A Survey of Power System State Estimation Using Multiple Data Sources: PMUs, SCADA, AMI, and Beyond

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***Abstract*—State estimation (SE) is indispensable for the situational awareness of power systems. Conventional SE is fed by measurements collected from the supervisory control and data acquisition (SCADA) system. In recent years, available data sources have been greatly enriched with the deployment of phasor measurement units (PMUs), advanced metering infrastructure (AMI), intelligent electronic devices (IEDs), etc. The integration of multiple data sources provides unprecedented opportunities for enhancing the performance of SE, but also presents major challenges to resolve, including optimal multi-type-sensor co-placement, multiple reporting rates and asynchronization, diverse types of measured quantities, correlations between measurements, integration of online and historical data sources, and system and measurement uncertainties. This paper outlines the state of the art and research opportunities in this area by providing a comprehensive literature review and extensive discussions. It starts by presenting the motivations and challenges, followed by a summary of existing data sources for SE in power systems. Subsequently, for both transmission system (static and dynamic) and distribution system SE, existing methods are systematically reviewed and categorized based on the addressed challenges. Interesting attempts of using novel measurements in SE are also studied. Finally, the paper concludes by providing a detailed discussion on the remaining research gaps and future research directions to be explored.**

***Index Terms*—State estimation, power system measurement, multiple data sources, situational awareness, phasor measurement unit, advanced metering infrastructure.**

I. Introduction

STATE estimation (SE) has been an essential concept and technology for the situational awareness of power systems since the pioneering work by Schweppe in 1970s [1]. The objective of SE is to capture the real-time operating conditions, characterized by a set of state variables, with imperfect measurement data and system models [2]. SE is an essential function supporting many advanced applications in today's Energy Management Systems (EMS) for transmission systems. Conventional measurement data are gathered by the supervisory control and data acquisition (SCADA) system from the remote terminal units (RTUs) deployed in substations. With increasing deployments of phasor measurement units (PMUs), measurement accuracy and redundancy have been improved. PMUs can provide synchronized voltage and current phasor measurements with time stamps from the global positioning system (GPS) [3]. In addition, intelligent electronic devices (IEDs) are replacing RTUs in SCADA systems [4]. Power distribution systems are historically measurement-scarce with only feeder terminal units (FTUs) at feeder heads, and therefore SE has not been a standard application of distribution management system (DMS). However, with the increasing numbers of distributed energy resources (DERs), SE is becoming a necessity also for distribution systems [5], [6]. Advanced metering infrastructure (AMI) consisting of smart meters (SMs), communication networks, and data management systems can report load profiles and allow bi-directional information flows [7], [8]. Moreover, micro-PMUs are emerging with lower cost and higher accuracy of phase angle measurements compared to conventional PMUs [9], [10]. These new types of sensing and communication infrastructures provide great opportunities for the implementation of SE for distribution networks.

As the performance of SE in noise filtering and bad data processing is closely related to measurement redundancy, integrating multiple types of available measurements is a natural way to improve performance. For example, in a vast majority of systems today, it is almost impossible to perform SE by exclusively using PMU measurements since they are not deployed in sufficient numbers. Thus, in transmission systems, PMU measurements are incorporated into the measurement set as redundant measurements along with existing SCADA measurements [11]. In distribution systems, the lack of real-time measurements is one of the major obstacles preventing the wide-spread implementation of SE. Pseudo-measurements derived from historical SM data or typical load profiles may be used to restore the observability of the system. Hence, incorporating historical SM measurements with SCADA or PMU

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measurements may enable the implementation and effective utilization of SE in distribution systems. With the continual advancement of communication technologies, some systems can now receive near-real-time measurements from SMs, yet their time resolution is still insufficient to match SE execution rate. The integration of multiple data sources in SE is an essential yet not straightforward task. A few widely recognized challenges are summarized as follows.

1) Optimal Multi-Type-Sensor Co-placement: The performance of SE is dependent on measurement configuration. With multiple data sources, it is necessary to perform optimal multi-type-sensor co-placement to determine the locations of measurements to satisfy observability, SE accuracy, and budgetary requirements [12], [13], [14], [15], [16], [17], [18], [19]. However, observability analysis and SE accuracy impact analysis vary with the different measured variables and reporting rates of sensors, which creates challenges for formulating the optimization problem.

2) Multiple Reporting Rates and Asynchronization: The reporting rates of different data sources vary widely. For example, SCADA typically reports every 2∼5 seconds [4], [20]; PMUs can provide measurements as fast as 60 samples per second [3], [21]; AMI updates every 15 minutes or hourly [7], [8]. The diversity of reporting rates may originate from the sensor designs, communication bandwidths, or data storage capacities. Furthermore, the reporting times of different data sources are uncoordinated, referred to as the asynchronization problem. This implies that measurements from different sources may not form a complete snapshot at the time of SE execution.

3) Diverse Types of Measured Quantities: The measured quantities from measurement devices are different. For example, SCADA reports voltage magnitude and active/reactive power measurements, while PMUs collect voltage and current phasor measurements. Such diversity leads to the following issues: i) combining different SE formulations, such as linear versus nonlinear measurement equations for PMUs and SCADA, respectively [2]; ii) numerical issues due to different orders of magnitude, such as FTU measurements in primary feeders and SM measurements in secondary feeders; iii) difficulty in initialization, such as infeasibility to initialize polar-form current phasors at the flat start [22]; and iv) drastically different accuracy classes and weight settings of measurements, such as those of virtual measurements at zero-injection nodes, i.e., zero-injection measurements at buses without any load or generation, and forecasted pseudo-measurements [23].

4) Correlations Between Measurements: In practice, available measurements may not be independent, as they may be derived from the same set of raw measurements [24]. For example, voltage and current phasors measured by PMUs and power measurements from SCADA may come from the same voltage transformer (VT) and current transformer (CT) via different algorithms. SE performance can be improved by exploiting temporal and spatial correlations among measurements [25].

5) Sparsity of Real-Time Measurements: One of the major challenges in distribution system monitoring is the lack of real-time measurements to ensure observability [26]. Effective means are needed to combine information from historical data sources (e.g., historical SM data) and online data sources (e.g., near-real-time SM data or real-time FTU/micro-PMU data).

6) Uncertainties and Missing/Delayed/Bad Data: The performance of SE is impacted by multiple sources of uncertainties, such as stochastic and intermittent outputs of distributed generations (DGs) and imprecise network parameters and topology [27], [28]. Moreover, the measurement accuracies and communication latencies are highly diverse [29], [30]. For example, PMUs can provide high-precision measurements with low latencies, while the measurements reported by SMs generally have lower accuracies and higher latencies. In addition, the failure, congestion, or cyber intrusion of communication networks may result in missing, delayed, bad, and false data to be tackled.

Despite the above challenges, the integration of multiple data sources in SE has drawn considerable attention at both transmission and distribution levels because of their obvious and significant benefits. Popularity of this topic is evident from the large number of papers published. It is foreseeable that this topic will continue to be popular with the deployment of new sensors, the proliferation of distributed resources, which must be duly monitored, and the advancement of data analytics. In recent years, several survey papers have been published in power system SE. In [31], [32], [33], SE in transmission systems is reviewed. Specifically, various algorithms of static SE (SSE) and dynamic SE (DSE) are summarized in [31] and motivations, definitions, methodologies, and roles of DSE in power systems are discussed in [32], [33]. In [5], [6], [26], [34], [35], [36], SE methods for distribution systems are summarized. These survey papers mainly focus on SE algorithms, measurement data and feeder models, system observability, metering system design and analysis, etc. In [7], [8], applications, methodologies, and challenges of SM data are reviewed in distribution system SE (DSSE). In addition, optimal meter placement [37], the inclusion of wide area measurement system (WAMS) in state estimation [38], [39], and the handling of corrupted measurements [40] have also been reviewed, respectively. However, none of the existing survey papers has systematically and comprehensively addressed the topic of power system state estimation using multiple data sources – to exhaustively cover all existing and emerging types of measurements, conceptually summarize the major challenges regarding multi-source data integration, and systematically review, categorize, and compare the existing solutions. In addition, the evolution of this topic is closely related to several recent technology advancements such as power-electronics-dominated power systems, integrated energy systems, cyber-physical systems, and Internet of Things, which have not been clearly revealed in the existing survey papers. Therefore, a comprehensive survey is felt to be timely and useful to depict the landscape of the research area and gain insight into the challenges to be further addressed. This is what this paper aims to accomplish. *It should be noted that in order to keep the uniqueness and concentration of the scope, this paper will focus on reviewing challenges and methods for integrating multiple data sources in SE, which already covers a substantial volume of literature; publications describing methods that use a single type of measurements for SE will not be reviewed, unless they provide interesting insight into multi-source data*

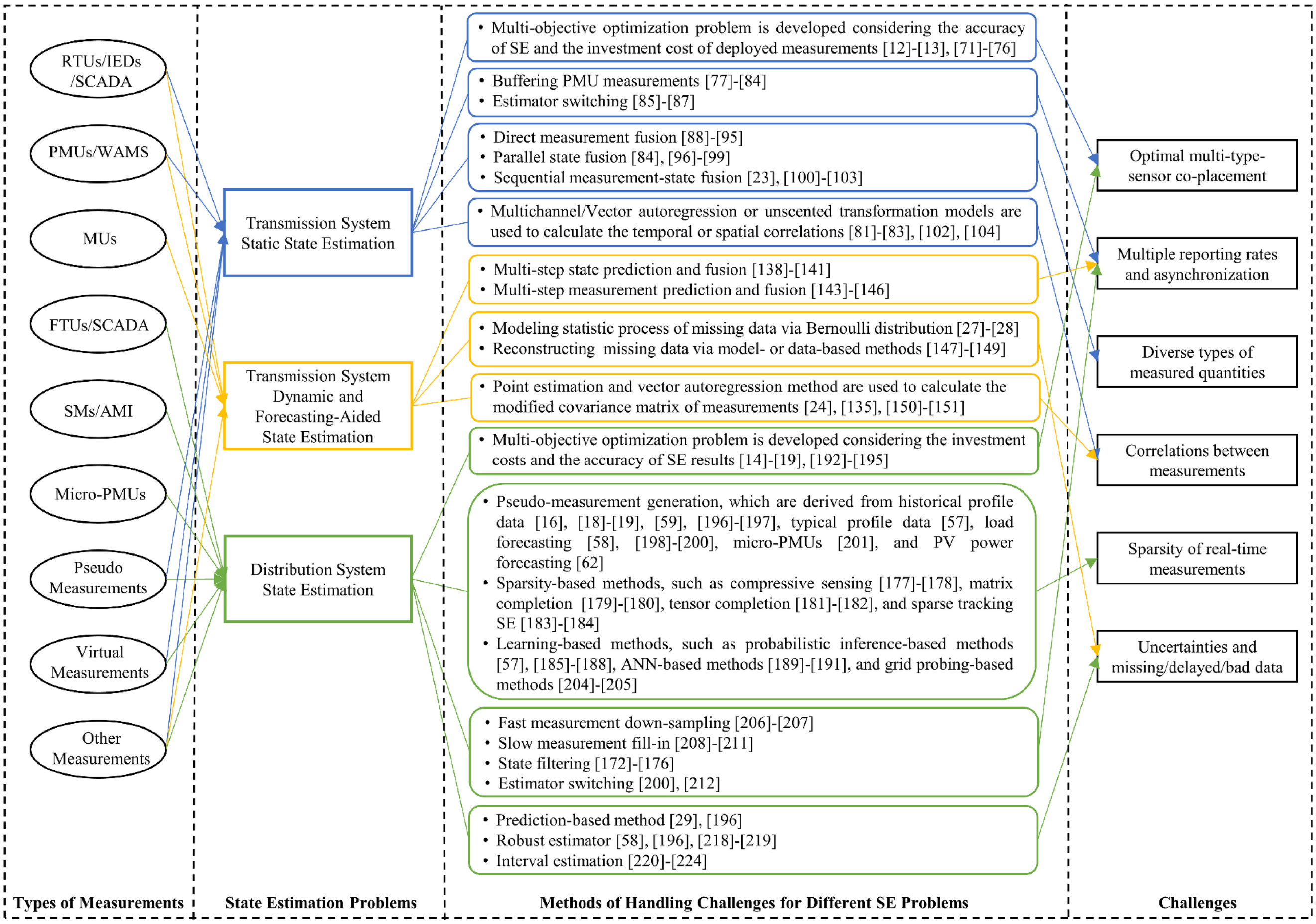

Fig. 1. Taxonomy of methods for multi-data-source integration in SE.

integration or involve highly novel measurement types in SE. The major contributions of this survey paper are as follows:

1) Summarizing the existing and emerging measurement types and the unique challenges introduced by integrating multiple data sources in power system SE.
2) Providing a comprehensive and in-depth taxonomy for the existing works based on the addressed challenges regarding multi-source data integration as well as the type of SE problems.
3) Discussing open research questions to be further investigated by the technical community, including those in the context of power-electronics-dominated power systems, integrated energy systems, cyber-physical systems, and Internet of Things.

Fig. 1 provides a taxonomy of research on SE using multiple data sources in power systems. It consists of four columns. In column 1, the most widely used types of measurements and other data sources (pseudo and virtual measurements) are listed. In column 2, the SE problems in power systems are categorized. Transmission system state estimation problems are categorized into SSE, DSE and forecasting-aided state estimation (FASE). DSSE problems are not further categorized as a vast majority of existing works adopt SSE. The match between columns 1 and 2 shows the types of measurements used in different SE problems. In column 4, the challenges of multiple-source data integration in SE are listed, as discussed in detail above. Column 3 categorizes the methods for handling challenges of multi-source data integration in SE. The methods addressing the same challenge in the same type of SE problem will be grouped into the same box. In a box, these methods will be further categorized into different items using the bullet points, and each bullet point corresponds to a particular type of method. Note that different SE problems may be faced with the same challenge, but handled by different methods, as indicated by the matches among columns 2, 3, and 4.

The rest of this paper is organized as follows. Common types of measurements and their properties are reviewed in Section II. In Sections III and IV, multi-source data integration methods in transmission system SSE and DSE/FASE are categorized, respectively. Section V categorizes multi-source data integration methods in DSSE. Applications of unconventional measurements in each SE problem are also reviewed in Sections III–V, respectively. Section VI discusses the computation and data requirement issues for different SE problems. Finally, Section VII provides concluding remarks and extensive discussions on future research directions.

II. Types of Measurements and Their Properties

A. Typical Measurement Sources in Transmission Systems

Most widely used measurements in transmission systems are SCADA and PMU measurements. IEDs and merging units (MUs) further enrich the measurement data sources in transmission system state estimation (TSSE).

1) RTUs/SCADA: SCADA systems are integrated technologies composed of RTUs, communication networks, master stations, and human-machine interfaces (HMI) [4]. Reported measurements are voltage magnitudes, active/reactive power injections, and active/reactive power flows. SCADA provides asynchronized data at a reporting rate of 2∼5 seconds [20].

2) PMUs/WAMS: WAMS are mainly composed of PMUs, communication networks, and phasor data concentrators (PDCs). PMUs are the measurement devices in WAMS [30]. They provide voltage and current phasor measurements with time stamps by GPS technology with high precision [3]. The reporting rate of PMUs typically ranges from 5 to 60 scans per second [21].

3) IEDs: An IED is defined as any device incorporating one or more processors with the capability to receive or send data/control from or to an external source (e.g., electronic multifunction meters, digital relays, controllers) [41]. With the integration and interoperability features, IEDs are gradually replacing RTUs in today's substations [4].

4) MUs: MUs can gather the sampled values from VTs and CTs and pass them to IEDs [4]. The reporting rate of MUs is 80 samples per cycle, i.e., 4000/4800 samples per second at 50/60 Hz [42], [43]. The high reporting rate allows them to capture electromagnetic transients of power systems. MU measurements are not always time-synchronized. Hence, they are typically used to run local SE for protection purposes [44], [45], [46].

B. Typical Measurement Sources in Distribution Systems

In DSSE, SCADA systems also play an essential role in providing real-time measurements as in TSSE. Additionally, AMI, micro-PMUs, and secondary substation- and feeder-level sensors also have great potential to provide data for SE.

1) FTUs/SCADA: A FTU is a kind of distribution RTUs deployed along feeders [47]. The primary functions of FTUs include measurement and control, fault detection, and communication. FTUs can monitor and report the status of switches and the measurements such as voltage magnitudes, current magnitudes, and active/reactive powers. FTUs are conventional data sources of DSSE [48].

2) SMs/AMI: AMI is an integrated infrastructure composed of SMs, data concentrators, communication networks, and data management systems [7], [8]. SMs can not only provide customer's electricity consumption data, but also report phases, voltages, currents, active/reactive powers, and power factors [7]. The firmware of a SM can be designed to capture samples as fast as 30 Hz, while the reporting rate is limited by communication channel bandwidths and data storage capacities. The locally stored data are submitted to the remote database only from time to time. Commonly, the reporting rate of AMI is once a day or two days, and thus SM measurements are ordinarily used as pseudo-measurements in DSSE. There are pilot projects with faster reporting rates as summarized in [8], where the SM datasets can report every 15 minutes, 30 minutes, or an hour and can be used as near-real-time measurements.

3) Micro-PMUs: Micro-PMUs are synchrophasor measurement devices specifically designed for distribution systems [10]. Compared to the widely used PMUs, micro-PMUs have faster reporting rates, higher accuracies of phase angle measurements, and much lower costs [9], [10]. In [10], it is reported that micro-PMUs can discern angle differences down to $\pm 0.01^\circ$ and report voltage and current waveforms as fast as 512 samples per cycle [10].

4) Secondary Substation and Feeder-level Sensors: Novel feeder-level sensors are also promising for DSSE applications [49], [50]. For example, fault current detectors can provide current magnitude measurements with little extra investment [49]. In [50], the meta-alert system (MAS) is proposed for DSSE and fault identification, providing not only electrical measurements such as voltage, current, frequency, and power, but also cable and ambient temperature measurements and leakage reports.

5) Behind-the-Meter Information: The importance of the data from behind-the-meter prosumers is being recognized in today's smart grids [51], [52]. Behind-the-meter information can be collected from rooftop photovoltaic (PV) systems [53], electrical charging stations [54], etc. While it may not be used in SE directly, correlations between different households can be used to provide accurate pseudo-measurements in DSSE. For example, unmeasured households or aggregated energy profiles can be inferred based on measured households [55]. It is possible to provide data with high time resolutions via wired or wireless media [52], [55]. For instance, rooftop PV systems can report data every 5 minutes, including power, AC voltage, DC string voltage/current, and the battery state-of-charge (SOC), accessible via cellular or any device connected to Internet [52], [55].

C. Pseudo-Measurements

In DSSE, the system observability cannot be guaranteed due to insufficient real-time measurements. Pseudo-measurements are common means to address the unobservability issue and enhance the measurement redundancy in DSSE [5], [6], [56]. The existing methods for generating pseudo-measurements can be categorized into probabilistic and statistical methods [18], [19], [57], [58], [59], [60], [61] and learning-based methods [62], [63], [64]. In probabilistic and statistical methods, the pseudo-measurement generation model is developed by employing the temporal and spatial correlation from historical data. Commonly, the pseudo-measurements are derived from historical or typical load profiles [18], [19], [57], load or generation forecasting based on historical SM measurements [58], or load probability density functions (PDFs) based on the Gaussian mixture model (GMM) [59]. Moreover, customer classification by the statistical processing of historical data can help the allocation of measured loads at MV nodes among unmeasured downstream nodes [5], [61].

In learning-based methods, first, the pseudo-measurement generation model is trained using abundant historical data in an offline fashion; then, the well-trained model will be used to predict unmeasured loads in an online fashion. The learning-based methods are performed by diverse means, such as artificial neural networks (ANNs) [62], probabilistic neural networks (PNNs) [63], clustering algorithms [64], etc. As pseudo-measurements have large uncertainties, they are much less accurate than real-time measurements. Hence, pseudo-measurements are usually assigned small weights in SE.

D. Virtual Measurements

Virtual measurements generally refer to zero injections at passive nodes without any load or generation, such as switching stations and the MV side of most MV/LV secondary transformers, zero voltage drops in closed switching devices, and zero power flows in open switching devices [5], [26]. Moreover, other measurements can also be treated as virtual measurements as long as they satisfy electrical/physical laws [46], [65], [66] or power/energy conservation laws [67], [68]. Virtual measurements can be used as high-accuracy measurements since these laws used are always valid and will not be affected by measurement noises. As drastically different accuracy classes and weight settings of measurements may result in an ill-conditioning problem in SE, virtual measurements are usually employed as equality constraints in SE formulations [2], [69]. For example, Lagrange multipliers are employed to handle virtual measurements in DSSE [70]. Virtual measurements can enhance measurement redundancy and quality without increasing sensor installation costs. Hence, they are particularly useful for DSSE as real-time measurements are insufficient in distribution systems.

III. Static State Estimation in Transmission Systems

SSE in transmission systems is the most widely deployed form of SE in power systems to date. It does not consider temporal correlations and estimates states using the measurements reported at the same instant only. SCADA measurements are the conventional data source in SSE. The deployment of PMUs enriches and improves the measurement profile of transmission systems. However, full observability may not be established by PMUs only. In this section, SE methods integrating SCADA and PMU measurements will be discussed based on the four addressed challenges in Sections III-A through III-D, respectively. Finally, in Section III-E, interesting attempts of using less common types of measurements in SSE will be reviewed.

A. Handling Optimal Multi-Type-Sensor Co-Placement

Optimization of sensor placement is a planning task that should be addressed prior to the operation of SE. The main goal is to determine the locations of various measurement devices in power systems with multiple objectives including observability, SE accuracy, and sensor installation cost. As multiple types of sensors are available for system monitoring, it is an important topic to study how to jointly and coordinately determine their locations across the system to achieve observability, SE accuracy, and economy goals. This is referred to as the multi-type-sensor co-placement problem. Existing optimal multi-type-sensor co-placement methods can be categorized into i) simultaneous placement of PMU and SCADA measurements [12], [13] and ii) placement of PMUs considering pre-existing SCADA measurements [71], [72], [73], [74], [75], [76].

In [12], essential PMU and SCADA measurements are determined by integer programming (IP) and genetic algorithm (GA), respectively. Then, optimal candidate measurements are selected via triangular factorization and binary IP (BIP) under single and multiple measurement losses. In [13], a multi-objective evolutionary algorithm is developed to determine the optimal numbers, types, and locations of measurement devices to achieve the required SE performance with minimum investment.

In [71], [72], [73], [74], [75], [76], optimal PMU placement in the presence of SCADA measurements is investigated. The integer linear programming (ILP) model [71], semi-definite programming (SDP) model with integer variables [72], and unified binary SDP (BSDP) model with binary decision variables [73], [75], [76] are proposed, and measurement losses [71], [72] and communication limitations [71], [73] are taken into account. In [74], the binary GA is used to search for the optimal PMU locations to ensure SE performance and to cover the critical regions of systems. In [73] and [75], [76], the linear matrix inequality (LMI) is used to form a strict (non-strict) convex constraint on the vector of decision variables when solving the developed BSDP problem. In [76], the optimal PMU placement formulation is extended to consider the case of two types of contingencies: single PMU loss and single branch outage.

B. Handling Multiple Reporting Rates and Asynchronization

A number of methods are proposed to address the significantly different reporting rates of PMU and SCADA measurements. These methods can be divided into two categories: buffering PMU measurements and estimator switching. Specifically, PMU buffering refers to the use of multiple scans of PMU measurements between a SCADA update window in SE, and estimator switching refers to the change between different SE formulations when receiving different types of measurements.

1) Buffering PMU Measurements: With higher reporting rates of PMUs, numerous PMU scans will be available during the time interval between two SCADA scans. The buffering strategy refers to the use of statistically derived information from a set of consecutive PMU measurement scans to perform SE jointly with the latest SCADA measurement scan [77], [78]. The purpose of buffering is to suppress the uncertainty of PMU errors by leveraging the abundance of data. The set of PMU scans from which the statistical information is derived is referred to as the buffer. A typical method is to take the mean and variance of buffered PMU measurements as the derived measurement and error variance to feed into SE, respectively.

The buffer length can be determined by two aspects: uncertainties of measurement noises and variations of system states [77]. Supposing invariant system operating point, measurement noise can be better suppressed with a longer buffer. In reality, however, power systems never operate in a perfectly steady state. Hence, the longer the buffer, the larger the variation of the true state, introducing another source of error. To achieve a trade-off between the two factors, the optimal buffer length is investigated in [77], [78], [79]. In [77], the optimal buffer length is determined by statistical hypothesis testing. In [78], three methods are tested to determine the buffer length. The main idea is to evaluate the mean and variance shift of a set of consecutive PMU measurements when a new scan is added. Once either the mean or variance shift is found to exceed a threshold, the buffer will be cut off. The shortcoming of the hypothesis testing methods [77], [78] is that oscillations caused by faults or switching transients will be captured by PMUs and impact the detection of mean and variance shifts [79]. A signal-dependent approach is developed in [79] to monitor and flag the mean shift of the buffered data by employing the Shewhart change detection test, which can handle the effect of oscillatory transients.

The buffered PMU measurements are widely used to address the time skewness yielded by different reporting rates [80], [81], [82], [83], [84]. Specifically, the asynchronization between SCADA and PMU measurements is mitigated by predicting the delayed PMU data or using prior SCADA data derived from the latest state information [83]. Moreover, the correlations of buffered PMU measurements are also utilized to enhance the performance of SE [81], [82], [83], as will be discussed in Section III-C.

2) Estimator Switching: The PMU data buffering method is suitable for the case where the SE execution frequency is the same as or lower than the SCADA reporting rate. Assuming a high SE execution frequency compatible with the high reporting rate of PMUs, an estimator switching framework is proposed in [85], [86], [87]. The weighted least squares (WLS) estimator is used in [85]. Specifically, when SCADA and PMU measurements are both received, a WLS-based nonlinear SE is performed. When only PMU measurements are received, a WLS-based linear SE is performed wherein the system is made observable by using calculated pseudo-SCADA measurements from previous state estimates. To improve the accuracy of SE, the weighted least absolute value (WLAV) estimator is adopted to ensure robustness against unreliable pseudo-SCADA measurements in [86]. In [87], the computational efficiency of this method is further via decentralization.

C. Handling Diverse Types of Measured Quantities

Hybrid state estimation (HSE) are SE methods integrating different measured quantities from multiple data sources. This paper categorizes HSE approaches into three groups: *1) Direct measurement fusion*; *2) Parallel state fusion*; and *3) Sequential measurement-state fusion*. The fundamental philosophies of the three types of methods are illustrated in Fig. 2. Detailed explanations will be given as follows.

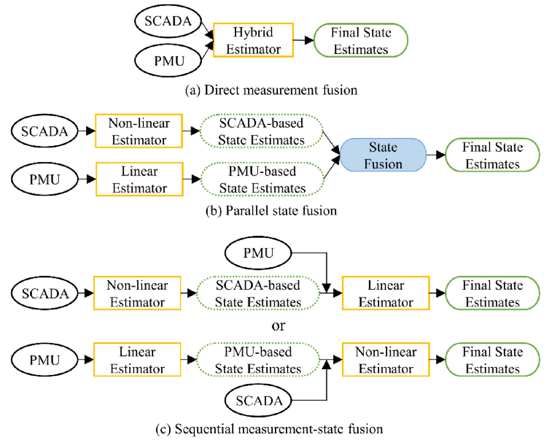

Fig. 2. High-level representation of three categories of HSE.

1) Direct Measurement Fusion. Direct measurement fusion refers to methods that employ a *single* hybrid estimator to directly fuse PMU measurements and SCADA measurements at a given time instant, as shown in Fig. 2-a. Buffered PMU measurements are widely used in *direct measurement fusion* to address the different reporting rate issue [80], [81], [82], [83], as discussed in Section III-A. The main challenges of *direct measurement fusion* include: i) the measurement function and Jacobian matrix need to be redeveloped [88]; ii) the inclusion of current phasor measurements may lead to an undefined Jacobian matrix at flat start [22]; and iii) different accuracy levels and weight settings of SCADA and PMU measurements may result in ill-conditioning and SE divergence [23].

To incorporate the voltage/current phasor measurements from PMUs into the conventional estimator, the measurement function and Jacobian matrix are redeveloped in [88], [89]. To address the numerical problem at the flat start, rectangular coordinates are adopted for current phasor measurements in [88], [89]. A shortcoming is that PMU errors are amplified with the transformation from polar to rectangular coordinates [90], [91]. To tackle the numerical problem while limiting transformation errors, rectangular coordinates are used for the problematic iteration [90] or the first iteration [91] only. In [92], a constrained HSE is developed, where auxiliary state variables, i.e., branch currents in polar coordinates, are introduced to facilitate the use of current phasor measurements. In addition, equality constraints, i.e., the voltage phasor at any bus adjacent to a PMU bus, can be expressed in terms of state variables and line parameters, mitigate the ill-conditioning problem in the presence of measurements with drastically different accuracy levels. In [93], [94], [95], HSE in complex variables is investigated. Specifically, the real-valued measurement function is expanded via Wirtinger calculus in terms of the nodal voltage phasors and their conjugates, facilitating the direct inclusion of PMU measurements in the hybrid estimator. In [94], a constant gain matrix method for HSE in the complex domain is developed by approximating the Jacobian matrix to be constant throughout iterations. The proposed perturbed

Gaussian-Newton method is computationally efficient for tracking operating states, especially for large-scale systems. In [95], zero-injection measurements are regarded as equality constraints, thus avoiding the potential ill-conditioning issue caused by assigning relatively much larger weights in the zero-injection measurements in the normal equations approach.

2) Parallel State Fusion. Parallel state fusion refers to methods that employ two estimators to separately process SCADA measurements and PMU measurements in parallel, then fuse the two state estimates to obtain the final SE solution, as illustrated in Fig. 2-b. In *parallel state fusion*, the PMU-based estimator may be faced with the unobservability problem and the time skew problem caused by the different reporting rates and synchronization with SCADA measurements.

In [96], SCADA and PMU measurements are respectively processed via a nonlinear estimator and a linear estimator in parallel. The unobservability problem in the PMU-based estimator is addressed using *a priori* information derived from SCADA-based estimates from previous instants [96], pseudo-states with large variances [97], or arbitrary voltage phasors [98]. Subsequently, the SCADA- and PMU-based state estimates are fused based on the Bar-Shalom-Campo (BSC) formula [84], [96], [97], [98], [99],

$$\widehat{\boldsymbol{x}}^{\text{final}} = \boldsymbol{W}_1\widehat{\boldsymbol{x}}^{\text{scada}} + \boldsymbol{W}_2\widehat{\boldsymbol{x}}^{\text{pmu}}, \tag{1}$$

where $\widehat{\boldsymbol{x}}^{\text{scada}}$ and $\widehat{\boldsymbol{x}}^{\text{pmu}}$ represent the state estimate vectors based on SCADA and PMU measurements, respectively; $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ represent the weights corresponding to $\widehat{\boldsymbol{x}}^{\text{scada}}$ and $\widehat{\boldsymbol{x}}^{\text{pmu}}$, respectively; and $\widehat{\boldsymbol{x}}^{\text{final}}$ is the final fused state estimates. Considering the unknown measurement noise statistics, a robust hybrid SE framework is proposed in [84], where the problem of different reporting rates is resolved by buffering PMU measurements. Two independent Schweppe-type Huber generalized maximum-likelihood (SHGM) estimators are adopted to individually process SCADA and PMU measurements before fusion via the BSC formula. In [99], a decentralized phasor-aided HSE is proposed. SCADA- and PMU-based estimators are separately performed in each subarea before fusion by the BSC formula.

3) Sequential Measurement-State Fusion. Sequential measurement-state fusion implies that SCADA- and PMU-based estimators are executed in sequence rather than in parallel. There are two sequences of processing the measurements, as illustrated in Fig. 2-c. References [100], [101], [102] first execute a non-linear estimator to process SCADA measurements and obtain SCADA-based state estimates, i.e., estimated voltage phasors, then transform SCADA-based state estimates into rectangular coordinates and integrate them with PMU measurements with a linear estimator. In [23] and [103], a reversed order of processing is implemented, where PMU measurements are processed by a linear estimator first, then PMU-based state estimates are integrated into a non-linear estimator with SCADA measurements to obtain the final SE solution. To tackle the unobservability problem in the linear estimator, only state variables at buses with or adjacent to PMUs are estimated in the first stage.

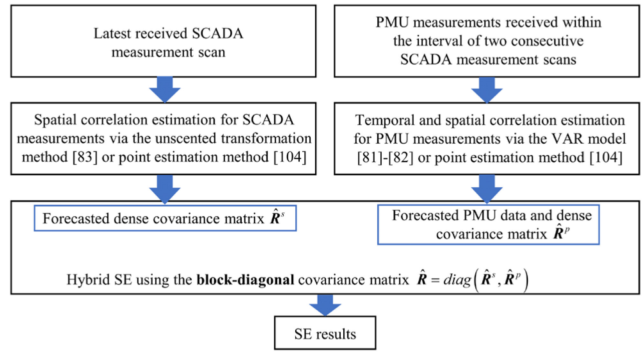

Fig. 3. Framework of considering temporal and spatial correlations.

D. Handling Correlations Between Measurements

The temporal and spatial correlations of buffered PMU measurements [81], [82], [83], the correlations of SCADA-based state estimates [102], and the correlations between SCADA and PMU measurements [104] are investigated and utilized to further enhance the performance of SSE. To improve the accuracy of SE, the temporal correlation is used to predict PMU data and the spatial correlation is used to form a dense covariance matrix instead of a conventionally diagonal one for measurement errors [25]. The framework of considering temporal and spatial correlations to improve SE is shown in Fig. 3. To improve the accuracy of SE, the temporal correlation is used to predict PMU data and the spatial correlation is used to form a dense covariance matrix instead of a conventionally diagonal one for measurement errors. The framework of considering temporal and spatial correlations to improve SE is shown in Fig. 3. In [81], [82], the multichannel or vector autoregressive (VAR) models are exploited to characterize the temporal and spatial correlations of buffered PMU measurements. Reference [83] uses the unscented transformation to calculate the correlation of SCADA measurements and integrates the forecasted PMU measurements and non-diagonal covariance matrix in the hybrid estimator. In [102], a two-stage hybrid estimator is developed, where the correlations between the real and imaginary parts of SCADA-based state estimates derived from the first stage are preserved in the second stage with a non-diagonal covariance matrix. In [104], the measurement error correlation between mixed PMU and SCADA measurements is calculated via the point estimation method yielding a non-diagonal measurement error covariance matrix.

E. SSE Using Other Types of Measurements

Besides SCADA and PMU measurements, other less common types of measurements [105], [106], [107], [108], [109], [110], [111] have been used in SSE.

1) SSE Using Transformer Tap-Related Measurements: In conventional SE, transformer tap settings are taken as fixed network parameters. However, this information could be unknown or reported erroneously in practice. Hence, the transformer tap-related parameters, i.e., phase-shift angles and turns ratios, are included into the measurement set and also treated as state variables in [105]. References [106], [107] address erroneous zero-injection measurements in the estimation of conventional state variables along with the transformer tap positions in [106].

2) SSE Using Line Temperature Measurements: Typically, the measurement devices supporting dynamic line rating applications can monitor not only currents and voltages, but also non-electrical measurements such as temperatures and expansion/sag angle of transmission lines [108]. Considering the temperature dependency of transmission line resistances, temperature measurements of overhead lines are integrated in measurements and state variables to enhance the accuracy of SE [108], [109]. It should be noted that DC transmission line resistance variation caused by temperature has more significant impact on the power flow than that of AC lines, strengthening the motivation of incorporating temperature measurements.

3) SSE Using Measurements in Integrated Energy Systems: Electric power systems are not standalone but are closely coupled with other energy infrastructures. Joint SE for the monitoring of integrated energy systems has been gaining popularity in recent years. Thermal and hydraulic measurements are incorporated with power grid measurements for joint SE in with *direct measurement fusion* scheme shown by Fig. 2-a [110], [111]. In [112], [113], gas network measurements, such as gas node pressures and node flows, are integrated with electrical measurements. Considering different reporting rates and the information gap between the operators of different subsystems, a data-driven method [112] and a distributed SE scheme [113] are proposed to integrate measurements of different subsystems. References [114], [115] investigates the joint SE for electricity-gas-heat systems. Considering the nonlinearity and complexity of the joint SE problem, the bilinear theory is used to transform it into an equivalent multi-stage problem by introducing intermediate transformation and auxiliary variables.

4) SSE Using DC Measurements in Hybrid AC/DC Grids: High voltage direct current (HVDC) is a favorable technique for long-distance power transmission and massive integration of renewable energy sources (RES) into the existing AC power grid [116]. DC-side measurements can not only capture fault transients for protection, control, and fault location, but also be exploited to improve the performance of SE in hybrid AC/DC systems [117]. Commonly, DC-side measurements include DC voltages of rectifiers and inverters, DC currents between rectifiers and inverters, and DC power flows, and DC-side state variables include DC voltages and currents, firing angles, and extinction angles [117], [118], [119], [120], [121], [122]. In [118], a sequential method for AC/MTDC (Multi-terminal DC) SE is proposed in which the MTDC system is solved followed by the AC system. In addition to aforementioned DC measurements, a few AC/DC interface system measurements, such as AC current into the converter, off-nominal converter transformer tap ratio, and firing angle, are also included. In [123], hybrid AC/DC grids are decomposed into AC systems and HVDC systems, and they are executed separately and coordinated iteratively through updated boundary information. In [119], [120], [121], [122], the PMU-based state estimator considering HVDC links is studied, where the AC network and DC links are combined together and solved simultaneously. Specifically, classical HVDC links [119], [120], voltage source converter-based HVDC (VSC-HVDC) links, and line commutated converter-based HVDC (LCC-HVDC) links are investigated. In [124], [125], [126], hybrid state estimators using SCADA and PMU measurements in AC/DC systems are studied. The state variable vector is extended by considering DC-side variables including voltage magnitudes and phase angles of voltage sources [124], nodal voltage magnitudes in DC networks, as well as state variables associated with VSC and DC-DC converters [125], and DC voltages, as well as firing and extinction angles [126]. In [127], unobservable VSC measurements are modeled via the GMM. The predicted pseudo-measurements will be used to conduct hybrid AC/DC SE. In [128] and [129], robust state estimators for hybrid AC/DC systems are developed, where the conventional LAV estimator [128] and the augmented LAV estimator [129] with an additional sparsity penalty term for the control input vector are adopted to achieve the robustness of SE.

IV. Dynamic or Forecasting-Aided State Estimation in Transmission Systems

Conventional SSE is designed for steady-state operating conditions. They are insufficient in capturing power system dynamics in that they i) are conventionally executed no faster than SCADA reporting rates and ii) do not incorporate dynamic models of components such as generators and loads [32], [33]. This deficiency is further aggravated in the face of the large-scale integration of stochastic and intermittent renewable energy generation. DSE and FASE are proposed to take into account the temporal dependency of system states [130], [131], [132].

Different from SSE, DSE and FASE are usually executed via two steps, namely the *prediction step* and the *filtering step*. The *prediction step* is used to predict the state variables via the discrete-time state-transition model given the previous state estimates. The *filtering step* is used to update or correct state variables using the latest received measurements. Although DSE and FASE have similar mathematical formulas, their definitions and motivations are different. DSE is driven by capturing the dynamics of internal states of a machine or a load at transient operating conditions. The state-transition model is formulated to describe electromechanical or electromagnetic processes. FASE is motivated by incorporating previous state estimates to improve the estimation accuracy at quasi-steady state conditions. The state-transition model is identified or learned from historical time series data [32]. In addition, tracking SE (TSE) is another concept often discussed, which is a simplified version of FASE with the assumption that the state transition matrix is an identity matrix and the change in the state vector is very small [32], [133], [134], [135], [136]. In DSE, PMUs play a critical role as they provide a high enough reporting rate for the monitoring of electromechanical transients. Meanwhile, they fall short in capturing electromagnetic transients as the reported quantities are in the phasor domain [137]. MUs can provide sampled values as fast as 80 samples per cycle for performing local DSE enabling

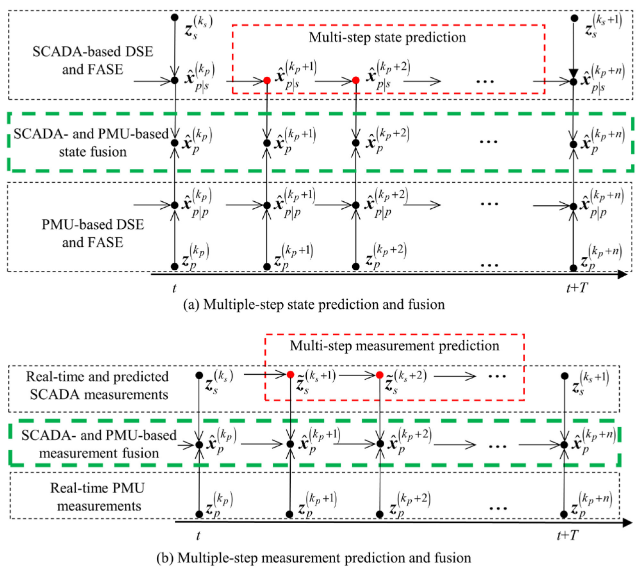

Fig. 4. Multi-step state/measurement prediction and fusion.

protection applications [44], [45], [46]. With PMUs and MUs, DSE is becoming technically feasible, yet the transition does not occur overnight due to economic constraints. Hence, integrating PMU/MU measurements with conventional SCADA measurements becomes a viable means.

In this section, existing methods for handling the challenges in the integration of SCADA and PMU measurements will be reviewed in Sections IV-A through IV-C, respectively. Attempts of integrating other types of measurements, including MUs, will be discussed in Section IV-D.

A. Handling Multiple Reporting Rates and Asynchronization

In SSE, buffering PMU measurements is a feasible method for handling the problem of multiple reporting rates, as the execution frequency of SSE is typically no higher than the reporting rate of SCADA, and thus much lower than the reporting rate of PMUs. However, DSE aims to capture the dynamics of power systems, and their execution frequencies are comparable to the PMU reporting rate, making buffering no longer a feasible option. Instead, the challenges become how to handle the low reporting rate of SCADA. To this end, two categories of methods are summarized as below.

1) Multi-Step State Prediction and Fusion: Due to the high execution frequency of DSE, lower-rate measurements, such as SCADA, will not be available at some instants at such a fine time scale, making the *filtering* step infeasible. To address this challenge, several methods adopt *multi-step state prediction and fusion* for the lower-rate measurements. These methods employ two separate estimators for SCADA and PMU measurements, respectively, both executed at the PMU reporting rate. The typical framework of *multi-step state prediction and fusion* [138] is shown in Fig. 4-a, where t represents the time instant; T is the reporting period of SCADA; $z_s^{(k_s)}$ and $z_p^{(k_p)}$ represent the k_s-th SCADA scan and the k_p-th PMU scan, respectively; n is the ratio between PMU and SCADA reporting rates; $\widehat{\boldsymbol{x}}_{p|s}^{(k_p)}$ and $\widehat{\boldsymbol{x}}_{p|p}^{(k_p)}$ represent the k_p-th state estimates derived from SCADA and PMU measurements at the PMU reporting rate, respectively; $\widehat{\boldsymbol{x}}_p^{(k_p)}$ is the k_p-th final fused state estimates. *For the PMU-based DSE and FASE, prediction step and filtering step are all executed at each time instant. For the SCADA-based DSE and FASE, when SCADA measurements are received, prediction step and filtering step are all executed, while when SCADA measurements are not received, only the prediction step is executed.* Finally, the state estimates separately obtained from the SCADA-based estimator and the PMU-based estimator are fused to achieve the final solution via the BSC formula [138], [139], [140] or the covariance intersection (CI) Kalman fuser [141]. The fusion process, i.e., the green dashed box in Fig. 4-a, can be expressed as follows,

$$\widehat{\boldsymbol{x}}_p^{(k_p)} = \boldsymbol{\alpha}_s \cdot \widehat{\boldsymbol{x}}_{p|s}^{(k_p)} + \boldsymbol{\alpha}_p \cdot \widehat{\boldsymbol{x}}_{p|p}^{(k_p)}, \tag{2}$$

where $\widehat{\boldsymbol{x}}_p^{(k_p)}$ is the k_p-th final fused state estimates, $\boldsymbol{\alpha}_s \in \mathbb{R}^{N\times N}$ and $\boldsymbol{\alpha}_p \in \mathbb{R}^{N\times N}$ are two weighting factors, which can be obtained by solving the BSC formula, and N is the number of state variables.

This work is further improved by investigating the nonlinearities of power system dynamics and by exploring the non-integer ratio of PMU and SCADA reporting rates in [139]. In [138] and [139], the Kalman-filter-based dynamic system model is unchanged when handling different types of measurements at different time instants. By contrast, a switched system consisting of two subsystems is proposed to implement the fusion SE in [140]. Specifically, *subsystem I* employs the widely used dynamic model with unit state transition matrix and zero control input, while s*ubsystem II* uses a pseudo-dynamic model derived from the linearization of the power flow equation. The two subsystems' transition equations and measurement equations are as follows,

- *Subsystem I*

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{w}_k, \tag{3}$$
$$z_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{v}_k, \tag{4}$$

- *Subsystem II*

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{J}^{-1}(\boldsymbol{u}_{k+1} - \boldsymbol{u}_k) + \boldsymbol{w}_k, \tag{5}$$
$$z_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{v}_k, \tag{6}$$

where $\boldsymbol{x}_k$, z_k, and $\boldsymbol{u}_k$ represent the state variable, measurement, and control input vectors at the k-th time instant, respectively; $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are the process noise and measurement noise vectors, respectively; and $\boldsymbol{J}$ is the power flow Jacobian matrix, which is equal to the derivate of power flow measurements over the state variables. *Subsystem I* and *subsystem II* are switched based on a designed criterion given by,

$$\min_{\alpha} \|\boldsymbol{h}_\alpha(\widehat{x}_{k-1}) - z_k\|_2, \ \ \alpha \in \{I, \mathrm{II}\}, \tag{7}$$

where $\boldsymbol{h}_\alpha(\widehat{x}_{k-1})$ is the forecasted measurement at time instant k of two subsystems. The goal of switching is to make a trade-off between the subsystems regarding estimation accuracy, convergence speed, and computational time. One of the limitations of BSC-based fusion is that the performance may be impacted by numerical divergence or gross errors. Hence, the CI Kalman fusion method, which can achieve consistent fusion results [142], is used to fuse the SCADA- and PMU-based state estimates [141].

2) Multi-Step Measurement Prediction and Fusion. In [138], [139], [140], [141], the low reporting rate of SCADA measurements is addressed by predicting state variables at a finer time scale. Different from the *multi-step state prediction and fusion*, where SCADA- and PMU-based DSE and FASE are separately conducted via different state estimators. In this method, SCADA and PMU measurements are directly fused via a single hybrid state estimator, i.e., the green dashed box in Fig. 4-b. Specifically, when SCADA and PMU measurements are received simultaneously, the two types of measurements will be directly fused in a single hybrid state estimator to implement DSE and FASE. When SCADA measurements are not received at some instants, firstly, they will be predicted using the historical data, i.e., the red dashed box in Fig. 4-b, where $\widetilde{z}_s^{(k_s+1)}$ represents the (k_s+1)-th predicted SCADA measurements; then, the predicted SCADA measurements and the real-time PMU measurements will be directly fused in a single hybrid state estimator to implement DSE and FASE. The prediction of SCADA measurements at a finer time scale can be achieved via load forecasting [143], [144], extrapolations [145], or measurement interpolations [146]. The framework of *multi-step measurement prediction and fusion* is illustrated in Fig. 4-b.

In [143], SCADA measurements are predicted at the PMU reporting rate using historical datasets. Denote Δt as the time between two consecutive PMU scans, the active and reactive power flows at time t+Δt are predicted using the power flow data and the average gradient of power curves at time t. In [144], a discrete-time state transition model is developed based on an ANN and the interdependency between loads and state variables; then SCADA measurements at a finer time scale are reconstructed by substituting the predicted state estimates into the measurement functions. The exponential moving average method is used to extrapolate the unavailable SCADA measurements at the PMU reporting rate in [145]. In [146], SCADA measurements are predicted and synchronized with PMU measurements by the interpolation synchronization method.

B. Handling Missing/Delayed Measurements

Measurement data may be lost or delayed due to sensor outages, communication failures, or bandwidth limits. This problem requires special attention in coordination between multiple data sources. In [27], [28] and [147], [148], [149], the mitigation of missing/delayed measurements is investigated for DSE.

In [27], [28], the stochastic process of missing measurements is modeled using Bernoulli probability distribution. Reference [27] selects a threshold time to determine whether the delayed measurement should be kept or discarded for DSE. In [28], the received measurement is described by

$$z = \boldsymbol{C} \cdot \boldsymbol{h}(\boldsymbol{x}) + \boldsymbol{v}, \tag{8}$$

where z, $\boldsymbol{x}$, and $\boldsymbol{v}$ represent the measurement, state, and measurement error vectors, respectively; $\boldsymbol{h}(\cdot)$ represents the measurement function; $\boldsymbol{C} = diag\{\gamma_1, \gamma_2, \ldots, \gamma_i, \ldots, \gamma_m\}$; γ_i is a random variable following Bernoulli distribution. The stochastic measurements in Eq. (8) are used to perform DSE via the extended Kalman filter (EKF) algorithm. In addition, model-based [147] and deep learning-based [148] methods are developed to recover missing measurements. In [147], missing measurements are predicted via the measurement function and the sigma points, i.e., state estimates. In [148], the residual generative adversarial network (RGAN) is used to reconstruct missing measurements. This model is trained by inputting incomplete and complete measurement data. Missing measurements are predicted by inputting incomplete data into the trained generator. In [149], the missing PMU measurements are recovered by exploiting the approximate low-rank property of PMU data and the low-rank matrix completion method. In addition, the matrix completion with correlated erasures is studied by characterizing the temporal and channel correlations in PMU data erasures.

C. Handling Correlations Between Measurements

The active/reactive power measurements from SCADA and voltage/current phasor measurements from PMUs may be derived from the same instantaneous voltage and current measurements from VTs and CTs. Therefore, the correlations between SCADA and PMU measurements should not be neglected when they are simultaneously exploited in DSE.

In [24], a novel correlated extended Kalman filter (CEKF) is developed by accounting for the correlations of SCADA and PMU measurement errors. The point estimation method is used to calculate the modified covariance matrix for the proposed CEKF. Reference [150] analyzes and demonstrates the measurement correlations between active/reactive powers and voltage/current phasors and verifies that DSE performance can be enhanced by leveraging measurement correlations. The cross-correlations between states and unknown control inputs are investigated in [151]. The temporal and spatial correlations are captured to derive the VAR model and incorporated with state transition and measurement models to estimate states and unknown inputs simultaneously. In [135], a TSE method is developed in which states and parameters are jointly estimated. Specifically, the measurement model is improved by introducing a concept of pseudo-measurement error for the uncertainty in line parameters, and the correlations between prediction errors and pseudo-measurement errors are considered in the proposed adaptive filtering procedure.

D. DSE and FASE Using Other Types of Measurements

Besides SCADA and PMUs, several other measurement devices have also been exploited for the applications of DSE and FASE, as will be reviewed below.

1) DSE and FASE Using IEDs. In [152], [153], synchronized IED measurements and non-synchronized measurements are coordinated to perform a distributed quasi-DSE to track electromechanical transients of electric machines and power electronics controls. In [154], a new substation centralized protection scheme is proposed for hidden failure detections.

Anomaly detection is achieved by examining the consistency between IED measurements and the substation model via DSE.

2) DSE and FASE Using MUs. With high reporting rates, MUs are suitable for tracking electromagnetic transients for local protection [42], [43]. DSE-based protection using MUs has been investigated in [44], [45], [46]. In [44], the status of DSE-based protection is analyzed, and a novel approach is proposed to mitigate issues related to misoperation. A transformer protection scheme [45] and a series compensated transmission line protection scheme [46] have been proposed based on DSE. The transformer states [45], including operating conditions and health status, and the transmission line fault position and type [46], can be quickly and accurately captured by sampled values of MUs.

3) DSE and FASE Incorporating Peripheral Measurements. In [155], [156], the frequency measured by PMUs is involved to enhance DSE performance under off-nominal frequency conditions. DSE for integrated electricity-gas systems is investigated in [157], where node densities and mass flow rates of the gas system are integrated with conventional power grid measurements. In [158], the rotor angle position and speed measurements of synchronous generators are adopted. Measurements of rotor speed and DC-link voltage in permanent magnet synchronous generator-based wind turbines (PMSG-WTs) are integrated into DSE in [159], [160]. The parameter estimation of PMSG-WTs and fully regulated synchronous generators are investigated in [161] and [162], respectively.

V. Distribution System State Estimation

The development of DSSE was inspired by the preceding success of TSSE. The pioneering work on DSSE dates back to the 1990s [163], [164], but it had not been sufficiently motivated until the rapid growth of DERs and new sensors in the recent decade [5], [6], [34]. DSSE aims to infer the operating state of distribution systems by filtering limited and unreliable measurement data. Compared with TSSE, multi-source data information is an even more challenging and imperative task for DSSE due to the sparser measurements (less observability guarantee), more heterogenous measurement data, and lower measurement quality. Typical measurements considered for DSSE include those collected from SCADA, AMI, micro-PMUs [10], and IEDs [41]. They have different reporting rates, synchronization conditions, measured quantities, and accuracy classes. In Sections V-A through V-D, existing methods for addressing a few significant challenges for integrating these measurements will be systematically reviewed. In Section V-E, efforts on integrating other novel types of measurements will be discussed. In addition to these major challenges introduced by incorporating multi-type measurements, many other issues are also interesting and worth investigation in DSSE. Examples include unbalanced three-phase DSSE decoupling to enhance the SE execution efficiency, such as the use of Fortescue transformation [165], [166], [167], [168], the treatment of different load connections (delta/wye) and transformer connections (delta/wye, lagging/leading, grounded/ungrounded) in multi-phase unbalanced DSSE [165], [166], [169], [170], [171], etc. As these issues are not strongly related to the main subject of this survey paper, they are not discussed in detail in this section.

In TSSE, the existing works are categorized into SSE, i.e., Section III, and DSE or FASE, i.e., Section IV. In DSSE, in contrast, we do not present the works in similar separate categorizations because most existing works belong to SSE. Only few works belong to DSE or FASE, such as [172], [173], [174], [175], [176]. Moreover, a few works that do not exactly follow the formulation of conventional SSE or DSE, i.e., the sparsity-based SE [177], [178], [179], [180], [181], [182], [183], [184] and learning-based SE [57], [185], [186], [187], [188], [189], [190], [191] when handling sparsity of real-time measurements in Section V-B.

A. Handling Optimal Multi-Type-Sensor Co-Placement

In distribution systems, sensor placement should jointly consider the properties of many types of sensors, which is a very challenging task. The optimal co-placements of micro-PMUs and SMs [14], [15], [16], micro-PMUs and voltage magnitude meters (VMMs) [17], and micro-PMUs and IEDs [18], [19], the optimal allocation of a prespecified number of measurements [192], [193], [194], and the observability analysis by add measurement placements on the boundary nodes [195] have been investigated.

In [14], the optimal co-placement of micro-PMUs and SMs is formulated to minimize the number of sensors with a targeted accuracy level of SE. In [15], the work in [14] is further extended by considering the uncertainties of DERs. In [16], the uncertainty of the real-time measurement of DGs is investigated. The Monte Carlo method and the GA are used to process the developed stochastic optimization problem [14], [15], [16]. Considering that the system configuration may change due to tie lines switching, robust near-optimal placement of micro-PMUs and VMMs is formulated in [17]. The optimal placement of micro-PMUs and IEDs is investigated in [18], [19], where a multi-objective optimization model is developed by considering the total investment cost and the root mean square errors of SE results. The multi-objective hybrid particle swarm optimization (PSO)-Krill Herb algorithm (KHA) and the hybrid estimation of distribution algorithm (EDA)-interior point method (IPM) are exploited as the solution algorithms in [18] and [19], respectively.

In addition, the optimal placement of a prespecified number of measurements is studied in [192], [193], [194]. In [192], the ordinal optimization method is adopted to ensure that the maximum relative error of state estimates does not exceed a specific threshold for 95% of the simulated cases. In [193], the optimal allocation aims to minimize the error variances of state estimates either for observable or non-observable networks. The optimization problem is formulated into a mixed integer SDP model by exploiting the M-optimal experimental design technique. In [194], the optimal placement aims to minimize errors of state estimates. The problem is formulated into a Boolean-convex model by utilizing the principles of Fisher information formalism and the D-optimality criterion. In [195], a topological method is developed to merge and extend the observable islands by adding injection measurements on the boundary nodes. The proposed method overcomes the difficulty in merging and extending observable islands formed by branch flow criteria.

B. Handling Sparsity of Real-Time Measurements

In distribution systems, real-time measurements are usually insufficient to deliver observability. Three categories of methods to address the sparsity of real-time measurements are summarized below: pseudo-measurement generation, sparsity-based methods, and learning-based methods.

1) Pseudo-Measurement Generation: Pseudo-measurement generation is the most conventional and commonly known means to address insufficient real-time measurements. Pseudo-measurements can be derived from historical data [16], [18], [19], [59], [196], [197], typical load profiles [57], load forecasting based on the load allocation method [198] or SM measurements [58], [199], [200], micro-PMU measurements [201], or PV power forecasting [62].

In [16], DG power injections are treated as pseudo-measurements and derived from historical profile data using the GMM. In [18], [19], pseudo-measurements are extracted from historical customer load data. In [59], the load PDF is fitted by the GMM using historical load data. In [196] and [197], SCADA, micro-PMU, and SM measurements are integrated into DSSE, where the pseudo-measurements are generated from the historical load profiles. The clustering of customer loads is employed to enhance the accuracy of pseudo-measurement generation [197]. In [57], pseudo-measurements are obtained from historical data or typical load curves. Pseudo-measurement generation via load forecasting based on load allocation [198] or historical SM data [58], [199], [200] is also investigated. In [198], loads in distribution networks are estimated via the load allocation method. In [58], the support vector machine (SVM) is used to forecast the short-term load and DER injections using historical SM data. In [199], [200], the historical time series of active/reactive power measurements collected from SMs are used to generate pseudo-measurements. Reference [201] calculates pseudo-measurements based on micro-PMU measurements and a three-phase line model. In [62], PV power generations are forecasted via the genetic algorithm improved extreme learning machine (GA-ELM) model and utilized as pseudo-measurements in DSSE.

2) Sparsity-Based Methods: Sparsity-based methods exploit the correlations among states or measurements in spatial and/or temporal domains to perform SE under the low observability of distribution systems. Essentially, they are based on underlying assumptions that the signals to be recovered as sparse or low-rank, and thus it is possible to recover the signals with much less information than conventionally required [202], [203]. The sparsity-based methods can be categorized into i) compressive sensing-based SE [177], [178], ii) matrix completion-based SE [179], [180], iii) tensor completion-based SE [181], [182], and iv) sparse tacking-based SE [183], [184].

In [177], 1-D (i.e., spatial or temporal correlation) and 2-D (i.e., spatio-temporal correlation) compressive sensing methods are developed and utilized to perform SE. In [178], the sparse current vector is recovered via l_1-norm optimization. In [179], [180], a matrix completion technique is employed to perform the low-rank DSSE augmented with noise-resilient power flow constraints. Considering that the classical matrix completion may not exploit the temporal and spatial correlation simultaneously, high-dimensional tensor completion is used to perform DSSE under low observability [181], [182]. Sparse tracking SE estimates sparse state variation vectors, where the estimation problem is formulated in the form of a least absolute shrinkage and selection operator (LASSO) [183], [184]. Sparsity-based methods are powerful tools for performing SE in distribution systems with limited real-time measurements, but successful applications require careful examination of the underlying sparsity or low-rank conditions.

3) Learning-Based Methods: For systems with abundant historical measurements but limited real-time measurements, learning-based methods are promising means for SE. Learning-based methods can be generally categorized into i) probabilistic inference-based methods [57], [185], [186], [187], [188], ii) ANN-based methods [189], [190], [191], and smart inverter grid probing-based methods [204], [205]. These methods have promising performances for DSSE but at the cost/condition of large historical datasets and long training times.

In probabilistic inference-based methods, system states are assumed to be a set of stochastic variables. Prior distributions of states are derived from historical measurements, which are refined into posterior distributions upon receipt of sparse real-time measurements. In [185], [186], a factor graph and a belief propagation algorithm are used to calculate the marginal posterior distribution of variable nodes for issuing state estimates. Bayesian inference-based approaches are studied in [57], [187], [188]. Multi-layered posterior estimation and multivariate Gaussian prior model are exploited in [57], where heterogenous data sources, i.e., SCADA, micro-PMUs, SMs, and pseudo-measurements, are integrated in SE. In [187], [188], the Bayesian SE for unobservable distribution systems is proposed using the minimum mean squared error (MMSE) estimator.

Similar to probabilistic inference-based methods, ANN-based methods train the model offline and predict state variables online with received real-time measurements. The difference is that the measurement-state mapping is captured by a neural network. In [189], a feed-forward ANN is utilized for training the model relating measurements and state variables. In [190], [191], a physics-aware neural network is proposed for SE. The physical grid topology is employed to design the connections between different hidden layers of the neural network.

Different from the probabilistic inference-based and ANN-based methods, the smart inverter grid probing-based method is developed in [204], [205]. Specifically, nonmetered loads are inferred by engaging power electronics to probe an electric grid and record its voltage response at actuated and metered buses. In [204], the Probing-to-Learn (P2L) technique is developed in which load inference via grid probing is formulated as an implicit non-linear system identification task. The P2L task is shown to be solvable under certain conditions that can be readily checked upon solving a max-flow problem on a bipartite graph derived from the feeder topology and the placement of probed and nonmetered buses. In [205], a methodology is proposed for designing probing injections abiding by inverter and network constraints to improve load estimates.

C. Handling Multiple Reporting Rates and Asynchronization

Drastically different reporting rates of various types of sensors is a major challenge for DSSE. Existing methods can be categorized as 1) fast measurement down-reporting [206], [207], 2) slow measurement fill-in [208], [209], [210], [211], 3) state filtering [172], [173], [174], [175], [176], and 4) estimator switching [200], [212].

1) Fast Measurement Down-Sampling: If the SE execution frequency is no higher than the reporting rate of the slowest type of measurements, a straightforward solution is to down-sample the faster types of measurements, e.g., only use a micro-PMU measurement scan that coincides with the latest SCADA measurement scan [206], [207]. Obviously, the shortcoming of fast measurement down-sampling methods is that the SE execution frequency is limited by the data source with the lowest reporting rate, and higher-rate data sources are not fully exploited.

2) Slow Measurement Fill-in: Instead of down-sampling fast measurements, the slow measurements could be predicted at some instants when they are not refreshed. This allows the SE execution frequency to go higher than the reporting rate of the slowest data source. It should be noted that *slow measurement fill-in* is different from *pseudo-measurement generation*. *Pseudo-measurement generation* is motivated by insufficient real-time measurements, while *slow measurement fill-in* is motivated by the difference of reporting rates.

In [208], three schemes, namely the *stepwise evolution* (9), *extrapolation* (10), and *interpolation* (11), are proposed to predict SM measurements at instants when they are not refreshed:

$$z_k = z_j, k = j, \ldots, j + n - 1, \tag{9}$$

$$z_k = z_j + \frac{t_k - t_j}{T_p}\left(z_j - z_{j-1}\right), k = j, \ldots, j + n - 1, \tag{10}$$

$$z_k = z_j + \frac{t_k - t_j}{T_p}\left(z_{j+1} - z_j\right), k = j, \ldots, j + n - 1, \tag{11}$$

where T_p represents the reporting period of SM measurements; z and t are index variables for measurements and time instants, respectively; the subscripts, i.e., k and j, indicate time instants. In [209], an HSE is developed to fuse SCADA and micro-PMU measurements, where state estimates at the last time instant will be used to calculate pseudo SCADA measurements when they are not refreshed. In [210], a quasi-dynamic SE is developed, where the measurements with low reporting rates are interpolated to ensure that they are available at each time instant. Reference [211] develops a robust FASE in distribution systems using mixed measurements. The previous micro-PMU-based SE results are used to predict RTU measurements when they are unavailable.

3) State Filtering: In [172], [173], [174], [175], [176], DSE and FASE in distribution systems are investigated, where the predicted states are fused with the sparse real-time measurements, ensuring that there is enough information to make an inference on every state variable even when lower-rate measurements are not refreshed. In [172], the feasibility, theory, and implementation of DSSE using a sequential discrete Kalman filter are studied. Reference [173] proposes a past-aware DSSE method accounting for a load evolution model and previous state estimates. The proposed past-aware DSSE is designed for capturing static states although it is based on ensemble Kalman filtering. In [174], [175], a robust FASE is proposed using the SHGM estimator and an adaptive process noise covariance matrix, respectively. In [176], a deep learning-based state forecasting model is proposed to imitate the spatio-temporal state correlations.

4) Estimator Switching: Different from the above discussed methods where a single estimator is applied, the estimator switching methods address the different reporting rate problem by switching between different estimators based on the type of measurements received at a given instant [200], [212]. In [200] where the integration of SCADA and micro-PMU measurements are considered, the method switches between a linear estimator and a nonlinear estimator depending on whether SCADA measurements are received. In [212], when only sparse SCADA measurements are received, a deep neural network (DNN) based estimator is executed without encountering observability issues; when SM and SCADA measurements are received simultaneously, a WLAV estimator is executed to ensure robustness.

In addition to multiple reporting rates, asynchronization problems in multi-source data integration are studied in [201], [213], [214]. In [201], the asynchronization problem is handled by a harmonic components model. The load variation is assumed to be a distorted sinusoid and captured as Fourier series, which is used to predict the non-refreshed SM data. In [213], load variation characteristics are modeled by a Gaussian distribution, and the asynchronization of SM measurements is alleviated by forecasting of short-term load variations. In [214], two methods are proposed to handle the asynchronization issue between SM and micro-PMU measurements. In the first method, the state variation vector between two consecutive instants is added to the WLS estimator as a penalty term to enhance convexity. The second method is a classical WLS estimator involving previously retrieved measurements within a time window.

Moreover, distribution system three-phase SE in complex variables is investigated in [215], [216]. Similar to that in TSSE, the real-valued measurement function is expanded via Wirtinger calculus in terms of the nodal voltage phasors and their conjugates. In [215], a linear SE formulation is developed by considering the practical assumption that bus voltage phase angle deviations for small changes in total feeder load are small. The complex variable-based estimator is intended to incorporate historical data, SM data, and synchronized phasor measurements. In [216], the measurement set consists of SCADA, PMU, pseudo, and virtual measurements. The vector of measurement functions includes a vector of complex-valued measurements and their conjugates, along with a vector of real-valued measurement functions. The usage of complex variables facilitates the incorporation of phasor measurements with the common measurement types in DSSE.

D. Handling Uncertainties and Missing/Delayed/Bad Data

The performance of DSSE is affected by many factors, such as the uncertainties of generation/load, network model, measurement/pseudo-measurement errors, communication delays and packet losses. For instance, the uncertainty of current measurements on overhead conductors collected by low-cost magnetic field sensors is investigated in [217]. To handle inevitable delayed or bad data in measurements, several categories of DSSE methods have been developed.

1) Prediction-based Methods: In [29], the missing data caused by sensor outages or communication failures are predicted by weighting the historical data and the interpolated/extrapolated measurements. In [196], the missing and delayed SM/SCADA measurements are handled by Kalman smoothing and the expectation-maximization (EM) algorithm. The Kalman filtering-based forward-backward recursion is used to compensate the missing measurements, and the EM algorithm is used to interpolate the delayed measurements.

2) Robust Estimator-Based Methods: In [58], the SHGM criterion is exploited to suppress bad data and model uncertainties. In [196], the projection statistics-based iterative reweighted least squares (IR-WLS) estimator is used to tackle leverage points, noisy measurements, and bad data in DSSE. In [218], [219], considering that SM measurements may include gross errors, a robust maximum normal measurement rate (MNMR)-based estimator is developed.

3) Interval Estimation-Based Methods: In order to account for the uncertainties of measurements, network parameters, and DERs, interval state estimation (ISE) models are proposed in [220], [221], [222], [223], [224]. They differ from the classical deterministic SE models in that the outputs of ISE are interval values indicating the "boundary" of states. To solve the ISE problems, the Krawczyk operator (KO) algorithm [220], the modified KO (MKO) algorithm [221], and the MKO in conjunction with the interval constraint-propagation (ICP) algorithm [222] are investigated and applied. In [223], the maximum and minimum values of states are estimated by solving an optimization problem with inequality constraints indicating the boundaries of estimated measurements derived from the measurement uncertainties. In [224], an ISE model based on the relative distance measure (RDM) arithmetic is proposed, which can provide more accurate estimated states and ensure the credibility of solutions.

E. DSSE Using Other Types of Measurements

In addition to the measurements collected from SCADA systems, AMI, and micro-PMUs, other unconventional types of measurements are also explored in DSSE.

1) DSSE Using Ampere Measurements: Ampere (i.e., current magnitude) measurements are commonly deployed along distribution feeders and exploited in DSSE [225], [226]. Reference [225] proposes a novel SE method to accommodate a large number of ampere measurements. It selects both powers and branch current magnitudes as state variables, yielding a simple and easily solvable SE model. In [226], a fast decoupled estimator is proposed, where the branch ampere measurements are equivalently reformulated as power flow losses.

2) DSSE Using Synthetic Measurements: In distribution systems, single-phase loads could be evenly allocated to phases a, b, and c along a three-phase secondary distribution feeder, which is connected to the three-phase primary distribution feeder via a three-phase transformer [246]. Low-voltage feeders, especially in residential areas, show a very low coupling between phases [227]. Each sensor typically measures a voltage or a current between one specific phase with the neutral conductor. The weak coupling between different phases may lead to ill-conditioning problems in the SE algorithm, making it difficult to obtain accurate voltage phase angle estimates. In [227], a novel method is proposed by embracing a different connection of measurement devices in line supervisors located at secondary transformer stations without the need for new hardware. Specifically, the three single-phase power measurement devices of the transformer station supervisor are fed with currents i_a, i_b, and i_c from current transformers but with the shifted set of phase-to-neutral voltages v_b, v_c, and v_a, respectively. Accordingly, measurement functions corresponding to synthetic active and reactive power flows and their related Jacobian terms in the Jacobian matrix also need to be modified to fit the synthetic measurements.

3) DSSE Using Power Electronic Measurements: In [228] and [67], PV generation system models are integrated with the conventional network models in DSSE. Joint SE is conducted by integrating conventional measurements with PV system-related measurements, such as solar irradiances, temperatures, output voltages and currents of PV arrays and power electronic converters. Similarly, in [229], the SOC estimation of battery energy storage systems (BESS) is jointly performed with DSSE. A WLS-form iterated extended Kalman filter (IEKF) is proposed to integrate the DSE problem for the SOC estimation of BESS and the SSE for the distribution network.

VI. Computation and Data Requirements

As SE is a critical application in EMS, computation and data requirements are important factors to evaluate for the feasibility of SE algorithms in a practical setting. It is not possible to have a rigorous comparison on the computation costs of methods proposed in all specific papers, since each paper has employed different test systems, measurement configurations, data volume, termination tolerances, and computing resources. However, this section attempts to comment on the computation and data requirements for different types of SE problems in several general aspects.

1) Static State Estimation Versus Dynamic State Estimation and Forecasting-Aided State Estimation: In SSE, it is assumed that power systems operate under a steady state [1], [2], [5], [6]. Hence, SSE can employ almost all available data sources, such as SCADA systems [4], [12], [13], [23], PMUs [9], [10], [11], [12], [13], [14], [15], SMs [7], [8], [15], [29], etc. By contrast, DSE aims to track the dynamics of power systems [31], [32], [33], [130]. Commonly, the phasor measurements collected by PMUs [21], [27], [28], [137] and sampled-value data gathered by MUs [42], [43] can be employed in DSE. In general, the computational requirements of the Kalman-filter-based DSE are much higher than that of the conventional WLS SSE, mainly owing to the need for explicitly computing and using dense covariance matrices [130], [133]. On the other hand, the execution frequency of DSE is much higher than that of SSE, mainly resulting from the need for promptly tracking the dynamics of power systems [32], [33]. Hence, DSE is typically applied to relatively small systems, such as a generator along with its control systems and a Thevenin equivalent of the external system, the protection system of a line or transformer [44], [45], [46], etc., or to a larger system in a distributed/decentralized fashion [28], [151]. FASE is a variation of the DSE concept for *quasi-steady* state conditions, and it is motived by incorporating previous state estimates to improve the estimation accuracy instead of by tracking dynamics of system states [131], [132]. Hence, execution frequency as computational demand of FASE is not as high as that of DSE.

2) Non-Robust State Estimation Versus Robust State Estimation: WLS SE is the most widely used non-robust state estimator in power systems, which can be solved via the Gaussian-Newton method [2], [62]. It is computationally advantageous, but not robust against gross measurement errors - if the state estimates remain insensitive to gross errors in a limited number of redundant measurements, then the corresponding estimator will be considered statistically robust [2], [58], [128], [129]. *Unfortunately, robustness is commonly achieved at the expense of computational complexity* [2], [58], [82], [83], [84], [110], [129]. For example, the LAV estimator is a widely used robust estimator, which needs more execution time than the non-robust WLS estimator in the same situation since a linear programming problem needs to be solved in LAV SE [2], [110], [129]. Hence, the computation efficiency of robust SE typically requires careful treatment especially when applied to large-scale systems.

3) State Estimation with Nonlinear Measurement Model-Based Versus Linear Measurement Model: The nonlinear (linear) measurement model means that state variables and measurement data are related via a nonlinear (linear) function [11], [80], [81], [215], [232]. The nonlinear measurement model-based SE is usually more time-consuming than the linear measurement model-based SE since the *nonlinear optimization problem is commonly solved by transformation into a successive set of linearized problems via expanding the Taylor series and neglecting the higher-order terms* [2], [230]. If the measurement model is linear, state estimates can be directly solved without iterations. Thus, the computation efficiency will be significantly enhanced. Commonly, voltage and current phasor measurements (collected by PMUs, micro-PMUs, etc.) are based on linear models and active/reactive power flows/injections (collected by SCADA systems, SMs, etc.) are based on nonlinear models when state variables are set to voltage phasors [77], [78], [79], [80], [81], [85], [86], [87], [200], [212]. In addition, the hybrid state estimator using SCADA and PMU measurements can also be treated as linear SE by properly rearranging measurement functions and adding auxiliary state variables [80].

4) Centralized State Estimation Versus Decentralized State Estimation: Generally, centralized SE is performed by processing all network parameters and measurements of the entire power system in a single problem [88], [89], [90], [91], [92], [93], [94], [95]. By contrast, decentralized SE is performed by dividing a system into several subsystems, which may be intersecting or non-intersecting, and the SE problem in each subsystem is solved separately by using local information [28], [87], [99], [151], [165], [166], [167], [168], [180]. *Decentralized SE is usually more computationally efficient than centralized SE since SE problems in different subsystems can be solved in parallel* [28], [87], [99], [165], [166], [167], [168]. In decentralized SE, a voltage magnitude measurement in each subsystem is necessary to ensure that each subsystem can be solved [87]. Moreover, a unique phase angle solution for the entire system can be achieved by sharing SE results at the buses in the overlapping regions between neighboring subsystems [87], [99]. Decentralized state estimation is more vulnerable at the boundaries of subsystems as the reduced measurement redundancy renders lower capability of bad data processing.

5) Model-Based State Estimation Versus Data-Driven State Estimation: Model-based SE is usually formulated into linear or nonlinear optimization problems [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [206], [207], [208], [209], [210], [211]. The execution time of model-based SE is affected by diverse factors, such as the formulation of the objective functions, types of measurements, types of estimators, scales of power systems, etc. Model-based SE typically does not require historical measurement data and only utilizes measurements of the current time. By contrast, data-driven SE is typically developed based on probabilistic inference-based methods [57], [185], [186], [187], [188] or machine learning-based methods [112], [189], [190], [191] without the need of accurate or complete physical models. Generally, data-driven SE consists of offline training and online testing procedures. The offline training usually requires massive historical data to characterize the system at the expense of excessive training time [57], [185], [186], [187], [188], [189], [190], [191]. In the online estimation, however, state estimates can be obtained by feeding forward real-time data with modest computation costs, which may even be lower than those required by the solution to model-based SE optimization problems.

VII. Conclusion and Future Work

In this paper, the literature on power system state estimation using multiple data sources is systematically reviewed and categorized. It starts by reviewing the motivations and major challenges of multi-source data integration, followed by an introduction to common types of data sources for SE. Then, existing methods are carefully categorized and reviewed based on the major challenges addressed. The survey covers various SE problems including SSE, DSE, and FASE in TSSE as well as DSSE. In addition, pioneering applications of novel measurement data sources are also studied for each SE problem.

Although abundant research work has been done in this field, significant gaps still remain for further investigation. Furthermore, the close relation between the evolution of this field as the technology advancement in a few other domains, such as power-electronics-dominated power systems, integrated energy systems, cyber-physical systems, and Internet of Things, should be further revealed, explored, and exploited. Therefore, possible directions for future research are recommended as below.

1) Asynchronous Measurements Reported over Continuous Time: Although many solutions have been proposed to address different reporting rates and asynchronization, almost all of them are based on a foundational assumption that measurements are reported at evenly-spaced discrete time steps, and the reporting rates of fast measurements are integer multiples of those of slow measurements. In reality, sensor reporting times are uncoordinated and individual asynchronous measurements are likely to arrive over *continuous time*, making it impossible to form an exact measurement "scan" at discrete time steps. It is worth investigating how to effectively integrate asynchronous measurements reported in a continuous-time system.

2) Attainability of State/Measurement Prediction Model: As observed in the literature review, state or measurement prediction are commonly used methods for integrating measurements with low reporting rates. However, a majority of the existing methods perform prediction by naïve heuristics such as weighted averages of preceding time-series data. These state/measurement transition models are neither theoretically justified nor based on sufficient empirical evidence, limiting the performance especially with the uncertainty of DERs. Learning-based methods for state/measurement transition modeling may achieve higher accuracy and are worth further investigation in the future.

3) Unknown Error Statistics of Data Sources and Bad Data Processing: SE's error filtering performance heavily depends on the knowledge on measurement error statistics. For example, the formulations of WLS and WLAV estimators imply Gaussian and Laplacian error assumptions with known variances, respectively. In reality, however, the true error statistics of measurements may be unknown or even time-varying with the change of operating conditions [231], [232]. This problem is intensified when multiple data sources are integrated as they have a wide range of accuracy classes and error distributions. Furthermore, bad data with gross errors may occur due to sensing or communication failures, which is ignored by a majority of existing publications. Accurate hypothesis testing for bad data detection is far from trivial when standard WLS normal equations are not adopted or measurement error statistics are unknown. Much more work is required for measurement error statistics estimation, sensor calibration, and bad data processing.

4) Multiple Solutions and Numerical Stability: A wide range of accuracy classes of measurements (i.e., weight settings), different orders of magnitudes of measured quantities, and network topology and parameter errors may result in SE divergence. Moreover, the multiplicity of solutions may occur when ampere measurements are employed as they do not provide the direction of the currents [233]. This typically happens at the distribution or sub-transmission levels where ampere measurements widely exist. More attention should be given to the numerical stability and solution multiplicity issues in SE.

5) Network Model Uncertainty and Estimation: Most existing SE methods implicitly assume that the network model is perfectly known. In reality. Network topology errors and parameter errors widely exist and heavily affect SE solutions. This issue is particularly significant in distribution systems where network models are often unavailable or inaccurate. Physics-informed data-driven methods that incorporate domain knowledge from network models with a vast amount of sensor data are worth investigating. Moreover, it is valuable to investigate the estimation of accurate or approximate (e.g., linear) system models using multiple data sources so as to enable volt/var control [234], [235] and other applications in distribution system operation.

6) Co-Optimization of Sensors and Communication Network: While numerous publications have been dedicated to the co-placement of multi-type sensors such as RTUs, PMUs, SMs, and IEDs, the communication network that supports data acquisition is rarely taken into account. In fact, communication network topology and parameters have major impacts on both the investment cost and the data quality (latency, packet loss, reliability, etc.). In cyber-physical power systems, coordinated planning of sensors and communication networks presents a significant gap to be filled by interdisciplinary research efforts [236], [237].

7) Generic Theory and Methodology for Integration of Arbitrary Types of Measurements: As has been reviewed, a vast majority of existing works provide ad-hoc solutions to the integration of specific types of measurements, e.g., between SCADA and PMU measurements, between SCADA and AMI measurements, etc. As innovative sensors are being deployed, the measurement assets will become more heterogenous in the future, and such ad-hoc solutions are not versatile enough to integrate new types of data sources. Similar to other engineering domains, it is desirable to develop generic theories and methodologies of multi-type-sensor data fusion of any arbitrary types of measurements into SE [238], [239].

8) Integration of Data Sources from Renewable Energy Sources: One of the main driving forces for improving SE technologies is the uncertainty and volatility of renewable energy generation. Smart inverter technologies allow inverters to report accurate and granular measurement data, providing abundant data sources for SE [240], [241]. Furthermore, under high renewable penetration, system operating points are strongly correlated with meteorological conditions such as wind speed, temperature, and solar irradiance. This implies that the integration of meteorological data sources may help improve SE performance especially when there are not enough electrical measurements. So far, little effort has been reported on the integration of smart inverters or weather station measurements into SE.

9) Integration of Data Sources From Interdependent Critical Infrastructures: Electric power systems are closely coupled with other critical infrastructures in modern societies. The interdependency between infrastructures is becoming stronger in the advent of Internet of Things (IoT), smart city (SC), and integrated energy system (IES) technologies. For example, the rapid growth of electric vehicles (EVs) creates strong ties between electricity networks and transportation networks, making traffic flow data potentially useful for estimating power flows [242]. Similarly, the coupling with gas, heating, water, and building systems makes it possible to improve the situational awareness of electric power systems with a wider range of data sources [68], [114]. Multi-source data integration from interdependent infrastructures is worth further investigation.

10) Fusion of Measurement Data Derived Based on Different Physical Models of the Same System (e.g., RMS Model and EMT Model): Today's power grids are incorporating more and more DERs, which are commonly interfaced with power grids through power electronic devices. As the faster dynamics of power-electronics-based systems are becoming more influential in power systems, advanced electromagnetic-transient (EMT) and root-mean-square (RMS) hybrid modeling and simulations have been drawing attention recently [243], [244], [245]. Commonly, phasor measurements, which are gathered by PMUs, micro-PMUs, etc., are derived based on the RMS model, while sampled-value measurements, which are collected by MUs, digital fault recorders, etc., are derived based on the EMT model. As different system models are designed for different time scales and dynamics, the integration of phasor data and sampled-value measurements in dynamic state estimation needs to be further studied.

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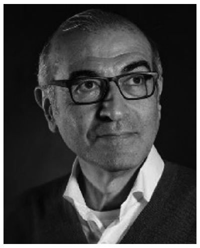

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