Review

The Challenges of Low Voltage Distribution System State Estimation—An Application Oriented Review

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Abstract: Global trends such as the growing share of renewable energy sources in the generation mix, electrification, e-mobility, and the increasing number of prosumers reshape the electricity value chain, and distribution systems are necessarily affected. These systems were planned, developed, and operated as a passive structure for decades with low level of observability. Due to the increasing number of system states, real time operation planning and flexibility services are the key in transition to an active grid management. In this pathway, distribution system state estimation (DSSE) has a great potential, but the real demonstration of this technique is in an early stage, especially on low-voltage level. This paper focuses on the gap between theory and practice and summarizes the limits of low-voltage DSSE implementation. The literature and the main findings follow the general structure of a state estimation process (meter placement, bad data detection, observability, etc.) giving a more essential and traceable overview structure. Moreover, the paper provides a comprehensive mapping of the possible use-cases state estimation and evaluates 27 different experimental sites to conclude on the practical applicability aspects.

Keywords: low voltage state estimation; distribution system state estimation; active distribution systems; low voltage grid control; observability; meter placement; pseudo data generation; grid models; pilot projects

1. Introduction

Since its first proposal by Schweppe in 1969, state estimation (SE) has become a central element of power system operation, especially in high voltage (HV) transmission networks. The challenges transforming power systems (electrification, smart grids, variable renewable energy sources, distributed generation, etc.) have brought the need for SE to the forefront of distribution network operation and planning as well. This has led to increased research activities culminating in hundreds of papers published in this field. High quality reviews of distribution system state estimation (DSSE) in general have been presented in a number of papers lately. Primadianto introduces a summary of state-of-the-art DSSE techniques, grouping scientific papers based on the type of algorithm they use [1]. A similar scientific scope was defined by Majdoub et al. in [2], with the aim of highlighting the spread of techniques that are based on evolutionary algorithms.

Dehghanpour et al. created a detailed comparison from the perspectives of mathematical problem formulation, application of pseudo-measurements, metering instrument placement, network topology issues, impacts of renewable penetration, and cybersecurity [3]. On the contrary, the potential value of DSSE in enabling smart grid features was focused by Ahmad et al. comparing main differences of transmission and distribution network applications of SE [4].

The present paper is intended to take a different approach on the subject and present recent advances in the perspective of practical applications of low voltage (LV) DSSE. LV distribution networks exhibit important differences compared to medium voltage (MV),

e.g., the presence of phase-unbalanced loads and subsystems that do not use all phases, the presence of the neutral conductor, and a different approach to topology processing.

The authors have performed an extensive literature review, which covers the timespan from 2016 to 2021 with a scope to emphasize the state-of-the-art LV DSSE solutions from around the world and provides an outlook to MV DSSE. The differences and unique barriers of MV/LV DSSE implementation are discussed in each section separately. While state estimation has been in daily use for decades in transmission system operation and control, different concepts have to be applied to LV networks because of the lack of measurements and other necessary information sources. There are several modern challenges at distribution level (smart grids, smart metering, high penetration of intermittent distributed generation, and dynamics of microgrids), which will benefit from well-performing LV DSSE, therefore the scope of the analysis was two-fold:

- Identify the constraints in each stage of the DSSE process which are applicable to a LV area;
- Create an assembly of practical applications, pilot projects, and experiences.

The paper was organized around the process of DSSE, as the important differences were collected regarding topology checks, grid structural constraints, meter placement and observability, algorithm specialties, and error calculation. The main contribution of this paper is a practical application-oriented review, which compares the novel theoretical methods while considering the limitations from actual grids. The assumptions are confirmed with a detailed analysis of pilot projects; therefore, the crucial challenges, as well as the state-of-the-art methods, are identified with an implementation focus.

The paper is organized as follows. An extensive DSSE application landscape and the set of possible application fields are introduced in Section 2. In addition, Section 3 contains an application-oriented review of DSSE systems and highlights the most important constraining factors, such as observability, meter placement, and algorithm optimization methods. Beyond the theoretical aspects, Section 3 introduces the main results of demonstrations and pilot projects, offering a comprehensive overview of the state-of-the-art solutions. Finally, Section 5 summarizes the main conclusions of the review and designates the path of development for a LV DSSE system.

2. Literature Review of DSSE Use-Cases

SE solutions are well known in industrial and academic areas. In the last couple of decades, the transmission system operators' (TSO) daily operation was based on SE calculation and estimation to formulate an optimal operation and to be prepared for the necessary control actions. The novelty of the approach described later is that the experience and knowledge, which was worked out in the TSO area in the last 30–40 years, plans to move into a new area: to the distribution level, focusing on medium and low voltage level adaptation.

Generally, at the LV level, outage management and control possibilities are usually not available, or cover a small part of the technical needs. The reason is simple: the investment needs of the assets and devices are high enough that there is no return at all. To give further support for distributed operation and control and to demonstrate how to utilize the available information in different heterogenous subsystems, E.ON Distribution system operator (DSO) Hungary decided to develop a unique LV supervisory control and data acquisition (SCADA) system focusing on workforce management functionality. There are several IT systems that can give useful information about the LV network, such as the geographical information system (GIS) or the SAP data management system. If these information types are connected, the data can be monitored on the same platform, and the possibility is given to perform data analysis and prediction, resulting in a more integrated DSO operation than before.

To extend the current functionality of LV SCADA, the focus of this chapter is to investigate the available applications in this area, to analyze the state-of-the-art DSSE solutions, and to select the most valuable use cases to offer effective modules to live

operating application. This indicates that the DSSE functionality provides new possible business use-cases on the advanced distribution management system (ADMS) platform. In that perspective, the ADMS will be extended with DSSE based new functionalities. In the following, a collection will be introduced about those business use cases, and in the next chapter, the possible enhancement suggestions will be described in consideration of DSSE algorithms and measurements themselves. Although actual pilot projects with on-site results of an operating DSSE and experiences are overviewed in Section 4, the use cases from those projects are all covered by the research examined here. In several studies, a dozen of use cases are introduced [5], such as load and generation profile creation, distributed energy resource management, active network element (on-load tap changing transformer, demand side management, and energy storage), topology analysis (feeder and phase detection) technical loss monitoring, or non-technical loss identification (illegal direct connections and tampered meters) [6]. One of the most common applications is short-circuit power estimation [7]. Another specific application is outage management [8]. The classical meaning of "generation and demand forecast" is expanding in the smart grid terminology with renewable generation estimation. To avoid the immediate investment needs, the planned connection allocation of renewable generation is a possible answer, e.g., Sampaio proposes [9].

A commonly appearing DSSE application is the fault localization on LV and MV grids. Jamali and Bahmanyar proposed an approach based on sparse measurement that enhances the localization method [10]. Several applications can be further developed, such as Jamali et al. using smart metering as a data source [11]. Liu and He utilized the most commonly used weighted last square (WLS) approach [12]. Furthermore, advanced information technology offers additional opportunities [13], as well as innovative architectures [14,15]. The current level of observability (lack of measurement devices and expert systems) makes effective fault localization difficult. Therefore, considerable human resource is used at the moment, which can be replaced by advanced DSSE. The most crucial performance index at the LV level is service availability, and the next is the quality of service. Consequently, power quality estimation is another important use case, as it is demonstrated in [15] by Yu and Cobben. One of the least common applications is about losses and harmonics, such as Melo et al. describes [16]. Voltage quality issues, e.g., sag and dip volume estimation, are also feasible [17].

Unique solutions include the e-mobility-specific or the LV observability enhancement solutions, which provide promising results if the circumstances are appropriate [18]. Table 1 summarizes the technical applications of DSSE in four main categories based on the literature review. Focusing on the LV level, the identified applications are not relevant (marked with italic): fault localization is not important due to the size of one MV/LV transformer area (the selective protection scheme accurately highlights the fault location), while short-circuit power estimation does not carry any useful information for operators at this level. Feeders are usually also trivial due to the radial structure and low level of automation. The group (third column of Table 1) of renewable and e-mobility integration highly depends on regulatory models (e.g., support schemes such as net metering excludes the controllability of renewables), existing market condition (no service is available for charging control), and technical limitations (communication devices are not available for remote control, or smart asset is not available). These groups are only relevant at exact locations, but the number of such LV areas are increasing as active distribution systems are developing.

Summarizing the DSSE application landscape, the key is considering the economic aspects, besides the tempting technical possibilities, due to the high investment costs of DSSE hardware. Collecting the value propositions is important in the conceptualization phase. The literature review showed that most of the DSSE-related functions are software developments; therefore, a prioritization is needed that considers the local parameters (incl. instrumentation specification of DSSE). This can help to identify the true values for LV SCADA expansion at the E.ON DSO Hungary.

Table 1. Classification of possible DSSE utilization based on the literature review.

Outage Management and Power Quality	Data Analysis	Renewable and E-Mobility Integration	Coordinated Control
Human workforce management	Profile creation	Curtailment	Power electronic controllers (distribution level)
Outage information handling (single & group faults)	*Feeder detection*	P-Q control setpoint	On-load tap changing distribution transformers
Fault localization, short circuit power estimation	Phase detection	Pattern analysis	Energy storage
Voltage limit violations	Loss monitoring	Accurate estimation	Demand side management
Asymmetry	Non-technical loss identification	Hosting capacity calculation	Voltage regulators

The two main drivers for DSSE in Hungary are:

- The necessity for capital expenditure (CAPEX) intensive network developments due to the increasing share of distributed generation (mainly photovoltaics (PV)) and the increasing amount of connection requests, and
- Growing power usage.

Therefore, any smart solution, e.g., active network components such as energy storage devices, voltage regulators, distributed generation control, and demand side management, is an alternative to conventional reinforcement methods. As the distribution system becomes more complex due to different active elements, observability is crucial for optimal control. DSSE can provide reliable input for grid operation software and can serve as the basis for further calculations (load flow and optimal dispatch calculations) in integrating flexibility, coordinated dispatch.

Another main value is the data that DSSE creates, as the power and voltage estimations are available for the analyzed grid. The necessary grid development calculations are usually conducted based on the static profile data and scarce measurements. Integration of the DSSE output enhances automatization of network calculations and increases modeling accuracy.

3. Process-Oriented Review of DSSE

Special characteristics of LV distribution networks are reflected in all segments of the SE process: network data, real, pseudo and virtual measurements, topology procession, observability analysis, and the SE algorithm itself. A vast amount of SE methods is published in the literature, including conventional voltage- or current-based static methods (weighted least squares, least mean squares, weighted least absolute value, least trimmed squares, etc.), use of artificial intelligence, and advanced techniques. A common approach in these studies is that they aim to decrease numerical errors and computational time of SE, usually benchmarking the improvement to the simple weighted least square (WLS) method. However, increasing the performance of SE methods beyond all seems to be unnecessary, since the perspective of typical DSSE applicability and the availability of measurement data have no such requirement. For this reason, the authors focus on those recent contributions in the literature, which have concentrated the LV DSSE, and present these studies in the field of measurements.

For achieving the aim to quantify and compare the impact of recent studies, the structure of the next sections follows the general build-up of SE algorithms. Section 3.1 discusses all the practical and theoretical criteria for fully observable network definition. Section 3.1.1 introduces the meter placement strategies both at the MV and the LV levels, using multivariate objective functions. Section 3.1.2 addresses the challenge of real time

metering, data acquisition, and bad data detection. In most cases (especially at the LV level), the supplement of metered dataset via pseudo measurement is also an elemental part of DSSE methods. The third part (3.1.3) reviews these pseudo data generation methodologies for various load patterns. Section 3.2 focuses on network data and representative network models that are used for comparing performance of different SE algorithms. Finally, Section 3.3 presents the SE algorithms themselves.

3.1. Observability Criteria

3.1.1. Classification of Meter Placement Techniques

Besides the observability condition of SE execution, a wide variety of practical aspects must be considered for the placement of phasor measurement units (PMU). These aspects are quantified by objective functions for the reduction of investment costs [19], maximization of the estimation accuracy [20,21], physical implementation constraints [22], or a combination of these [23], all of which are relevant from a DSO perspective.

Meter placement optimization algorithms are mainly implemented as a linear [24], mixed [25], non-linear [26], or binary [27] integer programming problem, but examples for genetic [28,29] and greedy algorithms [30] are also found.

Performance evaluation is generally validated on a test case network (see Section 3.2) setting out the applicability limits of the results. Since test grids usually represent MV/HV looped/meshed network topologies, the algorithms may result in suboptimal scenarios on radial LV grids. While test grids include fixed loads (constant grid state) dominantly, the proposed meter placement techniques often do not consider the need of pseudo data generation or the impact of bad or skewed data.

For a comparison, Table 2 shows the implementation objectives of six reviewed papers [31–36]. These validate the implemented PMU placement methods on IEEE 14 and IEEE 30 HV/MV bus systems, respectively. Despite the different optimization objectives, similar result patterns can be identified. In [32–36], an average of 10 PMUs were placed to 17 different buses with noticeable similarities on IEEE 30 bus system. Moreover, ref. [32–34] and [36] placed PMUs to the same four buses in case of an IEEE 14 network. These studies reflect approx. 20% PMU penetration at least, which will be capital-intensive at the distribution level.

Table 2. Classification of possible DSSE utilization.

Ref.	PMU Placement Objective	Optimization Algorithm
[31]	SE error minimization	particle swarm opt., artificial bee colony
[32]	minimize no. of PMUs	rational random walk
[33]	minimize no. of critical measurements and maximize redundancy	optimization using unreachability index
[34]	satisfy observability criteria	fruit fly optimization
[35]	minimize no. of PMUs	artificial bee colony
[36]	maximize redundancy	integer linear programming

3.1.2. Bad Data Detection

The accuracy of state estimation methodologies cannot be investigated individually, the evaluation performance highly depends on spatial and temporal data granularity as well as measurement accuracy. The observability criteria only represent the solvability of SE, but do not guarantee any authenticity of the estimation results. For this reason, input data assessment is an essential step in transition to the physical implementation of SE. Ali and Exposito revealed that 1% standard error of measurements may imply 10% standard error in SE [37]. The uncertainty of data measurement was evaluated in 76 papers of the reference list, the principally used solution was to define a constant uncertainty value [38], or modeling measurement error via a normal distribution function [39]. Beyond the few

real implementations, it is a reasonable assumption due to the lack of real metering dataset. However, this issue highlights the weakness of simulation environments and the use of test bus grid topologies.

Furthermore, the practical modeling of measurement accuracy has various aspects. At the LV level, the literature dominantly proposes the application of (micro) phasor measurement units (µPMUs). These synchronous devices can capture waveform samples in every 10 milliseconds and reconstruct the phasor quantities using angle and magnitude measurement, while remote terminal units (RTUs) only provide information about the temporal change of phasor values in every 2 to 6 s. Although PMU unit price had a significant decrease in the past decade, the major limiting factor of wide deployment is the investment cost of associated communication infrastructure (e.g., instrument transformers). Therefore, the parallel utilization of these technologies is an important step in transition to PMU-driven state estimation. Hybrid state estimation (HSE) enables the application of multiple input data granularity in two possible configurations: (i) one-phase HSE jointly process all the input data, and (ii) two-phase HSE manages RTU and PMU measurements in separate SE modules. Richter et al. proposed a mixed communication architecture and validated using HSE [40]. Beyond conceptual aspects, the technological challenges of using synchronized and non-synchronized measurements (e.g., communication delay, distortion of correction tables, digital-to-analog conversion, etc.) are discussed by Manousakis and Korres [41]. To eliminate temporal communication failures, Mosbah and El-Harawy introduced a dynamic estimation method using stochastic fractal search [42]. Saran and Miranda identified the erroneous metering data as a noise in the entire sample dataset [43]. The paper proposes a novel pre-filtering scheme of multiple autoencoders. Beyond temporary events and permanent meter device inaccuracies, outlier metering points are also widely discussed in the literature [44,45]. An alternative approach is introduced by Su et al. using circuit representation to estimate the non-observable part of the network and decreasing the number of necessary metering devices [46]. Othman et al. aimed to estimate active power losses in different configurations of radial low voltage networks [47].

3.1.3. Pseudo Data Generation Techniques

Despite the proliferation of smart metering technologies in energy industry, the LV distribution system operators usually have sparse spatial grid information due to the wide physical dimensions of the network. To fulfil observability criteria of the SE, pseudo measurement generation techniques are essential. However, the indicated increase in cumulative error of the metering points may question practical applicability of the DSSE results. The addressed problem results in various approaches to reduce pseudo data generation error to the scale of metering unit offset. The majority of the papers use historical load profiles and probability distributions for modeling the temporal change of node parameters [48,49]. Alternative predictor models use additional attributes (e.g., current state of the grid) or extract new features for better accuracy [50,51]. Pau et al. and Shafiei et al. addressed the spatial and temporal dependencies of pseudo data generation and the effect of meter placement strategies [52,53]. Teixeira et al. and Abdel-Majeed et al. introduced methodologies to compensate limitations (e.g., lack of power measurement, bad sampling frequency) of metering units. Due to the appearance of time-varying loads and expansion of distributed generation [54,55], Cheng et al. and Macii et al. focused on the influence of local prosumers on the accuracy of SE [56,57].

3.2. Grid Models in DSSE, Practical Limitations of Model Topologies

As the SE is to be performed on a specific network topology (or a set of topologies), it is important that all elements of the SE process should be tailored not only to the application supported by the SE but also to the characteristics of the tested network. The comparison of transmission and distribution networks is often discussed in the literature, but less emphasis is given to the differences of the MV and the LV distribution networks. Notable recent contributions in this field include the adequate handling of high R/X

ratios. Thukaram et al. [58] proposed and tested a robust three-phase SE for application in radial networks to handle this issue, while Abood et al. [59] used a regularized WLS SE to solve the problem of ill-conditioning, using an adjustable regularization parameter. The proper modeling of earthing and sequence components is discussed by Rankovic et al. [60], focusing on the modeling of distributed generators (DGs) with unbalanced output and by Liu et al. [61] who chose voltages as state variables of a WLS SE and pseudo-measurements of low-voltage systems to represent unbalances in the three-phase four conductor model. The analysis of symmetrical and asymmetrical network models is also discussed by many. Chusovitin et al. [62] compared a three-phase model to a decoupled model in which SE is solved for each phase. Chen et al. [63] used a three-phase DG model to represent unbalanced power injections, while Brinkmann et al. [64] developed a generic method that supports the decision between using the single- and three-phase state estimator method, depending on the network topology and metering configuration. Blazic [65] proposed the decoupling of the gain matrix to consider specific characteristics of low-voltage distribution network. SE was adapted to low currents by Svenda et al. [66] in accordance with back and forward sweep-based load flow calculations. Finally, the use of multi-area SE is demonstrated in [67] and [68], concluding that networks with large number of nodes can effectively be handled with such tools.

Literature on LV networks was also reviewed by authors, which was made difficult by misleading or incomplete descriptions at times. A total of 230 test cases were found for the DSSE, of which 223 included the description of the network model being used. A surprising finding was that ~43% of the papers used HV networks (typically IEEE standard models). The remaining 57% was dominated by MV networks (~48% of all cases), and only 9% of the reviewed test cases were performed at LV level, thus results of the vast majority of scientific studies were not validated for LV distribution networks.

The LV test cases included standard models (CGMES [69], CIGRÉ European LV [70], IEEE PES European LV [71]), real-world models from Germany [48,51,55,72], Australia [53], Portugal [54], the United Kingdom [59], and Slovenia [65,73]. The size of these networks shows large variations. Smaller ones have only 10–20 nodes, while the node count of wider areas exceeds 100. Cable and overhead networks are both found. No papers were identified in which standard models and real networks are both used, and most papers are also restricted to using a single network for demonstrating the DSSE.

3.3. Application Constraints of the Algorithms

As it was highlighted at the beginning of this section, the range of SE methods published in the literature is broad. Besides conventional solutions, large emphasis has been placed on the use of artificial intelligence: fuzzy logic [74,75], artificial neural network [76–79], particle swarm optimization [80,81], evolutionary algorithms [82], interior point optimization and brain storm optimization [83], biogeography based optimization [84], firefly algorithm [85], Kalman-filters [73,86–90] and advanced techniques (forecast-aided SE [50,73], multi-area SE [14,63,67,68,91–93], and event triggered approaches [94]).

Although these complex methods outperform conventional voltage- or current-based static SE, they often rely on data that is not available with the desired spatial and temporal resolution.

Typical use cases of LV network operation are related to voltage or energy management issues, both of which are handled with temporal resolutions greater than a minute [72]. Most power quality performance indicators have to be evaluated using 10 min averages, according to EN 50160, while the typical electricity settlement period is 15 min long. Exceptions include, e.g., real time identification of power injection [95].

Tsitsimelis and Antón-Haró presented a regularized SE algorithm that operates on two timescales; observations from the SCADA are handled every 15 min, while the PMU data are used to compute estimates between main time instants [96]. The method is presented to be robust against low redundancy measurement sets. A similar approach is used in [83] to create a framework for SE, using on-line and off-line computing, and

measurement data of different temporal resolution. Combining low-resolution advanced metering infrastructure (AMI) data with other observations is also proposed by [40,97–99], which discusses the general data protection regulation (GDPR) aspects of using smart meter data for SE, concluding that voltage measurements from smart meters can be seen as non-private data.

Another often emerging drawback of complex SE methods is that the personnel of the system operator are rarely trained in the mathematical background of these methods, thus tuning, adapting, or developing an algorithm after installation is a challenging task [100]. If the personnel are undertrained, it limits the exploitation of the SE's potential and may lead to obsolescence.

Rasmussen et al. presented an interval estimation method, which combines worst-case loading scenarios based on fuse ratings and observations from smart meters, concluding that reliable estimations can be created in the case of low observability, if reliable network data is available [70].

Brandalik and Wellssow proposed the duplicated use of active and reactive power measurements, while maintaining linearity, thus improving the observability of LV networks [71].

Caro presented a robust search algorithm that aims to minimize the error of voltage angle estimation variability by selecting the proper bus for reference [101]. Adaptability of the results to a radial topology may be of interest [102].

4. Evaluation of Pilot Projects

The scope of this section is to analyze pilot applications and compare the approaches to theoretical research, underlining the limitations occurring from the technical circumstances, economic viability, and the need of the DSOs.

Several project disseminations can be found in the literature, where pilot applications and field test results are also available. A total of 27 different projects were assessed during this review, considering both MV and LV levels, focusing on Europe but also including projects from the United States of America and China. Table 3 summarizes the main attributes, as the project name and location, voltage level, main use case, main algorithm specifics, and data sources. In general, most pilot studies are connected to research projects in which consortiums (research institutes, technology providers, and DSOs) work together to arrive at practical results. The topology is usually limited, and certain lines (MV) or MV/LV transformer areas (LV) are included in the pilot study. Major rollouts, with over 10,000 customers involved, at the LV level were conducted in Spain [103] and Poland [104]; other LV projects include only hundreds of customers.

The most common motivation for applying DSSE is renewable energy integration (as Table 3 describes), but the observability of networks in dense urban areas is also present [105]. Most of the pilots stressed the importance of observability; however, cost-benefit analysis was not found in any of the studies, which shows the immaturity of the DSSE.

Regarding data sources at the MV level, HV/MV substation measurements are commonly available (therefore not included in Table 3). Besides, remote-controlled pole switches [106], PMUs [107], distributed generation and storage [108] and MV/LV substation [109] measurements are used, when available. In the case of LV DSSE, pilot studies clearly indicate the lack of observability [103], which becomes the most important aspect of algorithm developments. Smart meter data is another usual source of data [110]; however, the penetration of meters vary from 5% to 100% in different projects, which makes the actual pilot study results hard to compare. Phasor measurement and synchronized data are usually missing at the LV level (instrument development was performed to solve this, e.g., the GridEye sensor in [111] or "micro" PMUs [51,112]), which limits the possible applications.

Two separate approaches are identified considering algorithms: dominantly, WLS SE is used (with minor modifications, see Table 3), which highlights a dissonance between the

algorithm development trends previously presented in Section 3 and the actual practical implementations. The structure of the distribution grid is usually radial and does not change over time, which can be exploited in simplifications, e.g., the reduction of nodes or the creation of virtual measurements by related power flows [113]. Advanced algorithms usually rely on data structures that cannot be constructed economically in practice; therefore, the simplest WLS solutions appear in the pilot projects. Conversely, the use of artificial intelligence (e.g., neural networks [114]) does not require accurate topology information and can be faster in computational time. However, the analysis of these models lacks long-term analysis (seasonal trends, effects of different day types such as weekdays, weekends, holidays), the advantages were only shown in limited datasets. The LV DSSE applications usually consider asymmetry and apply a three-phase and neutral model for the grid [115]. Most DSOs do not have a database for phase connections. This can be handled by measurements and examination of each area, but this requires a huge amount of human workforce in the case of a major roll-out. DSSE offers a possibility to create more accurate models for unbalanced operation and can help to identify phase connections based on measurements, instead of visual inspection [9,27,44].

The most common limitation of DSSE is data quality [45]. Redundancy is hard to achieve at such a low level of instrumentation, and if the sufficient level is reached, loss of data (usually due to communication errors) leads to unavailability of the DSSE in the control center. Therefore, the pilot studies assess different ways to create adequate pseudo measurements based on:

- nominal values [51];
- synthetic load profiles [107];
- control functions (Volt/VAR compensators, on-line tap changing transformer setpoints, inverter control, etc.) [116];
- weather data [117].

Table 3. Summary of the main attributes from pilot applications.

Project and Location	Topology Scope	Algorithm	Use Case	Metered Data Source
VENTEEA–France [106,113]	MV	WLS + Weighted Least Absolute	Closed-loop voltage control, hosting capacity increase	U, P, Q sensors, MV/LV transformer measurements, remote-controlled pole switches
Monica–Spain [103]	MV/LV	N/A (asymmetry consideration for LV)	Observability, non-technical loss identification	Smart meters, MV voltage sensors LV wide range of sensors (P, Q, U, I)
Smart Area Aachen–Germany [51]	MV	N/A (Monte carlo error function)	Renewable integration, observability, situational awareness	P, Q, I, U sensors at MV/LV transformers
UPGRID–Sweden [118]	MV/LV	N/A	Comparison and compatibility between different suppliers, network planning input, observability	RTU, fault indicators, smart meter
evolvDSO–France [114,119]	MV/LV	LV–Neural network/(MV-OPF)	Flexibility calculation (MV), voltage monitoring (LV)	Smart meter, U sensors
PRICE GDI–Spain [109]	MV	Hachtel Augmented Matrix Method	Hosting capacity increase	Generation measurements, Static compensators, RTU for MV/LV transformers
Low carbon London–Great Britain [105]	MV	WLS	Technical loss calculation, meter placement calculation	MV/LV transformer U, P measurement

Table 3. *Cont.*

Project and Location	Topology Scope	Algorithm	Use Case	Metered Data Source
A2A–Italy [120]	MV	N/A	Fault localization, loss of mains detection, local dispatch	MV PMU, generation measurements
A.S.SE.M–Italy [121]	MV	N/A	Loss of mains detection, voltage control	MV PMU, generation measurements
InteGRIDy–Italy [117,122]	MV	N/A	Loss reduction, storage operation enhancement, hosting capacity increase	Generation measurements, smart meter
France [123]	MV	Heuristic power adjustment	Algorithm development	PMU
Denmark [107]	MV	WLS	Minimal metering requirement calculation, improving pseudo measurements	PMU (end of the lines)
Sustainable–Portugal, Greece [124]	MV	WLS	DSSE evaluation, renewable integration	Smart meters, PMU
Korea, Canada [108]	MV	N/A	Event detection, voltage observation	Generation and energy storage measurements, PMU
Belgium [38]	MV	N/A	PMU application verification	PMU
ADMS4LV–Portugal [125]	LV	N/A	Phase connection verification	Smart meter
Integrid–Portugal [126]	LV	N/A	Flexibility market enhancement	N/A
RESOLVD [127]	LV	N/A	Power quality, renewable integration, flexibility management	PMU, smart meters, smart assets (e.g., storage)
Slovenia [73]	LV	Extended Kalman filter	Algorithm test, EV charging integration, voltage control	U sensors, P-Q data for nodes
SmartSCADA–Germany [45,110,115]	LV	Linear algorithm (from WLS)	Bad data detection	Smart meter
evolvDSO–Portugal [114,128]	LV	Neural network,	Observability	Smart meter, U sensors
LV SCADA–Portugal [129]	LV	Neural network, particle swarm optimization	Monitoring, observability	Smart meter, LV RTU, MV/LV On-line tap changing transformers
UPGRID–Portugal [130]	LV	N/A	Visualization for operators, group error identification, coordination between operators and electricians	Smart voltage regulators
UPGRID–Poland [104]	LV	N/A	Technical loss estimation, event detection	Fault indicators, Remote controlled pole switched, MV/LV transformer U, I measurements
Switzerland [111]	LV	WLS	Asset management, grid development input	Smart meter, "Grid-eye" sensors (U, I)
China [131]	MV	WLS-based	Use of multi-source measurements	Micro PMU, Smart meter
USA [132]	MV	WLS-based	Voltage monitoring	MV sensors, Smart meters

5. Conclusions and Outlook

This paper addressed the practically applicable best practices and constraints of DSSE. As the DSOs face challenges in integrating further amounts of distributed generation and load, conventional grid planning, development, and operation methods become too expensive, and smart grid solutions can be competitive. The LV grids are currently practically unobservable, but the new elements and technical solutions offer data that can be used to create tailored solutions for a practically applicable DSSE.

Over 20 different use cases showed that the potential values are widely identified in consideration of the DSSE. However, there is a large gap between theoretical research and constraints deriving from the grid; most of the papers tried to integrate new sources of measurement and information to increase accuracy. The different applications were clustered into four main categories:

- Outage management and power quality;
- Data analysis;
- Renewable and e-mobility integration.
- Coordinated control.

It is witnessed that multiple meter placement objectives do not necessarily result in different placement patterns. The importance of bad or skewed data detection is usually neglected, giving suboptimal SE results. Especially in the case of LV grid topologies, pseudo data generation is essential to complement the real metering devices due to economic considerations. The comprehensive introduction of pseudo data generation techniques concluded that the performance highly depends on the grid structure and the penetration of the metering points.

Algorithm developments are usually tested in a network environment with a level of observability that is inconceivable in practice. The vast majority of the network models used are IEEE test systems, while LV grid analysis is rare. Therefore, an important direction for the near future may be the creation of a test system for LV, which covers the different circumstances of the regions around the world. This indicates that most of the developments should focus on the currently and potentially available data. Research is focused on the diversification of data sources (beside measurements from the grid and customers, the weather, historical energy values, and effect of local prosumers) in the pseudo measurement generation.

The analyzed pilot projects showed great potential in exploiting the values, including in the case of low level and bad data quality. The WLS method covers a definitive part of the pilot projects, while advanced computational methods such as neural networks are also present. Data sources are similar due to the current operation of DSOs: HV/MV substations, pole switches, and fault indicators on the MV network, smart meters, voltage (and oftentimes current) sensors, and smart assets on the LV network provide input for tailored DSSE solutions. However, real-time phasor measurements are not common; therefore, pseudo measurement inclusion is a regular attribute of DSSE. At the LV level, a usual time interval of 15 min is present, and asymmetry is a key factor, thus three-phase and neutral models are usually developed. The reliability test of pseudo measurements is the most common contribution of the papers since the observability issue is a key area for development.

In sum, DSSE seems to be a valuable tool in the LV SCADA expansion for DSOs, as active elements become increasingly common, thus increasing complexity and the number of possible system states. This paper contributes to the definition of fundamental principles for practical application, starting from the idea in which the DSSE can bring value, through the appropriate handling methods for the most important challenges (observation and data sources). The review shows examples for how to tailor an algorithm for the actual circumstances and gives insight into the international best practices from pilot projects.

Abbreviations

The following abbreviations are used in this manuscript:

ADMS	Advanced distribution management system
CAPEX	Capital expenditure
DG	Distributed generator
DSSE	Distribution system state estimation
DSO	Distribution system operator
GDPR	General data protection regulation
GIS	Geographical information system
HSE	Hybrid State Estimation
HV	High voltage
LV	Low voltage
MV	Medium voltage
PMU	Phasor measurement unit
PV	Photovoltaic
RTU	Remote terminal unit
SCADA	Supervisory control and data acquisition
SE	State estimation
TSO	Transmission system operator
WLS	Weighted least square

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