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Review

A Review on Distribution System State Estimation Algorithms

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Abstract: The modern energy requirements and the orientation towards Renewable Energy Sources (RES) integration promote the transition of distribution grids from passive, unidirectional, fossil fuel-based into active, bidirectional, environmental-friendly architectures. For this purpose, advanced control algorithms and optimization processes are implemented, the performance of which relies on the Distribution System State Estimation (DSSE). DSSE algorithms provide the Distribution System Operator (DSO) with detailed information regarding the network's state in order to derive the optimal decisions. However, this task is quite complex as the distribution system has inherent unbalance issues, often faces lack of adequate measurements, etc. The purpose of this paper is to review the DSSE algorithms that a system can incorporate with emphasis on their particular requirements, the mathematical formulation of the problem, the analysis of the existing model-based and data-driven approaches and the recommended solutions regarding observability issues, bad data detection, and meter placement strategies. Furthermore, special attention is paid to DSSE applications, including the use cases where they can be deployed, the approaches that are usually followed, the integrated distributed power supply units, as well as their future trends and challenges, thus highlighting their business-related aspects.

Keywords: distribution system state estimation (DSSE); smart grid; unbalanced grid; weighted least square (WLS) method; data-driven approaches; observability; pseudo-measurements; bad data; meter placement; applications

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1. Introduction

Over the past few decades, in order to support the ongoing energy transition, the concept of the electrical network has gradually changed [1]. More specifically, for the purpose of sustainability and the enhancement of autonomy, Renewable Energy Sources (RES), storage systems and other environmental-friendly technologies have emerged, the implementation of which has transformed both Medium Voltage (MV) and Low Voltage (LV) distribution systems [2,3]. Hence, passive, fuel-based distribution is challenged by more active, viable, and decentralized concepts [4].

In order to support the operation of modern distribution systems, the Distribution System Operator (DSO) utilizes a variety of algorithms that provide the optimal results and decisions [5]. Naturally, in many cases, the input of the aforementioned algorithms relies heavily on the accurate and detailed monitoring of the system's status [6]. Consequently, an intermediate process between the acquisition of the system's available measurements and the use of control and decision-support algorithms is required. This process, i.e., Distribution System State Estimation (DSSE), constitutes an asset of great importance for the DSO as it can be used for multiple purposes, including loss monitoring, load and RES profile creation, detection of voltage limit violations and asymmetry, fault localization, outage handling, etc., as presented in Figure 1 [7].

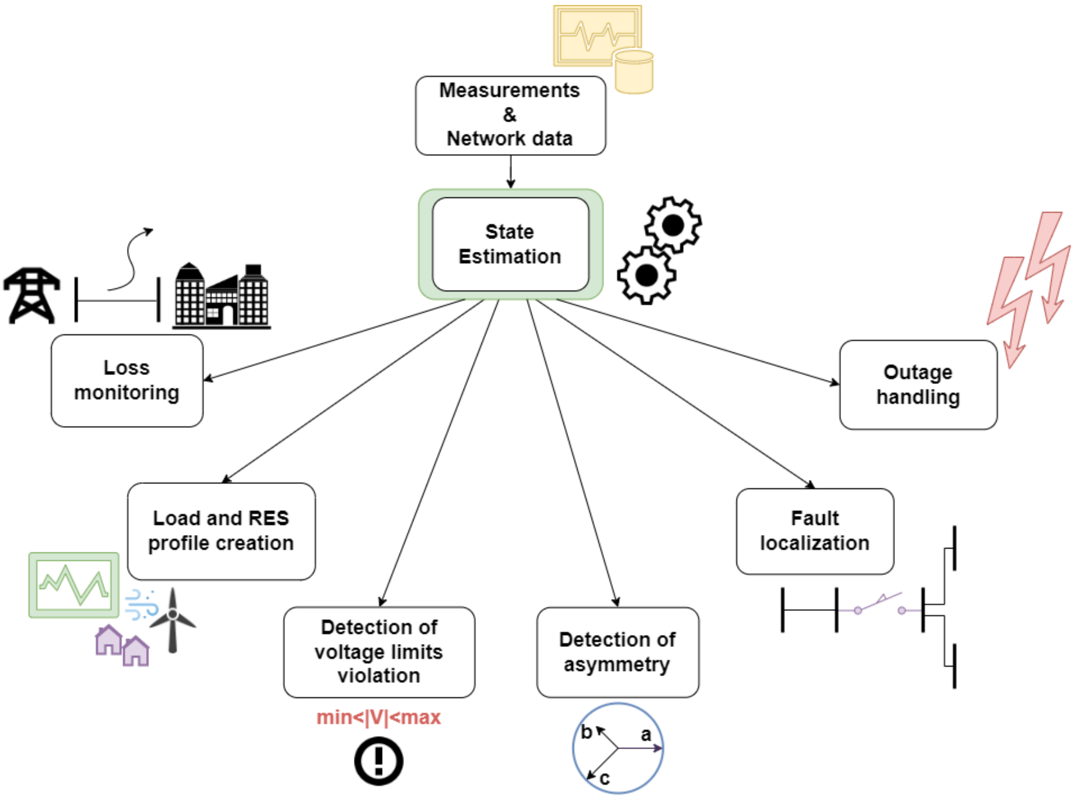

Figure 1. The value of DSSE for the DSO.

Overall, DSSE has evolved into a research field that has gathered the interest of many experts. More specifically, accurate and efficient DSSE is considered to be a complex task, not only due to the inherent unbalances of MV and LV grids, but also due to the lack of measurements, which may cause observability issues, as well as the possible existence of bad data (either caused by damaged/inaccurate metering instruments or by cyber-attacks) that need to be identified and excluded from the estimation, as presented in Figure 2 [8]. The aforementioned challenges may be approached in a variety of ways, usually through model-based or through more recently developed, data-driven strategies, providing a pool of multifarious solutions regarding DSSE implementation [9].

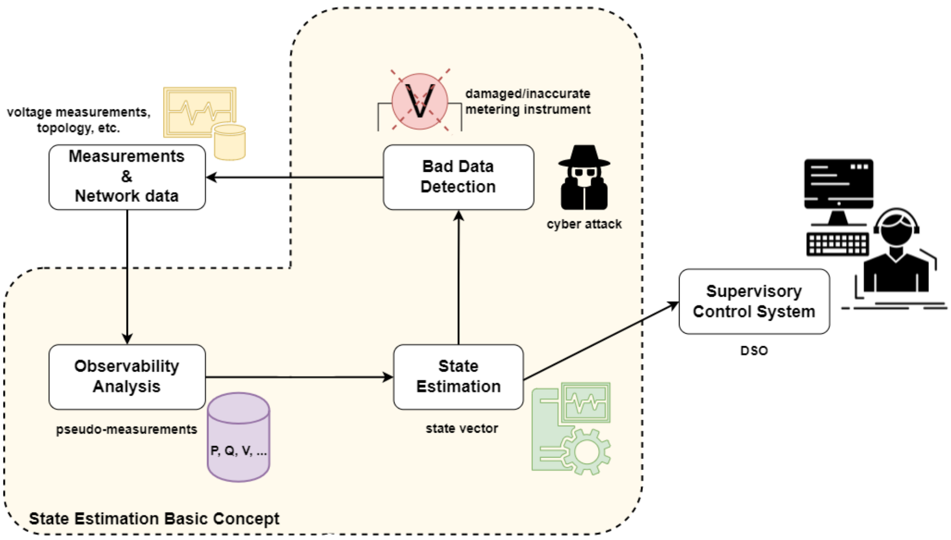

Figure 2. Basic concept of DSSE implementation.

In literature, the expertise and trends related to some of the main aspects of DSSE algorithms are analyzed. For example, the authors of [10] review the requirements of state estimation and the differences between state estimation in transmission and distribution systems. Furthermore, in [11], the authors focus on model-based and forecast aided DSSE algorithms, while in [12] the authors review DSSE algorithms with special attention to data-driven approaches. Regarding the particular requirements of DSSE, in [13], DSSE algorithms are reviewed with a focus on observability issues and the proposed solutions, and in [14], DSSE algorithms and False Data Injection (FDI) attacks are analyzed. Further, from another view point, the authors of [15] focus on pilot applications of DSSE.

The purpose of this paper is to present a comprehensive review and guidelines regarding the existing DSSE algorithms, including the recommended solutions for observability, bad data detection, and meter placement issues, as well as to highlight their applications with an emphasis on the technical and business-related aspects. Therefore, it provides a more holistic approach, including the mathematical/methodological but also the practical aspects of DSSE, thus expanding the purpose of [10–15]. The rest of the paper is organized as follows: Section 2 presents the DSSE challenging attributes, Section 3 reviews the state vector options as well as the model-based, forecast aided, and data-driven DSSE algorithms, Section 4 focuses on the distribution system's observability, bad data detection, and meter placement strategies, Section 5 presents the technical requirements and applications of DSSE, Section 6 presents the future trends and challenges and, finally, Section 7 summarizes the conclusions.

2. DSSE Special Attributes

Distribution systems have a number of special attributes that render their detailed representation more complex than transmission systems. Firstly, distribution systems are unbalanced by nature, as presented in Figure 3. This is a result of the unbalanced consumption as well as the existence of mutual impendences between the lines. It should be noted that in some parts of the grid, phases may be missing by design, according to the requirements and geographical location of the loads, thereby enhancing the occurring unbalances. Thus, the modelling of the components, including lines, transformers, loads, etc., as well as the power flow equations, need to be adjusted. For example, the impendence matrix of a distribution line is formulated as presented in (1), where Z is the impendence [16]. Furthermore, the active and reactive power flow between two nodes is formulated as presented in (2) and (3), respectively, and the power injection is formulated as presented in (4) and (5), where $P_{i,j}^{ph}$ and $Q_{i,j}^{ph}$ are the active and reactive power, respectively, flowing in phase ph between nodes i and j, P_{i}^{ph} and Q_{i}^{ph} are the active and reactive power injection, respectively, in phase ph at node i, V is the voltage magnitude and δ is the voltage angle, G and B refer to the real and imaginary parts of the admittance matrix, respectively, l is the index referring to each of the three phases of the line, and n refers to the number of neighboring nodes [17,18]. The complexity of these formulas lies in the separate calculation of each phase's values, as the occurring unbalances cannot be modelled via single-phase equivalent approaches [17,18].

$$Z = \begin{bmatrix} Z_{aa} & Z_{ab} & Z_{ac} \\ Z_{ba} & Z_{bb} & Z_{bc} \\ Z_{ca} & Z_{cb} & Z_{cc} \end{bmatrix}. \tag{1}$$

$$\begin{aligned} P_{i,j}^{ph} = {} & V_i^{ph} \sum_{l=1}^{3} V_i^{l} [G_{i,j}^{ph,l} \cos\left(\delta_i^{ph} - \delta_i^{l}\right) + B_{i,j}^{ph,l} \sin\left(\delta_i^{ph} - \delta_i^{l}\right)] \\ & - V_i^{ph} \sum_{l=1}^{3} V_j^{l} [G_{i,j}^{ph,l} \cos\left(\delta_i^{ph} - \delta_j^{l}\right) + B_{i,j}^{ph,l} \sin\left(\delta_i^{ph} - \delta_j^{l}\right)] \end{aligned} \tag{2}$$

$$Q_{i,j}^{ph} = -V_i^{ph}\sum_{l=1}^{3} V_i^l[G_{i,j}^{ph,l}\sin\left(\delta_i^{ph}-\delta_i^l\right) - B_{i,j}^{ph,l}\cos\left(\delta_i^{ph}-\delta_i^l\right)] \\ -V_i^{ph}\sum_{l=1}^{3} V_j^l[G_{i,j}^{ph,l}\sin\left(\delta_i^{ph}-\delta_j^l\right) - B_{i,j}^{ph,l}\cos\left(\delta_i^{ph}-\delta_j^l\right)] \quad (3)$$

$$P_i^{ph} = V_i^{ph}\sum_{l=1}^{3}\sum_{j=1}^{n} V_j^l[G_{i,j}^{ph,l}\cos\left(\delta_i^{ph}-\delta_j^l\right) + B_{i,j}^{ph,l}\sin\left(\delta_i^{ph}-\delta_j^l\right)] \quad (4)$$

$$Q_i^{ph} = V_i^{ph}\sum_{l=1}^{3}\sum_{j=1}^{n} V_j^l[G_{i,j}^{ph,l}\sin\left(\delta_i^{ph}-\delta_j^l\right) - B_{i,j}^{ph,l}\cos\left(\delta_i^{ph}-\delta_j^l\right)] \quad (5)$$

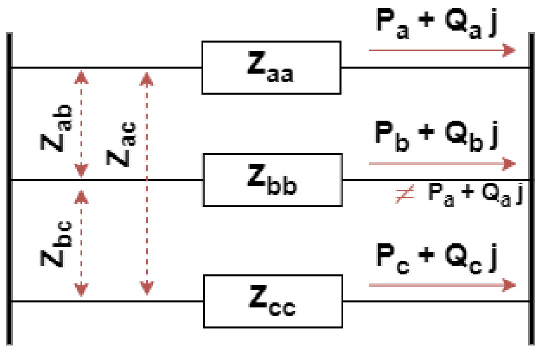

Figure 3. Unbalanced phases in the distribution system.

Another issue that the distribution systems face is the limited availability of real-time data as a result of the sparse meter placement. Therefore, the accuracy or even the convergence of the DSSE might be negatively affected. This is an issue that can be tackled either with the placement of more instruments, which provide the DSSE with more accuracy but have a certain cost, or with the use of pseudo-measurements [19]. Pseudo-measurements are used to augment the available real measurements and are usually calculated using short-term forecasts or historical data. As a result, they are not as accurate as an actual measurement, however they require no further actions or cost from the side of the DSO [20]. A more detailed analysis regarding the methods to obtain pseudo-measurements is presented in sub-Section 4.1.

An additional factor that adds complexity to the DSSE is the configuration of the system. First and foremost, a modern, universal DSSE needs to be adaptable and equally efficient in all sorts of configurations–not just radial (which is the conventional use case) [21]. For example, the integration of RES and various innovative architectures in the MV and LV levels has promoted the research and development on ring and/or meshed configurations. Moreover, for reasons related to the increase of the system's reliability, interconnected configurations (with more than one feeder) are studied. Other than the type of configuration, the status of the switches might sometimes be vague to the DSO, as they are not always monitored. In distribution networks, switches are mostly used in order to isolate a fault or mitigate congestion issues in the distribution system. A close switch of phase ph between nodes i and j is modeled as presented in (6)–(7), and an open switch is modeled as presented in (8)–(9) [17].

$$V_i^{ph} - V_j^{ph} = 0 \quad (6)$$

$$\delta_i^{ph} - \delta_j^{ph} = 0 \quad (7)$$

$$P_{i,j}^{ph} = 0 \quad (8)$$

$$Q_{i,j}^{ph} = 0 \quad (9)$$

Taking the aforementioned attributes into account, it is evident that the DSSE constitutes a challenging, complex task with multiple proposed approaches, which will be presented in the following Sections.

3. DSSE Fundamentals and Main Algorithms

The purpose of this Section is to analyze the foundations of DSSE, from the state vector options up to the main DSSE algorithms.

3.1. State Vectors

The state vector of the system is defined as a set of variables, which, unlike transmission systems, may be either Node-Voltage (NV)-based, i.e., NV-DSSE, or Branch-Current (BC)-based, i.e., BC-DSSE [13]. As there is no standard process, the selection of the appropriate state vector can be determined by the criteria presented in Table 1, which compares the two state vector options in terms of applicability, complexity, efficiency, and compatibility.

NV-DSSE includes the voltages of each node and can be formed using either polar or rectangular coordinates. These state vectors are the most common in literature and also constitute the default state vectors of transmission systems [10,22]. Their main advantage, aside from their wide implementation and rich literature analysis, is that they can be used for all sorts of configurations [23], such as radial, mesh, etc. In addition, this sort of state vector is recommended for the easy incorporation of voltage measurements. However, it is noted that NV-DSSE is highly sensitive to measurement weights and is likely to face convergence issues [12]. Work related to NV-DSSE can be found in [17,24,25] using polar coordinates and in [23,26] using rectangular coordinates.

BC-DSSE includes the currents of each branch and is usually formed using rectangular coordinates but can be also formed using polar coordinates [27,28]. For these state vectors, power measurements are expressed in terms of branch currents, and their use is recommended as a more straightforward process, especially when it comes to current measurements [9,11]. Even though BC-DSSE is mostly suitable for radial distribution networks, which is a major limitation, it should be mentioned that it is considered to have simple implementation, lower computational time, lower sensitivity (to measurement weights, etc.), and higher possibility to converge, compared to NV-DSSE [11,13]. Therefore, this approach is in many cases preferred to its counterpart. Research related to BC-DSSE is presented in [27,29] using rectangular coordinates and in [28,30] using polar coordinates.

Table 1. Comparison between NV-DSSE and BC-DSSE [9,11–13,22–30].

	NV-DSSE	**BC-DSSE**
Configurations	All (radial, meshed, etc.) [23]	Mostly limited to radial
Coordinates	Polar or rectangular [17,23–26]	Mostly rectangular [27–30]
Implementation	More complex	Relatively easy [9]
Sensitivity (weight variations, etc.) [11]	Higher (might affect convergence)	Lower
Computational time [9,11]	Higher	Lower
Compatibility with transmission system state estimation	Yes [22]	No

3.2. DSSE Algorithms

The DSSE algorithms can be categorized as model-based, forecasting-aided, and data-driven. The main mathematical formulas, advantages, disadvantages, and related research are presented below.

3.2.1. Conventional, Model-Based Algorithms

The most common approach regarding the core of DSSE is the Weighted Least Square (WLS) algorithm. This is a model-based solution, denoting that the details of the distribution network need to be known to the operator beforehand. The purpose of WLS is to minimize the weighted residuals between the estimated and measured values, subjected to the distribution network's constraints. Provided that the residual vector $\mathbf{r}$ is calculated with (10), where $\mathbf{z}$ is the measurement vector, $\mathbf{x}$ is the state vector, and $\mathbf{h}(\mathbf{x})$ is the measurement function calculated upon $\mathbf{x}$, the objective function of the WLS is presented in (11). In the objective function, $\mathbf{W}$ is the weight matrix that denotes the operator's confidence in the measured data. It should be noted that the size of $\mathbf{z}$ is $(\mathrm{m} \times 1)$ where m refers to the number of measurements, the size of $\mathbf{x}$ is $(\mathrm{n} \times 1)$ where n refers to the number of states, and the size of $\mathbf{W}$ is $(\mathrm{m} \times \mathrm{m})$. Obviously, m can only be lower than (or equal to) n.

$$\mathbf{r} = \mathbf{z} - \mathbf{h}(\mathbf{x}) \tag{10}$$

$$\min \mathrm{F} = \mathbf{r}^{\mathrm{T}} \mathbf{W} \mathbf{r} \tag{11}$$

The aforementioned method is characterized by its simplicity and wide use, e.g., implementation in the work of [31–36]. However, it is known to be sensitive to bad data, noise of measured values, etc. For this purpose, variations of WLS have been developed, improving its robustness at the cost of simplicity and computational resources. For example, the Least Absolute Value (LAV) constitutes a common alternative. According to this approach, the purpose is to minimize the sum of absolute values of measurement residuals, as presented in (12). Detailed implementation can be found in the work of [37,38]. This approach can be further enhanced by adding weights to each residual. This is also known as the Weighted Least Absolute Value (WLAV). The respective objective function is presented in (13), where $\mathrm{w_i}$ denotes the weight of the i-th residual. Research regarding WLAV can be found in [39].

$$\min \mathrm{F} = \sum_{\mathrm{i}=1}^{\mathrm{m}} |\mathrm{r}_{\mathrm{i}}| \tag{12}$$

$$\min \mathrm{F} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{w_i} |\mathrm{r}_{\mathrm{i}}| \tag{13}$$

Another advanced and robust model-based approach is the Least Trimmed Squares (LTS). In this case, the squared values of the residuals are calculated and ordered from the lowest to the highest. The objective function aims to select a total number, u, of lowest values and minimize their sum, as presented in (14). Related work can be found in [40].

$$\min \mathrm{F} = \sum_{\mathrm{i}=1}^{\mathrm{u}} \mathrm{r}_{\mathrm{i}}^2 \tag{14}$$

Furthermore, the Least Median of Squares (LMS) method has been used for DSSE by the authors of [41]. In this case, the aim of the objective function (15) is to minimize the median–instead of the sum–of the squared, weighted residuals, where $\mathbf{r}_{\mathbf{w}}^2$ is the matrix of squared, weighted residuals.

$$\min \mathrm{F} = \mathrm{median}(\mathbf{r}_{\mathbf{w}}^2) \tag{15}$$

The authors of [42,43] use a Generalized Maximum-likelihood (GM) approach, including normalized residuals, $\mathrm{r}_{\mathrm{S_i}}$, through the Huber cost function, $\rho(\mathrm{r}_{\mathrm{S_i}})$. The objective to be minimized is presented in (16). This approach detects and suppresses the influence of bad data and model uncertainties.

$$\min \mathrm{F} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{w}_{\mathrm{i}}^2 \rho(\mathrm{r}_{\mathrm{S_i}}) \tag{16}$$

3.2.2. Forecasting-Aided Algorithms

The aforementioned conventional DSSE algorithms rely on a single set of measurements, taken on a certain moment. In this way, the evolution of the states over successive measurements is disregarded. The solution to this issue is the use of Forecasting-Aided

State Estimation (FASE) [44,45]. The basic concept of FASE is to provide recursive updates of the estimated states. By these means, changes occurring during normal operation can be tracked. Moreover, since FASE is based on forecasts by nature, the usual problem of missing measurements can be addressed with the use of the forecasted states.

In these sort of algorithms, Kalman-based filters are adopted to capture the dynamics of the distribution system. A typical dynamic model is presented in (17), where k is the time instant, $\mathbf{F}(\mathrm{k})$ is the is $(\mathrm{n} \times \mathrm{n})$ state transition matrix, $\mathbf{g}(\mathrm{k})$ denotes the trend behavior of the state trajectory, with size equal to $(\mathrm{n} \times 1)$, and $\mathbf{w}(\mathrm{k})$, the size of which is also equal to $(\mathrm{n} \times 1)$, models the noise, which is usually assumed to follow a Gaussian distribution with zero mean [44].

$$\mathbf{x}(\mathrm{k}+1) = \mathbf{F}(\mathrm{k})\mathbf{x}(\mathrm{k}) + \mathbf{g}(\mathrm{k}) + \mathbf{w}(\mathrm{k}) \tag{17}$$

There is a variety of DSSE algorithms based on variations of the Kalman filter, as reported in [46–48]. In nonlinear systems, two commonly used variations are the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). More specifically, the EKF is based on the linearization of nonlinear systems via the Taylor series. This approach has been adopted by the authors of [49–52] for a variety of purposes, from simple, passive distribution systems up to systems including Photovoltaics (PVs), Electric Vehicles (EVs), etc. On the other hand, the UKF is a nonlinear filtration algorithm that uses Unscented Transformation (UT) as an alternative to the linearization of nonlinear equations with the use of the Taylor series. Therefore, unlike EKF, no explicit calculation of Jacobian or Hessian matrixes are necessary in order to implement this algorithm [53]. The UFK has been adopted in [52,53].

3.2.3. Data-Driven Algorithms

Due to the ascending amalgamation of Information Technologies (IT) in the energy sector, data-driven algorithms have gained popularity in the field of state estimation over the past few years [54]. A major advantage of data-driven algorithms is that they assist in overcoming the issues that are encountered in other DSSE algorithms, which depend on parameters and models of distribution networks, are complicated, time-consuming, and very sensitive to initial conditions. Nevertheless, it should be highlighted that for this purpose a significant amount of data are required [55,56].

In literature, there is a variety of Artificial Intelligence (AI) and Machine Learning (ML) approaches including: (i) supervised, (ii) unsupervised, and (iii) reinforcement learning [57] that are also utilized in several fields of study [58,59]. In supervised learning, a labeled dataset, including input data and their corresponding output, is required. In the training phase of the algorithm, the relation between the provided inputs and outputs is defined as a function. Artificial Neural Networks (ANN), the popularity of which is increased, fall in this sort of learning. In addition, it should be highlighted that a well-known subcategory of ANN are the Deep Neural Networks (DNN), which in contrast to simple ANN have more than one hidden layer. On the other hand, in unsupervised learning, there are no complete and clean-labeled datasets. This is a sort of learning that finds previously unknown patterns in datasets and discovers the output. Finally, reinforcement learning is based on the interaction with the environment. In this case, an agent interacts with the environment by performing actions and learns either from errors or rewards [60].

In literature, the most common data-driven DSSE algorithms are based on ANN. For example, the authors of [61,62] use ANN algorithms to perform DSSE in MV and LV levels. Studies and experimental tests show that once the ANN is trained, it is characterized by low computational complexity. Since the estimation process is computationally simple, a main advantage is that it can be executed on a low-cost hardware. Of course, the accuracy depends on the number and quality of the available measurements. Other developers choose to add more than one hidden layer to their ANN-based solutions, i.e., DNN. For example, the authors of [63] have developed a DNN framework to perform DSSE, which relies on a deep Recurrent Neural Network (RNN) postulating module. Additionally, following a more complex approach, in [64–66] physics-aware neural networks are proposed. In this case, the underlying physical model, meaning the structure of the distribution network, is exploited, unlike the previous learning models, where the physics of the underlying distribution network are overlooked. By pruning the unneeded neural network connections, the overfitting behavior of the algorithm is prohibited. Furthermore, according to the respective research, physics-aware neural networks are often compared to WLS in order to highlight the superiority of their performance.

Of course, there are also developers who prefer to combine data-driven and model-based approaches, resulting in hybrid DSSE algorithms [67,68]. Indicatively, the authors of [67] have developed a hybrid algorithm that combines a DNN state estimator and a WLAV state estimator in order to ensure robust results at a low time scale. In this case, except from the DNN, the methodology includes a random forest topology identification, which is also a data-driven approach.

3.2.4. Summary and Comparison between DSSE Algorithms

All the aforementioned DSSE algorithms are presented in Figure 4 and summarized in Table 2. It is highlighted that the WLS constitutes the most widely implemented solution. Yet, its model-based nature is directly linked with the accurate knowledge necessity of the distribution system's parameters, the dependency on the quality of the data, etc. This issue can be solved mostly through modern, data-based algorithms such as ANN, the ascending implementation of which challenges the dominance of their tested-in-time, model-based counterparts.

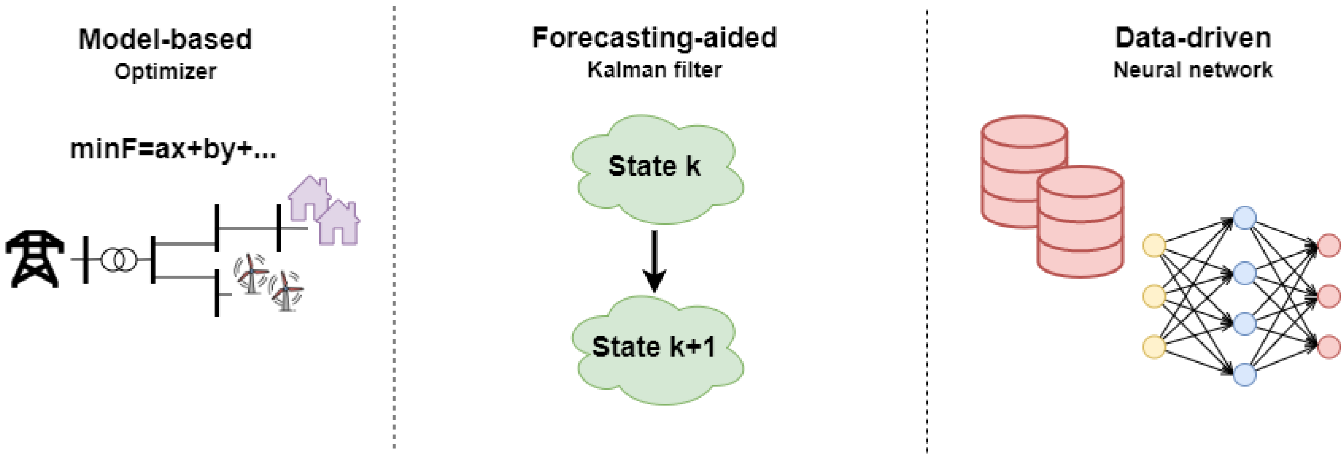

Figure 4. Main sorts of DSSE algorithms.

Table 2. DSSE algorithms [31–65].

Method	Description	Advantages and Disadvantages
WLS [31–36]	Minimization of the weighted residuals between the estimated and measured values. Objective function (11).	Common, simple, fast model-based approach, but sensitive to data.
LAV [37,38]	Minimization of the sum of absolute values of measurement residuals. Objective function (12).	Model-based approaches. Mostly variations of WLS, trying to overcome the issue of sensitivity to bad data and model parameters. Enhanced robustness but also limited implementation in literature and higher resources requirements such as computational cost, memory usage, etc. Information regarding the architecture and parameters of the distribution system is a necessity.
WLAV [39]	Variation of LAV including weights. Objective function (13).	
LTS [40]	Utilization of selected number of residuals in the objective function (14).	
LMS [41]	Use of the median in the objective function (15).	
GM [42,43]	Generalized maximum-likelihood approach using the Huber cost function in (16).	

Table 2. *Cont.*

Method	Description	Advantages and Disadvantages
Kalman filter [46–48]	FASE, providing recursive updates of the estimated states with the use of Kalman filter and dynamic models such as (17).	Changes in normal operation can be tracked. Further, since FASE is based on forecasts by nature, missing measurements can be addressed with the use of the forecasted states. However, this sort of algorithms is more complex and not as widely used as WLS.
EKF [49–52]	FASE, extended variation of Kalman filter with the use of Taylor series for linearization of nonlinear systems.	Widely used variation of Kalman filter for linearization of nonlinear systems. Yet, not as widely used as WLS.
UKF [52,53]	FASE, variation of Kalman filter with the use of UT for linearization of nonlinear systems.	Variation of Kalman filter for linearization of nonlinear systems where no explicit calculation of Jacobian or Hessian matrices is necessary. Limited use of this approach in literature.
ANN [61,62]	Purely data-driven DSSE approach including three layers, trained with data provided by the DSO.	Modern, data-driven approach, where the sensitivity/accuracy regarding model parameters, initial conditions, etc. does not affect the result. However, an adequate database is required.
DNN [63]	Data-driven approach, sub-category of ANN, with more hidden layers.	
Physics-aware neural network [64–66]	Data-driven approach where the neural network takes into account the structure of the distribution network.	Advanced, data-driven approach where the physics of the network are not overlooked, thus prohibiting the overfitting behavior of the algorithm. Yet, in this case too, an adequate database is required.
Hybrid [67,68]	Various possibilities, e.g., [67]: DNN-based DSSE, supported by random forest algorithm for topology identification. WLAV is used to ensure the robustness of the estimation.	Combination of the advantages of various sorts of algorithms at the cost of having a less simple methodology.

4. Auxiliary Algorithms

The main auxiliary algorithms that support the DSSE concern: (i) observability, (ii) bad data, and (iii) meter placement. The purpose of this Section is to review these algorithms.

4.1. Observability

The limited availability of real time data may challenge the observability of the distribution system. In order to provide the DSSE with enough data to converge and produce accurate results, pseudo-measurements are used [69]. Pseudo-measurements can be generated in a variety of ways. In literature, two main categories are distinguished, i.e., (i) probabilistic and statistical approaches and (ii) learning-based approaches [9,13], as presented in Table 3.

Following probabilistic and statistical approaches, the authors of [70–72] have used Gaussian Mixture Models (GMM) and Expectation Maximization (EM). The Gaussian mixture, $f(z|\gamma)$, comprises a weighted, finite sum of Gaussian probability density functions, $f(z|\mu_i, \Sigma_i)$, as presented in (18), where M_c is the number of mixture components. EM is used in order to obtain the parameters of the mixture components, i.e., weights, means, and variances, as presented in [73].

$$f(z|\gamma) = \sum_{i=1}^{M_c} w_i f(z|\mu_i, \Sigma_i) \tag{18}$$

Another way to obtain pseudo-measurements that falls into the category of probabilistic and statistical approaches is presented in [72] and involves the calculation of correlation coefficients between measurements obtained from the main substation and non-monitored electrical quantities and the application of regression analysis. The authors also compare the results provided by the correlation approach to the respective ones provided by the GMM.

When it comes to learning-based approaches, the popularity of DNN seems to be increased. For example, the authors of [74] have developed a DNN that produces pseudo-measurements, which are used as input in a typical WLS DSSE. It is reported that the computation time for the training of the DNN is approximately 10 min, using 17,520 sets of real power flow measurements and injections. Furthermore, the authors of [75] have developed a Parallel Distribution Processing network (PDP) for the generation of pseudo-measurements related to the load time-series of MV distribution networks. In a more complex manner, the authors of [76] propose the implementation of a nonlinear autoregressive exogenous (NARX) model for the efficient forecasting/estimation of loads.

Table 3. Auxiliary algorithms for the acquisition of pseudo-measurements [70–72,74–76].

Method	Description	Advantages and Disadvantages
GMM and EM [70–72]	Probabilistic and statistical approaches using Gaussian distributions, correlations, etc.	Mature algorithms, easy implementation, but with increased sensitivity and difficulties when it comes to large systems.
Correlation coefficients [72]		
DNN [74] PDP [75] NARX [76]	Solutions with learning-based approaches, using mostly neural networks.	Modern, advanced algorithms, but with database requirements.

4.2. Bad Data Detection

Bad data detection is of substantial importance for successfully estimating the system's true state. Bad data can stem from: (i) erroneous measuring data [77], (ii) system faults [78], and (iii) False Data Injection Attacks (FDIAs) [79–82]. Thus, the discovery of false data can also help DSOs identify possible attacks in their system.

The algorithms utilized for performing bad data detection can be classified into two main categories: (i) model-based detection algorithms and (ii) data-driven algorithms [83], as presented in Table 4.

Model-based detection algorithms are prediction methods that measure the similarity between the predicted states and the actual field measurements. In literature, model-based bad data detection algorithms are used extensively. In [84–89] the authors use the L_2-norm that is the Euclidean distance of the residual and compare it to a certain threshold as presented in (19), where measurement $\mathbf{z_i}$ is considered faulty when its Euclidean distance from its respective calculation upon the predicted state, $\mathbf{h}(\mathbf{x_i})$, is greater than the threshold, e.

$$\mathbf{P}_{L_2}(\mathbf{z_i}) = \begin{cases} 1, \text{ if } \|\mathbf{z_i} - \mathbf{h}(\mathbf{x_i})\|_2 > e \\ 0, \quad\quad\quad\quad \text{otherwise} \end{cases} \tag{19}$$

Similar to the previous one, the authors of [90–94] utilize the Largest Normalized Residual (LNR) test that is presented in (20), where, $\sigma_E = \text{diag}(\mathbf{E})$, is the residual error covariance matrix.

$$\mathbf{P}_{LNR}(\mathbf{z_i}) = \begin{cases} 1, \text{ if } \|\mathbf{z_i} - \mathbf{h}(\mathbf{x_i})/\sigma_E\|_\infty > e \\ 0, \quad\quad\quad\quad \text{otherwise} \end{cases} \tag{20}$$

Last but not least, in [78,95–97] the authors present the Chi-square test for the purpose of FDIA detection. Chi-squared is given by (21), where $J(\mathbf{x})$ is the cost function of the DSSE.

$$\mathbf{P}_{\chi^2}(\mathbf{z_i}) = \begin{cases} 1, \quad \text{if } J(\mathbf{x_i}) > e \\ 0, \quad \text{otherwise} \end{cases} \tag{21}$$

In certain applications, L_2-norm test outperformed the Chi-square test [78]. Finally, by combining the L_2-norm and the LNR tests, the authors of [98] achieved better results in FDIA detection than the cases of using only one detection test.

Unfortunately, it was mathematically proven by [79] that the model-based detection algorithms discussed above are vulnerable to attack vectors inserted from individuals that have prior knowledge of the system. These vectors are, in some cases, undetectable from the tests presented.

Data-driven methods for bad data detection can solve this issue. Supervised learning techniques, in which the ML models are trained with labeled data, are used extensively in literature. In more detail, the authors of [99] use Linear Regression (LR) to fit a measurement vector in the linear model. If the vector does not fit in the model, FDIA is detected. Another technique used is the Support Vector Machine (SVM), which is the most common ML technique for bad data detection. The authors of [96,100–103] utilize SVM classifiers for bad data and FDIA detection. Although they are extensively used, in most publications, SVMs play the role of the baseline algorithm for identifying whether the proposed ML method of the publication has a better performance. In [100], an ANN with one hidden layer that can automatically infer underlying physical relationships exploiting sensor data is shown. The authors of [104] train an ANN for forecasting current and voltage measurements and identifying whether FDIA occurs in the system. In [82], the RNNs' ability to exhibit temporal dynamic behavior, finding patterns in sequential data, is examined. Here the RNNs are utilized as sequence classifiers to detect potential measurement manipulation. The authors of [103] extend this work for detecting FDIAs in a subset of the system's nodes. More recently, the authors of [105] exploit the Convolutional Neural Networks' (CNNs) excellence in pattern recognition in FDIA detection. Similar to CNNs, another ML algorithm commonly used in image processing is employed in [102] for detecting FDIAs, called the Margin Setting Algorithm (MSA). MSA is compared with the SVM and ANN algorithms. Other supervised learning algorithms found in literature are the k-nearest neighbors (k-NN) and the extended nearest neighbor (ENN) algorithms [106].

Unsupervised learning, in which unlabeled data are provided for classification, is another ML technique used in bad data detection. In [107], a k-means clustering (KMC) algorithm is used. KMC's objective is to separate the unlabeled data into k different clusters. Another method similar to KMC is proposed in [108,109] and called the Fuzzy Clustering (FC) algorithm. The difference between FC and KMC is that in FC the boundaries of the clusters are overlapping, so a single sample could belong in multiple clusters.

Overall, data-driven algorithms for bad data detection are proven to be more accurate than their model-based counterparts. Although the model-based algorithms are simpler and more robust in most of the cases, their accuracy is a considerable tradeoff.

Table 4. Bad data detection methods [78,82,84–109].

Method	Description	Advantages and Disadvantages
Model-based [78,84–98]	L_2-norm [84–89], LNR [90–94], Chi-square [78,95–97], Combination [98]	Robust and simple methods. Not as accurate.
Data-driven [82,96,99–109]	LR [99], SVM [96,100–103], ANN [100,104], RNN [82,103], CNN [105], MSA [102], k-NN [106], ENN [106], KMC [107], FC [108,109]	Very accurate methods. Need large amounts of data.

4.3. Meter Placement

The meter placement in a distribution system constitutes a key decision problem. For this purpose, three main sorts of algorithms are distinguished: (i) rule-based, (ii) metaheuristic, and (iii) optimization with an objective function subjected to a set of constraints [110]. In more detail, rule-based algorithms comprise of a number of rules that lead to the easy and fast solution of a problem at the cost of providing non-optimal solutions. Metaheuristic algorithms are usually bio-inspired and more evolved than rule-based algorithms. Indicative examples are Particle Swarm Optimization (PSO), Tabu Search (TS), etc. [111]. By using these sort of algorithms, sufficiently good solutions can be obtained but global optimality is not guaranteed. However, the most recent trends indicate the use of optimizers, which aim to maximize/minimize an objective function, limited by constraints, in order to obtain the optimal solution [112]. The main idea is to model constraints such as energy balances, power flows, voltage limitations, etc., and create a space for possible/feasible decisions. The purpose is to find the optimal set of decisions that maximizes/minimizes the value of the objective function. These problems can be Mixed Integer Linear Programming (MILP), Mixed Integer Nonlinear Programming (MINLP), etc., depending on the nature of the problem [113].

In literature, all of the aforementioned strategies have been recruited for meter placement, as presented in Table 5. For example, a rule-based meter placement strategy is presented in [21]. The developed methodology is simple (but not optimal) and is applicable only to radial distribution networks. Its purpose is to reduce the overall meter cost. Metaheuristics have been used by the authors of [114–117]. More specifically, ref. [114] uses a Genetic Algorithm (GA) in order to ensure adequate accuracy at the lowest possible cost. In [115], binary PSO is implemented in order for the maximization of state estimation accuracy, limited by a maximum number of meters. Further, the authors of [116,117] use the fruit fly and TS metaheuristic algorithms, respectively, for the minimization of measurement units that can sustain observability. Regarding optimization approaches, ref. [19] proposes the use of Mixed Integer Semidefinite Programming (MISDP), which is a subfield of convex optimization, where the objective is the maximization of state estimation accuracy. The same objective is used in [118], approached with an optimization non-relaxed, Boolean convex model. The authors of [25] propose MISDP for the minimization of worst-case estimation errors.

Table 5. Meter placement strategies [19,21,25,114–118].

Method	Description	Advantages and Disadvantages
Rule-based [21]	Set of rules for meter placement with low cost.	Easy and fast algorithms, but not optimal.
Metaheuristic [114–117]	GA [114], PSO [115], fruit fly [116], TS [117], etc. for: (i) maximization of accuracy or, (ii) minimization of units while sustaining observability, etc.	Efficient bio-inspired algorithms which do not guarantee global optimal solutions.
Optimization [19,25,118]	MISDP, etc., usually for the maximization of accuracy.	Optimal, advanced algorithms, more demanding than the others.

It is evident that optimization algorithms constitute the most advanced approaches, while rule-based algorithms constitute the simplest and least optimal ones. This is a typical trade-off between more modern and more conventional approaches. Nevertheless, it is at the operator's discretion to choose the one that suits their purposes the best.

5. Technical Requirements and Applications

This Section is related to the practical and business-related aspects of DSSE, including technical requirements, potential applications, pilots, etc. The purpose is to showcase the components installed on the system, the computational resources, the applicability of the aforementioned algorithms, and the approaches that are usually followed in reality.

5.1. Technical Requirements

It is evident that the most important requirement for a DSSE algorithm is the availability of measurements. Installing metering devices on a system is a necessary step for monitoring its performance and achieve the desired observability [119]. For having an accurate and up to date representation of the network, DSSE needs to be applied at least once for every hour of the day, so new measurements are needed for every new application of the algorithm. For example, the authors of [120] apply the DSSE in 10 min intervals, and in [121] the algorithm is performed every 30 min. The most common measuring components found in distribution systems are Phasor Measurement Units (PMUs) and

Smart Meters (SM) [122–124]. PMUs offer synchronous power, voltage, and current measurements, as well as phase angles. SMs, on the other hand, record information such as energy consumption, voltage levels, current, and power factor. In specific distribution systems where only SMs exist and, consequently, no information concerning the phase angles, DSSE algorithms have to make assumptions about phase angle computation [125–127]. In addition, PMUs produce measurement samples in a higher frequency (reaching 30 kHz) than SMs (0.277 mHz–16.7 mHz) [13]. One can conclude that PMUs provide more sophisticated information than SMs. However, PMUs are not vastly used in distribution systems because of the high per unit costs. This demonstrates the need for developing algorithms for optimal PMU number and placement while lowering the costs [128].

The metering devices send measurement information to the Supervisory Control and Data Acquisition (SCADA) system under the IEC 60,870 communication protocol [129]. The SCADA is a control system architecture that contains computing devices, databases, and various interfaces that enable the real time monitoring and control of a distribution system [130]. Data-driven approaches of DSSE as well as algorithms associated with DSSE, such as forecasting models for pseudo-measurement creation and bad data detection, need large amounts of historical data to be trained and function properly. Thus, databases of SCADA, capable to perform DSSE, must be able to hold years of hourly or sub-hourly power, voltage, and current data [131].

In conclusion, a lot of resources are needed to perform DSSE successfully. Performing DSSE and evaluating the distribution system's state is paramount as RES penetration and the use of electrical cars is on the rise [132,133].

5.2. Applications

Having discussed all the basic theory and technical requirements regarding DSSE, this sub-Section is dedicated to applications as well as actual projects where DSSE has been implemented.

Regarding the applications of DSSE in distribution systems, research is mostly focused on RES penetration and "green" technologies, due to the ongoing energy transition. In this sense, it is quite common to find studies where DSSE is performed on distribution systems with high PV penetration. For example, the authors of [134] have performed DSSE in a distribution system with PVs using a typical WLS algorithm. Similar concepts have been studied by [51,135], with the use of a variation of WLAV and a variation of EKF, respectively. Moreover, ref. [136] has performed DSSE in a distribution system that includes not only PVs but also Wind Turbines (WTs). In this case, the DSSE utilizes a DNN. In a more interesting scenario, ref. [137] has performed DSSE in a hybrid AC/DC system including PVs, WTs and diesel generators. The estimation is performed with the use of WLS, supported by a DNN. Finally, in a slightly different direction, the authors of [50] perform DSSE in a distribution system that is used to charge Electric Vehicles (EVs). For this purpose, a variation of the EKF is deployed.

The various applications and methodologies found in literature are summarized in Table 6. It is noted that all sorts of algorithms that were discussed in sub-Section 3.2 have been used, meaning that there is no unique, optimal solution when it comes to actual implementation.

Table 6. Applications of DSSE [50,51,134–137].

Application	Approach
PV [51,134,135]	Model based, such as WLS [134], WLAV [135] but also FASE, such as EKF variations [51].
PV and WT [136]	Data-driven DSSE, with DNN [136].
PV, WT and diesel generator [137]	Model-based WLS DSSE coupled with DNN [137].
EV charging [50]	FASE DSSE, with a variation of EKF [50].

Furthermore, there are many research and innovation projects, pilot use cases, Horizon 2020 programs, etc., where DSSE is applied on real smart grids. A map of the most well-known cases is presented in Figure 5, indicating the sort of algorithm that was deployed. More specifically, in the context of EVOLVDSO, DSSE was implemented in a 74-node LV distribution system in Portugal and a 77-node LV distribution system in France [138]. In both cases, the overall approach was based on ANN. Furthermore, the French DSO, Enedis, applied WLS DSSE in a MV system called the VENTEEA smart grid demonstrator [120]. A WLS DSSE was also applied on a MV smart grid in the UK in the context of the Low Carbon London project [139]. The Swiss DSO applied WLS DSSE as well, in a LV 102-node distribution system located in Switzerland [140]. For the purpose of SuSTAINABLE project, a WLS DSSE was demonstrated in a MV/LV distribution system in Portugal [141]. The Slovenian Research Agency funded the development of an EKF-based DSSE in a 97-node LV distribution system in Slovenia [50]. In Denmark, a WLS DSSE supported by an ANN for the generation of pseudo-measurements was demonstrated in a MV 52-node distribution system [142]. The SmartSCADA project demonstrated a WLS DSSE in a LV distribution system in Germany [143]. The LV SCADA project developed an ANN DSSE and demonstrated it in a LV system in Portugal [144]. Finally, the largest contribution regarding actual DSSE application is the one of INTERPRETER, which is a Horizon 2020 program with three demo-sites, in Belgium, Spain, and Denmark, where WLS DSSE is implemented by the current research group [145,146].

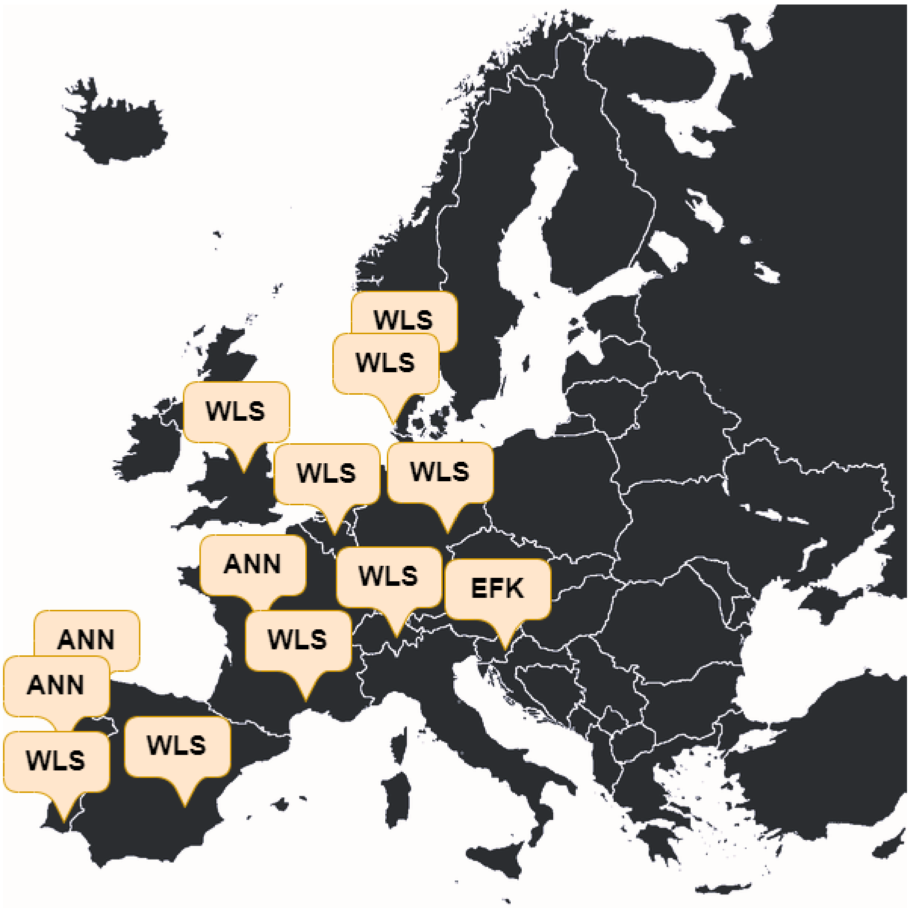

Figure 5. DSSE pilot project implementation [50,120,138–145].

Judging by the real-life applications, it can be concluded that the main option in DSSE remains WLS. This is mostly attributed to the fact that it constitutes an easy, fast, and tested-in-time algorithm.

6. Future Trends and Challenges

Taking the presented analysis into account, it is estimated that in the near future, DSSE will be implemented at a higher scale (instead of being mostly implemented in pilots) including large MV and LV distribution systems of all configurations, with a variety of DER, supporting advanced optimization algorithms that are nowadays utilized by the DSOs. In this sense, the DSOs are also expected to exploit the possible contribution of DSSE in the field of ancillary services which are derived from efficient monitoring, such as congestion management, black start, etc., thus further enhancing the cooperation between the DSOs and Transmission System Operators (TSOs) [147]. In addition, stability assessment–which is an important issue for power systems–could be related to DSSE algorithms for either stand-alone or connected systems, taking into account various aspects such as reduced order transfer function models of droop-controlled inverters via Jordan continued-fraction expansion [148,149], etc.

Furthermore, regarding the design of the DSSE, a future trend will probably be the more extended use of neural networks, which constitute a modern approach with an increasingly strong presence in the energy sector, either for state estimation per se or for pseudo-measurement generation and bad data detection [82].

However, all these benefits come with a few challenges. For example, a more standardized approach regarding the selection of state vectors, main and auxiliary algorithms, meter placement strategies, etc., needs to be established, promoting the easier implementation to future adopters, which is a major requirement for market penetration. Furthermore, it should be noted that the renovation of the distribution system, the installation of PMUs and SMs, etc., comes to a certain cost. Further, for the implementation of data-driven algorithms, large databases and advanced engineering expertise are required.

In the end, it can be concluded that, given the necessary requirements, DSSE may transform the passive, insufficiently monitored distribution system into an active, key part of the ongoing energy transition.

7. Conclusions

This paper presents a review of DSSE algorithms, aiming to provide an inclusive approach, from the purely theoretical up to the more business-related aspects. It highlights the usability of the DSSE and analyzes the main sorts of algorithms found in literature along with their advantages and disadvantages. In addition, it presents and compares the auxiliary algorithms that enhance the observability of the system, detect bad data, and guide the DSO towards the optimal meter placement strategies. Finally, it reviews the technical aspects and applications of DSSE, including requirements, potential use cases with enhanced RES penetration, and actual projects, thus providing a more practical analysis, paving the way towards market penetration. Overall, it is concluded that:

- WLS is the most commonly used algorithm, not only in theoretical development but also in actual applications.
- Data-driven algorithms challenge the dominance of model-based counterparts.
- DSSE can play an important role in the ongoing energy transition, but in order to do so in a large scale, standardized solutions should be established.

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