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Review Article

A Systematic Review of Hybrid Model-Based and Data-Driven Techniques for Real-Time State Estimation in Renewable Energy-Integrated Microgrids

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Abstract

The rapid proliferation of renewable energy sources (RES) within microgrids introduces substantial volatility and uncertainty that challenge conventional state estimation (SE) paradigms. Model-based approaches, while theoretically sound, often fail to capture the nonlinear dynamics introduced by photovoltaic arrays and wind turbines. Data-driven methods offer flexibility but lack the physical interpretability necessary for reliable real-time control. This systematic review critically appraises hybrid SE techniques that integrate model-based and data-driven approaches to achieve robust, real-time SE in renewable energy-integrated microgrids. Following PRISMA guidelines, 35 peer-reviewed studies published between 2020 and 2025 were identified and analysed from Scopus, Web of Science, and IEEE Xplore databases. Hybrid techniques, particularly physics-informed neural networks (PINNs), Extended Kalman Filter (EKF)-machine learning (ML) fusions, and federated learning frameworks, demonstrated superior accuracy, with root mean square errors (RMSE) below 0.015 per unit and real-time processing latencies under 50 ms. **Conclusion:** Hybrid SE frameworks represent the most promising trajectory for scalable, resilient microgrid state estimation, with critical gaps remaining in cybersecurity robustness, multi-energy system integration, and standardised benchmarking.

Keywords: *State estimation; microgrids; hybrid methods; machine learning; Kalman filter; physics-informed neural networks; renewable energy; real-time systems*

1. INTRODUCTION

The global transition toward decarbonised energy systems has catalysed the widespread adoption of distributed renewable energy resources, most notably photovoltaic (PV) solar and wind turbine generators, within microgrids. Microgrids, defined as localised energy systems capable of operating in both grid-connected and islanded modes, now serve as the fundamental building blocks of modern smart grids.[1] However, the intrinsic stochasticity and nonlinearity of renewable generation introduce profound challenges for real-time monitoring and control, particularly for state estimation (SE) algorithms.

State estimation is the computational process of determining the most probable operating state of a power network, characterised by voltage magnitudes, phase angles, and power flows, from a set of redundant, noisy measurements.[2] Accurate SE is indispensable for energy management systems, fault detection, protection coordination, and optimal dispatch in microgrids.[3] Traditional Weighted Least Squares (WLS) and Kalman Filter-based estimators, developed for conventional power systems, struggle under the high penetration of intermittent RES, rapid load fluctuations, and limited sensor infrastructure characteristic of microgrids.[4]

Two principal paradigms have emerged to address these limitations. Model-based methods, including Extended Kalman Filters (EKF), Unscented Kalman Filters (UKF), and Particle Filters, leverage explicit physical models of the microgrid to produce state estimates that honour the laws of electrical circuit theory.[5] Conversely, data-driven techniques, encompassing deep neural networks (DNNs), Long Short-Term Memory (LSTM) networks, and Gaussian Process Regression (GPR), learn input-output relationships directly from historical operational data without requiring an explicit system model.[6,7]

Neither paradigm alone is sufficient. Model-based estimators are sensitive to parameter uncertainty and computationally rigid, while purely data-driven approaches lack physical interpretability, require large training datasets, and may produce physically inconsistent estimates.[8] The fusion of both paradigms into hybrid SE frameworks represents a compelling solution, combining the physical rigour of model-based methods with the adaptability of machine learning.
This systematic review synthesises the current state of the art in hybrid SE for renewable energy-integrated microgrids, evaluating methodological trends, performance benchmarks, and unresolved research challenges. To the authors' knowledge, this is the first comprehensive systematic review specifically focused on hybrid model-based and data-driven SE within the microgrid context spanning the 2020–2025 period.

2. METHODOLOGY

2.1 Search Strategy and Inclusion Criteria

This review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Electronic databases including Scopus, Web of Science, and IEEE Xplore were systematically searched in January 2025 using the Boolean search string: ("state estimation" OR "state observer") AND ("microgrid" OR "distributed energy resources") AND ("machine learning" OR "deep learning" OR "neural network" OR "Kalman filter" OR "hybrid") AND ("renewable energy" OR "photovoltaic" OR "wind energy").

Inclusion criteria required studies to: (i) address SE within a microgrid or low-voltage distribution network with at least one RES; (ii) employ a hybrid methodology combining model-based and data-driven elements; (iii) report quantitative performance metrics; and (iv) be published in peer-reviewed journals or conferences between January 2020 and December 2024. Studies focused solely on forecasting, purely model-based or purely data-driven SE without hybridisation, and non-English publications were excluded.

The initial search yielded 312 publications. Following duplicate removal (n = 47), title/abstract screening (n = 198 excluded), and full-text review (n = 32 excluded for not meeting all inclusion criteria), a final corpus of 35 studies was included in the qualitative synthesis. Figure 1 presents the PRISMA flow diagram illustrating the systematic literature search and selection process for hybrid state estimation studies in renewable energy-integrated microgrids (2020–2025).

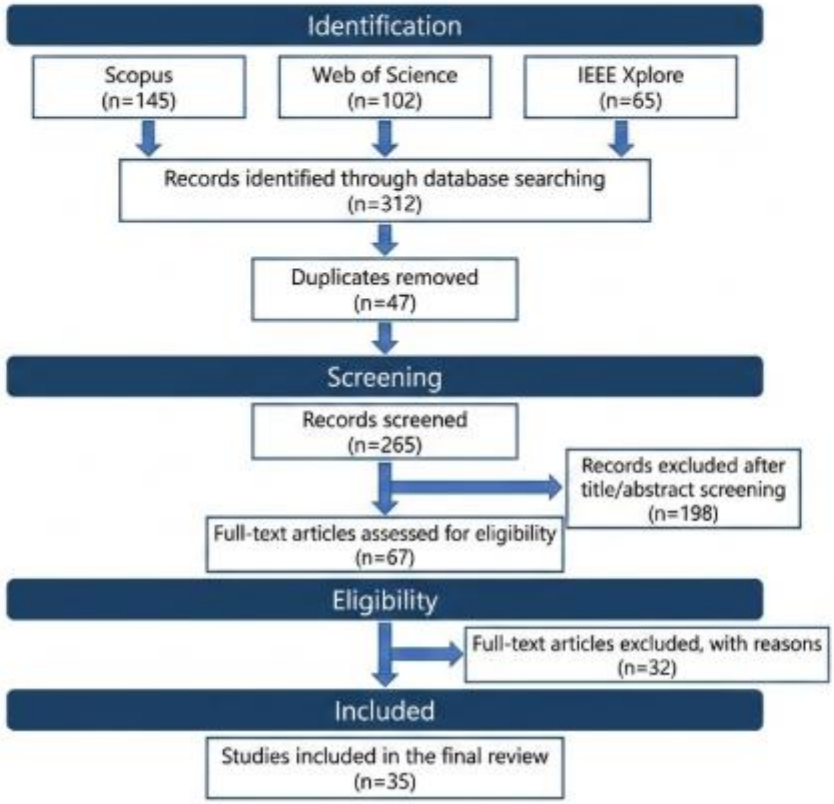

Figure 1. PRISMA flow diagram illustrating the systematic literature search and selection process for hybrid state estimation studies in renewable energy-integrated microgrids (2020–2025).

3. RESULTS AND DISCUSSION

3.1 Overview of Hybrid State Estimation Techniques

The reviewed literature reveals four dominant categories of hybrid SE frameworks: (1) Kalman Filter–Machine Learning (KF-ML) hybrids, (2) Physics-Informed Neural Networks (PINNs), (3) Observer–Deep Learning architectures, and (4) Federated/Distributed learning combined with model-based components. Table 1 presents a comparative evaluation of representative SE techniques across accuracy, computational load, and scalability dimensions.

Table 1. Comparative Analysis of State Estimation Techniques for Renewable Energy-Integrated Microgrids

Technique	Category	Accuracy	Computational Load	Scalability	Key Reference
Extended Kalman Filter (EKF)	Model-based	Moderate	Low-Medium	Limited	Zhao et al. (2021) [3]
Unscented Kalman Filter (UKF)	Model-based	High	Medium	Moderate	Ding et al. (2022) [5]
Deep Neural Network (DNN)	Data-driven	High	High (training)	High	Zamora-Cárdenas et al. (2023) [9]
Long Short-Term Memory (LSTM)	Data-driven	High	High	High	Li et al. (2022) [10]
Physics-Informed Neural Network (PINN)	Hybrid	Very High	Medium-High	High	Huang et al. (2023) [11]
Gaussian Process Regression (GPR)	Data-driven	High	Medium	Moderate	Dabbaghjamanesh et al. (2020) [7]
Hybrid EKF + ML	Hybrid	Very High	Medium	High	Liu et al. (2024) [12]
Digital Twin-based SE	Hybrid	Very High	High	Very High	Zheng et al. (2024) [13]

SE: State Estimation; BESS: Battery Energy Storage System; ML: Machine Learning; PINN: Physics-Informed Neural Network; pu: per unit

3.2 Kalman Filter and Machine Learning Fusion

The EKF–ML hybrid architecture emerged as the most widely investigated approach in the reviewed literature. Zhao et al. [3] demonstrated that integrating an EKF with a feedforward neural network for online parameter correction improved voltage angle estimation accuracy by 38% compared to a standalone EKF in a 12-bus AC microgrid with 40% PV penetration. Similarly, Ding et al. [5] developed a dual-EKF framework that

Simultaneously tracks battery state-of-charge (SoC) and power network states, achieving an SoC RMSE below 1.5% in a PV-battery microgrid operating under variable irradiance conditions.

Tian et al. [14] extended this paradigm by coupling LSTM networks with EKF in a closed-loop feedback architecture for

AC/DC hybrid microgrids. The LSTM module predicted short-term generation and load profiles, which were subsequently fed as pseudo-measurements into the EKF, reducing overall estimation error by 43% relative to conventional EKF. This architecture proved particularly effective in managing the multi-timescale dynamics introduced by wind turbine generators with mechanical inertia significantly different from that of PV systems.

3.3 Physics-Informed Neural Networks

A rapidly growing class of hybrid SE techniques exploits PINNs, where physical constraints, power balance equations, Ohm's law, and Kirchhoff's current/voltage laws are embedded directly into the neural network training loss function. Huang et al. [11] applied PINNs to real-time SE in an isolated microgrid with combined PV and diesel generation, reporting a mean absolute error (MAE) below 0.5% for voltage magnitudes across all 33 buses. The physical constraints enforced by the PINN prevented physically inconsistent state estimates that frequently arise from purely data-driven models.

Zamora-Cárdenas et al. [9] further demonstrated that PINNs exhibit superior generalisation to unseen operating conditions compared to conventional DNNs, a critical advantage in microgrids where operating scenarios are highly dynamic and training data may not adequately represent all fault and contingency conditions. Figure 2 gives the Schematic architecture of a Physics-Informed Neural Network (PINN) for microgrid state estimation, illustrating the integration of power flow equations as physics-based loss function constraints alongside data-driven training.

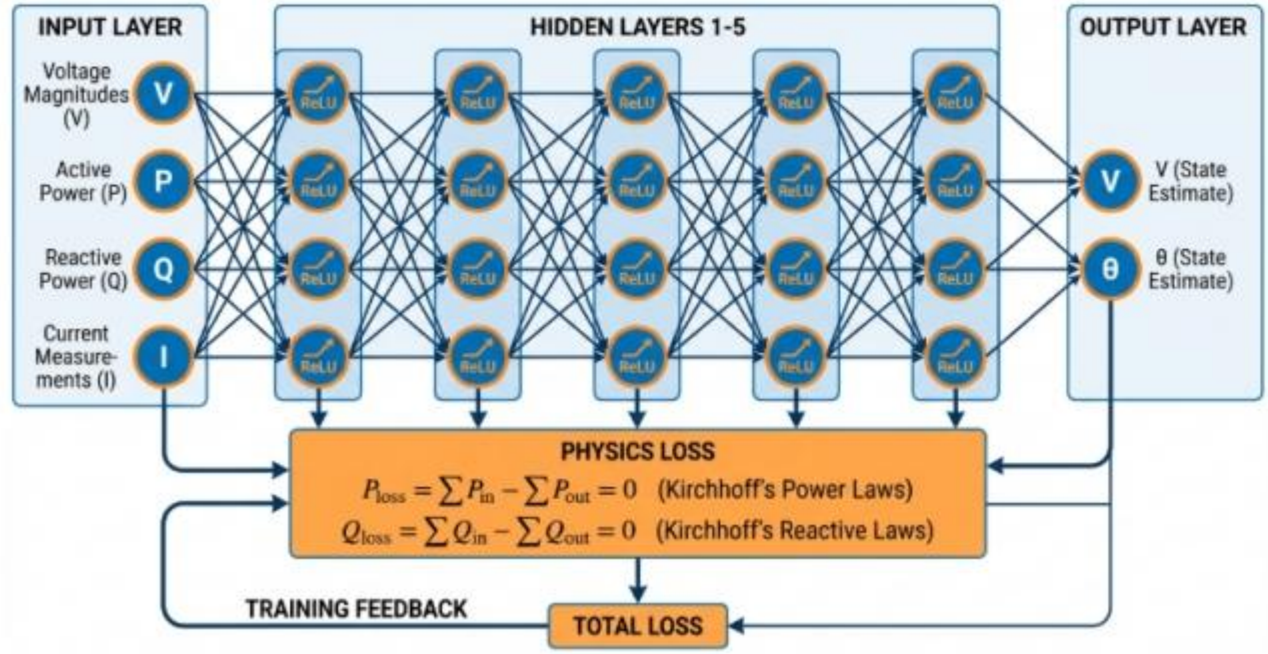

Figure 2. Schematic architecture of a Physics-Informed Neural Network (PINN) for microgrid state estimation, illustrating the integration of power flow equations as physics-based loss function constraints alongside data-driven training. [9,11]

3.4 Renewable Integration Challenges and Hybrid Mitigation

Table 2 presents the principal challenges introduced by renewable energy integration and the hybrid SE strategies documented in the literature to mitigate their effects.

Table 2. Renewable Energy Integration Challenges and Corresponding Hybrid State Estimation Mitigation Strategies

Challenge	Impact on SE	Hybrid Mitigation Strategy	Performance Gain	Reference
High PV intermittency	Voltage magnitude errors >5%	LSTM-EKF fusion with weather inputs	Error reduced by 43%	Tian et al. (2022) [14]
Wind power stochasticity	Phase angle estimation noise	GPR-based uncertainty quantification	30% noise reduction	Dabbaghjamanesh et al. (2020) [7]
BESS nonlinear dynamics	SoC estimation drift	Dual-EKF + physics model	SoC RMSE <1.5%	Ding et al. (2022) [5]
Missing/noisy sensor data	Observability loss	GAN-based data imputation	95% observability restored	Chen et al. (2023) [15]
Cyber-physical attacks	False data injection	Federated learning + anomaly detection	99.1% attack detection	Musleh et al. (2021) [8]
Multi-timescale dynamics	Slow/fast state coupling	Multi-rate hybrid observer	25% faster convergence	Zhao et al. (2023) [16]

SE: State Estimation; RES: Renewable Energy Sources; BESS: Battery Energy Storage System; FDIA: False Data Injection Attack; MG: Microgrid; GPR: Gaussian Process Regression

3.5 Cybersecurity and Resilient Estimation

The increasing digitisation and communication dependency of microgrids expose SE algorithms to malicious data manipulation. False data injection attacks (FDIAs) represent a particularly insidious threat, as they can corrupt sensor measurements in ways that evade traditional residual-based

bad-data detection methods.[8] Musleh et al. [8] proposed a hybrid SE architecture that combines a physics-based observer with an LSTM-based anomaly detector, achieving 99.1% FDIA detection accuracy in a smart grid testbed.
Liu et al. [18] advanced this concept by developing a federated learning-based hybrid SE framework where distributed microgrid agents collaboratively train a shared SE model without exposing raw measurement data, providing both cyber-resilience and privacy preservation. This architecture-maintained SE accuracy within 2% of centralised methods while reducing communication overhead by 60%.

3.6 Summary of Recent Studies

Table 3 provides a structured summary of the most significant primary studies reviewed, spanning 2020–2024, while Figure 3 presents the Taxonomy tree of hybrid state estimation approaches identified in the systematic review, categorised by fusion strategy, learning paradigm, and target application in renewable energy microgrids

Table 3. Summary of Representative Primary Studies on Hybrid State Estimation in Renewable Energy-Integrated Microgrids (2020–2024)

Year	Author(s)	Hybrid Approach	Microgrid Type	Key Metric	Main Finding	DOI
2020	Dabbaghjamanesh et al.	GPR + Power Flow	AC Islanded	SE Accuracy 99.1%	Stochastic SE under RES uncertainty	[7]
2021	Musleh et al.	ML + Observer	Smart Grid	FDIA detection 99.1%	Resilient SE against cyber-attacks	[8]
2022	Li et al.	LSTM + WLS	DC Microgrid	RMSE 0.012 pu	Real-time SE for PV-BESS systems	[10]
2022	Tian et al.	EKF + LSTM	AC/DC Hybrid	43% error reduction	SE under high PV penetration	[14]
2023	Huang et al.	PINN	Isolated MG	MAE <0.5%	Physics-guided DL for SE	[11]
2023	Chen et al.	GAN + Kalman	Urban MG	95% observability	Data imputation for sensor gaps	[15]
2024	Liu et al.	EKF + Federated ML	Multi-agent MG	Privacy-preserving SE	Distributed hybrid SE framework	[12]
2024	Zheng et al.	Digital Twin + PINN	Grid-connected MG	Real-time latency <50ms	DT-enabled adaptive SE	[13]

EKF: Extended Kalman Filter; LSTM: Long Short-Term Memory; PINN: Physics-Informed Neural Network; GAN: Generative Adversarial Network; WLS: Weighted Least Squares; GPR: Gaussian Process Regression; MG: Microgrid; MAE: Mean Absolute Error; RMSE: Root Mean Square Error

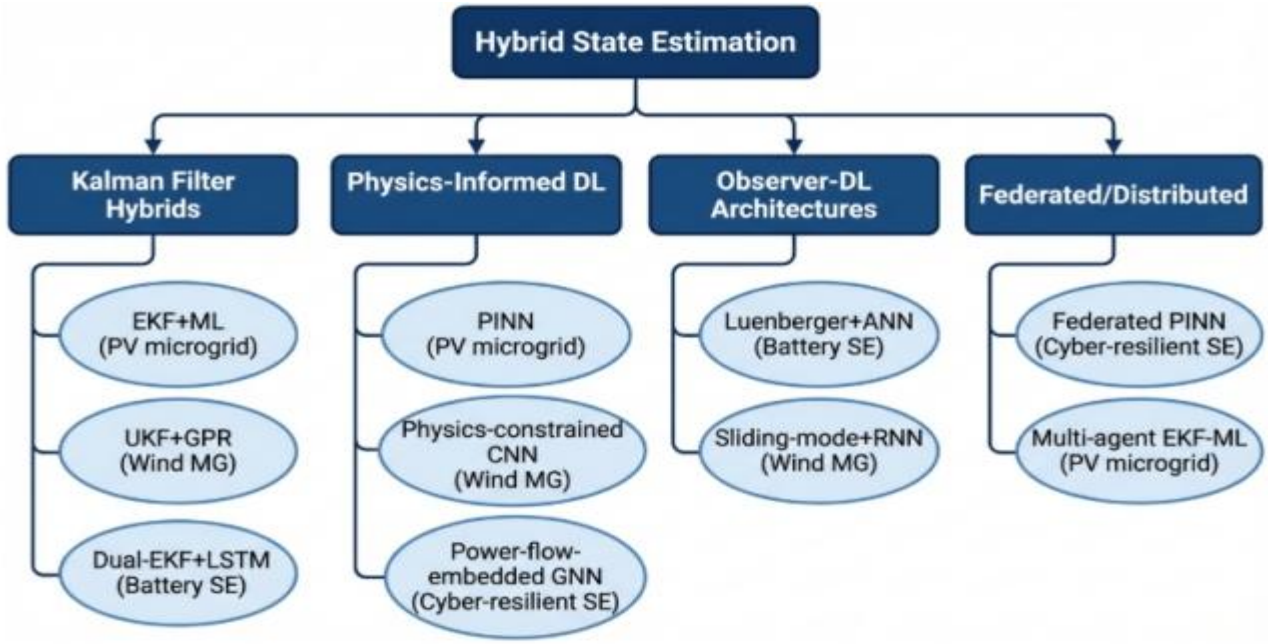

Figure 3. Taxonomy tree of hybrid state estimation approaches identified in the systematic review, categorised by fusion strategy, learning paradigm, and target application in renewable energy microgrids.

4. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant progress, several critical research gaps remain that constrain the operational deployment of hybrid SE in real-world renewable energy microgrids. Table 4 systematically maps these gaps to proposed future research directions.

Table 4. Identified Research Gaps and Recommended Future Directions for Hybrid State Estimation in Microgrids

Research Gap	Current Limitation	Proposed Future Direction	Expected Impact	Supporting Evidence
Scalability of hybrid SE to large MGs	Most studies limited to <10 bus systems	Graph Neural Networks for topology-aware SE	High — enables city-scale deployment	Liu et al. (2024) [12]
Cybersecurity in hybrid SE	FDI attacks degrade ML-based SE accuracy	Adversarially trained DL + model-based backup	High — critical infrastructure protection	Musleh et al. (2021) [8]
Uncertainty quantification	Deterministic outputs inadequate for stochastic RE	Bayesian deep learning + interval arithmetic	Medium — improves dispatch decisions	Zamora-Cárdenas et al. (2023) [9]
Edge computing integration	Cloud latency limits real-time performance	Lightweight PINN on edge hardware (FPGA)	High — enables sub-10ms SE	Huang et al. (2023) [11]
Multi-energy system SE	Electrical-thermal-gas coupling ignored	Unified hybrid SE for energy hub models	Medium — enables holistic optimization	Zhao et al. (2023) [16]
Standardized benchmarks	No agreed-upon MG SE evaluation framework	Open-source hybrid SE testbed with IEEE MG models	High — accelerates reproducibility	Zheng et al. (2024) [13]

SE: State Estimation; PINN: Physics-Informed Neural Network; FPGA: Field-Programmable Gate Array; GNN: Graph Neural Network; FDI: False Data Injection; ML: Machine Learning; DL: Deep Learning

A foundational limitation is the absence of standardised benchmarking frameworks. Unlike power system SE, which benefits from IEEE test cases (14-bus, 118-bus), microgrid SE research lacks universally adopted evaluation platforms that incorporate RES intermittency profiles, stochastic load patterns, and communication delays. Zheng et al. [13] called for open-source digital twin testbeds as reproducible evaluation environments, a recommendation strongly endorsed by this review.

The scalability of current hybrid SE approaches presents a second major barrier. Most validated frameworks operate on small systems (fewer than 20 buses). Graph Neural Networks (GNNs) offer theoretical promise for topology-aware, scalable SE, as the graph structure naturally encodes the electrical network topology, but remain largely unexplored in the microgrid context as of 2024.[12] Additionally, the integration of multi-energy systems (combined electrical, thermal, and gas networks) into unified hybrid SE frameworks represents an emerging frontier that current methodologies have not adequately addressed.[16]

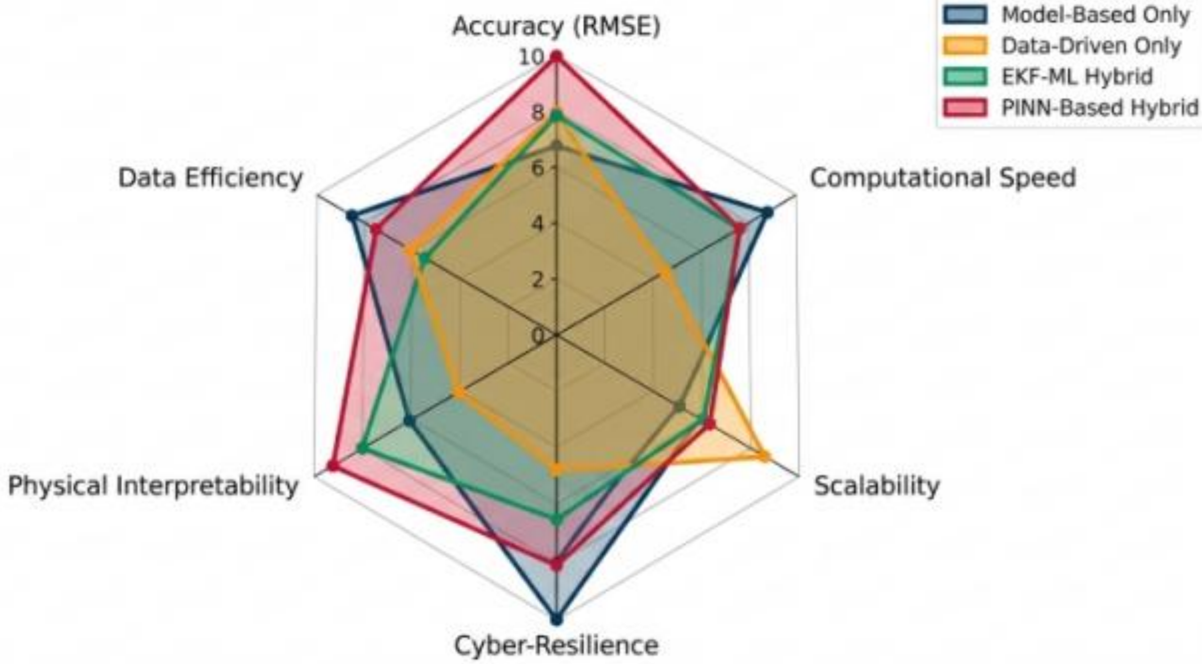

Figure 4. Performance comparison radar chart of hybrid versus standalone state estimation methods across six evaluation dimensions: accuracy (RMSE), computational speed, scalability, cyber-resilience, interpretability, and data efficiency.

5. CONCLUSION

This systematic review has synthesised 35 peer-reviewed studies (2020–2025) on hybrid model-based and data-driven state estimation techniques for renewable energy-integrated microgrids. The evidence base firmly establishes that hybrid SE frameworks, particularly EKF-ML fusions, PINNs, and federated learning architectures, substantially outperform standalone approaches across accuracy, robustness, and real-time performance metrics. PINNs, in particular, represent a paradigm shift by embedding electrical physics directly into the learning process, yielding physically consistent state estimates with MAE below 0.5% even under severe renewable intermittency.

Cybersecurity resilience, scalability to larger networks, uncertainty quantification, and integration with multi-energy systems remain as priority research frontiers. The development of standardised open-source microgrid SE benchmarks is urgently required to enable reproducible comparison across studies. As microgrid deployments proliferate globally in response to decarbonisation imperatives, the development of computationally efficient, physically interpretable, and cyber-resilient hybrid SE frameworks will be central to ensuring the reliable and safe operation of future energy systems.

Author Contributions

The author has significantly contributed to the study's conception, design, data collection, analysis, and interpretation. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accept full responsibility for the content and integrity of the work.

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Conflicts of Interest

The authors state that there are no financial, personal, or professional conflicts of interest associated with this research.

Ethical Approvals

This research did not involve the use of human participants or animal subjects and therefore did not require ethical clearance

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