Fundamental Research Challenges for Distribution State Estimation to Enable High-Performing Grids

Final Report | Report Number 18-37 | May 2018

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Fundamental Research Challenges for Distribution State Estimation to Enable High-Performing Grids

Final Report

Prepared for:

New York State Energy Research and Development Authority

Albany, NY

Michael Razanousky
Project Manager

Prepared by:

Smarter Grid Solutions

New York, NY

Kevin Morrissey
Project Manager

NYSERDA Report 18-37 NYSERDA Contract 112720 May 2018

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Preferred Citation

New York State Energy Research and Development Authority (NYSERDA). 2018. "Fundamental Research Challenges for Distribution State Estimation to Enable High-Performing Grids," NYSERDA Report Number 18-37. Prepared by Smarter Grid Solutions, New York, NY. nyserda.ny.gov/publications

Abstract

State estimation is a mathematical method used for determining the most-likely current behavior of a power grid based on a set of measurements and the structure of the network itself. This method has been used on transmission systems for decades to achieve and calibrate network visibility, but it is not yet widely adopted for distribution system operations outside demonstration areas.

This report concludes an investigation by Smarter Grid Solutions into the application of state estimation for distribution systems. Throughout the study on distribution state estimation (DSE), Smarter Grid Solutions evaluated (1) initiatives supporting DSE development in the U.S. and in New York State, (2) DSE Use Cases, (3) implementation challenges, (4) state-of-the-art literature on DSE issues, (5) gaps in literature and demonstration projects, and (6) best practices for DSE. In addition, Smarter Grid Solutions has prepared a software toolkit with which some DSE concepts may be explored in a hands-on experiential environment.

While research into DSE has gone on for two decades, there exists a real gap between academic understanding and operational practices. Many of the implementation challenges have their root in the fundamental differences between transmission and distribution systems. Most importantly, it is the passive nature with which distribution systems are operated that has reduced the need for measurement, communication, and centralized computing infrastructure necessary to operate a state estimator. The information presented in this report provides the material necessary to understand the context and workings of DSE, as well as offers practical information on how to evaluate a plan for implementing an estimator.

Keywords

state estimation; distribution system; observability; implementation challenges; visibility; measurements; pseudo-measurements; advanced metering infrastructure; state of the art review; literature review; algorithms; weighted least squares; bad data detection; network model; advanced distribution management system; toolkit; Octave; OpenDSS

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Acronyms and Abbreviations

ADMS	Advanced distribution management system
AMI	Advanced metering infrastructure
ANM	Active network management
CIM	Common Information Model
DER	Distributed Energy Resource
DOE	United States Department of Energy
DSE	Distribution State Estimation
GMLC	Grid Modernization Laboratory Consortium
HPG	High-Performing Grids
HV	High Voltage (>35 kV)
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
LV	Low Voltage (<2 kV)
MV	Medium voltage (~2 kV to 35 kV)
NREL	National Renewable Energy Laboratory
NYPA	New York Power Authority
PMU	Phasor Measurement Unit
PNNL	Pacific Northwest National Laboratory
PV	Photovoltaic
REV	Reforming the Energy Vision
RI	Redundancy index
SCADA	Supervisory control and data acquisition
VVO	Volt-VAR Optimization
WLS	Weighted-least-squares

Summary

State estimation is a method for analyzing power systems in which all known information regarding a live power network is used to assemble the most-likely internal state of the system. As a tool, state estimation is extensively applied to transmission systems to support system visibility, optimization, and market operation. However, distribution state estimation (DSE) has not yet seen widespread adoption due to the relatively low monitoring and oversight of distribution systems compared to transmission. Despite lack of adoption, DSE is an important aspect of the dynamically managed distribution systems envisioned by utilities and policymakers such as New York State's Reforming the Energy Vision (REV) and the New York State Energy Research and Development Authority (NYSERDA).

This report concludes Smarter Grid Solutions' (SGS) research on navigating the challenges and approaches to DSE. SGS approached this problem with the following key questions:

Figure S-1. Distribution State Estimation—Key Questions

Why install a distribution state estimator?

- How does DSE fit into current grid modernization initiatives?
- What problems does DSE solve?
- What system operation functions does DSE enable?

What are possibilities for navigating implementation challenges?

- What challenges exist for DSE implementation?
- What measurement and monitoring infrastructure is necessary?
- How accurate must the network model be?

What decisions must be made regarding implementation?

- In what circumstance would DSE implementation make sense?
- Are system upgrades justified by performance?
- What methods are best suited to a given system?

S.1 Project Phases

SGS pursued this investigation into DSE in three phases:

1. DSE Context: Initiatives and Utility Usage
2. State-of-the-Art Review
3. DSE Software Toolkit

In its initial research on DSE context, SGS studied the place of DSE among distribution modernization initiatives. High-level objectives were as described by policymakers in New York State, the United States, and abroad, while implementation plans were laid out by distribution utilities themselves. SGS had conversations with these utilities as well as with industry and academic experts in order to frame the problem and formulate its approach. This information was used to compile an overview of DSE use cases and implementation challenges.

The wealth of academic research on the topic as well as conversations with leaders in academia contributed heavily to this project. SGS broke down the necessary components of DSE and provided an in-depth review of current research in the state-of-the-art review. As part of this review, SGS documented published studies and demonstration programs into DSE, and identified gaps where the body of literature might be further developed to benefit operational DSE installations. Gaps identified by SGS included a standardized metric for evaluating a utility's measurement infrastructure and a critical analysis on using forecasted pseudo-measurements for bad data detection.

Lastly, SGS put together a DSE software toolkit: A software-based DSE example for users to download and be guided through DSE concepts. This toolkit enables users to run three-phase DSE through different scenarios and custom measurement configurations. Users can easily examine the performance of the estimator in relation to the underlying "true state" of the system and are given the power to further extend and explore the toolkit capabilities—as all code is provided in a sandbox environment with documentation. The goal of this task is to provide interested parties a hands-on opportunity to familiarize themselves with DSE concepts presented in this report.

S.2 Project Takeaways

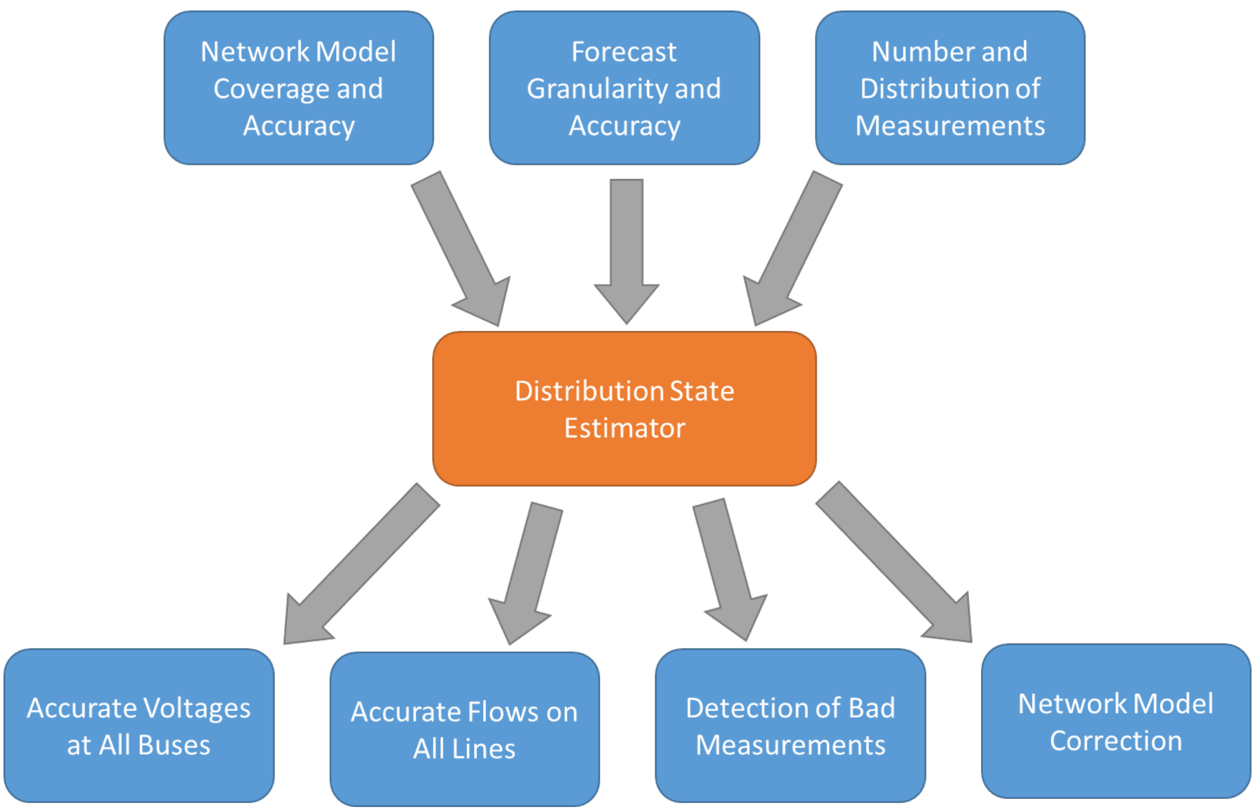
State estimation is only as powerful as the information that it is given. In understanding the goals of network visibility and the infrastructure available to the utility, it can be determined if upgrading the system to support DSE is expedient. At its most basic, Table S-1 is a summary of what must be considered to implement DSE:

Table S-1. DSE Minimum Requirements

What items are necessary to support DSE?	
1	An up-to-date network model
2	At least two pieces of operating data about each system node • Examples of this could be (among others): ○ Real and reactive customer load ○ Voltage magnitude and angle • This can take the form of load forecasts—understanding the compromise in system accuracy and inability to detect bad data
3	A communication infrastructure to support real-time measurements and model updates
4	A state estimation engine

It should be noted that having a state estimation engine is just as important to DSE as having any one of the first three items. Without upgrading all four items in a convergent manner, the effectiveness of DSE implementation will suffer. To demonstrate this, the relation between input quality and potential outputs are summarized in Figure S-2.

Figure S-2. Input Quality versus Possible Outputs to a Distribution State Estimator



The four outputs shown in Figure 13 are results that could benefit the operation of any utility. However, the effectiveness with which DSE can realize these results is a direct result of the quality of the three inputs shown at the top of the figure. For instance, both detection of bad measurements and network model correction are impossible without redundancy in the system measurements. It is vital that utilities understand the relation between what goes into the state estimator versus what the state estimator can provide.

The largest challenges to DSE implementation are summarized in the Table S-2:

Table S-2. DSE Implementation Challenges Summary

Implementation Challenges	Accuracy and Effectiveness Challenges
Observability	Uncertainty in Network Parameters
Communication Infrastructure	Uncertainty in Topology
Complexity of Network	Uncertainty in Load and Forecast
Line Parameters	

As every distribution system faces its own challenges and has a unique mix of visibility and control applications, no two solutions will have the same approach. However, there are common characteristics to successful DSE implementations. One of the most important components is a network model that can be updated dynamically and shared in real-time. The Common Information Model (CIM) not only enables the network model to be communicable across platforms, but also enables upgrades in flexibility and automation that are necessary for DSE.

Beyond network model considerations, the measurement infrastructure is the most important factor for a DSE implementation. With the sparse placement of measurement points on distribution systems, DSE must rely heavily on load forecasts to maintain an observable network. While there are limits to the benefits obtained from using forecasts as measurements, it is reasonable to focus first on how to maximize their accuracy. Even small levels of advanced metering infrastructure (AMI) adoption can lead to more granular, targeted, and accurate load forecasts throughout the system. Furthermore, load allocation methods powered by AMI and iterating with DSE can improve performance all around.

With measurements being at the core of a state estimator, their placement is of utmost importance. The financial burden of widespread measurement placement means optimizing the types of measurements placed, their accuracy, and where on the network they will reside. Once a state estimator has been modelled, a utility will be able to run assessments on how each measurement considered for placement will beneficially impact the visibility of the system.

This report outlines the motivations and findings of SGS' research into DSE, as well as providing an overview of all previous phases of the project. The project should provide clarity to utilities investigating DSE as an upgrade to their system visibility. The topic of system visibility is difficult, without a simple prescribed avenue to success. However, the best way to implement a successful state estimator is to become familiar with DSE as a method and a tool that is as powerful as the systems built around it.

1 Introduction

1.1 Project Background

State estimation is a method for analyzing power systems in which all known information regarding a live power network is used to assemble the most-likely internal state of the system. More simply, it is the calculation of voltages and power flows from a distribution of measurements and forecasts. Offline power analysis often makes the assumption of perfect knowledge or worst-case scenario. However, during operation, no knowledge is absolute—measurements include a level of uncertainty and the possibility for data corruption. Using state estimation, an operator can use any available information (including measurements, forecasts, and network considerations) to create the most-likely state of current operation.

As a tool, state estimation is extensively applied to transmission systems to support system visibility, optimization, and market operation. While in-the-loop operation of state estimation has been widely adopted for transmission systems, the same has not been the case for distribution systems. There are few examples of distribution state estimation (DSE) that go beyond controlled research settings, in large part because the measurement and communication infrastructure is not built to support such system-wide real-time analytics.

Despite lack of adoption, DSE is an important aspect of the dynamically managed distribution systems envisioned by utilities and policymakers. Widespread distributed energy resource (DER) integration in particular is driving the need for better monitoring and control throughout distribution systems—capabilities enabled by DSE. The need for advanced distribution systems with state estimation capability has been described as crucial to the successful implementation of New York State's Reforming the Energy Vision (REV) markets and the High-Performing Grids (HPG) initiative driven by the New York State Energy Research and Development Authority (NYSERDA).

Smarter Grid Solutions (SGS) has provided unbiased assessment of the current state of DSE in order to provide guidance to New York State utilities on the implementation of DSE on their systems in accordance with REV and HPG objectives. This includes identifying current public initiatives supporting the development of DSE, reviewing current academic literature including demonstrations and pilot programs, and developing a toolkit for utilities to experiment with DSE concepts. As an outcome of this project, the State's utilities will be better equipped to make decisions on DSE integration, which in turn will facilitate a more dynamically managed grid.

This report concludes SGS's research on navigating the challenges and approaches to DSE and encompasses all the research findings, which include (1) identification of public policy initiatives, (2) implementation use cases and challenges, (3) a review of the state-of-the-art techniques, and (4) a software toolkit developed with open-sourced tools to allow hands-on study of DSE concepts. The software toolkit is available as an accompaniment to this report.

To bring context to this project, SGS identified three key questions regarding DSE. The questions encapsulate the goals of the assessment and are presented in Figure 1.

Figure 1. Distribution State Estimation—Key Questions

Why install a distribution state estimator?

- How does DSE fit into current grid modernization initiatives?
- What problems does DSE solve?
- What system operation functions does DSE enable?

What are possibilities for navigating implementation challenges?

- What challenges exist for DSE implementation?
- What measurement and monitoring infrastructure is necessary?
- How accurate must the network model be?

What decisions must be made regarding implementation?

- In what circumstance would DSE implementation make sense?
- Are system upgrades justified by performance?
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In providing answers to these questions, SGS will guide the State's utilities in navigating the state estimation landscape at the distribution level. Instead of performing a demonstration of DSE feasibility as has been done in several other studies, SGS identified the most valuable approach would be to lay out the fundamental concepts, challenges, and approaches of state estimation.

SGS pursued this investigation into DSE in three phases:

1. DSE Context: Initiatives and Utility Usage
2. State-of-the-Art Review
3. DSE Software Toolkit

In its initial research on DSE context, SGS studied the place of DSE among distribution modernization initiatives. High-level objectives were as described by policymakers in the State, the United States, and abroad, while implementation plans were laid out by distribution utilities themselves. SGS had conversations with these utilities, as well as with industry and academic experts in order to frame the problem and formulate its approach. This information was used to compile an overview of DSE use cases and implementation challenges.

The wealth of academic research on the topic as well as conversations with leaders in academia contributed heavily to this project. SGS broke down the necessary components of DSE and provided an in-depth review of current research in the state-of-the-art review. As part of this review, SGS documented published studies and demonstration programs into DSE, and identified gaps where the body of literature might be further developed to benefit operational DSE installations. Gaps identified by SGS included a standardized metric for evaluating a utility's measurement infrastructure and a critical analysis on using forecasted pseudo-measurements for bad data detection.

Lastly, SGS put together a DSE software toolkit: A software-based DSE example for users to download and be guided through DSE concepts. This toolkit enables users to run three-phase DSE through different scenarios and custom measurement configurations. Users can easily examine the performance of the estimator in relation to the underlying "true state" of the system and are given the power to further extend and explore the toolkit capabilities—as all code is provided in a sandbox environment with documentation. The goal of this task is to provide interested parties a hands-on opportunity to familiarize themselves with DSE concepts presented in this report.

1.2 Using This Report: Structure and Intended Audience

This report presents the research results from several different phases of SGS' investigation into DSE, with the intended audience ranging from policymakers to utility engineers and academics. The following table has been provided to elaborate on the content of each section so that the reader can focus their attention on the most important parts of the project.

Table 1. Report Phase and Section Overview

Phase	Detail	Section	Detail
1. Introduction			
DSE Context: Initiatives and Utilities	The four sections which comprise this phase of the DSE project lay a groundwork for the context of DSE in modern distribution systems. This phase provides insight into the state of DSE in the distribution industry.	**2. State Estimation Definition and Utilization**	Introduction to the mathematical method of state estimation, and how it compares to other approaches to network visibility.
		3. Public Policy Initiatives	Discussion of State and Federal initiatives that incentivize DSE, including relevant findings from agency-funded reports and assessments of distribution modernization.
		4. DSE Use Cases	Discussion of the place of DSE among other smart grid objectives, and the potential benefits of DSE as an enabling technology.
		5. DSE Implementation Challenges	Roadblocks to DSE implementation, breaking down the fundamental differences between distribution and transmission systems that impede widespread adoption of DSE.
State-of-the- Art Review	The state-of-the-art review covered by these five sections is a thorough dive into the research surrounding every block in the DSE process. The review also includes documentation of and lessons learned from implementations of DSE in various studies and field demonstrations, and a look at where further research is required.	**6. Origin of DSE Literature**	Summary of initial state estimation research and how it transitioned from transmission to distribution systems. This section provides context for the DSE literature cited in the review.
		7. Components of a State Estimator	Outlining the building blocks of a fully functional state estimator. This section goes in-depth on current research surrounding each vital component of DSE.
		8. State Estimation Algorithms	In-depth study of many of the most common algorithms for solving the state estimation problem.
		9. Documented Implementations	Thorough documentation of all known implementations of DSE in real systems—both in offline studies and in online demonstration projects.
		10. Gap Analysis	Analysis of areas where further research would be beneficial to the widespread adoption of DSE, both in academia and in demonstrations.
DSE Software Toolkit	The DSE Software Toolkit is a companion tool that may be downloaded to provide a hands-on experience for interested users to investigate the concepts discussed in this report.	**11. DSE Software Toolkit: Overview and**	Overview of the DSE Software Toolkit which is provided as an accompaniment to this report. This includes a guided example for running a simple DSE case.
		12. DSE Software Toolkit: Further Guidance and Advanced Functionality	Further documentation of the DSE Software Toolkit that enables users to customize the tool and explore DSE concepts on their own.
13. Project Takeaways: Challenges and Best Practices			
14. Concluding Remarks			

Note

Throughout the report, important takeaways that are particularly applicable to distribution system implementation are highlighted. Many of these takeaways can be found in boxes such as this one.

2 State Estimation Definition and Utilization

State estimation is a mathematical method that has a well-studied set of inputs, outputs, and methods from which a solution may be obtained. State estimation is the most thorough method with which network information can be used to determine the behavior of a power system. However, it is not the only method. Depending on the available information and its quality, there are a range of methods available to estimate network flows and voltages with varying accuracy. Therefore, it is important to define the state estimation problem and its relation to other methods.

In this section, a high-level description of the state estimation problem is presented. This is an overview of the context, inputs/outputs, and methodology of state estimation as it compares to other power system functions.

Approaches to distribution network visibility are then discussed in order to provide a context for state estimation. The reader should come away from this section with a clear understanding of how state estimation differs from other approaches to visibility in terms of requirements and quality of result.

2.1 State Estimation

In a state estimation problem, no bus values are assumed to be known, and no measurement device is assumed to be absolute. Instead, the knowledge base is composed of a set of distributed measurements, each with a specified amount of error. Any new measured point in the power system improves the state estimation result. Load forecasts and other known characteristics can also be incorporated in a state estimator as measurements and assigned an error tolerance.

The known values are therefore:

- Any system measurements (injection, bus, line, etc.)
- Load forecasts and known characteristics
- Network topology
- Network model

From these known values, the most-likely system state is calculated, which will be a feasible power flow solution that minimizes the deviation from the known values it is given.

Measurement points can be any electrical characteristic of the system that is measured in real time. This could be node voltage magnitude and/or angle, line current magnitude and/or angle, line power or load/generation power. Note that angle measurements are only possible when using phasor measurement units (PMUs). These measurements are incorporated into a calculation that incorporates the physical behavior of the network model and weighs each measurement based on the confidence placed on the individual measurement.

Depending on how many measurement points exist in a network, a system state solution may or may not exist. This is what is referred to as observability—a system is only observable when there are requisite measurements with which the state might be recreated. Because the state of a power system is defined as two values (voltage magnitude and angle or any other two independent values) at each node (or bus), it is necessary to have measurements numbering at least twice the number of nodes in order to have a solution. This number is used as a benchmark in Table 2.

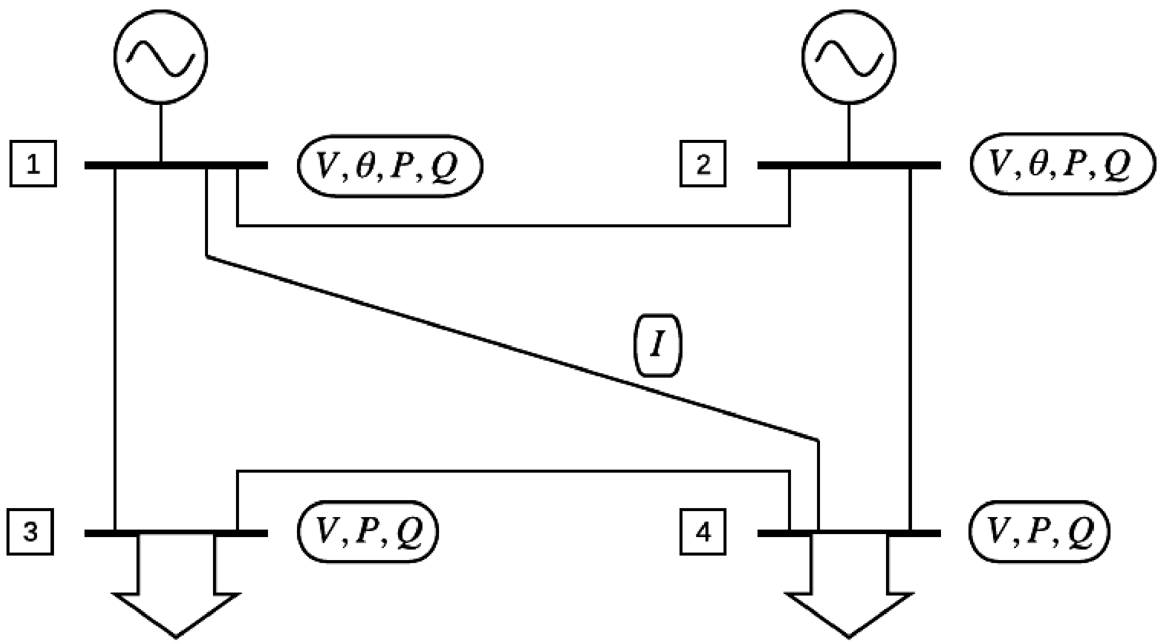
Table 2. Determination Levels of System Observability

System Classification	Number of Measurement Points	Ramification
Underdetermined	Less than twice the number of system nodes.	Infinite solutions; Not enough information to calculate state estimate
Determined	Approximately equal to twice the number of system nodes.	One exact solution; No redundancy; Subject to erroneous measurements Measurements must be distributed across system nodes to achieve observability.
Overdetermined	Greater than twice the number of system nodes.	No exact solution; Redundancy; Measurements weighted based on their accuracy to achieve a solution; Resilient to erroneous measurements

State estimation is impossible when the system is underdetermined. In the case of a determined system, the system has no measure with which to incorporate measurement accuracy, but the state estimation calculation is possible. An overdetermined system allows state estimation to be resilient to measurement errors, as it is able to identify measurements which do not match a feasible power flow solution.

Figure 2 depicts a four-bus system in order to demonstrate overdetermined (redundant) state estimation.

Figure 2. State Estimation Example



Notice that there are 15 measurements on the four-bus system. Because there are more measurements (15) than unknown state variables (8), this is an overdetermined system. There are no exact solutions to an overdetermined system as some measurements will be conflicting—however, the problem is solved by determining the *most-likely* solution: one which minimizes the discrepancy between the measurements and the underlying state. The result of this approach is a state estimate which is more accurate than even the measurements used to solve it, as the measurements and network model are combined to find the best mathematical solution to the problem. Increasing the number of measurements can only improve the state estimate—and this redundancy can lead to useful applications such as eliminating erroneous data points from consideration.

If the measurements were reduced until there were only two at each bus, it would be a determined system. There would not be any room for minimizing error or eliminating bad data as there would only be one feasible solution.

If the measurements were further reduced, it would be an underdetermined system. There are infinite solutions to an undetermined system, and therefore it is not solvable as a state estimation problem. Additional information such as load forecasts or new installed measurements would be necessary in order to solve the problem.

Exceptional textbook overviews of the state estimation problem are provided by Monticelli [1] and Abur and Gómez-Expósito [2]. Both have provided extensive background knowledge for this report.

2.2 Approaches to Network Visibility

State estimation is not the only approach to visualizing the electrical characteristics and behavior of distribution systems. Depending on the extent of measurement infrastructure, network visibility can take one of several forms. Approaches to network visibility are summarized in Table 3, in increasing order of breadth and accuracy.

Table 3. Approaches to Network Visibility

Approach	Necessary Information	Description	Visibility
Point monitoring	• Critical constraint point measurements	Infer secure operation based on certain critical bottleneck conditions.	None
Load allocation	• Upstream transformer load measurement or estimate • Locational load forecasts • loads assigned to transformers	Estimate loads at each bus based on customer forecast rectified with upstream transformer loads.	Customer loads
Load flow	• Upstream transformer load measurement or estimate • Distributed power injection (load and generation) measurements of forecasts • Network model and topology	Predict or calculate internal system state based on input injected power and estimated customer loads.	Entire system state (assumed)
Non-redundant state estimation	• Same requirements as load flow • Additional line and bus measurements	Rectify load flow results with measurements for realistic state estimate.	Entire system state
Redundant state estimation	• Distributed SCADA, line/bus, and customer measurements • Locational load forecasts • Network model and topology	More measurements resulting in improved state estimation accuracy. Ability to detect bad data inputs.	Entire system state Bad data inputs

Many utilities do not operate with real-time measurements in the loop, relying on forecasts and assuming normal operation unless alerted to a contingency, at which point measurements may be used to ensure normal operation. When real-time measurements are used in day-to-day operations, the most common tools for network visibility and operation for utilities are point monitoring and load allocation. Load flows are often pursued in the network planning and expansion phase to calculate worst-case conditions and plan for contingencies.

The introduction of distribution management systems (DMSs) and advanced DMSs (ADMSs) to distribution utilities have helped streamline and modernize distribution operations, centralizing information across utility platforms to reduce outages and improve efficiency. However, while an ADMS may have the capability to perform all five functions listed in Table 3, the systems in practice rarely perform extended load flows or state estimations due to the challenges surrounding the passive operation of distribution grids.

Each function from Table 3 is described in more detail in the following sections, with additional references provided for further reading.

2.2.1 Point Monitoring

The simplest and most common use of real-time measurement point monitoring is the collection of operating characteristics from select points on the distribution network to ensure constraints are not being violated and the system is running as intended. Some common examples of measurement points:

- Distribution automation (DA) and protection measurements
- Bottleneck line flow measurements
- End-of-line voltage sensors

In most cases, current distribution systems operate in a passive, predictable manner. Distribution networks are mostly radial, with customers aggregated to transformers and power flowing in a single direction at all times. Operating the network means maintaining flows within bounds to protect equipment, and isolating equipment when constraints are breached (often an automated process). Certain lines may be identified as bottlenecks—more likely to be overloaded or more vital to system operation—and might be monitored for control systems such as active network management (ANM).

One-way flows result in predictable voltage decreases along a feeder, with the end-of-line representing the lowest voltage on the feeder. Therefore, voltages can be ensured within bounds with an end-of-line voltage sensor. Reactive and other voltage-supporting elements may be engaged along the feeder to adjust voltage based on the end-of-line or upstream transformer measurements. In this way, simple volt-VAR control (VVC) and even some volt-VAR optimization including conservation voltage reduction (CVR) may be implemented with only a few voltage measurements [3].

The predictable, passive, and unidirectional paradigm of traditional distribution networks that allows point monitoring to be an effective method for network visibility relies on a set of assumptions that becoming less reliable in modern systems. This approach may need to be updated to keep up with elements of modernized distribution systems such as distributed energy resources (DER).

2.2.2 Load Allocation

Load allocation is the process with which forecasts or measurements of customer loads or secondary transformers are mapped to corresponding upstream transformer loads. This process can take many forms and can be used for different end goals, such as determining the peak flow at a given time or visualizing network operations in real-time. The general load allocation process uses estimated load curves, based on customer type and often with many time steps per day, to interpolate the behavior of downstream loads based on upstream measurements or forecasts. One example of this methodology is shown by Carmona, et al. [4], detailing how load allocation can include iterations until the best estimate of load distribution has been reached based on the available information.

Miranda, Pereira, and Saraiva [5] discuss load allocation in the context of generating inputs for DMS load flow functionality with a lack of customer load measurement data. Kersting and Phillips [6] expand the discussion to include 15-minute meter readings in the context of load allocation, comparing various methods under different circumstances. Both papers recognize the limitations of estimating load distribution based on very minimal (or no) measurements and emphasize that measurements should take precedent when making control decisions. However, both papers also describe the importance of accurately estimated loads both for planning and as inputs to other distribution management functions.

Load allocation can be an important step to calculating power injections for load flow or to generating pseudo-measurements for state estimation, as is described by Carmona-Delgado, Romero-Ramos, and Riquelme-Santos [7]. Arritt and Dugan [8] compare four different methods for allocating loads intended for input into DSE. Wan and Miu [9] describe a method of load allocation based on weighted least squares (WLS).

2.2.3 Load Flow

Load flow, otherwise known as power flow, is a fundamental calculation in which a power system is solved for the internal state based on the power injections and generation voltages present at each system bus.

In load flow, the information known is as follows:

- Reference bus voltage and angle (e.g., substation)
- Real and reactive power injection at each node (load and generation)
- Additional generation buses where real power and voltage magnitude are set
- Network model and topology information

The system state is then calculated based on this known information. It is sufficient to have two known data points per network node to solve the load flow problem. The system state is generally considered to be full-system knowledge of node voltage and angles. With this state information, the line currents as well as real and reactive power flows may be calculated in a trivial manner.

In operation, load flow is currently used primarily as a planning tool. Planning software uses the most up-to-date and accurate network model available, then uses load distributions and growth forecasts to predict operating conditions under various worst-case conditions such as maximum or minimum load, as well as any number of contingency scenarios.

With the introduction of ADMS platforms, using load flow as an on-line operational resource has become more common. In order to run a load flow, real and reactive power injections must be known at each bus, as well as voltage at the feeding transformer. These injections could be load forecasts (or the output of a load allocation application), or they could also be measurements based on transformer automation sensors or advanced metering infrastructure (AMI). The number of known state variables must be equal to the number of unknown state variables to calculate a state solution.

However, load flow itself has its own limitations:

- Load flow is not structured to incorporate real-time measurements of line flows or bus voltage
- Load flow does not easily allow breaking the problem into sub-problems
- Load flow is sensitive to error in its input injections or network model

Per the first item, should a load flow result be different from the true internal operation of the system, there is no straightforward mechanism to rectify the two. The second item limits the potential for high-performance computing or parallelization, and additionally makes it difficult to focus the problem on a specific region of the network without network reduction techniques. The third item describes a limitation for day-to-day operation: there is no mechanism to detect unrealistic input data or incorrect network parameters or topology, and therefore the output is susceptible to errors when present on the network.

2.2.4 Non-redundant State Estimation

Non-redundant state estimation is a state estimation problem where similar types of inputs to a load flow are introduced to the formulation of a state estimation problem. Formulated as a state estimation problem, the system has the capability to incorporate line flow and bus voltage measurements as well as the injection measurements and forecasts that are used for load flow. If the inputs to the problem are the same as load flow, the result will be the same—though each additional measurement improves this result. This category is distinct from a redundant state estimation in that there are approximately as many measurements as state variables (a determined system)—with no redundancy to further improve the accuracy of the system.

In addition to improved accuracy in real-time network visibility over load flow due to incorporation of measurements, state estimation allows the network to be broken into sub-problems. This means that areas of the network with better measurement infrastructure can be considered on their own, or the computation can be parallelized for fast convergence with high-sample rates.

Non-redundant state estimation is the most realistic implementation of state estimation for modern-day distribution utilities as many of these utilities have the capability to run a load flow on their system, if only offline. Implementation of this function requires up-to-date network model and topology, load forecasts with the desired resolution in both time and location, and synchronization with real-time measurements—probably from a distribution supervisory control and data acquisition (SCADA) system.

This state estimation problem is considered to be observable because it can utilize the inputs of the load flow problem—even if these inputs are just forecasts. However, without an extensive measurement infrastructure, there will be little to no measurement redundancy required to detect erroneous data, so this problem is still sensitive to input error. For detail on the requirement of measurement redundancy in order to run the bad data detection and identification application, see section 7.4.1.

2.2.5 Redundant State Estimation

The best possible method of visualizing internal power network operations based on available information is a state estimator with redundant measurements. This problem includes all the benefits of non-redundant state estimation, with the improved measurement infrastructure providing redundancy that makes operations resilient to erroneous data points, measurement calibration, or network parameters and topology.

A redundant state estimator typically has on the order of at least twice the number of measurements as unknown state variables, though any introduction of new measurements improves the result of the state estimator. The redundant formulation has the advantage of making the fewest assumptions from the options discussed in this section. It is closest to the state estimation example given in section 2.1.

2.2.5.1 Notes on Comparing State Estimation and Power Flow

State estimation relies on many of the same assumptions as load flow, such as an accurate network model, but its foundation in measurements as opposed to generation schedules and load forecasts inherently makes it the better option for monitoring and operating a system in real-time. If a generation schedule or load forecast were significantly inaccurate, the state estimator would still give an accurate estimate of the state and may identify these data sources as erroneous.

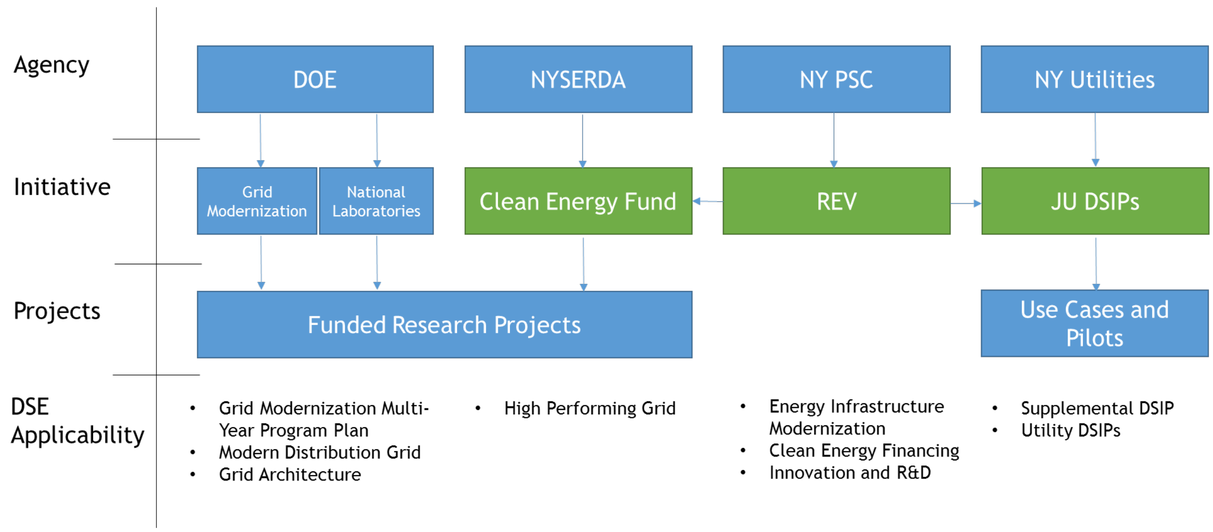
Additionally, while the power flow problem cannot easily be broken down into sub-problems, this comes naturally to a state estimation problem. In order to refocus the problem on a subset (or "island") of the entire network model, the flows along lines connecting the island to the larger model become unknown variables. Because a power flow is dependent on knowing power injections at each bus, increasing the number of unknown injections can make the problem difficult. Meanwhile, a state estimation solution is not dependent on predicated knowledge of bus injections and thus is more flexible to diversity in known values.

However, for all its advantages, state estimation on distribution systems suffers from issues in implementation such as too few measurements and inaccurate network models.

3 Public Policy Initiatives

Research into DSE has been incentivized as part of initiatives at both the federal and state levels. The U.S. Department of Energy (DOE) has funded national laboratories as well as university researchers and industry as part of the Grid Modernization Initiative. The State has seen a number of agencies come together to support the goals of the NYS REV. Figure 3 shows a breakdown of some major initiatives that directly or indirectly support research into DSE.

Figure 3: Initiatives Supporting DSE



3.1 Federal Initiatives

DOE supports research into grid modernization at a national level. Its Grid Modernization Initiative (GMI) works with both public and private entities, including national laboratories to support research and facilitate discussions. SGS reviewed several avenues in which DOE is supporting DSE development both directly and indirectly.

3.1.1 Grid Modernization Laboratory Consortium

DOE's Grid Modernization Laboratory Consortium (GMLC) is a partnership between DOE and national laboratories that oversees mentorship and funding of research projects on the subject of grid modernization for academic and industry recipients. It funds projects in a wide range of areas, several of which have a direct or indirect relation to DSE. These projects are summarized in Table 4. There are also many projects not highlighted in this table which assume good knowledge of the distribution grid state to begin with—meaning that implementation of much of the research in this area is predicated on DSE being present on the system.

Table 4. DOE GMLC Award Topics, Key Projects, and Relation to DSE

Subject Area	Project and Laboratory	Relation to DSE
Core Activities	**Project 6—ORNL:** Grid Sensing and Measurement Strategies: Requirements for Full System Visibility	• Advanced sensing and measurement placement tools to achieve state visibility • Improved telemetry is a precursor to DSE adoption.
Regional Partnerships	**Project 14—BNL, NYSERDA et al:** Technical Support to the NYS REV	• Technical support in policy, planning/operations, and DER integration in the State.
Crosscutting Activities	**Project 19—ORNL et al:** Advanced Sensor Development	• Developing low-cost sensors and asset monitoring • Cheaper sensors are more deployable in distribution networks to support DSE.
	Project 20—LANL et al: Multi Scale Data Analytics and machine Learning for the Grid	• Distributed and machine learning algorithms for enhanced network information exchange, analysis, and forecasting. • Highlights need for reliable system state information and seeks to improve knowledge base.
Buildings	**No identified projects with relevance to DSE**	
Fuel Cells		
Solar Energy	**Project 8—NREL:** Opportunistic Hybrid Communications Systems for Distributed PV Coordination	• Communications system based on variety of data sources and channels for coordinating photovoltaic (PV) generation. • Research will allow gaps to be filled with measured data and inferences from state estimation. • Distributed steady and dynamic state estimation techniques for PV generation and multiple levels of the power grid.
	Project 13—ANL et al: Integrated Tool for Improving Grid Performance and Reliability of Combined Transmission-Distribution with High Solar Penetration	• Includes development of unbalanced DSE tool using semi-definite programming with noisy/missing measurements. • Unbalanced, three-phase DSE tool benchmarked against IEEE systems.
	Project 15—SLAC: Visualization and Analytics of Distribution Systems with Deep Penetration of Distributed Energy Resources (VADER)	• Machine learning-based power flow as advancement on DMS and state estimation • Takes state estimation and power flow as traditional approach to distribution analytics.

Table 4 continued

Vehicles	**No identified projects with relevance to DSE**	
Wind and Water Power		
Advanced Grid Modelling		
ADMS	**Project 1—IPNNL, NREL:** Development of an Open-Source Platform for ADMS	• Developing ADMS in utility-centric environment • Leveraging increased types and volume of data with communication between applications. • New applications will greatly enhance observability and controllability. • No mention of DSE, but it would fit as a tool to leverage observability and improve data. • DSE could be an application within ADMS.
Energy Systems Risk and Prediction	**No identified projects with relevance to DSE**	
Energy Storage		
Smart Grid		
Transmission Reliability		
Transformers		
Cybersecurity		

* U.S. Department of Energy, "DOE Grid Modernization Laboratory Consortium (GMLC) - Awards," 2016. Accessed 8 September 2017, https://energy.gov/under-secretary-science-and-energy/doe-grid-modernization-laboratory-consortium-gmlc-awards.

3.1.2 PNNL Modern Distribution Grid Documents

The Modern Distribution Grid, presented in three volumes, is a series of informational documents published by Pacific Northwest National Laboratory (PNNL) in 2017 with the aim of facilitating discussions and decisions among policymakers, utilities, and industry [12] [13] [14]. It serves as a roadmap for utilities and regulators alike in adopting modern distribution technologies and navigate decisions.

State estimation is mentioned as a key enabler for a number of advanced distribution applications. Volume I provides a mapping of state estimation, along with other applications, to many modern distribution functions. The context of state estimation in this map is described in Table 5.

Table 5. Mapping State Estimation to Modern Distribution Functions

Distribution System Planning	Distribution Grid Operations	Distribution Market Operations
• Forecasting, Comparison, and Cost/Benefit Analysis • DER Locational Value Analysis • System Operations Planning: Outages, Reconfigurations, Analysis • Telecommunications for Connecting Intelligent Devices • Analytics • DER Development and Market Participant Information Access	• Observability • Distribution Grid Controls • Asset Optimization • Integrated Operational Engineering & System Operations • Distribution System Model • Transmission-Distribution Interface Coordination • Steady-State Volt-VAR Management • Power Quality Management • DER Operational Control • Data Management and Data Processing/Storage • Reliability Management • Operational Forecasting	• DER Portfolio Management

This list of distribution functions facilitated by state estimation feeds into SGS' discussions regarding context of DSE implementation and use cases in the modern system. Despite being such a broad enabling technology, Volume II identifies DSE as firmly in the "Operational Demonstration" phase.

The findings of Volume II align with SGS' own research: while there are several documented demonstrations and pilot projects featuring DSE, there are few if no examples of in-the-loop utility operations making use of DSE. This is in contrast to other applications which may fall under the umbrella of a DMS or other planning/analysis software. While DSE has been advertised as one of many modules of these broader tools, SGS is not aware of any utilities using it for day-to-day operations. Volume III identifies challenges associated with DSE, which help to explain the lack of commercial deployment.

3.1.3 PNNL Grid Architecture Documents

PNNL's Dr. Jeffrey Taft released a series of two documents entitled Grid Architecture [15] [16]. While Grid Architecture is focused on the grid as a whole, and much of it covers transmission systems, distribution system operation does feature as an important aspect of the larger architecture. Specifically, the Architectural Insights relevant to DSE are shown in Table 6.

Table 6. PNNL Grid Architecture—Architectural Insights Relevant to DSE

Architectural Insight	Summary	Relevance to DSE
Grid Architecture 1: Architectural Insight 17	Distribution suffers from poor observability. Adjustable load flow and partial meshing help ease constraints with more DERs.	DSE improves observability by making best use of the available measurements. This supports distribution control functions.
Grid Architecture 2: Architectural Insight 10	Current distribution control does not meet modern environment requirement: DERs, distribution markets, locational value.	DSE is beneficial if not a necessary step in bridging the gap between current distribution control and the requirements of the modern environment.

Dr. Taft references the importance of measurement and observability on the distribution system, especially in the evolving context of locational real-time pricing. DSE is a vital component of this observability as well as generates situational electricity prices based on the state of the system. It is situational awareness that DSE provides that enables system-wide control, coordination, and real-time locational markets to take place.

3.2 New York State Initiatives

The State itself is a leader in public policy initiatives for the modern "smart grid." The State Public Service Commission's (PSC) REV is a pioneer among state-led programs for sparking change in our energy systems, and this has manifested in several initiatives across different agencies, including NYSERDA.

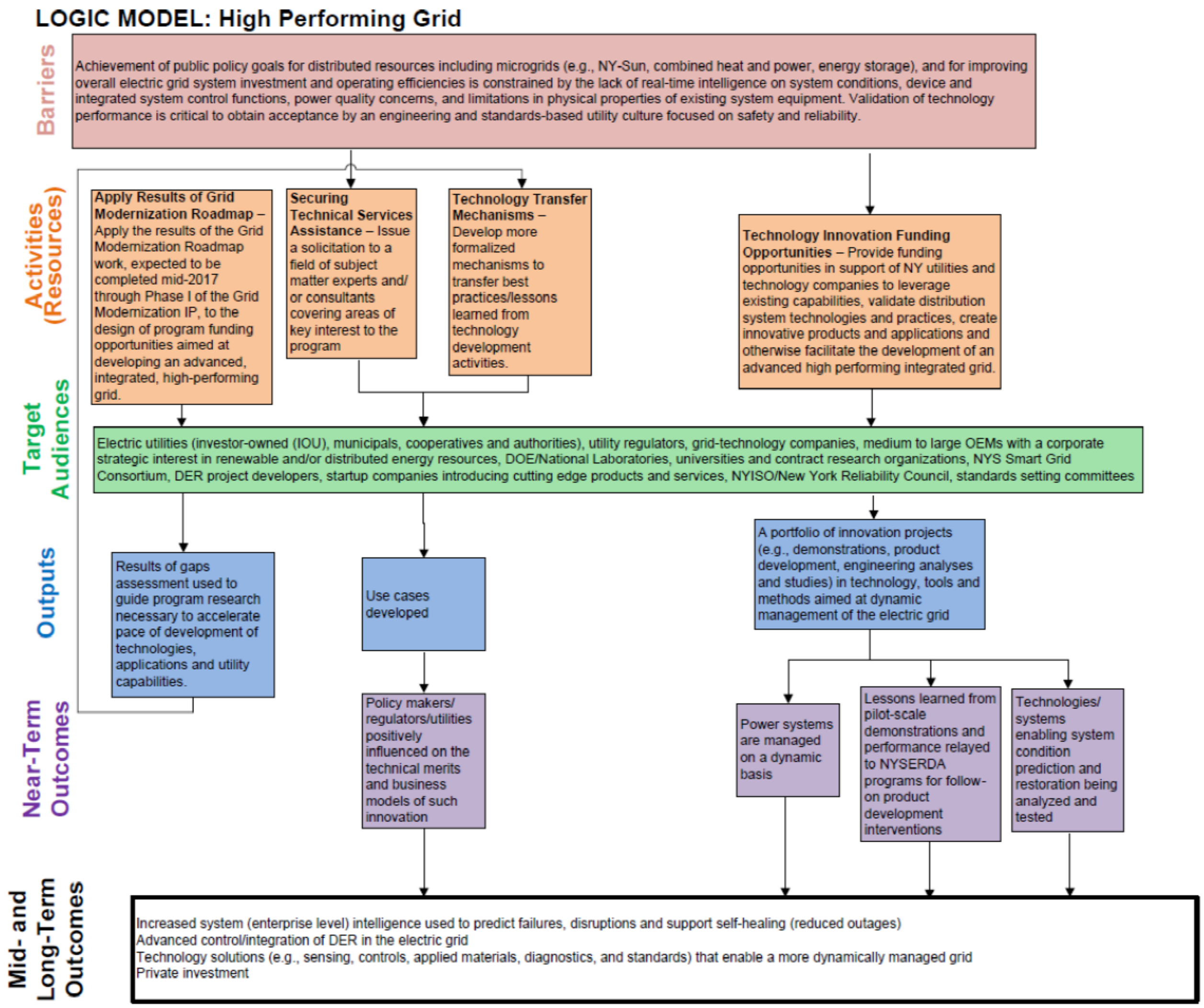
3.2.1 NYSERDA Clean Energy Fund

As part of the NYS REV, NYSERA established the Clean Energy Fund (CEF) to spur innovation in the State's energy system by way of a number of investment plans. Among these investment plans is the Grid Modernization Chapter, which features three initiatives:

- DER Interconnection
- Next Generation Power Electronics
- High-Performing Grids (HPG)

It is the HPG initiative that has provided funding to this project. The goal of HPG is to create a digitally enhanced and dynamically managed electric grid. The detailed plan broken down in Figure 4.

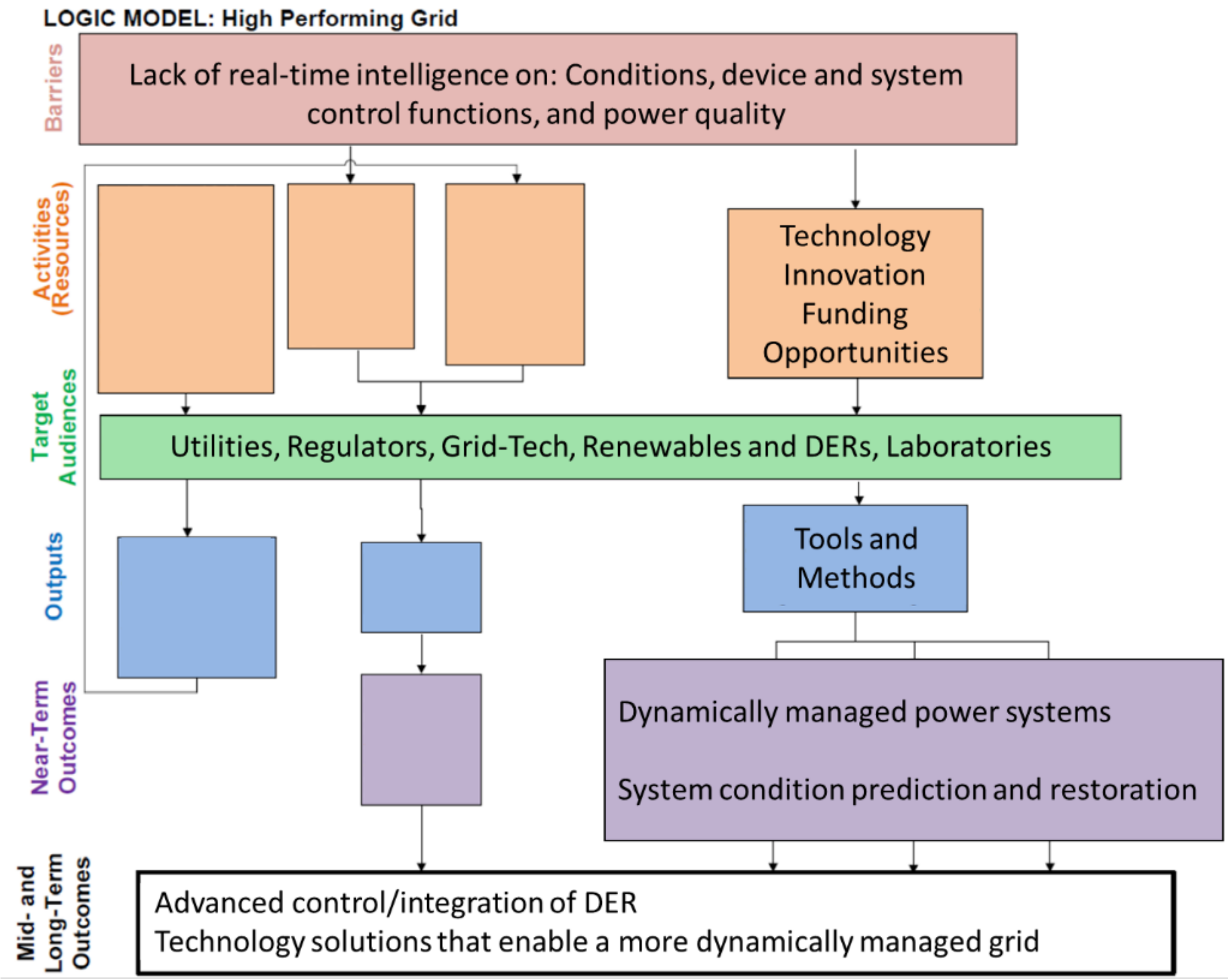
Figure 4. NYSERDA High-Performing Grid Logic Model



* The New York State Energy Research and Development Authority, "Clean Energy Fund Investment Plan: Grid Modernization Chapter. Portfolio: Innovation & Research," Albany, NY, 2016, Revised 2017. Page 35.

DSE is a vital component of the HPG outcomes as presented in this logic model. It allows for visualization and accurate dynamic management of distribution systems, including support of many auxiliary grid operations functions. The relevance of this DSE assessment and toolkit project to the HPG Logic Model is highlighted in Figure 5.

Figure 5. DSE Relevance to HPG Logic Model



This figure shows the aspects of the logic model that apply to DSE by quoting passages from relevant logic blocks. The key takeaway is that DSE a tool to improve observability of a system, can help overcome lack of intelligence by extending and improving confidence in system data and models. Without a state estimator, it is difficult to observe the impact of grid control functions in real time—an issue when it comes to optimizing performance in a dynamic fashion. Utilities and research entities are all interested in DSE implementation methods to improve distribution network performance.

3.2.2 New York State REV

The NYS REV features a number of avenues that benefit from research into state estimation. The REV is organized into three pillars which each support the seven initiatives, as shown in Table 7. Descriptions of the pillars and corresponding agencies are given, as well as notes on how DSE relates to the REV initiatives.

Table 7. New York State REV—Pillars and Initiatives

Strategic Pillars	
Regulatory Reform	• State PSC • Support clean energy markets • Catalyze and leverage innovation
Market Activation	• NYSERDA CEF • Self-sustaining clean energy markets • Innovation and research • Reducing adoption barriers
Leading by Example	• NYPA • Public power example • Deploy clean energy solutions

Initiatives and Relevance to DSE	
Renewable Energy	• DER state monitoring and estimation
Building & Energy Efficiency	No identified relevance to DSE
Clean Energy Financing	• NYSERDA CEF funds this DSE assessment project
Sustainable & Resilient Communities	• State estimation for islanded microgrids
Energy Infrastructure Modernization	• DSE improves utilization of measurements
Innovation and R&D	• NYSERDA CEF • DSE technology transfer to industry
Transportation	No identified relevance to DSE

* New York State Public Service Commission, "Reforming The Energy Vision: REV," 2016.

The NYSERDA CEF is the key agency behind the Market Activation pillar which drives industry growth and innovation. However, it can be seen that all three pillars have a role to play for the REV initiatives, including the development of DSE technology.

3.2.3 Joint Utilities of New York State

The Joint Utilities of the State (JUs) were formed under the NYS REV as a method of collaborating on grid advancement technologies to achieve the policy- and grid-modernization goals outlined by NYS PSC. The JU support members in releasing documents outlining plans, guidance, and expectations for implementing modern distribution systems. The utilities as well as industry stakeholders collaborate periodically to discuss avenues of development, data availability, and the needs of their customers and industry partners.

Each member of the JU has released a Distribution System Implementation Plan (DSIP) outlining the goals for distribution system modernization on their networks. Each document is a thorough account of the tools and functions that will be rolling out in the next five years in order to handle the evolution of distribution grids to dynamically managed, distributed networks. In addition, the JUs together released a Supplemental DSIP which outlines the tools and processes that will be developed jointly by all member utilities.

While documenting distribution network modernization, the DSIPs bring context to DSE on their systems, as detailed in Table 8.

Table 8. Joint Utility Distribution System Implementation Plans

Utility DSIP	Mentions DSE?	Relevance to DSE
Avangrid (NYSEG & RG&E) [19]	No	• Plan to build-out existing telemetry and AMI for improved operational visibility. • ADMS to expand current DMS to include power flow and optimization. ○ This will improve visibility. • DA for automated VVO and circuit switching.
Central Hudson Gas and Electric [20]	No	• Planning upgrades for increased functionality, visibility, and control. • Integrated System Model supports advanced network functions. • AMI is not currently a planned roll out. • Installation of a DMS and improved DA, these will improve system visibility and enable optimization. ○ DSE can help achieve both of these goals, potentially as part of DMS.

Consolidated Edison [21]	Yes	• State estimation is a key technology platform for achieving REV goals.
		    ○ Would be implemented based on their load flow software.
		• Existing system does not have the full system visibility necessary for optimization.
		    ○ Optimization in targeted circuits.
		• Current AMI roll out.

National Grid [22]	Yes	• Goal to install ADMS for visibility and optimization.
		• State estimation as future technology for optimizing platform.
		• Only half of feeders have interval monitoring
		    ○ No ability for system-wide visibility and optimization.
		    ○ VVO in targeted locations.
		• Proposed implementation of AMI.

Table 8 Continued

Utility DSIP	Mentions DSE?	Relevance to DSE
Orange & Rockland [23]	Yes	• Integrated System Model supports advanced network functions. • Long term, ADMS leads to state estimation. • System-wide VVO requires AMI & state estimation among other inputs. • AMI deployment pending, will support DSE. • Increased visibility required to support REV implementation.
JU Supplemental DSIP [24]	Yes	• DSE used for distribution LMP formulation. • Increased grid complexity drives need for increased distribution system visibility. • Increased visibility is supported by DMS, DA, and AMI rollouts by most of the JUs. • Utilities will expand forecasting capabilities. This supports DSE pseudo-measurements.

While not all DSIPs mention DSE by name, all members of the JU have the goal of increasing system visibility. This is most often planned by using a combination of AMI and ADMS advancements, which will allow utilities to model feeder voltage profiles and loads in a more accurate and dynamic fashion. Where DSE is discussed, it is most often to explain on a high level that state estimation is necessary for some system-wide calculations—such as volt-VAR optimization (VVO) or locational marginal prices (LMPs). Only Consolidated Edison reports their intention to implement DSE in some fashion.

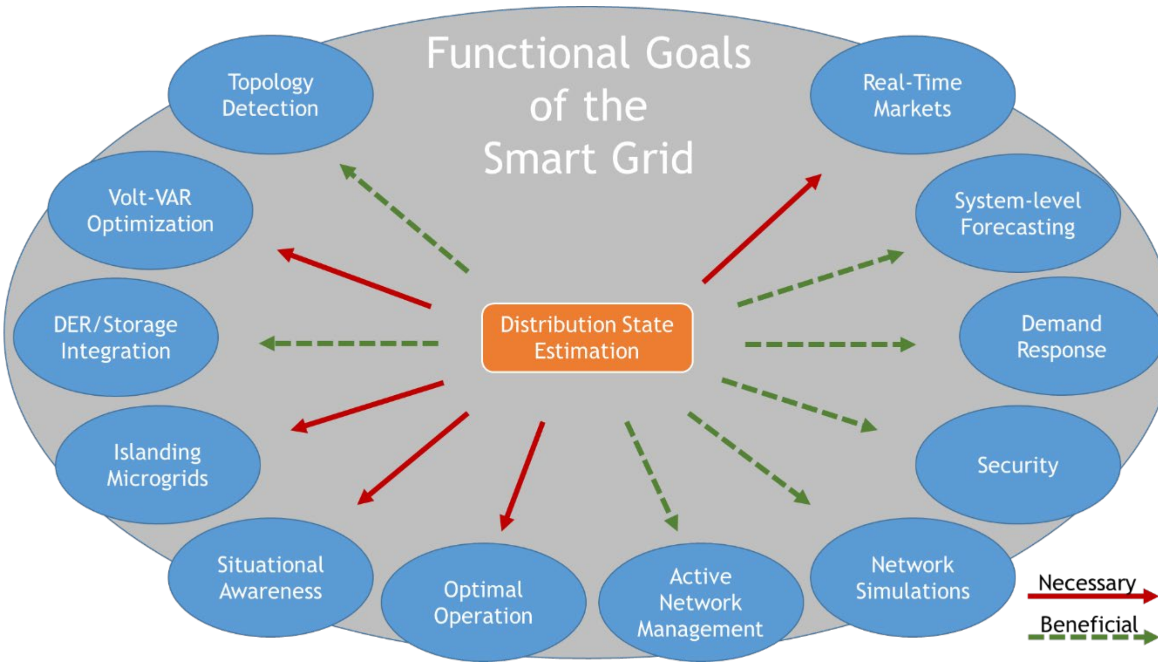
Each DSIP discusses the utility's plans in terms of implementing AMI. This technology has been widely discussed as a catalyst to modernized distribution systems, and with good reason—it enables high-resolution (generally 15 minute) customer load and voltage data to be collected automatically by distribution utility systems. It could support certain implementations of DSE, though its contribution varies based on the planned estimator. Its greatest contribution will be in load forecast calibration and enhancement, as 15-minute load measurements will be a huge step forward for systems that often rely on monthly meter readings to estimate daily and hourly forecasts. Using AMI as a measurement is less straightforward, as challenges arise in calibrating the customer connection parameters in the network model and syncing the often-delayed meter readings with more real-time SCADA measurements.

4 DSE Use Cases

DSE is regarded as an enabling function: it is not an application in and of itself, but it allows and assists the use of other, more practical operation functions. Similar to a power flow, which calculates system state based on power injections, state estimation provides a better picture upon which operators may make decisions. While some functions require a state estimator to enable full capability, its most important use is to provide expanded system data with improved confidence—which truly benefits all operations.

This concept of a modern "smart grid" encompasses a wide range of modern network operation applications that benefit all stakeholders, including regulators, utilities, and ratepayers themselves. It is such a broad concept that its purpose cannot be simplified to one goal. Thus, Figure 6 shows how DSE feeds into the main components of what is known as the "smart grid."

Figure 6. DSE Context in the Modernized Distribution System



Each of the functions depicted in Figure 6 could be implemented to some degree without a distribution state estimator. However, all of the functions benefit from the improvement in data confidence that DSE provides. For the items marked with red "necessary" arrows, SGS determined that a fully functional system-wide implementation of this element would require DSE, even if it could be implemented to some extent without DSE—perhaps as a targeted approach with spot measurements.

For instance, VVO may be implemented on a feeder by taking a few spot measurements: generally, in the substation, the end of the line, and any critical points and locations of reactive elements. Voltage optimization may occur using assumptions that the system is radial with one-way flows, but these assumptions will become less reliable in modernized distribution networks, with increased meshing and DER causing backwards flows. Without the strength of these assumptions, the function moves from volt-VAR optimization to simpler volt-VAR control (VVC) based on end-of-line voltage. DSE can not only improve the knowledge of system voltages along the feeder by incorporating other measurements (loads, currents, etc.), but can give a more holistic view of VVO across feeders and distribution levels.

As part of the requirements analysis, SGS identified use cases where utilities might use DSE to perform functions on their networks. SGS has identified nine categories of use cases, as shown in Table 9. It should be noted that DSE is a facilitator of network operations. While it has applicability in many different areas, it must in many cases be supported both by improved infrastructure and additional analytic functions.

Table 9. DSE Use Case Categories

Use Case Category	Summary of Use Cases
Data Cleansing	• True state estimate • Bad data detection • Historical data cleansing
Visibility	• Measurement placement • Improved forecasting methods • Measurement inferences • Billing inferences
Optimization	• Volt-VAR optimization • Optimal power flow • DER scheduling
Network and Topology	• Network calibration • Topology detection
System Reliability: Preventative Measures	• Contingency studies • Network topology changes • Health of system
System Reliability: Corrective Measures	• Fault location • Condition-based maintenance
Dynamic Energy Prices	• Locational marginal prices • Energy price forecasting • LMP+D: “The value of D” • Transactive energy

Table 9 continued

Use Case Category	Summary of Use Cases
Distribution Operation	• Firming dataset for operation • Extending measurement network • Network simulation and forecasting • Network diagnostics • Demand response
Advanced Distribution Operation	• System-level optimization • Combined transmission-distribution operation • System-level active network management • Islanding microgrids

The use cases outlined in this table are presented with more detail in the sub-sections to follow.

4.1 Data Cleansing

Data cleansing is the act of improving confidence in network measurement, state, and load forecast data. This "hardening" of the dataset (i.e., minimizing error) is often considered the primary objective of state estimation.

Table 10. Use Cases—Data Cleansing

True State Estimate Provide higher accuracy given a measurement tolerance	• Each measurement offers a certain range of confidence • DSE can improve the accuracy by providing a reduced tolerance window • Calculate line flow direction • State corresponds with mathematical solution
Bad Data Detection Use redundant data to identify erroneous values	• Identify inaccurate measurements which are introducing error • Remove bad measurements from state estimation calculation to improve accuracy • Repair and replace bad measurement devices
Historical Data Cleansing Improve accuracy of historical data	• Planning studies require analysis of historical dataset • DSE can remove bad data and reduce error • Meter data collected in post-real time can be used to correct system state

4.2 Visibility

System visibility involves providing the network operator with up-to-date knowledge on what is happening on the system. The goal of full-system visibility is knowledge of the system state in real-time, though current distribution systems are often limited to basic knowledge such as the on/off status of protection equipment.

Table 11. Use Cases—Visibility

Measurement Placement Real-time visibility of system state with minimal measurements and forecasts	• Measure current observability • Determine optimal measurements for desired system visibility • Analyze boost in data confidence with additional measurements • Determine minimum number of load forecasts to introduce as measurements
Improved Forecasting Methods Use system state to calibrate and improve forecasts	• Incorporating measurements improves the accuracy of forecasts • Evaluate new forecasting techniques for their effect on system state accuracy
Measurement Inferences Use system state to measure points where no measurements are present	• Placing measurements in certain location may be precluded by cost or practicality • Use system state as measurement device for network management decisions • Local measurements allow inference of specific unmeasured point (e.g., line flow)
Billing Inferences Use DSE to estimate customer billing information	• If real-time metering unavailable, utilities can give customers estimate of bill [25] • No AMI present at node, or temporary error in device or communication

4.3 Optimization

Optimization is utilization of resources in the best possible way, given the constraints of the system. A power system may be optimized subject to different goals (or “objective functions”) such as constraint management, energy efficiency, and cost of operation. Optimization could occur at scales ranging from the system level to the component level.

Table 12. Use Cases—Optimization

Volt-VAR Optimization Optimal allocation of voltage support	• Voltage controls and reactive elements on distribution system can be centrally allocated. • Improve system voltage, reliability. • CVR: Conservation Voltage Reduction. • Important to have accurate depiction of node voltages. • Optimization must be based on accurate system state.

Optimal Power Flow
Minimize cost of generation subject to network constraints
	• If generation is present on distribution system, optimal dispatch and scheduling.
	  ○ Minimizing system losses.
	  ○ Important to have accurate depiction of loads and line flows to optimize generation.
	• Optimization must be based on accurate system state.

DER Scheduling Optimizing dispatch of distributed energy resources for reactive support or generation	• DERs are a valuable resource that can be dispatched for VVO or optimal power flow. • Optimized resource scheduling in the context of real-time markets.

4.4 Network and Topology

The network model is a vital piece of information that describes the electrical parameters of the power delivery system. Without an accurate network model, many operation functions result in error. The topology refers to the current settings of the network such as switch states and transformer tap ratios. This information is also important for grid operation, though its discrete nature means it can be monitored or deduced from measurements or system state.

Table 13. Use Cases—Network and Topology

Network Calibration Correct an inaccurate/incomplete knowledge of system model or topology	• One-time offline study to identify errors in network model. • Calibrate load forecasts, line flows, bus voltages, switch positions. • Basis for network planning and analysis. • May require manpower to update model ○ Tradeoff: accurate model ↔ accurate state estimate

Topology Detection
Determine topology as output of real-time DSE
	• In-the-loop method of monitoring topology changes.
	  ○ Switch positions, capacitor banks, transformer taps, lines removed.
	• Method 1: Bad topology detection.
	  ○ Error in measurements identifies location of topology error.
	  ○ Run scenarios to minimize error.
	• Method 2: Topology as state vector.
	  ○ Solve for topology as part of the system state.

4.5 System Reliability: Preventative Measures

Distribution utilities have the goal of delivering electrical power with the highest possible reliability. In order to achieve this goal, they enact preventative measures to avoid contingencies before they happen. This is done by enforcing network constraints and identifying components for upgrade.

Table 14. Use Cases—System Reliability: Preventative Measures

Contingency Analysis Use current state to determine effect of losing N components	• Contingency analysis must be based on most accurate voltages and flows. • Determine which components in which combination will cause constraint violation. • Manage network and determine necessary upgrades.
Network Topology Changes Consider unmonitored changes in topology	• Using topology detection, DSE may determine unmonitored changes in network topology. • Changes such as down lines may not violate constraints but may bring system closer to contingency. • Determine where to send field crews and how to manage grid to prevent contingency.
Health of System Monitor usage conditions of components to predict when they might fail	• Components (such as transformers) are rated for lifetime based on maximum load. • If a component is utilized at lower than maximum load, lifetime estimates may differ. • Use DSE to monitor accurate usage of components and estimate lifetime.

4.6 System Reliability: Corrective Measures

In order to maintain delivery to the most customers with the highest reliability, distribution utilities must react quickly and effectively to restore operation in any contingency after it occurs.

Table 15. Use Cases—System Reliability: Corrective Measures

Fault Location Real-time topology detection may indicate location of fault, isolated component, topology error	• Running DSE with topology detection will aid in locations of faults and isolated components • Improve upon asset monitoring for system reliability. o Direct field crews to faulted location.
Condition-Based Maintenance Monitor signs of component wear and upcoming failure	• Use DSE to accurately monitor real-time usage of components. • Detect signs of wear that could indicate potential failure. • Replace failing components.

4.7 Dynamic Energy Prices

In transmission networks, electricity prices are volatile and depend on the current generation dispatch as well as locational and temporal constraints. In distribution systems, the ability to differentiate prices by time and location is limited by the primitive visibility on the system. One of the directives of the State's REV goals aims to modernize electricity markets for distributed generators, and to financially evaluate the benefit to the system of generation at particular locations.

Table 16. Use Cases—Dynamic Energy Prices

Locational Marginal Prices
System state as basis for LMP determination
	• LMPs are based on cost of delivering an incremental increase in power to a specific location.
	• Factors for determining price:
	  ○ Cost of generation
	  ○ Line flow limitation
	  ○ Voltage constraints
	• Generation must be re-dispatched if constraints are violated, increasing price.
	• Determination of constraint violation is based on an accurate state estimate.

Energy Price Forecasting LMP forecast based on load, system, and state	• Combine calibrated load forecasts with system data to determine future LMPs. • Predict how load will respond to market and other signals.
LMP+D: "The Value of DER" Value of DERs at distribution locations	• Based on LMPs and scenario assessment, the value of DER at grid locations can be calculated. • DSE helps improve accuracy of simulation model to forecast the "Value of D."
Transactive Energy Controlling energy system using market-based signals	• Real time electricity prices and incentives can create dynamic loads and generation. • DSE is the basis for optimizing which resources should be incentivized using prices. ○ Peak shaving, ancillary services, etc.

4.8 Distribution Operation

Distribution operations can benefit from DSE in a number of ways. Some of the potential use cases for distribution operation have been presented in previous sections—this section aims to bring them into the context of planning and in-the-loop use cases to aid in distribution network decision-making.

Table 17. Use Cases—Distribution Operation

Firming of Dataset DSE solidifies confidence in dataset for operations and analysis across the board	• Eliminate discrepancies between load flow and system state. • Enable visibility in areas with fewer measurements. • Create a more accurate baseline for expansion planning and hosting capacity.
Extending Measurement Network Increase utility of current set of measurement devices	• Combine load forecasts with real-time measurements to describe system behavior. • Accumulate different types of measurements at different time resolutions. ○ All measurements benefit the state estimate.
Network Simulation and Forecasting DSE calibrates network and forecasts for more accurate analysis	• Forecasts can be compared to real-time system behavior to improve models. ○ Improved load forecasting. • Calibrate how system responds to changes based on modelled response. • Improve simulations and planning studies.

Network Diagnostics
Use output of DSE to locate and diagnose network issues
	• Topology detection identifies normally unmonitored changes.
	• Identify the nature of discrepancies between measurements and state.
	  ○ Incorrect mapping of loads and measurements.
	  ○ Measurement error vs topology error
	  ○ Identifying faults.
	• Condition-based maintenance and planning.

Demand Response Dynamically manage loads for peak shaving and other benefits	• DSE improves the basis for sending load-altering signals to dynamic consumers. • Added confidence to justify customer load alteration.

4.9 Advanced Distribution Operation

Many research topics in DSE assume a level of network maturity not currently present on the distribution system. The broad applicability of DSE extends to many of these use cases which may require significant system improvements before they are realized.

Table 18. Use Cases—Advanced Distribution Operation

System-level Optimization Move optimization from local to system-wide	• VVO and reactive support along feeders and across primary and secondary networks. • Optimize loss reductions across system. • Optimal dispatch of generation. ○ Active network management (ANM).
Combined Transmission-Distribution Operation Unified approach to operating both co-dependent networks	• DSE improves load forecasting techniques and accuracy of current state for integration into transmission model. • Accurate load models integrated into transmission system. • Predict how transmission changes will impact distribution system.
System-Level Active Network Management Improve current ANM techniques at a system level	• Optimize DER generation dispatch. ○ Not just local constraints, but for system-wide operation. • Extend measurement functionality. • Monitor adaptable line ratings.
Islanding Microgrids DSE improves visibility at distributed level to support islanding microgrids	• DSE uses “observable island” approach to monitoring system. • DSE necessary for monitoring island tie-lines and islanded state. ○ Islanded systems change more rapidly.

5 DSE Implementation Challenges

With the policy goals, definition, and use cases of DSE having been laid out in previous sections, the following section discusses the context of DSE in relation to current distribution utility operations.

5.1 DSE Implementation Challenges

State estimation is a well-established practice in most transmission systems—however it has almost no established usage in distribution systems. This discrepancy is attributed to a variety of differences between transmission and distribution systems that make bridging this gap challenging. At the root of the challenge facing DSE is the fact that while transmission networks are highly monitored and controlled on a real-time basis, distribution networks have traditionally been managed in a passive manner with limited system visibility, knowledge of the network, and control opportunities. A summary of the challenges regarding the adoption of state estimation in distribution systems is provided in Table 19.

Table 19. Challenges Blocking the Road to DSE

Challenge	Description
Implementation Challenges	
Observability	• Lack of visibility requires forecasts of load and DER generation as pseudo-measurements. • Real-time measurements often only located at protection and transformers.
Communication Infrastructure	• Network model must be on-line and updated with latest topological changes. • Measurements must be relayed to control point in real-time. • Incorporating AMI increases infrastructure requirements by an order of magnitude. • Incorporating AMI also means combining data from protection/operation systems with customer data.
Complexity of Network	• High number of nodes due to customer connections. • Phase imbalance necessitates three-phase modeling, further increasing the number of nodes and the complexity of the method.
Line Parameters	• High resistance to impedance ratio on low-voltage lines restricts possible methods and can impact convergence.
Accuracy and Effectiveness Challenges	
Uncertainty in Network Parameters	• Distribution network models are updated and calibrated infrequently. • Solution is sensitive to parameter error due to lack of measurements. • Incorporating AMI requires accurate customer connection models.
Uncertainty in Topology	• Frequent and underreported changes in network topology. • Limited topology and asset monitoring.
Uncertainty in Load and Forecast	• Un-aggregated loads are harder to forecast than aggregations. • High rate of change with DERs. • Over-reliance on forecasted pseudo-measurements increases system error. • Forecasts may be at system- or feeder-level, not at the bus. • Forecasts may be hourly, while the state estimator may operate at a much faster frequency.

Each distribution system intending to install a distribution state estimator must address each of these 11 challenges, though the challenges may have different solutions depending on the nature of the network, and some may be more difficult to solve than others. Some of these challenges merit further discussion due to their scope in the following sections.

5.1.1 Observability

Observability is the biggest challenge in DSE implementation. In control theory, observability is the ability to infer a system's state based upon a set of outputs. This definition applies as well to power systems, with the outputs being the measurements incorporated into state estimation. Note that there is a mathematical difference between *monitoring* a network and *observing* a network. For instance, while a feeder may be *monitored* using an end-of-line node to ensure its voltage stays within constraints, the feeder is only *observable* if the DSE features sufficient measurements along the length of the feeder. The system state cannot be inferred using several spot measurements unless they form a cohesive set that fully describes each node.

A general rule of thumb for observability is that there must be two measurements per node, as there are two characteristics that describe each node (voltage and angle) and two characteristics that describe each line (real and reactive flow). Any two known characteristics can be used to describe the other two at a system level. The location of these measurements also affects its observability, as they must be distributed such that information from each node may be obtained.

Distribution systems face the challenge of observability because there are very rarely two measurements for each node in the system. This makes the system underdetermined and means that additional information is required in order to make any determination in terms of system state. This additional information usually comes in the form of pseudo-measurements and virtual measurements.

Pseudo-Measurement

A load forecast specific to the load at one node on the network, which is used in the paradigm of a measurement with a specified error tolerance. This tolerance is generally much greater than that of an actual measurement and could be as high as 50% depending on the forecast.

Virtual -Measurement

A known quantity on the network (e.g., a bus with no load) that is used in the paradigm of a measurement with little or no error.

Given a lack of additional information, other measures may be taken such as performing topology simplification or focusing on observable islands.

Topology Simplification

Identifying and removing parts of the network from consideration in the state estimator by considering them as part of a single bus or load. This reduces the number of unknown state variables but does not give insight into the state of the removed nodes.

Observable Islands

In this approach, certain regions or branches of a network with sufficient observability are estimated, while others are left uncalculated. This may or may not be suitable for a given use case as it sheds no knowledge on uncalculated parts of the network. Also, using pseudo-measurements to fill in the missing information, even if they are inaccurate, often allows the network to be solved as a whole.

5.1.2 Complexity of Network

Compounding the issue of limited monitoring on distribution networks is the issue of scale: distribution networks, in general, have many more buses than transmission networks due to the large number of requisite customer connections.

To compound this, distribution networks tend to operate with imbalance between the phases, which means that each phase must be analyzed individually. A three-phase solution to the state estimation problem triples the number of state variables per bus and therefore increases the complexity of the problem. In a three-phase unbalanced system, there must be two measurements per node, *per phase*, in order to achieve observability.

Solving a state estimation problem on a distribution network therefore requires higher power computing than transmission for a given network size. To reduce computing time in a real-time implementation, utilities and operators may opt for topology simplification, parallel computing with network regions, or to focus only on certain regions and voltage levels of the distribution system.

5.1.3 Gaps and Uncertainty in Network Parameters, Topology, and Load

A glaring issue at the distribution level is the uncertainty of the entire system. In Table 19 this was presented as three separate items: Uncertainty in Network Parameters, Topology, and Load/Forecast. The uncertainty involved in distribution systems takes root in the traditionally passive nature of the systems. While transmission networks are meticulously monitored, optimized, and planned, distribution networks have been designed to deliver power to the most customers with the highest reliability, under the assumption of unidirectional power flows from substations to customers. Unidirectional flow made unnecessary advanced monitoring and control techniques applied to transmission systems. Thus, distribution networks have little automation and many processes are manned instead of automated, limiting the flow and reliability of information that could be used in a state estimator.

5.1.3.1 Network Parameters

The network model itself is a source of uncertainty in distribution systems. Depending on the system level, a distribution utility may not have full confidence in its network model and continuously updates and improves the model. Inaccuracy of the network model can cause error in a state estimator, as it will converge a solution to an incorrect problem formulation.

Utility confidence in the network model tends to decrease as the voltage level decreases, and lower voltage networks and the associated customer connections may be almost entirely unmodeled. Particularly with the use of AMI, the connection between the customer and the distribution network is a vital piece of information that is often not included in the network model. Parameters might change as maintenance crews repair lines, but updates may not make it back into the network model. With constant expansions and upgrades to host new customers, it is difficult to maintain an accurate distribution network model.

In addition, as reactance levels are lower on distribution networks than on transmission networks, the model is more sensitive to changes in system reactance due to changes in loading and temperature, which can be unpredictable. This adds another challenge in maintaining accurate network parameter values.

5.1.3.2 Topology

The network topology refers to network equipment settings, such as transformer tap ratios, protection equipment, reactive components, and reconfiguration switches. In distribution systems, many of these components may be unmonitored. Reactive components and transformer taps are often automated based on local measurements that are not delivered to central operations.

Distribution networks are much more susceptible to faults than transmission networks. After a fault, a line may be taken down by network protection elements, which may not be monitored by the control center. Particularly in meshed secondary networks where missing lines may not cause an interruption in service, these topology changes often remain unknown to network operators. Additionally, in contingency situations, networks can be reconfigured to maintain connection to certain customers. These reconfigurations are performed by crews on site and the information may not make it back into the system's network model.

5.1.3.3 Load

DSE generally makes heavy use of load forecasts as pseudo-measurements. Current utility forecasting methods often focus on the worst-case peak loads in a day. Depending on the particular DSE implementation, these peak-load forecasts may need to be interpolated with higher resolution data points such as hourly or sub-hourly pseudo-measurements. This interpolation in combination with the high reliance on pseudo-measurements in DSE is a source of error.

Depending on the level of the distribution network being estimated, these load forecasts are aggregated to a certain extent at network buses. However, the number of aggregated loads at each bus is much lower than in a transmission system, where each load might be an entire distribution network. When estimating secondary networks, there may be no aggregation at all. The issue this presents is in predictability of load forecasts: as a rule, aggregated loads are more predictable than disaggregated loads, as the behavior of a large group of people will typically remain within a standard deviation of the forecast while an individual may not. This introduces additional error in load forecasting techniques.

In current distribution systems, the most common monitoring that occurs at customer loads is the monthly energy bill. Many utilities are resolving this issue with the roll-out of AMI. However, not all utilities are following this approach, and utilities that are installing AMI will take a matter of years to complete the implementation and centralization of load data. AMI often takes the form of 15-minute measurements of load and voltage data points—though depending on telemetry, this information may not make it to the operations center for a delayed period of time. One area where AMI will be particularly useful is in calibrating advanced load forecasting techniques, significantly reducing the error of high-resolution forecasts that was discussed previously.

All of these sources of error in load forecasting and measurement are made more complicated with the introduction of higher penetration of DERs. Especially in the case of PV, these resources can be highly volatile—causing large, fast, and unpredictable changes in net load at their respective load. Momentary reductions in DER generation can reveal "masked load," or load that was previously unknown due to net metering. Masked load in particular can cause large ramping at customer loads. Fast changes in DER generation add yet another source of error to distribution loads which compound with the sources previously mentioned.

5.1.4 Diversity of Network

Distribution systems, when compared to transmission systems, are extremely diverse. There is a wide range of voltage levels, from sub-transmission voltage to feeder voltage and down to delivery voltage on secondary systems. Each level of the distribution system has a different topographical nature and can vary from meshed to slightly meshed to entirely radial. Beyond this, the diversity among radial systems alone causes difficulty in the observability analysis, as each network will require a different approach to consolidated observable and unobservable areas. Compromises will have to be made in terms of omitting certain unobservable areas of the system, which will depend on the nature of the particular distribution network and its customers.

Measurement and protection devices also vary between networks. Some higher voltage networks may have real-time SCADA and protection measurements arriving at the control center periodically, while others may rely on customer smart meter data, or some combination of the two. The challenges involved with centralizing these data sources and incorporating them into a unified state estimator will vary based on the measurement, metering, protection, and telemetry architectures.

The diversity of networks in distribution systems therefore ensures that no two solutions will be the same. Software and in-house implementations will be significantly different between different utilities, and also between different networks under the same utility umbrella. This is important to keep in mind when studying DSE, as a proposed solution or software product may be applicable to only a subset of distribution systems.

6 Origin of DSE Literature

State estimation has become a vital aspect of power system operations and control. Since the concept of state estimation was first applied to power systems by Fred Schweppe in 1970 [26], the body of literature has grown, and applications have become more widespread. However, power system state estimation has historically been applicable only to high-voltage transmission systems. In power transmission, measurement devices are prevalent in order to protect expensive high-voltage equipment from contingency, which at the transmission level could mean loss of power to a region. These thorough networks of measurement devices allow state estimation to occur, enabling highly accurate knowledge of the power system's behavior which in turn enables outcomes such as real-time power markets and optimized generation dispatch.

State estimation was not considered applicable to distribution networks until the 1990s [27] [28] [29]. This delay was the combined result of several factors differentiating transmission and distribution systems:

- Distribution networks feature far fewer measurements, accompanied by less mature communications and telemetry. SCADA implementations are less commonly implemented in distribution substations.
- Distribution networks have many more buses and lines than transmission systems due to the geographic distribution of customer loads, making the unknown variables much more numerous.
- Distribution networks historically operate on a passive basis—meaning that the control centers have not had the ability to perform actions and therefore have not had real-time visibility. Distribution equipment is therefore built to handle worst-case conditions.
- Contingencies and outages for distribution systems have less severe consequences than for transmission systems, as they service smaller geographic areas and feature less costly equipment. This further reduces the need for real-time network visibility and in-the-loop control. Distribution utilities typically perform actions after a contingency event is reported.
- The radial nature of distribution systems along with predictable one-way power flows permits inferences of the system state by ensuring conditions at the feeder head and end-of-line, the distribution utility assumes proper operation of the entire feeder.

Bringing state estimation theory from transmission systems to distribution systems in the 1990s involves considering the minimal set of measurements required to perform the state estimation function at the minimal resolution to provide operational benefit. This was the case for one of the earliest demonstrations of the technology, which was implemented in Rochester, NY and was published in 2000 [30].

However, as has been described in the first phase of this project, the incentives and use cases for DSE have expanded in recent years—especially due to the transforming role of distribution utilities into system operators in the modern distributed environment. Building upon research into DSE policy initiatives, use cases, and challenges, this study serves as a review of the state of the art, including academic literature and published implementations on the subject. It also includes an analysis of literature gaps that may become vital to fill for the purposes of widespread implementation of DSE.

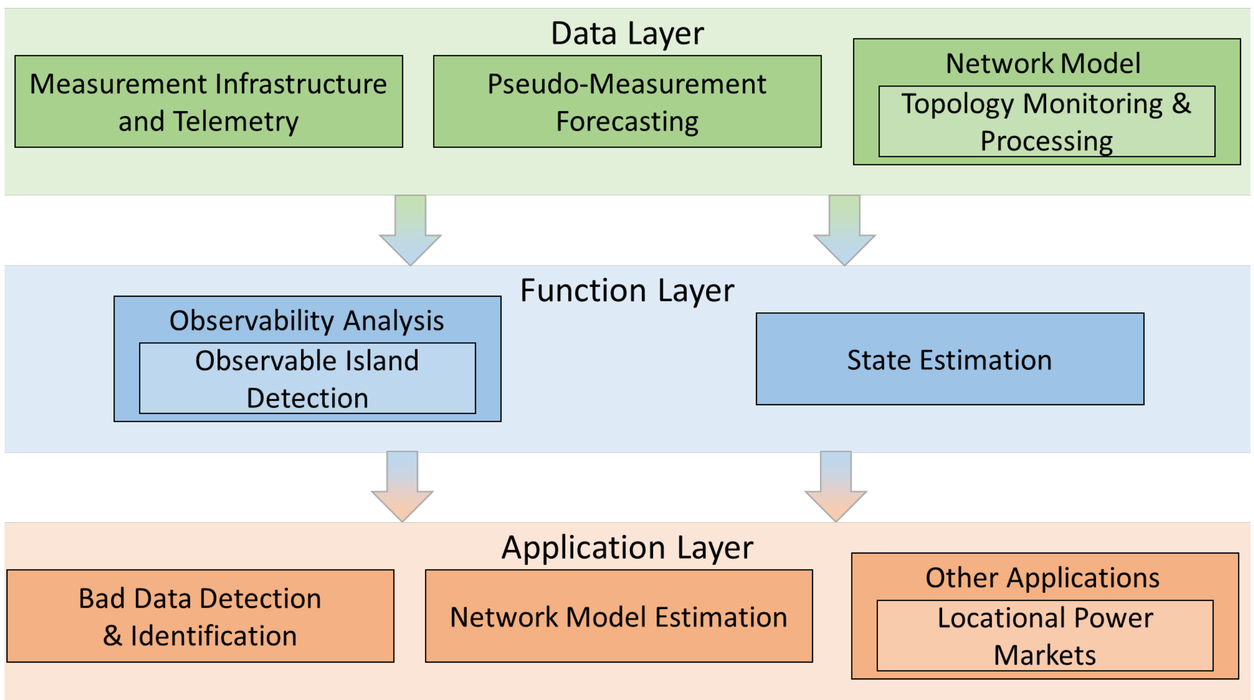
This review is a survey of the current research on DSE with the perspective of evaluating useful contributions towards utility implementation. In the depth of material discussed from all angles of DSE implementation, this work is unique. However, other holistic studies on the subject provide useful references:

- For concise literature reviews on DSE, reference authors Chan-Nan [31] and Ahmad, et al. [32].
- For a discussion on DSE methods together with implementation challenges, reference Liao and Milanović [33].
- A survey of algorithms for DSE and forecasting as well as planned implementation and algorithm details was documented as part of a European project in 2015 [34].
- For more detailed tutorials on core state estimation methods, reference the textbooks by Monticelli [1] and Abur and Gómez-Expósito [2]. The latter textbook was used as the primary background reference for state estimation methods in this report.

7 Components of a State Estimator

The preceding conversation regarding algorithms for DSE—a discussion of the building blocks comprising the function—is necessary, largely because the greatest challenges that exist in implementation are not due to the algorithms used to solve the problem but to the building blocks that contribute to the system. An overview of the functionality broken down into layers is shown in Figure 7.

Figure 7. DSE Components and Layers



7.1 Data Layer

The data layer comprises the information technology and physical attributes that are accumulated in the control center of a distribution utility. The data layer is the input of the state estimator, that is, all knowledge of the system that could impact the result of state estimation—this characterizes the network. The information includes measurements and forecasts as well as network model and topology.

7.1.1 System Measurements

Measurements are the most important aspect of the state estimator. Without adequate measurements, state estimation could either be unsolvable or unusable. There are three main criteria to consider regarding the measurement infrastructure of a utility network:

- Distribution and placement
- Accuracy
- Temporal resolution

These topics are expanded in subsections below. In addition, special attention is given to the use of AMI, smart inverters, and PMUs in subsequent subsections.

7.1.1.1 Measurement Distribution and Placement

Measurement distribution impacts the observability and redundancy of the state estimator. For a state estimator to be fully observable, the measurements must be distributed such that there are at least the same number of independent measurements as there are unknown states—this is generally on the order of two measurements per bus. Note that a single device can constitute multiple measurements so long as it is measuring independent quantities. For instance, PMU could potentially measure bus voltage and voltage angle as well as a number of line currents and current angles—all of which are independent of each other and count as measurements.

Academic literature is strong in terms of determining optimal measurement of measurements, dating back to foundational papers in the 1980s that proposed methods for placing measurements to achieve observability [35] [36]. Dr. Abur has more recently become a prominent author on the subject and co-authored a textbook with Dr. Antonio Gómez-Expósito [2] and several additional papers on measurement placement.

In Abur's (et al.) works on measurement placement for state estimation, he primarily discusses measurement placement for achieving system-wide observability. As part of this discussion, Abur (et al.) considers merging existing observable islands into a single observable system and achieving redundant observability resilient to loss of measurements. Abur has co-authored papers on measurement placement with Magnago [37], Gou [38], Huang [39], Xu [40] [41] [42], Yoon [42], and Emami [43].

As PMUs are the most capable measurement equipment and widely used on transmission and certain distribution networks, Abur's work focuses on them in these papers. However, Gou and Abur [38] analyze non-PMU measurements such as voltage and current magnitude or real/reactive power flow. Findings from his works regarding PMU placement can also be applied to non-PMU measurement placement.

Other works on measurement placement focus on improving accuracy of the result, with the understanding that the system is already observable:

- Shafiu, Jenkins, and Strbac [44], Korres, Xygkis, and Manousakis [45], and Nusrat [46] discuss approaches to placing voltage and power measurements to improve estimator accuracy, with Nusrat providing a thorough description of placement algorithms.
- Singh, Pal, and Vinter [47] present a sequential approach placing voltage and power measurements to improve estimator accuracy.
- Singh, et al. [48] present a non-iterative approach for efficiently determining the minimal voltage magnitude and real/reactive power measurements for achieving desired accuracy.
- Wang and Schulz [49] discuss improvements in accuracy by measurement type (voltage magnitude, current magnitude, and real/reactive power flow) on state estimation with branch state variables.
- Li [50] analyzes the impact of measurement placement on the accuracy of DSE.
- Akingeneye, Wu, and Yang [51] discusses limited PMU placement for improving accuracy of state estimation.
- Rice and Heydt [52] provide an extensive report that discusses results and various consideration factors for PMU placement to improve accuracy, and also proposes a method for eliminating phase angle estimation in favor of directly using the measurement of the PMU as the state.
- Kahunzire and Awodele [53] investigate PMU placement distribution consideration for DSE and the effect on improved monitoring and accuracy.
- Liu, et al. [54] investigate a design approach for optimizing the measurement infrastructure, including PMUs in addition to more traditional distribution system monitoring devices.

7.1.1.2 Measurement Accuracy

Accuracy is the second defining characteristic of the measurement infrastructure for state estimation. In the foundational weighted-least-squares (WLS) formulation, measurements are incorporated into the estimator with a weight corresponding to their known accuracy. Other formulations of the state estimation problem have a similar mechanism. In this way, measurements with higher accuracy have a stronger influence on the result than those with a lower accuracy.

Distribution state estimators typically have less advanced measurement equipment than transmission systems. Particularly when using a large number of pseudo-measurements with high uncertainty.

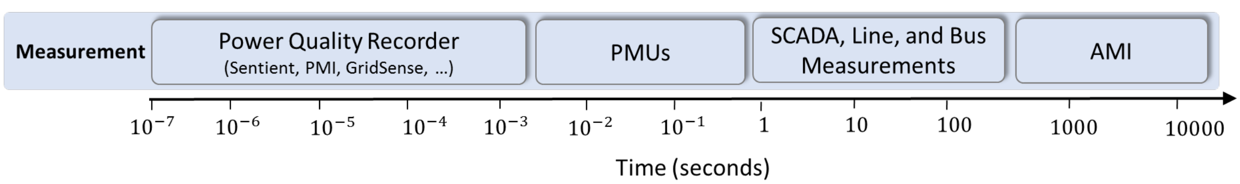
Several studies have addressed the issue of measurement accuracy:

- Xu, et al. [55] present an algorithm for working with uncertainty of measurements in a three-phase state estimator using the unknown-but-bounded theory.
- Huang, et al. [56] provide a method of reducing uncertainty in historical data state estimation used for planning purposes.
- Li [50] analyzes the impact of measurement accuracy on the resulting accuracy of DSE.

7.1.1.3 Measurement Temporal Resolution

Distribution state estimators are commonly made up of a wide variety of measurement sources. As most distribution systems do not have system-wide deployments of on-line bus measurements, operators need to take advantage of every piece of information available in order to achieve useful state estimation. This leads to conglomerate systems taking in data with a wide range of temporal resolution. Common data resolutions for distribution measurement equipment are shown in Figure 8.

Figure 8. Distribution Measurement Temporal Resolution



There are two options for real-time state estimation when confronted with measurements of varying temporal resolution:

- Perform the state estimation at the resolution of the lowest measurement frequency.
- Perform the state estimation at a resolution higher than the lowest measurement frequency using a method to incorporate older and out-of-sync measurements.

Depending on the needs of the system, the first option may not be suitable for operations. When pursuing the second option, one has to consider the fact that older measurements have less relevance to the current state than newer measurements. Direct inclusion with no adjustment to the state estimation method is possible, but this can introduce error to the state estimator as these measurements will be influencing the solution of a system state that may have changed.

A variety of literature has been published on the subject of incorporating measurements of different timescales:

- Gómez-Expósito, Gómez-Quiles, and Džafic [57] discuss an architecture for a distribution state estimator at two levels and timescales: load-based pseudo-measurements and AMI, and higher resolution SCADA measurements. The paper is a valuable and holistic approach to DSE.
- Alimardani, et al. [58] approach unsynchronized measurements in DSE on the bases of each measurement's credibility, adjusting the variance based on their age.
- Han, et al. [59] discuss the issues regarding synchronously accommodating 10-minute resolution measurements for a real-time DSE, including loss of communication issues.
- Stanković, et al. [60] propose a method for managing irregular sensor samples using a Kalman filter, providing data alignment for PMU and SCADA measurements in a hybrid state estimator.
- Janssen, Sezi, and Maun [61] similarly propose a synchronization method for PMUs on a distribution system, with an underdetermined three-phase radial network system.

7.1.1.4 Advanced Metering Infrastructure

One of the largest current initiatives for modernizing distribution systems is the installation of smart metering at the customer level. Known as AMI, this program is incentivized by benefits across the spectrum of distribution utility operation. In addition to automating the meter-reading and billing process, AMI provides data that allows for great improvements in the accuracy and granularity of forecasts, and also that can be incorporated into central operation functions, such as state estimation.

AMI generally consists of a full deployment to all customers of smart meters in a geographic area that measure real power, and potentially voltage and reactive power as well. Accumulated energy is calculated as well for billing purposes. The resolution is usually around 15 minutes.

AMI can benefit the effectiveness of state estimation in one of two ways:

- Incorporation directly into the state estimator as measurements
- Enabling advanced forecasting at the customer level, generating accurate pseudo-measurements

Incorporating AMI directly as measurements is the best-case scenario for utilization. However, there are challenges that may prevent real-time incorporation of measurements into an on-line estimator. Primarily, there is the challenge of having sufficient telemetry infrastructure to relay data points back to the control center. Distribution systems cover a wide geographic area, and with the rapid rollout of smart meters, many systems do not have the bandwidth to transmit measurements to the data hub without significant delay. Frequently the system is designed to receive an extended period of data at one time, even upwards of 24 hours, such that there is no periodicity to the measurements. This setup prohibits real-time use of AMI measurements, though historical state estimation would still be possible—and could be applied to event playback or steady state network diagnosis.

Additionally, there is the challenge of hosting and processing the large amount of data accumulated by the meter data management system (MDMS) from the smart meters. AMI data is not necessarily in the correct format for input into grid operations, and the sheer quantity of data can cause delays in the system.

A third challenge could be the protection of customer privacy, and issues related to obtaining high-resolution data that could theoretically be used to ascertain customer behavior. The extent to which this affects utilities varies widely by the region and its customer privacy laws.

Without a strong communications network to support on-line state estimation, a good option for utilizing AMI is in advanced forecasting techniques. Forecasting loads is doubtless a goal for any utility pursuing an AMI program, as many utilities use feeder-level or transmission-level forecasts as a basis for loading predictions. AMI enables forecasts to be customized to consumers and correlated to narrow timeframes— significantly improving the accuracy of the forecast and corresponding pseudo-measurement. For brevity, a review of forecasting methods will not be presented in this report—though a discussion of pseudo-measurements appears in section 7.1.2.

Another consideration in the use of AMI is that meters are often located on the secondary distribution network. If the distribution state estimator does not estimate buses near these measurements, they cannot necessarily be used as measurements and must feed into the forecasting application for pseudo-measurements.

In its report on Voltage and Reactive Power Optimization [62], Pacific Gas and Electric Company (PG&E) presents the results of a VVO project where AMI was used to verify the voltage results. As part of the report, PG&E discusses the challenges faced with the smart meters:

- Temporary data unavailability due to communication network limitations. Improving the communications network to prevent this is proposed as a way of improving project performance.
- Data management issues in terms of storage and processing. As AMI was deployed primarily to streamline billing, the data infrastructure is not conducive to utilizing measurements for operations. A better MDMS would benefit network operations, including state estimation.

Several existing works discuss the design of a state estimator to include AMI data:

- Baran and McDermott [63] analyze branch-current-formulated state estimation of a radial distribution network using AMI first as input for pseudo-measurements and second as real-time measurements—comparing the results of the two approaches.
- Alimardani, et al. [58] present a method to incorporate non-synchronized meter data from AMI and other sources into the same estimator on the bases of age of measurements.
- Xygkis, et al. [64] discuss using AMI both as near-real-time measurements and as inputs into load estimation and forecasting for a state estimator.
- Wakeel, Wu, and Jenkins [65] use AMI data to extend the observability of a state estimator on an 11-kV distribution system, using the data both as real-time measurements and to support pseudo-measurements.
- Abdel-Majeed and Braun [66] investigate the use of accurate smart meter data for performing observability analysis and state estimation in low-voltage networks.
- Feng, Yang, and Peterson [67] discuss incorporating AMI data into an existing state estimator that uses SCADA data. Because of AMI limitations, the data is incorporated into forecasts as pseudo-measurements.
- Samarakoon, et al. [68] present a method to using AMI data from the previous day to integrate with real-time system measurements and provide an accurate state estimate.
- Pau, et al. [69] present an architecture for a cloud-based AMI platform that integrates with a computationally efficient and parallel two-level, low-voltage state estimator.
- Huang, Lu, and Lo [70] approach AMI integration into the heterogeneous utility dataset from a holistic operational standpoint, including offline and online operations and state estimation and forecasting.

7.1.1.5 Smart Inverters and DERs

An increase in DERs is one of the driving factors for distribution network modernization, including the push for grid visibility and state estimation. DERs present a challenge to the traditional, passive, and unidirectional operation of distribution systems, but at the same time offer opportunity as well. In addition to acting as participating elements in power markets and voltage support, the connection point has the potential to be a source of measurement.

While many existing DERs on current distribution systems do not feature controllability or measurement capability, new standards for such interconnection such as IEEE 1547 and its complementary standards set the stage for smarter interoperability [71]. Utilities may opt to require adherence to these standards for DER connection, in this way ensuring not only the controllability of assets but the availability of generation data.

Challenges to incorporating DER data from smart inverters into a distribution state estimator include:

- Navigating the landscape of data ownership with developers who own the inverters and resources.
- Handling outages in data availability with developers.
- Synchronization of measurements with utility measurement infrastructure.
- Telemetry and communications protocols to relay data to control center.

One project funded by the U.S. Department of Energy (DOE) under the GMLC and the SunShot National Laboratory Multiyear Partnership (SuNLaMP) seeks to address some of these challenges. Led by the National Renewable Energy Laboratory (NREL), this project designs an opportunistic communications infrastructure to take advantage of various existing communications systems to provide reliable streams of data. Additionally, the project includes advanced PV estimation methods such that lost data sources can be interpolated based on nearby measurements. All of these innovations are incorporated into a state estimator for distribution network visibility [72]. This project is ongoing.

Other resources on smart inverters relevant to DSE:

- Ranković and Sarić [73] present an algorithm to include both monitored and unmonitored DERs into a distribution state estimator, discussing the generation of pseudo-measurements for distributed generation.
- Shabaninia, et al. [74] propose a formulation for DSE that is tailored to systems with uncertainty in DER generation for the purposes of preventative control of the system.
- Pau, et al. [69] present a cloud-based smart metering infrastructure used for DSE.

7.1.1.6 Phasor Measurement Units

A PMU is an advanced piece of measurement equipment that is currently widespread in transmission systems. However, its accuracy and temporal resolution make it more expensive than other meters, and the ideal case of placing PMUs throughout a distribution system remains unrealistic in the near future. They are much more commonly found on transmission systems, where network visibility is more vital to system operations and security, and there are fewer buses to monitor. Use of PMUs for state estimation in the State dates back to a report by Fardanesh, et al. on synchronized measurements in the New York Power Authority (NYPA) transmission system [75].

A PMU takes many samples per second of a waveform in order to determine the phase angle with respect to a reference angle (in addition to magnitude information). The PMU is generally connected to a bus to determine three-phase bus voltage, as well as to at least one line to measure three-phase current. Depending of the device, multiple current branches may potentially be measured at once.

Phase angle is an important state variable that has direct bearing on line flows. In fact, the simplified "DC power flow" method, which omits reactive flows, also omits voltage magnitude: phase angle is the *only* state variable in this case. This is because real power flow is approximately proportional to phase angle difference. The inability to directly measure phase angles without a PMU therefore poses a limitation on distribution networks. Without a PMU, a state estimator will simply assign a reference angle as a virtual measurement and estimate the relative angles of the system based on the flow patterns.

Introduction of a PMU to a distribution network can provide a host of benefits for accuracy and performance. The development of a smaller and less expensive PMU form factor designed for distribution systems, called a µPMU (micro-PMU) has opened the door to more widespread introduction of the technology [76]. Recent works have analyzed the importance of µPMUs in DSE:

- Silva, Laburu, and Almeida [77] discuss methodology and benefit to using µPMUs in branch-current-formulated state estimation.
- Chen, Tseng, and Amaratunga [78] discuss methodology to incorporate µPMUs into node-voltage-formulated state estimation.
- Janssen, et al. [61] explore the handling of unsynchronized PMU measurements on a three-phase distribution system.
- Zhang, et al. [79] investigate the optimal selection of buffer length for calibrating PMUs for periodic state estimation.
- Macii, Barchi, and Schenato [80] discuss the tradeoffs associated with installing PMUs for DSE, identifying a diminishing returns of system accuracy, and exploring a method for directly using the phasor measurement as the state value.
- Bolognani, Carli, and Todescato [81] propose a scalable state estimation algorithm for poorly synchronized PMU measurements placed on every bus for multi-area DSE.

As discussed earlier, Abur, et al. have several articles on the placement of PMUs to achieve redundant observability [37] [39] [40] [41] [42] [43].

Similarly discussed, Akingeneye, et al. [51] and Rice, et al. [52] investigate the effect of incorporating PMUs on system accuracy.

Zhao, et al. [82] discuss the potential causes of error on PMUs and the impact this error has on applications of PMU data, which is relevant for state estimators reliant on this data.

Works that discuss state estimation with widespread installments of PMUs may not have direct influence on the direction of DSE, but include papers by Zhao and Abur [83], Pegoraro, et al. [84], Fardanesh [85], and Jiang, et al. [86].

One application that relies heavily on PMUs being present throughout the system is the development of a phasor-only state estimator, as described by Fernandes, et al. [87], Lackner [88], and Lackner, Zhang, and Chow [89]. Vanfretti, et al. [90] discuss phasor-only state estimation as a potential supplement to traditional state estimation, and with PMUs not necessarily on every system bus. Chiocel, et al. [91] explore applications of the phasor-only state estimator.

Transient (or dynamic) state estimation takes into account generator and substation dynamics that are only obtainable through high-resolution measurement devices such as PMUs. This is more applicable to the transmission level where these measurements are more widely available, though notable works include those by Watson and Yu [92], Watson and Farzanehrafat [93], Zima-Bockarjova, Zima and Andersson [94], Zhou, et al. [95], Akhlaghi, Ning, and Zhenyu [96], Huang, et al. [97], Zhao and Mili [98].

7.1.1.7 Other Notes on Measurements

The measurement infrastructure of a utility is the most critical aspect of running a state estimator. Likewise, it has been a focus thus far in this report and has been well-studied in the academic literature. This sub-section presents insights into the measurement infrastructure that do not correspond to the previous sections but are important contributions to consider for DSE implementation.

As discussed in section 7.1.1.4, the communications telemetry can become a bottleneck for real-time DSE implementation. Without a strong communications network, the latency for retrieving measurements can limit both the frequency of update and the accuracy of the system. To mitigate this issue, Alam, Natarajan and Pahwa [99] discuss data compression in the context of DSE, evaluating performance with different levels of measurement compression.

Muscas, et al. [100] discuss the impact of correlation among measurements, pseudo-measurements, or both. The authors analyze this correlation and the effect it has on the results and different methods that can be incorporated to mitigate these effects.

Similarly, errors in device calibration can add systematic error to the state estimator and be difficult even for DSE with a bad data detector to pick up and correct. Zhong and Abur [101] investigate this issue by proposing a solution in which the control center can “remotely calibrate” these measurements through a state estimation scheme.

Offline methods to adjust or determine measurement weights based on the accompanying measurement residuals are discussed by Zhong and Abur [102].

7.1.2 Pseudo-Measurements

Pseudo-measurements are pieces of data that are estimated about the power system that can be converted into useable measurements for state estimation. The most common application of pseudo-measurements is in the form of load forecasts at distribution transformers or customer connections. This is distinct with “virtual measurements,” which are precisely known pieces of information about the network—such as zero-power injections at buses.

Pseudo-measurements are vital to DSE, as these systems are very rarely observable solely on the basis of actual measurements and require additional information. As such, many of the algorithms for placing measurements presented in section 7.1.1.1 mention the introduction of pseudo-measurements.

7.1.2.1 Generating Pseudo-Measurements

While pseudo-measurements at load points can be directly obtained from load forecasts, most utilities do not have the capability to generate forecasts at the locational and temporal granularity required for DSE. Many utilities use high-level forecasts from the transmission or substation level that may not be appropriately scaled to more granular small-scale loads. Compounding this problem is the decrease in aggregation in lower-voltage systems: fewer customer loads averaged together means less predictability and more variation.

Load forecasting is a broad topic that will not be exhaustively covered in this report, though a few relevant papers to distribution load forecasting have been presented here:

- Hernandez, et al. [103] describe on the use of automated neural network (ANN) for load forecasts, with the focus on microgrid systems. It does not tie these forecasts to DSE pseudo-measurements.
- Couraud and Roche [104] present a method for using ANN as well as SCADA data from the transmission connection point to accurately forecast distribution loads.
- Sun, et al. [105] pursue a hierarchical load forecasting method also based on neural networks that accounts for distribution-specific challenges such as network topology and high number of customer loads.
- Kampezidou and Grijalva [106] present two linear load forecasting methods for forecasting distribution transformer loads in the presence of highly variable DERs.
- Jiang, et al. [107] present a high-resolution distribution forecasting method making use of support vector regression and particle swarm optimization.

Papers describing forecast methods specifically for incorporation into state estimation as pseudo-measurements are detailed below:

- Ghosh, et al. [108] and Ghosh, Lubkeman, and Jones [109] are early (1997) examples of working to apply stochastic load forecasts and models to DSE inputs.
- Arritt and Dugan [8] compare four methods of load allocation that can be used to generate pseudo-measurements and compares them for their accuracy in predicting different aspects of distribution operation.
- Manitsas, et al. [110] present two methods for generating pseudo-measurements: a method correlating load estimates with real-time measurements, and a Gaussian mixture model method.
- Singh, Pal, and Jabr [111] propose a method for generating pseudo-measurements the Gaussian mixture model.
- Manitsas, et al. [112] discuss the use of ANN for modeling pseudo-measurements.
- Dansk Energi [34] provides an overview of different load and generation forecasting methods.

The load allocation methods discussed in section 2.2.2 can also be used as part of the forecasting and pseudo-measurement generation process. External factors such as day-of-week and weather measurements can also come into the pseudo-measurement generation process.

7.1.2.2 Integrating Pseudo-Measurements into DSE Algorithms

As pseudo-measurements are forecasts of system loads, there is a level of uncertainty associated with them that is much higher than the uncertainty related to actual measurements (a value commonly associated with pseudo-measurement uncertainty is ±50%). As this accuracy is difficult to quantify because pseudo-measurements have no relation to current network operation, the weight selection can be adjusted in a tuning process in an attempt to improve results. This process has been described and tested by Atanackovic and Dabic [113], who found it difficult to establish a reliable tuning method.

In their study on state estimation in two simultaneous time scales [57], Gómez-Expósito, et al. discuss the different approaches to incorporating pseudo-measurements based on the nature of the available data. This discussion includes extrapolating pseudo-measurements if future forecasts are available and interpolating pseudo-measurements to account for states between pseudo-measurement time steps.

When using load allocation as a means of generating pseudo-measurements, the outputs of state estimation can be used to update the load allocation function in closed-loop. Once state estimation has been run, the aggregated load point that is used to govern load allocation can be updated with a more accurate state estimate. In addition, the line losses calculated from state estimation can be incorporated into the load allocation method to adjust load points accordingly. After load allocation has been updated, the new results are re-incorporated into updated pseudo-measurements and in this iterative fashion the two combined functions can converge to a more accurate result. Several studies have investigated this iterative closed-loop integration of load allocation and state estimation, beginning in 2003 with Wan, et al. [9]. Iterative load allocation with state estimation was subsequently investigated by Carmona-Delgado, et al. [7], Hayes, Gruber, and Prodanovic [114], and Karimi, Mokhlis, and Bakra [115], and was demonstrated on real systems by Deng, He, and Zhang [116] and Gonzalez, et al. [117].

Note that pseudo-measurements should not be used to improve measurement redundancy for the purposes of bad data detection and identification because they do not reflect the current state of the system. This is further explored in section 7.4.1.

7.1.2.3 Impact of Pseudo-Measurements on Results

Likewise, there may be concern that adding this type of data might have a negative effect on the result. The following theorem from Monticelli and Wu [118] sheds light on this discussion:

> ***Theorem***
>
> If a minimal set of additional non-redundant (pseudo)-measurements is so selected that they make the network barely observable, then the estimated states of the already observable islands will not be affected by these pseudo-measurements.

This theorem puts forth that the addition of pseudo-measurements to achieve observability does not necessarily affect the accuracy of system states with monitoring. It does not, however, claim that pseudo-measurements do not have a negative impact on accuracy, as the theorem deals with only the pseudo-measurements necessary to ensure base observability.

Clements [119] further explores the impact of integrating pseudo-measurements on accuracy. Beyond the aforementioned theorem, the author finds that pseudo-measurement errors negatively impact the calculated states of branches that are not otherwise observable. The author also finds that pseudo-measurements beyond what is required to ensure observability can have a negative impact on the accuracy of the estimator, with the impact depending on the weight associated with the pseudo-measurements.

7.1.3 Network Model

The state estimator relies on the assumption of an accurate network model in order to base its calculations. Because the "most-likely state" is based on the physical relations between branches and buses, an error in the model leads to an error in the physical relations and therefore the state estimate. The quantified impact of network model errors on the result of state estimation are discussed by Reig and Alvarez [120] as well as Zarco and Gomez [121].

Inaccuracy and incompleteness of the network model is an area of particular weakness in distribution systems. Maintaining an accurate model is less important to a utility when the system is operated passively, and many utilities do not have accurate parameters or up-to-date knowledge of the entire system.

Fortunately, the innate ability of a state estimator to break down a system into sub-networks allows a partial work-around, that is, if only a portion of the network is accurately modeled, the state estimator can be programed to only solve that portion. This is useful if only a few higher-voltage areas of the system require accurate monitoring.

7.1.3.1 Network Parameters

Network parameters are all permanent characteristics of a power system that do not change in day-to-day operation. Most notably, network parameters include:

- Network connectivity/incidence mapping
- Line parameters (line and mutual impedance, phase configuration, etc.)
- Bus parameters (connected customers, network equipment, shunt elements, etc.)
- Equipment parameters (transformers, switches, protection elements, etc.)

Utility advancements in network modeling include the use of a geographic information system (GIS) to map the physical architecture of power networks, including line distance, into a network model application. These systems can help keep the network parameters up-to-date with expansions, though many systems still experience a lack of calibration of line parameters with these systems.

An additional challenge, as was discussed in section 7.1.1.4, is the modeling of the customer connection when integrating AMI measurements into the system. Many utilities have a gap between the end of the network model and the location of a smart meter, a gap which can lead to an unknown voltage drop. In order to incorporate these measurements, a utility might have to measure these lines to determine the missing parameters.

In place of field measurements to correct the network model, online measurements can be used to calculate parameters as well. Chapter 7 of the textbook *Power System State Estimation* by Abur and Gómez-Expósito [2] gives a good overview of parameter estimation. It includes a discussion of the possibility of using the state estimator itself to correct parameter errors, which will be discussed further as part of the Application Layer in section 7.4. It is notable that this function is only possible in the presence of redundant measurements, and the resulting parameters have associated error proportional to the error used to estimate them.

Yu, Weng, and Rajagopal [122] present a more recent data-driven approach for estimating both line parameters and network topology accounting for measurement errors on distribution networks. However, this approach (as well as other parameter estimation techniques) relies on the use of PMUs at many system buses and therefore may not be applicable for many distribution systems.

Other useful resources for parameter estimation have been authored by Prostejovsky, et al. [123], Davis, et al. [124] (using historical data), and Zarco and Gómez-Expósito [125] (a survey of parameter estimation approaches, dated 2000).

7.1.3.2 Network Topology

In addition to the network model and line parameters, a state estimator requires up-to-date information on the topology configuration. Network topology is the elements of the network that are configurable during regular operation, and may include:

- Switch positions
- Auto-transformer tap ratios
- Protection equipment status
- Reactive element status

On distribution systems, topology changes are both frequent and under-reported. Many aspects of distribution automation, such as transformer tap ratios, can happen without relaying the information back to the control center. Others, such as reconfiguration switches, might be a manual field crew action that by process should be reported, but can at times go unreported due to human error. Errors in topology can lead to valid measurements being discarded as erroneous or non-convergence of the state estimator.

When topology changes are unreported, or unreported in real-time, estimation of the topology is necessary. This often occurs as part of a topology processor which uses known information and measurements to create the most-likely topology configuration. The topology processor then creates a simplified network model that provides only the necessary information for state estimation.

The textbook *Power System State Estimation* by Abur and Gómez-Expósito [2] again gives a good overview of topology processing and estimation in chapters 7 and 8. Like parameter estimation, this process can occur as an output of state estimation, and will be discussed further as part of the Application Layer in section 7.4. It should be noted that this function is only possible when the desired topology variables are observable via real measurements.

Other useful resources for topology estimation include:

- Vempati, et al. [126] present a simplified estimation model to be run prior to state estimation for topology estimation. This model requires real power flow measurements to be present on the system.
- Weng, Faloutsos, and Ilic [127] present a more recent data-driven regression approach to topology estimation.

- Shahsavari, et al. [128] present a distribution monitoring approach using very few feeder-level µPMUs to estimate the status of switch-bank capacitors. This approach can potentially be generalized to other topological changes.
- Sharon, et al. [129] present a stochastic approach to topology identification using maximum likelihood of the topology based on the probability distribution for a set of measurements.
- Bolognani, et al. [130] presents an analysis of voltage measurement correlation to reconstruct distribution network topology.

7.1.3.3 Network Model Format and Flexibility: The Common Information Model (CIM)

The method in which the network model is stored can have an impact on the involvement required for implementation of DSE. This is primarily because of three oft-overlooked challenges:

- **Central Operation:** The network model is central to many distribution operation applications, from online operation to planning analysis. All these applications require up-to-date model and topology information, though not necessarily in the same time scales or the same detail. A central network model must deliver the appropriate information to each application.
- **Compatibility:** Likewise, each application might not operate in the same data format. Planning, outage, and online operations applications might each run on different proprietary software platforms which keep different network model formats and variables. In addition, any interface with external entities such as a transmission system operator might require a specific data format.
- **Real-Time Information:** Distribution network topology is constantly changing, and this must be reflected in real-time updates to the network model. Any central model must be compatible with topology information coming from the control center or a topology processor.

In the context of these challenges, utilities can find the implementation of real-time DSE to be difficult. Modernizing the network model approach to be an automated up-to-date system compatible will all network applications and external connections is an implementation challenge in itself. Traditional network models reside in the planning application and are not synchronized with topology updates, nor are they easily communicable to real-time applications such as a state estimator. It is a challenging task to rectify the static network model maintained by many utilities with real-time information from

SCADA and other sources so that state estimation can be effectively run. Obstacles in regard to keeping an up-to-date network model have been discussed by Lightner, McDermott, and Baran [131], Mutanen, et al. [132], and Hollingworth, Lloyd, and Hetherington [133]. An automated and standardized approach is therefore vital for success, or else countless hours of manpower will be required on a regular basis to tend to the model.

The most recognized approach to address the issue of network model incompatibility is the publication of a set of standards referred to as the Common Information Model (CIM): IEC 61970 and IEC 61968 [134]. CIM is a standardized method of representing network model information. It is prescribed in unified modeling language (UML), in which the relations and attributes of network components are defined as structures. CIM does not define the data format used to store this information, but instead defines a standard extensible markup language (XML) in which network model information can be exchanged using the resource description framework (RDF).

What CIM offers is a standardized, flexible, and communicable method to store network model information, which facilitates integration with internal and external applications as well as upkeep of the model. Many planning applications and DMSs already support integration with CIM, and several utilities have either considered or have already adopted it as their approach to network modeling.

Resources on CIM:

- Simmins [135] provides a good instructional overview of CIM, including the RDF XML communications format, application integration, and various tutorials.
- McMorran, et al. [136] give a presentation of the benefits to using CIM to integrate models for existing transmission and distribution systems.
- Celik [137] presents a discussion on a generalized DSE using CIM as a network model interface.
- Wang, Shulz, and Neumann [138] convert the IEEE radial test feeders into CIM-based XML documents.
- The Environmental Systems Research Institute (EPRI) [139] provides a guide by the leader in GIS software for translating GIS model information into CIM.
- McMorran, et al. [140] discuss the translation of CIM data into proprietary format to interface with in-house or legacy applications.

7.1.3.4 Three-Phase Network Model

Compared to transmission systems, many distribution networks operate with some amount of imbalance. Indeed, some distribution systems might be designed to partition exactly one-third of the power delivery to each customer on each phase, creating balance. Other systems might deliver a single phase to each customer, or even deliver power to an entire branch of the network on a single phase—and this practice can create imbalance in the three phases. In addition, failure to transpose power lines in order to mitigate the effect of asymmetric delivery towers can add further imbalance—and this practice is less common on distribution systems as well.

Depending on the amount of imbalance on the system, maintaining a three-phase network model may be necessary. As distribution systems are much more susceptible to imbalance than transmission, this problem is specific to DSE. Certain distribution systems may have asymmetrical network models where one or two individual phases branch off from the main three-phase feeder as laterals—a condition which requires three-phase modeling.

Modeling a distribution network in three-phases has been thoroughly analyzed in Kersting's textbook on distribution modeling [141].

Zhong and Abur [142] investigate the effects on state estimation of modeling a network with both non-transposed lines and unbalanced loads in single phase instead of in three-phase. The authors found that both sources of imbalance affect the results and could introduce error to the point of triggering the bad data detection mechanism. Unbalanced loads were found to introduce more error than non-transposed lines. These results should be considered when determining if a system warrants three-phase modeling.

Note that three-phase networks can feature four wires in a line: three phases and a neutral. When using a three-phase model, the neutral wire must be incorporated into the three-state model by use of a Kron reduction or similar technique [141].

In its discussion of DSE studies, section 9 lists the studies that have used three-phase models.

7.2 Function Layer

The function layer comprises the core functionality of a state estimator, where the input data is processed to determine the most-likely state of the power system. The main components of the function layer are the observability analysis and the state estimation algorithm itself.

7.2.1 Observability Analysis

The goal of the observability analysis is to determine if the data provided to the system is sufficient to determine the electrical state of the power network. This definition of observability is very similar to the definition present in control theory, which measures whether the internal state of a system can be determined from its outputs. This analysis is a vital process to the estimator—without observability, state estimation is not possible. As a rule of thumb, there must be approximately two measured values on the system for each observable bus. This number changes based on the nature of the network architecture.

The textbook *Power System State Estimation* by Abur and Gómez-Expósito [2] provides a thorough and fundamental discussion on the observability analysis for state estimation. Figure 9 provides an overview of the structure and terminology involved with the observability analysis.

Figure 9. Overview of the Observability Analysis

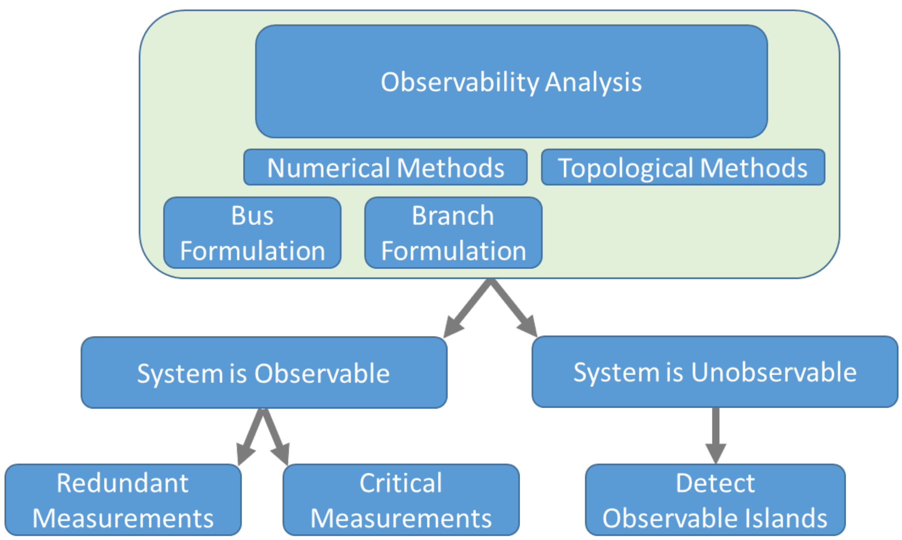


Figure 9 shows the observability analysis process, including the various method formulations for the function. These processes will be described in the following subsections, including discussion of current literature on the subject.

7.2.1.1 Numerical versus Topological Methods

Observability can be determined using either numerical methods or topological methods. It is independent of both network parameters and system state, depending only on the type and location of measurements and the network model architecture.

Topological methods, as outlined by Krumpholz, Clements and Davis [143], uses a spanning tree technique to determine if the system is reducible to one observable tree or to several sub-network trees. However, this method focuses only on real power measurements to generate the trees, assuming that power measurements are paired with reactive power, and magnitude-only current measurements are not present. This might not always be the case with distribution systems. Topological methods have computation speed advantages over numerical methods and are agnostic to the state estimation problem formulation.

Numerical methods for observability are more widely applicable for a variety of measurements available, though they involve going through steps similar to the state estimation problem itself. The basis for numerical methods is determining the rank of the gain matrix using factorization techniques. The gain matrix is a square matrix that factors in information about both measurements and their associated weights. The numerical observability can be formulated using bus state variables (outlined by Monticelli and Wu [144]) or branch state variables (outlined by Gómez-Expósito and Abur [145]). Depending on the formulation of the state estimator itself, one or the other of these formulations might be preferable as the gain matrix generated will be essentially the same as for the main problem. However, Abur and Exposito mention in *Power System State Estimation* [2] that the branch formulation is preferred as a non-iterative and less computationally expensive analysis.

Other resources for observability analysis:

- Magnago, Zhang, and Celik [146] present numerical observability analysis from a three-phase distribution perspective.
- Thukaram, Jerome, and Surapong [147] present a topological approach to radial distribution system observability.
- Gelagaev, et al. [148] present a numerical observability analysis for distribution systems, considering the high resistance-to-reactance ratio of distribution lines.
- Benedito, et al. [149] combine concepts from both topological and numerical ideas to create a simple and efficient observability analysis.
- Habiballah and Irving [150] present a linear programming optimization approach to observability analysis.
- Montenegro and Ramos [151] provide an overview and example usage of the real-time observability analysis tool that is part of DS Sim-RT, a distribution network simulator based on the open-sourced tool OpenDSS.

It should be noted that certain formulations of the state estimation problem disallow seamless integration with some observability analysis methods. A state estimation method that relies on matrix or other characteristics beyond what is verified in a standard observability analysis may run into issues. It therefore must be investigated whether the method used for state estimation is compatible with the observability analysis.

This is particularly true of Hachtel's augmented matrix method and other methods with equality constraints, which do not use the gain matrix analyzed in the numerical methods and therefore can be numerically unstable when coupled with a standard observability analysis. Methods for observability analysis specific to Hachtel's method have been investigated by Wu, et al. [152] and Bei [153]. The similar equality-constrained formulation is investigated by Wu, Liu, and Lun [154].

7.2.1.2 Evaluating the Extent of Observability

When a system is observable as a whole, state estimation can be performed. Measurements in an observable system are either redundant or critical—the difference is that loss of a critical measurement leads to unobservability. When a critical measurement is in error, it will not be detected in a residual analysis as bad data and instead introduce error into the state result. It is therefore desirable to have redundant measurements, as several benefits of state estimation including bad data detection, parameter estimation, and topology estimation are only possible when measurements are redundant.

For a system with n states, any measurement past n will introduce redundancy to the system. Critical measurements can be located by means of the observability analysis algorithm, with methods discussed in *Power System State Estimation* by Abur and Gómez-Expósito [2]. Magnago and Abur [37] and Emami and Abur [43] discuss measurement placement to achieve redundancy against loss of measurements.

Other resources on critical measurements:

- London, Alberto, and Bretas [155] discuss tools for assessment of measurement sets and their impact, including detecting critical measurements.
- Bretas, et al. [156] present a topological method for detecting critical measurements.

When a system is unobservable, the goal of the observability analysis is to locate the subnetworks which do have observability, called “observable islands.” While section 7.1.1.1 discusses placing additional measurements to achieve observability and section 7.1.2 discusses using load forecasts as pseudo-measurements for observability, at the point of the observability analysis it is assumed that all additional measurements and pseudo-measurements have been placed.

Observable island detection is performed as part of any observability analysis algorithm based on the location of zero pivots in the gain matrix (or, in topological methods, of locating isolated trees) and is discussed in *Power System State Estimation*. Each observable island is solved for its internal state independently with its own assigned reference angle unless there is PMU present across islands. In the presence of PMUs, observable islands can more easily be merged together, as described by Xu and Abur [40] [41] and Xu, et al. [42].

Due to the isolated reference angles, the flow along unobservable branches cannot be calculated except by additional placement of measurements. In some cases, the observable islands are sufficient for the necessary network operation and control, and unobservable downstream network zones can be simplified to be considered loads on the observable zones, as described by Simendic, Strezoski, and Svenda [157].

Other resources on detecting observable islands:

- Magnago, et al. [146] present detection of observable islands from a three-phase distribution perspective, with an island existing only when all three phases are observable throughout the island.
- Gou and Abur [158] present a direct, non-iterative numerical approach to detecting observable islands.
- Gou [159] presents observable island detection for numerical methods using Gaussian elimination on the Jacobian matrix.

7.3 State Estimator

The state estimator is the core solver. It uses the inputs from the data layer in addition to the observability analysis outputs (i.e., the observable islands) to generate the most-likely operating state of the power system. While more details surrounding the different algorithms used to solve the state estimation problem is presented in section 8, this section provides a background that is necessary to provide context for the layers of state estimation. This information is foundational and may be obtained from many of the references in this report, most notably from the original paper by Schweppe and Wildes [26], or the textbooks by Monticelli [1], and Abur and Gómez-Expósito [2]. Note that the following discussion is presented based on the bus state variable formulation, but that it is extensible to the branch state formulation as well.

At its most basic, state estimation has the objective of minimizing the difference between measurements and the estimated electrical state while upholding the physical properties of power flowing through a system. Any given measured value z is taken as a function of the true underlying state x and some amount of unknown (Gaussian) error e:

Equation 1 $$\boldsymbol{z} = \boldsymbol{h}(\boldsymbol{x}) + \boldsymbol{e}$$

The goal of the problem is to solve for the most-likely electrical state x by minimizing the error e. As each measurement might have a different level of confidence, the importance of measurements is weighted based on their variance. The variance of each measurements is included in a covariance matrix R, which will be a diagonal matrix of measurement variances unless measurements have bias or correlation in their errors. This covariance matrix R is inverted to determine measurement weights.

The measurements must be mapped from the internal true state via the measurement function $h(x)$, which consists of the power flow relations between measurements and state variables. While the function mapping a voltage magnitude state to a voltage magnitude measurement is a trivial identity function, other functions are highly nonlinear. For instance, if the measurement is real power flow along a line, the function mapping voltage magnitude state at the receiving bus to real power flow would be:

Equation 2 $$\boldsymbol{h}(\boldsymbol{V_j}) = \boldsymbol{P_{ij}^{meas}} - \boldsymbol{e} = \boldsymbol{V_i^2}(\boldsymbol{g_{si}} + \boldsymbol{g_{ij}}) - \boldsymbol{V_i V_j}(\boldsymbol{g_{ij} cos\theta_{ij}} + \boldsymbol{b_{ij} sin\theta_{ij}})$$

Where:

- V_i and V_j are the voltage magnitude at the sending and receiving bus, respectively
- θ_{ij} is the voltage angle difference between the sending and receiving bus
- P_{ij}^{meas} is the measured real power between the two buses
- g_{si} is the shunt conductance of the sending bus
- g_{ij} and b_{ij} are the line conductance and susceptance, respectively

This equation is based directly on power flow equations relating real power flow to voltage angle and magnitude at each bus (i and j), where g and b are admittance values from the network model.

In order to solve the state estimation problem, using these nonlinear measurement functions, a measurement Jacobian H is created that relates changes in the measurement variables to changes in electrical state:

Equation 3.
$$\boldsymbol{H}(\boldsymbol{X}) = \begin{bmatrix} \frac{\partial \boldsymbol{P}(\boldsymbol{X})}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{P}(\boldsymbol{X})}{\partial \boldsymbol{V}} \\ \frac{\partial \boldsymbol{Q}(\boldsymbol{X})}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{Q}(\boldsymbol{X})}{\partial \boldsymbol{V}} \\ \frac{\partial \boldsymbol{I}(\boldsymbol{X})}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{I}(\boldsymbol{X})}{\partial \boldsymbol{V}} \\ \frac{\partial \boldsymbol{V_m}(\boldsymbol{X})}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{V_m}(\boldsymbol{X})}{\partial \boldsymbol{V}} \end{bmatrix}$$

Where:

- X is the state vector
- P is the set of real power measurements
- Q is the set of reactive power measurements
- I is the set of current magnitude measurements
- V_m is the set of voltage magnitude measurements
- V is the set of voltage magnitude state variables
- θ is the set of voltage angle state variables

This allows the state estimation problem to be solved iteratively by evaluating a new value of H based on the current internal state at each iteration.

State estimation and observability analysis approaches make use of what is called the gain matrix G, which is a square matrix that incorporates both the measurements and the weights, and is equivalent to:

Equation 4
$$\boldsymbol{G}(\boldsymbol{X}) = \boldsymbol{H}^{\boldsymbol{T}}(\boldsymbol{X})\boldsymbol{R}^{-1}\boldsymbol{H}(\boldsymbol{X})$$

The algorithm chosen to solve the state estimation problem determines how these matrices are used to approach the most-likely electrical state estimate.

7.3.1 Evaluating State Estimation Results

After a state estimator has converged to the most-likely solution, it is important to look at the accuracy of the result. As a rule, the resulting accuracy from a state estimator will be limited by the accuracy of the measurements used as inputs to the process.

A common way to look back at the results is to analyze the residuals between the measurements and underlying state of the system. This is possible by going back to (1) – the residual r associated with each measurement is therefore given as follows:

Equation 5 $$\boldsymbol{r} = \boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})$$

Residuals can be normalized so that they are comparable across measurements. To do this, the residual sensitivity matrix S, which describes the sensitivity of residuals to measurement error, must be created:

Equation 6 $$\boldsymbol{S} = (\boldsymbol{I} - \boldsymbol{H}\boldsymbol{G}^{-1}\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{R}^{-1})$$

Where I is the identity matrix. The standard deviation of the residual σ_r can be taken from the square root of the residual covariance matrix diagonal:

Equation 7. $$\boldsymbol{\sigma_r} = \sqrt{\boldsymbol{diag}(\boldsymbol{SR})}$$

Finally, the normalized residual r^N can be calculated:

Equation 8 $$\boldsymbol{r^N} = \frac{|\boldsymbol{r}|}{\boldsymbol{\sigma_r}}$$

Normalized residuals are used extensively in bad data detection and identification as well as network model estimation, as discussed in sections 7.4.1 and 7.4.2. Large residuals indicate sources of error in the state estimation framework, as the estimator has determined that the measurement cannot be closely related to the underlying state.

Methods for evaluating performance include error estimation and quality indices are presented in works by Wan, et al. [9], Maciel-Barbosa, Vide and Carvalho [160], The SuSTAINABLE Project [161], and Therrien [162]. Approaches to these indices vary, but they each give an evaluation of how well the state estimator is representing the underlying state from a certain aspect such as convergence, normalized residuals, or accuracy.

Cobelo, et al. [163] present the generation of variances in the state variables based on the creation of a new Jacobian matrix of state variables with respect to themselves, K:

Equation 9 $$var(X) = diag(KG^{-1}K^T)$$

Singh, Pal and Jabr [164] present practices for determining the bias and consistency of a state estimator. Bias is an evaluation of the degree to which residuals are centered on zero, while consistency is an evaluation of whether the residuals correspond to the variance of the measurements.

It is also possible to adaptively tune the measurement and pseudo-measurement weights in an effort to improve accuracy. This is a nontrivial process, as error is generally detected in the form of normalized residuals and those residuals depend on the assigned measurement weight. Additionally, residuals only appear when redundancy is present—and the inclusion of pseudo-measurements is usually a sign of low or no redundancy. Approaches and challenges to tuning measurement weights have been discussed by Atanackovic, et al. [113].

It is a given that the performance of a state estimator is only as good as the data provided to it. Therefore, another valuable metric is the sensitivity of the state estimator to input errors. Stuart [165] provides a series of sensitivity analysis methods, which vary the values of different measurements or network parameters and monitory the corresponding change in the state estimate. From this analysis, a level of confidence in the state estimate can be deduced based on its sensitivity – a resilient state variable is more likely to be accurate than one very sensitive to error.

Al-Othman and Irving [166] approach this same concept of sensitivity to error using linear programming to determine estimator error after state estimation has been run.

7.4 Application Layer

The application layer covers useful power network functions that are directly enabled by state estimation. While state estimation truly benefits all grid functions by improving the accuracy of network visualization, the most integrated applications are of state estimation and are described in this section: Bad data detection and identification and topology and parameter estimation. A brief discussion of other applications such as locational power markets is also presented.

7.4.1 Bad Data Detection and Identification

Bad data detection and identification is one of the most common applications to be run directly from the output of a state estimator. This is the process with which the output of the state estimator is able to detect erroneous measurements. *Power System State Estimation* by Abur and Gómez-Expósito [2] provides a thorough background on the approaches to this problem.

To detect the existence of bad data in the system, this application looks at the residuals between the measurements and the corresponding estimated state and decides if error has been introduced to the system. The two most common methods for this are the chi-squares test, where total system error is compared to a realistic threshold, and the largest normalized residual test, where the largest normalized discrepancy between measurement and state is analyzed. *Power System State Estimation* asserts that the largest normalized residual test can in certain circumstances be more accurate than chi-squares.

Once bad data has been detected, the source of the bad data must be located. This is done based on the normalized residuals of the measurements and can be a non-trivial problem especially when there are multiple sources of bad data. The simplest method is to remove the measurement with the largest residual, and then run state estimation again to detect if the bad data issue has been resolved (repeat until no bad data detected). This approach may be inaccurate if multiple measurements have correlated error. Another more robust approach to bad data identification is hypothesis testing, where a set of measurements with high residuals is analyzed with various bad data hypotheses for the most-likely outcome.

Other resources on bad data detection:

- Mili, Van Cutsem and Ribbens-Pavella [167] compare different strategies for identifying and dealing with different types of bad data, including data elimination and hypothesis testing.
- Wu, et al. [152] and Wu, Liu, and Lun [154] extend the normalized residuals test to hatchel's augmented matrix method and the similar equality constraints case, respectively.
- Chen and Abur [168] discuss a placement algorithm for PMUs to improve the capabilities of bad data detection and identification
- Weng, et al. [169] presents a method to formulate bad data identification and detection as a convex optimization problem.

7.4.1.1 Critical Measurements

The capabilities of bad data detection and identification depend on the strength of the measurement infrastructure, in regard to, critical measurements (which were defined in section 7.2.1.2). This is highlighted with two important notes outlined below.

> ***Note***
>
> A critical measurement will have a residual of zero, and therefore will not be detected by a bad data detection application if it is providing erroneous data.

This is true because a critical measurement indicates a determined system, where there is only one solution—with no room to adjust based on error tolerance. For instance, this is the case with a load flow (section 2.2.3), as it is a set of equations with a single solution. When a critical measurement is erroneous, it will cause the state solution to adjust so the erroneous value appears correct.

Note also that pseudo-measurements should not be used to improve measurement redundancy because they do not reflect the current state of the system. The use of pseudo-measurements for bad data detection has been investigated by Mutanen, et al. [132] to limited success. In the real implementation, a change in customer load due to weather patterns caused good data to be detected as bad data, as the pseudo-measurements based on historical data used did not account for the change.

> ***Note***
>
> An erroneous value that is part of a critical pair of measurements may be detected by a bad data detection application, but it will not be able to be distinguished from its pair as the erroneous measurement as they will have equal normalized residuals.

A critical pair is a set of two measurements where the removal of both causes the system to become unobservable. When a critical pair of measurements disagrees with each other, the state estimator chooses a value that is between the two of them such that their normalized residuals are equal. Therefore, if one of the measurements is erroneous, both measurements will have the same normalized residual and the erroneous measurement will not be identified.

7.4.1.2 Improved Robust Methods and Leverage Measurements

A leverage measurement is a redundant measurement that is still difficult for bad data detection and identification to target. This is because the measurement play reflects an important point in the distribution system, and error in the measurement strongly influences the surrounding state estimate. *Power System State Estimation* by Abur and Gómez-Expósito [2] identifies four common causes for leverage measurements, which be described in light of distribution systems as shown in Table 20.

Circuit breakers may not always be saved as part of the network model, and in certain cases must be added into the model once a section of the network is determined suspect. This means that the circuit breaker locations must be readily available to insert into the model in an automated way, a process that is facilitated by CIM (section 7.1.3.3).

Notes on network topology estimation:

> ***Note***
>
> In order to enable network topology estimation on switch status, there must be redundancy in actual measurements neighboring to the estimated switch.

This requirement is identical to that for network parameter estimation. Without redundancy, there are no residuals on which to base the analysis. Pseudo-measurements should not be used because they do not reflect the time-varying nature of the network topology.

> ***Note***
>
> Single topology errors on critical branches are not detectable. Single topology errors on one of a critical pair of branches are not identifiable.

A critical branch is defined as one whose removal causes the system to lose observability, while a critical pair is two branches whose simultaneous removal cause unobservability. This stipulation is therefore based on the same reasoning as for critical measurements in section 7.4.1.1.

As an additional note, bad data should be detected and removed prior to topology estimation process and must be discernable from topology error which generally affects several measurements instead of just one.

Additional resources on topology estimation since the publication of *Power System State Estimation*:

- Lourenco, et al. [184] present a method for topology detection and identification using collinearity of the Lagrange multipliers of the covariance matrix, in the context of an augmented state vector.
- Vosgerau, et al. [185] present a coordinated WLS state estimator with an on-line WLAV topology estimator.
- Weng, et al. [169] discuss convexification of the topology detection error detection problem, improving on solvers that might only locate a local solution instead of a global one.

The applicability of robust methods to DSE has been questioned by Nusrat [46] and Singh, et al. [164]. Both of these studies note that the absence of redundancy in the measurement infrastructure and subsequent reliance on pseudo-measurements that is common in DSE prevents these robust methods from being effective. Robust methods tend to de-emphasize certain pseudo-measurements as erroneous and may not be able to determine which ones are introducing error to the system.

7.4.2 Network Model Estimation

In section 7.1.3, the impact of inaccuracies in the network model (specifically, the parameters and topology) was discussed. Accuracy in these data points is necessary to maintain a converging and useful state estimator. However, a state estimator with redundant measurements has the ability to estimate and correct suspicious aspects of the network model.

Network model estimation can happen in one of two ways. The first option is similar to the way bad data is detected and identified, using residuals in the electrical state of the system versus the measurements. The second option is to incorporate these data points into the state vector that is solved parallel to the electrical state.

Power System State Estimation by Abur and Gómez-Expósito [2] gives a thorough summary of the different methods used to estimate errors in both network parameters and topology in chapters 7 and 8, using both residuals and state vectors. The following discussion is therefore a brief summary of the important points from this chapter. Further detail should be obtained from *Power System State Estimation* and its extensive list of references, some of which are indicated here for direction.

Before discussing estimation techniques for the network model, it should be noted that detection of network model errors often requires an analysis of the residuals to decide if errors are based on bad data, incorrect parameters, or incorrect topology. Approaching one of these estimation problems requires knowledge of which type of information is being corrected, lest bad data be disguised as a network model error. Resources which have discussed this discernment problem:

- *Power System State Estimation* discusses common patterns that can be used to discern different types of errors, such as correlation or errors on either side of a branch. It asserts that bad data must be removed prior to parameter or topology estimation, assuming that bad data appears as a single large residual unrelated to other errors on the system.
- Zhu and Abur [178] present a method for identifying incorrect parameters that distinguishes them from bad measurements without state vector augmentation.

7.4.2.1 Network Parameter Error Estimation

Network parameter errors can be viewed as analog errors, where the impedance value of lines or equipment is incorrect in some capacity and must be re-adjusted. Parameter errors often appear to the state estimate as a series of correlated measurement errors.

The method using measurement residuals begins by detecting the presence of bad data. If bad data are correlated to a particular network parameter, a sensitivity of the state result to variations in that parameter is carried out to determine if the residuals can be explained by correction of the parameter.

The method using network parameters as part of an augmented state vector can be solved in two ways. The first is using the standard network equations with an additional entry into the measurement Jacobian matrix corresponding to the suspect parameter, which will converge to an estimate of the parameter [179]. The second augmented state vector method makes use of the Kalman filter over a time-series of state snapshots. The assumption that parameters are constant over time drives their estimation, as their effect on the result can be filtered out from the changing network states [180] [181].

Parameter estimation can also occur on historical data using either method, which has the advantage of running offline and updating the network parameters for the on-line estimator as needed. Using historical data also takes into account the constant nature of network parameters, as with the Kalman filter method. Reference Reig and Alvarez [120] and Zarco and Gomez [121] for further detail.

Line length can be viewed as a parameter on its own, being a direct contributor to impedance values on a line. Line resistance and reactance become scaled values from the line length. The line length parameter is more difficult to estimate when the line flows are relatively very low.

Parameter estimation methods often make use of a new type of pseudo-measurement, which is an estimation of the parameter value – perhaps the existing parameter value that is suspect and in need of revision.

Power System State Estimation by Abur and Gómez-Expósito [2] gives the following guidance on choosing methods for network parameter estimation:

- Analysis including residuals is necessary to identify suspect branches to define which parameters to estimate, but the task of estimation is more accurate when using an augmented state vector.
- Similarly, using historical data in multiple snapshots improves redundancy, and therefore accuracy, in the presence of time-invariant parameters. Time-varying parameters may similarly be estimated with snapshots using a Kalman filter approach with a snapshot horizon.
- Time-invariant network parameters are best estimated offline.

Notes on network parameter error estimation:

> ***Note***
>
> In order to enable network parameter error estimation, there must be redundancy in actual measurements neighboring to the estimated parameter. Each redundant measurement permits estimation of one parameter.

This is true for the same reasons as for bad data detection and identification: without redundancy, there are no measurement residuals and therefore no basis on which to identify and correct a parameter error. While pseudo-measurements from forecasts could theoretically be used for redundancy if they are based on previous system states (under the assumption network parameters do not change), they are not effective for parameter estimation due to the following additional note:

> ***Note***
>
> The estimated value of a network parameter will have an accuracy no greater than the accuracy of the local measurements used to estimate the value.

This note is intuitive but also very important. A parameter that already has a certain level of confidence greater than the nearby measurements should not be estimated, as the estimated value cannot improve the parameter value. This is also a reason why forecasted pseudo-measurements should not be used for parameter estimation. Note that pseudo-measurements that represent the parameters themselves are often incorporated into the estimation algorithm and are useful for this purpose.

Additional notes on network parameter estimation:

- Candidate parameters should be identified beforehand. This is either a suspicious parameter identified based on residuals, or a set of parameters identified to potentially have error.
- Bad data should be detected and removed prior to this process, and be discernable from correlated parameter error.

An additional resource on parameter estimation since the publication of *Power System State Estimation*:

- Zhu and Abur [178] present a method for parameter estimation without augmented state vectors that does not require a set of suspected parameters.

7.4.2.2 Network Topology Error Estimation

Network topology errors are discrete errors, where integer network variables have an incorrect value. Most commonly, this translates to incorrect switch positions and transformer tap ratios. Topology errors, especially switch positions, often result in large residuals in the close proximity to the error – and could cause the problem to be unable to converge. Topology errors can also cause nearby injection measurements to be flagged as bad data due to the incorrect knowledge of local power flows.

The method using measurement residuals isolates the expected value of the normalized residuals as a linear combination of potential topology errors. This problem can get very large as network size increases, however, and cannot detect multiple interacting topology errors. Reference Qu and Liu [182] for more detail on this method.

The method using network parameters as part of an augmented state vector uses a binary variable as a state variable for each suspected line connection, which is 1 in the case of a connected line and 0 in the case of disconnection. It then introduces constraints in order to limit the value of this variable to 0 or 1 and lets the state estimator converge to the correct value. Reference Gómez-Expósito, Zarco, and Quintana [183] for more detail on this method.

Power System State Estimation also discusses estimation of substation configuration, which can feature many zero-impedance switches. However, as distribution systems typically have very few substations, this discussion is less relevant than the others. Further, *Power System State Estimation* presents considerations for the observability analysis that depend on the estimated switch configurations. These are particularly applicable to substations but could be extended to reconfiguration switches on distribution systems as well.

Circuit breakers may not always be saved as part of the network model, and in certain cases must be added into the model once a section of the network is determined suspect. This means that the circuit breaker locations must be readily available to insert into the model in an automated way, a process that is facilitated by CIM (section 7.1.3.3).

Notes on network topology estimation:

> ***Note***
>
> In order to enable network topology estimation on switch status, there must be redundancy in actual measurements neighboring to the estimated switch.

This requirement is identical to that for network parameter estimation. Without redundancy, there are no residuals on which to base the analysis. Pseudo-measurements should not be used because they do not reflect the time-varying nature of the network topology.

> ***Note***
>
> Single topology errors on critical branches are not detectable. Single topology errors on one of a critical pair of branches are not identifiable.

A critical branch is defined as one whose removal causes the system to lose observability, while a critical pair is two branches whose simultaneous removal cause unobservability. This stipulation is therefore based on the same reasoning as for critical measurements in section 7.4.1.1.

As an additional note, bad data should be detected and removed prior to topology estimation process and must be discernable from topology error which generally affects several measurements instead of just one.

Additional resources on topology estimation since the publication of *Power System State Estimation*:

- Lourenco, et al. [184] present a method for topology detection and identification using collinearity of the Lagrange multipliers of the covariance matrix, in the context of an augmented state vector.
- Vosgerau, et al. [185] present a coordinated WLS state estimator with an on-line WLAV topology estimator.
- Weng, et al. [169] discuss convexification of the topology detection error detection problem, improving on solvers that might only locate a local solution instead of a global one.

- Korres and Manousakis [186] present an alternate augmented state vector approach to topology identification, and also investigates the network splitting problem in the context of observability analysis.
- Xygkis, et al. [187] apply this same augmented state vector approach from [186] to topology identification on a Greek distribution system with limited measurements.
- Zhu and Giannakis [188] present a method for identification of down lines. [189] and [190] take this further with a method to detect topology changes and down lines after a cyber-attack has eliminated measurement communication from a certain area of the system and bringing the analysis from the DC to the AC power flow model.
- Hoffman [191] discusses topology estimation incorporating customer-reported outages as a measurement source.

7.4.2.3 Transformer Tap Estimation

The transformer tap ratio is sometimes considered a parameter (as it is a non-binary variable), but being a discrete variable, its estimation can be more similar to topology estimation. Regardless, the methods for estimation are sufficiently different as to warrant a separate section.

Autotransformers are commonly used in distribution systems to support radial distribution voltage, but are rarely telemetered, such that their tap ratio is known at the control center. This makes transformer tap estimation an important topic for DSE.

Like parameters and topology, transformer tap estimation can also be solved either using residuals or augmented state vectors. The residual method as studied by Fletcher and Stadlin [192] uses a function of the residuals for measurements of terminal voltage magnitude and reactive power flow in the transformer to detect anomalies. The augmented state vector method as studied by Teixeira, et al. [193] includes additional sensitivity factors relating the turns ratio to the other state variables surrounding the transformer. This method is more accurate than the residuals method as it uses more state variables in the calculation. Often the transformer tap is estimated as a continuous variable and rounded to be a discrete value.

A note on implementation of transformer tap estimation:

> ***Note***
>
> In order to enable transformer tap estimation, measurements (or accurate real-time estimates) of the voltage at each terminal and the reactive power flow are necessary.

Without measurements of the terminal voltages, estimating the tap ratio is not possible. The reactive power flow through the transformer is another critical variable, as reactive power flow is heavily dependent on the difference in voltage magnitude between the two ends.

Additional resources on topology since the publication of *Power System State Estimation* [2]:

- Therrien, Kocar and Jatskevich [194] extend the augmented state vector approach introduced in Teixeira, et al. [193] by including it into a broader "unified" state estimator for three-phase distribution system.
- Nanchian, Majumdar and Pal [195] describe the application of ordinal optimization to three-phase DSE for estimating transformer tap ratios as discrete variables.
- Korres, Katsikas and Contaxis [196] discuss the observability of transformer taps and incorporates this into a numerical observability analysis.
- Pires, Mili and Lemos [197] presents an augmented state vector approach to transformer tap estimation using robust estimation techniques that are resilient to bad data, including leverage measurement error.

7.4.2.4 Generalized State Estimation

State estimators which are designed to include methods for many or all of the aforementioned data correction techniques (bad data, parameters, topology, transformer taps) are frequently referred to as *generalized state estimators* because they broaden the scope of state estimation from simply the electrical characteristics to more general knowledge of the network. The concept of a generalized estimator was first introduced by Alsac, et al. [198] as a summation of network estimation methods. These methods were further expanded in collected form in Monticelli's textbook *State Estimation in Electric Power Systems* [1]. Since this time, other authors have come to refer to a state estimation implementation with bad data detection and network model correction in this way.

Zhu, et al. [199] take this one step further with the concept of an "enhanced" state estimator which not only includes bad data and network model correction, but generalizes the state estimator to multi-area coverage, measurement and PMU placement, and flexible multiphase support.

Celik [137] describes the advanced and need in generalized state estimation for a flexible network model that can be easily adapted, simplified, updated, and communicated. He supports the adoption of CIM for this purpose (section 7.1.3.3)

7.4.3 Other Applications

The primary benefit of state estimation to utility operations is an improved level of confidence in system data. The potential applications of the resulting state estimate have been described in detail in section 4 most of these applications stem from the assumption that the state estimator provides an accurate real-time depiction of the electrical state. While some of these applications might be possible without the use of state estimation, there are several for which a high level of confidence over a large part or entirety of the system—a level of confidence all but requiring a state estimator in the loop.

An example of an application for which a state estimator is necessary is the creation of a locational power market. Locational markets are one of the priorities of the NYS REV initiative [200]. The vision is that trading power in real time at prices that represent their value to the system at a whole will create an environment incentivizing the third-party provision of distributed and renewable energy sources at critical locations. Representing the power market in terms of locational-marginal prices (LMPs) self-supports a level of efficiency that benefits system resiliency and incentivizes infrastructure and generation improvements.

LMPs represent the real-time cost of energy for an incremental increase in demand at a given location. In order for these prices to be determined, there must be an accurate estimate of system state in relation to constraints such as flow and voltage. For instance, if a certain branch is nearing its limit for current flow, the LMPs will be calculated in such a way as to incentivize demand/generation changes to reduce the current to manageable levels. The importance of having an accurate state estimate is therefore apparent.

The role of state estimation in the generation of LMPs for a locational power markets has been investigated by Ristanovic [201] and Liu, et al. [202].

8 State Estimation Algorithms

While Section 7.3 describes the background, overall theory, and context of the state estimation function, this section will provide more detail on the methods with which the problem is solved. The first and most fundamental method for state estimation is the weighted least squares (WLS) approach presented by Schweppe [26]. Since this foundational paper, the WLS method has been used extensively in the majority of state estimation applications. In some cases, WLS has been adapted for use with equality constraints (Constrained WLS (CWLS)), with augmented Jacobian matrices (Hachtel's method), and has been applied to distributed problems as well. The state estimation problem has also been reformulated as an optimization problem to solve with linear programming (LP) or semi-definite programming (SDP). This section will provide a brief overview of each of these methods focusing on their differences and strengths and describe how they have been demonstrated for distribution systems.

> ***Note***
>
> The DC model is a simplified power flow model that can be used for fast and approximate calculations, including for state estimation. However, the DC model relies on assumptions such as low resistance-to-reactance line ratios that do not hold for distribution systems, and therefore may be unsuitable for DSE.
>
> The decoupled power flow model operates on similar assumptions and likewise may be unsuitable for DSE.

8.1 Weighted Least Squares Estimators

The WLS estimator has been described thoroughly in the foundational paper [26] as well as in more recent textbooks on the subject [1] [2]. The WLS algorithm approaches the problem by minimizing a weighted sum of residuals, with the weights based on measurement accuracy as described in section 7.3:

Equation 10
$$\bar{\boldsymbol{X}} = \underset{\boldsymbol{X}}{\boldsymbol{arg\,min}}\ \boldsymbol{J} = \sum_{\boldsymbol{i<m}} \frac{(\boldsymbol{z_i} - \boldsymbol{h}(\boldsymbol{x_i}))^2}{\boldsymbol{\sigma_i^2}}$$

Where J is the sum-of-squares objective function. This minimization problem can be solved by setting the gradient of J to zero, resulting in a nonlinear matrix equation:

Equation 11
$$\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{x}}(\boldsymbol{X}) = -\boldsymbol{H^T}(\boldsymbol{X})\boldsymbol{R^{-1}}[\boldsymbol{Z} - \boldsymbol{h}(\boldsymbol{X})] = \boldsymbol{0}$$

This equation can be solved iteratively using low-order Taylor series approximation, with the gain matrix representing the first order expansion:

Equation 12 $$\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{x}}(\boldsymbol{X}) \cong \frac{\partial \boldsymbol{J}}{\partial \boldsymbol{x}}(\boldsymbol{X_k}) + \boldsymbol{G}(\boldsymbol{X_k})(\Delta \boldsymbol{x})$$

Yielding

Equation 13 $$\boldsymbol{X_{k+1}} = \boldsymbol{X_k} - \boldsymbol{G^{-1}}(\boldsymbol{X_k})\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{x}}(\boldsymbol{X_k})$$

Which can be solved using a flat start for X (bus voltages are nominal; phase angles are zero). The Computational complexity and stability issues stem from inverting the gain matrix G. Computational complexity can be mitigated using sparse matrix techniques and matrix factorization. However, if there are stability issues due to poor condition of the gain matrix, a modified approach may be necessary.

Ill-condition of the gain matrix is a particular problem in DSE and can cause convergence issues and output error. *Power System State Estimation* by Abur and Gómez-Expósito [2] lists three contributing factors towards ill-condition of this matrix, which have been presented below in the context of relevance to DSE.

Table 21. Factors Contributing to Ill-Condition of the Gain Matrix and Relevance to DSE

Contributing Factor	Relevance to DSE
Relatively large weights on measurements	• DSE depends on additional information in the form of zero injection buses, which can be frequent along feeders. These are incorporated in WLS as virtual measurements with large weights. • Reliance on inexpensive (and less accurate) measurement equipment to achieve observability means any high-accuracy device such as a PMU will have a relatively large weight.
Simultaneous short and long lines connected at a bus	• Wide geographic reach leads to diversity in line lengths. Long feeder lines may be connected to short delivery lines.
Large proportion of injection measurements	• DSE relies heavily on injection measurements such as customer smart meters and DERs with smart inverters.

The condition of the gain matrix can be mitigated with decomposition methods such as LU and QR decomposition. These methods can be computationally expensive, however.

8.1.1 Constrained Weighted Least Squares and Hachtel's Method

Power System State Estimation [2] presents multiple matrix decomposition approaches towards mitigating the condition of the gain matrix. However, the WLS problem can be formulated in such a way that the gain matrix is not created in the same way as was described earlier. These are the CWLS method and Hachtel's method of augmented matrices.

In the CWLS approach introduced by Aschmoneit, Peterson and Adrian [203], any equality constraints such as virtual measurements are removed from the measurement Jacobian and reintroduced as a separate set of constraints $c(x)$ (which is differentiated to form the constraint Jacobian C). The constraint Jacobian and gain matrix are solved simultaneously to determine the electrical state as well as the Lagrange multipliers λ for the constraints. This removes the large weights from the gain matrix, and also allows a scaling factor α to be introduced to further improve the condition of the matrix. This formulation is shown below, which simplifies to (13) in the case of no equality constraints:

Equation 14 $$\boldsymbol{\lambda^T c(x) = 0}$$

Equation 15 $$\boldsymbol{C = \frac{\partial c(x)}{\partial x}}$$

Equation 16 $$\begin{bmatrix} \boldsymbol{\alpha G} & \boldsymbol{C^T} \\ \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\Delta x} \\ \boldsymbol{-\lambda} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\alpha \frac{\partial J}{\partial x}(X_k)} \\ \boldsymbol{-c(x)} \end{bmatrix}$$

Where α is any scaling factor. Hachtel's augmented matrix approach presented by Gjelsvik, Aam and Holten [204] is similar in its approach, though it introduces additional constraints for the residuals with their own Lagrange multipliers μ, as shown in the below reformulation of the WLS problem:

Equation 17 $$\boldsymbol{\mu^T [r - z + h(x)] = 0}$$

Equation 18 $$\begin{bmatrix} \boldsymbol{\alpha^{-1} R} & \boldsymbol{H} & \boldsymbol{0} \\ \boldsymbol{H^T} & \boldsymbol{0} & \boldsymbol{C^T} \\ \boldsymbol{0} & \boldsymbol{C^T} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\mu} \\ \boldsymbol{\Delta x} \\ \boldsymbol{\lambda} \end{bmatrix} = \begin{bmatrix} \boldsymbol{Z - h(X_k)} \\ \boldsymbol{0} \\ \boldsymbol{-c(x_k)} \end{bmatrix}$$

The matrix solution in (18) further augments the use of constraints and scaling factors, and indeed entirely avoids the generation of the gain matrix that can be ill-conditioned. This is therefore a stable method for mitigating an ill-conditioned gain matrix.

While under normal conditions, these constrained cases are more of a computational burden than the simpler WLS approach, they are less burdensome and more stable in the presence of the factors listed in Table 21. Therefore, a study of the system under test is in order to determine if these approaches are warranted.

Alvaro and Tinney [205] further expand the augmented matrix concept to larger blocked matrices that separate injection measurements from the measurement set to mitigate their impact on matrix condition. In the case where condition remains an issue, further augmentation may be necessary.

Nusrat [46] performs an analysis on the various WLS estimators. The determination made by the author Nusrat is that Hachtel's method is the most appropriate for the challenges of DSE, as it features a fast convergence time and superior matrix condition.

8.2 Other Approaches

The WLS estimator solves a minimization problem and so it qualifies as an optimization of the objective function. However, it is constructed in such a way as to provide a straightforward solution using an iterative method for solving nonlinear equations. Other formulations and solvers for the state estimation problem are described in this section.

8.2.1 Robust and Reweighted Estimators

State estimation techniques designed for robustness against bad data were discussed in section 7.4.1.2. These techniques involve reformulating the objective function away from the squared-residuals approach in (10). The new objective functions are based on statistics theory and feature different methods of incorporating negative residual feedback into the optimization problem. Instead of squaring the residuals, these new functions include other quadratic functions, square roots, absolute value, among others. This is described by Abur and Gómez-Expósito [2] and Pires, Costa and Milli [177]. Robust state estimators (Huber or M-estimators) often make use of reweighting the residuals to reduce the impact of suspect measurements [177]. The absolute value formulation (WLAV) can be solved efficiently using linear programming as well, as shown by Irving, Owen and Stirling [173].

Singh, et al. [164] analyzes the use of WLAV and a generalized Hubor or M-estimator on DSE, finding that robust estimators require redundancy to enable bad data mitigation, and in the presence of redundancy could flag pseudo-measurements as bad data points. The authors therefore recommend against using robust estimators for WLS.

8.2.2 Semidefinite Programming

The semi-definite programming (SDP) approach to state estimation was first presented by Zhu and Giannakis [206], and was subsequently reviewed and expanded to an approximate case by Weng, et al. [207]. It has most recently been applied in a DOE GMLC and SuNLaMP project under Argonne National Lab (Abhyankar) and Illinois Institute of Technology (Flueck). The state estimation aspect of the project investigates DSE in the context of a tool suite for joint transmission and distribution operation [208], with publications forthcoming.

In SDP, the state space of the state estimator is mapped to a higher dimension. This equates to taking nonlinear terms in the network equations (for instance, the product V_iV_j) and representing it as a new singular variable x. This same process is used for the direct non-iterative approach to state estimation presented by Fardanesh, et al. [85], which is designed for high-accuracy measurements such as PMUs.

This change of variables transforms the nonlinear measurement model into a linear one and can be solved using eigenvalue decomposition of the new state matrix. However, a requirement of SDP is that this matrix must have rank-one, as this designates a unique solution to the problem. If rank is more than one, there exists more than one possible solution.

Weng, et al. [207] indicates that SDP is a more accurate state estimator than WLS, but that it requires more computation time than its simpler predecessor. SDP also has the advantage of avoiding nonlinear iterative techniques that could potentially not converge or reach a local solution instead of a global one. The drawback that SDP may feature multiple global solutions is therefore the tradeoff in this respect.

8.2.3 Other Optimization Techniques

A method for solving state estimation for distribution systems using hybrid particle swarm optimization (HPSO) was presented by Naka, et al. [209] and extended to three-phase systems with transformer tap estimation by Nanchian, Majumdar and Pal [210]. This method is an alteration of particle swarm optimization (PSO) where the starting point of the state has less of an impact and convergence is achieved more quickly. Each state constitutes a particle and is given a "velocity" as it approaches the true electrical state. HPSO can take much longer to converge than WLS but achieves benefits such as more accurate estimation of losses and modeling of transformer taps as discrete variables.

Similarly, Nanchian, Majumdar and Pal [195] present an ordinal optimization (OO) technique for three-phase DSE, also to include transformer taps as discrete variables. OO is based on the idea that it is easier to solve order comparisons (which variable is larger) than to solve for exact variable values. OO investigates samples of measurements using the WLS objective function, searching for the optimal solution. OO improves both upon the slow convergence time of HPSO and its accuracy for loss estimation, though it remains slower than the simpler WLS formulation.

8.2.4 Linear Estimators

A linear state estimator is presented by Haughton and Heydt [211] that is designed for distribution systems. In the linear estimator, the measurement functions are linearized around their expected operating point. Once linearized, the WLS estimator can be implemented in a direct, non-iterative method that is effectively a linear approximation of true WLS. The paper includes three-phase unbalanced formulation. Results are comparable to traditional WLS in the test cases, with less computation time—though accuracy for wider application is not shown.

8.2.5 Forward-Backward Sweep

Forward-backward sweep (FBS) is a method of solving power flow problems by separately and iteratively solving for voltages and currents on the system using simple circuit equations. The solver is specific to radial networks, as meshed components disrupt the trivial node voltage and current equations. This algorithm has been demonstrated for three-phase DSE by Thukaram, Jerome and Surapong [147]. It is a simple formulation and therefore computationally cheap but is not suitable with meshing in the network topology. FBS converges very fast, especially for networks with little redundancy. When redundancy in measurement occurs, a weighted average or WLS approach is taken for those nodes.

Power System State Estimation by Abur and Gómez-Expósito [2] gives the following guidance on choosing methods for network parameter estimation:

- Analysis including residuals is necessary to identify suspect branches to define which parameters to estimate, but the task of estimation is more accurate when using an augmented state vector.
- Similarly, using historical data in multiple snapshots improves redundancy, and therefore accuracy, in the presence of time-invariant parameters. Time-varying parameters may similarly be estimated with snapshots using a Kalman filter approach with a snapshot horizon.
- Time-invariant network parameters are best estimated offline.

Notes on network parameter error estimation:

Note

In order to enable network parameter error estimation, there must be redundancy in actual measurements neighboring to the estimated parameter. Each redundant measurement permits estimation of one parameter.

This is true for the same reasons as for bad data detection and identification: without redundancy, there are no measurement residuals and therefore no basis on which to identify and correct a parameter error. While pseudo-measurements from forecasts could theoretically be used for redundancy if they are based on previous system states (under the assumption network parameters do not change), they are not effective for parameter estimation due to the following additional note:

Note

The estimated value of a network parameter will have an accuracy no greater than the accuracy of the local measurements used to estimate the value.

This note is intuitive but also very important. A parameter that already has a certain level of confidence greater than the nearby measurements should not be estimated, as the estimated value cannot improve the parameter value. This is also a reason why forecasted pseudo-measurements should not be used for parameter estimation. Note that pseudo-measurements that represent the parameters themselves are often incorporated into the estimation algorithm and are useful for this purpose.

and are more manageable when using the branch state formulation. Because of the direct relations between current state variables and current and power flow measurements common on distribution systems, it can converge faster than when using bus voltages. Branch current state variables also allow easier decoupling into individual phases, which allows better treatment of single-phase laterals in distribution networks.

Note that when using branch currents, the relations between bus voltages is obtainable but not their value. Therefore, a reference voltage must be set to make use of these relations, preferably at the feeder head. Certain investigations have even discussed using the power flows (real and reactive) as the state vector, such as Shabaninia, et al. [74] and Gómez-Expósito, et al. [57].

When a system is able to be solved with one state variable formulation, any of the formulations will work as well, and with the same accuracy, as shown by Pau, Pegoraro, and Sulis [218]. The use of different state variables has an effect on the measurement functions $h(x)$ and the measurement Jacobian H, as the measurements will be mapped differently to the underlying state in different ways. One important consideration when deciding on state variables is therefore the nature of the measurements. Approaches to state variable formulation are summarized in Table 22.

Table 22. Approaches to State Variable Formulation

State Vector	Coordinate	Advantages	Drawbacks
Bus (Node) Voltage	Polar	• Direct estimation of voltage magnitude and phase • Suitable for meshed networks	• Many non-linear measurement functions • High computational burden
	Rectangular	• Linearization of many measurement functions • High computational speed • Suitable for meshed networks	• Difficult treatment of current magnitude measurements
Branch (Line) Current	Polar	• Easy handling of current magnitude measurements • Easier handling of single-phase laterals branching from feeder	• Many non-linear measurement functions • High computational burden • Only practical for radial/weakly meshed grids
	Rectangular	• Linearization of many measurement functions • Sparse system matrices • High computational speed	• Only practical for radial/weakly meshed grids
Power	Rectangular	• Practical for underdetermined systems • Linear line flow measurements	• Computational burden for calculating relevant states

8.3.2 Distributed Algorithms

One method of handling the computational burden of large distribution systems with many nodes is to break the system into zones that are solved in parallel. State estimation, when compared to power flow or other network visibility applications, has the ability to break down the system into parts, so long as each portion of the system maintains observability. In the case of isolated observable islands, a parallel approach must be pursued. Three primary methods for formulating distributed state estimation are:

- **Parallel estimation:** each zone converges simultaneously on a global solution.
- **Sequential estimation:** each zone converges and sequentially informs the neighboring zones.
- **Two-level estimation:** zones are solved independently, and then incorporated into a global solution.

Distributed algorithms can feature improved computational efficiency and convergence speed for large systems—but for smaller systems the increased complexity could be unwarranted. An analysis should therefore be undertaken to determine if distributed methods will improve computation speed. For real-time implementations powered by frequent measurement updates on large distribution systems, distributed methods can be the only way to maintain an up-to-date state estimate.

Each of these methods has been explored in the following works:

- De Alvaro Garcia and Grenard [219] compare parallel and sequential DSE, including accuracy and processing time in different configurations.
- Nusrat, Irving and Taylor [220] discuss parallel and sequential DSE algorithms and investigates the differential evolution algorithm (DEA) for parallel processing.
- Nusrat, et al. [221] present an overlapping zone approach (OZA), which runs parallel DSE
- Nusrat [46] compares two parallel methods, DEA and OZA, and presents an application combining the two methods.
- Pau, et al. [69] and Gómez-Expósito and Jaen [222] present two-level DSE algorithms.

8.3.3 Three-Phase Algorithms

Section 7.1.3.4 discussed the consideration of a three-phase network model. If an unbalanced system is modeled as a balanced single-phase system, errors in the output may result. Expansion of an algorithm designed for single phase to three phases is possible and has been shown with all of the most common state estimation algorithms, each of which are summarized in this section. three-phase algorithms naturally feature increased computational burden than single phase ones.

8.3.4 Load Models

Customer loads are diverse in their nature, as they are composed of appliances and electronics that consume power in different ways. A common way to categorize customer loads is to view them in terms of being “constant power,” “constant current,” or “constant impedance.” These three types of loads differ in the relations between power consumed and voltage at the connection, as shown in Table 23. Note that in this table, Z refers to device impedance, not a measurement vector.

Table 23. Load Characteristics and Voltage Sensitivity

Load Characteristic	Relation to Voltage	Voltage Sensitivity Equation
Constant Power	Constant	$\boldsymbol{P+Q=P+Q}$
Constant Current	Linear	$\boldsymbol{P+Q=I*V}$
Constant Impedance	Quadratic	$\boldsymbol{P+Q={V^2}/{Z}}$

The simplest and most common method of incorporating loads into state estimation is to use the constant power method. However, depending on the diversity in customer loads, it may be appropriate to introduce more advanced load models. This is especially true for distribution systems, as lower voltage networks have less customer load aggregation which leads to stronger variations from node to node.

One of the more robust methods of incorporating different types of customer loads into any sort of power analysis is the ZIP model, which is well-presented in Kersting’s distribution modeling textbook [141]. In the ZIP model, each load is calculated as a mixture of the three load characteristics in Table 23—the combination of which is based on customer load data, studies, and statistics. The WLS method may be used to make the determination of the correct load combinations.

Application of load modeling in DSE can occur in one of two ways:

- By introduction of customer load models into the network equations to govern injections.
- By solving state estimation with the constant power model, correcting the customer loads based on the resulting voltage, and iteratively repeating this process.

Research into applying different load models, including the ZIP model, to state estimation is described below:

- Majumdar and Pal [223] and Nanchian, Majumdar and Pal [210] apply the ZIP model to DSE network equations using DSE algorithms.
- Bila [224] explores the application of the ZIP load model to dynamic state estimation.
- Thukaram, et al. [147] incorporates different load characteristics into the FBS network equations.
- Karimi, et al. [115] iteratively updates the customer loads based on categorized load characteristics.

8.3.5 Current Magnitude Measurements

It is necessary to mention that inclusion of current magnitude ampere measurements can introduce computational issues into the state estimator. Because direction of current is generally not a part of a current magnitude measurement, this piece of information has to either be assumed (in the case of unidirectional radial feeders) or omitted. To omit current direction, the magnitude is squared. This property of current magnitude measurements is thoroughly described in chapter 9 of *Power System State Estimation* by Abur and Gómez-Expósito [2]. This chapter and its associated references discuss methods of incorporating current magnitude measurements into the problem.

The chapter also raises the discussion of a system being "uniquely observable." For a system to be uniquely observable, it must be observable in the sense discussed in section 7.2.1, with the additional caveat that the direction of power flow must be known as well. Without knowledge of flow direction, the solution may not be unique. This brings up the possibility of a system that is observable, but not uniquely observable. In addition, there may then be measurements that are "uniqueness-critical"—the loss of which causes loss of uniqueness observability.

Villa Jaen and Gómez-Expósito [225] discuss the use of current magnitude measurements in a generalized state estimator, including issues involving topology estimation techniques.

Mapping from current magnitude to bus voltage states in the measurement functions increases problem complexity, which translates to convergence time. The use of branch currents as state variables facilitates the incorporation of current magnitude measurements into the state estimation problem, as the measurement function is no longer nonlinear. There are several literary examples of DSE research making use of branch state variables: Deng, et al. [116], Wang, et al. [49], Baran, et al. [63], Mutanen, et al. [132], Therrien, et al. [194], Muscas, et al. [100], Pau, et al. [218], and Lightner, et al. [131].

Using branch variables as the state vector has become one of the most common approaches to feasible DSE. When using branch variables, a similar issue to current magnitude measurements occurs when using voltage magnitude measurements. This issue has been described by Baran, Jung, and McDermott [226].

8.4 Distribution State Estimation Studies

Having covered the various aspects of a state estimator, including a discussion of the layers and components to a complete estimator as well as descriptions of the methods that have been used, a thorough review of investigations into DSE is presented next. The roadblocks to implementation of state estimation on distribution are largely based on the readiness of the subject utility to build the layers as described in section 7. The following summary matrix presents the most up-to-date theoretical contributions into DSE research—applying transmission state estimation concepts and developing new concepts specific to distribution systems. Applications of these concepts on real systems is discussed in a later section.

A brief note is necessary on the voltage of distribution systems. Distribution is a broad term that can include anything from sub-transmission to 120 V customer voltage. As a rule, higher voltage systems have better monitoring and telemetry, and are more meshed. High voltage (HV) systems can therefore be treated more like transmission systems. Medium voltage (MV) systems are the most common systems on which DSE is studied, having some real-time measurements and topology monitoring available. They are generally radial or weakly meshed. Low voltage (LV) systems are very rarely monitored except for at the distribution transformer and at any customer smart meters connected to the system.

Table 25 presents a large body of existing research into DSE algorithms. The acronyms used in this table are listed below for reference.

Table 24. List of Acronyms and Abbreviations for DSE Studies

AMI	Advanced metering infrastructure
ANN	Automated neural network
CWLS	Constrained weighted-least-squares
DER	Distributed energy resource
DKF	Discrete Kalman filter
DMS	Distribution management system
FBS	Forward-backward sweep
HPSO	Hybrid particle swarm optimization
IEEE	Institute of Electrical and Electronics Engineers
IRWLS	Iteratively-reweighted-least-squares
NYS	New York State
OO	Ordinal optimization
PMU	Phasor measurement unit
RBTS	Roy Billinton test system
Rec	Rectangular state variable formulation (As opposed to standard polar formulation)
RTDS	Real-time distribution simulator
TRX	Quasi-symmetric reduced impedance matrix
UKGDS	UK Generic Distribution System
WLAV	Weighted-least-absolute-values
WLS	Weighted-least-squares

Table 25. DSE Studies

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurements							Largest Test System and # Buses	Intended Contribution to DSE
						Injection	Flow	Ampere Magnitude	Voltage Magnitude	PMU	Customer Meter	Pseudo		
[108] [109]	1997	FBS	Bus		3	*			*			*	NYS 934	Probabilistic load allocation for DSE
[147]	2000	FBS	Bus		3	*						*	Custom 18	FBS algorithm overview
[9]	2003	CWLS	Bus		3		*	*	*			*	Real 394	Iterative load estimation methods, load constraint
[49]	2004	WLS	Branch		3		*	*	*		*	*	IEEE 123	Meter type versus estimator error
[63]	2009	WLS	Branch		3		*	*	*		*	*	IEEE 34	Inclusion of AMI data
[111]	2009	WLS	Bus		1	*			*			*	UKGDS 95	Gaussian mixture model load forecast
[164]	2009	3 Methods	Bus		1	*	*		*	*		*	UKGDS 95	Comparing WLS, WLAV, Huber
[220]	2011	WLS	Bus	*	1	*			*			*	UKGDS 16	Distributed algorithms
[132]	2011	CWLS	Branch		3	*	*		*		*	*	IEEE 37	RTDS demo, implementation compared with DMS
[68]	2011	IRWLS	Bus		1	*			*		*	*	UKGDS 75	IRWLS, batch smart meter data
[112]	2012	WLS	Bus		1		*		*			*	UKGDS 95	ANN load forecast and error modeling
[217]	2012	CWLS	Rec Bus		1	*			*				IEEE 4	Reduced impedance matrix TRX
[74]	2012	Optimization	Power		3	*	*					*	None	DER operation optimization approach
[61]	2012	Hachtel’s	Bus		3	*			*	*		*	Custom 38	Unsynchronized PMUs
[213]	2012	DKF	Rec Bus		1	*				*			IEEE 13	Assessment of DKF algorithm with PMUs
[7]	2013	Hachtel’s	Bus		1	*	*				*	*	Spanish 99	Iterative load allocation and DSE, load profiles
[115]	2013	WLS	Bus		1	*	*		*			*	Malaya 34	Minimal measurements
[211]	2013	Linear	Rec Bus		3	*			*	*	*	*	RBTS 20	Linear DSE formulation, load forecast
[227]	2013	Huber	Bus		1	*	*					*	Custom 33	Machine learning for load forecast
[194]	2013	Hachtel’s	Branch		3	*	*	*	*			*	IEEE 8500	Tap-changer modeling included
[228]	2013	WLS	(Rec) Branch		3			*	*	*		*	UKGDS 95	DSE Options: PMUs, meshing, rectangular state

Table 25 Continued

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurements							Largest Test System and # Buses	Intended Contribution to DSE
						Injection	Flow	Ampere Magnitude	Voltage Magnitude	PMU	Customer Meter	Pseudo		
[81]	2014	WLS	Rec Bus	*	3			*	*	*			IEEE 123	PMU synchronization error
[100]	2014	WLS	Rec Branch		1	*	*	*	*	*		*	Custom 95	Measurement correlation
[80]	2014	WLS	Bus		1	*	*	*	*	*		*	IEEE 33	Applying PMUs to DSE
[46]	2015	5 Methods	Bus	*	1	*	*	*	*		*	*	UKGDS 711	Central & distributed methods, meter placement
[229]	2015	CWLS	Bus		3	*		*	*			*	IEEE 8500	Reduced impedance matrix TRX
[230]	2015	WLS	Bus		3	*	*	*	*			*	IEEE 34	Impact of input perturbations
[221]	2015	Hachtel’s	Bus	*	1	*			*			*	UKGDS 711	Overlapping zones, hot initialization
[210]	2015	HPSO	Bus		3	*	*		*			*	IEEE 123	HPSO for DSE with tap changers
[57]	2015	WLS	Power		1	*	*	*	*		*	*	Custom 100	Two-time scales, limited measurements
[114]	2015	WLS	Bus		1	*			*		*	*	Real 46	Non-linear load estimation
[58]	2015	WLS	Bus		3	*			*		*	*	IEEE 123	Considering unsynchronized meters
[218]	2015	WLS	4 Methods		3	*	*	*	*			*	IEEE 123	Comparing state variable formulations
[69]	2016	WLS	Rec Bus		3	*			*		*	*	RTDS 5	Cloud-based smart metering, RTDS
[195]	2017	OO	Bus		3	*	*		*			*	IEEE 123	OO for DSE with tap changers

9 Documented Implementations

In addition to the research that has been conducted on different DSE algorithms and approaches, an effort has been made on several occasions to demonstrate feasibility of DSE on real systems. Most of the earlier implementations simply take a utility network model and realistic set of measurements to investigate potential algorithms and evaluate results. Since 2010, however, an effort has been made to demonstrate the feasibility of DSE in real time on updated networks. This section describes the current published work in both categories.

In the evaluation of the studies in this section, a "redundancy index" is used, which is calculated based on the following equation:

Equation 19
$$\boldsymbol{RI = \frac{M}{N}}$$

Where M is the number of measurements and N is the number of states. $RI = 1$ refers to a non-redundant system with the same number of measurements and states. The redundancy index values in the section are approximate.

A brief discussion of existing DSE software solutions has also been presented.

9.1 Offline Algorithm Demonstrations

Research studies applying various algorithms to utility distribution systems to obtain realistic results are presented in Table 27. Some of these examples manufacture their own data sources in a realistic setting, while others (generally those using SCADA measurements) use actual measured utility data. The acronyms used in this table are listed below for reference (this table augments the previous Table 24).

Table 26. List of Acronyms and Abbreviations for Documented DSE Online/Real-Time Implementations

EDF	EDF Energy United Kingdom
EG	Elektro Gorenjska
GPC	Guizhou Power Corporation
LV	Low voltage (<2 kV)
MV	Medium voltage (~2 kV to 35 kV)
OZA	Overlapping zone approach
RI	Redundancy index
RG&E	Rochester Gas & Electric

Table 27. Documented DSE Offline Implementations

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurement Infrastructure						*RI*	Test System	Resolution	Duration	Takeaways and Contributions
						SCADA	Protection	Line Meters	PMUs	Customer Meters	Pseudo					
[30]	2000	WLS	Bus		1		*	*			*	1	• RG&E MV circuit • 8 buses	15 min – 1 hr	3 weeks	• Feasibility based on historical data • Load estimation
[116]	2002	FBS	Branch		1			*			*	1	• Chinese MV circuit • 116 buses	Not given	Not given	• Iterative load estimation
[157]	2005	WLS	Bus	*	1		*	*			*	1	• Serbian MV circuit • 6 feeders • 135 load points	Not given	3 days	• Topology simplification • Observable islands • Measurement verification • Load calibration
[110]	2008	WLS	Bus		1	*					*	1	• EDF MV circuit • 2 feeders • 14 buses	1 min	1 day	• Load modelling strategy and performance • Substation-only measurements
[219]	2011	WLS	Bus	*	1	*					*	1	• French MV circuit • 2 substations • 6 feeders	1-3 min	Not given	• Parallel and series zonal approaches
[67]	2012	Hachtel's	Bus		3			*			*	1	• 3 North American circuits • 11 feeders	Not given	Not Given	• Feasibility study for DMS
[73]	2012	WLS	Rec Bus		1	*					*	1	• Serbian MV circuit • 40 buses	Not given	1 day	• Optimal load/generation reallocation • Incorporation of weather data

Table 27 Continued

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurement Infrastructure: SCADA	Protection	Line Meters	PMUs	Customer Meters	Pseudo	RI	Test System	Resolution	Duration	Takeaways and Contributions
[59]	2013	FBS	Not Given		3			*		*	*	≥1	• Danish LV circuit • 1 feeder • 13 buses	10 min	1 day	• LV demonstration • Measurement combinations • Missing data
[231]	2013	WLS	Bus	*	1						*	1	• GPC MV circuit • 6 substations	1 hour	1 week	• Quality of historical data • Load flow correction • Topology simplification • Observable islands • Measurement verification • Load calibration
[161]	2014	WLS & Hubor	Bus		1	*		*		*	*	≥1	• Greek MV circuit • 1 substation • 2 feeders	1 hr	1 week	• Topology detection • Error estimation • Meter placement • Objective function comparison • Measurement analysis • Observable islands
[46]	2015	Hachtel's	Bus	*	1	*		*		*	*	1	• 2 EG MV circuits • 83 buses	5-15 min	1 week	• Comparison of algorithms, distributed methods • Measurement placement • Distributed OZA

These offline implementations are generally intended to be a more realistic test of the associated DSE algorithms than a generalized test feeder. Maintaining a measurement set that might feature actual utility data, these algorithms can be evaluated prior to any implementation.

Several of the later works are quite useful in making determinations about DSE implementations. Nusrat [46] provides a good background and comparison of algorithms and proposes both a centralized and distributed algorithm together with a measurement placement strategy. Han, et al. [59] evaluate the impact of using different combinations of measurement sets: for instance, relying solely on substation data versus having access to customer measurements. Ranković and Sarić [73] investigates a future scenario where significant DER generation is available for optimal re-dispatch, and couples this with a state estimation prototype.

9.2 Online Utility Pilot Systems

The second category of implementations consists of those which demonstrate real-time, online operation of DSE in various forms. These studies partner with utilities to tie into their measurement systems so that the state estimator might monitor the network in real time. Table 29 presents these systems. The acronyms used in this table are listed below for reference (this table augments the previous Table 24 and Table 28).

Table 28. List of Acronyms and Abbreviations for Documented DSE Online/Real-Time Implementations

DKF	Discrete Kalman filter
EPFL	École Polytechnique Fédérale de Lausanne
HV	High Voltage (> 35 kV)
SMUD	Sacramento Municipal Utility District
VVO	Volt-VAR Optimization

Table 29. Documented DSE Online/Real-Time Implementations

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurement Infrastructure						*RI*	Test System	Resolution	Duration	Takeaways and Contributions
						SCADA	Protection	Line Meters	PMUs	Customer Meters	Pseudo					
[232]	2010	WLS	Bus	*	3	*	*		*		*	≥8	• St. Thomas HV/MV circuit • Generating plant • 5 substations	4/sec	2 days	• Substation PMU calibration • High redundancy • Transmission with some distribution
[131]	2010	WLS	Rec Branch		3	*		*		*		1	• Southern California Edison MV circuit • 1 feeder	Not given	Not given	• Outage management capability • Fault location • No final report
[131]	2010	WLS	Rec Branch		3	*				*		1	• Southern Company MV circuit	Not given	Not given	• AMI integration • Customer phase identification • No final report
[132]	2011	CWLS	Branch		3	*		*		*		1	• Finnish MV circuit • 10 buses	1 hr	1 week	• Issues detecting bad data from pseudo data • Comparison to DMS
[233]	2012	WLS	Bus		1			*			*	1	• Salzburg Netz GmbH Lungau MV circuit • 2 substations • 18 MV generators • 29 LV generators	5-15 min	Ongoing	• Commissioning of DSE for VVO • Smart inverters • Potential expansion to rest of Austria
[113]	2013	WLS	Bus		3	*		*			*	≥1	• BC Hydro, several substations • Results from one feeder	10-20 /day	1 day, Ongoing	• Load flow powering DSE load curves • Measurement & pseudo-measurement tuning
[133]	2014	Not given				*				*		1	• Northern Powergrid circuit • 4 network areas	15 min	Ongoing	• DSE for optimal operation & control • AMI integration • Network model synchronization • Tuning & calibration

Table 29 Continued

Reference	Year	Algorithm	State Variables	Distributed	# Phases	Measurement Infrastructure						*RI*	Test System	Resolution	Duration	Takeaways and Contributions
						SCADA	Protection	Line Meters	PMUs	Customer Meters	Pseudo					
[215]	2015	DKF	Rec Bus		3				*			1.8	• EPFL Campus MV circuit • 6 buses	50/sec	5 min	• WLS vs Kalman algorithm • System latency • Phasor data concentrator, synchronization
[234]	2015	WLS	Bus		3				*	*	*	1	• SMUD MV circuit • 1 feeder	60/sec	Not given	• High-speed real-time DSE • Load allocation • Measurement verification
[117]	2016	Not given						*			*	1	• Spanish MV circuit • 1 feeder	1 hour	6 months	• Iterative load allocation and DSE • Effect of load curves
[235]	2016	WLS	Branch		3			*		*		1	• 3 utility demos: Ostkraft, Unareti, Gas Natural Fenosa	10 min	Ongoing	• Joint MV & LV operation • Initial state forecasting • Load & generation forecasting • Data management
[216]	2017	4 methods	Rec Bus		3				*			1.8	• EPFL Campus MV circuit • 6 buses	50/sec	Not given	• Extension of [215] • Comparison of method performance: DKF, WLS, WLAV, & Linear • Fault detection
[236]	2017	Not given	Not given	*	3		*	*		*	*	≥2	• Malaga Smart City MONICA (Spain) • 2 MV feeders & their LV feeders	5-15 min	Ongoing	• Redundant DSE • Smart city operational support • Smart inverters • 2-level LV/MV estimation

The projects documented in Table 29 are useful as examples for distribution utilities looking to implement a state estimator. There are some general trends of which to take note:

- Almost all of these examples have no redundant measurements outside the substation, relying on pseudo-measurements for observability along the feeder.
- The vast majority of pilot systems implement three-phase solutions, indicating that imbalance is a common issue on distribution systems.
- There are a number of examples of branch state variables, indicating that the authors determined this alternate formulation was more suitable for their distribution system.
- Many of the pilots used AMI with telemetry that was designed for real-time estimation. Of those that did not have adequate telemetry often used AMI to generate pseudo-measurements.

There are four implementations that feature measurement redundancy, though this level monitoring is the exception rather than the rule: Meliopoulos, et al. [232] presents a sub-transmission state estimator with distribution networks that is relatable to DSE, and Carillo [236] utilizes a designated "smart city" that included big investments to upgrade the measurement and telemetry infrastructure. Pignat, et al. [215] and Zanni [216] use the same system of 6 buses, each bus featuring a PMU. The non-redundant state estimators should therefore be viewed as a more realistic option for utilities seeking cost-effective DSE in the near future.

Other useful lessons learned from these implementations:

- Atanackovic, et al. [113] faced difficulty in tuning the measurement weights for state estimation, finding that no one tuning method gave reliable improvements in accuracy.
- Hollingworth, et al. [133] cited difficulty in synchronizing the network model and topology as well as calibrating state estimation error, recommending that data maintenance processes be automated and that the state estimator be implemented early on so that the output can be evaluated and corrected.
- Gonzalez, et al. [117] records accuracy improvements when load allocation and state estimation are used together to iteratively update load forecasts.
- The Ideal Grid for All project [235] and its DSE background paper by Dansk Energi [34] lay out a robust architecture for DSE, including strategies for handling different types of measurements and database strategies for handling the large volumes of measurement and load forecast data. It was funded by the European Union and implemented on multiple distribution systems.
- Pignati, et al. [215] and Zanni [216] demonstrate PMU-only Kalman filter state estimation on a small MV network. The studies evaluate how previous states might be used to lessen the computation time and evaluate the computation time against other algorithms. Robust communication networks including phasor data aggregation and consideration of delays are demonstrated as well. The application of state estimation for fault detection is considered by Zanni [216].

9.3 Existing DSE Software Solutions

There currently exist several software solutions for performing state estimation on distribution systems. These commercial solutions are an add-on to existing distribution planning, analysis, and operation software, and are designed to perform the algorithms presented in section 8 with considerations for distribution networks. A brief description of some of the most relevant commercially available solutions is presented in this section. This discussion is not intended to be an evaluation or review of commercial software, but rather a description of the types of software on the market and their intended use.

DSE software can be a streamlined way to handle the processing of distribution system data. This software has been designed to bring transmission state estimation to the distribution level, and includes many concepts described in this report.

However, like the focus of this report, the state estimation algorithms are just one of many considerations for DSE implementation. The software might act as a hub, but it must be supported with a strong measurement infrastructure, communications system, and up-to-date network model information. Compatibility across all utility platforms is vital.

Additionally, the software must be supervised so that issues such as measurement calibration and non-convergence can be addressed without detriment to operations. The bad data detection must be supervised so that the correct diagnosis and corrections are applied, and good measurements are not erroneously removed.

> ***Note***
>
> DSE software should be viewed as a tool with which DSE implementation can be facilitated – the "state estimation engine" which does central computation based on available data. Considerations such as measurement infrastructure, communication, network model, and information compatibility are equally as important as the state estimation engine.

9.3.1 Planning and Analysis Software

CYME is a planning and analysis software that is owned by Eaton Corporation [237]. It is very commonly used among distribution utilities, particularly for hosting GIS network models and running load flow analysis under different scenarios for planning and expansion purposes, among many other functions. CYME features an optional module for distribution state estimation, with the purpose of cleansing the dataset and achieving a more accurate network profile to support the other analysis functions. While CYME is typically an offline power analysis tool, it can be used to study historical periods (e.g., day-after estimation) and incorporate delayed measurements from AMI. The tool can be used to diagnose network parameter issues and errors in the network model and features a number of quality indices described in section 7.3.1.1 that evaluate the accuracy of the state estimate.

Grid360 by Nexant [238] is another analysis tool that can be used both for offline planning and analysis and in-the-loop operation. The web-based tool suite includes features scenario playback, load flow, and other useful tools. The distribution state estimation tool allows customization options and GIS visualization, such that the use of observable islands and the bad data detection and convergence thresholds can be edited. It also features topology estimation so that the incorrect switch statuses can be detected and corrected. Grid360 uses CIM protocols to communicate network model and measurement data, and so can be integrated into systems for on-line network model hosting and operation. The result of the state estimate can be used to improve the accuracy of other analysis tools.

9.3.2 Distribution Management Systems

While the aforementioned planning and analysis tools can integrate with control center operations for real-time feedback, a DMS can be used as a more comprehensive in-the-loop controls and operation platform and can feature state estimation as well. Many companies that offer DMS and ADMS platforms such as ABB [239], GE [240], Schneider [241], and Siemens [242] advertise state estimators as one of the building blocks to their systems. DMS platforms are integrated with utility SCADA systems and control operations, and host network models. This makes them ideal for in-the-loop state estimation to process the available measurement information.

In the ideal integrated system presented by DMS vendors, the state estimator is the first step in operations, taking SCADA, AMI, and other measurement data and calculating the most-likely state of the system. From this first process, the rest of the DMS functions can run real-time optimization functions.

Siemens has applied for a patent covering their method for estimating loads for pseudo-measurements, including screening of certain types of bad data using these estimates and incorporating the result into DSE [243].

ABB has obtained a patent for their two-level state estimator. This is not specific to distribution systems but could be applied to a coordinated transmission-distribution control system [244].

10 Gap Analysis

The body of work surround DSE is wide, as has been shown in the previous sections outlining the entire DSE implementation process. However, very few operational state estimators been developed to benefit day-to-day operations in distribution utilities. This section is devoted to identifying the gaps that exist in the literature in which further work would benefit utilities seeking to implement DSE. This is not an exhaustive list of areas for future work, as such a report governing all research opportunities in the area would be impractical. It instead focuses on the gaps that most directly affect DSE implementation.

The gaps discussed in this section are categorized as gaps in methods and gaps in demonstrations.

10.1 Gaps in Methods

Identified gaps in methodology are presented in this section. These are items not currently covered by research publications in which SGS believes further research is warranted to benefit potential implementations.

10.1.1 Quantifying the Measurement Infrastructure

For a utility to make meaningful decisions on improving its measurement infrastructure, it must have a quantification of its measurements the observability of its network. Nearly all distribution systems are unobservable in terms of actual measurements, so simply marking the system as “unobservable” or “lightly monitored” carries little meaning. When implementing state estimators on distribution systems, it is important to note that that the capabilities of a state estimator are directly correlated with the capabilities of the measurement infrastructure.

> ***Note***
>
> The capabilities of a state estimator are directly correlated with the capabilities of the measurement infrastructure from which it gets information. Pseudo-measurements are insufficient in most circumstances to enable accurate real-time visibility and bad data detecting capabilities.

All decisions regarding algorithms and performance are irrelevant when a system is unobservable, and most distribution systems are unobservable. Introduction of pseudo-measurements to obtain observability enables the state estimator to converge on a solution—it does not empower the state estimator to become an accurate real-time visualization tool with bad data detecting and network estimating capabilities. There are methods to improve pseudo-measurement forecasting and calibration, and even to use pseudo-measurements to correct unrealistic data inputs. While they can provide several benefits to DSE systems, they do not take the place of actual real-time data in terms of measurement redundancy.

When a system is observable, authors will frequently assign a value to the redundancy on a system: a network with twice as many measurements as state variables will have a redundancy of 2. This gives rise to what can be called the "redundancy index," which has been previously defined in (19).

This redundancy index is useful when comparing the measurement capabilities of systems and has been used in Table 27 and Table 29 to this end. However, unobservable systems with added pseudo-measurements are referred to simply as "non-redundant," with $RI = 1$ – having no other quantitative differentiating factor. Utilities might refer to their systems as "10%" monitored, SGS believes greater standardization of observability metrics is necessary to compare the measurement infrastructure of different systems and investment plans.

This index could be as simple as a redundancy index that omits pseudo-measurements from the numerator and therefore can be less than one:

Equation 20

$$\boldsymbol{OI} = \frac{\boldsymbol{M}\ (\boldsymbol{no\ pseudo})}{\boldsymbol{N}}$$

Where M is the number of measurements and N is the number of states. In this context, a feeder with 10% of its buses featuring real and reactive load meters will have $OI = 0.1$. The utility may then evaluate a plan to improve its index to $OI = 0.2$ by placing additional meters, referring to section 7.1.1.1 for guidance on placement.

Consideration for other factors such as measurement accuracy and temporal resolution can also be included in measurement quantification. For instance, the addition of a PMU to a system brings more to the measurement infrastructure than a few additional measurement points: it also features high accuracy, high frequency, and a phase angle reference. Alternately, the impact of AMI can be augmented by improvements to the telemetry and communication systems that allow the measurements to be used in real time.

Given that there is generally better equipment and telemetry at the head of the feeder, and measurements as less frequent the farther they are from the substation, there is a geographic dependence to measurement infrastructure. The infrastructure analysis could therefore include a geographic component to evaluate network areas with greater need for measurements. Going further, it would be useful to see such an evaluation overlaid on top of a network model—a heat map of measurement infrastructure index to plan out system upgrades.

Further work in this area could include development of better measurement evaluation indices to quantify measurement prevalence, accuracy, and temporal resolution on a feeder, circuit, or network. Demonstration of a geographic component presented with the network model would also be beneficial. The goal of this work should be to provide a sound basis on which to evaluate measurement upgrades and infrastructure capability.

10.1.2 Pseudo-Measurements for Bad Data Detection

As discussed in section 7.4.1, pseudo-measurements do not provide the same benefit to detecting bad input data (as well as network model errors) as actual measurements do. Even when the inclusion of pseudo-measurements creates redundancy, these data points do not have any bearing on the real-time operation of the system and therefore would not be able to work with conditions outside the forecasted "normal operation."

Bad data detection is one of the most cited reasons for implementing state estimation, so research into overcoming the shortcomings of pseudo-measurements would be useful in pursuing these goals.

Mutanen, et al. [132] describe an attempt to use pseudo-measurements to evaluate normalized residuals and detect bad data from the result. However, the authors found that when pseudo-measurements were used for this purpose, certain unexpected changes in system operation could cause good measurements to be identified as bad. For instance, as was the case in the paper by Mutanen, et al. [132], uncommon warm weather caused a change in customer heating load patterns, and the normalized residual test provided a false positive.

Another potential scenario could be the charging of electric vehicles: these units consume a large amount of power compared to traditional customer loads. If the customer electric vehicle charging patterns were to change, abnormal loading conditions might cause good system measurements to be detected as bad.

Despite the aforementioned shortcomings, there is potential for pseudo-measurements to be incorporated into the bad data detection analysis. However, any such analysis would have to include consideration for abnormal loading conditions and any other factor that might result in a false positive.

10.1.3 Pseudo-Measurement Tuning

The weight associated with pseudo-measurements is generally obtained based on the supposed accuracy of the load forecasting method used. Likewise, all pseudo-measurements are likely to have a similar weight, which will be significantly greater (around a factor of 10 or more) than actual measurement weights. In the presence of residuals, Zhong and Abur [102] present methods to determine the weights of measurements based on error variances – however applications are not generally applicable to pseudo-measurements. Similarly, IRWLS methods that adaptively re-weight measurements do not perform well with pseudo-measurements.

Especially in low-redundancy systems, discerning which pseudo-measurements are closer to the true state and adjusting their weights accordingly is a nontrivial process, as there are few residuals to indicate accuracy. Atanackovic, et al. [113] discuss the issues faced with tuning measurement weights in a DSE implementation, as they did not have a formal process that produced well-performing weights.

In many cases, pseudo-measurement weights are adjusted in order to achieve a converging state estimator. However, a converging solution does not necessarily indicate an accurate one. Significantly altering the inputs to appease the DSE solver may introduce unnecessary error, and the system might need infrastructure and calibration improvements to be useable.

Treatment of pseudo-measurement weights to improve DSE results is an area with little research coverage that should be explored in the future.

10.1.4 Discerning Between Bad Data and Inaccurate Network Model

When a system has sufficient redundancy to permit both bad data detection and network model estimation, some determination must be made to diagnose the error in the system as being from measurement values or the network model. Further, if the network model is the source of error, it must be determined if the incorrect elements are line parameters, topology variables, or transformer tap ratios. This is because the methods for handling each type of error are different. Especially with parameter and topology errors, the suspected element is re-evaluated. If the re-evaluation is based on flawed information, the estimation will be incorrect.

Methods for detection, identification, and calibration of input errors assume that the type of error is known, and that bad data has been removed prior to network model estimation. *Power System State Estimation* by Abur and Gómez-Expósito [2] describes common trends associated with each type of input error, but does not include a robust process with which these errors can be categorized. Incorrect parameters can appear as a small bias in surrounding data points, while switch status errors result in large residuals on either side of the switch. However, multiple bad data in the area of the suspicious network element could mislead the state estimator application. Trial-and-error applications.

Exhaustive hypothesis testing could be one solution to this issue. However, with the enormity of many distribution systems and the number of potential input variable errors, this problem very quickly becomes computationally prohibitive.

A thorough description of robust methods to discern between different types of input errors would be beneficial to the development of DSE. This is particularly important as distribution systems have more error in their network models and less monitoring of topology variables than transmission.

10.1.5 Low Voltage/Secondary System Estimation

The vast majority of DSE research is evaluated based on MV network models comprising distribution substations, feeders, and associated laterals. This is expected, as the MV portion of the distribution network is a valuable asset that is indicative of the performance of the system as a whole. Additionally, MV networks typically have some monitoring so that load allocation and state estimation functions can be performed.

LV networks can pose significant challenges to the distribution system and are largely unmonitored, but many utilities could benefit from visualization of these assets as well. Very few DSE investigations consider the LV network, and only two DSE implementations from section 9 include LV as part of the estimated system: Han, et al. [59] and Baran, et al. [236].

In many ways, LV systems can present entirely new problems to the DSE approach. Not only do LV networks have even fewer (and less accurate) measurements than MV systems, but the corresponding network models are less accurate as well. Many distribution utilities do not include secondary networks or customer connections in their GIS network models, and therefore have little basis for state estimation. However, secondary network conditions are more closely related to customer power quality, and service interruptions are commonly associated with issues on the secondary.

LV network state estimation strategies should be a focus in future research in DSE for two main reasons:

- Many urban distribution utilities have large secondary networks whose operation would benefit from greater visibility.
- Incorporation of AMI and other customer-side measurements requires accurate modeling of the associated LV network.

Especially in urban areas, LV networks may be highly meshed, distinguishing them from MV networks. Methods such as FBS and using branch currents as state variables may not work on these secondary grids, so further research into under-monitored LV systems should be conducted.

In terms of incorporating AMI, when there is a gap in knowledge between the end of the network model and the customer meter connection, there can be an un-modeled voltage drop due to the high resistance (and low voltage) on customer connection cables. This is compounded when the model of the secondary network is not accurate, and the full advantages of implementing AMI are lost. This is further evidence that state estimation on the secondary is necessary for a fully functioning visibility system.

While state estimation on LV systems might be a long-term process as these systems have fewer measurements than MV systems, it is a worthwhile exploit, and a chief concern among utilities that primarily operate in urban areas.

10.1.6 State Estimation under Contingency

The most important function of a distribution utility is to keep the lights on. Likewise, incentives behind installing state estimators on these systems include increased reliability. However, as with all other distribution operations, the state estimator must also plan for contingency. Under contingency, assumptions change and there is a new network model. DSE must be designed such that the network model can be updated in real-time as the network is reconfigured, and observability must be reconsidered as sections of line go down. Additionally, the communications infrastructure may rely on power line carrier (PLC), in which case communications with measurements will also be interrupted.

State estimation can be a useful tool for evaluating pre- and post-contingency conditions and can help with scenario analysis and reconfiguration studies when the system is being brought back online. However, there is no broad base of literature considering these distribution challenges in the context of state estimation. Given that DSE meant to improve reliability and operation of distribution utilities, this would be a worthwhile area of study.

10.2 Gaps in Demonstrations

In addition to the methodological gaps described in the previous section, many DSE concepts presented by the literature have not yet been demonstrated on distribution systems. Utilities are risk-averse, so having results from proven demonstrations of the capabilities and associated DSE functions would provide guidance for implementation and investment decisions. It is possible that these areas have been investigated by certain implementation projects, but any results from these investigations have not been made public. Section 9 describes the DSE projects that have been demonstrated on real systems, showcasing several DSE algorithms and concepts. The following is a list of topics that have been discussed in this report but have not been demonstrated by projects in section 9, where further research into practical application would be beneficial. Each includes a reference to the associated section of the report:

- Network model estimation, including augmented state vector approach (section 7.4.2)
- Network topology real-time update and maintenance (section 7.1.3.3)
- State estimation under contingency (section 10.1.6)
- Measurement calibration and tuning (section 7.1.1.7)
- Distribution system locational power markets with DERs (section 7.4.3)
- Meshed LV secondary grid DSE with very few measurement points (section 10.1.5)

11 DSE Software Toolkit: Overview and Guide

11.1 Distribution State Estimation Toolkit Overview

Smarter Grid Solutions has developed a toolkit to guide interested users in exploring the concepts and capabilities of DSE. This document servers as the user guide to this toolkit. The toolkit application applies DSE to a test system in a highly-configurable manner. The purpose of this guide is to provide instruction and technical context to the discussion surrounding implementation of DSE. By following the steps laid out in this guide, the user will be able to operate a simulated three-phase DSE instance and explore the associated possibilities of the tool.

Table 30. DSE Software Toolkit Features

Features of this DSE Toolkit
Simple interface to run three-phase DSE on an example network.
Ready-made plots of state estimates versus true values.
User-configurable measurement placement.
Freedom to investigate observability and accuracy considerations in sandbox environment.
Introduction and detection of bad measurement data.
Open-source code enables further customization and extension.
Octave and Matlab environments allow user to manipulate the output variables themselves.

11.1.1 Nodes on the Open-Sourced Software Required for this Toolkit

All software required to run this toolkit are open-sourced, meaning they are free to download and use as long as this is done within range the original developers' intentions, as described in their license files. Using open-source software allows this toolkit to reach a broad range of users, eliminating any paywall to reaping the benefits of the DSE investigation. The software included with this toolkit is described below.

Table 31. Open-Sourced Software Required to Run DSE Software Toolkit

Software	Purpose	Description and Purpose for Toolkit
Octave [245]	**Sandbox Scientific Coding Environment**	Octave is a scientific programming language and environment hosted by GNU. The language syntax is identical to Matlab, as it runs based on the same .m files. There are several functions and packages that are specific to either Octave or Matlab.
		This toolkit makes use of Octave as the environment in which state estimation is realized. All code developed is compatible with both Octave and Matlab.
OpenDSS [246]	**Distribution System Simulator**	OpenDSS is a distribution system simulator hosted by EPRI that runs a multitude of functions on power networks, including unbalanced three-phase power flow.
		This toolkit makes use of OpenDSS to hold the test system model and run an initial power flow to achieve true underlying system values.
Python [247]	**All-Purpose Programming Language**	Python is one of the most popular programming languages of engineers and developers. It can be applied to many different problems.
		This toolkit makes use of Python as part of the interface between Octave and OpenDSS.

> ***Note***
>
> All Octave code developed for this toolkit has been tested in and will work just as well when run using Matlab.

11.1.2 Details on the DSE Application

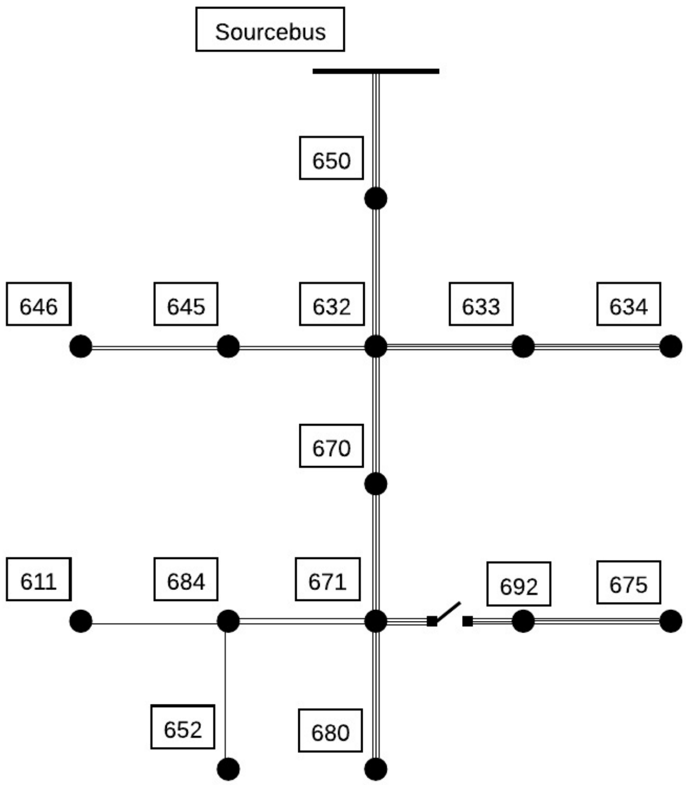
The state estimation problem can be approached with a number of different approaches. The following table describes the approach taken by this DSE application, and the surrounding network parameters.

Table 32. DSE Application Details

Parameter	Description
Default Network Model	A three-phase, 13-bus system based on the IEEE 13-bus test distribution system that is included as an example within the OpenDSS download. The IEEE 13-bus system has been simplified to remove capacitors and transformers. The system has 13 buses, 35 nodes (bus phases), 12 lines, one switch, and several single- and double-phase laterals. Loads are present at most buses. There are 70 unknown state variables. Buses 650, 632, and 684 all have zero-power injections at all phases.
State Variables	Bus voltages and voltage angles. From these values, the entire power system may be calculated.
State Estimation Algorithm	Hachtel's augmented matrix method for WLS. This is a robust method for modelling zero-injection buses without negatively affecting the condition of the inverted matrix.
State Estimation Parameters	The convergence threshold has been set to $1\text{x}10^{-5}$. The maximum number of iterations has been set to 50. The threshold for detecting an outlying normalized residual is seven standard deviations away from the mean normalized residual. The base power is 1 MVA. All of these parameters are editable for interested users in the .mat file "advanced_parameters.mat."
Possible Measurements	• Voltage magnitude • Voltage angle • Current magnitude • One-phase real and reactive power flows and injections (loads) • Three-phase sum of real and reactive power flows and injections (loads) • Virtual measurements: zero-injection buses and voltage angle reference
Bad Data Detection Algorithm	Largest normalized residual. When the largest normalized residual is above a certain threshold, the corresponding measurement is removed, and the state estimation process is repeated. The threshold for detecting an outlying normalized residual is seven standard deviations away from the mean normalized residual, as mentioned under "parameters."

The simple 13-bus network used for the example in this toolkit is shown in Figure 10. This network is based on the framework for the IEEE 13-bus network. This network is three-phase unbalanced to model distribution system behavior in the State. It includes single- and double-phase laterals and a switch, though does not model transformers or any other controllable or reactive element.

Figure 10. Simple 13-Bus Test Network Used for Toolkit



11.2 Toolkit Installation

The files necessary to install and run this toolkit are all located in the same location as this guide, on the NYSERDA portal:

> https://www.nyserda.ny.gov/About/Publications/Research-and-Development-Technical-Reports/Electric-Power-Transmission-and-Distribution-Reports

The necessary files are all located within a zipped folder entitled **DSE_Toolkit.zip**. The installer files located within this folder are all for 64-bit Windows systems. If this is not the operating system, a URL has been given to find the appropriate installer.

1. Download DSE_Toolkit.zip
2. Extract it to an easily accessible folder (not a remote or network drive)
3. Run the installers for each of the open-sourced software, as outlined in the following section

> ***Note***
>
> The DSE Toolkit has been tested only on Windows systems. Compatibility with other platforms is not guaranteed in the as-is state of the toolkit, though the source code may to be edited to accommodate these platforms.

11.2.1 Installing Octave

Octave is the environment with which the user will interface to run the toolkit. To install:

1. Navigate to the GNU webpage to obtain the installer file:
   https://www.gnu.org/software/octave/download.html
2. Open the installer file and follow the prompts to install the software.

11.2.2 Installing OpenDSS

OpenDSS doesn't need to be open for the toolkit to run. However, the network model (including customer loads) are all hosted within the OpenDSS framework and should be edited in the program. To install:

1. Navigate to the Sourceforge webpage to obtain the installer file:
   https://sourceforge.net/projects/electricdss/
2. Open the installer file and follow the prompts to install the software.
   - If the user is on Windows 10, there will be a message box saying Windows 10 is not fully supported. This is acceptable, and the Toolkit should work. At worst, the application might crash occasionally and need to be restarted.

11.2.3 Installing Python

Python is used in communications between Octave and OpenDSS. To install:

1. Navigate to the Python webpage to obtain the installer file.
   https://www.python.org/downloads/windows/
2. Open the installer file and follow the prompts to install the software.
   - The user will likely need to have the pywin32 package installed to communicate with OpenDSS. However, the DSE Toolkit will install this package automatically upon its first run.

11.3 Running a Basic Example

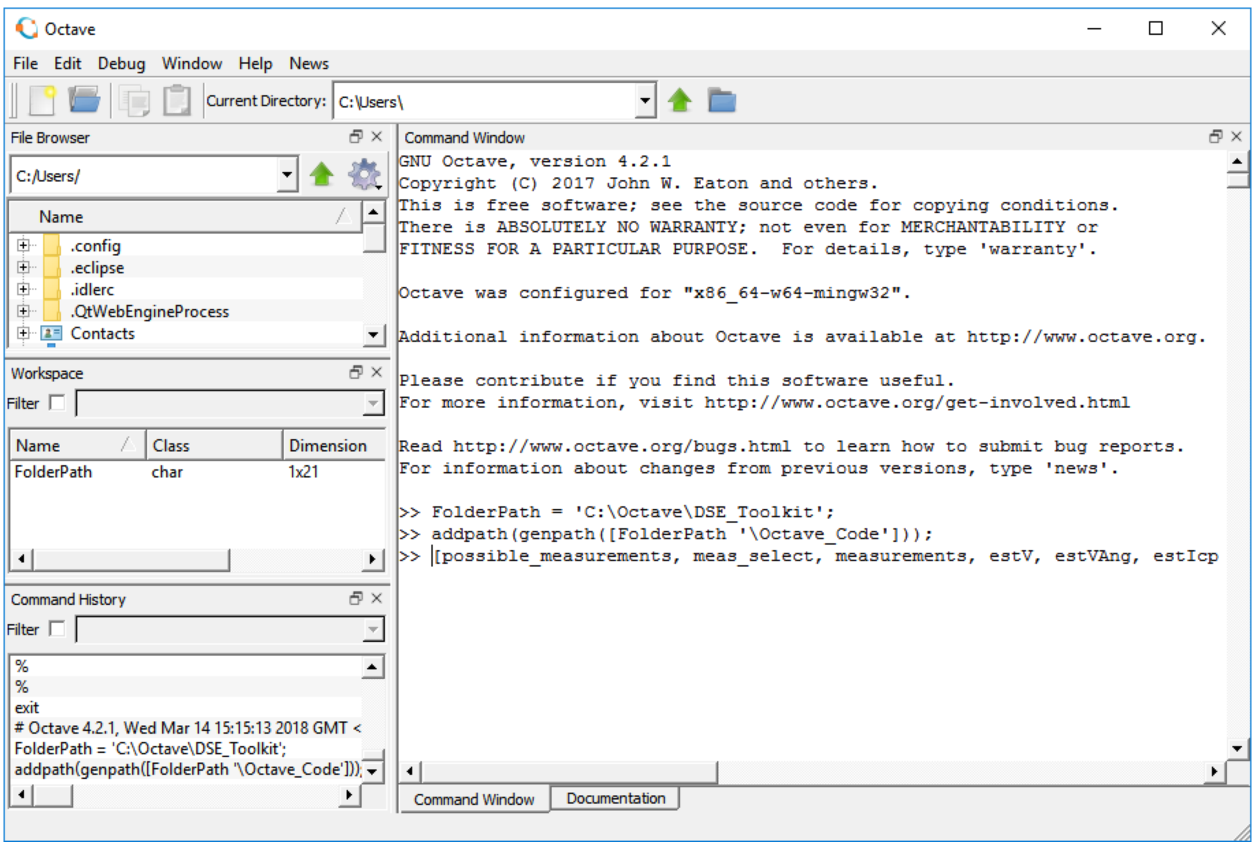
These instructions will guide the user through the simplest implementation of DSE using this toolkit.

1. Open the Octave GUI.

2. Tell Octave where the toolkit files have been placed with the command:
`FolderPath = ‘FOLDER PATH HERE’;`
    - (The folder path string should be in single quotes)
3. Tell Octave where to find the functions needed to run the toolkit with the command:
addpath(genpath([FolderPath ‘\Octave_Code’]));
4. Run the toolkit with the command:
[possible_measurements, meas_select, measurements,
estVcpx, estIcpx, estS, trueV, trueI, trueS, baseV, baseS, Network_Model] =
run_basic_DSE_toolkit(FolderPath);

At this stage, before the final command is registered, the Octave console should look similar to the following screenshot:

Figure 11. Example Screenshot of Initial Octave Console

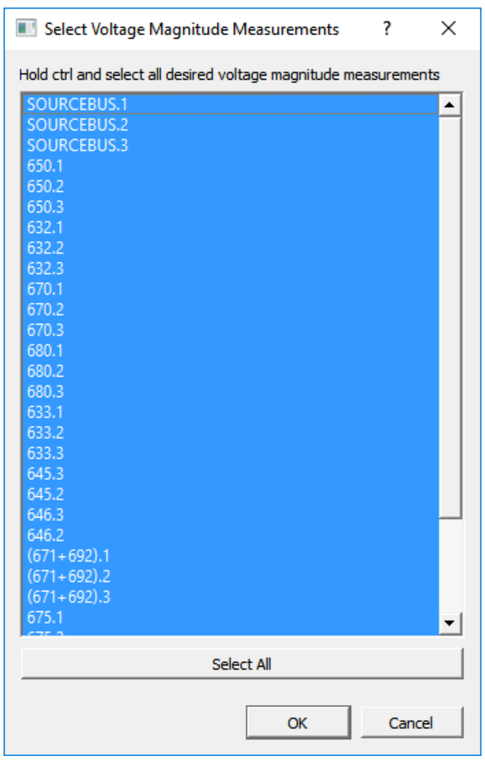


5. The console will display the following information:
    - If the pywin32 package is missing from the Python installation, the application will download and install the package (this will happen only once per computer).
    - The results of the OpenDSS load flow simulation with metrics such as buses, nodes, maximum and minimum voltage, total power, and total losses.

- When using the default case 13-bus network (which is based on the IEEE 13-bus test system), a message will display that two buses have been combined. This is because there is zero-impedance between the two buses (the result of a closed switch), and as a result the number of unknown state variables reduces from 70 to 64.

6. The toolkit will ask the user if the previous measurement configuration should be loaded. There will be no previous configuration if this is the first instance.
   - Reply with no.
7. The toolkit will then tell the user how many unknown state variables there are in the system (64 for the default case) and ask the user to select measurements, either randomly or by hand.
   - Select By Hand.
8. Place voltage magnitude measurement at every node by pressing **Select All** and **OK**
   - The measurement selection window for voltage magnitude should look like the following image:

Figure 12. Example Screenshot of Voltage Magnitude Measurement Selection



   - Set the standard deviation of the voltage magnitude measurements as **0.1%**.
9. Do the same for voltage angle measurements: press **Select All** and **OK**
   - Set the standard deviation of the voltage angle measurements as **0.1%**.

> ***Note***
>
> With a voltage magnitude and angle measurement at every bus, the user has effectively placed a phasor-measurement unit (PMU) at every bus in the distribution feeder. This is not a realistic scenario, as most distribution systems have no PMUs at all. However, it is the most straightforward way to demonstrate observability of the system.

10. No additional measurements are necessary to ensure observability. Simply press OK without selecting any measurements for the following:
    - Current magnitude measurements
    - One-phase power flow measurements
    - One-phase power injection measurements
    - Three-phase power measurements
11. No additional configuration is necessary. Simply respond NO to the following prompts:
    - Edit zero-injection bus constraints?
    - Add any additional random measurements?
    - Introduce bad data?
12. The state estimation process now begins.
    - The application will list the number of each type of measurement—which for this example will be 32 voltage magnitude and 32 voltage angle measurements.
    - State estimation should conclude in a single iteration given that the measurements map one-to-one with the unknown state variables.
    - There should be no bad data detected.
    - The average percent error in node voltage should be less than 0.1%.
13. The application asks the user if a list of measurements should be listed for reference. Responding yes will list all 32-voltage magnitude and 32 voltage angle measurements.
14. The application asks the user if the results should be plotted. Responding yes will cause the application to ask the user about plotting estimated values against true values in three phases:
    - Voltage magnitude, voltage angle, current magnitude, current angle, real and reactive power flow, real and reactive power injection, and system losses.
15. The DSE application has now concluded. At this point, the user should re-start the application and play with different parameters, such as measurement configuration, zero-injection buses, bad data introduction, etc.

11.3.1 Toolkit Output

In addition to plotting the variables versus the true underlying values, as outline in the previous example, all important variables will be output to the console for further manipulation. As a result of running the example, the following variables will be added to the console workspace:

Table 33. Console Output after Running the DSE Toolkit

<table>
<tr><th>Variable</th><th>Description</th></tr>
<tr><td>**possible_measurements**</td><td>A list of all the possible measurement points on the system.</td></tr>
<tr><td>**meas_select**</td><td>The selection of measurements and associated standard deviations used to run the DSE application. The values in this vector correspond to the respective entries in “possible_measurements.”</td></tr>
<tr><td>**measurements**</td><td>The measurement values used to run state estimation. The values in this vector correspond to the respective entries in “possible_measurements.”</td></tr>
<tr><td>**estV, estVAng, estIcpx, estS**</td><td>The estimated voltage, and voltage angle, complex current, and power (real and reactive, flows and injections).</td></tr>
<tr><td>**trueV, trueI, trueS**</td><td>The true underlying voltage, current and apparent power generated from the load flow.</td></tr>
<tr><td>**baseV**</td><td>The base voltage for each bus.</td></tr>
<tr><td>**Network_Model**</td><td>A compressed representation of the network model used by the toolkit. A key to the variables within this data structure is given below:
<table>
<tr><th>Network Model Characteristic</th><th>Extraction Command</th></tr>
<tr><td>**Number of buses**</td><td>Network_Model{1}</td></tr>
<tr><td>**Bus names**</td><td>Network_Model{2}</td></tr>
<tr><td>**Number of nodes (bus phases)**</td><td>Network_Model{3}</td></tr>
<tr><td>**Node names**</td><td>Network_Model{4}</td></tr>
<tr><td>**Number of lines**</td><td>Network_Model{5}</td></tr>
<tr><td>**Line information**</td><td>Network_Model{6}</td></tr>
<tr><td>**Number of connections (line phases)**</td><td>Network_Model{7}</td></tr>
<tr><td>**Map of connections**</td><td>Network_Model{8}</td></tr>
<tr><td>**Numerical map of connections**</td><td>Network_Model{9}</td></tr>
<tr><td>**Number of terminals (all power points)**</td><td>Network_Model{10}</td></tr>
<tr><td>**Terminal names**</td><td>Network_Model{11}</td></tr>
</table>
</td></tr>
</table>

12 DSE Software Toolkit: Further Guidance and Advanced Functionality

12.1 Helpful Toolkit Information

12.1.1 Measurement Selection

- To generate measurements, the DSE Toolkit takes the underlying true values from the OpenDSS load flow and adds random error corresponding to the user specification. Depending on how many measurements are "placed" by the user and how accurate they are, the state estimator's result will have a different level of accuracy.
- The application supports the following measurement options:
    - Voltage magnitude
    - Voltage angle (requires a corresponding voltage magnitude measurement)
    - Current magnitude
    - One-phase power flow
    - One-phase power injection
    - Three-phase power flow and injection
- The program will save the previously generated measurement configuration. Once the previous configuration has been re-loaded, the user may further configure it by hand or with random measurements.
    - Saved configurations persist even if Octave is closed or the computer is restarted.
- Configuring measurements:
    - When configuring measurements by hand:
        - Hold 'ctrl' to make multiple selections
        - Hold 'select' to select a range of measurements.
        - To deselect all measurements: select a single measurement, then hold 'ctrl' and select that same measurement again. All measurement fields should then be blank.
    - When configuring measurements randomly or adding additional random measurements to a hand-selection, measurements will be randomly populated into currently non-existing measurement slots for a given category.
- For each measurement set added to the system, the user will be asked to give the standard deviation of the measurement. This represents the accuracy of the measurement device, and a normal distribution.
    - A standard deviation of 1% means that there is a 68% chance of the measurement being within 1% of the true underlying value.
    - The user cannot select a standard deviation of zero. This would cause a divide-by-zero error—any measurements given a standard deviation of zero are removed from the system.
    - By convention the standard deviation should be positive. However, a negative standard deviation will have the same result.

- Power measurements can take the form of either:
    - Flow measurements (e.g., “BusA-BusB”) which measure power flow between buses on a line.
    - Injection measurements (e.g., “BusA.inj”) which measure the power injection to the bus from outside the network.
        - Power sources, such as a transmission connection, are a positive injection. They are “adding power” to the network.
        - Loads, such as a customer connection, are a negative injection. They are “removing power” from the network.
- If injection measurements are selected, the application asks the user if these constitute pseudo-measurements (load forecasts). Designating them as pseudo-measurements does not alter how the application handles them, apart from the following:
    - The user is given the option to adjust the weights of pseudo-measurements. The application only supports either all or none of the 1-phase injection measurements being pseudo-measurements and will change the weight of all to the same value.
        - The weight is a metric which tells the application how accurate the measurement probably is. In the case of pseudo-measurements, the accuracy itself is uncertain, and therefore the weight is subjective.

12.1.2 Equality Constraints

- If no voltage magnitude or no angle measurements are placed, there is no basis with which to compare any of the state variables.
    - If no voltage magnitude measurements are selected, the application will ask the user if a voltage reference should be added to the source bus. This voltage reference takes the form of three equality constraints representing voltage magnitudes of 1 per unit on each phase.
    - If no angle measurements are selected, the application will ask the user if an angle reference should be added to the source bus. This angle reference takes the form of three equality constraints representing balanced angles at the source bus: 0°, -120°, and 120°.
    - If either voltage magnitude or angle measurements are added at a later time, these reference constraints are removed. Ensure the measurements cover all three phases.
- The user is given the option to add zero-injection bus constraints to any bus not containing an injection measurement.
    - Zero-injection buses are buses that exist as a connection between other network elements, and do not feature transmission connections, distribution transformers, or customer connections that could constitute a source or a load.
    - Zero-injection buses are modelled as equality constraints that are solved in parallel with the WLS state estimation problem.
    - Zero-injection buses can also be modelled as injection measurements. However, this gives the state estimator room to diverge from the zero-injection. Additionally, if a high weight is associated with these injection measurements to enforce them, this can negatively affect the condition of the inverted matrix—introducing error to the result.

- For the default 13-bus model, the buses with zero injection are: 650, 632, and 684. The problem may still converge if other buses are selected for zero injection, though there will be error introduced.

12.1.3 Bad Data

- The user is given the option to add bad data to the measurements. When this option is selected, the user chooses which class of measurements to add bad data to, and how many bad data points to add.
  - The bad data is introduced to random measurements within the class. For instance, if the user elects to introduce 2 bad data points to voltage magnitude, additional error will be introduced to 2 pre-existing voltage magnitude measurements at random.
  - The error introduced as "bad data" takes the form of an additional 20% to 60% error either added or subtracted from the value of a given measurement. The exact amount of error, and whether the error is positive or negative, is random.
- After state estimation has run, the system looks for bad data inputs. This is done by analyzing the difference between the converged system state and the measurement values that went into it. If there is a large discrepancy between one or many measurements and the resultant state, bad data has been detected.
  - The discrepancy between a measurement and the system state is called a "residual." These residuals are normalized for their value and standard deviation.
  - Determining if a normalized residual is large enough to be considered "bad" involves the use of a threshold. The threshold has been set at seven standard deviations away from the mean residual value. This threshold can be customized, see section 12.2.2.
  - After bad data is detected, the application identifies the measurement with the largest residual as the erroneous measurement. This measurement is removed from consideration, and state estimation restarts with the remaining measurements.

> ***Note***
>
> If a measurement is critical to the observability of a system—or it is part of a "critical pair" with another measurement—it cannot be identified as bad data. This is because the measurement is influential to the system state and will have a low residual—even if it is erroneous.

12.1.4 Observability Guidelines

- If the chosen measurement configuration is unobservable, the program will display which states it was unable to calculate, and then exit.
  - In this case, the user should re-start the program, load the previous measurement configuration, and try adding measurements, zero-injection buses, or angle references to create observability.

- Two data points (measurements) about each node are required in order to achieve observability.
  - The application must be able to solve for voltage magnitude and angle at each node in order to get the state estimate, so the user must provide at least as many known values. Furthermore, these values must be distributed such that there are two known values pertaining to each bus.
  - These data points can take the form of the following:
    - Voltage magnitude and/or angle measurements at the node
    - Power injection measurements at the node
    - Neighboring current magnitude or power flow measurements
- In order to calculate bus angles, measurement points must provide complex information. This includes angle measurements but could also take the form of a real and reactive power measurement pair.
  - Current and voltage magnitude measurements do not contain complex information.
- Three-phase (summed) power measurements are a useful tool, but they do not contain individual-phase information and therefore will help achieve redundancy but not observability.
- The DSE Toolkit does not give an option to break a system into observable islands.
  - This decision is based on a paper by Monticelli [118] determining that adding pseudo-measurements to achieve non-redundant observability does not impact the state estimate of the already-observable parts of the network.
  - Therefore, a network that might in practice be broken into multiple observable islands can instead be modelled as a fully observable network, with pseudo-measurements filling the gaps for unobservable states. The result is then same as if the system were broken into observable islands.

12.1.5 State Estimation: Iterations and Convergence

- While the state estimation process runs, the console will output the progress after each iteration. There is a maximum number of iterations (default 50) in which the application moves towards the optimal solution. After many iterations, the state estimator gives up and prints that the problem has not converged.
- Convergence occurs when the largest difference between any state variable and its previous value is less than the tolerance value. This ensures the problem has narrowed in on a solution and will not change significantly with more iterations.
- Non-convergence generally occurs when the problem is nonconvex—meaning there is either multiple or possibly zero viable solutions. There are a number of possible reasons that a problem may not converge:
  - Low measurement accuracy.
  - Too much bad data.
  - Not enough redundancy in measurements.
  - Over-reliance on current magnitude measurements.

        - Current magnitude measurements do not have information on direction of flow and introduce more opportunities for error when solving for bus voltages.
        - Certain measurements or too many of them may present the estimator multiple solutions.
        - This issue can be rectified by using current magnitude and angles as the state variables themselves. This requires a reformulation of the state estimation engine, but in some distribution scenarios may be preferable to voltage state variables.

- When a problem does not converge, the application will print this information and ask the user if the application should search for bad data.
    - If the user elects to search for bad data, and bad data is found, the state estimation application will remove the erroneous measurement and repeat.
    - In some cases, despite the problem not converging, the estimated values are very close to the true values. This indicates that the problem was oscillating between two solutions, both of which were close to the true state.
- The user is encouraged to restart the application and has the option of modifying the measurement selection and accuracy, or even trying the same configuration again—as the measurement error is randomized with every run.

12.1.6 Note on Three-Phase Power Systems Analysis

This toolkit only supports three-phase distribution networks. This is because many distribution systems in the State and the United States are not designed to be balanced, and therefore cannot be simplified to a one-phase model. The imbalance stems from customer loads drawing from one phase instead of all three, and certain feeder laterals pulling off of only one or two phases. In Europe, distribution networks are often designed with balance in mind.

Interested users should review materials on three-phase networks in order to understand the fundamental differences between one- and three-phase systems. However, for the purposes of operating this toolkit, only a rudimental knowledge is necessary:

- Most buses consist of three phases. Each of these bus-phases is called a “node” in this application. Each node can only have one voltage value, but the three nodes per bus can have different voltages.
    - In the ideal balanced case, the three nodes at a bus should have the same voltage magnitude, and voltage angles that are 120° out of phase with each other.
- Lines between buses will usually have as many phases as the buses they are connected to. Each of these line-phases is called a “connection” in this application. The same balance principles apply for connections as for nodes.
- In most cases, a measurement device on the system will measure all three phases of a bus or line. When in doubt, apply measurements to all available phases.
    - To achieve observability, sufficient measurements must be placed on all phases.

- When evaluating results, it is usually a good approximation to consider only a single phase. Considering all three phases will indicate the level of phase imbalance.

12.1.7 Useful Octave Commands

- To interrupt and close the application while it is running:
  - Press "ctrl + c"
- To clear the terminal of all previous commands:
  - Enter `clc`
- To delete all variables in the current workspace:
  - Enter `clear`
  - Enter `clear [variable name]` to delete a specific variable
- To close all plot windows at once:
  - Enter `close all`
- To call a previous command:
  - Press "up" on the keyboard
- To call a previous command with that starts with a series of letters:
  - Type the series of letters and press "up" on the keyboard.
  - For example, instead of re-typing the `FolderPath` and `addpath` commands at the start of each Octave session, one can simply type "F" or "a" and press "up" on the keyboard.
- To display the value of any variables from the workspace, type its name in the console. Putting a semicolon at the end of a line suppresses output to the console, so do not include a semicolon when asking Octave to display variables to the console.

12.2 Advanced Toolkit Instructions and Scenarios

In this section, instructions will be given to investigate some of the more advanced options and scenarios enabled by this toolkit. These scenarios should serve as a jumping off point for users to explore more of the functionality of the DSE Toolkit than the basic example from section 11.3 provides.

12.2.1 Modelling Load Forecast Pseudo-Measurements

Pseudo-measurements are auxiliary sources of information that are used in state estimation to fill gaps in real measurements and establish observability. In the majority of cases, pseudo-measurements take the form of customer load forecasts. This information can be pulled from network planning studies, extrapolated from transmission data, or generated in-house by utility forecast engines.

Pseudo-measurements make a solvable problem out of an unobservable one. Regardless of the method used to create them, the data itself carries a large amount of error because it is not tied to the true real-time operation of the system. This is modeled by using a low weight corresponding to these measurements – the weight being inversely related to the standard deviation (expected error) of the measurements. Using a low weight tells the application that these pseudo-measurements may not be very accurate, and the internal state can be different from what they would indicate.

To model load forecast pseudo-measurements as part of the measurement infrastructure:

1. Load forecasts fall under the category of "single phase power injection measurements." When selecting measurements, select injection measurements corresponding to the desired load forecasts. This could be all of them (except the source bus).
2. When setting the standard deviation of these injection measurements, use a relatively high standard deviation. This could be as high as 20% or even 50%. This does two things:
   - Introduces a high amount of error into the measurements per a normal distribution
     - In the absence of a forecasting mechanism or historical data, introducing error to the measurements suffices to represent pseudo-measurements not based on real-time data.
   - Assigns a low weight to these measurements so the application knows to diverge from their values if necessary.

12.2.1.1 Tuning Pseudo-Measurement Weights

During actual DSE operation (as in this toolkit), there may be instances where the application does not converge because the pseudo-measurements are farther away from current operating conditions than was expected. In many situations, network operators have no additional information and have to determine how to get an answer from the program anyway.

Unlike real measurements, pseudo-measurements do not have any technical specifications from which to determine their accuracy. The rough accuracy of the forecasting method may be estimated, but operators will not know when they are close to modeling underlying conditions and when they are not. Therefore, the choice of pseudo-measurement weight is somewhat arbitrary.

When running the toolkit with pseudo-measurements, the user will be given the option to change their weights at the start as well as after the application runs. If interested, the user is encouraged to experiment with tuning the pseudo-measurement weights—especially if the problem does not converge. Note that setting a weight that is many orders of magnitude different from the average weight of the rest of the system could disrupt the state estimator.

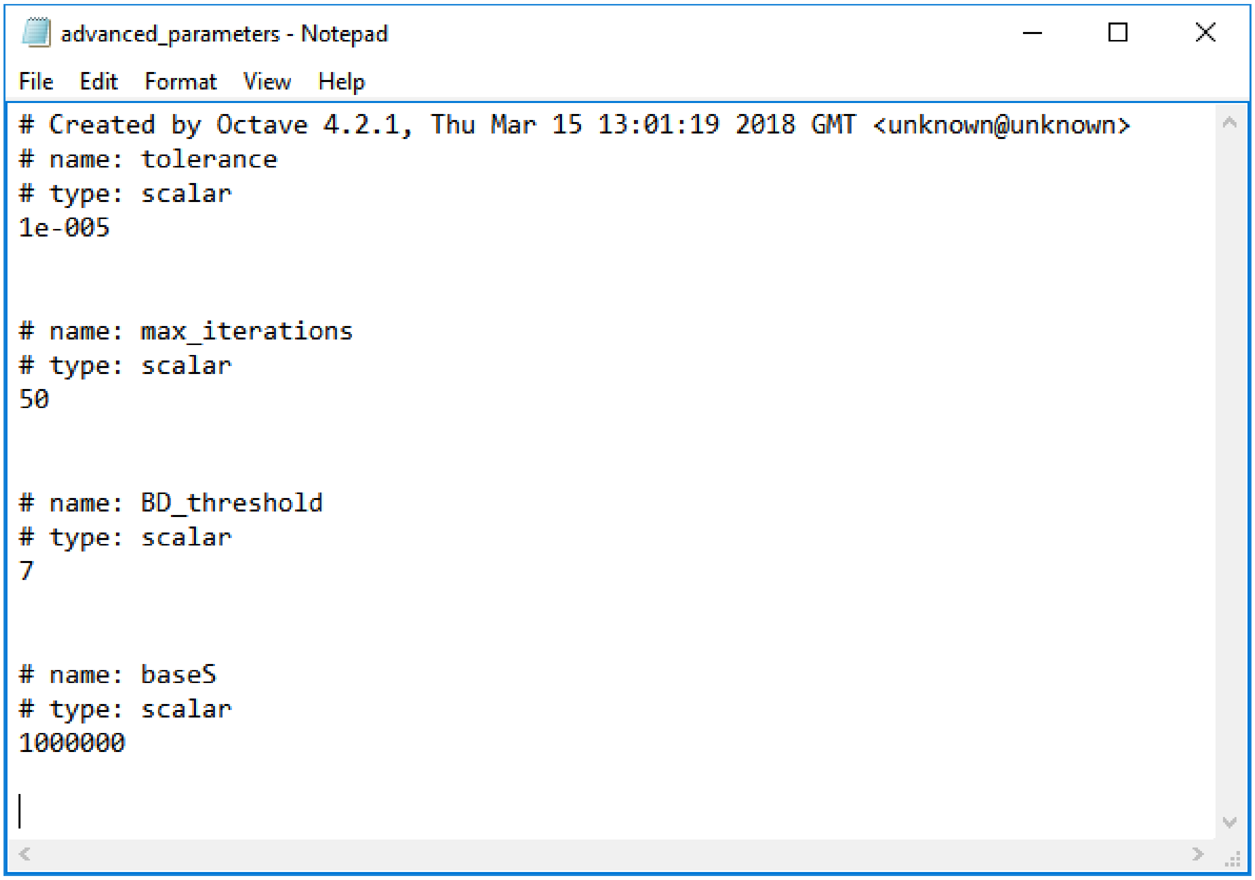
> ***Note***
>
> If a pseudo-measurement is critical to the observability of a system, tuning its weight does not impact the resulting state estimate. This is because despite its error, the system has no information with which to second-guess the pseudo-measurement's value adjusts the estimated state to fit the data.

12.2.2 Editing Advanced Parameters

- There are three configurable parameters that are not presented during the course of the application. It is not necessary to edit them, as their default values are sufficient for most applications. However, they may be edited by users looking for further customization:
    - **tolerance** (default value = $1x10^{-5}$)
        - The tolerance parameter specifies the criteria for determining convergence. After every iteration, the application compares the current state estimate with that of the previous iteration. If the largest difference between any state variable and its previous value is less than the tolerance value, the problem is considered converged and solved.
        - Lowering the tolerance value may improve accuracy, though it may also increase the number of required iterations (and time) before convergence.
    - **max_iterations** (default value = 50)
        - The max_iterations parameter dictates the number of iterations that must be attempted before the application determines the problem will not converge.
        - Increasing max_iterations will increase computation time for non-converging problems, though it may enable a solution to problems that take more iterations to converge.
    - **BD_threshold** (default value = 7)
        - The BD_threshold parameter is a measure of how strict the application is in determining if there is an outlier in the input dataset. It corresponds to how many standard deviations a normalized residual must be away from the mean before it is considered an outlier (Note: this is not the same as the number of standard deviations away from the measurement's expected value).
        - Increasing BD_threshold reduces the likelihood of good data being detected as bad, though it increases the likelihood of bad data going undetected. Vice versa for decreasing BD_threshold.
    - **baseS** (default value = 1 MVA)
        - This is the base power with which the system is converted to per unit. 1 MVA is a common standard base for distribution systems. This value can be edited if the test model is changed to a much larger or smaller case. Changing this number will not affect the accuracy of the estimator, though it will change the scale to which per unit current and power are applied.
        - To calculate the per unit current on each line, divide **baseS** by the base voltage operating on the line.

- These parameters are located in the file **advanced_parameters.mat**, which is located in the home folder **DSE_Toolkit.** To edit them, open the file in a text editor and edit the numeric values. The following screenshot shows the layout of this file. Note: there needs to be two empty lines under each variable value, including the last one.

Table 34. Screenshot Showing advanced_parameters.mat




```
# Created by Octave 4.2.1, Thu Mar 15 13:01:19 2018 GMT <unknown@unknown>
# name: tolerance
# type: scalar
1e-005


# name: max_iterations
# type: scalar
50


# name: BD_threshold
# type: scalar
7


# name: baseS
# type: scalar
1000000


```

12.2.3 Editing the Customer Loads and Network Model (in OpenDSS)

To edit the customer loads or the network model, the user must open the .dss network model file. This should be done in OpenDSS, but any text editor will work. There are three important parts to the .dss network model. Note that “!” at the start of a line designates a comment.

- **Line Codes:** Specify the impedance matrices for the various types of lines in the system. These codes are taken from the OpenDSS IEEE 13-bus Example.
- **Line Definitions:** Define the network architecture in terms of lines and their ending buses.
    - Buses are not explicitly defined – rather they exist by fact of having a connected line in the Line Definitions section.

- **Load Definitions:** Define the any loads that are located on buses
    - To add lines and buses, create a "New Line" in the Line Definitions section. This can be done by copy-pasting an existing line.
    - To add loads, create a "New Load" in the Load Definitions section. This can be done by copy-pasting an existing load. To modify existing loads, simply change their kW or kvar value.
    - Note that if the network model is altered, the saved measurement configuration in the DSE Toolkit will no longer apply to the new model. Attempting to load the previous measurement configuration will result in an error.
- Instructions:
    - The switch between buses 671 and 692 is closed by default. To open it, change the command in this section to "**Open Line.671692**." Keep in mind that this isolates buses 692 and 675 from the source and effectively removes them from the system.

12.2.3.1 Running a Model within OpenDSS

The user is able to test any model within OpenDSS itself. The simplest way to do this is to highlight the lines the user would like to run and pressing '**ctrl+D**' on the keyboard (alternatively, navigate to **Do -> Select Lines**).

- To run the entire model, press "**ctrl+A**" to highlight all lines in the document and run them with "**ctrl+D**."
- To display results, type any of the following lines, highlight them, and run them with '**ctrl+D**':
    - show voltages
    - show currents
    - show powers
    - Examples of these commands are also given at the bottom of the "**Simple13.dss**' network model file.
    - Results can also be exported to .csv by navigating to "**Export**" on the top menu.

12.2.4 Fully Custom Measurement Selection

The measurement selection process presented by the application has limitations, in that each chosen measurement of a certain type must have the same standard deviation. To have full control over the measurement selection process, this section instructs users on manipulating the necessary vector in Octave.

- First, load the previous measurement configuration to get a template. It is necessary that the DSE Toolkit application has been run at least once:

```
load('previous_meas_select.mat');
```

- To view the list of possible measurements and the current measurement configuration:

```
possible_measurements

meas_select
```

  - The `meas_select` vector corresponds to the same indices as the `possible_measurements` vector. There are zeros where a measurement is not present, and a value where there is a measurement (the value corresponds to the standard deviation).
- Edit the `meas_select` vector. This can be done in a number of different ways. If the user is in a Matlab environment, the `meas_select` vector can be edited as in a spreadsheet.
  - Remove all measurements:

```
meas_select(:) = 0;
```

  - Verify that an index corresponds to a certain measurement:

```
possible_measurements(index)
```

  - Set a measurement at a desired index. For this example, the standard deviation for the measurement is 1%:

```
meas_select(index) = 0.01;
```

  - Set a range of measurements with 1% accuracy

```
meas_select(index1:index2) = 0.01;
```

- Save the new measurement configuration

```
save('previous_meas_select.mat','meas_select','ang_ref','zinj_list','pseudo');
```

- To save a specific measurement configuration from being overwritten by the DSE Toolkit application, navigate to the folder "**DSE_Toolkit\OpenDSS_Models**" and change the name of "**previous_meas_select.mat**" to any other name.
  - To re-instate this configuration and run it with the toolkit, change the name back to "**previous_meas_select.mat**". You may need to delete the other saved file.

13 Project Takeaways: Challenges and Best Practices

The most important step towards implementing DSE is to understand state estimation as a tool. State estimation is only as powerful as the information that it is given. In understanding the goals of network visibility and the infrastructure available to the utility, it can be determined if upgrading the system to support DSE is a good fit. At its most basic, here is a summary of what must be considered to implement DSE:

Table 35. DSE Minimum Requirements

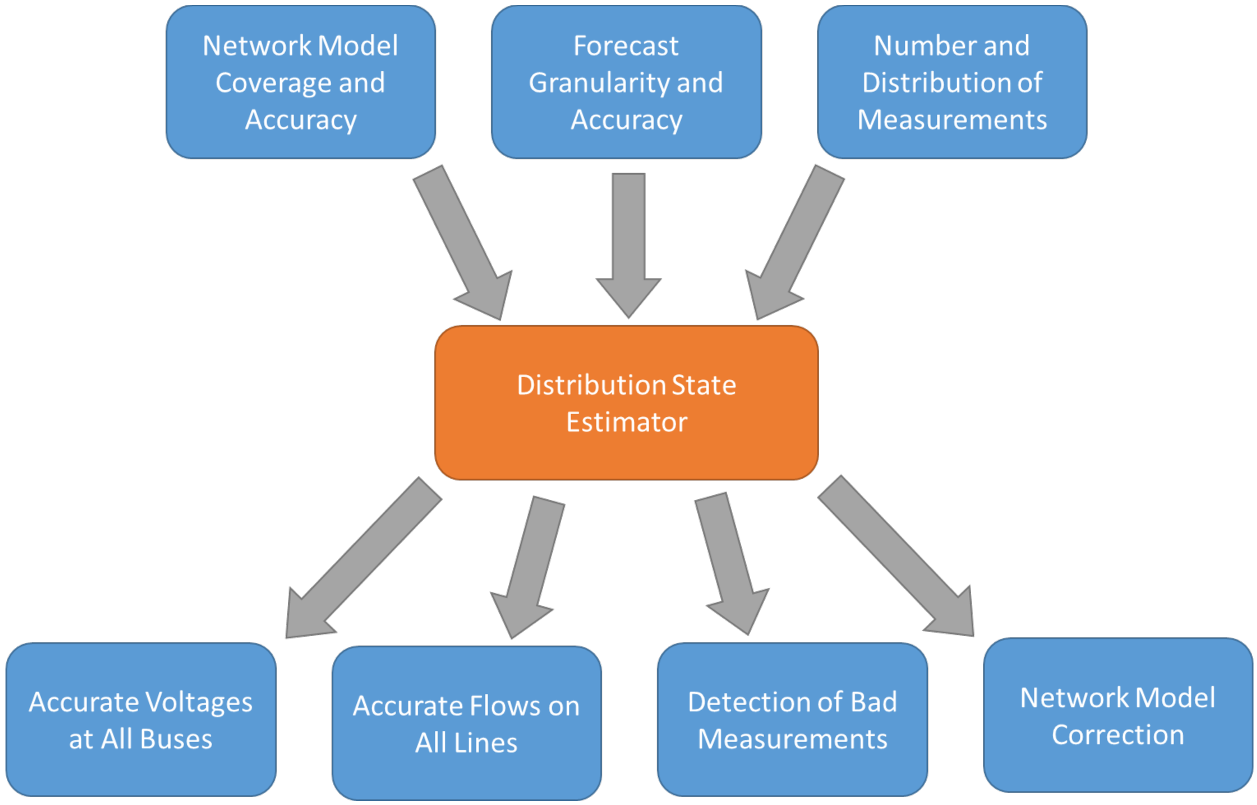
What items are necessary to support DSE?	
1	An up-to-date network model

2	At least two pieces of operating data about each system node
	• Examples of this could be (among others):
	    ○ Real & reactive customer load
	    ○ Voltage magnitude & angle
	• This can take the form of load forecasts – understanding the compromise in system accuracy and inability to detect bad data

3	A communication infrastructure to support real-time measurements and model updates
4	A state estimation engine

It should be noted that having a state estimation engine is just as important to DSE as having any one of the first three items. Without upgrading all four items in a convergent manner, the effectiveness of DSE implementation will suffer. To demonstrate this, the relation between input quality and potential outputs are summarized in Figure 13.

Figure 13. Input Quality versus Possible Outputs to a Distribution State Estimator



The four outputs shown in Figure 13 are results that could benefit the operation of any utility. However, the effectiveness with which DSE can realize these results is a direct result of the quality of the three inputs shown at the top of the figure. It is vital that utilities understand the relation between what goes into the state estimator versus what the state estimator can provide.

The most challenging step towards implementing DSE is not installing the state estimation engine at the center of Figure 13, but in providing good data inputs from the peripheral supporting processes. At its minimum, on a traditional distribution system with few monitoring points, DSE results are little better than a forecasted load flow. However, with key distribution system operational improvements over the base case, the benefits shown in Figure 13 can be realized.

13.1 DSE Challenges

The challenges to DSE adoption do not lie in the methods. The challenges lie in the data.

State estimation is a well-established practice in most transmission systems—however it has almost no established usage in distribution systems. This discrepancy is attributed to a variety of differences between transmission and distribution systems that make bridging this gap challenging. At the root of the challenges facing DSE is the fact that while transmission networks are highly monitored and controlled on a real-time basis, distribution networks have traditionally been managed in an infrequent, passive manner with limited system visibility, knowledge of the network, and control opportunities. In fact, the algorithms behind state estimation are very similar in both transmission and distribution systems—the primary difference is the quality and types of data used to power them.

A summary of the implementation challenges of DSE and challenges to maintaining an accurate and effective result is provided in Table 36. This is a summarized table based on Table 19.

Table 36. Summary of Challenges for DSE

Implementation Challenges	Accuracy and Effectiveness Challenges
Observability	Uncertainty in Network Parameters
Communication Infrastructure	Uncertainty in Topology
Complexity of Network	Uncertainty in Load and Forecast
Line Parameters	

The state estimate can only be as accurate as the data provided. Sources of error can come from any or all of the inputs and will compound with each other. Beyond the error that can be introduced through the above factors, the capabilities of DSE in realizing bad data detection and network model correction are limited by the measurement infrastructure. For a state estimator to be able to determine which inputs or parameters are introducing error, it must be able to create a full and accurate system state without these pieces of information. In other words, measurements must be redundant. If an erroneous measurement is part of the critical dataset, it cannot be detected. Take the following as a conceptual example:

Redundancy for Bad Data Detection: Conceptual Example

Picture a table with four legs. If one of those legs is too short (this is the bad measurement), it will not reach the ground. It is easy to identify the leg that is an outlier because its removal will be of no consequence: the table does not need that redundant leg to stay upright (meaning it is redundant).

Now picture a table with three legs. This table needs all three legs in order to stay upright. If one leg is too short, the table surface will tilt so that all three legs still touch the ground. It is no longer easy to identify the leg that is in error without additional information, such as the angle of the table surface. Furthermore, even if the erroneous leg could be identified, it could not be removed else the table would collapse. The leg is non-redundant, or critical.

Apply this concept to state estimation, and one can see that a measurement that is critical to solving the power network cannot be detected as erroneous. Bad data and network model correction is therefore only possible with the presence of measurement redundancy.

An extensive measurement infrastructure is a vital part of a good state estimator. Most practical implementations of DSE rely on load forecasts as pseudo-measurements to create the necessary observability. Accurate load forecasts based on machine learning and weather patterns (for renewable sources) can greatly improve the accuracy of a state estimator.

However, when bad data detection and network model correction are desired outputs from DSE, these pseudo-measurements do not contribute to measurement redundancy. Even the most accurate load forecasts are less likely to be correct than a measurement placed in the network.

13.2 DSE Best Practices

The purpose of identifying these limitations is to help readers understand what should be expected from a DSE implementation. While DSE is a crucial stepping stone towards many of the grid modernization goals outlined by state and national initiatives, there are numerous challenges that could both impede implementation and decrease effectiveness of the result. In order for DSE to truly benefit the future of distribution systems, utilities must target their investments towards upgrades that work directly towards DSE outcomes.

13.2.1 On Line Network Model: The Common Information Model (CIM)

Many distribution utilities upgrade their network model only a few times a year for planning purposes. However, maintaining a state estimator in-the-loop requires that the network model be the following:

- **Central:** The network model is core to many distribution operation applications. A central network model must aggregate updates and other information coming in, ready to deliver the most accurate version for any application or analysis as needed. It must also maintain a library of all measurement points and their locations.
- **Real-Time:** Distribution network topology is constantly changing, and this must be reflected in real-time updates to the network model. The model must be able to process topology updates (such as switch status changes) as well as reconfigurations, outages, and regular expansion updates.
- **Compatible:** Planning, outage, and on-line operations applications might run on different proprietary software platforms which keep different network model formats and variables. In addition, any interface with external entities such as a transmission system operator might require a specific data format.

In the context of these requirements, utilities can find the implementation of real-time DSE to be difficult. Modernizing the network model to be an automated up-to-date system compatible will all network applications and external connections is an implementation challenge in itself. An automated and standardized approach is vital for success, else countless hours of manpower will be required on a regular basis to babysit the network model.

The most recognized approach to address the issue of network model incompatibility is the publication of a set of standards referred to as the CIM: IEC 61970 and IEC 61968 [134]. CIM is a standardized method of representing network model information. What CIM offers is a standardized, flexible, and communicable method to store network model information, which facilitates integration with internal and external applications as well as upkeep of the model. Many planning applications and DMSs already support integration with CIM, and several utilities have either considered or have already adopted it as their approach to network modelling.

13.2.2 Leveraging AMI for Load Forecasting

DSE is not possible without multiple data points at every node in the system. Some utilities may have widespread AMI systems with adequate communications infrastructure to centralize all the measurement data in real-time. Due to the magnitude of that approach, however, it may be out of reach in the near term for most distribution utilities. In the absence of measurements at every bus in the system, DSE is only possible (and observable) with load forecasts at distribution transformers and/or customer connections.

The bulk of the information coming from these forecasts means that any improvement on their accuracy will have a dramatic improvement on the accuracy of the state estimator as a whole. While system-wide AMI adoption with real-time data acquisition might be a tall order, utilities can make the best use of their AMI systems by leveraging them to power their load forecasts. Tools such as machine learning can make use of 15-minute load and voltage data from AMI to generate and condition accurate predictions based on any number of factors. Incorporating weather forecasts will can not only train these forecast models to adjust DER deployments but can predict the HVAC usage of its customers.

Load and DER forecasting are entirely separate problems from state estimation, but the fruits of forecasting algorithms are vital to the success of DSE. While utilities should understand that load forecasts can only take DSE so far in terms of measurement redundancy and bad data detection, their importance should not be undervalued.

Once forecasts have been created, DSE can be used as a tool to revise their output. For instance, DSE will calculate system losses, which can be wrapped back into the load forecasting and allocation methods to further improve them. This has been done in distribution demonstration projects to benefit DSE implementation and accuracy. Reference Gonzalez, et al. [117] for an example of this type of demonstration.

AMI is the single most important tool when it comes to predicting customer and DER behavior. The state-of-the-art review provides a detailed breakdown of forecasting methods and how they can be incorporated with DSE, including a number of research sources for further reading.

13.2.3 Optimizing and Targeting Measurement Upgrades

With measurements being at the core of a state estimator, their placement is of utmost importance. The financial burden of widespread measurement placement means optimizing the types of measurements placed, their accuracy, and where on the network they will reside. This becomes a discussion of the value of an accurate estimate of system voltages and flows to the distribution utility.

As described in the previous section, DSE is only possible when there exist multiple data points at every node in the system. AMI is a powerful tool for obtaining this information, though with the enormous associated cost with placing a smart meter at every customer connection it might not be a consideration when the only goal is to enable state estimation. AMI installation is best viewed as an enabling technology for a number of advanced distribution analysis applications.

The DSE Toolkit available with this project provides an example system in which users can explore system observability and measurement placement. Once a state estimator has been modelled as in the toolkit, a utility will be able to run assessments on how each measurement considered for placement will beneficially impact the accuracy of the system state. For instance, installing PMUs would provide a great boost in accuracy for the state variables in the surrounding network nodes. With limited resources, a distribution might only budget for a few of these devices. Reference the state-of-the-art review for detailed discussion and further academic references regarding the optimal placement of limited numbers of PMUs for best performance.

14 Concluding Remarks

Distribution state estimation is a powerful tool—one that has been identified as an essential step on the road to modernized and dynamically managed distribution networks. Distribution utilities in the State and elsewhere are upgrading the visibility, communication, and control capabilities of their systems, and investigating DSE as an application to further these goals. For every system, a DSE implementation will take a different shape, but many utilities will have similar questions. At its most basic, here is a summary of what must be considered to implement DSE:

Table 35 Revisited

<table>
<tr><th colspan="2">What items are necessary to support DSE?</th></tr>
<tr><td>1</td><td>An up-to-date network model</td></tr>
<tr><td>2</td><td>At least two pieces of operating data about each system node
Examples of this could be (among others):
Real & reactive customer load
Voltage magnitude & angle
This can take the form of load forecasts—understanding the compromise in system accuracy and inability to detect bad data</td></tr>
<tr><td>3</td><td>A communication infrastructure to support real-time measurements and model updates</td></tr>
<tr><td>4</td><td>A state estimation engine</td></tr>
</table>

Many utilities might satisfy some or all of these above criteria, in which case DSE is an application within their reach. Especially in the State, utilities have begun to roll out their AMI programs, vastly improving the number of measurement points. AMI can go a long way towards item two in the list above, providing real and reactive loads at each monitored customer connection and often voltage information as well. However, systems with AMI still need to satisfy items one and three: network model that reaches the customer connection, and infrastructure to transmit AMI measurements to the control center in real time. Without these items, AMI cannot be used as a measurement and can only benefit load forecasts.

The above discussion regarding the usefulness of AMI is just one of many that must happen at the utility level for a DSE implementation to be successful. With compromised quality in any one of the four items, the resulting effectiveness will suffer. The reality is that prior to AMI rollout, most distribution systems are largely unmonitored outside the substation. However, with a concerted effort to evaluate and upgrade all four items to the necessary level for desired DSE effectiveness, utilities will be able to leverage DSE to greatly improve the depth of their distribution visibility. The resources provided by this project are provided to better facilitate these discussions and evaluations.

14.1 Future Work

This project draws heavily upon the academic research on DSE, so likewise there exists a wealth of information for interested parties to study further. The state-of-the-art review is a summary of current research on the subject and works as a jumping off point to find resources on a number of topics. However, this project only starts to fill the gap between academic research and widespread adoption. The following two items are topics that could be investigated further to extend this project:

14.1.1 Guided Graphical Observability Analysis

In selecting measurements, the user is given guidelines for how many measurements to select and is told which states the system was unable to calculate. However, this could be improved by presenting a graphic interface with the network model shown, telling the user exactly where additional measurements must be placed to achieve observability. In this way, users could better understand the impact that their measurement choices make on observability.

14.1.2 Using AMI to Generate Advanced Forecasts

There is ample academic research on generating load forecasts in a variety of methods, including machine learning. A useful extension to this project would be to implement some of these methods to imitate the use of AMI to generate pseudo-measurements for the DSE Toolkit. With this analysis, a user could investigate different forecasting methods for their impact on DSE accuracy and compare them to traditional methods not powered by AMI.

14.1.3 Using Line Flow Current as a State Variable

The state variables used in the DSE Toolkit are bus voltages and angles—a standard approach for general state estimation. However, in some distribution systems, current measurements are more common than voltage measurements. Additionally, line flow constraints can often be the critical pain points of a distribution network.

Changing the state variables from voltages to currents requires alterations to the state estimation process, but it can also reduce estimation error in the line currents and improve convergence speed when current magnitude measurements are prevalent.

14.1.4 Time-Series Simulation

The DSE analysis presented in the Toolkit considers a single snapshot in time. While this is useful for exploring most of the important state estimation concepts, it could be augmented with a time-series analysis that simulates an entire day, week, or year. This way, customer load profiles can be incorporated, and even used to generate pseudo-measurements. Additionally, the application would be able to study the challenges of synchronizing measurement updates and incorporated measurements which have different pulling frequencies.

14.1.5 Monetary DSE Analysis

The decisions regarding which distribution assets are worth upgrades are unique for each utility—but at the bottom line is always a return on investment. The DSE Toolkit presents a sandbox in which DSE concepts can be explored free from financial considerations. This could be extended to include an analysis of the cost to achieve a given DSE implementation, including cost per measurement point, and a rough analysis of cost versus system accuracy. This would give an example of what considerations must be prioritized on a monetary basis.

15 Contact

For questions and inquiries regarding this report, the DSE Toolkit, or for further discussion on the topic of distribution state estimation, contact:

Kevin Morrissey
kmorrissey@smartergridsolutions.com
Research & Development Engineer
Smarter Grid Solutions

Alternatively, send a general inquiry to info@smartergridsolutions.com.

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New York State
Energy Research and
Development Authority

17 Columbia Circle
Albany, NY 12203-6399

toll free: 866-NYSERDA
local: 518-862-1090
fax: 518-862-1091

info@nyserda.ny.gov
nyserda.ny.gov