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Review

A Review of Distribution System State Estimation Methods and Their Applications in Power Systems

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Abstract: This paper summarizes a review of the distribution system state estimation (DSSE) methods, techniques, and their applications in power systems. In recent years, the implementation of a distributed generation has affected the behavior of the distribution networks. In order to improve the performance of the distribution networks, it is necessary to implement state estimation methods. As transmission networks and distribution networks are not similar due to variations in line parameters, buses, and measuring instruments, transmission state estimation cannot be implemented in distribution state estimation. So, some aspects, such as accuracy, computational time, and efficiency, should be taken into account when designing distribution state estimation methods. In this paper, the traditional methods are reviewed and analyzed with data-driven techniques in order to present the advantages and disadvantages of the various methods.

Keywords: distribution system state estimation; distribution phasor measurement units (D-PMU); model-based state estimation; data-based state estimation

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1. Introduction

Real-time measurements, power management, and the control of active distribution networks (ADNs) are difficult due to a smaller number of smart monitoring devices, the complex arrangements of distribution networks, and the inclusion of distributed generations [1]. State estimation methods are implemented to control the active distribution networks. The state estimation methods make a connection between measuring devices and control areas to observe each and every parameter in ADNs [1]. With the introduction of various power electronic devices, several power quality issues that are related to harmonics have arisen in practice [2]. State estimation methods were implemented long ago in the transmission network, but in distribution networks, the state estimation methods were not implemented directly [3]. Both transmission and distribution networks vary substantially in their respective cases. In [1], measuring devices were generally placed in a limited bus, where all buses were observed by measuring devices. The work in [4] showed that the distribution networks are mainly arranged in simple meshed networks, whereas the arrangement of transmission networks is complicated. The work in [5] shows that in a distribution network with a larger number of buses, the complex arrangement creates major differences when compared to the simple arrangement of the transmission networks. Work in [6] shows that the X/R ratio is small in the distribution systems. The length of the lines in power distribution systems is much shorter when compared to that of transmission systems, and hence, inductance has a minimum value, thereby the X/R ratio is small. The decoupled state estimation algorithm cannot be implemented in distribution systems. Therefore, suitable state estimation techniques must be implemented to establish the relationships between the monitoring devices and the control areas to determine the efficiency of ADNs [6]. Historically, the first distribution state estimation (DSSE) technique was recorded in the year 1990 when the SCADA system was presented [7]. DSSE plays a vital role in the control of ADNs because error identification and the discovery of bad data in the measurements are achievable through the DSSE data. The reliability of the state estimation depends on the data obtained from the measuring devices, which include SCADA, phasor measurement units (PMU) [8], and micro-PMUs (μPMU) [9].

In general, an electrical power system consists of three different systems, i.e., generation, transmission, and distribution. The generated power can be transmitted through transmission lines and deals with high voltages [10]. The consumers from households and industries which connect to the power substations, and the relevant voltages respective to the distribution systems, are very low, when compared to the transmission systems [11]. As the transmission system in a power grid has to deal with higher voltage ranges, in actual practice, these systems are given more priority and come with several control techniques, while in the case of distribution systems, the priorities and advances in the implementation of control technologies are relatively low [12]. During the past years, the implementation of the distributed generation in practice has required adequate control and monitoring of the distribution network, and the distribution management system was employed to achieve this goal. State estimation and control scheduling are two main parts of the distribution management system [13]. The concept of state estimation in a distribution network is currently the subject of ongoing research [14]. There is a great need to assess and monitor the generation of harmonics and their propagation [15]. In order to locate the sources of harmonic content and estimate the distribution of harmonic voltages in the distribution system, harmonic state estimation should be used in practice [16]. In an unobservable system, there may be observable islands as well as unobservable regions within the network [17]. Pseudo-measurements are not obtained from meters but are typically calculated using historical data or short-term load forecasting [18].

1.1. Motivation

In actual practice, Phasor measurement units (PMUs) have been widely deployed in electricity transmission systems and are used in major power system applications, such as phenomenon monitoring, protection, and control [19]. In a distribution network, when the set of available measurements is sufficient to calculate the state vector of the system, it is referred to as an observable system [20]. In order to monitor the power system in real-time, an observability test should be performed prior to the state estimation [21]. If a system is observable, then state estimation may be carried out straight away [22]. However, in an unobservable system, the states of the network can be estimated using pseudo measurements [23]. The objective of the power system state estimation is to monitor the power system or transmission/distributed networks [24].

The objective of state estimation is to obtain a computer model that accurately represents the current conditions of the power system. This paper mainly addresses a review of various methods of state estimation in a distributed power system network.

1.2. Survey of the Literature

Developments and challenges in distribution system state estimation, along with Cramer–Rao lower bound analysis, were proposed by the authors in [14]. One of the state estimation methods, i.e., the WLS method and fast heuristic optimization algorithm were discussed in [3]. A discussion on the optimal allocation of measuring units using a multi-objective evolutionary algorithm was proposed by the authors in [4]. A method of dynamic state estimation (DSE) optimization in accordance with back/forward sweep-based load flow calculations was discussed in paper [5]. A new PMU-DSSE formulation to estimate NEVs was proposed in [6].

Weighted least squares (WLS), the extended Kalman filter (EKF), the unscented Kalman filter (UKF), and invariant unscented Kalman filter (IUKF) methods were proposed in [7]. A new multi-grounded secure state estimation SSE-PMU-based formulation was presented in [8]. The branch current-based state estimation (BCSE) method was proposed in [9]. An analysis of the state estimation results for two different models of the network tested was presented in [10]. A hybrid algorithm of state estimation based on hybrid measurements was proposed by the authors in [11]. The concept of intelligent meter placement and a hybrid state estimator for the achievement of optimal operations was presented in [12]. A methodology for distribution state estimation using pseudo-measurements was proposed in [13]. A discussion on the linearized, three-phase distribution class SE algorithm for applications in smart distribution systems was presented in [14]. A discussion on the reliability of satisfying accuracy constraints (RSACs) was presented in [15]. A mathematical model of an electricity-gas interconnected integrated energy system and its state estimation method was proposed in [15]. An ANN-based load forecasting model was proposed to improve the distribution system state estimation accuracy [16]. The PASE method was proposed to improve the accuracy of the current one, using EnKF [17]. An information fusion estimation approach was presented for distributed network systems with data random transmission time delays and lost and disordered packets [18].

An approach using branch currents as state variables and an explanation regarding the weakly meshed distribution system was proposed in [19]. An analysis of low-voltage power distribution systems (PDS) from the SE perspective was proposed in [20]. A bibliographic review of different methods used for state estimation in an electric power distribution network was presented [21]. A study of different types of topology changes in distribution systems in the initial stages was discussed in [22]. SE with different measurements based on the WLS approach was proposed in [23]. The effect of synchro phasor measurements from multiple PMUs on the multi-area state estimator (MASE) in the distribution grid (DG) was discussed in [24].

The estimation of network parameters is described in [25]. A new algorithm that belonged to the group of harmonic state estimation (HSEs) was proposed in [26]. A study of the application of error covariance in DSE by using the augmented complex Kalman filter (ACKF) was proposed in [27]. A high-performance DSSE method that can handle the PMUs along with all the measurement types commonly used in industrial DSSE was proposed in [28]. A comparison between the branch-current-based distribution system state estimation in polar and rectangular coordinates was presented by the authors in [29]. The singular value decomposition (SVD) method and Principal component analysis (PCA) algorithm were proposed in [30]. A discussion on predictive variables was proposed in [31]. A detailed review of DSSE techniques was proposed in [32]. A numerical method to identify the topology and estimation of line parameters without the information of voltage angles was proposed in [33]. A PMU-based algorithm was discussed in [34]. An empirical wavelet transform based on D-PMU was discussed in [35]. IEEE 14-bus and 33-bus distribution systems were tested by the proposed heuristic algorithm [36]. The Monte Carlo simulation was used in [37]. A heuristic algorithm for optimizing the deployment of real-time measuring points was discussed in [38]. A novel PMU-DSSE formulation was proposed in [39]. The performance analysis of WLS (static estimator), EKF, and UKF (dynamic state estimators) was proposed in [40]. Earthing resistances in the optimization problem were studied in [41]. A branch current-based state estimation was discussed in [42]. Performance analysis of two different models of the grid over the state estimation results was conducted in [43]. A hybrid algorithm of state estimation was explained in [44]. The placement of a smart meter and hybrid state estimator was proposed in [45]. The evaluation of the proposed algorithm could be performed by a calculation of the mean percentage errors of the estimated pseudo measurements [46]. A state estimation algorithm was proposed in smart distribution systems [44]. The reliability of satisfying accuracy constraints was proposed in [47]. A mathematical model and state estimation method of the electricity-gas interconnected integrated energy system were proposed in [48]. An artificial neural network-based load forecasting model to improve the accuracy of DSSE was proposed in [49]. The PASE method with ensemble Kalman filter (EnKF) to improve accuracy was proposed in [33]. A novel information fusion estimation methodology for distributed networked systems was proposed in [50]. The calculations for the weak meshed distribution system were presented in [51]. Low voltage power distribution systems in the state estimation domain were analyzed in [52]. A study of various topological changes in distributed energy systems was proposed in [53]. State estimation based on the WLS technique was proposed in [54]. Novel two-step multi-area state estimation (MASE) algorithm testing was proposed in [55]. A methodology for estimating network parameters was discussed in [56]. A novel power system-robust hybrid state estimation (PS-RHSE) algorithm was proposed in [57]. An augmented complex Kalman filter (ACKF) was proposed in [38]. Hachtel's matrix method was presented in [58]. Micro-PMU measurements were presented in [59]. The singular value decomposition (SVD) method and Principal component analysis (PCA) algorithm were proposed in [60]. The state of risk in a distribution network was realized in [61]. A WLS algorithm based on DSSE was presented in [62]. The identification of topology and estimation of line parameters were performed by introducing a numerical method [63]. Line parameters in a three-phase distribution network were estimated by using a PMU-based algorithm [64]. A pre-filtering method was proposed to avoid the errors which arose due to the presence of spectral leakage [65].

The remainder of the paper is organized as follows. The D-PMU is discussed in Section 2; the distribution system state estimation is discussed in Section 3. The mathematical formulation of the distribution system state estimation and a summary table discussing the proposed topics and contributions made by various authors in all the references added in this paper are presented in Section 4, followed by the Conclusions and Future scope in Section 5.

2. Distribution Phasor Measurement Units

There is a need to develop better and more accurate real-time distribution level PMUs [66]. The outline is mainly focused on the basic structure of PMU s, the key characteristics of distribution level signals, and the discussion of a new D-PMU scheme [67]. The basic diagram of a conventional phasor measurement unit (PMU) is shown in Figure 1.

The voltage or current signals obtained from CTs and PTs are considered analog input. They are then sent to the sampler for the purpose of sampling. From the Nyquist sampling theorem, it follows that the sampling frequency has to be greater than or equal to twice the maximum frequency component available in the signal. The data sampled in this way is fed into a microprocessor, where the phasor estimation technique is deployed [68]. The GPS receiver provides a UTC signal that serves two purposes, (i) it helps in synchronizing the sampled data across all the PMUs, (ii) it also provides a timestamp in the PMU output. Finally, the output of the PMU is expected to be the magnitude of the voltage and its phase angle, the frequency, the rate of change in frequency, and the timestamp [69]. This information is transmitted to a central place known as the phasor data concentrator (PDC) [70]. The major difference between the PMU and various signal parameter estimators is the phasor measurement technique in the PMU, which conforms to particular synchro phasor standards [71]. There are three options as far as phasor estimation techniques are concerned. These include (a) time-domain state estimation techniques, (b) frequency-domain state estimation techniques, and (c) time-frequency-domain state estimation techniques [72].

The time domain state estimation techniques, such as the weighted least squares (WLS) technique, cannot provide data on the available frequency component in the signal [73]. Most time, domain systems require a matrix inversion that creates a computational burden, and sometimes, it may not be possible to obtain the matrix inversion, i.e., it may be a single matrix [74]. The frequency domain state estimation techniques, such as the discrete

Fourier transform (DFT)-based techniques, also have some drawbacks [75]. Once a signal is transformed from the time domain to the frequency domain, time information is lost [67].

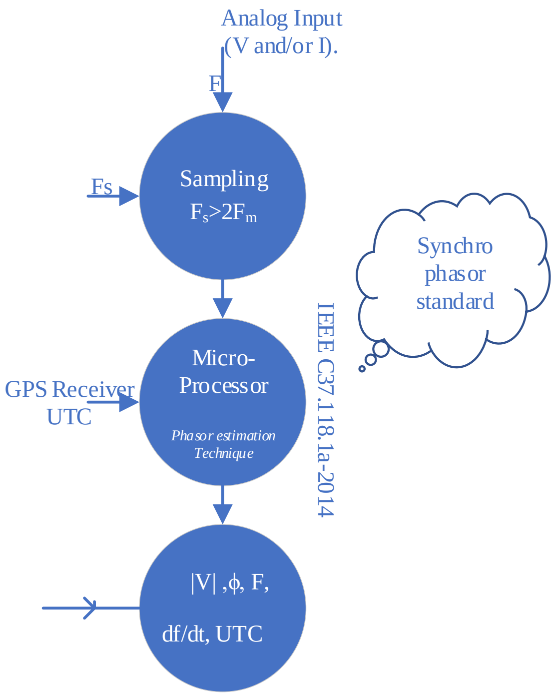

Figure 1. Conventional phasor measurement unit (PMU).

They are very sensitive to frequency deviations. The outcomes may be abnormal due to spectral leakage problems [76]. Therefore, it is better to consider time and frequency-based state estimation techniques, such as the short-time Fourier transform (STFT)-based method or the wavelet-based method [77]. Finally, the physical measurement unit (PMU) has a sinusoidal input, and the GPS satellite provides a time stamp and synchronizes the sampling to the PMU. Based on the algorithm present in the PMU, a synchro phasor data packet can be obtained and sent to the PDC [78].

According to the IEEE standards, there are two types of PMUs. These are P(protection)-class and M(monitor)-class. M-class PMUs are used for wide-area monitoring applications, and P-class PMUs are used for wide-area protection and control applications [79]. The M-class PMUs place more emphasis on accuracy, while the P-class PMUs can be used for a faster response rather than accuracy [80]. The accuracy or efficacy of the phasor estimator can be checked based on the total vector error (TVE). For an M-class PMU, the TVE should be less than 1%, and for a P-class PMU, the TVE should be relaxed up to 3% [81]. Under no circumstances should the TVE be greater than 3%. PMU algorithms must be tested under stringent conditions such as harmonics, signal modulation, Out-of-band interference (OOB), frequency deviation, frequency ramp, etc. There are several other desired characteristics for the distribution level or micro-PMUs [82]. Distribution level signals consist of more bad data, and therefore, more noise must be considered. Since there is little power flowing in the distribution level, the angle phasor estimation should be highly accurate [25]. The estimation time should be very fast because of the rapidly changing dynamics due to RES [74,75]. Finally, D-PMUs should be able to detect various PQ events in the signal [83]. An empirical wavelet transform-based D-PMU, which is a time and frequency-based technique, is shown in Figure 2.

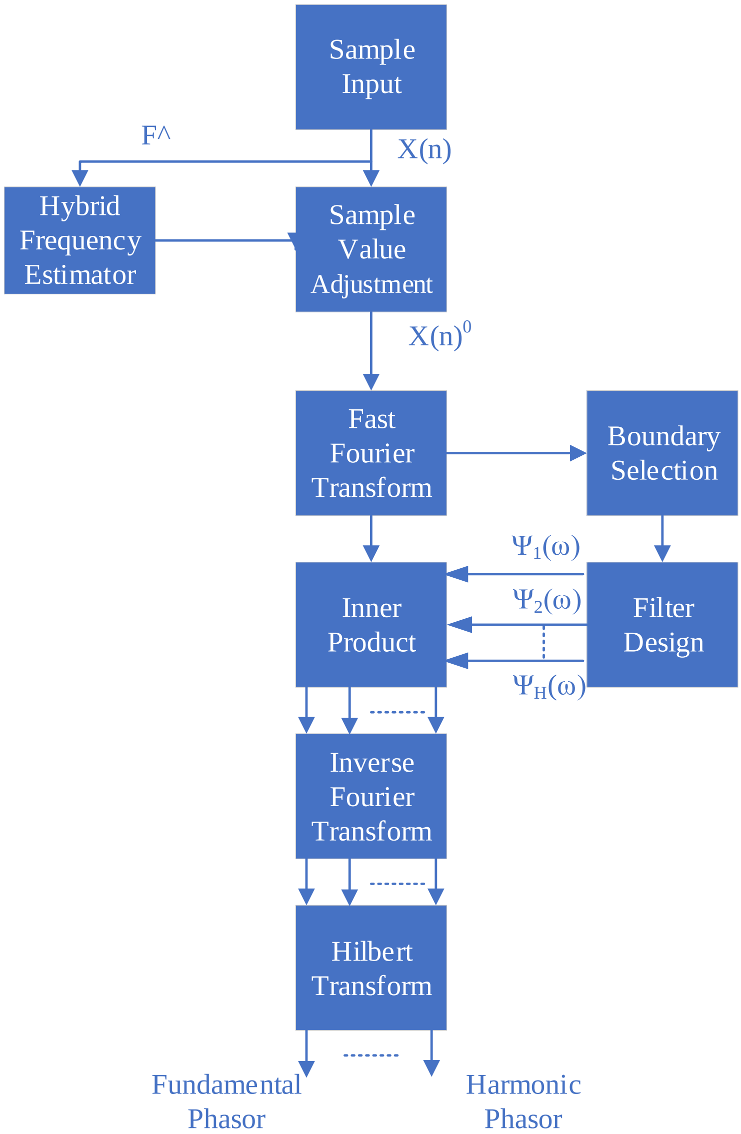

Figure 2. Example of empirical wavelet transform empirical wavelet transform-based D-PMU.

The sampled input is passed through the frequency estimator. Since, in most cases, it is off the nominal frequency in the distribution network, it is passed through a sample value adjustment (SVA). This is an interpolation technique to dispose of the nominal effect of the frequency [26]. The clean signal is sent to the FFT to obtain the number of dominant frequency components present in the signal [84]. Based on this, the boundaries are selected, and the filter coefficients are found to design the filter [85]. In order to have the estimated phasor, the filter is passed through a Hilbert transform to obtain orthogonal components [27].

3. Distribution System State Estimation

State estimation [4] is nothing more than the estimation of the states of the distribution network, as in the case of the transmission network. The voltage magnitude and the phase angle at every node of the grid are considered states. If the values of these states are known, we can determine the value of power as well as the direction of power flow at every branch [28]. The three phases in a distribution system network are not balanced as in the case of the transmission system network. Additionally, these systems employ radial topology and there are many other aspects present that differentiate between the estimation topology of the distribution system and the transmission system [5,8]. The current operating state of the system can be identified with the help of state estimators, which can facilitate the monitoring of operational constraints on quantities in an efficient manner [29].

The state estimation includes the following main functions: [1] topology processor, observability analysis, state estimation solution, bad data processing, and parameter and structural error processing [41]. The topology processor helps to collect data regarding the status of CBs and switches [30]. The observability analysis is used to determine whether the solution resulting from state estimation could be obtained or not with the available set of measurements [31]. States in the unobservable regions of the network can be estimated by adding additional measurements using "pseudo measurements". The best estimates for transformer taps, line flows, loads, and generator outputs can be determined using the state estimation solution [32]. Bad data processing always helps to detect errors in the set of measurements [86]. The estimation of several network parameters, detection of structural errors in the network configurations, and identification of the status of erroneous breakers can be conducted by parameter and structural error processing [2].

When there is a discussion on topology estimation, there is an assumption that we actually consider in practice, and hence all state estimation methods, in general, are based on the assumption that the system network is available with an accurate system model [33]. However, in actual practice, in the case of distribution systems, sometimes the states of the switching mechanism that are used may not be known. Under such conditions, the system network experiences some topological errors, and, in general, topology processing algorithms play a role in detecting these errors in an efficient and accurate manner [34]. The network topology processor, in actual practice, is used to determine the connectivity of the electrical network and the location of the metering devices in the system [35]. There are several methods of state estimation, and, of these, the WLS method is given priority, although the main disadvantage of this method is that it has slow convergence [87]. The orthogonal transformation method (Q-R method) directly performs the Q-R decomposition of the Jacobian matrix [33].

The determination of state estimation and the existence of bad data can be performed after the completion of topology processing [88]. In practice, to perform state estimation in a transmission network, the amount of measured data available is very abundant, but in a distribution system network, it is very low. Therefore, in order to make state estimation programs work more efficiently, the use of pseudo-measurements should be considered [13]. Pseudo measurements can be added by using historical data regarding loads of feeders and distribution transformers, whereby Pseudo measurements using historical data always increase the over-abundance of data for state estimations [78,89,90]. There are many methods available for the modeling of loads in order to improve the accuracy of pseudo measurements for state estimations [65]. Possible measurements include real power flow, reactive power flow, current flow magnitude, voltage magnitude, injected real power, and injected reactive power [19,91].

Modern distribution system algorithms and tools are constantly improving, but their functionality is only as good as the utility model of their grid. In conventional methods, compiling records of installations through manual data entry can be error-prone, and these techniques have little validation with measurements [92]. These problems can be overcome by using data-driven modeling. It uses advanced metering infrastructure (AMI) data and validates system models. These techniques have granular, high accuracy, high resolution, and fidelity. The model dynamically adjusts itself and updates itself automatically based on the system conditions. It assumes knowledge regarding the possible network topology configurations and distribution line resistance-to-reactance ratios; the framework for identifying the true network topology configuration and the corresponding line parameters uses only a few measurements of voltage magnitudes and power injections. The data-driven framework is intrinsically adaptive to changes in system conditions, such as unknown topology reconfiguration [93].

4. Mathematical Formulation of Distribution System State Estimation

In any state estimation exercise, the number of measurements is always taken to be randomly large when compared to the number of states to be estimated, and the below equation has been taken from [14,15,24].

If m is the number of measurements and n is the number of states, then always $m > n$. If any bad data are found during the estimation, then the number of measurements is reduced. The estimation of the state means is conducted by estimating the voltage and phase angles (represented by V_i and θ_i)

$$\begin{array}{l} Let \\ \overline{x} = \begin{bmatrix} \overline{v}^T & \overline{\theta}^T \end{bmatrix} \\ where \\ \overline{v}^T = \begin{bmatrix} V_1 & V_2 \ldots\ldots\ldots & V_N \end{bmatrix} \\ \overline{\theta}^T = \begin{bmatrix} \theta_2 & \theta_3 \ldots\ldots\ldots & \theta_N \end{bmatrix} \\ \begin{bmatrix} \overline{v}^T & \overline{\theta}^T \end{bmatrix} = \begin{bmatrix} V_1 & V_2 \ldots\ldots\ldots & V_N \theta_2 & \theta_3 \ldots\ldots\ldots & \theta_N \end{bmatrix} \\ \begin{bmatrix} \overline{v}^T & \overline{\theta}^T \end{bmatrix}^T = \begin{bmatrix} V_1 & V_2 \ldots\ldots\ldots & V_N \theta_2 & \theta_3 \ldots\ldots\ldots & \theta_N \end{bmatrix}^T \end{array}, \quad (1)$$

Hence, $\overline{x}$ is a column vector with a dimension of $(2N - 1)$.

The measurement vector for a simple DC circuit is given by:

$$\overline{Z} = H\overline{x} + \overline{e}, \quad (2)$$

where, H is the constant matrix.

If P_i is the injected real power at bus "i" and Q_i is an injective reactive power at bus "i", then

$$P_i = \sum_{k=1}^{N} V_i V_k Y_{ik} cos(\theta_i - \theta_k - \alpha_{ik}), \quad (3)$$

$$Q_i = \sum_{k=1}^{N} V_i V_k Y_{ik} sin(\theta_i - \theta_k - \alpha_{ik}). \quad (4)$$

Equations (1) and (2) are non-linear equations and can be written as follows.

$$P_i = P_i(\overline{V}, \overline{\theta}), \quad (5)$$

$$Q_i = Q_i(\overline{V}, \overline{\theta}). \quad (6)$$

In general, in power system state estimation, the measured quantities are non-linear functions of state variables. Since the measured quantities are non-linear functions, the mathematical description is as follows:

$$\left\{ \begin{array}{c} Z_1 = h_1(x) + e_1 \\ Z_2 = h_2(x) + e_2 \\ . \\ . \\ Z_m = h_m(x) + e_m \end{array} \right\}, \quad (7)$$

The vector x is represented by a vector and can be written as

$$\overline{x} = \begin{bmatrix} x_1 & x_2 \ldots\ldots\ldots & x_n \end{bmatrix}^T. \quad (8)$$

After substituting Equation (8) into Equation (7) the measurement vector has the following form

$$\left\{\begin{array}{c} \overline{Z}_1 = h_1(\; x_1 \quad x_2 \ldots\ldots\ldots \quad x_n \;) + e_1 \\ \overline{Z}_2 = h_2(\; x_1 \quad x_2 \ldots\ldots\ldots \quad x_n \;) + e_2 \\ . \\ . \\ \overline{Z}_m = h_m(\; x_1 \quad x_2 \ldots\ldots\ldots \quad x_n \;) + e_m \end{array}\right\}. \tag{9}$$

Equation (9) represents the general measurement model of the distribution system state estimation, and the functions used in this model are essentially non-linear.

Let us now consider a certain initial vector, $\overline{x}^{(0)} = \left[x_1{}^{(0)} x_2{}^{(0)} \ldots\ldots \quad x_n{}^{(0)}\right]^T$ and with this initial assumption, the Taylor series expansion up to the first order is applied. The set of components of the measurement vector has the following form:

$$\left\{\begin{array}{c} \overline{Z}_1 = h_1(x_1{}^{(0)} x_2{}^{(0)} \ldots\ldots \quad x_n{}^{(0)}) + \frac{\partial h_1}{\partial x_1}\Delta x_1 + \frac{\partial h_1}{\partial x_2}\Delta x_2 + \ldots\ldots \frac{\partial h_1}{\partial x_n}\Delta x_n + e_1 \\ \overline{Z}_2 = h_2(x_1{}^{(0)} x_2{}^{(0)} \ldots\ldots \quad x_n{}^{(0)}) + \frac{\partial h_1}{\partial x_1}\Delta x_1 + \frac{\partial h_2}{\partial x_2}\Delta x_1 + \ldots\ldots \frac{\partial h_n}{\partial x_n}\Delta x_1 + e_2 \\ . \\ . \\ \overline{Z}_m = h_m(x_1{}^{(0)} x_2{}^{(0)} \ldots\ldots \quad x_n{}^{(0)}) + \frac{\partial h_m}{\partial x_1}\Delta x_1 + \frac{\partial h_m}{\partial x_2}\Delta x_1 + \ldots\ldots \frac{\partial h_m}{\partial x_n}\Delta x_1 + e_m \end{array}\right\} \tag{10}$$

Next, Equation (10) can be written as:

$$\left\{\begin{array}{c} \overline{Z}_1 - h_1(\overline{x}^{(0)}) = \frac{\partial h_1}{\partial x_1}\Delta x_1 + \frac{\partial h_1}{\partial x_2}\Delta x_2 + \ldots\ldots \frac{\partial h_1}{\partial x_n}\Delta x_n + e_1 \\ \overline{Z}_2 - h_2(\overline{x}^{(0)}) = \frac{\partial h_2}{\partial x_1}\Delta x_1 + \frac{\partial h_2}{\partial x_2}\Delta x_1 + \ldots\ldots \frac{\partial h_n}{\partial x_n}\Delta x_1 + e_2 \\ . \\ . \\ \overline{Z}_m - h_m(\overline{x}^{(0)}) = \frac{\partial h_m}{\partial x_1}\Delta x_1 + \frac{\partial h_m}{\partial x_2}\Delta x_1 + \ldots\ldots \frac{\partial h_m}{\partial x_n}\Delta x_1 + e_m \end{array}\right\}. \tag{11}$$

Taking into account the matrix transformation, the set of Equation (11) can be replaced by:

$$\begin{bmatrix} \overline{Z}_1 - h_1(\overline{x}^{(0)} \\ \overline{Z}_2 - h_2(\overline{x}^{(0)}) \\ . \\ . \\ \overline{Z}_m - h_m(\overline{x}^{(0)}) \end{bmatrix} = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & . & . & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & . & . & \frac{\partial h_2}{\partial x_n} \\ . \; . & . & . & . & \\ . & . & . & . & \\ \frac{\partial h_m}{\partial x_1} & \frac{\partial h_m}{\partial x_2} & . & . & \frac{\partial h_m}{\partial x_n} \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ . \\ . \\ \Delta x_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ . \\ . \\ e_n \end{bmatrix} \tag{12}$$

Equation (11) can be written as:

$$\begin{bmatrix} \Delta Z_1 \\ \Delta Z_2 \\ . \\ . \\ \Delta Z_n \end{bmatrix} = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & . & . & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & . & . & \frac{\partial h_2}{\partial x_n} \\ . \; . & . & . & . & \\ . & . & . & . & \\ \frac{\partial h_m}{\partial x_1} & \frac{\partial h_m}{\partial x_2} & . & . & \frac{\partial h_m}{\partial x_n} \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ . \\ . \\ \Delta x_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ . \\ . \\ e_n \end{bmatrix}, \tag{13}$$

where $\Delta Z_k = \overline{Z}_k - h_k\left(\overline{x}^{(0)}\right)$, $k = 1, 2, \ldots, n$.

The Jacobian matrix of the measurement vector is:

$$H\overline{x}(0) = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & . & . & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & . & . & \frac{\partial h_2}{\partial x_n} \\ . & . & . & . & \\ . & . & . & . & \\ \frac{\partial h_m}{\partial x_1} & \frac{\partial h_m}{\partial x_2} & . & . & \frac{\partial h_m}{\partial x_n} \end{bmatrix}. \tag{14}$$

The linearized measurement model is represented by:

$$\Delta\overline{Z} = H\overline{x}(0)\Delta\overline{x} + \overline{e}, \tag{15}$$

where, $\Delta x = [\Delta x_1 \quad \Delta x_2 \quad \Delta x_3 \ldots\ldots \Delta x_n]^T$ is the vector of increments and $H\overline{x}(0)$ is the Jacobian matrix evaluated at initial iteration $\overline{x}$=$\overline{x}^{(0)}$,$e = [e_1 \quad e_2 \quad e_3 \ldots\ldots e_n]^T$. [94].

The power systems should be continuously subjected to a monitoring or observation process, which helps to keep the operational limits under control, and in order to achieve this, state estimators are used. Furthermore, state estimators can be operated as a filter against some incorrect measurements [94].

A detailed summary of the contributions made by various authors is shown in Table 1.

Table 1. Summary of various state estimation methods made by different authors.

Ref. No.	Authors	Proposed Work/Technique/Method
[2]	Louis	Investigation of error covariance in DSE with the help of an augmented complex Kalman filter (ACKF).
[14]	G. Wang	The Cramer–Rao is lower bound in order to indicate the unbiased estimator's performance was proposed.
[75]	Carquex, Rosenberg and Bhattacharya	Firstly, in order to improve the accuracy, the PASE method with EnKF has been proposed.
[36]	Jiao	IEEE 14-bus and 33-bus distribution systems were tested by the proposed heuristic algorithm and indicated an acceleration of up to 50% inaccuracy
[37]	Hassannejad Marzouni, Zakariazadeh and Siano	In order to show the exact robustness of the method proposed by the authors, some conditions have to be developed, and, to achieve this, the Monte Carlo simulation is used
[38]	Švenda, Strezoski and Kanjuh	Real-time measuring points were optimized to improve accuracy and, for this purpose, the authors proposed a heuristic algorithm thus optimizing the deployment of the real-time measurement points
[39]	De Oliveira-De Jesus, Celeita and Ramos	The estimation of NEVs, a novel PMU-DSSE formulation, was proposed.
[40]	Ahmad	The performance analysis of WLS (static estimator), as well as EKF and UKF (dynamic state estimators), was proposed.
[41]	Deoliveira-Dejesus	Earthing resistances are incorporated as both state variables and field measurements in the optimization problem.
[42]	Baran and McDermott	The operating condition can be estimated using the BCSE method, i.e., branch current-based state estimation.
[43]	Chusovitin, Polyakov and Pazderin	Performance analysis of two different models of the grid with respect to the state estimation results.
[44]	S. Wang and Liu	The advantages of the proposed hybrid algorithm of the state estimation were clarified in the numerical simulation process using the IEEE 13-bus system.
[45]	Ramesh	Two aspects, i.e., of a smart meter placement and hybrid state estimator were proposed and an algorithm was formulated and verified with both the IEEE and the TNEB benchmark systems.
[46]	Soares	The proposed technique was evaluated by calculating the mean percentage errors of the estimated pseudo measurements.
[35]	Haughton and Heydt	A state estimation algorithm in smart distribution systems was proposed.
[47]	Gholami	The reliability of satisfying accuracy constraints was postulated
[48]	Zhou	A study of the mathematical model and methods of state estimation of the electricity-gas interconnected integrated energy system was proposed; in addition to this, distribution state estimation calculations were formulated.

Table 1. *Cont.*

Ref. No.	Authors	Proposed Work/Technique/Method
[49]	Carcangiu	In order to improve the accuracy of distribution state estimation, a load forecasting model based on an artificial neural network was proposed.
[55]	Carquex, Rosenberg and Bhattacharya	First, in order to improve accuracy, the PASE method with EnKF was proposed
[50]	L. Liu	A novel information fusion estimation methodology for distributed networked systems.
[51]	Khan, Rehman, and Ahmad	A methodology where branch currents were considered to be state variables was proposed and working for a weak meshed distribution system was presented.
[52]	Da Silva	A low-voltage power distribution system in the state estimation domain was analyzed
[12]	Prasad and Kumar	A detailed discussion of state estimation methods, computational intelligence techniques, and heuristic algorithms for state estimation was proposed.
[53]	Zamani and Baran	A study of various topological changes in distributed energy systems were proposed
[54]	M. Liu	State estimation based on the WLS technique was proposed. Analysis of the various effects of installing AMI and PMU for the estimation of accuracy for the DSSE was proposed.
[55]	Fatima	Testing and verification of a novel two-step MASE algorithm was proposed.
[56]	Logic and Heydt	The methodology for estimating network parameters was discussed.
[57]	Dubey, Chakrabarti and Terzija	A novel PS-RHSE algorithm was proposed.
[58]	Dzafic, Jabr and Hrnjic	A high-performance DSSE method was proposed and analyzed. In addition to this, Hachtel's matrix method was presented.
[59]	Almutairi, Miao and Fan	A comparative analysis of the branch current-based DSSE in polar and rectangular coordinates was presented in addition to Micro-PMU measurements.
[60]	Radhoush, Shabaninia and Lin	The singular value decomposition (SVD) method and Principal component analysis (PCA) algorithm were proposed.
[61]	Jia, Liu, Tang and Zhang	Analysis of the state of risk in the distribution network was conducted, and safety-related indicators for the distribution network were calculated based on the state estimation results.
[62]	Majdoub	A detailed overview of the DSSE-based WLS algorithm and evaluation algorithms were presented.
[63]	Zhang, Wang, Weng and Zhang	Topology identification and estimation of line parameters were conducted by introducing a numerical method.
[64]	Puddu	The line parameters in a three-phase distribution network were estimated using a PMU-based algorithm, and the method of isolating systematic errors from random errors was presented.
[65]	Chauhan, Reddy and Sodhi	A prefiltering method was proposed in order to avoid the errors which arise due to the presence of spectral leakage.
[95]	Dechang Yang	A data-driven optimization approach for a dynamic reconfiguration of the distribution network was proposed. The main advantage of the data-driven optimization approach is that it uses historical data to obtain the optimal control strategy.
[92]	Hasala Dharmawardena	A distributed data-driven framework based on cellular computational networks (CCN) for power distribution system modeling was presented.
[93]	Nayara Aguiar, Vijay Gupta	A data-driven technique for the detection of incidents relevant to the operation of energy storage systems in distribution networks was proposed.
[96]	Matthew J. Reno	The creation of a fundamental change from models based on manual entry to data-driven modeling.
[97]	H. Xu, A. D. Domínguez-García, V. V. Veeravalli and P. W. Sauer	Development of a data-driven framework for controlling distributed energy resources (DERs) in a balanced radial power distribution system.
[98]	Rizwan, M.; Waseem, M.; Liaqat, R.; Sajjad, I.A.	Selective particle swarm optimization technique-based model was formulated to reduce distribution loss by optimal sizing and placing of DGs.

The advantages, disadvantages, and applications have been presented in Table 2.

Table 2. Advantages, disadvantages, and applications of various DSSE methods.

DSSE Method	Advantages	Disadvantages	Applications
WLS	Simple and fast	Sensitivity issues	Solar PV systems
LMS	high robustness, less sensitive to data	high computational cost, huge memory usage	PV systems and wind turbine systems
EKF	used for non-linear systems	Huge system complexity	Solar PV systems, EV charging
ANN	Good sensitivity and more accuracy	Proper data base is recommended	PV systems and wind turbine, systems
UKF	Used for non-linear systems	Less recommendation method	PV and Wind

5. Conclusions and Future Scope

This paper discusses a review analysis of distribution system state estimation (DSSE). In addition to this, D-PMU and its block diagram were explained. The concept of distribution state estimation methods and applications to distribution systems were also discussed in detail. According to the study, the majority of the authors mostly focused on modified state estimation methods to improve efficiency. The mathematical analysis of DSSE has been presented. The weighted least squares method was found to be more efficient when compared to other methods in terms of various factors such as robustness, accuracy, and time of computation. The scope of this review is setting up a wide range of platforms for future studies to realize the vision of smarter grids. According to the study, most authors have focused on modified state estimation methods aimed at improving efficiency. A mathematical analysis of DSSE was presented. The scope of this review is to set a broad platform for future studies to realize the vision of smarter grids. In the future, algorithms based on machine learning will be used to solve the DSSE problems. In our future papers, we aim to explore how various types of distributed generations, such as wind power plants, small-scale hydropower plants, and energy storage in distribution systems, could change the performance of the proposed approach.

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