A REVIEW OF HYBRID STATE ESTIMATION TECHNIQUE INTEGRATING SCADA AND SYNCHROPHASOR DATA FOR IMPROVED OBSERVABILITY IN ACTIVE DISTRIBUTION NETWORKS

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Abstract - *State estimation plays a fundamental role in the monitoring, control, and secure operation of modern power systems. With the evolution of smart grids and the increasing penetration of distributed energy resources, traditional distribution networks are transforming into active distribution networks characterized by bidirectional power flows, dynamic operating conditions, and increased system complexity. Conventional state estimation techniques primarily rely on Supervisory Control and Data Acquisition (SCADA) measurements, which typically have low sampling rates and limited measurement coverage. These limitations often lead to insufficient system observability and reduced estimation accuracy, particularly in distribution networks with sparse measurement infrastructure. The development of synchrophasor technology through Phasor Measurement Units (PMUs) has introduced high-resolution, time-synchronized measurements that provide precise voltage and current phasor information. However, the high installation and communication costs of PMUs restrict their widespread deployment across the entire network. As a result, hybrid state estimation techniques that integrate SCADA and synchrophasor data have emerged as a promising solution for enhancing system observability and improving estimation performance. This review paper presents a comprehensive analysis of hybrid state estimation approaches used in active distribution networks. The study examines the fundamental concepts of state estimation, the characteristics of SCADA and synchrophasor measurement systems, and the methodological frameworks developed to combine these heterogeneous data sources. Furthermore, existing research contributions are systematically reviewed and categorized based on estimation models, data integration strategies, and application scenarios. The paper also highlights key challenges, including measurement synchronization, multi-rate data processing, and cybersecurity concerns. Finally, potential research directions are discussed to support the development of more accurate, scalable, and resilient hybrid state estimation techniques for future smart grid applications.*

***Key Words*: Hybrid State Estimation; SCADA; Synchrophasor; Phasor Measurement Unit (PMU); Active Distribution Networks; Power System Observability; Smart Grid.**

1. INTRODUCTION

1.1 Background of Modern Power Systems

1.1.1 Evolution Toward Smart Grids and Active Distribution Networks

Modern power systems are undergoing a significant transformation from conventional centralized generation structures to highly dynamic and decentralized networks. This transition is largely driven by the rapid development of smart grid technologies, which integrate advanced communication systems, intelligent monitoring devices, and automated control mechanisms into the electrical infrastructure. Traditional power systems were designed primarily for unidirectional power flow from large centralized generation units to consumers. However, the increasing deployment of advanced digital technologies, automation, and distributed control systems has enabled utilities to monitor and manage the grid more efficiently and reliably. As a result, the concept of Active Distribution Networks (ADNs) has emerged, where distribution systems are no longer passive but actively participate in power management and system optimization (Farhangi, 2010).

1.1.2 Integration of Renewable Energy and Distributed Generation

Another important driver of modern power system evolution is the growing penetration of renewable energy resources and distributed generation (DG). Technologies such as solar photovoltaic systems, wind turbines, and small-scale energy storage systems are increasingly connected to distribution networks. These distributed energy resources introduce variability and uncertainty into the grid because their generation depends on environmental conditions. Furthermore, the integration of DG units enables bidirectional power flows, where electricity can flow not only from the grid to consumers but also from consumers back to the grid. While this improves energy sustainability and system flexibility, it also increases the complexity of monitoring and operating the power system, requiring more advanced analytical and estimation tools (Lopes et al., 2007).

1.2 Importance of State Estimation in Power System Operation

1.2.1 Role of State Estimation in Energy Management Systems

State estimation is a fundamental analytical function within the Energy Management System (EMS) used by power system operators. It processes various measurement data collected from field devices and estimates the most probable operating state of the power system. The state variables generally include the voltage magnitudes and phase angles at different buses in the network. Since direct measurement of all state variables is not feasible, state estimation algorithms utilize redundant measurements to determine the system state while minimizing measurement errors. This process enables operators to obtain an accurate and consistent snapshot of the system's operating condition, which is essential for real-time monitoring and operational decision-making (Abur and Exposito, 2004).

1.2.2 Importance for Monitoring, Stability, and Control

Accurate state estimation is crucial for maintaining the reliability, stability, and security of power systems. By providing a reliable estimate of system conditions, operators can detect abnormal operating states, identify potential faults, and take preventive actions before disturbances propagate through the network. State estimation also supports several advanced applications such as contingency analysis, optimal power flow, and load forecasting. In modern active distribution networks, where system conditions change rapidly due to renewable generation and fluctuating loads, precise state estimation becomes even more critical to ensure efficient system control and secure grid operation (Monticelli, 1999).

1.3 Limitations of Conventional SCADA-Based State Estimation

1.3.1 Low Sampling Rate of SCADA Measurements

Conventional state estimation in power systems primarily relies on measurements collected through Supervisory Control and Data Acquisition (SCADA) systems. Although SCADA systems have been widely used for several decades, they typically provide measurements at relatively low sampling rates, usually ranging from 2 to 6 seconds. Such slow data acquisition limits the ability of the control center to capture fast system dynamics and transient disturbances. Consequently, the estimation results may not accurately reflect the real-time operating condition of the power system, particularly during rapidly changing events (Phadke and Thorp, 2008).

1.3.2 Limited Observability of Distribution Networks

Another major limitation of SCADA-based state estimation is the limited observability of power networks. In many distribution systems, measurement devices are sparsely installed due to economic and infrastructural constraints. As a result, the available measurements may not be sufficient to fully observe the system state, leading to estimation uncertainties. Inadequate observ ability becomes particularly problematic in modern distribution networks with numerous distributed energy resources and complex power flow patterns (Baran and Kelley, 1994).

1.3.3 Measurement Inaccuracies and Data Quality Issues

SCADA measurements are also subject to various data quality issues, including measurement noise, communication delays, and equipment calibration errors. These inaccuracies can degrade the performance of conventional state estimation algorithms and lead to incorrect system state predictions. Additionally, the absence of synchronized measurement timestamps makes it difficult to accurately correlate measurements collected from different parts of the network, further reducing estimation reliability.

1.4 Emergence of Synchrophasor Technology

1.4.1 Phasor Measurement Units and Wide Area Monitoring Systems

The limitations of conventional measurement systems have led to the development of synchrophasor technology, which relies on Phasor Measurement Units (PMUs). PMUs are advanced measurement devices capable of providing synchronized voltage and current phasor measurements using precise time signals obtained from the Global Positioning System (GPS). These devices are typically integrated into Wide Area Monitoring Systems (WAMS), which enable real-time monitoring of power system dynamics across large geographic regions. The availability of synchronized phasor measurements significantly enhances the accuracy and speed of power system monitoring and analysis (Phadke and Thorp, 2008).

1.4.2 Advantages of High-Speed and Time-Synchronized Measurements

One of the major advantages of PMU technology is its ability to provide measurements at very high sampling rates, typically 30–60 samples per second, which is significantly faster than conventional SCADA systems. In addition, PMUs measure voltage and current phasors directly and provide accurate phase angle information synchronized across the entire grid. This synchronized measurement capability allows system operators to observe system dynamics more precisely and detect disturbances almost instantaneously. In fact, PMU measurements can be nearly 100 times faster than traditional SCADA measurements, making them highly suitable for real-time monitoring and advanced grid control applications (Phadke and Thorp, 2008).

2. FUNDAMENTALS OF POWER SYSTEM STATE ESTIMATION

2.1 Concept of Power System State Estimation

2.1.1 Definition of System States in Power Networks

Power system state estimation is a computational technique used to determine the most probable operating condition of an electrical power network based on available measurement data. In practical power system operation, it is not feasible to directly measure all variables that describe the system state due to economic and technical limitations. Therefore, state estimation algorithms utilize redundant and partially available measurements collected from field devices to infer the unknown system variables. The estimated values represent the best approximation of the real-time operating condition of the power grid and provide operators with a consistent and reliable system snapshot for monitoring and decision-making (Abur and Gómez-Expósito, 2004).

In power system analysis, the state variables are typically defined as the voltage magnitudes and voltage phase angles at each bus of the network. These variables completely describe the electrical condition of the system and enable the calculation of other important parameters such as line power flows, power injections, and system losses. Since most measurements obtained from the field—such as power flows and injections—are nonlinear functions of voltage magnitude and phase angle, state estimation becomes an essential tool for determining these fundamental variables indirectly (Monticelli, 1999).

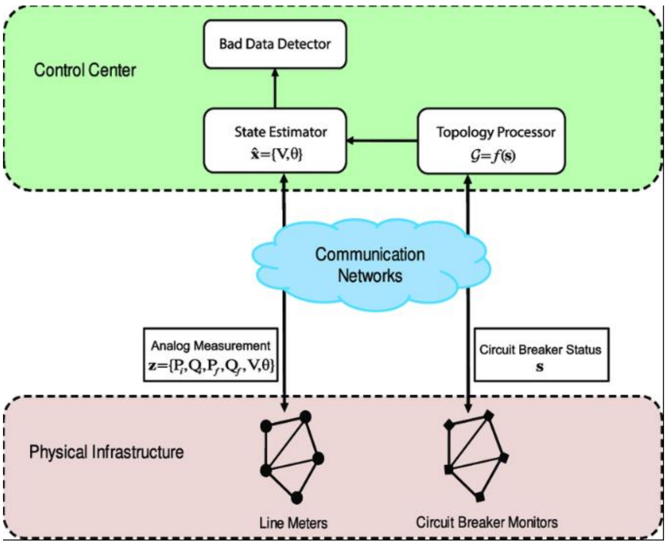

Figure-1:Basic Architecture of Power System State Estimation

2.2 Mathematical Formulation of State Estimation

2.2.1 Measurement Equations

The mathematical formulation of power system state estimation is generally expressed through a set of measurement equations that relate the measured quantities to the system state variables. In this formulation, the measurement vector consists of data obtained from monitoring devices such as power flows, bus voltages, current magnitudes, and power injections. These measurements are related to the unknown state vector through nonlinear functions that represent the physical laws governing power system operation, such as Ohm's law and Kirchhoff's laws.

2.2.2 Nonlinear Estimation Problem

Because the relationship between measurements and system states is nonlinear, power system state estimation is inherently a nonlinear optimization problem. The estimation algorithm must iteratively update the state variables until the difference between the measured values and calculated values is minimized. This iterative process requires linearization of the nonlinear equations around an initial operating point and repeated updates until convergence is achieved. Techniques such as the Newton–Raphson method are commonly used for this purpose. Accurate modeling of measurement errors and system parameters is essential to ensure reliable estimation results and fast algorithm convergence (Conejo, Carrion and Morales, 2010).

2.3 Conventional Weighted Least Squares (WLS) Method

2.3.1 Classical Approach in SCADA-Based State Estimation

The Weighted Least Squares (WLS) method is the most widely used technique for state estimation in traditional power system control centers. In this method, the objective is to minimize the weighted sum of squared differences between the measured values and the values calculated from the estimated state variables. Each measurement is assigned a weight based on its accuracy, meaning that measurements with higher reliability have greater influence on the final estimation results.

2.4 Observability Analysis

2.4.1 Definition and Importance of Observability

Observability is a critical concept in power system state estimation that refers to the ability to uniquely determine the system state variables using the available set of measurements. A power system is considered observable if the collected measurement data are sufficient to estimate all state variables within the network. If the system lacks adequate measurements, some state variables cannot be determined, leading to inaccurate or incomplete estimation results. Observability analysis is therefore performed prior to the state estimation process to ensure that the measurement configuration is adequate for reliable system monitoring (Kundur, 1994).

Maintaining network observability is particularly important in large-scale power systems and modern distribution networks where measurement devices may be sparsely installed. Insufficient observability can lead to inaccurate operational decisions, which may compromise system stability and reliability.

2.4.2 Topological and Numerical Observability

Observability in power systems can be analyzed using two primary approaches: topological observability and numerical observability. Topological observability focuses on the connectivity structure of the network and examines whether the measurement placement allows the system states to be determined based on network topology alone. This approach is generally computationally efficient and is often used for planning measurement placement.

3. MEASUREMENT INFRASTRUCTURE IN MODERN POWER SYSTEMS

3.1 Supervisory Control and Data Acquisition (SCADA)

3.1.1 Architecture and Components

Supervisory Control and Data Acquisition (SCADA) systems form the backbone of monitoring and control operations in traditional power systems. A SCADA system is designed to collect real-time data from various field devices, transmit the data to a centralized control center, and allow operators to supervise and control system operations remotely. The architecture of SCADA typically consists of Remote Terminal Units (RTUs), communication networks, data acquisition servers, and control center applications.

3.1.2 Measurement Types

SCADA systems collect several types of electrical measurements that are used for system monitoring and state estimation. These measurements provide indirect information about the electrical state of the network and are typically obtained through analog sensors installed at substations.

Power Injections

Power injection measurements represent the active and reactive power entering or leaving a bus in the power network. These values are calculated based on current and voltage measurements obtained at substations and are essential for analyzing the power balance at each node of the system. Injection measurements help operators understand how much power is being generated, consumed, or transferred within different parts of the network.

Line Flows

Line flow measurements indicate the amount of active and reactive power flowing through transmission or distribution lines. These measurements are crucial for monitoring network loading conditions and ensuring that transmission lines operate within their thermal and stability limits. Accurate line flow measurements assist system operators in identifying congestion conditions and preventing potential overloads in the network.

Voltage Magnitudes

Voltage magnitude measurements represent the RMS value of voltage at a particular bus or substation. Maintaining appropriate voltage levels is essential for system stability and power quality. SCADA systems continuously monitor voltage magnitudes to ensure that they remain within acceptable operating limits and to support voltage regulation strategies in power system operation (Gómez-Expósito, Conejo and Cañizares, 2009).

3.2 Phasor Measurement Units (PMUs)

3.2.1 Working Principle

Phasor Measurement Units (PMUs) are advanced monitoring devices designed to measure electrical quantities in a power system with high precision and synchronized timing. Unlike conventional measurement devices, PMUs utilize Global Positioning System (GPS) signals to synchronize measurements taken at geographically dispersed locations. This time synchronization enables PMUs to provide measurements that are referenced to a common time frame across the entire power system.

3.2.2 Synchrophasor Measurements

PMUs provide a category of measurements known as synchrophasors, which represent synchronized phasor quantities measured across the network. These measurements offer detailed information about the electrical state of the system and significantly improve the accuracy of monitoring and state estimation.

Voltage Magnitude

PMUs directly measure the magnitude of bus voltages with high precision and at high sampling rates. Unlike SCADA measurements, which are updated every few seconds, PMU voltage measurements are reported many times per second. This allows operators to observe rapid changes in system conditions and detect disturbances in near real time.

Phase Angle

One of the most important features of PMU technology is the ability to measure voltage phase angles accurately and synchronously across different locations in the network. Phase angle measurements provide valuable information about power transfer patterns and system stability. Differences in voltage phase angles between buses are directly related to power flow in the network, making these measurements highly useful for advanced monitoring and control applications.

Current Phasors

In addition to voltage phasors, PMUs also measure current phasors flowing through transmission lines or transformers. These measurements provide both magnitude and phase angle information for current signals, enabling accurate calculation of power flows and network conditions. The availability of synchronized current measurements further enhances system visibility and supports applications such as fault detection and dynamic stability monitoring (Terzija et al., 2011).

3.3 Comparison Between SCADA and PMU Measurements

SCADA and PMU systems differ significantly in terms of measurement characteristics, data acquisition speed, and accuracy. SCADA systems provide measurements such as power flows, injections, and voltage magnitudes with relatively slow update rates. In contrast, PMUs provide synchronized phasor measurements with high sampling rates and precise timing information. These differences make PMUs highly suitable for real-time monitoring of power system dynamics.

Table-1: Comparison Between SCADA and PMU Measurements

Feature	SCADA	PMU
Sampling rate	2–6 s	30–60 samples/sec
Time synchronization	No	GPS synchronized
Measurement type	Power flows	Voltage & current phasors
Accuracy	Moderate	High

4. HYBRID STATE ESTIMATION (HSE) FRAMEWORK

4.1 Concept of Hybrid State Estimation

4.1.1 Integration of SCADA and Synchrophasor Measurements

Hybrid State Estimation (HSE) is an advanced estimation framework developed to enhance the accuracy and reliability of power system monitoring by integrating measurement data from multiple sources. Traditional state estimation methods rely primarily on SCADA measurements, which include power injections, line flows, and voltage magnitudes collected at relatively slow sampling rates. However, the introduction of Phasor Measurement Units (PMUs) has enabled the acquisition of highly accurate and time-synchronized measurements of voltage and current phasors. Hybrid state estimation combines these two complementary measurement systems to exploit their respective advantages. While SCADA provides wide coverage of the network, PMUs offer high temporal resolution and precise phase angle information. By integrating these heterogeneous data sources into a unified estimation framework, hybrid state estimation significantly improves the overall quality of system state estimation (Zhang, Bose and Tomsovic, 2010).

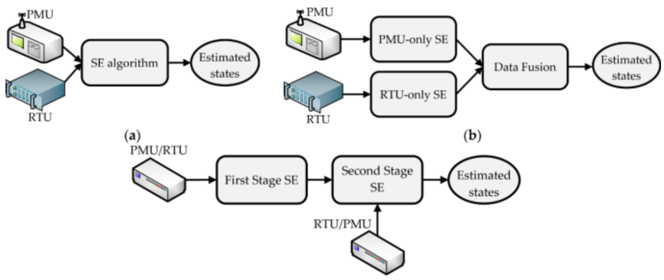

Figure-2: Hybrid State Estimation Framework Using SCADA and PMU

4.2 Static Hybrid State Estimation (SHSE)

4.2.1 Steady-State Based Estimation Framework

Static Hybrid State Estimation (SHSE) refers to estimation approaches that assume the power system is operating under steady-state conditions during the estimation process. In this framework, the system variables are assumed to remain constant within the time interval in which measurements are collected. As a result, SHSE treats the estimation problem as a static optimization task in which the state variables are determined based on a snapshot of measurement data obtained from both SCADA and PMU devices.

4.2.2 Weighted Least Squares Based Hybrid Estimation

Most static hybrid estimation methods employ the Weighted Least Squares (WLS) technique as the underlying optimization algorithm. In this approach, the objective function minimizes the weighted difference between measured and estimated values while accounting for measurement accuracy. PMU measurements generally receive higher weights due to their superior precision compared with conventional SCADA measurements. The inclusion of synchrophasor data within the WLS framework significantly improves the numerical conditioning of the estimation problem and enhances convergence characteristics. Consequently, SHSE methods have been widely adopted as an extension of conventional SCADA-based state estimation systems in modern power system control centers.

4.3 Dynamic Hybrid State Estimation (DHSE)

4.3.1 Consideration of Time-Varying System Dynamics

Dynamic Hybrid State Estimation (DHSE) extends the static estimation framework by considering the time-varying behavior of power systems. In real-world operation, power system states change continuously due to fluctuations in load demand, renewable generation, and network disturbances. Static estimation methods cannot fully capture these dynamic variations because they treat each estimation cycle independently. Dynamic hybrid estimation addresses this limitation by incorporating temporal relationships between consecutive system states.

4.3.2 Kalman Filtering and Recursive Estimation Techniques

Dynamic hybrid estimation commonly relies on Kalman filtering techniques, which are recursive algorithms designed for estimating the state of dynamic systems in the presence of measurement noise. The Kalman filter predicts the system state based on a mathematical model and then updates the estimate using incoming measurements.

4.4 Benefits of Hybrid State Estimation

4.4.1 Improved System Observability

One of the most significant advantages of hybrid state estimation is the improvement in system observability. The inclusion of PMU measurements provides direct information about voltage phasors, which reduces the dependence on indirect measurements such as power flows. Even with limited PMU deployment, the additional information obtained from synchrophasor devices can greatly enhance the ability of the estimator to determine the system state accurately.

4.4.2 Higher Estimation Accuracy

Hybrid state estimation improves the overall accuracy of estimated state variables because PMU measurements have higher precision and are synchronized in time. The integration of these measurements reduces uncertainty in the estimation process and minimizes the impact of measurement noise. As a result, hybrid estimators can produce more reliable estimates of voltage magnitudes and phase angles compared with conventional SCADA-based methods.

4.4.3 Faster Convergence of Estimation Algorithms

The presence of direct phasor measurements also improves the numerical properties of the estimation problem. Because PMUs provide voltage angle measurements directly, the estimator requires fewer iterations to converge to the optimal solution. This faster convergence enhances computational efficiency and allows state estimation to be performed more frequently, supporting near real-time monitoring of power system conditions.

4.4.4 Enhanced Detection of Bad Data

Another important advantage of hybrid state estimation is its improved capability for bad data detection. Measurement errors, sensor malfunctions, or communication faults can introduce incorrect data into the estimation process. The redundancy created by combining SCADA and PMU measurements allows the estimator to identify inconsistencies more effectively and isolate erroneous measurements. This improves the reliability of the estimation results and helps maintain the security and stability of the power system (Abur and Gómez-Expósito, 2004).

5. LITERATURE REVIEW OF HYBRID STATE ESTIMATION TECHNIQUES

5.1 Early Research on Hybrid SCADA–PMU State Estimation

5.1.1 Integration of PMU Data into Classical State Estimation Frameworks

The earliest studies on hybrid state estimation focused on incorporating Phasor Measurement Unit (PMU) data into conventional SCADA-based state estimation frameworks. Traditionally, power system state estimation relied on the Weighted Least Squares (WLS) method using measurements such as power flows and voltage magnitudes obtained from SCADA systems. However, the introduction of PMU technology enabled direct measurement of voltage and current phasors with precise time synchronization. Early research explored methods for integrating these synchrophasor measurements into the existing WLS framework to enhance estimation accuracy and observability.

5.2 Two-Stage Hybrid Estimation Methods

5.2.1 Sequential Integration of PMU and SCADA Measurements

Two-stage hybrid estimation methods were developed to address the challenges associated with combining measurements that have different sampling rates and accuracy levels. In these approaches, the estimation process is performed in two sequential stages. The first stage utilizes high-precision PMU measurements to estimate a subset of system states, typically focusing on buses where PMUs are installed. Since PMU measurements provide direct phasor information, this stage produces accurate estimates for those parts of the network with PMU coverage.

5.3 Unified Hybrid Estimation Models

5.3.1 Simultaneous Processing of SCADA and PMU Data

Unified hybrid state estimation models represent a more integrated approach in which SCADA and PMU measurements are processed simultaneously within a single estimation framework. Instead of treating the two measurement sources separately, unified models incorporate all measurements into a single mathematical formulation. This approach enables the estimator to fully exploit the complementary characteristics of both measurement systems.

5.4 Dynamic Hybrid State Estimation Methods

5.4.1 Extended Kalman Filter Based Estimation

Dynamic hybrid state estimation methods extend the traditional estimation framework by considering the temporal evolution of system states. One of the most widely used approaches for dynamic estimation is the Extended Kalman Filter (EKF), which is designed to estimate the state of nonlinear dynamic systems.

5.4.2 Unscented Kalman Filter Based Estimation

Another advanced approach for dynamic hybrid estimation is the Unscented Kalman Filter (UKF), which addresses some of the limitations associated with the EKF. Unlike the EKF, the UKF does not require explicit linearization of nonlinear functions. Instead, it uses a deterministic sampling technique known as the unscented transformation to propagate state uncertainties through nonlinear system models.

5.5 Data-Driven and Machine Learning Based Approaches

5.5.1 Neural Network Based Estimation Methods

With the increasing availability of large volumes of power system data, data-driven approaches have emerged as promising alternatives to traditional model-based estimation methods. Neural networks have been widely investigated for state estimation applications because of their ability to learn complex nonlinear relationships between measurements and system states. In these methods, neural networks are trained using historical measurement data to approximate the mapping between input measurements and corresponding system states.

5.5.2 Deep Learning and Data-Driven Hybrid Estimators

Recent advancements in deep learning have further expanded the possibilities for data-driven state estimation. Deep neural networks, convolutional neural networks, and recurrent neural networks have been applied to power system monitoring tasks due to their ability to extract complex patterns from large datasets. In hybrid state estimation frameworks, deep learning models can integrate data from SCADA systems, PMUs, and advanced metering infrastructure (AMI) to estimate system states with high accuracy.

5.6 Hybrid State Estimation for Active Distribution Networks

5.6.1 Challenges Introduced by Distributed Generation

The increasing penetration of distributed generation (DG) and renewable energy resources has introduced new challenges for power system state estimation, particularly in distribution networks. Unlike traditional transmission systems, distribution networks often have limited measurement infrastructure and exhibit complex operational characteristics such as unbalanced loads and bidirectional power flows. These factors make accurate state estimation more difficult.

5.6.2 Impact of Renewable Energy Variability

Renewable energy sources such as solar and wind generation introduce significant variability into power system operation. Rapid fluctuations in generation output can cause frequent changes in system states, making it challenging for traditional estimation methods to maintain accurate monitoring. Hybrid estimation approaches that incorporate high-frequency PMU measurements are better suited to capture these dynamic variations and support reliable operation of active distribution networks.

6. HYBRID STATE ESTIMATION IN ACTIVE DISTRIBUTION NETWORKS

6.1 Characteristics of Active Distribution Networks

6.1.1 High Penetration of Distributed Energy Resources

Active Distribution Networks (ADNs) represent an advanced form of conventional distribution systems in which distributed energy resources (DERs), renewable energy generation, and intelligent control technologies are integrated into the network. In traditional power systems, electricity flows from centralized generation units through transmission networks to passive distribution systems.

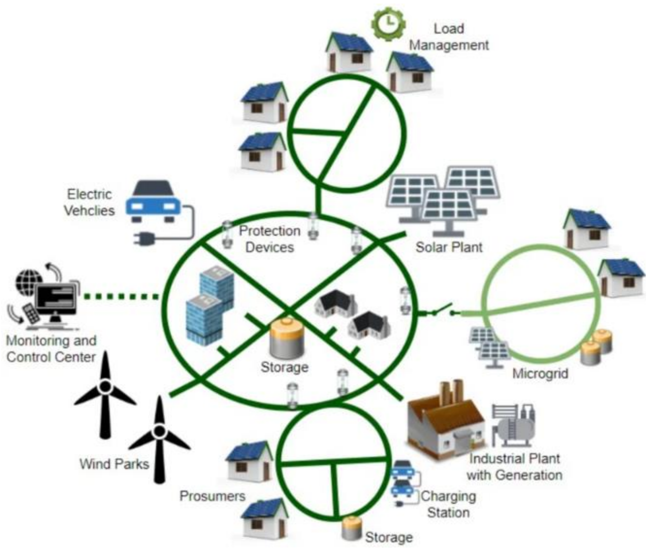

Figure-3: Distribution System State Estimation in Active Distribution Networks

6.1.2 Bidirectional Power Flows

Another important characteristic of active distribution networks is the presence of bidirectional power flows. In conventional radial distribution systems, electricity typically flows in a single direction from the substation to end users. However, the integration of distributed generation allows consumers to also act as energy producers, often referred to as prosumers. When local generation exceeds local consumption, excess power can be injected back into the grid, causing reverse power flows.

6.2 Challenges in Distribution System State Estimation (DSSE)

6.2.1 Limited Measurement Infrastructure

One of the major challenges in implementing effective Distribution System State Estimation (DSSE) is the limited availability of measurement devices in distribution networks. Unlike transmission systems, where extensive monitoring infrastructure is typically installed, distribution systems often have sparse measurement coverage due to economic constraints and the large number of network nodes. Many distribution feeders rely primarily on limited SCADA measurements at substations, while intermediate nodes may not have direct monitoring devices.

6.3 Role of Hybrid Estimation in Improving Obser vability

6.3.1 Integration of Multiple Measurement Technologies

Hybrid state estimation plays a critical role in enhancing the observability and monitoring capability of active distribution networks by integrating data from multiple measurement technologies. In addition to traditional SCADA measurements and high-speed PMU data, modern distribution systems also utilize information from Advanced Metering Infrastructure (AMI), smart meters, and other intelligent sensors. Each of these measurement sources provides different types of information about system operation. For example, SCADA systems provide supervisory measurements at substations, PMUs deliver high-resolution synchronized phasor data, while AMI and smart meters offer detailed consumption information at the customer level.

6.3.2 Enhanced Monitoring and Operational Awareness

The improved observ ability provided by hybrid estimation techniques supports a wide range of operational applications in active distribution networks. Accurate state estimation enables system operators to detect voltage violations, monitor line loading conditions, and identify potential network disturbances in real time. Furthermore, hybrid estimation provides valuable input for advanced applications such as voltage control, demand response management, and distributed energy resource coordination. As distribution networks continue to evolve toward highly decentralized and renewable-based energy systems, hybrid state estimation will remain an essential tool for maintaining system reliability and operational efficiency.

7. CHALLENGES IN HYBRID STATE ESTIMATION

Hybrid state estimation integrates heterogeneous measurement sources such as SCADA systems, PMUs, and smart meters to enhance monitoring and observ ability in modern power systems. While this integration significantly improves estimation accuracy, it also introduces several technical challenges related to data synchronization, communication infrastructure, computational requirements, and data reliability. Addressing these challenges is essential for ensuring the successful implementation of hybrid estimation frameworks in real-world power networks.

7.1 Measurement Synchronization Issues

7.1.1 Time Alignment of Heterogeneous Measurements

One of the primary challenges in hybrid state estimation arises from measurement synchronization issues between different monitoring systems. SCADA measurements are typically collected at relatively slow intervals, often every few seconds, whereas PMUs provide high-speed synchronized measurements at rates of 30–60 samples per second. Although PMU measurements are precisely synchronized using Global Positioning System (GPS) signals, SCADA measurements are generally not time-stamped with the same level of precision. As a result, integrating these two types of data into a single estimation framework requires careful time alignment and data processing techniques.

7.2 Multi-Rate Data Fusion

7.2.1 Integration of Measurements with Different Sampling Rates

Another important challenge in hybrid state estimation is the fusion of data obtained at different sampling rates. SCADA systems typically update measurements every 2–6 seconds, whereas PMU devices provide measurements at much higher frequencies. This large difference in sampling rates creates difficulties in integrating the two datasets within a unified estimation framework.

7.3 Communication and Cybersecurity Concerns

7.3.1 Reliability and Security of Measurement Data

Hybrid state estimation relies heavily on communication networks for transmitting measurement data from geographically distributed devices to control centers. As the number of monitoring devices increases, the communication infrastructure becomes more complex and susceptible to failures or delays. Communication latency, packet loss, and network congestion can degrade the quality of measurement data and affect the performance of state estimation algorithms.

7.4 Bad Data Detection and Robustness

7.4.1 Handling Measurement Errors and Data Anomalies

Measurement data used in state estimation may contain errors, noise, or abnormal values, commonly referred to as bad data. These errors can arise due to sensor malfunctions, communication failures, calibration errors, or external disturbances. If bad data are not properly detected and removed, they can significantly distort the estimation results and lead to incorrect system monitoring decisions.

7.5 Computational Complexity

7.5.1 Scalability of Hybrid Estimation Algorithms

As power systems continue to expand and incorporate large numbers of measurement devices, the computational complexity of hybrid state estimation algorithms becomes a significant concern. The integration of high-frequency PMU measurements with conventional SCADA data increases the volume of data that must be processed in real time. This large data volume can impose heavy computational burdens on estimation algorithms, particularly in large-scale power networks.

8. EMERGING TRENDS AND FUTURE RESEARCH DIRECTIONS

The rapid evolution of smart grid technologies and the increasing complexity of power systems have created new opportunities for improving hybrid state estimation techniques. Recent research has focused on integrating advanced computational methods, intelligent algorithms, and distributed monitoring systems to enhance the accuracy and efficiency of state estimation in modern power networks.

8.1 AI and Machine Learning Based State Estimation

8.1.1 Intelligent Data-Driven Estimation Techniques

Artificial intelligence (AI) and machine learning (ML) techniques are increasingly being explored for power system monitoring and state estimation applications. These approaches use historical measurement data to learn complex relationships between system variables and measurement signals without relying solely on detailed physical models of the network. Machine learning models such as artificial neural networks, support vector machines, and deep learning architectures can process large volumes of measurement data and extract hidden patterns that may not be captured by traditional estimation methods.

8.2 Distributed and Decentralized State Estimation

8.2.1 Scalable Estimation for Large Power Networks

Another emerging trend in hybrid state estimation is the development of distributed and decentralized estimation techniques. In large-scale power systems, centralized state estimation may become computationally inefficient and vulnerable to communication failures. Distributed estimation methods address this issue by dividing the network into multiple regions and performing estimation locally within each region.

8.3 Integration with Smart Grid Technologies

8.3.1 Utilization of Advanced Monitoring Infrastructure

The advancement of smart grid technologies has significantly expanded the range of measurement devices available for power system monitoring. Modern distribution networks increasingly incorporate technologies such as Advanced Metering Infrastructure (AMI), smart sensors, and Internet of Things (IoT) devices. These technologies generate large volumes of real-time data that can be utilized to improve state estimation accuracy.

8.4 Optimal PMU Placement Strategies

8.4.1 Improving Observability with Limited Resources

Because PMUs are relatively expensive devices, it is often impractical to install them at every bus in a power network. Therefore, determining the optimal placement of PMUs is an important research problem aimed at maximizing system observability while minimizing installation costs. Various optimization techniques have been proposed to identify the most effective locations for PMU deployment.

8.5 Cyber-Resilient State Estimation

8.5.1 Protection Against Cyber Attacks

As power systems become more interconnected and reliant on digital communication technologies, ensuring the cybersecurity of state estimation systems has become a critical research priority. Hybrid state estimation frameworks must be capable of detecting and mitigating cyber attacks that target measurement data or communication networks. One particularly dangerous type of attack is the false data injection attack, in which an attacker manipulates measurement data to mislead the estimation process.

9. CONCLUSION

Hybrid state estimation has emerged as a crucial approach for improving the monitoring and operational awareness of modern power systems, particularly in the context of evolving smart grid infrastructures and active distribution networks. Traditional state estimation methods based solely on SCADA measurements often suffer from limited observability and relatively slow data acquisition rates. The integration of Phasor Measurement Units (PMUs) with conventional measurement systems has significantly enhanced the accuracy, reliability, and real-time capability of state estimation processes. By combining synchronized phasor measurements with conventional data sources, hybrid estimation techniques provide a more comprehensive representation of system states, including voltage magnitudes and phase angles across the network.

This review has examined the fundamental concepts of power system state estimation, including the mathematical formulation of estimation problems and conventional Weighted Least Squares (WLS) approaches. It has also discussed the growing importance of hybrid state estimation in addressing the challenges associated with active distribution networks characterized by distributed energy resources, bidirectional power flows, and increasingly complex network structures. Furthermore, key challenges such as measurement synchronization, multi-rate data fusion, communication reliability, cybersecurity threats, bad data detection, and computational complexity have been critically analyzed.

In addition, emerging research trends including artificial intelligence-based estimation methods, distributed and decentralized estimation frameworks, smart grid integration, optimal PMU placement strategies, and cyber-resilient estimation techniques have been highlighted as promising directions for future work. Overall, hybrid state estimation represents a significant advancement in power system monitoring, offering improved accuracy and situational awareness necessary for reliable grid operation. Continued research and technological development in this area will play a vital role in supporting the efficient management and stability of future intelligent power systems.

10. LIMITATIONS OF THE REVIEW

Despite providing a comprehensive overview of hybrid state estimation techniques and their applications in modern power systems, this review has certain limitations. The study primarily focuses on conceptual frameworks, methodological approaches, and selected research contributions reported in the existing literature. Due to the broad scope of the topic, it was not possible to include all recently proposed algorithms and experimental implementations related to hybrid state estimation. In addition, the review mainly discusses theoretical and simulation-based studies, while large-scale real-world deployment experiences remain relatively limited. Variations in network configurations, measurement infrastructures, and data availability across different power systems may also influence the practical applicability of the reviewed techniques. Future reviews could incorporate more empirical studies and comparative experimental evaluations.

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