A Review on Distribution System State Estimation

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***Abstract*—Transition to a sustainable energy environment results in aggregated generator and load dynamics in the distribution network. State estimation is a key function in building adequate network models for online monitoring and analyzes. The requirements of distribution system state estimation (DSSE) is becoming stringent because of the needs of new system modeling and operation practices associated with integration of distributed energy resources and the adoption of advanced technologies in distribution network. This paper summarizes the state-of-the-art technology, major hurdles, and challenges in DSSE development. The opportunities, paradigm shift, and future research directions that could facilitate the need of DSSE are discussed.**

***Index Terms*—Distribution network analysis, distribution system state estimation, renewable integration, smart grid, system operation and planning.**

I. Introduction

POWER system state estimation (SE) is "a data processing algorithm for converting redundant meter readings and other available information into an estimate of the state of an electric power system." After more than four decades of development, sufficient measurement redundancy in the transmission network has enabled the system observability and bad data processing for SE. Assuming balanced (positive sequence) mesh operation, circuit breaker status, on-line tap changer position and analog measurements, including real and reactive power flows, bus power injections, voltages and phasor measurements, are utilized in Transmission System SE (TSSE) which usually uses voltage magnitude and phase angle as state variables. TSSE is a basic tool in power control center and is executed along with the security assessment functions every 2 minutes or less to ensure secure system operations.

Computers have been used since the 1960s for on-line load flow analyses of primary distribution systems based on estimated load models [1], [3]. Books authored by Kersting [4] and Gonen [5] provide effective distribution system modeling and analysis methods. Distribution networks under radial and weakly-meshed operations have numerous unbalanced three-phase branches with high r/x ratios and unbalanced loads separated by short distances. Algorithms developed for TSSE need to be adapted to be suitable for Distribution System State Estimation (DSSE). In the distribution network, real-time measurements (mostly current and voltage magnitudes) are limited and network observability is not achieved unless pseudo measurements are used. Despite low measurement coverage, pioneer works on DSSE were conducted in 1990s [6]–[11]. Various estimators, adopting branch-current or node-voltage variables in polar or rectangular forms as state variables were tested. DSSE algorithms can further differ depending on the measurements types and how they are incorporated into the estimator model. Thus far, due to the lack of observability downstream the substations, only a limited number of utility companies have implemented DSSE [12]–[15]. Field tests indicate that DSSE is feasible and sufficiently accurate for the purpose of real-time management of distribution networks. Contributions of real-time measurements and estimation verification and calibration have significant impact on the quality of the estimation results [13], [14]. One of the difficult tasks in DSSE deployment is related to the tuning of measurement weights [15].

Complex interactions in distribution network, e.g., Distributed Energy Resources (DER) integrations and demand side management, have changed the network load profile and configuration. To improve the situation, smart grid initiatives have been deployed and created new sources of data at unprecedented volumes. The use of digital relays, Phasor Measurement Units (PMUs), Intelligent Electronic Devices (IEDs), automated feeder switches and voltage regulators, and smart inverters of DER, has provided an opportunity to increase system observability. Regular polling and on-demand reads of the customer interval demand through the Advanced Metering Infrastructure (AMI) will enhance the accuracy of distribution network on-line model [16]–[21].

Consumers drive increased power system flexibility as they shift from passive buyers to active users, and as they install solar panels, distributed generators and purchase equipment that enable them to better manage power usage. This prosumer movement has replaced the conventional one-way generation-transmission-distribution-consumer model with increased number of services provided by power network [22], [23]. Due to the integration of DER, microgrids, aggregated demand response, Electric Vehicle (EV) charging and customer participation in the power market, system operators will have to play a more active role to face with the increasing variable and less predictable load profiles in the network. System operation practice not only seeks to improve the reliability and efficiency of the network, but also to maximize utilization of existing assets to accommodate DER integrations without compromising the established operating constraints [24]–[27]. A DSSE based

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real-time network model has become an essential tool in the control and protection of the distribution network to meet the changes in technology, environment and commerce [28], [29].

Many important issues in the DSSE development have been deliberated in previous literatures [29]–[36]. This paper addresses the requirements of DSSE in the Distribution Management System (DMS) and reviews the most important algorithms currently available. We also identify emerging techniques and future directions for DSSE as a part of the smart grid vision.

II. Data and feeder Model used in DSSE

Data from several sources in DMS are required in supporting DSSE, such as:

1) Equipment connectivity status from Automated Mapping and Facility Management (AM/FM) systems, Geographic Information System (GIS) and Outage Management Systems (OMS).
2) Real-time voltage, current and power flow measurements from Distribution Automations (DA), SCADA systems, IEDs and PMUs.
3) Customer interval demands and DER output data from Customer Information System (CIS) and Meter Data Management System (MDMS)

Interface functions are developed to convert "maps" and attribute data that have been created in an AM/FM/GIS environment to the operational database structure that supports DSSE and distribution analyses. Feeder topology, parameters and measurements required are gathered by connectivity tracing and data query tools searching through CIS, OMS (AM/FM/GIS), substation and feeder SCADA databases, and MDMS. To develop an efficient and seamless on-line model for conducting various operational and business processes, a Common Information Model (CIM) is important to address the data interoperability and facilitate data exchange. Data can be accessed by multiple utility applications through the CIM data layer that includes adapters for converting data into the CIM-compliant data definitions and for accessing data in databases. In the DMS environment, the application software and data management systems can communicate with each other through CIM over the enterprise service bus [16].

A. Distribution Network Topology

Network topology processor builds the network topology and parameters required in DSSE which processes the latest actual and estimated measurements. Topological change is of concern in managing an active distribution grid. Object oriented approach was proposed to process distribution network topology [37], [38]. Due to the extent of a distribution network and its three-phase property, phase errors are frequent. Instead of treating network topology as known and fixed, a generalized SE algorithm proposed in [39] integrates the estimation of topology information with the SE process using real-time measurements by modeling parts of the distribution systems at bus-section/switching-device level. Autonomous network operation with SE can identify changes in the system state and automatically update the system model [40]. Power line carrier techniques can be used to identify the connectivity of customers to service transformers such that the AMI metering data can be used in distribution transformer (feeder bus) load modeling and DSSE.

B. Feeder Model Used in DSSE

Based on the assumption that the ground wire is at zero potential at both ends of a branch (feeder section) the Kron reduction method can be used to eliminate the neutral wire to represent the node voltage relationship of a branch with a 3 x 3 impedance matrix. Another method, referred to as the neutral return reduction method, assumes that the return current follows the path through the neutral, and all loads are grounded. Because delta-connected loads are present in medium voltage (MV) feeders and a neutral wire may not always represent zero potential, four-wire model with 4 x 4 matrices, without the elimination of the neutral wire, may be needed for unbalanced system [7].

The single- and three-phase loads are connected to the MV feeders through different transformer connections. More detail feeder models include distribution transformers with losses. Unmetered DER can be modeled according to their characteristics as a constant power factor, constant voltage, or variable reactive power models in the analyses [24]–[27]. Modeling each component as accurately as possible is crucial; however, models that are overly detailed and computationally impractical for on-line analyses should be avoided.

C. Measurement Data Used in DSSE

1) Real-Time Measurement: In DA, measurements of feeder bus voltages, branch currents, powers and switch status at a few feeder locations are gathered. SCADA data are available in every few seconds and some are reported by exception [15]. The deployment of smart meters and IEDs equipped with two-way communications is increasing. Customer smart meters report demand data in every fifteen minutes or longer intervals. Synchrophasor information from IEDs is available at settable rates of 1–60 messages per second. Several DSSE methods focus on the inclusion of PMU data in the algorithm. Some algorithms exploit the phase angle information to simplify the computation process and increase the computation efficiency [41]–[45]. An issue that should be addressed in using different types of measurements is the time skew problem, i.e., the difference in the time reference. To incorporate unsynchronized measurements, a synchronization operator can be introduced that allows the resynchronization of the measurements to the time reference [44].

Limited real-time measurement causes an observability problem, whereas numerous measurements require a communication infrastructure with large bandwidth and high reliability, thus leading to data overload and economic problems [34]. With an adequate number of measurements for system observability, data compression can be used such that the transmitted measurement data can be reduced [46].

2) Pseudo Measurement: The use of pseudo measurements is a crucial characteristic of DSSE. Pseudo power injection measurements at feeder buses can be defined as Gaussian distributions with their means at half the transformer rating, or determined based on customer billing data and typical load profiles. Customer class load curves with stochastic contents are utilized. The behavior of power consumption may change because of new tariff structures, behind the meter renewable outputs and EV charging. Customers can become producers, and therefore the conventional load modeling techniques should be adjusted to handle these uncertainties. The Gaussian mixture model (GMM), a combination of several normal distributions, can be used to represent the load probability density function if the loads do not follow any distribution function [47].

The load demands have been aggregated at the MV nodes by using customer data collected at low voltage (LV) nodes. Customer classification by the statistical processing of historical data can help the allocation of measured loads of selected nodes among unmeasured downstream nodes [45], [48]–[50]. The correlation and dynamic analyses of real-time measurements in the substation and unmonitored variable in other buses and the use of a load probability density function were adopted to enhance pseudo measurements (loads) modeling. Artificial neural network (ANN) technique was also proposed for modelling characteristics of feeder bus loads [51].

The smart meter data are updated less frequently (e.g. every 15 min) and generally involve considerable delays (up to a day). Without effective implementation, these data cannot be used directly as inputs to a measurement profiling module to estimate the measurements for DSSE. The problems of pseudo measurement modeling based on different time scale unsynchronized and delayed measurements were addressed in [52]–[56]. The accuracy of pseudo measurements and DSSE can be improved by using closed-loop scheme in which the DSSE output is fed back to the load model calculation function [52], [53].

3) Virtual Measurement: Virtual measurements are zero voltage drops in closed switching devices, zero power flows in open switching devices, and zero bus injections that can be found at the nodes such as a switching station. The assignment of high weights to virtual measurements and low weights to pseudo measurements may cause ill-conditioned system. The use of Lagrange multipliers was proposed to handle virtual measurements [57], [58].

III. DSSE Algorithms

Based on the timing and evolution of the estimates, state variables chosen, and the treatment of load and bad data, the existing DSSE methodologies can be classified into different paradigms.

A. WLS-Based Static DSSE

Weighted Least Square (WLS) estimators are the most popular and considerable efforts have been devoted to reduce the computational requirements. The main differences among proposals are basically the choice of the state variables, the simplifications to speed up the estimation, and the techniques to incorporate heterogeneous measurements. Two main categories were proposed for the choice of state variables, node-voltage and branch-current based state estimators. Both can be formulated in polar and rectangular coordinates. Weights associated with the actual measurements are proportional to the accuracy of the measurements and non-zero mutual terms in the measurement weight matrix can be included if correlations of measurements are considered [45].

1) Node Voltage Based DSSE Methods: When bus voltages in polar form are chosen as state variables, the entries of measurement Jacobian and gain matrix in the normal equation must be recalculated at each iteration [6], [59]. Similar to the Z_B Gauss method [24] that uses the sparse bifactored Y_{bus} matrix and equivalent current injections to solve the distribution power flow problem, an algorithm proposed in [7] uses a bus injection current-based formulation that converts bus power injection measurements to their corresponding current injection equivalents in rectangular form. By adopting node voltage in rectangular form as the state variables, the Jacobian terms of the converted bus current injection measurements become constant. Bus injection power and voltage magnitude measurements can be converted into equivalent bus injection current and voltage measurements in rectangular forms based on the calculated bus voltage in the previous iteration. Actual feeder branch power and current magnitude measurements can be converted into their rectangular branch current equivalences. This rectangular form-based method requires factorization of the gain matrix only once in the solution procedure.

Another node voltage-based DSSE uses a complex node voltage and load scaling parameter as state variables. Exploiting the radial nature of the distribution network topology after single branch estimation, a load allocation is conducted to modify the pseudo measurements and enhance DSSE results [60]. A modified augmented nodal analysis formulation was proposed in [61] to improve the condition number of the system and allow integration of different measurements at various network topologies.

2) Branch Current Based DSSE Methods: This approach is by far the most popular method tested. Feeder branch currents in rectangular form are chosen as state variables. It is computationally efficient for radial networks. Power and current magnitude measurements are converted into their equivalent current measurements functions expressed in terms of branch currents to ensure that all Jacobian matrix elements are constants. Forward and back substitutions are required to obtain the estimated node voltage for measurement conversion. The inclusion of voltage measurements causes additional efforts in the solution procedure but help retain the benefits of the branch current formulation [62], [63]. Several variants of the branch current-based method are available. Phase decoupled version of the branch current-based method exhibits a satisfactory performance under various r/x ratio conditions.

Instead of using branch currents in a rectangular form, magnitude and phase angle of the feeder branch current were also chosen as state variables [64]. Technique proposed in [58] exploits a particular formulation of the branch current based estimators to deal with zero injection and mesh constraints. The use of synchronized phasor measurements in branch current based estimators was demonstrated in [65]. It has been shown that when slack bus voltage is included into the state vector, the solution accuracy can be improved [35], [65].

Comparisons of accuracy, performance and bad data detection capability of the WLS based methods were reported in

[35], [66], [67]. A comprehensive analysis of the performance of DSSE algorithms indicates that estimators based on node voltage and branch current would give similar accuracy. Due to the linear measurement functions used, rectangular branch current based DSSE through inclusion of the slack bus voltage into the state vector would require less execution time. However, since voltage measurements result in non-zero Jacobian terms for all the derivatives with respect to the branch currents, when several voltage measurements are used, rectangular branch current based method could be slower than rectangular node based method [35].

3) Adjustment of Equivalent Measurements Variances: One of the difficult tasks in DSSE deployment is related to tuning of measurement weights [15]. Objective of tuning weights is to narrow down measurement residuals and obtain optimal performance indices. Some existing WLS based methods convert actual measurements into their equivalences to be used in the linearized SE formulations [7], [8]. When actual measurements are converted, the same weights may not be assigned to the equivalent measurements. Without suitable weight adjustment, the obtained solution may not be a solution to the original problem. An approach was presented in [66] for calculating the variances of equivalent measurements without considering the correlations among measurements. Effects of actual and pseudo measurements' correlation in DSSE were discussed in [45].

B. Load Adjustment DSSE Methods

In the load adjustment approach, the loads are adjusted on the basis of a load modeling technique which is based on the customer load profile curves. Load adjustment SE methods generally adjust the load values (bus current injection or power injection) such that the values conform to the measurement data [10]–[12]. The measurement data are specified as solution constraints in the algorithm. A probabilistic distribution power flow that uses the measured variables and the radial topology of distribution networks was proposed in [9]. Iterative procedures presented in [13], [14] strive to adjust the bus loads based on a Gauss–Seidel load flow algorithm by treating voltage and power measurements in a substation, and voltage and current magnitude measurements along the feeder as completely accurate information.

Considering the nonlinear characteristics of distribution system equipment, a hybrid particle swarm optimization-based technique was proposed in [69]. The objective function is the same as that of WLS DSSE to minimize the difference between measured and calculated voltages and currents by using power load value and DER output as state variables.

A load group and reduced network concept proposed in [68] adjusts the forecasted load values to conform the measurements at the boundaries of the measurement areas. A measurement area is defined as a connected subnetwork, which does not include any branch measurements and is connected to other subnetworks via branches that have telemetered flow measurements. The loads within a measurement area that have the same weights are grouped together in a load group.

C. Robust DSSE Methods

Bad data detection and identification is crucial for obtaining accurate SE results. A robust estimator generally suppresses the influence of bad data during the solution procedure by reducing the weights assigned to the suspected bad data points. When the estimated states remain unaffected by major deviations in a limited number of redundant measurements, the corresponding estimator can be considered statistically robust. Machine learning algorithms can be used to provide load estimates and conceive robust DSSE algorithms [52]. The robust DSSE algorithms proposed in [70], [71] use a weight function that is based on the influence function concept of the robust estimation theory. A weight function could be formulated such that when the influence of a certain measurement on a solution is considerably high (known as leverage measurement), the weight of that particular measurement is reduced. Hence, the effect of measurements with a high residual can be reduced. If a closed loop scheme is adopted, the DSSE solution can be fed back to the machine learning function to increase its accuracy [53].

An M-estimator that combines WLS and weighted least absolute value estimator techniques was proposed in [72] to suppress the effect of bad data in the solution process. One drawback of the M-estimator is that its output is not consistent in a large distribution system. Modifications need to be made to apply M-estimator for DSSE, because typical distribution networks consist of numerous nodes, and most measurements are pseudo measurements, which have higher residuals.

D. Dynamic DSSE Methods

Dynamic State Estimation (DySE), also known as Forecasting-Aided SE (FASE), is a recursive estimation method based on several measurement snapshots in a time sequence. If the computation requirement of a large system is a concern and measurements arrive at different frequencies, the newly received measurements can be processed together with the available *a priori* estimate (forecasted) and used to forecast state variations between complete DSSE executions.

Performance comparison between WLS and Iterated Kalman Filter (IKF) methods integrating PMUs in DSSE and a sensitivity analysis of the performance of IKF as a function of the measurements and process covariance matrices were presented in [67]. A comprehensive survey of FASE focusing on extended Kalman filter (EKF)-based SE was detailed in [73]. The unscented Kalman filter (UKF) method that combines the unscented transformation (UT) with the Kalman filter theory can provide improved results for the estimation [74]. UT is used to obtain a set of vectors, called sigma points, to capture the mean and covariance of the original distribution of the states. The UKF is advantageous over the EKF because it avoids the linearization process. There is no loss of higher order information, thus, improving the properties of the estimator. Since no Jacobian or Hessian matrices are required, thus, offering computational advantages over the EKF.

The use of large heterogeneous measurement data with different data formats, polling cycles, and accuracy are essential to establish immediate past and future feeder models for on-line operations. Considering the bandwidth and speed limitations of SCADA and AMI data communications in a DMS environment, a framework was proposed in [21] to use on-line and off-line computing powers to update distribution feeder models for on-line operation purposes. Between two SCADA data scans, IEDs and PMUs data can be used to execute FASE followed by static DSSE with actual and pseudo measurement (load forecast) data.

E. Distributed DSSE Methods

Compared with transmission networks, distribution grids consist of numerous regional substations, feeders, and nodes. Hence, it requires a high computing time for the whole network SE. Distributed DSSE known as multi-area state estimation (MASE) divides the distribution network into several sub-areas according to geographical, topological, and measurement points and solves the problem in local estimators. Another SE can be performed on all areas by using previous estimation results and the estimates of border quantities provided by adjacent areas as the measurement data [75], [76]. Distributed DSSE can execute several estimators in sequence or parallel [77], [78]. A distributed agent-based state estimation that uses a token to periodically traverse the secondary substations, was presented in [79]. The primary substation controls the token handling process and it can react on exceptions by spontaneously initiating a token outside of normal and periodic behavior. The practical implementation of distributed DSSE is challenging due to a limited number of actual measurements, communication delay, and unsynchronized measurements that are detrimental to the solution accuracy of MASE. Despite the difficulties, the distributed SE could satisfy the real-time requirements [80].

IV. Bad Data Detection and Identification

The capabilities of bad data and network configuration error detection and identification depend strongly on the measurement set. Since the measurement redundancy is low and load models are quite uncertain, the detection of bad data is difficult. In the WLS-based methods, it is conducted after the estimation process. Robust estimators reduce the weight of measurement with a high residual during the estimation process such that the influence of bad data on the solution is minimized [72].

Bad data detection tests have been reported in [66], [81]–[84]. The bad data analysis is usually performed using the residual analysis based on chi-square and normalized residual tests. A real-life demonstration of a branch current based DSSE method presented in [84] concluded that the commonly used 3σ bad data detection threshold is inadequate when using load profile data to detect errors in feeder line flow measurements. In [81], it was shown that a geometrical approach which uses composed measurement error and composed normalized error outperforms the residual analysis in detection, identification and correction of gross errors in DSSE. Test results indicated that gross error level would affect the bad data detection and the load models influence the gross error correction.

Detection of bad pseudo measurements in a radial distribution network is even more challenging due to measurement interactivity. Measurement interaction is mostly due to network topology, measurement location, and the weight assigned to each measurement. In a set of interacting measurements, an error in one measurement considerably affects the residuals of other measurements. In the case of two or more interacting measurements containing conforming errors, the largest normalized residual test may fail to identify either error. A branch-and-bound algorithm proposed in [82] could solve the problem. Considering measurement scarcity, ANN based method was proposed to correct erroneous measurements in DSSE [83]. Global search methods, such as particle swarm optimization and genetic algorithm-based algorithms [85] have been tested to determine a DSSE solution in which the number of data declared as bad is minimized.

V. Meter Placement

If a large number of pseudo measurements with large uncertainties are used to make a distribution network observable, the estimated state could deviate from the actual system state. More real-time measurements are necessary to fulfill the requirements of real-time operation applications. The cost of adding measurement devices may be high, and careful selection of new measurement locations is important. To handle the problem, the uncertainty of DSSE results can be taken into account in the meter placement to determine the network observability according to the accuracy of the estimated results. Algorithms are proposed to determine the optimal number and location of new measurement points to achieve required accuracy [86]–[89]. Other algorithms aim to maximize the solution accuracy with a pre-specified number of additional measurements [90], [91]. PMUs and smart meters can be installed in strategic locations to enhance system monitoring and DSSE accuracy [43], [92]–[94].

VI. DSSE Applications

DSSE enables real-time distribution grid monitoring and provides the initial state/condition for many DMS applications. Its accuracy will have high impacts to the network operations. The DMS is expected to provide a growing number of applications, including volt/VAr control, capacitor switching,energy loss minimization, Conservation Voltage Reduction (CVR), congestion management, distribution transformer usage optimization, feeder reconfiguration and service restoration, control of switches and reclosers, demand side management, and price signal determination.

The integration of distributed generations poses new operational challenges, such as the occurrence of over voltages at the distribution level. An accurate on-line model obtained from DSSE would assist system operator for effective volt/Var control under normal condition and feeder reconfiguration under emergency. A control framework for voltage support with DER-injected reactive power by using an EKF-based dynamic SE was presented in [95]. A multi-layer control scheme based on day ahead-planning and near real-time DSSE results was proposed to support the active control of a distribution grid, which optimizes the distributed renewable generation and energy storage control [96]. Estimating the system states in the context of transversal transmission and distribution (T&D) voltage controls would bring optimization of the T&D losses and voltage security of the system. A multi-level state estimation paradigm for smart grids could avoid inefficiency in operation planning, integration of demand side response and DER [97].

The DSSE solution can also be used to drive the calculation of pricing signals to assist efficient market operations, which in turn affects the system controls [98]. With the current system operation point obtained from DSSE, an incremental linearized formulation can be used to calculate the distribution system locational marginal price [99].

Distribution network designers use a transformer load-management system to estimate and examine the historical and current loading of transformers and to test proposed load situations. The DSSE results can be used in transformer load modeling and management [100]. With more accurate distribution transformer load model, CVR scheme can be performed to conserve energy and reduce the transformer and feeder loading during emergency conditions.

The deployment of smart meters at $\mathrm{MV/LV}$ distribution transformers would enhance DSSE accuracy and allow power balance verification and non-technical loss detection. A consistent DSSE solution provides a guided search of potential irregularity of electricity usage [101] and the voltage unbalance factor in the network [102]. When the model does not represent the actual network condition, DSSE could detect, locate, and repair the erroneous information [103], [104].

VII. Concluding Remarks and future directions

Considering distinct characteristics and the development in the distribution network, research works on different paradigms of DSSE methodologies have been conducted in the past two decades. Many existing methods provide efficient procedure for building on-line network models. However, due to the lack of observability downstream the substations, updated and accurate network model, easy access to data from different parts of the organization and unified data format, only a few utility companies have implemented DSSE. New techniques and reliable source of data to remove the hurdles for wide application of DSSE are required.

Transition to a sustainable energy future would result in complex and fast aggregated generator and load dynamics, which will lead to operation impacts on distribution networks. Distribution system monitoring process is made complicated not only because of special network characteristics and low redundancy of measurements but also due to the high number of nodes, the geographical extension of the networks and the integrations of DER. Challenges are still open and new monitoring and management solutions are required, such as:,

1) Accurate, adaptive and efficient feeder modeling and DSSE methodologies for wide area monitoring and coping with the active nature of the distribution network.
2) Data synergy and fusion techniques for exploiting a large amount of heterogeneous data in DMS environment
3) Communication infrastructures, big data and edge computing techniques to tackle the problem of efficiently collecting and coordinating the measurement results.
4) A global and multi-level state estimation concept for better interaction between distribution and transmission system operators

Network modeling in DSSE is never perfect and contains inaccuracies. Uncertainties of network parameters, topology, measurements, data correlation and operating conditions impact the DSSE results. Parameter Estimation (PE), topology and measurement bad data processors are important functions due to the complexity of database maintenance. PE process can be improved by using the combined information from multiple measurement snapshots. When pseudo measurements are used, conforming interactive bad data would be hard to be detected and need further investigation. DSSE deployment experiences have shown that measurement weights tuning is one of the main tasks in field trials. If measurements are not used directly and translated into their equivalences for solution efficiency enhancement, the measurement error variances should be carefully re-examined to ensure that solutions are close to the original problem.

The model of secondary (LV) network needs to be improved since a large share of DER is integrated in LV network. Multi-level MV/LV regional SE provides useful loading and voltage information at regions. Modeling each component as accurately as possible is crucial and high performance (distributed and parallel) computing algorithms will help. To realize wide area DSSE, the model and method adopted need to be computationally practical for on-line monitoring and analyses. Network reduction in certain areas may be needed when database becomes excessively large.

To enhance the observability and accuracy of on-line model, the synergy of a large amount of heterogeneous data from various information systems with different data formats, unsynchronized polling cycles, communication delay and accuracy, is crucial. Innovative algorithms that consider the high sampling rate phasor data from micro-PMUs, IEDs, and digital relays in conjunction with delayed interval data from smart meters for DSSE will improve overall accuracy. The use of big data is beneficial for model calibration [105]. Cloud-based IoT platform [106], CIM [107] and data fusion techniques [108] are valuable for effective measurement data processing and monitoring active system situations.

The fleet of automation islands and micro-grids is evolving from a collection of sensors platforms that provide information to regional data center and upload filtered sensor data to the cloud; to a network of autonomous regions that exchange data among each other in order to optimize a defined utility functions. MASE methods augmented with a small-area SE to form hierarchical DSSE would meet the near real-time operation requirements. In this respect, a consensus algorithm [109], [110] is an alternative for local control area DSSE that provides intelligence as well as topology, observability and bad data analyses to local SE. MASE begins with many local SE, communicate their estimates to neighboring areas continuously, and eventually making all local estimates converge to the centralized state estimation result [111].

The variations of the voltage values and other indicators can be used in adaptive DSSE to cope with active nature of distribution network. An event triggered approach for sensing, communicating and information processing would be attractive to reduce computation and communication burdens. Using report-by-exception scheme, the measurement data are sent to the DSSE at higher rates and the estimation process runs consequently on a finer time scale to achieve a bandwidth-efficient and smart data transmission [36], [106].

In smart grid architectures, intelligence and supporting analytics may be moved outside of the control center to substations and beyond. In distributed models, analytics elements at substations interact and cooperate with analytics at the control center [112]. Edge computing architectures push intelligence beyond the substations to edge devices. Network devices, such as data concentrators in AMI and feeder terminal units in DA are logical homes for grid intelligence. The edge computing capability augments regional surveillance and could provide aggregated information to enhance DSSE efficiency and accuracy. In this regard, new DSSE paradigms and software to exploit the hardware need to be developed.

Evolutions in the grid operation sector will require a closer cooperation between Transmission System Operators (TSO) and Distribution System Operators (DSO). A process can be developed to avoid TSO-DSO transformer congestion by using flexibility in the distribution grid. In this respect, a global state estimation that includes MV distribution feeder and the bulk high voltage transmission network for estimating the global consistent state of the whole network is advantageous in smart grid operations [97], [113].

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