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Real-Time Grid Visibility in Active Distribution Networks and Microgrids: A Review of Data Fusion, State Estimation, and Topology Identification

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ABSTRACT Modern power distribution systems and microgrids are undergoing a rapid transformation fueled by the growth of distributed generation, flexible loads, data centers, grid-edge sensing, and decentralized control. While distributed assets offer enhanced local generation and operational flexibility, they also introduce operational complexities that traditional snapshot-based monitoring and control approaches can no longer adequately manage. These changes are driving the need for real-time grid visibility that supports reliable monitoring, topology tracking, state estimation, and operator decision-making under sparse, heterogeneous, asynchronous, and uncertain measurements. Existing reviews often address distribution system state estimation, data fusion, topology identification, or microgrid monitoring as separate topics. This paper provides an integrated review of these methods as coupled building blocks for active distribution networks and microgrids. We first examine major data streams, including SCADA, AMI, remote terminal units, intelligent electronic devices, micro-phasor measurement units, grid-edge resource monitors, and pseudo-measurements. We then review classical, robust, probabilistic, AI-based, and physics-informed distribution system state estimation methods, emphasizing observability, uncertainty, scalability, and real-time applicability. Next, we survey data fusion approaches for multimodal and multi-timescale measurements, followed by topology identification methods ranging from analytical and DSSE-assisted approaches to graph-based and learning-enabled techniques. Finally, we synthesize research gaps and future opportunities, including field validation, uncertainty-aware fusion, topology-adaptive estimation, cyber-physical resilience, and scalable physics-informed graph learning. The review highlights that grid visibility requires coordinated integration of sensing, communication, data fusion, state estimation, topology identification, and decision-support functions.

INDEX TERMS Real-time state inference, Power distribution systems, Microgrids, Data fusion, Distribution system state estimation, Topology identification, Graph neural networks, Physics-informed machine learning, Artificial intelligence.

I. INTRODUCTION

Modern power distribution systems and microgrids are evolving rapidly with the growing integration of distributed generation, flexible loads, electric vehicles, data centers, grid-edge sensing, and decentralized control. This transformation introduces new operational complexities, including dynamic and bidirectional power flows, unbalanced feeder conditions, and inherently uncertain renewable generation. Additionally, the emergence of third-party aggregators and decentralized coordinators has unlocked the potential of distributed resources for localized generation and control, particularly within microgrids that can operate either grid-connected or

in islanded mode to enhance reliability. Advances in sensing and communication technologies now enable more sophisticated control and optimization strategies, strengthening grid resilience. Realizing these capabilities, however, depends critically on advanced state estimation techniques that provide accurate, real-time situational awareness.

Both industry and research are shifting from static, snapshot-based analyses toward a real-time grid visibility paradigm. Conventional methods, constrained by delayed or isolated measurements, are no longer sufficient for managing increasingly dynamic distribution networks. Operators now aim for continuous monitoring of voltages, currents, and power flows, paired with short-term forecasting of operating states, to enable proactive, data-driven decision-making [1]. Realizing this vision requires overcoming three central challenges: sparse and asynchronous measurements, complex and unbalanced feeder topologies, and the inherently dynamic behavior of microgrids that can rapidly transition between grid-connected and islanded modes.

To address these challenges, a holistic framework that unifies diverse data streams with advanced analytical tools is imperative. We outline four interdependent building blocks that form its foundation, reflecting how core analytical functions in modern distribution systems are increasingly data-driven and tightly coupled. Data fusion serves as the cornerstone, integrating heterogeneous measurements from supervisory control and data acquisition (SCADA), advanced metering infrastructure (AMI), micro phasor measurement units (μPMUs), and distributed asset monitors into a coherent dataset that mitigates data sparsity and asynchronous sampling. Building on this, distribution system state estimation (DSSE) reconstructs the complete network state voltage magnitudes and angles using methods that range from weighted least squares to machine learning and physics-informed models. Topology identification then tracks the real-time configuration of switches and reclosers, which is essential for accurate power flow modeling in active networks and microgrids. Together, these capabilities enable real-time grid visibility and decision support, allowing operators to detect faults, manage voltage and reactive power, and optimally dispatch distributed resources under both grid-connected and islanded conditions.

Despite advances in sensing, communication, and computational technologies, distribution systems continue to face visibility challenges distinct from those at the transmission level such as limited synchrophasor coverage, asynchronous data acquisition, and fragmented ownership of FDAs that restrict data access. Recent work demonstrates that distribution-system state estimation remains an active and rapidly diversifying research area. Robust model-based methods now address parameter mismatch and limited measurements [2], [3], while probabilistic formulations represent time-varying noise, data asynchrony, and limited-information uncertainty [4], [5]. Learning-based studies have introduced noise-trained estimators, federated learning, and generative state reconstruction [6]–[8]. Physics-informed methods increasingly embed measurement equations, solver iterations, or feeder graphs into the learning architecture [9], [10]. Current methodologies often treat state estimation and data fusion as separate problems, or overlook the importance of timely topology identification. Significant gaps also remain in unifying multi-timescale and multimodal data, from minute-level AMI readings to sub-second phasor measurements, within a coherent grid visibility framework. Furthermore, the rapid evolution of AI and machine learning approaches frequently occurs in isolation from physics-based modeling, widening the gap between data-driven inference and the underlying physical behavior of distribution grids and microgrids. Previous reviews have explored specific facets of this landscape, including AI-driven state estimation [11], estimation under uncertainty [12], and grid visibility in microgrids [13]. However, a unified perspective that explicitly integrates data fusion, state estimation, topology identification, and real-time grid visibility within the distinctive context of active distribution systems and microgrids remains scarce.

A. CONTRIBUTIONS

This paper provides an integrated review of real-time grid visibility in active distribution networks and microgrids by treating data fusion, DSSE, and topology identification as coupled functions rather than independent research problems. The main contributions are as follows:

- We organize data fusion, DSSE, topology identification, and decision support as interdependent building blocks of a real-time operational pipeline for active distribution networks and microgrids.
- We examine major data sources used for distribution-system and microgrid monitoring, including SCADA, AMI, μPMUs, line sensors, inverter telemetry, grid-edge resource monitors, and pseudo-measurements, with emphasis on measurement resolution, latency, observability, and data-integration challenges.
- We synthesize classical weighted least squares (WLS)-based estimators, robust estimation techniques, probabilistic methods, AI/ML-based models, graph-based approaches, and physics-informed learning methods, and compare them in terms of measurement errors, observability, topology changes, robustness, uncertainty quantification, and real-time applicability.
- We review multimodal and multi-timescale data fusion approaches, including super-resolution, probabilistic fusion, information fusion, and AI-enabled fusion, and connect these methods to topology identification techniques needed for dynamic and reconfigurable distribution networks.
- We identify open challenges related to sparse and asynchronous measurements, topology-adaptive estimation, scalable physics-informed graph learning, field validation, cyber-physical resilience, and operator-facing uncertainty quantification, and outline future opportunities for deployable situational-awareness frameworks.

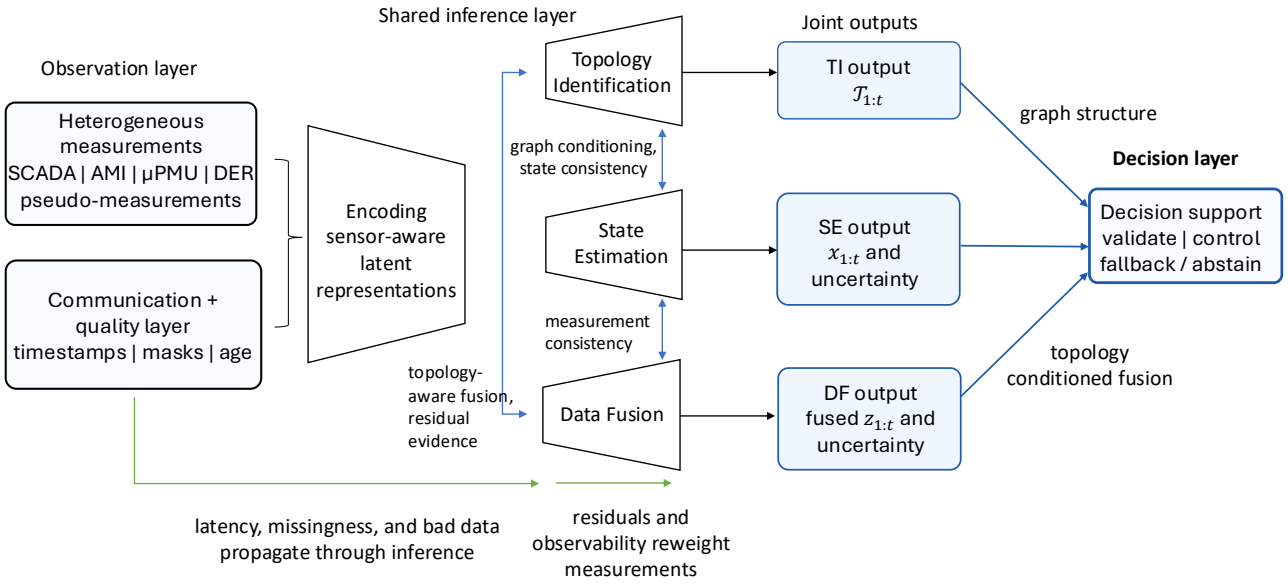


FIGURE 1: Unified grid-visibility framework for coupled data fusion (DF), topology inference (TI), and state estimation (SE). Sequential pipelines can be useful when topology is known and measurements are well synchronized, but dynamic distribution operation requires bidirectional feedback because topology, observation quality, and state uncertainty are mutually dependent.

Overall, this review emphasizes that real-time grid visibility cannot be achieved by collecting more data or developing isolated estimation algorithms alone. Instead, it requires the coordinated integration of sensing, communication, data fusion, DSSE, topology identification, uncertainty quantification, and decision-support functions into a resilient and operationally useful framework. Fig. 1 summarizes the integrated perspective used throughout this Review. The figure contrasts the sequential handoff common in the literature with the bidirectional inference required for operational visibility: topology affects which measurements are physically comparable, fused observations affect both topology and state estimation, and residuals and uncertainty from state estimation fed back to measurement quality assessment and topology inference.

B. REVIEW METHODOLOGY

To strengthen the methodological basis of this Review, we organized the literature around how distribution-system state estimation and topology-aware grid visibility have evolved from classical physics-embedded formulations to observationally driven, simulator-driven, and hybrid learning paradigms. We searched major engineering and scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, Wiley, ACM Digital Library, arXiv, and Google Scholar, with emphasis on power-systems venues and interdisciplinary energy-AI journals. The search covered work on distribution-system state estimation, topology identification, AMI/SCADA/PMU/μPMU data fusion, physics-informed learning, graph and transformer models, probabilistic inference, digital twins, and cyberphysical power-grid operation. The review primarily emphasizes literature from 2015 onward, while retaining earlier classical methods when they define foundational state-estimation principles such as weighted least squares, observability analysis, Kalman filtering, measurement-error modeling, and topology-error detection. We classify the reviewed methods along two complementary axes. The first axis captures the dominant modeling paradigm: classical physics-embedded state estimation, observational data-driven methods, simulator data-driven methods, and hybrid physics-informed approaches that combine field measurements with power-flow simulations or synthetic training data. The second axis evaluates whether each method satisfies key operational requirements for active distribution grids: explicit treatment of measurement errors, topology identification, dynamic topology reconfiguration, robustness to bad or missing data, multi-modality across AMI, SCADA, PMU, μPMU, and other sensing streams, multi-time-scale inference under asynchronous measurements, handling of missing timestamps, uncertainty quantification, and utilization of all available measurements. This taxonomy allows the Review to move beyond a chronological survey and instead assess how different model classes support high-resolution, interpretable, and uncertainty-aware grid visibility for distribution grids.

The review primarily considered papers published over the past two decades, with stronger emphasis on recent work from approximately 2015 onward, reflecting the growth of AMI deployment, sparse distribution-level PMUs, flexible distributed assets (FDAs) integration, and AI-based modeling. Earlier classical methods were retained when they established concepts such as weighted least squares, Bayesian filtering, observability analysis, and topology-error detection. Papers were included if they addressed at least one of the following: estimation of distribution-system states,

inference or validation of topology, fusion of heterogeneous measurements, treatment of sparse or delayed observations, uncertainty-aware inference, or learning-based representations for grid operation. We excluded studies focused only on transmission-level state estimation unless they introduced transferable methodological principles, papers without clear relevance to operational inference, and purely algorithmic AI studies that did not engage with power-system constraints, sensing structure, or deployment requirements.

The remainder of this review is structured as follows: Section II reviews data sources in distribution systems and microgrids, examining their measurement characteristics, limitations, and contributions to situational awareness. Section III then analyzes DSSE methods, including classical optimization techniques, AI-based approaches, and physics-informed models. Section IV first reviews data-fusion methodologies for heterogeneous and asynchronous measurements. Section V investigates topology identification techniques essential for accurate network modeling. Section VII synthesizes persistent challenges, open research questions, and future directions, and Section VIII concludes the review.

II. DATA STREAMS IN DISTRIBUTION SYSTEMS AND MICROGRIDS

Modern distribution systems increasingly integrate a wide variety of sensors and measurement devices that can collectively contribute to grid visibility when utilized effectively to accommodate bidirectional power flows, high R/X ratios, and the proliferation of FDAs. In parallel, microgrids, capable of operating both grid-connected and in islanded mode, add further complexity through localized generation, storage, and rapidly changing operational modes. This section reviews the principal data streams and monitoring infrastructures that enable grid visibility in these evolving networks, highlighting their inherent characteristics (e.g., multimodality, multi-timescale), discussing the critical role of communication infrastructure and latency, and identifying the key challenges in data collection, integration, and security.

Distribution systems connect the transmission grid to substations and medium-voltage feeders, and increasingly, to microgrids at the point of common coupling. At the transmission-distribution interface, sensors for voltage, current, and power factor, often supplemented by PMUs, provide essential data for load management and system stability. On the microgrid side, inverters and specialized frequency sensors monitor synchronization with the main grid, while protection relays isolate the microgrid during out-of-sync events or severe faults [14]. Microgrids further complicate operations by introducing local generation, energy storage, and flexible loads that can operate in islanded mode or grid-connected mode.

Non-utility programs and third-party aggregators also influence data availability. Initiatives such as community solar projects, peer-to-peer trading platforms, and demand response solutions (e.g., Nest Thermostat's Rush Hour Rewards [15]) generate operational data or affect power flows outside of utility-owned systems. Consequently, data ownership and accessibility become more complex, often necessitating contractual agreements or technical frameworks to enable real-time data sharing among utilities, aggregators, and end users.

Modern distribution systems rely on a mix of sensing and monitoring devices, each operating at different time scales and serving distinct functions. Traditional SCADA systems collect substation and feeder data every few seconds to minutes, while IEDs provide real-time protection and control information. Smart meters (AMI) report customer-level data every 15–60 minutes, and μPMUs record synchronized voltage and current phasors at 30–120 samples per second, capturing rapid transients and dynamic states. Line sensors and reclosers measure at sub-second or kilohertz rates to detect and isolate faults, whereas transformer monitors typically log temperature and loading data every few seconds to minutes. At the grid edge, FDA inverters and load forecast pseudo-measurements expand visibility to customer-owned assets and unmonitored nodes, though their reporting intervals vary, from real-time telemetry to hourly updates. A comprehensive illustration of the data flow is presented in Fig. 2. Although such monitoring technologies have significantly improved distribution system visibility, they also generate substantial data volume, presenting new demands for processing, storage, and real-time analytics. A concise overview of these devices, their roles, and typical measurement intervals is provided in Table 4 (Appendix A).

A. DATA CHARACTERISTICS

Modern power distribution systems produce vast and complex data streams characterized by three fundamental challenges: incompleteness, heterogeneity, and asynchrony. These issues stem from the grid's inherently socio-technical nature, where diverse sensors, communication infrastructures, and autonomous entities operate across multiple spatial and temporal scales.

1) Incompleteness

Incompleteness arises when measurements are unavailable at certain nodes due to sparse sensor deployment or communication gaps. In many regions, utilities lack real-time visibility of load and generation across the network, relying instead on estimates derived from installed capacity and historical consumption patterns. Some, however, have begun integrating distributed generation data; for example, Hawaiian Electric actively monitors solar output from residential and commercial PV systems as part of its grid modernization initiatives [16]. Such data gaps introduce substantial uncertainty into state estimation and hinder accurate situational awareness.

2) Multimodality

Heterogeneity arises from the coexistence of multiple measurement types across devices such as SCADA systems, AMI, PMUs, and grid-edge resource monitors. Each operates with distinct sampling rates, precision levels, and data

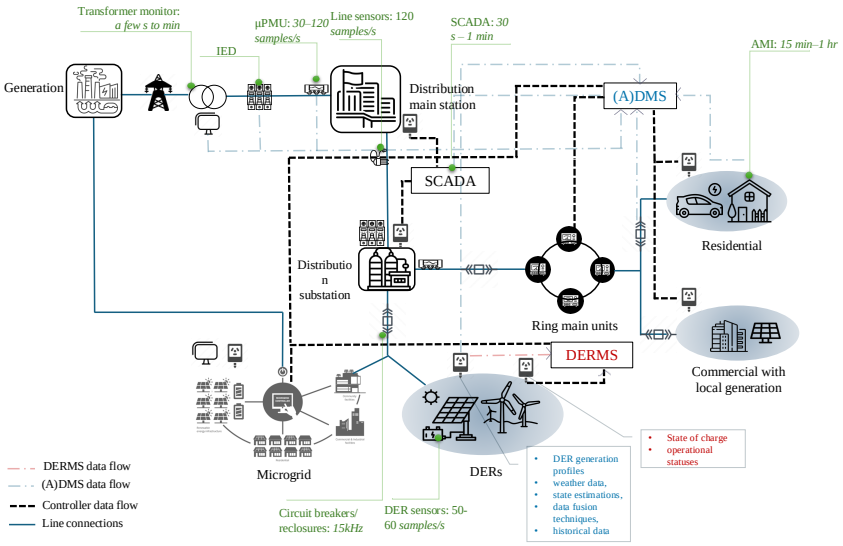


FIGURE 2: Distribution network components with data streams.

formats, reflecting designs optimized for specific operational tasks rather than system-wide observability. For instance, SCADA systems typically record data every few seconds, whereas AMI systems report at intervals ranging from minutes to hours. This multimodal landscape complicates the integration of measurements into a unified DSSE framework, as conventional models often assume homogeneous data quality. The resulting inconsistencies across modalities can significantly impair estimation accuracy and real-time situational awareness.

3) Multi-timescale Data

Asynchrony arises because measurements from different sensors are reported at vastly different intervals, from subsecond PMU recordings and five-minute control updates to hourly market data and monthly billing reports. The lack of synchronized sampling introduces temporal misalignment, blurring fast transients and diminishing the fidelity of dynamic state estimation. Accurately capturing network dynamics therefore demands either models tailored to individual sampling rates or unified, adaptive frameworks capable of integrating information coherently across multiple time scales.

For state estimation, SCADA-aggregated RTU measurements typically provide bus voltages and line currents every few seconds to minutes, while AMI measurements of active and reactive power are reported at 15-minute intervals. High-resolution voltage phasors sampled at 120 Hz are often averaged to the same 15-minute scale, which is too coarse to capture fast dynamics in modern distribution networks.

When smart meters are unavailable or access is restricted, estimating consumer demand at finer temporal resolution becomes critical for accurate DSSE. ML models address this gap by disaggregating coarse monthly consumption into finer temporal patterns [17]. Multi-timescale learning further reconstructs detailed load profiles and peak demand behavior, improving observability and estimation accuracy [18], [19]. Under low-observability conditions, reliable DSSE depends on reconciling sparse, heterogeneous time-series measurements with different sampling rates [20].

B. CHALLENGES IN DATA COLLECTION AND INTEGRATION

The rapid transformation of the energy sector, driven by automation and the proliferation of smart sensing technologies, has produced an unprecedented volume of data across the electric power industry. Yet, accompanying this growth are persistent data quality challenges that compromise the reliability of data-driven models, limit reliable data analytics, model development, and reproducible validation.

The inherent variability of FDAs poses major challenges for maintaining balance in distribution networks, motivating extensive research into stochastic modeling and uncertainty management. FDAs introduce uncertainty through both forecast errors and time-varying operating conditions. Cui et al. [21] use copula-based probabilistic forecasting to represent wind-power ramps, while [22] formulate stochastic operation across multiple timescales. [23] develop short-term, high-resolution distribution-load forecasting. Farzin et al. [24] incorporate uncertainty into microgrid storage scheduling, whereas Gazijahani et al. [25] use point estimation for stochastic distribution-system operation. Stochastic formulations have been widely adopted to capture fluctuations in photovoltaic and wind generation outputs, with many studies employing single Gaussian models to approximate aggregated forecasting errors [26]–[28]. Baker et al. [26] account for forecast uncertainty in storage sizing, Bienstock et al. [27] use chance constraints for risk-aware network operation. To better represent diverse error patterns from heterogeneous sources, [29] proposed a Gaussian

Mixture Model, later extended by [30] through an expectation–maximization–based genetic algorithm for adaptive component selection within the aggregated error distribution.

1) Privacy and Information Security Issues

Infrastructure data protection is governed by key regulatory agencies. The North American Electric Reliability Corporation (NERC) oversees the reliability of North America's bulk power system and enforces Critical Infrastructure Protection (CIP) standards to protect critical assets from misuse [31]. Similarly, the Federal Energy Regulatory Commission (FERC) defines Critical Energy Infrastructure Information (CEII) as sensitive engineering information whose disclosure could pose security risks.

At the same time, access to customer electricity usage data is important for researchers, agencies, and third parties working on grid research and energy policy. However, such access raises privacy and security concerns [32]. Without proper aggregation or anonymization, raw smart meter data combined with other customer information can enable re-identification of individuals or entities.

These data protection, privacy, and accessibility challenges can limit the performance of traditional DSSE methods. Advanced DSSE approaches must therefore accommodate diverse and restricted data characteristics while supporting robust, real-time visibility in distribution systems and microgrids. Integrating heterogeneous data streams with control and management platforms is essential for real-time decision-making, operational optimization, and reliable operation of increasingly complex energy networks.

2) Communication Infrastructure and Latency

While many advanced estimation and control algorithms assume timely, high-fidelity data, real-world communication infrastructures impose significant constraints on what is practically achievable. Distribution networks typically rely on a patchwork of wired (fiber, DSL) and wireless (RF mesh, cellular, LoRaWAN) systems with varying bandwidth, reliability, and latency profiles. Communication infrastructures form the digital backbone of modern distribution systems, where each layer of connectivity shapes how information flows, synchronizes, and scales. Protocols and standards such as DNP3, IEC 60870-5-104, and IEC 61850 underpin substation automation, while AMI networks often rely on proprietary RF mesh or IEEE 802.15.4-based links. These protocols define latency and throughput constraints that directly govern data refresh rates across SCADA, AMI, and μPMU systems.

Finally, bandwidth and scalability emerge as key bottlenecks. High-frequency streams from μPMUs and line sensors can easily saturate limited communication channels, particularly in rural or resource-constrained feeders. Without intelligent strategies for compression, sampling, or adaptive polling, the vision of real-time grid visibility remains out of reach. These communication bottlenecks and latencies must be explicitly considered when designing real-time DSSE and data fusion frameworks.

Communication latency should be distinguished from both sensor sampling rate and estimator execution time. For an operational estimate, the end-to-end delay can be represented as

$$T_{\mathrm{e2e}} = T_{\mathrm{acq}} + T_{\mathrm{local}} + T_{\mathrm{comm}} + T_{\mathrm{align}} + T_{\mathrm{infer}} + T_{\mathrm{delivery}},$$

where the terms respectively describe measurement acquisition, local processing or buffering, communication, temporal alignment, inference, and delivery to the operational application. A sensor may therefore sample at a high rate while still providing stale information because of slow polling, buffering, retransmission, or timestamp misalignment. For example, the absence of synchronized TTU measurements prevents direct comparison of phase angles, while congestion and packet loss can introduce larger time offsets and substantial power-measurement errors, leading to incorrect topology identification [33].

Visibility requirements in a microgrid depend on its operating mode. During grid-connected operation, state estimation primarily tracks feeder voltages, currents, power exchange at the point of common coupling, and the availability of local resources. During an islanding transition, the topology and electrical reference can change simultaneously. Breaker status, frequency, rate of change of frequency, and the operating modes of grid-forming and grid-following inverters must therefore be resolved with shorter latency. Sustained islanded operation further requires visibility of active-power imbalance, storage state of charge, available reserve, and protection margins. Reconnection requires confirmation of topology together with voltage, frequency, and phase synchronization. Black start and restoration require knowledge of the energized-island topology, source capability, critical-load status, and cold-load pickup. Consequently, performance demonstrated only on steady grid-connected snapshots does not establish readiness for microgrid transitions or restoration.

3) Cybersecurity, Communication Failures, and Resilient Visibility

Integrity attacks can alter or replay sensor measurements, pseudo-measurements, switch-status information, and network parameters. Structured false-data injection attacks are particularly challenging because they can preserve conventional residual statistics while biasing the estimated state. Interval-DSSE and learning-based detectors have therefore been proposed to determine whether estimated states or distributed measurement patterns remain within physically credible operating regions [5], [34], [35]. Availability and timing failures produce a different but related loss of visibility. Denial-of-service attacks, burst packet loss, network congestion, clock drift, timestamp loss, GPS spoofing, and out-of-order delivery can reduce observability or combine measurements corresponding to different physical states. For example, [33] shows that high TTU latency caused by communication congestion can introduce substantial power-measurement errors, while [36] demonstrates that

communication-component and radio-channel failures can directly degrade state-estimation accuracy.

In microgrids, delayed or corrupted point-of-common-coupling breaker status, frequency, phase, or inverter telemetry can additionally cause the estimator to infer an incorrect grid-connected, islanded, or reconnecting operating mode. Resilient grid visibility therefore requires more than attack detection or robustness to independent Gaussian measurement noise. The complete estimation pipeline should authenticate measurements and timing metadata, compare redundant and cross-modal observations, and test consistency among measurements, topology, and physical constraints. It must also degrade safely when part of the sensing or communication infrastructure becomes unavailable. Attack-aware filtering, adaptive uncertainty inflation, redundant sensing and communication paths, and fallback to a trusted physics-based estimator can preserve partial visibility. When the remaining measurements cannot support a credible estimate, the system should declare loss of observability or abstain rather than return an overconfident state. Evaluation should consequently report state-estimation degradation under attack or communication loss, attack-detection precision and delay, false-alarm rate, operational availability, and recovery time. Combined stress cases are particularly important because a communication outage can conceal an integrity attack, while legitimate switching, faults, or islanding transitions can resemble malicious topology or measurement manipulation. Resilience should therefore be assessed by the ability to maintain bounded uncertainty, provide graceful degradation, and recover trustworthy visibility rather than by clean-data accuracy alone.

III. DISTRIBUTION SYSTEM STATE ESTIMATION (DSSE)

In DSSE, measurement (z_i) is modeled as a function of the state variables x (i.e., the bus voltage magnitudes and angles) according to the measurement function $f_i(x)$:

$$z_i = f_i(x) + e_i, \tag{1}$$

where $f_i(x)$ is the measurement function describing the expected value based on the state vector x and e_i represents the measurement error. The function $f_i(x)$ is parameterized by the network configuration and parameters such as line impedance and bus admittances, which are treated as known constants in the DSSE problem. Since $f_i(x)$ is nonlinear owing to the nonlinear nature of AC power flow equations, iterative methods are required for optimization. Common techniques include Newton's method or the Gauss-Newton method, which linearize the problem and iteratively updates the state estimates [48].

Following the foundational WLS formulation [49], distribution-specific developments included branch estimation for radial feeders [50] and an augmented-matrix formulation [51]. Teng [52] and Baran et al. [53] incorporated voltage measurements into branch-current estimation. Wang and Schulz [54] revised the branch-current estimator and examined meter-placement effects, while Pau et al. [55] efficiently incorporated synchronized measurements. These WLS-based estimators minimize the sum of the weighted squared errors, expressed as

$$J(x) = \sum_{i=1}^{n} w_i \left(z_i - f_i(x)\right)^2, \tag{2}$$

where w_i is the weight for each measurement, typically chosen to be inversely proportional to the variance of e_i. Although this weighting scheme ensures that measurements with lower uncertainty have a greater influence on the state estimates, it also means that large deviations (or outliers) in z_i can disproportionately affect the solution. To mitigate this sensitivity, early efforts in the 1980s explored least absolute value minimization,

$$J(x) = \sum_{i=1}^{n} w_i \left|z_i - f_i(x)\right|, \tag{3}$$

and later, between the 1990s and 2000s, researchers introduced M-estimators to define robust residual functions $\phi(r_i)$ with adaptive weights w_i .

In many distribution networks, the assumption of fixed bus admittances in $f(x)$ fails due to these incomplete network models and the unpredictable nature of renewable outputs. With the widespread deployment of μPMUs from the late 2010s onward, there has been a shift toward using high-fidelity observational data to learn the inverse mapping $h : Z \rightarrow X$, which approximates $f^{-1}(z)$ in a black-box manner. This new approach leverages statistical or machine learning models, expressed as $h(z \mid x, \eta)$, where η represents model parameters, thus ushering in a new era of data-driven state estimation. A detailed discussion of these methods follows in Section III-B.

While purely observational data-driven models are promising for ever-expanding distribution systems, they can produce estimates that violate power flow equations and constraints. For example, predicted voltage magnitudes and angles might fall outside feasible operating ranges, potentially leading to unrealistic or unstable grid conditions. High-fidelity data is critical, and optimizing the model parameters η often requires the integration of physics-specific constraints. The 2020s have seen a surge in physics-informed data-driven methods, which integrate $h(z|x, \eta)$ with power flow simulations to enrich training data or refine loss functions to penalize violations of physical constraints. Section III-C provides a detailed overview of these hybrid methods. We categorize recent data-driven and physics-informed DSSE methods based on a set of key evaluation features summarized in Table 1. Specifically, the table assesses each method based on the following criteria:

- Measurement errors (ME): Does the method explicitly handle inaccuracies in measurements?
- Topology identification ($\mathcal{T}$-I) : Can it identify the network topology effectively?
- Dynamic reconfiguration ($\mathcal{T}$-R) : Does it consider changes in the distribution system network?

TABLE 1: Source-reported quantitative evidence and capability coverage for representative DSSE and topology-identification methods. NR stands for not reported. ✓† denotes capability that was demonstrated only under specific conditions.

Study and method	Validation, data, and reported accuracy	Runtime, complexity, and scale	Capability coverage							
			ME	$\mathcal{T}$-I	$\mathcal{T}$-R	$\mathcal{R}$	MM	MS	TS	$\mathcal{U}$Q	AM
(a) State estimation and joint state–topology estimation											
[37] **Hierarchical WLS + actor–critic DSSE**	60-node utility feeder; real SCADA/AMI; 44 secondary circuits and 238 customers. $\lvert V\rvert$/angle MAPE: 1.1/0.26% over $> 1{,}500$ points.	0.4–0.5 s vs. 3 s WLS; action 0.02 s. Modular feeder decomposition; formal complexity NR.	✓	×	✓	×	✓	×	×	×	×
[38] **Feature-graph robust DSSE**	IEEE 33-node feeder; three topologies; branch-power/pseudo data; 1,000/100/200 train/validation/test. Normal $\lvert V\rvert$/angle MAE: 3.09×10^{-4} p.u./9.22×10^{-3}°; missing/noisy: 8.00×10^{-4}/20.1×10^{-3}.	Runtime/complexity NR; tested on 33 nodes with up to six incorrect graph links.	✓	✓	✓	✓†	✓	×	×	×	×
[39] **Joint DNN state–topology estimator**	IEEE 34-node and real 240-node utility systems; 84 topologies; 12,500 DSSE samples; 72 measurements for 924 states. Topology accuracy 99.19%; angle MAE 0.15°; $\lvert V\rvert$ MAPE 0.26%.	Inference ∼0.01 s; unseen-topology adaptation ∼1 min vs. ∼2 h retraining. Labeled topology data required.	✓	✓	✓	✓†	×	✓	✓	×	×
[40] **Graphical network + multitask GP**	IEEE 33/119/342-node systems; SCADA, two μPMUs, and pseudo-measurements; 50% pseudo noise. 33-node $\lvert V\rvert$/angle MAE: 6.61×10^{-4} p.u./4.03×10^{-3}°; maximum missingness: 12.3×10^{-4}/11.7×10^{-3}.	1.99/2.96 ms (33/119 nodes) vs. WLS 93.7/142 ms; evaluated to 342 nodes. Communication/graph cost NR.	✓	✓	✓	✓†	✓	✓	×	✓	×
[41] **Collaborative filtering + deep-GP pseudo-measurements**	One year of real data from 1,120 customers; reconstructs 5-min data from hourly data. Pseudo-measurement MAPE 4.67%; RMSE 1.7883; downstream state error NR.	Full GP $\mathcal{O}(N^3)$; sparse GP $\mathcal{O}(NM^2)$, $M \ll N$; inference NR; feeder-level DSSE not evaluated.	✓	×	×	✓†	×	✓	✓	✓	✓
[42] **Kalman-filter LV state estimation**	Actual 99-bus Slovenian network; 68 homes, ten meters; 10-s updates; 500 steps with 10–20% missing/erroneous data. Aggregate voltage MAE/RMSE NR; tracking and gross-error suppression shown.	Median 0.07 s vs. 0.28 s WLS. Field evidence; scale beyond 99 buses and full-state ground truth NR.	✓	×	×	✓†	✓	×	✓	×	×
[43] **Sequential hybrid AMI–μPMU DSSE**	13/34/37/390/800/1,500-node systems; pilot: three substations, 22 feeders, ∼100 μPMUs and ∼600 AMI. No common aggregate error; accuracy degrades above ∼2% phase unbalance.	0.13 s (34), 6.32 s (390), 15.32 s (1,500) vs. WLS 2.34/16.13/43.22 s; field accuracy NR.	✓	×	×	×	✓	✓	×	✓	✓
[5] **Interval-probability uncertain DSSE**	14/18/51–57/141/2,383-bus systems; NREL PV/Elia wind; up to 400 DGs. Scalar state error/coverage NR; separate FDIA F1 94.30–94.69%.	6.881 s (14), 2.7669 s (141), 0.247 h (2,383; 9 DGs); 5.132/11.24 h for 200/400 DGs. Not real-time at high DG count.	✓	✓	×	✓†	×	×	×	×	×
[44] **Deep Statistical Solver (DSS^2)**	CIGRE 14-bus and Oberrhein 70/179-bus systems; 8,640 hourly scenarios; 80/10/10 split. Voltage RMSE: $2.5/1.5/2.3\times10^{-3}$ p.u. for 14/70/179 buses.	4.7/26/58 ms vs. WLS 86/123/1,212 ms. Favorable scaling; simulation-only evidence.	✓	✓	×	✓†	×	×	×	×	×
[45] **Physics-aware neural network (PAWNN)**	Unbalanced IEEE 37-node feeder; six DERs; 100,000 simulated points; five μPMUs and 103 direct/pseudo measurements. Normalized error $\nu = 1.273\times10^{-3}$ vs. 8.341×10^{-2} shallow NN and 5.833×10^{-1} Gauss–Newton.	1.146 ms vs. 124/866 ms. Very fast, but one feeder and a large simulated training set.	✓	✓	✓	✓†	✓	✓	×	×	✓
[46] **Data-driven learning-based optimization**	Unbalanced IEEE 37-node feeder; six DERs; 100,000 scenarios; four PMUs and 103 measurements. $\nu = 9.558\times10^{-3}$ vs. 9.845×10^{-2} Gauss–Newton; 0 vs. 28 divergences in 1,000 tests.	347 ms vs. 2.468 s; 0.429–2.339 s after topology changes; major reconfiguration may require minutes of retraining.	✓	×	✓†	✓	✓	✓	×	×	✓
(b) Topology-identification methods											
[47] **Split-EM topology identification**	IEEE 33-bus (1,024 topologies), modified 135-bus (12,000/1,200 train/test), and partitioned 874-bus systems. Accuracy 97.2–98.0%; Bayesian correction 99.9%; three-phase SVM 99.17%.	Classifier 0.01–0.35 s; Bayesian 6.09 s; historical search 307–2,816 s (30–70 nodes). Switch-count scaling is combinatorial.	✓	✓	✓	×	✓	×	×	×	×
[33] **Asynchronous TTU-based identification**	Modified 33/69/123-bus systems; 48/64/144 configurations; 15-min $\lvert V\rvert$, P, and Q from each TTU. Low/high-error accuracy: 99.4/93.8%, 97.2/91.4%, and 96.4/92.1%.	6.5–8.4 s (33), 13.8–20.7 s (69), 26.9–28.6 s (123). MIQCP scaling combinatorial; full TTU coverage/known impedances required.	✓	✓	✓	×	×	✓	×	×	×
[39] **Joint DNN topology estimator**	Real 240-node utility network; nine switches, 84 feasible topologies, ∼1,000 samples/topology; four devices. Topology accuracy 99.19%.	Inference ∼0.01 s; unseen-topology fine-tuning ∼1 min vs. ∼2 h retraining; labeled/adaptation data required.	✓	✓	✓	✓†	×	✓	✓	×	×

- Robustness ($\mathcal{R}$): Is the method resilient to bad data or capable of handling missing data?
- Multi-modality (MM): Does it account for diverse types of measurement data?
- Multi-time scale (MS): Can it address asynchronous data across different time scales, including time-synchronization challenges?
- Handling missing timestamps (TS): Is it capable of processing data with missing time information?
- Uncertainty quantification ($\mathcal{U}$Q): Does the method quantify uncertainty in its estimations?
- Utilization of all measurements (AM): Does it leverage all available measurement types in the estimation process?

The quantitative evidence reveals a clear trade-off between offline data generation, online computational cost, and demonstrated system scale. Physics-aware and learned estimators can substantially reduce online latency after training. However, PAWNN [45] and the learning-based optimization method [46] each require 100,000 simulated operating points on a 37-node feeder, while the joint state–topology estimator [39] uses 12,500 state-estimation samples in addition to approximately 1,000 labeled samples for each of 84 topologies. By contrast, the recursive Kalman-filter estimator [42] and the sequential hybrid-measurement method [43] require less supervised training, but retain stronger dependence on feeder models, measurement placement, and observability.

Evidence of scalability is also uneven. The sequential hybrid-measurement method [43] reports runtime results for systems containing up to 1,500 nodes; the Split-EM topology method [47] applies subsystem partitioning to an 874-bus model; the multiarea graphical and multitask-GP estimator [40] is evaluated on a 342-node unbalanced network; and the joint state–topology DNN [39] considers a 240-node utility network. In contrast, several high-accuracy physics-aware and graph-enabled estimators remain validated primarily on 33–37-node feeders [38], [45], [46]. Moreover, reported millisecond-level inference times should not be interpreted as end-to-end operational latency because measurement acquisition, communication, temporal alignment, preprocessing, topology updating, and model adaptation or retraining are generally excluded. Finally, the diversity of reported metrics, including MAE, MAPE, RMSE, normalized state error, uncertainty intervals, and topology-classification accuracy,

precludes a direct numerical ranking. Standardized test systems, sensing configurations, error models, data partitions, hardware descriptions, and runtime-reporting protocols are therefore needed for reproducible DSSE benchmarking.

A. TRADITIONAL STATE ESTIMATION TECHNIQUES

Traditional state estimation methods use fixed models and assume accurate data in stable conditions. The measurements are often observed with errors: systematic (consistent, predictable biases or deviations) and stochastic (random variations typically caused by environmental conditions) components attributed to the measurement process. Traditional probabilistic formulations for state estimation assume a normal probability distribution on errors to fit the data, in a hope of minimizing systematic part of aggregated errors. Typically, in state estimation the function of residuals $r_i = y_i - h(x_i)$ is optimized for states variables $\boldsymbol{x}$. In WLS-based probabilistic formulations, the residual function is the sum of squared residuals [56]; in the least absolute value estimator, it's the sum of absolute residuals. In both functions, each measurement is given equal confidence when optimizing for states, making these approaches un-robust to bad data—an unavoidable issue in real-world measurements.

Classical WLS is generally accompanied by an explicit bad-data-processing loop. After convergence, a global χ^2 test on $J(\hat{\boldsymbol{x}})$ assesses whether the aggregate residual is consistent with the assumed measurement-error covariance. If the test is rejected, normalized-residual or largest-normalized-residual tests localize suspect measurements, which can then be removed, corrected, or reconstructed before re-estimation. Geometric analysis further establishes the conditions under which single or multiple gross errors are detectable and identifiable [57]. These principles have also been adapted to DSSE. [58] compared conventional residual tests with composed-measurement-error geometry under load pseudo-measurements. [59] developed per-phase detection, identification, and correction of multiple gross errors for unbalanced three-phase WLS DSSE, while [60] combined decoupled χ^2 tests for bad-area localization with whitening-based identification. Later work introduced PMU-based detection and temporal measurement correction [61], and compressed-sensing DSSE modified the largest-normalized-residual statistic for low-observability unbalanced feeders [62]. These methods retain WLS as the state estimator while adding explicit data-quality diagnostics. Their effectiveness nevertheless depends on measurement redundancy, credible covariance and network models, and the absence of critical or interacting error configurations. Robust estimators therefore complement, rather than replace, explicit bad-data detection and identification.

Robust WLS methods effectively handle bad measurements as long as the errors are isolated, random, and limited to single dimensions [63]–[65]. By employing advanced techniques—such as residual functions derived from M-estimators [66], iterative re-weighting schemes [67], Bayesian approaches, or machine learning-based loss functions—they effectively limit the impact of bad data on state estimation.[1]

Recent analytical methods for DSSE offer innovative solutions to challenges like integrating diverse data sources, addressing unobservability, and meeting industrial needs. Building on this, Akrami et al. [69] tackled unobservability, specifically the lack of synchrophasor measurements, by proposing a sparsity-promoting method that minimizes the sum of squared errors, allowing robust estimation with limited data. For industrial applications, Žafić et al. [70] developed a high-performance DSSE method that integrates PMU data using complex variables and Wirtinger calculus, overcoming the limitations of traditional load scaling techniques and improving computational efficiency. These advancements highlight efforts to enhance the accuracy, adaptability, and efficiency of DSSE in complex systems.

Recent model-based developments increasingly address imperfections in both the network model and the observation process, with a clear shift from idealized formulations toward practical grid conditions. A first group of studies focuses on correcting structural model inaccuracies: In [2], the authors explicitly couple robust state estimation with line-parameter correction, relaxing the assumption of a perfectly known feeder model, while Nikzad et al. [71] reformulate the problem into a line-wise optimization structure that improves numerical stability and scalability. A second group targets measurement limitations and realism in data acquisition. De Jongh et al. [3] incorporate pseudo-measurements to compensate for sparse sensing, and Zuckerman et al. [72] extend the measurement model to explicitly handle asynchronous and delayed flow and injection data, reflecting realistic communication constraints in modern distribution grids. A third line of work improves robustness under adverse estimation conditions: Zhou and Centeno [73] propose adaptive linear estimation tailored to unbalanced systems, while Rajasekaran et al. extend compressed-sensing DSSE with enhanced bad-data detection under low observability [62].

Traditional DSSE methods rely heavily on accurate system models, including network topology and parameters, which are often incomplete or unreliable in real-world settings. They also face challenges in managing noisy data, missing measurements, and dynamic system changes. In contrast, data-driven methods overcome these limitations by learning patterns and relationships directly from observational data.

B. DATA-DRIVEN MODELS

Although effective at inferring states from observational data, data-driven methods are not well-suited for DSSE in unobserved or sparsely monitored distribution systems. Power system unobservability $\mathcal{O}(\boldsymbol{z})$ arises when sensors are too few or poorly distributed, leaving insufficient independent measurements to uniquely determine the state variables. This creates an under-determined system, where the number of unknown states exceeds the available measurements. A sys-

[1] See [68] for a comprehensive discussion of methods up to the year 2018.

tem that is initially observable can become unobservable due to sensor faults, missing data, or tampering by malicious agents [74]. Many distribution systems lack sufficient sensor coverage, leading to unobservable regions or variables. FDAs introduce uncertainty $\mathcal{U}(\boldsymbol{z})$, which must be managed during the estimation of $\boldsymbol{x}, h, \boldsymbol{\eta}$. Noisy data demands robust methods $\mathcal{R}(\boldsymbol{x})$, while topology changes call for real-time $\mathcal{T}$-estimation.

We categorize data-driven methods into AI-based approaches, including neural network-driven techniques, and statistical approaches that formulate DSSE within probabilistic or stochastic frameworks, such as Bayesian methods.

1) AI methods

AI-based data-driven methods specifically address $\mathcal{O}(\boldsymbol{z})$ by training neural networks on historical data, creating pseudo-measurements for missing data, and using task-specific learning models. [39] employs two deep neural networks (DNNs): one for real-time $\mathcal{T}$ and another for estimating $\boldsymbol{x}$. $\mathcal{R}(\boldsymbol{x})$ is demonstrated with non-Gaussian noise. [75] focused on enhancing observability in smart grids by proposing a two-step approach: a model-specific DNN for $\boldsymbol{x}$ estimation, designed with unrolled prox-linear solver layers and skip connections for efficient training, and a deep recurrent neural networks to capture complex time series dependencies with fixed parameters. To enhance pseudo-measurement generation, [76] proposed a transfer learning approach for predicting day-ahead load variables. By updating Bayesian estimates of forecast residuals throughout the day, the model transfers knowledge from one task, such as forecasting at a source substation, to related tasks at target substations.

Building on the observation that distribution feeders face simultaneous challenges of incomplete observability, topology uncertainty, and non-Gaussian measurement noise, [77] propose a unified deep-learning pipeline that couples topology identification with DSSE under sparse sensing. The topology identification module treats switch-status inference as a supervised classification problem fed by time-synchronized phasor measurements from sparsely placed smart measurement devices, and its outputs are then consumed by a three-phase unbalanced DSSE that operates on both radial and meshed topologies. A key practical insight is the use of transfer learning to handle topology changes: instead of retraining DSSE from scratch after switching events, the authors fine-tune a pre-trained estimator, exploiting shared representations to adapt quickly with limited additional data.

Reinforcement learning (RL) frameworks interact with the environment, adjusting strategies based on rewards to maximize cumulative outcomes. These methods can be adapted to estimate $\boldsymbol{x}$ across distribution network levels while considering FDA-specific variability in $\mathcal{U}(\boldsymbol{z})$. For instance, [37] proposed a novel hierarchical reinforcement learning-aided for jointly estimating $\boldsymbol{x}$ for both primary and secondary levels of distribution grids. First layer estimates $\boldsymbol{x}$ of main distribution lines using WLS. At the second layer, low-voltage circuit states are estimated using deep actor-critic modules. They also account for the impact of solar photovoltaic systems located at the edges of the grid. RL typically treats the distribution system as an abstract environment and focuses on optimizing actions to maximize rewards [78]. Traditional deep learning methods based SE (e.g., fully connected or convolutional neural networks) don't inherently account for the underlying topological structure of the distribution system since they process data in a flat or grid-like format, losing the spatial and relational context between buses and lines [79].

GNNs propagate information iteratively across nodes and edges, enabling localized learning that aggregates information from neighbors. This helps in capturing dependencies between buses and lines more effectively, ideal for $\mathcal{T}$-I. The increasing complexity of distribution networks has led to a surge in methods that extract maximal information from observational data for $\mathcal{T}$ [33], [47]. Notably, [38] proposes a GNN that model the $\boldsymbol{x}$ estimation problem as node-level prediction tasks on the graph representations, using state measurement matrices and tensors as input features. To enhance performance, feature scaling (for normalizing inputs) and pseudo-measurement generation (to supplement missing data) phases are introduced. Algorithms for $\mathcal{T}$-estimation are discussed in the Section V.

AI methods use data to model the relationship f^{-1}, but the learned black-box models are hard to interpret and integrate into making decisions. To make them practical, we need explanations of how the model generates its predictions and how power engineers can apply them. Explainable AI [2] methods aim to generate integrable explanation maps, global or local, that highlight the relevance of input features in output predictions [80]. Various methods in the literature focus on power systems: classifying conditions as stable or unstable or assessing grid security. However, their use in state estimation is limited. To the best of our knowledge, [81] is the only study testing SHAP, LIME, and LRP algorithms for AutoML in power system state estimation, concluding that further research is required to validate their utility in operational settings.

AI-based DSSE can reduce repeated online nonlinear solves, but it redistributes computation rather than eliminating it. For network-wide models, the input and output dimensions grow with the feeder, while topology changes alter the learned measurement-to-state mapping. The 240-node joint topology–state estimator in [39] reports an online evaluation time of approximately 0.01 s. However, its topology classifier covers 84 feasible configurations using 1,000 samples per configuration, and its DSSE network uses 12,500 samples. A previously unseen topology still requires approximately 1 min of fine-tuning with 3,000 samples, compared with approximately 2 h for complete retraining. Similarly, the physics-aware network in [45] achieves millisecond-level

[2]A good review of explainable AI applications in transient stability, voltage and frequency control, and fault detection is available in [80]

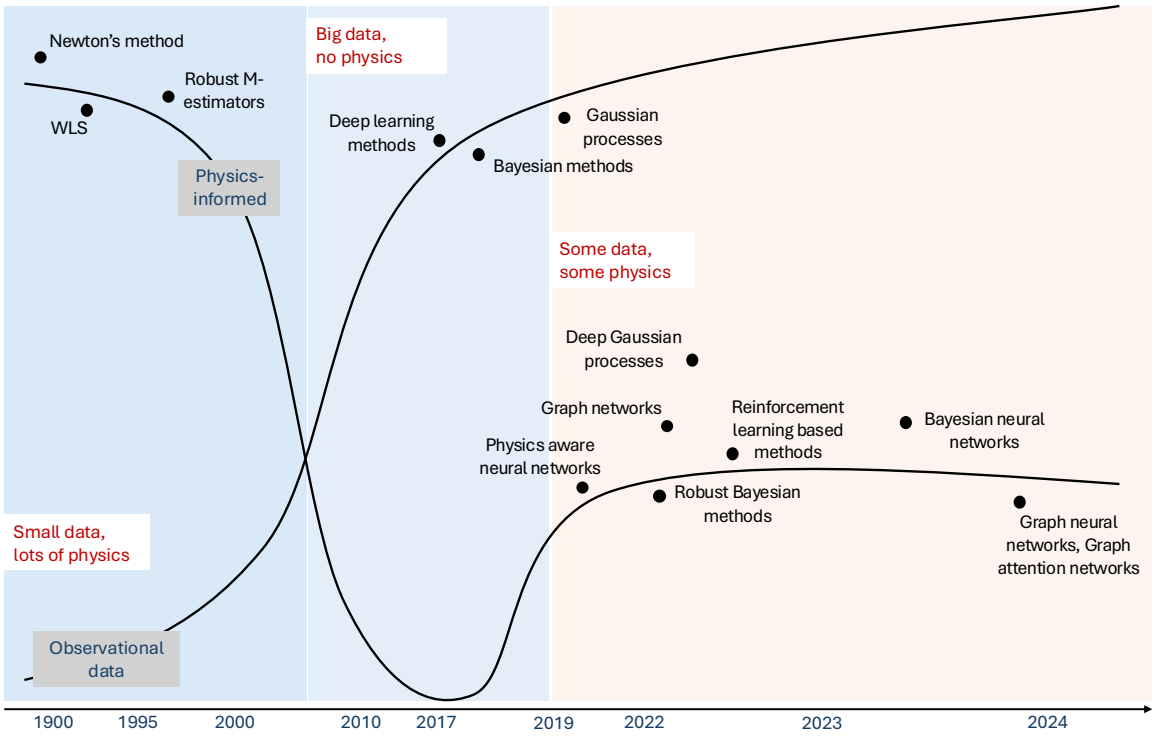


FIGURE 3: Distribution Network Data and Physical Scenarios Juxtaposed with the Evolution of DSSE Methods

inference on a 37-node feeder only after generating 100,000 simulated operating points, while the hybrid estimator in [46] retains Gauss–Newton iterations during online estimation. The feature-graph estimator in [38] is evaluated on a 33-node feeder but does not report online runtime or formal complexity. DSS^2 [44] extends graph-based estimation to 179 buses, whereas [82] evaluates a physics-informed graphical estimator on the IEEE 8500-node feeder. The latter nevertheless reports that model depth and width increase with network size and estimates near-quadratic computational complexity. Thus, fast inference on one feeder does not establish scalable training, memory use, or adaptation across utility networks.

One route to feeder-scale deployment is to replace a single network-wide model with multiple smaller local estimators. The hierarchical method in [37] couples primary-feeder WLS with one actor–critic estimator per secondary circuit. On a utility-derived system with a 60-node primary feeder and 44 secondary circuits, this structure reduces total computation from approximately 3 s to 0.5 s. The multiarea graph and multitask-GP framework in [40] similarly combines centralized training with distributed inference. Such decomposition limits the size of each model and supports parallel execution, but it creates model-lifecycle and coordination burdens. Local estimators must be trained, versioned, and recalibrated for heterogeneous circuits. Boundary states and timestamps must remain consistent across areas. Switching actions can invalidate graph edges, normalization statistics, and sensor-to-node mappings. Large-scale studies should therefore report scenario-generation and adaptation costs, model size and hardware requirements, graph-reconstruction overhead, inter-area communication, and end-to-end latency from measurement acquisition to DMS delivery. Operational deployment also requires confidence monitoring and a fallback estimator for unseen topology or sensor configurations.

Recent data-driven AI methods increasingly move beyond single-model feedforward learning toward architectures that explicitly address data scarcity, heterogeneity, and system dynamics. One major trend is robustness under imperfect or limited measurements: Liu et al. [6] improve generalization by training neural estimators on corrupted measurements to better handle noise and FDA variability, while De la Varga et al. [83] focus on state inference under severely limited real-time observability. A second trend is the use of advanced learning paradigms to handle distributional shifts and decentralized data. Han et al. [7] introduce tensor decomposition combined with personalized federated learning to capture feeder-specific and time-varying behavior without centralized data aggregation, and Xie et al. [84] explore large-language-model-assisted edge learning to coordinate distributed estimation tasks. A third direction leverages generative and structured deep learning models to reconstruct missing or unobserved states: Hua et al. [8] employ spatiotemporal diffusion models for state reconstruction under low observability, while Zhao et al. [85] combine generative adversarial networks with graph attention mechanisms to jointly model spatial dependencies and data generation.

2) Statistical methods (probabilistic/ stochastic)

Statistical methods employ probabilistic frameworks; for example, Gaussian processes (GPs) model f^{-1} as a multivariate Gaussian distribution over latent functions. This inherently enables $\{\mathcal{U}(\boldsymbol{x}),\mathcal{U}(h),\mathcal{U}(\eta)\}$, offering a distinct advantage over non-probabilistic approaches. Mestav et al. [74] introduced a Bayesian state estimation approach using distribution learning to model the probability distributions of fast-timescale power injections. Markov chain Monte Carlo techniques are then used to generate samples, creating a training dataset through power flow simulations. This method diverges from relying on pseudo-measurements, data inferred from historical or interpolated values, to achieve a determined system, as proposed by Filho et al. [86], [87].

Managing multi-timescale data streams effectively is crucial for accurate $\boldsymbol{x}$ estimation, especially when using unconventional sources like smart meter data, which is not typically designed for this purpose [88], [89]. Researchers [42], [43] proposed fast timescale state estimation methods to resolve the mismatch in measurement resolution between slow timescale smart meter data and fast timescale real-time measurements, such as current magnitudes at feeders and substations. Xu et.al. [41] proposed a collaborative filtering approach addressed this issue by analyzing measurement correlations of smart meter data to create pseudo-measurements. Gaussian processes model the data, with deep Gaussian processes added for feature extraction and robustness. Combining smart meter data with real-time measurements, as expected, led to improved estimation accuracy of $\boldsymbol{x}$.

In parallel, efforts have also concentrated on modeling FDA uncertainties and nonlinear correlations [90]. Notably, [5] introduces an interval-probability-based DSSE framework to uniquely tackle challenges caused by nonlinear correlations and limited data from distributed generators (DGs). The authors design a joint Dempster-Shafer structure that uses clustering algorithms and evidence theory to model DG uncertainties while capturing their nonlinear dependencies. They divide the uncertainty space into smaller regions, assigning probabilities based on the available observations.

Multi-area $\boldsymbol{x}$ estimation divides the network into multiple interconnected regions, allowing for localized estimation with coordinated global consistency. Building on this concept, [40] proposed a robust $\boldsymbol{x}$ estimation framework that integrates a physics-informed decentralized graphical network with GP-based multi-area estimators. This approach maps real-time and pseudo-measurements onto a tree-structured graph, where a graph attention network captures measurement relationships. A centralized pre-training phase extracts global information from historical data for distributed inference across subregions. These features are fed into a multitask GP model, using a kernel to determine task relevance between subregions, improving accuracy while reducing communication overhead. This structure enhances the method's ability to handle outliers and quantify $\mathcal{U}(\boldsymbol{x})$.

Purely observational data-driven methods rely on pseudo-measurements to compensate for missing data and address $\mathcal{O}(\boldsymbol{z})$, but this can compromise their accuracy and suitability for real-time $\boldsymbol{x}$ predictions required for situational awareness. Using only observed data risks generating predictions that may not align with the distribution system's physical constraints. Studies have shown that power flow simulators help address missing measurements, improving alignment with the physical reality of the distribution system. However, in distribution systems where network configuration details are often incomplete, $\mathcal{T}$-I techniques incorporating network constraints can provide a solution.

Recursive Bayesian filters propagate conditional state-error covariance; recent variational and adaptive formulations also infer process, measurement, or out-of-date smart-meter variances under sudden changes, unknown noise, and asynchrony [4], [91], [92]. These covariances mainly represent aleatoric uncertainty under an assumed topology and network model. GP methods operate at different stages of the visibility pipeline: [41] quantifies fast pseudo-measurement forecast uncertainty; multitask and semi-supervised GPs produce state-level intervals [40], [93]; and correlated GPs model cross-state dependence but are evaluated mainly through point-estimation error [94]. Calibration evidence is uneven: [93] reports coverage and sharpness through PICP and MPIW, whereas several studies emphasize MAE or RMSE. Interval and evidence methods instead represent limited-information epistemic uncertainty; the P-boxes in [5] bound plausible CDFs and are not Bayesian credible or frequentist confidence intervals. A unified visibility framework must propagate source-specific uncertainty through data fusion, topology inference, and state estimation.

Recent probabilistic DSSE research reflects a broad shift from fixed Gaussian assumptions toward richer and more structured uncertainty representations. One stream of work focuses on adaptive statistical inference, where uncertainty is learned jointly with the state: Cetenovic et al. [4] embed variational Bayesian inference within an unscented Kalman filter to continuously adapt noise statistics during operation, while Chatterjee et al. extend Bayesian modeling to explicitly handle smart-meter asynchrony and unknown noise distributions in forecasting-aided DSSE [91], [92]. A second stream addresses situations with limited or heterogeneous information, where classical probabilistic assumptions break down. In this context, Liu et al. combine evidence theory, affine arithmetic, and probability boxes to represent nonlinear correlations under scarce DG observations [5], and Hu and Xu introduce Gaussian-process regularization to stabilize graphical learning when labeled state data are limited [93]. A third direction emphasizes structured dependency modeling, moving beyond independent state uncertainty: Zhang et al. integrate multi-fidelity information within a Bayesian neural network framework [95], while more recent work on correlated Gaussian processes explicitly preserves spatial dependencies among state variables rather than treating them independently [94].

C. PHYSICS INFORMED DATA-DRIVEN METHODS

In DSSE, measurement functions are typically available, and simulator data can be generated when $\mathcal{O}(\boldsymbol{x})$ is not satisfied. Probabilistic Bayesian methods often use physics-informed priors to enforce system constraints [96]. This reduces the need for extensive simulator computations when sufficient observed data is available, making physics-informed data-driven methods increasingly popular.

Efforts to integrate domain knowledge into machine learning and optimization for DSSE began in 2019 with Ostrometzky et al. [97] introducing a physics-informed DNN for limited $\mathcal{O}(\boldsymbol{z})$, incorporating admittance matrix-based regularization into the DNN optimization process. Building on this, Zamzam et al. [45] proposed a neural network architecture that leverages power grid structure to reduce the number of parameters needed to map $\boldsymbol{z} \rightarrow \boldsymbol{x}$. Earlier, they introduced a shallow neural network trained on historical or simulation data to initialize the Gauss-Newton method for DSSE [46]. Subsequently, graphical neural networks gained traction, as the distribution system's network architecture is naturally suited for representation and analysis through graphs [98].

Recent studies reflect a growing trend in DSSE research: the fusion of physics-informed principles with advanced graph learning techniques using attention mechanism [99], [100]. They have focused on addressing inaccuracies in $\mathcal{T}$-topology estimation and improving the robustness of state estimation ($\mathcal{R}(\boldsymbol{x})$). [44] propose a deep statistical solver for DSSE, which utilizes GNNs to account for the network structure and physical power flow equations. This method employs a weakly supervised learning approach, allowing it to learn from noisy measurements without requiring ideal labeled data. It has shown superior performance in accuracy, convergence, and computational efficiency compared to conventional WLS algorithms. Notably, [38] presents a robust physics-informed $\boldsymbol{x}$ estimation with inaccurate $\mathcal{T}$ information, utilizing an aggregated $k-$nearest neighbor graph (to handle $\mathcal{U}(\mathcal{T})$) and an adaptive multi-channel graph attention model (for graph propagation and aggregation) to fuse feature and topology-based graphs, ensuring resilience to anomalous measurements $\mathcal{R}(\boldsymbol{x})$ through an attention module (for adaptive weight assignment). With a spatial-temporal graph neural network, [82] proposed a physics-informed graphical learning approach that integrates model-based dynamic state estimation using a high-accuracy Kalman filter for PMU measurements. The use of an attention module for adaptive weight assignment ensures resilience to anomalous measurements, enhancing the robustness of the estimation process.

Conclusively, the evolution of methods from physics-based classical approaches in the early 1900s to modern AI methods is illustrated in Fig. 3. The figure highlights the transition from purely WLS-based methods, where physics was directly embedded in the measurement functions and only limited synchronous data were available, to deep learning-based flat models trained on larger datasets but with little physical grounding, often leading to DSSE outputs that violated typical operating ranges. More recently, GNN-based models have emerged, where physics is incorporated as an inductive bias through the underlying electrical network structure.

Physics-informed learning in DSSE spans different strengths of physical integration and should not be treated as a single model class. Purely data-driven DNNs such as [39] learn a direct measurement-to-state mapping from labeled operating scenarios. Although power-flow simulations may be used to generate these labels, the measurement equations are bypassed during inference; low test error therefore does not guarantee that an estimated state is electrically feasible or remains accurate under topology, parameter, sensor-layout, or operating-distribution shifts. Structure-aware approaches occupy an intermediate level. PAWNN [45] sparsifies neural connections according to feeder partitions and admittance structure, while [38] combines the supplied topology graph with a measurement-derived feature graph. These are meaningful inductive biases because they reduce the hypothesis space, lower the number of trainable parameters, and localize the influence of corrupted measurements. However, graph adjacency alone does not enforce Kirchhoff's laws or the AC power-flow equations. Stronger physics integration appears in [97], which adds an AC power-flow residual to the training objective, and in DSS^2 [44], which passes predicted states through the measurement functions and minimizes a WLS-type residual without requiring exact state labels. These remain soft constraints; DSS^2 explicitly notes that feasible test-time solutions are not guaranteed. The hybrid method in [46] instead learns only a Gauss–Newton initialization and obtains the final estimate through the physics-based estimator, improving model consistency at the cost of iterative computation and dependence on the assumed network model. Physics-informed methods can therefore improve data efficiency and physical plausibility relative to unconstrained DNNs, but their benefit depends on where physics is imposed and on the accuracy of the embedded topology and parameters.

Recent physics-informed DSSE methods can be grouped according to how explicitly they embed electrical knowledge into learning architectures. One class of methods integrates physical structure directly into the learning process. Rout and Natarajan achieve this through deep unfolding, where iterations of a classical optimization-based estimator are mapped into trainable network layers, preserving the structure of the original solver [9]. A second class enforces physical consistency through graph-structured representations of the grid. Hu et al. and Wu et al. both exploit feeder topology and measurement relationships, combining graph-based learning with robustness mechanisms such as anomaly resistance and meta-learning for adaptation under changing conditions [101], [102]. A third class introduces physics constraints as regularization or loss terms, as in Iliadis et al., where violations of power-system equations are penalized during training [103]. More recent developments extend these ideas further by coupling neural inference with explicit physical solvers or factorized representations: El Semaan et al. design

physics-informed estimators for low-voltage systems [10], Zhang et al. integrate neural prediction with a subsequent physics-based estimation stage [104], and Kim et al. combine recurrent and graph-based learning to improve generalization to unseen networks [105]. In parallel, factor-graph neural networks and power-flow-constrained learning frameworks explicitly encode measurement and network equations within the learning architecture [106], [107]. Across these approaches, a clear hierarchy emerges: from soft constraint enforcement, to structured graph embedding, to solver-coupled and unfolding-based methods. While all improve physical consistency compared to unconstrained learning, their ability to guarantee feasibility still depends on the strength and correctness of the embedded physical model, and soft constraints alone may not fully prevent physically inconsistent outputs under model mismatch.

D. ROLE OF PSEUDO-MEASUREMENTS

A standard approach to addressing unobservability is the use of pseudo-measurements, which are generated from interpolated observations or forecasts based on historical data. While pseudo-measurements have been a dominant theme in DSSE, these techniques are inherently ad hoc and fail to guarantee the quality of the estimates [108]. More importantly, historical data are often limited in scope and lack the temporal resolution necessary to capture the dynamic nature of real-time state changes.

Pseudo-measurements should be distinguished according to how they are constructed. Major classes include historical or load-allocation profiles, forecast-aided estimates, probabilistic or generative models, transfer-learning approaches, and reconstructions learned jointly with DSSE. These methods can improve numerical conditioning and practical observability, but they do not create independent physical information. Their bias, covariance, cross-correlation, and dependence on the feeder topology and customer-to-transformer mapping must therefore be propagated into the state estimator. Treating multiple pseudo-measurements derived from shared weather inputs, historical profiles, or common training data as independent can create apparent observability and produce overconfident state estimates. Their quality can also change with season, customer composition, FDA adoption, and network reconfiguration. Evaluation should consequently report both pseudo-measurement prediction error and its downstream effect on state-estimation accuracy and uncertainty [40], [41], [43].

The limitations of pseudo-measurements in accuracy and real-time adaptability have led to the rise of AI/ML-based data fusion, which integrate, process, and refine observational data from diverse sources for more reliable state estimation.

IV. APPLICATION OF AI/ML IN DATA FUSION

In distribution systems, high-resolution μPMUs provide detailed data but are costly and need optimal placement. Meanwhile, low-resolution SCADA data are more widely available but do not always complement μPMUs effectively. High-resolution state estimation is essential for capturing real-time load changes, FDA fluctuations, and topology reconfigurations, matching the millisecond-level precision of μPMUs. Moreover, properly addressing the different time scales inherent to the measurements enables evaluating distinct types of events (such as fast transients and slow trends). To enhance grid visibility in the distribution network, it is necessary to address source heterogeneity and varying time scales and prioritize real-time data over historical measurements.

Data fusion, the process of integrating multiple data sources to produce consistent, accurate, and useful information, initially started on as data pre-processing technique. With more sensor data available, researchers have shifted to feature- and decision-level data fusion to enhance DSSE [109]. Machine learning algorithms, particularly their seamless classification capabilities, offer significant enhancements to data fusion techniques. Owing to their growth in developing data fusion algorithms, several reviews have emerged: [110] classifies supervised and unsupervised machine learning algorithms as data fusion at signal, feature, and decision levels, while [111] covers probabilistic and mathematical techniques, and [112] focuses on deep learning-based methods.

Several machine learning implementations have influenced data fusion for state estimation, including: [113] proposed DeepFusion, a unified multi-sensor deep learning framework, to learn informative representations of heterogeneous sensory data. The idea was to combine different sensors' information weighted by the quality of their data including their cross-sensor correlations mainly for applications where there are usually multiple different sensors monitoring the same object. [114] proposed a multimodal data fusion framework, the deep multimodal encoder (DME), based on deep learning techniques for sensor data compression, missing data imputation, and new modality prediction under multimodal scenarios. While traditional methods capture only the intramodal correlations, DME is able to mine both the intramodal correlations in the initial layers and the enhanced intermodal correlations in the deeper layers. In this way, the statistical structure of sensor data may be better exploited for data compression.

Early DSSE approaches addressed improved convergence and incorporated three-phase unbalanced network models while ignoring temporal aspects of measurements, leading to the mixing of asynchronous updates and varying sampling rates within the measurement vector [115]. With the coexistence of measurements from SCADA, PMUs, smart meters, and other sensors, data fusion, initially focused on transmission systems [116]–[118], emerged as a framework for enabling high resolution state estimation. Liu et al. [116] survey WAMS–SCADA fusion in the broader power-system context. Deng et al. [117] examine PMU-assisted multi-source fusion for distribution-system state estimation, whereas Zhu et al. [118] develop PMU–SCADA fusion within a state-estimation framework. High-resolution DSSE is achieved through: A. Super-resolution methods, which

enhance resolution of measurements from diverse sources before estimation, often through interpolation, deep learning, or signal processing techniques, and B. Information fusion, which integrates data from multiple estimators or sources to improve accuracy and reliability of estimation.

A. SUPER-RESOLUTION METHODS

Super-resolution enhances raw sensor data by improving its spatial or temporal resolution before state estimation. In DSSE, it commonly interpolates low-frequency SCADA measurements to align with high-frequency PMU data, thereby generating refined inputs for state estimation.

More recently, Liu et al. [119] reviewed super-resolution methods and categorized them into three classes: (1) interpolation-based mathematical techniques, (2) DNN-based supervised learning that reconstructs high-frequency data from low-frequency historical measurements and integrates with DNN-based state estimation, and (3) GAN-based semi-supervised learning. [120] applied a super-resolution imputation framework with bilinear neural networks to improve state estimation in low-observability distribution networks.

Super-resolution methods enhance features such as voltage magnitudes, frequency variations, and load patterns by reconstructing missing measurements and refining spatiotemporal patterns [121]. Although supervised learning is constrained by sparse labeled data from unobservable nodes and incomplete measurements, semi-supervised learning improves estimation accuracy by leveraging unlabeled data alongside limited labeled samples without significantly increasing computational complexity [122].

B. INFORMATION FUSION BASED METHODS

Information fusion enhances the DSSE by integrating measurements with diverse temporal, physical, and statistical characteristics. Earlier approaches weight measurements based on sampling rates [55], [123], incorporating them into specialized DSSE algorithms or assigning greater weight to certain measurements to offset synchronization issues [88].

1) Probabilistic methods

A Bayesian information fusion processes prior state estimates with new observations via maximum a posteriori estimation [109], [124]. Using Bayesian inference to integrate multi-rate measurements in distribution networks, the method proposed in [109] organizes data from smart meters, SCADA systems, PMUs, and pseudo-measurements into sampling layers based on update rates. To address ill-conditioning, an orthogonal numerical method enhances stability and reliability. Additional probabilistic frameworks include [125].

Departing from traditional data fusion approaches, [126] proposes a PMU-based strategy that integrates an unscented Kalman filter to handle nonlinearities while eliminating the need for Jacobian matrix computations, a key limitation of extended Kalman filtering methods. Similarly, [127] highlights the shortcomings of weighted averaging operators in DSSE data fusion, showing that they are less effective under uncertainties, packet loss, and cyberattacks compared to machine learning regression models such as random forests.

2) AI methods

Emerging trends in AI-driven data fusion methods focus on targeted fusion. For example, [128] proposed an estimation fusion framework that processes SCADA and smart meter measurements separately before integration. The authors used a model-free tensor completion method to exploit spatial and temporal correlations, filling in gaps caused by missing or bad data. This structured approach ensures that different data sources are incorporated in a way that maximizes their respective contributions to state estimation preserving measurement redundancy.

[120] takes a different approach, using deep reinforcement learning to dynamically adapt to asynchronous and multi-rate measurement streams, addressing challenges related to missing or delayed data, allowing the model to adjust in real-time based on stochastic variations in the network. This marks a shift towards self-learning models that continuously refine their estimation accuracy. For low-observability systems and addresses emerging challenges posed by electric vehicle (EV) integration, where network conditions change rapidly, [129] introduced a meta physics-informed graph TimesNet, a novel approach that integrates graph convolutional networks and TimesNet to model spatio-temporal correlations for dynamic topology estimation.

Data fusion methods integrate multiple data sources to enhance DSSE. Topology identification is equally crucial for real-time grid visibility as it ensures that state estimation models accurately reflect the actual network structure. Given the dynamic nature of modern distribution networks with network reconfigurations and switching events, it is essential to continuously monitor and identify the topology to maintain estimation accuracy and operational reliability.

V. TOPOLOGY IDENTIFICATION

Network topology changes caused by switching operations and load balancing reconfigurations, if unaccounted for, can lead to DSSE failures, undermining optimal power flow, effective voltage management, and prompt fault response. Therefore, accurate knowledge of the actual network topology ($\mathcal{T}$), often referred to as topology detection, identification, or awareness, is critical for the effective operation, control, and protection of power systems. While DSSE methods traditionally learn power flow relationships in a black-box manner (see Section III), topology identification enhances network interpretability by detecting and mapping the current grid configuration in real-time. By ensuring that state estimation models accurately reflect the physical grid, topology identification enables more reliable DSSE and overall efficient grid control [130].

In conventional passive distribution networks, which operate without significant FDA penetration, fewer tap changes occur due to unidirectional power flow and predictable load profiles. In contrast, active distribution networks (ADNs) experience frequent topology changes, sometimes with switching actions occurring up to 10 times per day, driven by the integration of FDAs. Advanced functionalities in ADNs, including Volt-VAr optimization, restoration, outage management, FDA dispatch coordination, demand-side management, and fault location, depend critically on accurate and up-to-date topology information. Moreover, traditional transmission topology processors often fall short in distribution networks because FDAs require frequent switching that may go unreported to the DMS, and FDA/EV owners are not network operators, leaving utilities with incomplete information regarding connection status.

Methods for topology identification can be broadly classified into three categories: (i) approaches that integrate DSSE to generate additional data for topology identification, (ii) purely end to end data-driven methods that rely exclusively on measurement data, and (iii) numerical or analytical methods. Prior to 2017, DSSE-based techniques dominated; however, rapid advancements in metering infrastructure and the deployment of high-tech devices such as μPMUs have shifted the focus toward learning algorithms, such as machine learning, deep learning, and unsupervised learning, for topology identification. These methods can process either single-shot (static) data or capture time-varying (dynamic) topologies, with the topology often estimated in terms of state variables such as line power flows, admittance matrices, voltage sensitivities, or tree topologies.

GNNs have gained popularity for topology identification because they facilitate fast DSSE and reduce the impact of bad measurements; however, achieving higher precision often requires deeper graph layers [45], [131]. To better capture areal information, Wu et al. [132] proposed spatiotemporal graph convolutional networks, while Cao et al. [99] developed a robust GNN-based estimator. Given the challenges of outdated or inaccurate network parameters (e.g., line impedances, load data), unsupervised data-driven methods have emerged to train topology identification algorithms without the need for explicit output labels.

More recently, Madbhavi et al. [98] have advanced the field by integrating graph-based techniques with data fusion strategies. Similarly, Ma et al. [47] introduced a split expectation-maximization method that handles mixed topologies in historical data without prior assumptions about the number of configurations, offering greater adaptability. In another notable approach, Gotti et al. [133] presented a DNN-based method for real-time topology identification that uses measurement data typically collected for state estimation, achieving high accuracy with low computational cost.

Since the reviewed studies use different networks, sensing configurations, and evaluation metrics, deployment readiness cannot be inferred from estimation accuracy alone. Table 2 therefore provides a category-level comparison based on the strengths, limitations, and validation evidence reported across the reviewed methods.

VI. PUBLIC BENCHMARKS AND FIELD VALIDATION

Publicly accessible resources for distribution-system research can be separated into three broad classes: model-based benchmark networks, hybrid network–time-series resources, and field-measurement repositories. Model-based benchmarks provide a known network model and allow exact electrical states to be generated through power-flow simulation. Hybrid resources combine network models with realistic or utility-derived operating profiles. Field repositories provide measurements obtained from physical distribution systems and therefore expose practical effects such as missing samples, imperfect synchronization, sensor bias, communication interruptions, and undocumented operator actions. Field repositories, however, rarely provide independently measured voltage magnitudes and phase angles at every node. Synthetic benchmarks offer complete state labels but limited field realism, whereas field datasets offer realistic observations but incomplete state ground truth.

Table 3 summarizes publicly accessible resources relevant to data fusion, distribution-system state estimation, and topology identification. The use of field-derived load profiles does not, by itself, constitute field validation. In this review, a study is classified as field validated only when actual measurements from a physical network enter the estimation or identification process and the resulting output is assessed using an independent reference. Such a reference may consist of withheld calibrated measurements, utility-verified topology information, physical inspection, or an operational deployment in which the complete acquisition-to-estimation chain is evaluated.

Representative studies illustrate several forms of field evidence. Pignati et al. demonstrated a synchrophasor-based state estimator on an operating medium-voltage campus network and reported both the state-refresh rate and end-to-end latency [134]. Groß et al. and Früh et al. evaluated three-phase DSSE using measurements from real medium- and low-voltage feeders. Because the true states of unmeasured buses were unavailable, their evaluations relied on deviations from available reference measurements [135], [136]. In topology identification, Lee et al. evaluated phase and transformer–meter pairing on multiple utility feeders and used GIS checks and field inspection by utility personnel to verify the inferred connectivity. These validation mechanisms are stronger than simulation alone, although none provides measured full-state ground truth over an entire feeder [137].

The resources summarized in Table 3 also expose an important benchmark gap. No single resource in the reviewed set jointly provides a complete three-phase network model, heterogeneous asynchronous measurements, independently measured full-state ground truth, verified switching events, naturally occurring communication failures, and long-duration operation over multiple feeders. Developing a

TABLE 2: Category-level comparison of major grid-visibility methods and their deployment readiness.

Method category	Main advantages	Principal limitations	Deployment readiness
Classical and robust model-based DSSE [42], [43], [134]	Uses explicit measurement functions and error models. Provides interpretable residuals, observability analysis, and mature bad-data processing without requiring labeled training data.	Requires credible topology, parameters, error covariance, and measurement redundancy. Repeated numerical solves and structural model errors can limit real-time performance.	**D2–D3:** field/pilot to operational
Probabilistic and interval DSSE [5], [40], [41]	Represents uncertainty in FDA outputs, pseudo-measurements, and estimated states through distributions, intervals, or probability bounds, supporting risk-aware decisions.	Depends on prior, distribution, correlation, and calibration assumptions. Uncertainty propagation can be conservative or computationally expensive, and field calibration is rarely reported.	**D1:** research prototype
Purely data-driven AI [37], [39]	Learns nonlinear measurement-to-state mappings and can provide fast online inference under sparse sensing. Joint state and topology tasks can also be learned.	Requires representative training scenarios and labels. Performance can degrade under unseen topology, sensor placement, operating conditions, or measurement distributions. Calibration, retraining, and safe fallback remain unresolved.	**D1–D2:** simulation to utility-data evidence
Physics-informed and graph learning [38], [44]–[46]	Uses electrical connectivity, locality, or measurement equations to reduce model size, improve data efficiency, and encourage physically plausible estimates.	Graph and physical priors can transmit topology or parameter errors. Physical constraints are often imposed softly and do not guarantee feasible outputs. Graph updating, model adaptation, and field validation remain limited.	**D1:** research prototype
Data fusion and pseudo-measurement methods [40], [41], [43]	Combines heterogeneous and multi-rate measurements to improve observability, reconstruct unavailable quantities, and exploit complementary sensor information.	Requires temporal alignment and credible cross-sensor uncertainty models. Missingness, restricted data access, and inaccurate pseudo-measurements can propagate errors into downstream DSSE. End-to-end evaluations remain uncommon.	**D1–D2:** offline to field-data evidence
Topology identification and joint state–topology inference [33], [39], [47]	Maintains consistency between the estimator and the operating feeder configuration. Model-based methods can use existing SCADA or TTU measurements, while learned methods can provide fast online classification.	Model-based formulations may be combinatorial. Learned methods require representative topology labels or adaptation data. Communication latency, parameter errors, and incorrect topology decisions can directly bias DSSE.	**D1–D2:** simulation to pilot-oriented

Readiness scale: **D1** denotes simulation or offline research-prototype evidence; **D2** denotes utility- or field-data evaluation, laboratory validation, or pilot integration; and **D3** denotes an end-to-end online operational demonstration. Ranges reflect heterogeneous evidence within a category and are not formal technology-readiness levels. They do not imply that every method in a category attains the upper level.

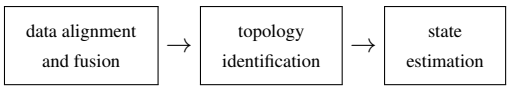
benchmark with these properties would materially improve the reproducibility and operational relevance of future grid-visibility research.

VII. CHALLENGES AND FUTURE DIRECTIONS

A. RESEARCH GAPS

The reviewed literature has begun to connect the main components of real-time grid visibility, but the integration remains predominantly pairwise. Methods that combine data fusion with state estimation assimilate heterogeneous field measurements and pseudo-measurements into a common estimator. For example, Massignan et al. formulate Bayesian information fusion for DSSE [109], while sequential hybrid-measurement methods combine AMI and μPMU information within the state-estimation process [43]. These approaches improve observability and reconcile measurements with different characteristics, but the fusion process generally conditions on a supplied network topology. A different body of work couples topology identification with state estimation. Soltani et al. jointly formulate robust state estimation, topology-error processing, and outage detection while accounting for unsynchronized, missing, and bad measurements [151]. Azimian et al. estimate topology and state using two separately trained DNNs, with the inferred topology determining the DSSE model used for state prediction [39]. Zhang et al. introduce temporal coupling through a forecasting-aided Bayesian non-parametric model that represents changing topology as a latent process [152]. These methods move beyond fixed-topology DSSE, but their observation processing remains prescribed. They do not jointly adapt the contribution of each sensor modality while topology and state remain uncertain.

Data processing has also been coupled with topology identification, although it is generally treated as a preprocessing stage. Xu et al. reconstruct power measurements affected by high TTU latency before solving a mixed-integer topology-identification problem [33]. The identified topology is subsequently provided to state estimation and other control-center applications. Yu et. al. [153] instead uses noisy historical measurements from latent operating regimes to jointly identify network topology and line parameters. However, it remains a system-identification framework rather than a real-time fusion and state-estimation model. Taken together, the literature largely addresses one of three pairwise problems: data fusion with state estimation, topology identification with state estimation, or data processing with topology identification. The dominant architecture therefore remains a one-way chain,



This separation creates brittle handoffs. An incorrect topology decision can be treated as certain by the downstream state estimator. A physically inconsistent state estimate is rarely used to reconsider the inferred topology. Likewise, estimation residuals are seldom returned to the fusion stage to down-weight a delayed sensor, revise a pseudo-measurement, or identify an unreliable modality. Selecting a single topology before DSSE also discards structural uncertainty when several feeder configurations are consistent with the available observations.

The unresolved problem is therefore a shared inference framework in which the fused observation representation, network topology, and electrical state are estimated together:

$$p\left(\boldsymbol{x}_{1:t}, \mathcal{T}_{1:t}, \boldsymbol{z}_{1:t}, \middle| \{\boldsymbol{y}_{\tau}^{(m)}, \tau^{(m)}, \boldsymbol{m}_{\tau}^{(m)}\}_{m=1}^{M}\right),$$

Each measurement modality m has its own timestamps $\tau^{(m)}$ and availability mask $\boldsymbol{m}_{\tau}^{(m)}$. In such a framework, fusion should be conditioned on topology because switching

TABLE 3: Publicly accessible benchmark systems and datasets for distribution-grid visibility.

Resource	Class and scale	Time series, model, and labels	Relevant uses	Access and principal limitation
(a) Network benchmarks and hybrid network–time-series resources				
IEEE PES Distribution Test Feeders [138]	Synthetic unbalanced 4/13/34/37/123/342/8500-node systems; radial/meshed cases.	Mostly static; one LV feeder has a one-day load series. Topology, phases, parameters, controls, and switches vary; power flow supplies exact simulated states.	DSSE, observability, meter placement, topology changes, and scale tests.	Direct download; usually no measured streams, natural failures, or operator switching records.
CIGRE benchmark networks [139]	Synthetic HV/MV/LV reference networks with DER variants.	Detailed topology/equipment data; user-generated trajectories; no native field streams.	DER-rich DSSE, active-network/microgrid studies, and voltage-level comparisons.	Open implementations; original brochure may require membership or purchase.
PNNL taxonomy feeders [140]	Twenty-four prototypical, mainly unbalanced radial GridLAB-D feeders derived from 575 utility feeders.	Complete synthetic topology/components; users assign load/DER profiles; no labeled events.	Regional generalization, feeder transfer, and synthetic-population studies.	Public models; synthetic operation/events; coordinates often absent or not to scale.
SimBench [141]	Synthetic German LV–EHV and cross-voltage networks, including future scenarios.	One year of 15-min load, generation, and storage profiles with network/component assignments.	Time-series DSSE, DER variability, reconfiguration, planning, and operations.	ODbL 1.0; assigned/synthetic measurements omit realistic communication artifacts.
SMART-DS [142]	Large synthetic OpenDSS regions for San Francisco, Greensboro, and Austin.	Fifteen-minute load/building end-use profiles; detailed networks yield complete simulated states.	Large-scale DSSE, graph scalability, transfer, placement, and city-scale stress tests.	Public via OEDI; drift, bad data, failures, and switching must be generated.
PSML [143]	Open joint transmission–distribution multiscale dataset.	Three years of minute field-derived profiles; one year of simulated minute synchrophasors; $> 1{,}000$ labeled millisecond disturbances.	Multirate fusion, disturbance localization, forecasting, and representation learning.	Open via Zenodo/GitHub; grid voltage/current tasks use simulation-generated measurements.
Iowa Distribution Test Systems [144]	Real municipal system: three feeders, 240 primary nodes, 1,120 customers.	One year of hourly privacy-aggregated AMI; real topology/component parameters.	Pseudo-measurements, time-series DSSE, load models, and utility-data evaluation.	Public; hourly aggregation and no synchronized full-state ground truth.
CINELDI MV reference system [145]	Anonymized 124-node, 22-kV radial model from a Norwegian system.	One year of hourly demand, scenarios, reliability data, topology, parameters, and load points.	Utility-derived DSSE, flexibility, self-healing, reliability, and planning.	Public processed reference model, not synchronized field-sensor data.
Porsgrunn MV/LV network and AMI [146]	Processed Norwegian DSO network; approximately 6,809 end users.	Hourly active/reactive AMI (2022–2024), weather/prices, and mapped MV/LV models.	Utility-profile DSSE, pseudo-measurements, forecasting, and AMI–network integration.	CC BY 4.0; no measured angle ground truth or comprehensive labeled switching.
(b) Field-measurement datasets				
SoCal 28-Bus Digital Twin [147]	Anonymized California distribution system/microgrids; complete resource > 10 TB.	RMS at 1 s, phasors at 10 s, and 2.5-kHz waveforms; topology, breaker status, metadata, and outage switching.	Heterogeneous fusion, DSSE, joint state–topology inference, and digital-twin validation.	Sample open; full access requires approval; some parameters uncertain and gaps occur.
LBNL Open μPMU/event library [148]	Three connected μPMUs; Oct.–Dec. 2015; approximately 130 GB plus 26 sag events.	Three-phase magnitudes/angles at 120 Hz; partial circuit metadata; no complete feeder/full-state reference.	Data quality, event/alignment analysis, anomaly detection, and high-rate fusion.	Open raw data; only three locations, preventing feeder-wide state-error evaluation.
FeederBW [149]	Real 2023–2025 measurements from 200 German LV feeders.	One-minute electrical/weather data and feeder metadata; no detailed topology/full-state labels.	Load/DER variability, pseudo-measurements, domain shift, missing data, and forecasting.	Public on Zenodo; aggregated feeder data, not a topology-resolved DSSE benchmark.
Northern Powergrid aggregated smart meters [150]	Real data aggregated by LV feeder and distribution substation.	Half-hourly active/reactive energy with natural gaps; no complete topology/connectivity/full-state labels.	AMI aggregation, imputation, pseudo-measurements, forecasting, and natural missing-data tests.	Public portal; no error handling; intervals with fewer than five meters suppressed.

changes the spatial meaning and physical consistency of measurements. Topology inference should use state residuals and cross-modal agreement to distinguish a switching event from a sensor, timing, or parameter error. State estimation should preserve a distribution over plausible topologies rather than conditioning on a single hard configuration. The framework must also reconcile the different timescales of continuous state evolution, discrete switching actions, and asynchronous sensor updates. Its central validation target should be joint structural and observational generalization: topology changes should be evaluated together with changes in sensor availability, reporting rate, and measurement quality. Evaluation should trace how reconstruction error affects topology confidence, how topology uncertainty propagates into state uncertainty, and whether the resulting estimate remains reliable for downstream decisions. Among the reviewed studies, we did not identify an end-to-end framework that provides these capabilities within one bidirectional, uncertainty-aware inference process.

The framework above defines the required coupling among observation fusion, topology inference, and state estimation. Realizing such a framework, however, exposes two unresolved problems that are not adequately addressed by the current literature.

The first is joint adaptation when the physical model and the observation process change at the same time. Most studies perturb topology, measurements, latency, parameters, or operating conditions separately, although these changes are coupled in practice. Communication congestion can alter both the timestamp and the numerical value of measurements used for topology inference [33]. The hybrid estimator in [46] assumes that the changed topology is already known and loses its initialization advantage under severe reconfiguration unless it is retrained. The joint DNN in [39] reduces this cost through fine-tuning, but still requires data from the new topology. DSS^2 [44] further shows that soft power-flow penalties do not guarantee a feasible test-time estimate and that generalization degrades outside the operating range represented during training. The challenge is therefore not simply to develop another topology-robust estimator. A real-time visibility framework must determine whether a mismatch originates from the measurements, their timing, the topology, or the network parameters. It must then update only the affected model components and invoke a trusted fallback when the cause cannot be resolved. Evaluation should consequently combine topology switching with parameter errors, asynchronous measurements, and changing sensor availability rather than perturbing one factor at a time.

The second is converting an estimated state into decision-grade evidence under limited observability. Topology-learning studies identify nonlinear and meshed operation, correlated injections, low signal-to-noise ratios, mobile microgrids, adversarial corruption, and closed-loop use as insufficiently resolved settings [154]. Industrial DSSE experience exposes a related attribution problem: residuals may not reliably distinguish a bad measurement from an incorrect line parameter, phase label, or meter configuration. This motivates joint state–parameter estimation, automated model

cleaning, and root-cause diagnosis [155]. Probabilistic and interval methods can represent uncertainty under sparse or limited information [5], [40], but their outputs become operationally useful only when they are calibrated to the decisions they support. Future studies should test whether uncertainty retains empirical coverage after topology and sensor changes. They should also report whether the method recognizes loss of observability and whether downstream actions remain safe. A deployable visibility service should therefore return the state and topology together with the dominant source of uncertainty and an explicit accept, caution, fallback, or abstain decision.

B. FUTURE OPPORTUNITIES

Addressing the identified research gaps requires an integrated approach, leveraging both technological innovations and interdisciplinary collaboration. Effective DSSE must achieve minimal estimation errors, low parameter sensitivity, robustness against noise and anomalies, and robust uncertainty quantification, particularly in consideration of variable generation, FDAs, and human factors. As discussed in Section IV, traditional model-based state estimation approaches are computationally demanding and typically unsuitable for online real-time applications. AI-based estimators can reduce repeated online numerical optimization after training. However, their total computational burden also includes scenario generation, data preprocessing and alignment, graph construction, model adaptation, hardware and memory requirements, communication, validation, and fallback execution.

The evidence-derived gaps above suggest that future work should be organized around testable deployment capabilities rather than individual model improvements. In particular, new methods should demonstrate failure-source attribution, selective adaptation, calibrated uncertainty under compound shifts, and safe fallback within an end-to-end sensing-to-decision workflow.

Lastly, advanced sensor deployment strategies and standardized data communication protocols are essential for enhancing the availability and quality of real-time data streams. Practical initiatives, such as establishing common frameworks for secure and efficient data sharing between utilities, researchers, and third-party aggregators (e.g., standardized platforms for integrating AMI and μPMU data), will significantly facilitate research collaboration and innovation. Cyber-physical resilience is an integral requirement of real-time grid visibility rather than an external implementation concern. As discussed in Section II-B3, evaluation should include integrity, availability, timing, and model-integrity failures and should report estimation degradation, detection delay, false-alarm rate, operational availability, and recovery time.

VIII. CONCLUSION

Real-time grid visibility is essential for managing modern power distribution systems and microgrids amid rapid FDA integration, evolving network topologies, and increasing data complexity. This review provides a comprehensive survey of DSSE methods, highlighting traditional approaches such as WLS and contrasting them with emerging AI-based and physics-informed techniques. We examined the critical roles of data fusion, state estimation, and topology identification in forming a cohesive framework that supports proactive decision-making and robust grid operation. Integrating advanced DSSE techniques into control and management platforms is crucial for effective fault detection, optimal distributed generation dispatch, and overall grid stability. Future research should focus on developing scalable, robust, and adaptive DSSE algorithms capable of integrating multimodal, asynchronous, and high-resolution data in real time. Addressing challenges such as dynamic topology reconfiguration, uncertainty quantification, and the efficient fusion of heterogeneous data sources will be vital for the successful implementation of these methods. Ultimately, continued advancements in DSSE will contribute significantly to the development of resilient and efficient distribution networks.

Real-time grid visibility should therefore be designed as an end-to-end capability, not as a collection of isolated sensing, data-fusion, topology-identification, or state-estimation functions. Reliable visibility emerges when measurement reconstruction, topology inference, and state estimation inform and constrain one another. Uncertainty and residual evidence must also propagate across these tasks so that errors are detected and corrected instead of silently compounding throughout the inference process. The full information chain—from sensing and communication to data-quality assessment, joint inference, and uncertainty-aware decision support—must operate coherently. More sensors, a standalone fusion module, or a more accurate estimator cannot by itself deliver decision-ready visibility when another part of this chain remains unreliable.

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APPENDIX A EXAMPLE MEASUREMENT DEVICES

TABLE 4: Monitoring Devices in Power Distribution Systems*

Device	Example (Company & Model)	Installation Location	Measurements Collected	Measurement Interval	Communication Delay	Communication Protocol
SCADA Systems	ABB MicroSCADA Pro [156]	Control center	Voltage (V) and Current (A) Breaker/Switch status (Open/Close) Transformer load (kVA) Power flow (kW, kVAR) Alarms and faults (location, type)	2 second	1–3 second	DNP3, IEC 60870-5-104, Modbus
Advanced Metering Infrastructure or Smart Meters	Itron OpenWay Riva [157]	Customer premises	Energy consumption (kWh) Voltage and Current (accuracy: $\pm$0.2%) Power factor	15 minute	1–5 minute	ZigBee, Wi-SUN, LTE, LoRaWAN
Micro Phasor Measurement Units (μPMUs)	Arbiter Systems Model 1133A Power Sentinel [158]	Substations, key points	V and I phasors (accuracy: $\pm$0.05%) Frequency (accuracy: $\pm$0.001 Hz) ROCOF (Hz/s)	30 samples/sec	$\leq$ 20 ms	IEEE C37.118, IEC 61850
Grid-Edge Resources Monitors / Inverters	Fronius Primo Inverter [159]	FDA sites (e.g., solar PV)	Generation output (kW) Voltage and Current (accuracy: $\pm$0.5%) Frequency (accuracy: $\pm$0.01 Hz) Power factor Inverter status and faults	5 second	5–10 second	SunSpec Modbus, IEEE 2030.5, OPC-UA
Remote Terminal Units (RTUs)	Schneider Electric SCADAPack 300 [160]	Substations, network points	Breaker/Switch status (Open/Close) Voltage and Current (accuracy: $\pm$0.1%) Alarms/Events	1 second	$\leq$ 1 second	Modbus, DNP3, IEC 60870-5-104
Line Sensors	Sentient Energy MM3 Overhead Line Sensor [161]	Overhead lines	Current and voltage waveforms Conductor temperature Fault detection and location Power flow direction	128 samples/cycle	Less than 1 second	Proprietary protocols, ZigBee, LTE
Transformer Monitors	GRID20/20 OptaNODE DTU [162]	Distribution transformers	Load current (accuracy: $\pm$0.5%) Voltage (accuracy: $\pm$0.5%) Temperature (accuracy: $\pm$1°C) Harmonics (up to 13th order)	5 minute	30–60 second	IEC 61850, Modbus
Capacitor Bank Monitors	Beckwith M-6280A [163]	Capacitor banks	Voltage and Current (accuracy: $\pm$0.2%) Reactive power (VARs) Temperature Status (On/Off)	2 second	1–2 second	DNP3, Modbus
Voltage Regulator Controllers	Eaton Cooper CL-7 [164]	Voltage regulators	Voltage and Current (accuracy: $\pm$0.1%) Tap position Power factor	2 second	1–2 second	DNP3, Modbus
Reclosers	S&C IntelliRupter [165]	Feeder points	Current and Voltage Fault detection Device status	Sampling at 15.36 kHz	$\leq$ 1 second	IEC 61850, DNP3
Power Quality Meters	Dranetz HDPQ Guide [166]	Substations, critical nodes	Voltage sags/swells Harmonic distortion (up to 63rd harmonic) Transients (sampling up to 1 MHz) Flicker	High-resolution sampling	Immediate; varies by network	IEC 61000-4-30, DNP3
Feeder Monitors	GE Multilin F650 [167]	Substations, feeders	Voltage and Current (accuracy: $\pm$0.2%) Power flow (kW, kVAR) Frequency	1 second	$\leq$ 1 second	Modbus, DNP3

Device	Example (Company & Model)	Installation Location	Measurements Collected	Measurement Interval	Communication Delay	Communication Protocol
Weather Sensors	Vaisala WXT530 [168]	Service area	Temperature (accuracy: $\pm$0.3°C) Humidity Wind speed/direction, etc.	1 minute	$\leq$ 5 second	RS-232, RS-485, Modbus
BESS Monitors	Tesla Megapack [169]	BESS sites	State of Charge (SoC) Voltage and Current (accuracy: $\pm$0.5%) Temperature Charge/Discharge rates	1 second	$\leq$ 1 second	SunSpec Modbus, IEC 61850

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