectiveness in active distribution networks.
[51]	PMU placement optimization to minimize cost and maximize system observability	DG integration, ZIBs, and tie-switches	Proposes a cost-effective D-PMU placement method for ADN SE, considering DG, ZIBs, and tie-switches.
[52]	Hybrid PSO-Krill Herd optimization for measurement placement	Smart distribution networks with DG	Proposes a hybrid optimization approach for measurement device placement in smart distribution networks with DG integration.
[53]	Multi-objective PSO for PMU placement	DG integration	Proposes a multi-objective PSO algorithm for optimal PMU placement in DG-integrated distribution networks.

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