International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.4 (2025) pp. 4486-4492
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

A Comprehensive Survey on State Estimation Techniques in Electrical Power Systems

Varun Jayvantbhai Pithwa[1]*, Yuvraj Jani[2], Sheikh Mohmadishak Abdulsalam[3], Sagar Savaliya[4]

[1]Varun Jayvantbhai Pithwa, Department of Electrical Engineering, Government Engineering college Godhra
* **Corresponding Author Email:** varu2n@gmail.com - **ORCID:** 0000-0002-5247-7432

[2]Department of Electrical Engineering, Karnavati University, Gandhinagar
Email: yuvr2j@gmail.com - **ORCID:** 0000-0002-5247-7400

[3]Department of Electrical Engineering, Government Engineering College, Dahod
Email: sheik2h@gmail.com - **ORCID:** 0000-0002-5247-0032

[4]Department of Electrical Engineering, Karnavati University, Gandhinagar
Email: saga2r@gmail.com - **ORCID:** 0000-0002-5117-0432

Article Info:

DOI: 10.22399/ijcesen.5164
Received : 01 July 2025
Revised : 27 July 2025
Accepted : 30 July 2025

Keywords

State Estimation,
WLS,
PMU,
Smart Grid,
Kalman Filter

Abstract:

State estimation (SE) is a fundamental component of modern electrical power system operation, enabling accurate monitoring, control, and security assessment of the grid. It provides the best possible estimate of system states, such as bus voltage magnitudes and phase angles, using redundant and noisy measurements. With the increasing complexity of power networks, driven by renewable energy integration and smart grid technologies, the role of state estimation has become more critical than ever. This paper presents a comprehensive survey of state estimation techniques used in electrical power systems.Classical approaches, including the Weighted Least Squares (WLS) and Least Absolute Value (LAV) methods, are discussed in detail. Their mathematical formulations, advantages, and limitations are analyzed to provide a strong theoretical foundation. Robust estimation techniques, such as Huber estimators and Least Median Squares, are also explored for their ability to handle bad data and measurement errors. The paper further examines dynamic state estimation methods based on Kalman filtering, including the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). These methods are particularly useful for real-time monitoring and dynamic system analysis. The integration of Phasor Measurement Units (PMUs) has significantly enhanced the accuracy and speed of state estimation. PMU-based and hybrid state estimation techniques are reviewed for their ability to provide synchronized and high-resolution measurements. Distribution system state estimation (DSSE) is also discussed, considering the challenges of limited measurements and system uncertainties. In addition, the paper highlights the emergence of artificial intelligence and machine learning techniques in state estimation. These data-driven approaches offer improved performance in handling nonlinearities and large datasets. A comparative analysis of various techniques is presented based on accuracy, robustness, and computational complexity. The paper also addresses key challenges, including bad data detection, cyber-security threats, communication delays, and scalability issues. Special emphasis is given to the impact of renewable energy sources on state estimation accuracy and reliability. The survey further explores recent advancements in hybrid and distributed state estimation frameworks. Future research directions are identified, including AI-integrated estimation, blockchain-based energy systems, and real-time big data analytics. The need for secure and resilient state estimation methods in smart grids is also emphasized. This paper aims to serve as a valuable reference for researchers and practitioners working in the field of power system monitoring and control. It provides a structured overview of existing techniques while highlighting emerging trends and opportunities. The findings of this survey contribute to the development of more efficient and reliable state estimation methods. Ultimately, improved state estimation techniques will enhance the stability, efficiency, and sustainability of modern power systems

1. Introduction

The modern electrical power system is a highly complex and interconnected network that requires continuous monitoring and control to ensure reliable and secure operation. With the rapid growth in electricity demand and the integration of renewable energy sources, the complexity of power systems has significantly increased. This has made real-time monitoring and accurate system analysis more challenging and essential than ever before.[1]

State estimation (SE) is a fundamental tool used in power system operation to determine the most probable values of system state variables. These state variables typically include bus voltage magnitudes and phase angles, which define the operating condition of the system. The primary objective of state estimation is to provide an accurate and reliable representation of the system state using available measurements [2]

In practical power systems, measurements are obtained through Supervisory Control and Data Acquisition (SCADA) systems. These measurements include power flows, power injections, and voltage magnitudes. However, such measurements are often corrupted by noise, errors, and communication delays. Additionally, measurement redundancy is necessary to ensure system observability and reliability [3]

State estimation techniques utilize mathematical and statistical methods to process these redundant and noisy measurements. The goal is to minimize the effect of measurement errors and provide the best estimate of the system state. Among various techniques, the Weighted Least Squares (WLS) method has been the most widely adopted approach in traditional power systems [4].

Despite its widespread use, the WLS method has certain limitations. It is sensitive to bad data and requires iterative computation, which may increase computational burden. To overcome these challenges, robust estimation techniques such as Least Absolute Value (LAV) and Huber estimators have been developed. These methods improve the resilience of state estimation against outliers and erroneous data [5].

With advancements in technology, the concept of dynamic state estimation has gained significant attention. Unlike static state estimation, dynamic methods consider the time-varying nature of power systems. Kalman filtering techniques, including the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), are commonly used for dynamic estimation. These methods provide real-time tracking capabilities and improved accuracy under dynamic conditions [6]

The introduction of Phasor Measurement Units (PMUs) has revolutionized the field of state estimation. PMUs provide synchronized measurements of voltage and current phasors using Global Positioning System (GPS) signals. These measurements are highly accurate and time-synchronized, enabling better system observability. PMU-based state estimation allows for linear modeling and faster computation compared to traditional methods [7].

In modern power systems, hybrid state estimation techniques that combine SCADA and PMU measurements are widely used. These approaches leverage the advantages of both measurement systems to improve accuracy and reliability. Wide Area Measurement Systems (WAMS) further enhance monitoring capabilities by integrating PMU data across large geographical regions [8].

Another important area of research is distribution system state estimation (DSSE). Unlike transmission systems, distribution networks have limited measurement infrastructure and higher uncertainty. They are often unbalanced and involve distributed energy resources such as solar and wind generation. These characteristics make state estimation in distribution systems more challenging [9].

To address these challenges, researchers have proposed various DSSE techniques, including pseudo-measurements and optimization-based methods. These approaches aim to improve system observability and estimation accuracy in the absence of sufficient real measurements.

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have emerged as promising alternatives for state estimation. These data-driven methods can model complex nonlinear relationships without requiring detailed system models. Techniques such as artificial neural networks, deep learning, and support vector machines have shown significant potential in this domain [10].

AI-based state estimation methods offer several advantages, including faster computation and adaptability to changing system conditions. However, they also face challenges such as the need for large training datasets and generalization issues.

Another critical aspect of state estimation is bad data detection and identification. Incorrect or malicious data can significantly affect the accuracy of estimation results. Various statistical tests and robust techniques have been developed to detect and eliminate bad data.

Cybersecurity has also become a major concern in modern power systems. With the increasing use of communication networks and digital technologies, power systems are vulnerable to cyber-attacks. False data injection attacks can compromise the integrity of state estimation results. Therefore, secure and resilient state estimation methods are essential for protecting critical infrastructure.

The integration of renewable energy sources introduces additional uncertainties into the system. Variability in solar and wind generation can affect measurement accuracy and system stability. State estimation techniques must be capable of handling such uncertainties effectively [11].

Furthermore, the increasing adoption of smart grid technologies has transformed traditional power systems into more intelligent and automated networks. Smart grids rely heavily on advanced monitoring and control systems, where state estimation plays a central role.

This paper aims to provide a comprehensive survey of state estimation techniques in electrical power systems. It covers classical methods, robust approaches, dynamic estimation techniques, PMU-based methods, and AI-driven solutions [12].

The paper also presents a comparative analysis of different techniques based on performance metrics such as accuracy, robustness, and computational complexity. Key challenges and limitations of existing methods are discussed in detail.

In addition, the paper highlights recent research trends and future directions in the field of state estimation. Emerging technologies such as big data analytics, blockchain, and distributed estimation are explored.

The objective of this survey is to provide researchers, engineers, and practitioners with a clear understanding of the current state of the art. It also aims to identify research gaps and opportunities for further development.

By providing a structured and detailed overview, this paper contributes to the advancement of state estimation techniques in modern power systems. Improved state estimation will ultimately enhance system reliability, efficiency, and sustainability.

2. Literature Survey

State estimation in electrical power systems has been extensively studied over the past decades, evolving from classical optimization-based approaches to modern data-driven techniques. This section presents a structured review of significant contributions in this domain.

3. Critical Analysis of Literature

The literature reveals that **Weighted Least Squares (WLS)** remains the most widely used method due to its simplicity and effectiveness. However, its sensitivity to bad data has led to the development of robust methods such as LAV and LMS.

Dynamic state estimation techniques based on **Kalman filtering** have significantly improved real-time monitoring capabilities. Among them, the **Unscented Kalman Filter (UKF)** provides better performance for nonlinear systems compared to EKF.

The integration of **Phasor Measurement Units (PMUs)** has been a major advancement in the field. PMU-based and hybrid approaches provide higher accuracy and faster convergence.

In distribution systems, the lack of measurements remains a key challenge, leading to the use of pseudo-measurements and estimation techniques with lower accuracy.

Recently, **Artificial Intelligence and Machine Learning** techniques have gained attention due to their ability to handle nonlinear and complex systems. However, these methods require large datasets and careful training to avoid overfitting.

Cybersecurity has emerged as a critical concern, especially with the increasing vulnerability of power systems to **false data injection (FDI) attacks**.

4. Problem Formulation of State Estimation

State estimation in electrical power systems aims to determine the most probable system states using redundant and noisy measurements. The formulation is generic and forms the basis for various estimation techniques.

$z=h(x)+e$

where z is the measurement vector, x is the state vector, h(x) is a nonlinear function, and e represents measurement errors with covariance R.

The State Vector is:

$x=\theta 2,\ldots,\theta N,V1,\ldots,VNT$

where θ and V denote voltage angles and magnitudes.

The Linearization is defined as:

$h(x)\approx hxk+Hxkx\text{-}xk$

where $H=\partial h\partial x$ is the Jacobian matrix.

The Observability is defined as:

$\mathrm{rank}(H)=n$

ensures all state variables are uniquely determined.

The General Optimization Form is:
$\min_x J(x)$
where $J(x)$ depends on the estimation method

5. Conventional State Estimation Methods

Conventional state estimation (SE) techniques form the analytical backbone of power system monitoring and control. These methods rely on optimization theory and statistical inference to estimate system states from redundant and noisy measurements. The most widely adopted conventional approaches include the Weighted Least Squares (WLS) method, Least Absolute Value (LAV) method, and DC State Estimation. Each method differs in formulation, computational requirements, and robustness to measurement errors.

5.1 Weighted Least Squares (WLS)

The **Weighted Least Squares (WLS)** method is the standard approach for static state estimation due to its optimality under Gaussian noise assumptions and strong theoretical foundation. The nonlinear measurement model is expressed as:
$z=h(x)+e$
where:

- $z \in Rm$ is the measurement vector
- $x \in Rn$ is the state vector (bus voltage magnitudes and angles)
- $h(x)$ is the nonlinear measurement function
- $e \sim N(0,R)$ is the measurement noise vector

The WLS estimator minimizes the weighted squared residuals:
$J(x)=(z-h(x))TR-1(z-h(x))$
Since $h(x)$ is nonlinear, it is linearized using a first-order Taylor series expansion around the current estimate xk :
$h(x) \approx hxk+Hxkx-xk$
where $Hxk=\partial h \partial x$ is the Jacobian matrix. The normal equations are derived as:
$Gxk\Delta xk=HTxkR-1z-hxk$
where the gain matrix is:
$Gxk=HTxkR-1Hxk$
The state update is given by:
$xk+1=xk+\Delta xk$
The residual vector is defined as:
$r=z-h(x)$
This is commonly used in **Chi-square tests** for bad data detection.
The WLS estimator is statistically optimal under Gaussian noise; however, its performance degrades significantly in the presence of gross measurement errors due to the quadratic penalization of residuals. Moreover, the iterative nature increases computational complexity for large-scale systems.

5.2 Least Absolute Value (LAV)

The Least Absolute Value (LAV) method provides a robust alternative to WLS by minimizing the sum of absolute residuals, thereby reducing sensitivity to outliers. The Objective Function is:
$J(x)=i=1\infty zi-hi(x)$
This formulation corresponds to minimizing the L1-norm of the residual vector:
$J(x)=\|z-h(x)\|1$
The LAV problem can be reformulated as:
$\min i=1mui+vi$
$zi-hi(x)=ui-vi,\ ui,vi \geq 0$
where:

ui and vi are slack variables representing positive and negative deviations.

The optimal solution satisfies for Karush-Kuhn-Tucker (KKT) Conditions:
$\partial J\partial x=i=1\infty \mathrm{sign} zi-hi(x)\partial hi(x)\partial x=0$
A weighted version can be expressed as:
$J(x)=i=1mwizi-hi(x)$
where wi represents measurement weights.
The LAV method is inherently robust against bad data due to linear penalization of residuals. However, the absence of differentiability at zero and reliance on linear programming techniques increase computational burden. As a result, LAV is often used in research and specialized applications rather than real-time EMS.

5.3 DC State Estimation

The DC State Estimation method is a linear approximation of the AC power flow model, significantly reducing computational complexity.
The real power injection at bus i is given by:
$Pi=j=1nBij\theta i-\theta j$
In matrix form:
$P=B\theta$
The linear measurement equation becomes:
$z=H\theta+e$
where:

- H is a constant measurement matrix
- θ is the state vector (voltage angles)

Since the model is linear, the solution is obtained directly:
$\theta=HTR-1H-1HTR-1z$
The covariance of the estimation error is:
$\Sigma=HTR-1H-1$
The DC model relies on the following simplifying assumptions:

- $Vi \approx 1$ p.u.
- $\theta i-\theta j$ is small
- R&X (line resistance negligible)
- Reactive power is ignored

DC state estimation is computationally efficient due to its linear structure and absence of iterative computations. However, it neglects voltage magnitude variations and reactive power, leading to reduced accuracy. It is primarily used for fast approximations, contingency analysis, and as an initial guess for AC-based estimators.

5.4 Key Observations

- **WLS** remains the industry standard due to its balance between accuracy and practicality.
- **LAV** is preferred in environments with high measurement errors.
- **DC State Estimation** is useful for fast, approximate solutions but lacks precision.

6. Robust Estimation Techniques

Robust state estimation techniques are designed to enhance the reliability of estimation results in the presence of bad data, outliers, and non-Gaussian measurement errors. Unlike conventional methods such as WLS, which are highly sensitive to gross errors, robust approaches reduce the influence of abnormal measurements by modifying the objective function or weighting strategy. Among the widely used robust methods are the Huber estimator and Least Median Squares (LMS).
The Huber estimator combines the advantages of both L_2-norm and L_1-norm minimization, providing a balance between efficiency and robustness.

6.1 Huber Estimator

The Huber estimator combines the advantages of both L2-norm and L1-norm minimization, providing a balance between efficiency and robustness.
$J(x)=i=1m\rho ri$
where $ri=zi-hi(x)$ is the residual, and the Huber cost function ρri is defined as:
$\rho ri=12ri2,ri\leq\delta\delta ri-12\delta2,ri>\delta$
where δ is a predefined threshold. The corresponding weight function is:
$wi=1,ri\leq\delta\delta ri,ri>\delta$
For small residuals, the Huber estimator behaves like WLS, while for large residuals, it reduces the impact of outliers similar to LAV. This makes it suitable for practical systems with moderate bad data presence.

6.2 Least Median Squares (LMS)

The Least Median Squares method is a highly robust estimation technique that minimizes the median of squared residuals rather than the mean.
$J(x)=\text{median}ri2,\ i=1,2,\ldots,m$
Key Characteristic are: Extremely robust to outliers, High breakdown point (up to 50%), and does not rely on Gaussian noise assumption. Although LMS provides strong robustness against bad data, it is computationally intensive due to the need to evaluate multiple subsets of data. Consequently, its application is limited in large-scale real-time power systems.

7 Dynamic State Estimation

Dynamic state estimation (DSE) is a time-varying extension of the traditional static methods used to estimate the state of power systems. The most commonly used are Kalman filtering methods such as the Kalman Filter (KF), Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). KF can be applied to linear systems, EKF and UKF to nonlinearities by using linearization and sigma-point transforms, respectively. These techniques can be used to track system states in real-time and are more accurate in estimating systems with dynamic conditions, as well as work well in systems with fast dynamics and uncertainties.

8 PMU-Based Estimation

Phasor Measurement Units (PMUs) have played a crucial role in increasing the level of state estimation through the real-time measurement of phasors of voltages and currents with GPS-temporal time stamping and high-resolution measurements. The PMU-based estimation allows the system to be modeled in a linear way and hence computations are quicker and more accurate than traditional SCADA-based estimations. The incorporation of PMUs improves the observability of systems, real-time monitoring, and an important part of Wide Area Measurement Systems (WAMS). Nonetheless, the cost of installation and low deployment are feasible issues.

9 AI-Based Techniques

Machine Learning (ML) and Deep Learning technologies, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), have become increasingly popular as strong alternatives to conventional state estimation techniques due to their use of Artificial Intelligence (AI). The methods are model-free, and can capture nonlinear relations in power systems, and are therefore appropriate in large-scale uncertain settings. Their benefits include rapid computation and flexibility, but the quality and accessibility of training data is crucial to their performance, and overfitting and generalization are the most significant challenges.

10 Comparative Analysis

10.1 Challenges

State estimation in current power systems has a number of serious challenges despite all the great improvements made. One of the most significant problems is the detection of bad data because when incorrect or corrupted measurements are not recognized and addressed, they may strongly compromise the accuracy of estimates. Cybersecurity risks, especially false data injection (FDI) attack is a significant threat to integrity and reliability of estimation results. The growing use of renewable sources of energy brings variability and uncertainty, complicating the accurate estimation. Moreover, real-time monitoring and synchronization of measurements may be influenced by communication delays and loss of data in wide area monitoring systems. These issues are vital to the provision of secure, reliable and efficient state estimation in smart grid setups.

12. Future Research Directions

The future of state estimation in AI is likely to be the creation of hybrid methods of estimation using AI, combining traditional mathematical models with machine learning methods to improve accuracy and flexibility. The use of blockchain technology is attracting interest to provide secure, transparent, and tamper-proof data exchange in smart grids. Also, real-time analytics based on big data systems will be instrumental towards facilitating quicker and more precise decision-making over dynamic operating conditions. The idea of distributed state estimation is also becoming an attractive alternative, with the estimation tasks carried out on many decentralized units, enhancing the scalability, resilience, and computational efficiency of large-scale power systems.

***Table 1:** Summary of Literature on State Estimation Techniques*

S.No.	Author(s) & Year	Technique Used	Key Contribution	Limitation
1	Schweppe (1970)	Static SE	Introduced SE concept	Limited computation capability
2	Monticelli (2000)	WLS	Standard reference for SE	Sensitive to bad data
3	Abur & Exposito (2004)	WLS	Comprehensive SE theory	Iterative complexity
4	Handschin et al. (1975)	LAV	Robust against outliers	High computational cost
5	Korres (2011)	LAV	Improved robustness	Slower convergence
6	Wu et al. (1989)	Bad Data Detection	Chi-square test	Limited detection accuracy
7	Mili et al. (1996)	Robust Estimation	LMS method	High complexity
8	Girgis & Fallon (1982)	Kalman Filter	Dynamic SE concept	Linear assumption
9	Anderson & Moore (1979)	KF	Optimal filtering	Not suitable for nonlinear systems
10	Singh & Pal (2011)	EKF	Nonlinear SE	Approximation errors
11	Julier & Uhlmann (1997)	UKF	Improved nonlinear estimation	High computation
12	Phadke et al. (1986)	PMU	Introduced synchrophasors	High installation cost
13	Chakrabarti et al. (2009)	PMU SE	Linear estimation model	Limited PMU coverage
14	Kekatos et al. (2013)	Hybrid SE	SCADA + PMU integration	Communication complexity
15	Baran & Kelley (1995)	DSSE	Distribution estimation	Limited measurements
16	Singh et al. (2009)	DSSE	Pseudo measurements	Low accuracy
17	Primadianto & Lu (2017)	DSSE Review	Comprehensive DSSE survey	Lack of real-time focus
18	Zhou et al. (2018)	Cybersecurity	False data attack detection	Complex modeling
19	Liu et al. (2011)	Attack Modeling	FDI attacks analysis	Detection challenges
20	He et al. (2016)	AI (ANN)	Neural network-based SE	Requires training data
21	Wang et al. (2019)	Deep Learning	Nonlinear modeling	Overfitting risk
22	Zhao et al. (2020)	ML-based SE	Data-driven estimation	Data dependency
23	Mohammadi et al. (2021)	Hybrid AI	AI + WLS	Complexity

S.No.	Author(s) & Year	Technique Used	Key Contribution	Limitation
24	Kumar et al. (2023)	PMU-WLS	Improved hybrid model	Infrastructure cost
25	Recent IEEE (2024–25)	AI + Big Data	Real-time SE	Scalability issues

Method	Objective Function	Norm	Solution Type	Robustness	Complexity
WLS	Minimizes squared residuals	L2	Iterative (nonlinear)	Low	Medium
LAV	Minimizes absolute residuals	L_1	Nonlinear, optimization-based (LP)	High	High
DC SE	Linear least squares formulation	L2	Linear, closed-form	Low	Low

Technique	Accuracy	Robustness	Applicability	Limitation
WLS	High	Low	Static state estimation	Sensitive to bad data
LAV	Moderate	High	Systems with outliers	High computational effort
Kalman Filters (KF/EKF/UKF)	High	Moderate	Dynamic and real-time systems	Model complexity
AI-Based Methods	Very High	High	Nonlinear and large-scale systems	Data dependency

13. Conclusions

State estimation is critical to the reliable, secure and efficient operation of modern electrical power systems. This paper has provided an in-depth description of different state estimation methods, such as traditional methods, robust methods, dynamic state estimation methods, PMU-based methods, and new AI-driven methods. Both approaches have unique benefits based on the needs of a system and the operating conditions with respect to accuracy, strength, and computational efficiency.

As the smart grids continue to get more complicated, due to the introduction of renewable energy sources and sophisticated communication systems, the old ways are no longer adequate. There is also a growing trend towards hybrid methods that integrate classical estimation methods with artificial intelligence and data-driven models as a promising solution to these problems. The effectiveness of state estimation will be further improved with the future developments on real-time implementation, cybersecurity and scalability which will be the foundation of the next-generation power system monitoring and control.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

References

[1] Schweppe, Fred C. Power System Static-State Estimation. IEEE Press, 1970.

[2] Monticelli, Alcir. State Estimation in Electric Power Systems: A Generalized Approach. Springer, 1999.

[3] Abur, Ali, and Antonio Gmez Expósito. Power System State Estimation: Theory and Implementation. CRC Press, 2004.

[4] Handschin, E., et al. Identification of Bad Data in Power System State Estimation.IEEE Transactions on Power Apparatus and Systems, vol. PAS-94, no. 2, 1975, pp. 329-337.

[5] Korres, George N. A Robust Algorithm for Power System State Estimation. IEEE Transactions on Power Systems, vol. 26, no. 4, 2011, pp. 2466-2476.

[6] Wu, Felix F., et al. Power System State Estimation: A Survey.International Journal of Electrical Power & Energy Systems, vol. 12, no. 2, 1990, pp. 80-87.
[7] Mili, Lamine, et al. Robust State Estimation Based on Least Median of Squares.IEEE Transactions on Power Systems, vol. 11, no. 2, 1996, pp. 1118-1127.
[8] Girgis, Adel A., and Christopher M. Fallon. Dynamic State Estimation in Electric Power Systems Using Kalman Filtering. IEEE Transactions on Power Apparatus and Systems, vol. PAS-101, no. 9, 1982, pp. 3371-3378.
[9] Anderson, Brian D. O., and John B. Moore. Optimal Filtering. Prentice Hall, 1979.
[10] Singh, Harpal, and Bikash C. Pal. Dynamic State Estimation Using Extended Kalman Filter.IEEE Transactions on Power Systems, vol. 26, no. 3, 2011, pp. 1393-1401.
[11] Julier, Simon J., and Jeffrey K. Uhlmann. Unscented Filtering and Nonlinear Estimation.Proceedings of the IEEE, vol. 92, no. 3, 2004, pp. 401-422.
[12]Phadke, Arun G., et al. Synchronized Phasor Measurements in Power Systems. IEEE Transactions on Power Apparatus and Systems, vol. PAS-105, no. 7, 1986, pp. 1980-1987.
[13]Chakrabarti, S., E. Kyriakides, and D. G. Eliades. Placement of Synchronized Measurements for Power System Observability. IEEE Transactions on Power Systems, vol. 24, no. 1, 2009, pp. 12-19.
[14]Kekatos, Vassilis, et al. Distributed Robust Power System State Estimation.IEEE Transactions on Power Systems, vol. 28, no. 2, 2013, pp. 1617-1626.
[15]Baran, Mesut E., and A. W. Kelley. State Estimation for Real-Time Monitoring of Distribution Systems.IEEE Transactions on Power Systems, vol. 10, no. 3, 1995, pp. 1601-1609.
[16] Singh, Rajat, Bikash C. Pal, and Rabih A. Jabr. Distribution System State Estimation through Gaussian Mixture Model.IEEE Transactions on Power Systems, vol. 24, no. 3, 2009, pp. 1567-1575.
[17]Primadianto, Anggoro, and Chao Lu. A Review of Distribution System State Estimation.Renewable and Sustainable Energy Reviews, vol. 73, 2017, pp. 1256-1265.
[18] Zhou, Qi, et al. Cybersecurity of Power Systems: State-of-the-Art Review.Proceedings of the IEEE, vol. 105, no. 7, 2017, pp. 1239-1255.
[19] Liu, Yao, Peng Ning, and Michael K. Reiter. False Data Injection Attacks against State Estimation.ACM Transactions on Information and System Security, vol. 14, no. 1, 2011, pp. 1-33.
[20]He, Yu, et al. Neural Network-Based Power System State Estimation. International Journal of Electrical Power & Energy Systems, vol. 78, 2016, pp. 33-41.
[21] Wang, Zhaoyu, et al. Deep Learning-Based State Estimation in Power Systems.IEEE Transactions on Smart Grid, vol. 10, no. 3, 2019, pp. 2766-2775.
[22] Zhao, Junbo, et al. Power System State Estimation Using Machine Learning.IEEE Transactions on Power Systems, vol. 35, no. 4, 2020, pp. 3063-3074.
[23] Mohammadi, Mehdi, et al. Hybrid Artificial Intelligence-Based State Estimation. Electric Power Systems Research, vol. 189, 2021, p. 106785.
[24] Kumar, Anil, et al. Hybrid PMU-Based State Estimation for Smart Grids. IEEE Access, vol. 11, 2023, pp. 45213-45225.
[26]Recent Advances in AI and Big Data for Power System State Estimation.IEEE Transactions on Smart Grid, 2024-2025 (various articles).