Detection and Elimination of Cyber Security Threats in Distribution System State Estimation

M Tech Phase I
Report

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Abstract

Today's distribution systems are expected to include a variety of distributed energy sources, and their application is broadening every day. We must cope with the new characteristics that these new entities bring as we add more of them to the distribution system. In these circumstances, accurate state estimation of distribution systems with different distributed energy sources becomes more crucial. At the distribution system level, phasor measurement units, remote terminal units, and smart meters are used because more precise and synchronized measurements are required to execute the state estimation effectively. Due to their unique properties, the various techniques employed in transmission system state estimation are not relevant to distribution system state estimation (DSSE).

The modern power system is evolving toward a cyber-physical power system, which combines computers and a physical power system, in response to technological and computing advances. This makes the system susceptible to cyberattacks due to its cyber component. Extreme circumstances involving these cyberattacks may have severe consequences. As a result of certain blackouts and accidents that have happened throughout the world in recent years, it is now vital to assess the cyber security of power systems in order to defend them against potential attacks. The security of a communication network and computer systems that are part of a cyber-physical power system is referred to as "cyber security of power systems."

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Chapter 1

Introduction

This chapter initially discusses the history of power system state estimation and the Phasor Measurement Unit (PMU). Distribution system state estimation will also be introduced in this chapter. The motivation and goals of the work done and to be done during this study are then presented in the next section.

1.1 Background

1.1.1 Electric Power System and State Estimation

The electric power system has evolved over the past century to become one of the essential infrastructural systems. The generation, transmission, and distribution systems make up the majority of the contemporary power system. The generation system uses a variety of sources, including fossil fuels, wind energy, and solar energy to produce electricity in power plants. The power being produced is at the level of the generation voltage. The voltage level is then raised using transformers to reduce copper losses during long-distance power transmission. After that comes the distribution network, where power is sent to users via distribution lines or cables after being stepped down in voltage at the substations [1]. According to the operating conditions, a power system might be in one of three states: normal, emergency, or restorative. Utilizing specialized tools like load forecasting, state estimation, security assessment, and others, system operators continuously plan, monitor, analyze, and control the functioning of the power grid in order to keep it in a normal, secure state and meet consumer demands for dependable power. The very first phase of security analysis, which attempts to keep the system in its typical secure state, is continuous monitoring of the system conditions [2, 3]. Schweppe developed the state estimation problem and presented the idea of power system state estimate (SE) in 1970 [4].

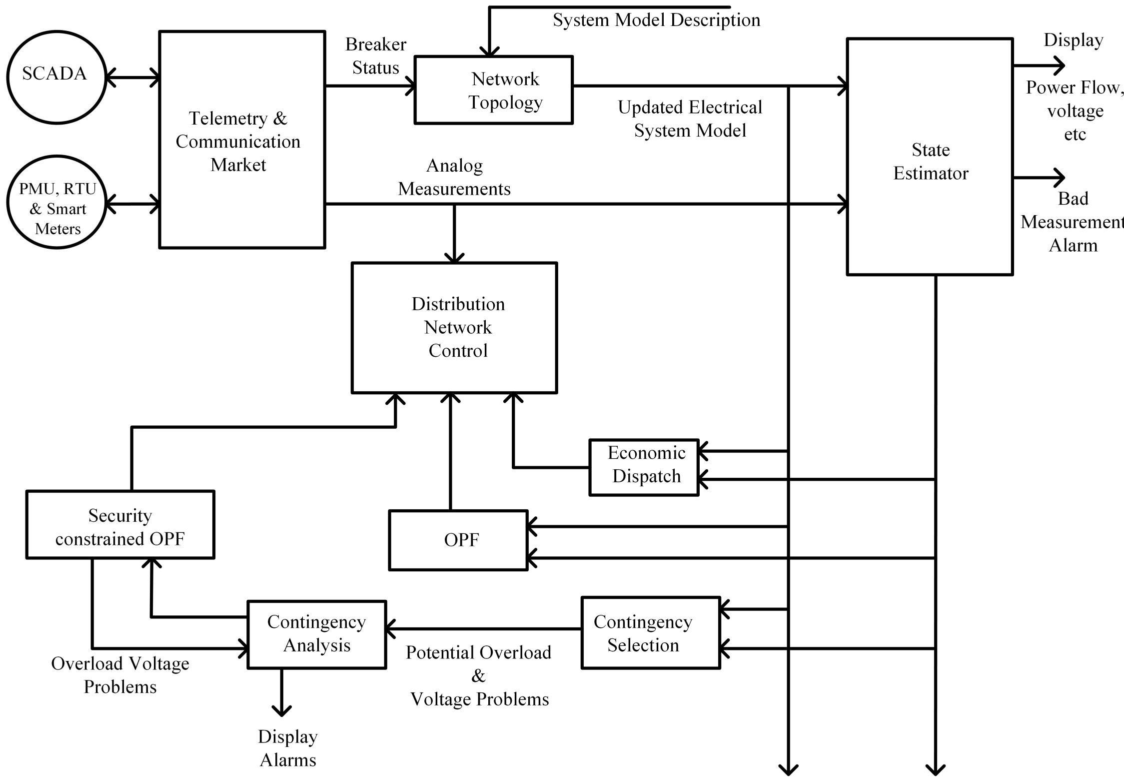

Figure 1.1: General block diagram for application of State Estimation .

State estimation, as shown in Figure 1.1, uses measurement data and network topology information to produce the best approximation of the current state of a power system [2]. The power flow in lines and the power injections at each node may be calculated using the system status along with the network structure and impedances. State estimate is therefore essential for the safe running of power systems, and system operators require the state estimation solution to understand how the system is operating. In the majority of historical instances, if the system operator had been given more precise and up-to-date information on the system's operating state, the magnitude of the blackout might have decreased [3]. The topology processor, observability analysis, state estimation solution, and bad data processing are often included in the state estimator. It transforms the unprocessed measurement data gathered from the sensors and creates a database of the system's present status for application functions [1, 3]. Voltage, current, real power and reactive powers are common measurements used in state estimation. Since these data are connected to the system states through non-linear interactions, the majority of state estimators in use today use a set of non-linear equations. The process of the general state estimation method is shown in Fig 1.2.

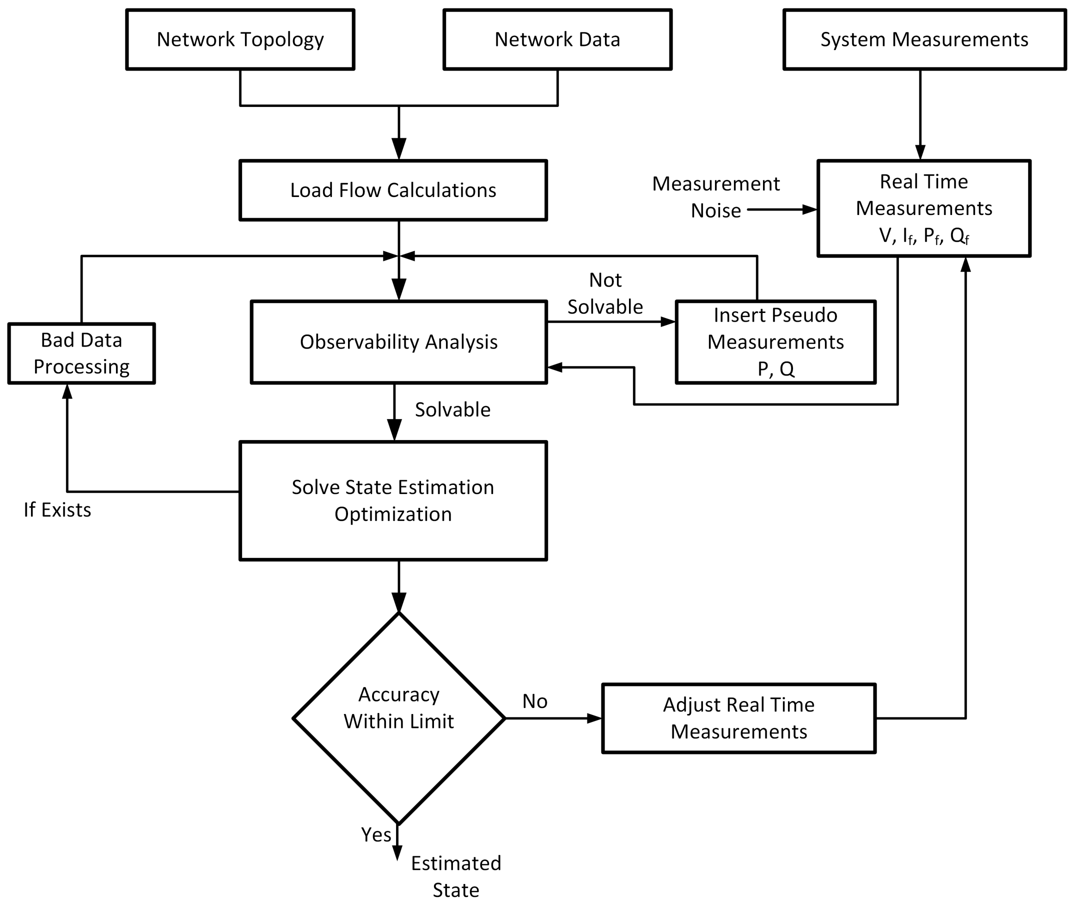

Figure 1.2: General process of state estimation.

1.1.2 Phasor Measurement Unit

The phasor measurement unit (PMU), which was created in the middle of the 1980s, is a cutting-edge measuring tool that can deliver time synchronized and precise voltage and current phasor measurements in a power system [5]. PMUs perform the conversion into phasors of the observed parameters at a rate of generally 30 or more values per second. Synchrophasors are phasors that have a precise time stamp added to them by PMUs through the integration of a GPS sensor. These phasors, which are produced by PMUs at various locations that may be positioned far away and across several electric utility companies, can be matched, time-aligned, and merged with the aid of the time stamp. Power system operators are provided with a real-time, high-resolution "image" of the grid's state thanks to the data that is generated [3, 5]. Phase angle measurement is a constant worry for power system operators since the phase angle between the voltage and current phasors is used to assess the health of power networks [6]. The sine of the angle difference between the voltage phasors at the two terminals of the line is theoretically proportional to the real power flow in a transmission line [7]. As a result, PMUs are being used in power systems all over the world and are becoming more and more common because of their capacity to deliver precise and synchronized phasors of voltages and currents [8]. In a similar way, RTU and smart meters can be used in the distribution system.

1.2 Distribution System State Estimation and μPMU

The use of state estimation in a distribution system has not gained significant interest, compared to state estimation of transmission networks, which has been thoroughly studied since the early 1970s. Distribution systems have traditionally been designed to work in a radial configuration, where power flow only occurs in one direction and is therefore relatively simple to forecast and regulate. Due to the development of renewable energy, rising environmental awareness, and deregulation of the energy market, there is a tendency for more distributed generation (DG) systems to be connected to the distribution system in recent years [9]. The distribution system must now be continuously monitored because of the rising penetration of renewable energy sources, which introduces new characteristics including bi-directional power flows and voltage problem concerns [10]. In comparison to transmission systems, distribution systems have fewer measurements of their properties, necessitating a state estimation with generally less redundancy. In addition to having low redundancy, the distribution system's three phases are not balanced, which further distinguishes the estimate for a distribution system from that of a transmission system. Another distinction between distribution systems and transmission systems is that, as was already established, most of them have radial topologies. Additionally, distribution systems have a relatively high number of nodes and a high resistance reactance ratio (r/x) in their lines, which presents extra difficulties for the traditional estimators used for transmission systems. The monitoring and state estimate of distribution networks can be done using phasor measurement units, which have been widely employed in transmission networks. However, because distribution system applications are more difficult, typical PMUs are not appropriate in distribution networks [10–12]. For instance, the voltage angle differences on a distribution circuit can vary by up to two orders of magnitude less than those in transmission networks, making it impossible to detect them properly with a normal PMU. This is due to the fact that distribution networks often transport a little quantity of power compared to transmission networks, which typically transfer significantly more power. Furthermore, given the lower power delivered and lower profit in distribution networks, the cost of conventional PMU is too high to justify using it for applications in those networks. Taking into account the aforementioned factors, the micro-phasor measuring unit (μPMU) was created to measure the angles between voltage and current phasors in distribution networks [8, 10]. In contrast to traditional PMUs utilized on transmission networks, the μPMUs give measurements with extreme precision and at a fair price.

Chapter 2

Literature Review

The history of power system state estimation is covered in this chapter, which is followed by a detailed introduction to the mathematical formulation of the forecasting-aided state estimation technique(FASE). Finally, methods for phasor measurement inclusion in state estimation are presented.

2.1 Power System State Estimation

The method of power system state estimation uses network topology data and faulty measurement data to produce the most accurate estimates of the power system's present condition. The sum of the voltage magnitudes and angles at each network bus represents the status of an electric power system. Schweppe conceived and launched power system state estimation in 1970 [4]. The supervisory control and data acquisition (SCADA) systems' capabilities can be expanded by utilizing measurement redundancy. Real and reactive power flows and injections with a certain voltage magnitude were employed as the measurement data for the state estimate. Synchronized phasor measurements are also utilized in state estimation as part of the development of PMU [6, 13]. For power systems to operate safely, state estimate is crucial. For operators to understand the system's operational conditions and to carry out efficient and optimal economic operation and planning, state estimation solutions are required [4, 14]. Solving state estimating equations is the foundation of a state estimator; this topic will be covered in more detail in the following section. In addition to the state estimation solution, the state estimator also does topology processing, observability analysis, and bad data processing. The topology processor verifies the status of the circuit breakers and switches and provides the configuration of the system in order to produce an accurate system model for state estimation. Without enough measurement data, the state estimator is unable to provide state estimates for the entire system [15]. So, prior to state estimation, observability analysis must be carried out. Using the measurement data that is readily available, this function can establish the observable area. Additionally, measurement inaccuracies are detected and identified through poor data processing and then corrected.

2.2 FASE

Suppose the vector z is the measurement vector, RTUs offer data for every measurement in traditional static state estimation. The subscripts v, pf, qf, $pinj$, and $qinj$, respectively, stand for voltage magnitudes, active and reactive power flows, and active and reactive power injections, while the m is the number of measurements, x is the state vector, and the number of state variables is n [16, 17].

$$\mathbf{z} = \begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \\ \vdots \\ \mathbf{z}_n \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2, \cdots, x_n) \\ h_2(x_1, x_2, \cdots, x_n) \\ \vdots \\ h_n(x_1, x_2, \cdots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} = \mathbf{h}(x) + \mathbf{e} \tag{2.1}$$

in this equation $\mathbf{h}^T = [h_1(x), h_2(x), \cdots, h_n(x)]$

$\mathbf{h}_i(x)$ is the nonlinear function relating measurement i to the state vector $\mathbf{x}$

$\mathbf{x}_T = [x_1, x_2, \cdots, x_n]$ is system state vector,

$\mathbf{e}_T = [e_1, e_2, \cdots, e_n]$ is measurement error vector.

Typically, the dynamical distribution system's state-space model looks like

$$\mathbf{x}_k = \mathbf{f}(x_{k-1}) + \mathbf{w}_k \tag{2.2}$$

$$\mathbf{z}_k = \mathbf{h}(x_k) + \mathbf{v}_k \tag{2.3}$$

where $\mathbf{x}_k$ stands for the state vector at the sampled time k. The state transition function is known as $\mathbf{f}(.)$ that connects the state vector $\mathbf{x}_k$ to the state vector $\mathbf{x}_{k-1}$ at a prior time instant. The measurement vector is indicated by $\mathbf{z}_k$. The measuring function is shown by $\mathbf{h}$. Process and measurement noises, denoted by $\mathbf{w}_k$ and $\mathbf{v}_k$, are typically thought of as Gaussian white noise, and their corresponding covariance matrices are given by $\mathbf{Q}_k$ and $\mathbf{R}_k$.

2.2.1 State Transition model

In [17], state transition models were discussed in order to reflect the dynamic changes in the distribution system. One of the most widely utilized listed method is Holt's two-parameter exponential smoothing method. It is a type of time series forecasting technique. When the state variables are comparatively independent, it can ensure a stronger forecasting result and can also be utilized as a load forecasting technique. This approach is suited for online usage and has the advantages of simple calculation and little storage space. Assume that $\mathbf{x}_k$ is the distribution network's state estimate value and $\hat{\mathbf{x}}_{k-1}$ is the state prediction value derived from the state equation. The transition function of the state in a distribution network can be depicted as follows using Holt's method:

$$\mathbf{f}(x_k) = \mathbf{a}_{k-1} + \mathbf{b}_{k-1} \tag{2.4}$$

$$\mathbf{a}_{k-1} = \alpha_k \mathbf{x}_{k-1} + (1 - \beta_k)\hat{\mathbf{x}}_{k-1} \tag{2.5}$$

$$\mathbf{b}_{k-1} = \beta_k(\mathbf{a}_{k-1} - \mathbf{a}_{k-2}) + (1 - \beta_k)\mathbf{b}_{k-2} \tag{2.6}$$

Here, $\mathbf{a}_{k-1}$ and $\mathbf{b}_{k-1}$ are the smoothed value and the estimate of the trend of the time series at step $k-1$, respectively, and $\hat{\mathbf{x}}_{k|k-1}$ is the predicted value of the state vector at time k. α_k and β_k are the parameters, and their values range from 0 to 1. The transition function can be derived as follows by taking into account process noise.

$$\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1} + \mathbf{w}_{k-1} \tag{2.7}$$

where,

$$\mathbf{F}_k = \alpha_k(1 + \beta_k)\mathbf{I} \tag{2.8}$$

$$\mathbf{G}_k = (1 + \beta_k)(1 - \alpha_k)\hat{\mathbf{x}}_{k|k-1} - \beta_k \mathbf{a}_{k-1} + (1 - \beta_k)\mathbf{b}_{k-1} \tag{2.9}$$

where, $\mathbf{F}_{k-1}$ is the state transition matrix $\mathbf{G}_{k-1}$ is the trend-setting vector.

2.2.2 Measurement Model

The measurement equation is given in eq. 2.1 can be linearized and modeled as:

$$\Delta \mathbf{z}_k = \mathbf{H}_k \Delta \mathbf{x}_k + \mathbf{r}_k \tag{2.10}$$

where, $\mathbf{H}$ is the non-linear measurement function vector, $\mathbf{r}_k$ is the white Gaussian noise vector with zero mean and covariance, and $\mathbf{H}_k = \partial \mathbf{h} / \partial \mathbf{x}$ is the measurement Jacobian matrix The linearized state vector, the measurement deviation vector, and the operating point are denoted by $\mathbf{R}_k$, $\mathbf{x}_k$, and $\mathbf{z}_k$ respectively. In addition to process and measurement errors, there will also be some errors in the estimations, thus those errors must also be corrected. The equation controls their behavior:

$$\mathbf{P}_k = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T + \mathbf{Q} \tag{2.11}$$

where, $\mathbf{P}_k$ is the estimated error covariance at time k Here, the measurements and the new state vector must be changed along with the old state vector. A gain known as "Kalman Gain" is utilized during that procedure, which will be explained in more detail below, in order to reasonably compensate for the accuracy of the preceding states and the measurements. The details of the Kalman Gain Matrix ($\mathbf{K}$) at time k are as follows:

$$\mathbf{K}_k = \frac{\mathbf{P}_k \mathbf{H}^T}{\mathbf{H}\mathbf{P}_k \mathbf{H}^T + \mathbf{R}} \tag{2.12}$$

And the new State Vector $\hat{\mathbf{x}}_{k+1}$ and the new Estimate Covariance Matrix $\mathbf{P}_k$ are calculated as:

$$\hat{\mathbf{x}}_k = \mathbf{x}_k + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k) \tag{2.13}$$

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H})\mathbf{P}_k \tag{2.14}$$

Here, from Kalman Gain in Eq.2.12, it can be observed that the Kalman Gain increases as the measurement covariance $\mathbf{R}$ gets closer to zero (indicating that the measurements are accurate), and from Eq. 2.12, the Gain weights more heavily on $\mathbf{z}_k$, the measurement vector, indicating that the new state vector is more reliant on the measurements than the predicted states.

The Kalman Gain is reduced and, from Eq. 2.12, the Gain weighs less heavily on $\mathbf{z}_k$, indicating that the new state vector is more inclined to trust the predicted states than the measurements when the estimated error covariance $\mathbf{P}$ approaches zero (which indicates that the predicted states are accurate and close to the true values).

2.3 State Estimation with Synchrophasor Measurements

Measurements like active power and reactive power injection have a nonlinear relationship with the system states, leading to a nonlinear state estimation equation that must be solved repeatedly and adds computational weight. The availability of novel measuring technologies, such as PMU, where the measurements are linearly related to the system states, is facilitated by the growth of synchronous phasor measurements. State estimation is therefore a logical application of PMU measurements [18]. Traditional SCADA cannot be replaced by PMU overnight because of the high cost of implementation of PMUs and the complexity of today's power systems. In order to merge SCADA and PMU measurements before the power systems are fully observed by PMUs, hybrid SE is therefore proposed [19, 20]. Because PMU measurements differ significantly from traditional SCADA measurements in terms of refresh rates and accuracy level, hybrid SE faces unique obstacles [21, 22]. PMU readings typically update 30 times per second, but SCADA systems only take snapshots every 2–6 seconds. Voltage and current phasors are measured by PMUs. To modify the nonlinear estimating process, these phasor observations can be interpreted as voltage magnitudes, phase angles, the real component, and the imaginary component of current phasors.

The primary source of measurement data for a considerable amount of time was Remote Terminal Units (RTU), which provided measurements of bus voltage magnitudes as well as active and reactive power flows and injections. One of the most popular techniques in SE, the Weighted Least Square (WLS) method, has relied on RTU data for many years. This method generates measurement functions from power flow equations, which results in a fundamentally nonlinear issue. Voltage magnitudes, active and reactive power flows, and active and reactive power injections can all be measured by RTUs [16].

Smart meters are mostly used for billing at the moment, but distribution system operators(DSO) are beginning to examine historical smart meter data to learn more about their infrastructure. With the necessary adjustments to the advanced metering infrastructure setup, smart meters may be used to increase grid observability [23]. Modern smart meters are capable of precisely measuring several electrical characteristics as well as energy usage and transmitting the data to the DSO's control center. Smart meters have the ability to collect and transmit measured data at time steps of a few minutes (usually 15 minutes), which enhances the temporal resolution of the data that is captured [24].

Chapter 3

Motivation and Problem Formulation

State estimation faces two fundamental obstacles. To enhance the performance of estimators, one method is to use PMU measurements. The other is dealing with issues brought on by state estimates and PMU measurement integration [1]. While the first challenge's answer has advanced recently, the second challenge's many issues remain unresolved. The low computational efficiency brought on by the integration presents the second challenge [2]. There is little doubt that adding PMU measurements can increase estimation accuracy, but doing so may also result in a significant increase in computational work [10]. This issue, which is yet not entirely resolved, is a crucial one to take into account in the practical application of state estimation using both RTU and PMU data [25]. This is one of the main driving forces behind this topic. The computational efficiency of the linear estimating method based on PMU data is astoundingly high. This quality has greater significance in a vast and complex power system. However, the requirement that all measurements be provided by PMUs limits the practical implementation of this method due to its inherent disadvantage [15]. FASE techniques can provide correct information on the system's dynamic states, which is necessary for the effective monitoring of the power system. With more PMUs being deployed, which offer synchronous measurements with high sampling resolutions, implementing FASE becomes more promising [16]. Various strategies for using PMU data for FASE in power systems have been developed. However, in the literature consideration of μPMU, RTU and smart meter combined with Kalman filter estimation are missing which will be the focus for further study. Also, the effect of various cyber security attacks will be tested on the same developed algorithm.

Chapter 4

Methodology

Implementation of the Kalman filter-based Forecast-aided state estimation(FASE) algorithm on the IEEE 33 bus system is covered in this chapter, which is followed by μPMU integration to Kalman filter estimation. Finally, RTU and smart meter measurements are also considered in the algorithm.

4.1 Implimentation of FASE Algorithm

4.1.1 System under study

One must take the radial distribution system into consideration in order to mimic a real-world distribution system scenario. A radial bus system network that can be used to implement the state estimation algorithm is the IEEE 33 bus system. IEEE 33 bus system is a radial network with 33 buses out of which 1^{st} bus is connected to the substation and can be considered as a generator bus and all other buses are load buses as shown in Figure 4.1. This system has a rated voltage of 12.66 kV, and a total demand of 3.715 MW and 2.3 MVAr

However, in order to compare it to actual values, one must know the precise values of all of its variables, including bus voltages, line currents, the load present at each bus, the active and reactive power flow through each line, and the power injection at each bus. Load flow analysis must be carried out on the same system in order to produce those true and accurate results. To do this, the Forward-Backward sweep method is used, and all true quantities for the variables specified above are obtained. The true values to compare with FASE results are those derived via load flow analysis.

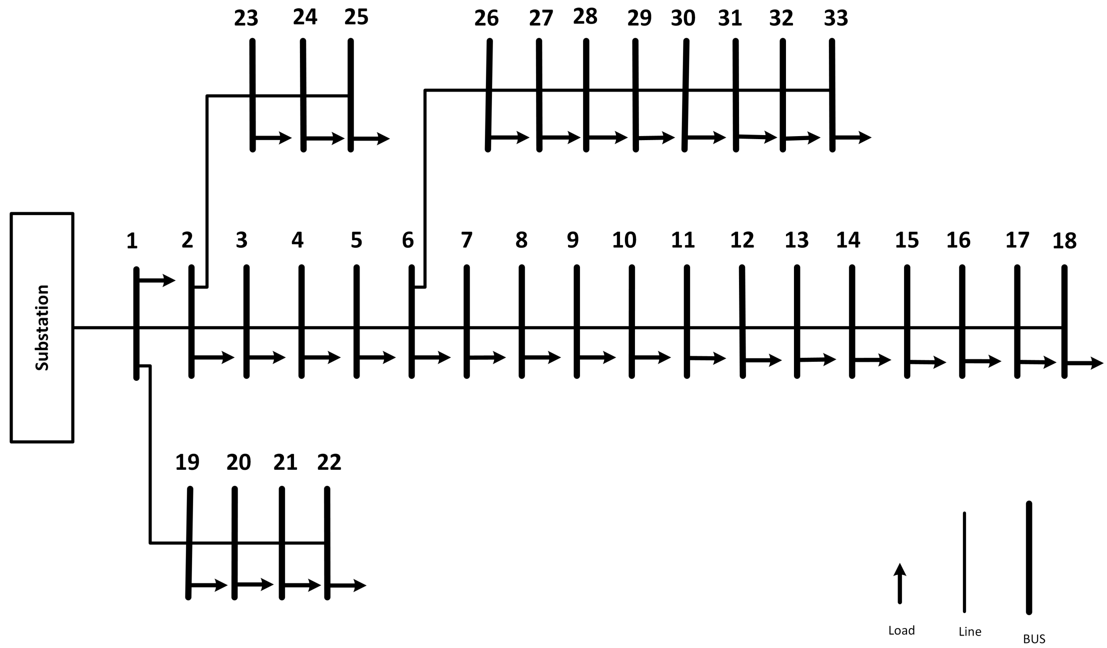

Figure 4.1: IEEE 33 bus system configuration

4.1.2 Kalman Filter Algorithm

The Kalman filter, when certain presumption criteria are met, is essentially a series of mathematical equations that implement a predictor-corrector type estimator that is optimal so that it minimizes the estimated error covariance. Despite the initial predicted values being quite far from the true values and the measurement errors, the Kalman Filter can estimate accurate values. Following a description of the mathematical formulas and notations used in the Kalman filter, the procedure is explained. The Kalman filter estimates a process by utilizing a type of feedback control: the filter estimates the state of the process at a particular moment and then collects feedback in the form of measurements (noisy). As a result, the equations for the Kalman filter can be divided into two groups: equations for time updates and equations for measurement updates. The present state and error covariance estimates are projected forward (in time) by the time update equations to produce the "prior estimates" for the "next time step." The feedback is handled by the measurement update equations, which incorporate a "new measurement" into "prior estimates" from the "previous time step" to produce an "enhanced new estimate". In this case, the measurement update equations can be thought of as corrector equations and the time update equations as predictor equations as shown in Figure 4.2. As a result, the final

Kalman Fir estimation algorithm for predicting the states is similar to a predictor-corrector approach.

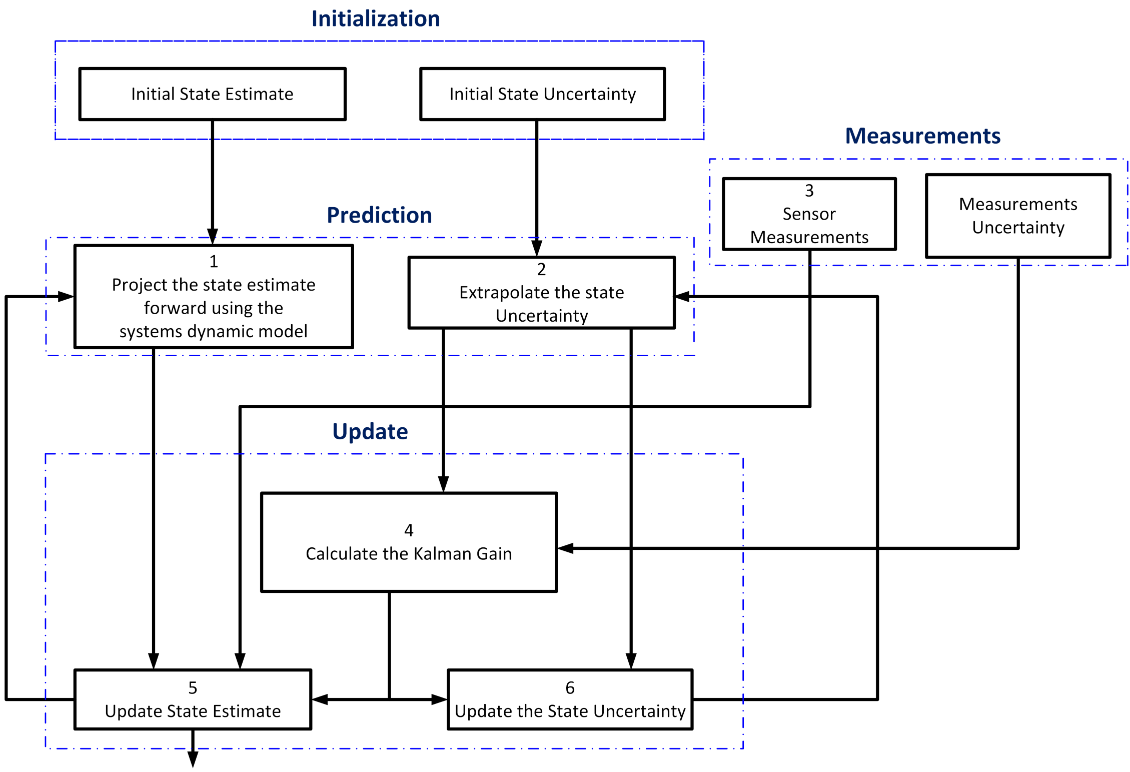

Figure 4.2: Kalman filter algorithm

As a result, the aforementioned equations can be divided into two categories: time update equations and measurement update equations. Two things should be noted in this case:

1. At the start of the algorithm, predicted initial estimates are to be given for the State vector ($\mathbf{x}$) as well as the Estimate Covariance ($\mathbf{P}$),

2. The variables having subscripts as $k-1$ are to be considered as the values in the previous time step.

Combining all equations for the algorithm referred from chapter 2 can be categorized as follows

Time Update(Prediction):

(1) Project the state ahead

$$\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1} + \mathbf{w}_{k-1} \tag{4.1}$$

(2) Project the error covariance ahead

$$\mathbf{P}_k = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T + \mathbf{Q} \tag{4.2}$$

Measurement Update(Update):

(1) Compute the Kalman gain

$$\mathbf{K}_k = \frac{\mathbf{P}_k\mathbf{H}^T}{\mathbf{H}\mathbf{P}_k\mathbf{H}^T + \mathbf{R}} \tag{4.3}$$

(2) Update estimate with measurement $\mathbf{z}_k$

$$\hat{\mathbf{x}}_k = \mathbf{x}_k + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k) \tag{4.4}$$

(3) Update the error covariance

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\mathbf{P}_k \tag{4.5}$$

The algorithm process for a cycle can be described as follows:

1. Initial predicted values of state vector $\mathbf{x}$ and estimate covariance $\mathbf{P}$ are given to Eq. 4.1 and Eq. 4.2 so that $\mathbf{x}_k$ and $\mathbf{P}_k$ are calculated.
2. Kalman Gain is calculated from Eq. 4.3
3. New State vector $\hat{\mathbf{x}}_k$ and new estimate covariance $\hat{\mathbf{P}}_k$ are calculated from Eq. 4.4 and Eq. 4.5 respectively.
4. The new state vector and new estimate covariance are given to Eq. 4.1, and Eq. 4.2 and the cycle repeats till the new state vector gets approached the true value and the estimated error covariance gets minimized.

Quantities collected via load flow analysis are subjected to random error and then fed into the FASE algorithm to produce findings, just as real-time measurements are subjected to measurement noise. To obtain a clearer picture of the results, all computations are performed using the per-unit method. The results of the same are shown in the next chapter.

4.2 FASE using μPMU measurements

The measured values provided by the μPMU are voltage phasors and current phasors; in order to produce those measurements, random errors are added to the voltage and current values to produce 300 consecutive measurements.

$$\mathbf{z}_{PMU} = \begin{bmatrix}\mathbf{z}_v & \mathbf{z}_a & \mathbf{z}_{iRe} & \mathbf{z}_{iIm}\end{bmatrix} \tag{4.6}$$

Depending upon the measurements considered noise matrix dimensions and values will change. Bus 1 is typically regarded as the reference bus in systems with N buses, hence its phase angle is fixed to 0 degrees. The state vector x includes the following expression for its $(2N-1)$ elements, which include N bus voltage magnitudes and $(N-1)$ phase angles:

$$\mathbf{x}^T = [\delta_2 \quad \delta_3 \quad \dots \quad \delta_N \quad V_1 \quad V_2 \quad \dots \quad V_N] \tag{4.7}$$

For the time being, to have complete observability μPMU is considered to be present on each bus. In $\mathbf{H}$ calculation high-frequency noise may give very high values so measurements are smoothed using the Holts Exponential smoothing method, which can also predict the future value of each measurement in case of sensor malfunctioning. The measurement Jacobian H will have the following structure.

$$\mathbf{H} = \begin{bmatrix} \frac{\partial V_i}{\partial \delta} & \frac{\partial V_i}{\partial V} \\ \frac{\partial \delta_i}{\partial \delta} & \frac{\partial \delta_i}{\partial V} \\ \frac{\partial Ire_{ij}}{\partial \delta} & \frac{\partial Ire_{ij}}{\partial V} \\ \frac{\partial Iim_{ij}}{\partial \delta} & \frac{\partial Vim_{il}}{\partial V} \end{bmatrix} \tag{4.8}$$

By giving these values the FASE algorithm is performed and the results are discussed in the next chapter.

4.3 FASE using RTU measurements

The measured values provided by the RTU are voltage magnitude, power flow and power injection; in order to produce those measurements, random errors are added to the voltage magnitude, power flow, and power injection values to produce 300 consecutive measurements.

$$\mathbf{z}_{RTU} = \begin{bmatrix} \mathbf{z}_v & \mathbf{z}_{pf} & \mathbf{z}_{qf} & \mathbf{z}_{Pinj} & \mathbf{z}_{Qinj} \end{bmatrix} \tag{4.9}$$

Depending upon the measurements considered noise matrix dimensions and values will change. Bus 1 is typically regarded as the reference bus in systems with N buses, hence its phase angle is fixed to 0 degrees. Because of this, the state vector matrix remains the same as μPMU. For the time being, to have complete observability RTU is considered present on each bus. Also, measurements are smoothened to avoid high-frequency derivatives while calculating the $\mathbf{H}$ matrix. The measurement Jacobian $\mathbf{H}$ will have the following structure.

$$\mathbf{H} = \begin{bmatrix} \frac{\partial V_i}{\partial \delta} & \frac{\partial V_i}{\partial V} \\ \frac{\partial P_{ij}}{\partial \delta} & \frac{\partial P_{ij}}{\partial V} \\ \frac{\partial Q_{ij}}{\partial \delta} & \frac{\partial Q_{ij}}{\partial V} \\ \frac{\partial P_{inj}}{\partial \delta} & \frac{\partial P_{inj}}{\partial V} \\ \frac{\partial Q_{inj}}{\partial \delta} & \frac{\partial Q_{inl}}{\partial V} \end{bmatrix} \tag{4.10}$$

But these power injection measurements aren't taken into account because they obviously don't affect estimation accuracy but would also add a lot of complexity. By giving these values the FASE algorithm is performed and results are discussed in the Results and Discussion section.

4.4 FASE using Smart Meter Measurements

The measured values provided by the smart meter are active and reactive power; in order to produce those measurements, random errors are added to the active and reactive power values to produce 300 measurements. some smart meters even provide voltage measurements as well, but here we are not considering the case, here

$$\mathbf{z}_{sm} = \begin{bmatrix} \mathbf{z}_{Pf} & \mathbf{z}_{Qf} \end{bmatrix} \tag{4.11}$$

Depending upon the measurements considered noise matrix dimensions and values will change. Bus 1 is typically regarded as the reference bus in systems with N buses, hence its phase angle is fixed to 0 degrees. Because of this, the state vector matrix remains the same as μPMU.

For the time being, to have complete observability smart meter is considered present on each bus. Also, measurements are smoothened to avoid high-frequency derivatives while calculating the $\mathbf{H}$ matrix. The measurement Jacobian $\mathbf{H}$ will have the following structure.

$$\mathbf{H} = \begin{bmatrix} \frac{\partial V_i}{\partial \delta} & \frac{\partial V_i}{\partial V} \\ \frac{\partial P_{ij}}{\partial \delta} & \frac{\partial P_{ij}}{\partial V} \\ \frac{\partial Q_{ij}}{\partial \delta} & \frac{\partial Q_{ij}}{\partial V} \end{bmatrix} \tag{4.12}$$

Here to make the algorithm fast and more accurate pseudo measurements are used for voltage values. The predicted values given by the Kalman filter algorithm are used directly as measured voltage quantities. The FASE algorithm is executed using these variables, and the results are presented in the Results and Discussion section.

Chapter 5

Results and Discussion

Forecast-aided state estimation is used for a variety of measurements on the IEEE 33 bus system, as mentioned in the previous chapter, and the findings are discussed in this chapter.

5.1 Forecast-aided State Estimation

The State Estimation was done by taking voltage and angle measurements with random errors introduced in true values. The comparison between estimated and true values of voltages is shown in fig 5.1, the same comparison is done for voltage angles in fig 5.2.

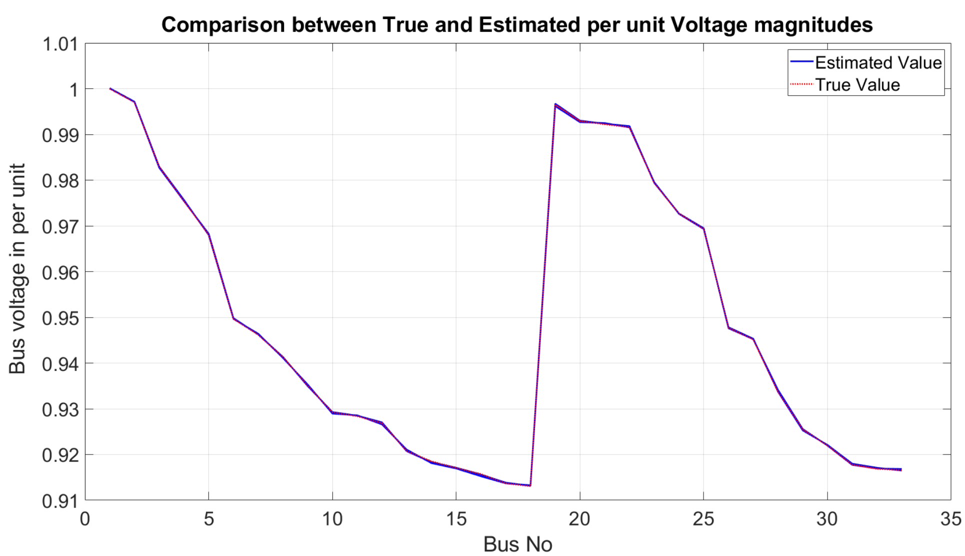

Figure 5.1: FASE output for voltage magnitude

Here estimated value is tracking the true value except for some small errors, so it can be concluded that the FASE algorithm can be simulated further with various synchronous measurements.

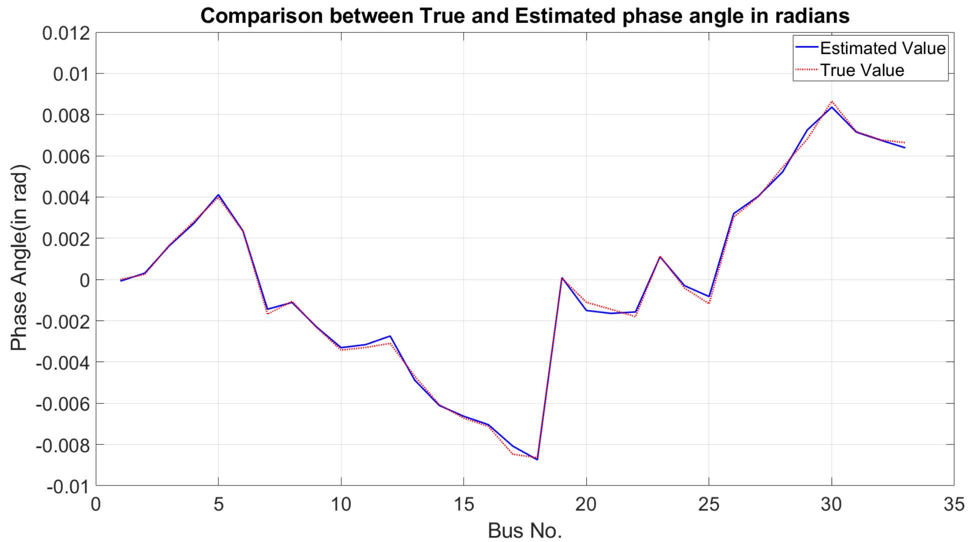

Figure 5.2: FASE output for voltage angles

5.2 FASE with μPMU measurements

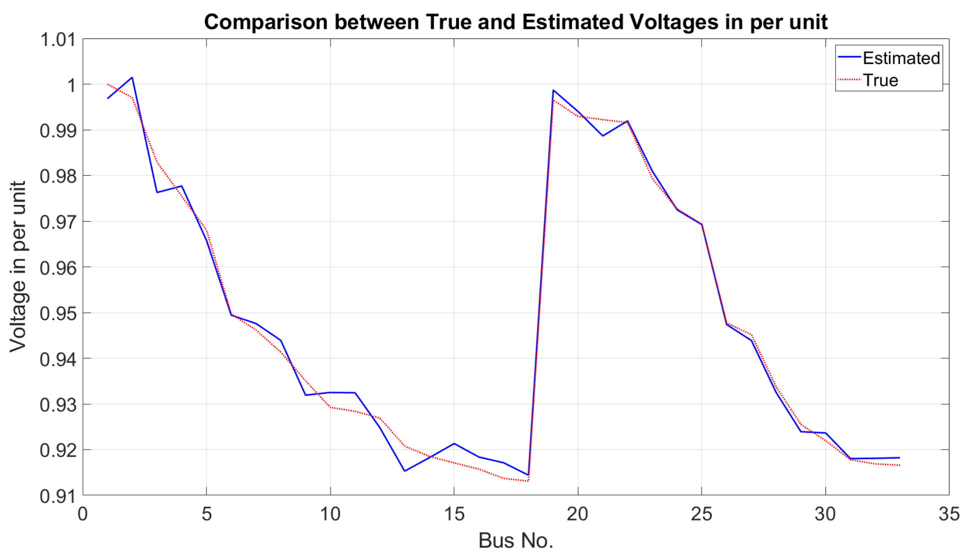

Figure 5.3: FASE output for voltage magnitude with μPMU measurements

The State Estimation was done by taking voltage and angle measurements with random errors introduced in true values. The comparison between estimated and true values of voltages is shown in fig 5.3, the same comparison is done for voltage angles in fig 5.4. Here estimate is converging and aligns with the true state which ensures that the algorithm can be used for this type of system.

Figure 5.4: FASE output for voltage angles with μPMU measurements

5.3 FASE with RTU Measurements

The State Estimation was done by taking voltage and angle measurements with random errors introduced in true values. The comparison between estimated and true values of voltages is shown in fig 5.5, the same comparison is done for voltage angles in fig 5.6.

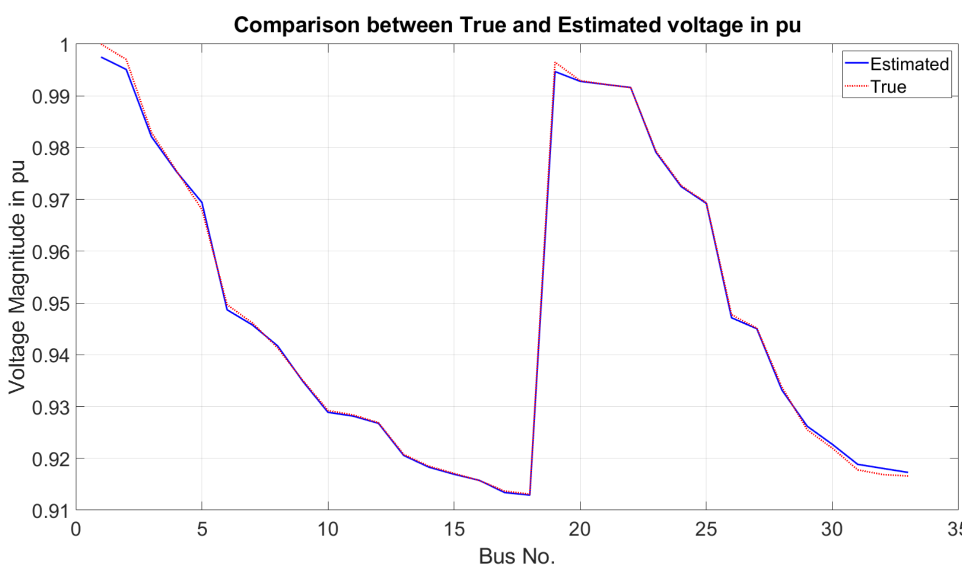

Figure 5.5: FASE output for voltage magnitude with RTU measurements

For RTU measurements with FASE estimated values are aligning with the true ones, which can be read as the algorithm is developed enough to apply to such a system.

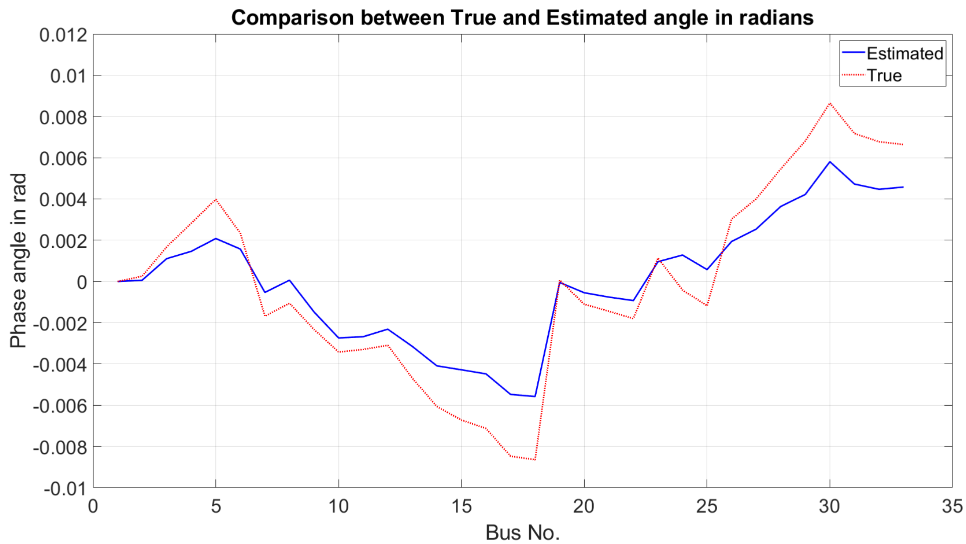

Figure 5.6: FASE output for voltage angles with RTU measurements

5.4 FASE with smart meter measurements

The State Estimation was done by taking voltage and angle measurements with random errors introduced in true values. The comparison between estimated and true values of voltages is shown in fig 5.7, the same comparison is done for voltage angles in fig 5.8.

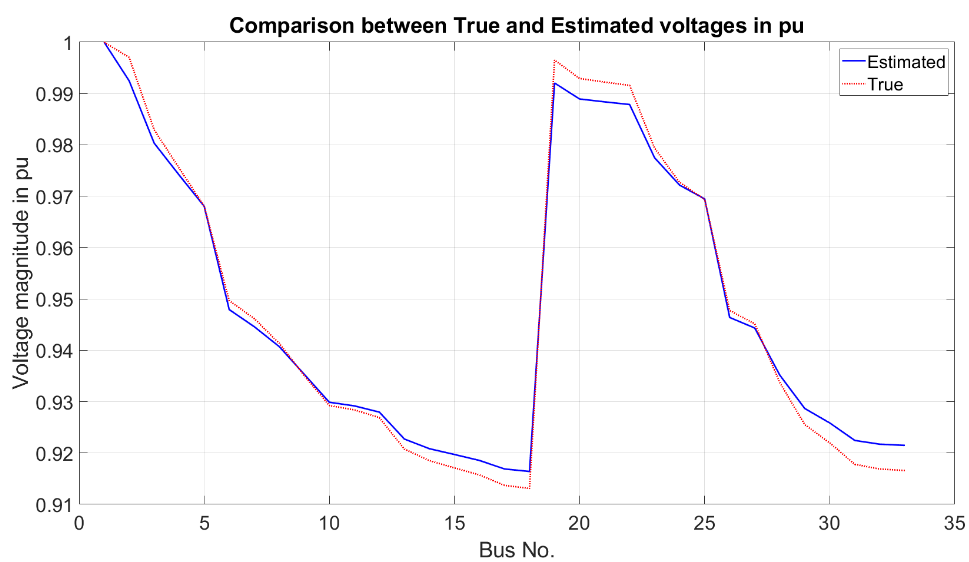

Figure 5.7: FASE output for voltage magnitude with smart-meter measurements

Here, just power measurements are taken into account, and the results are achieved by tak-

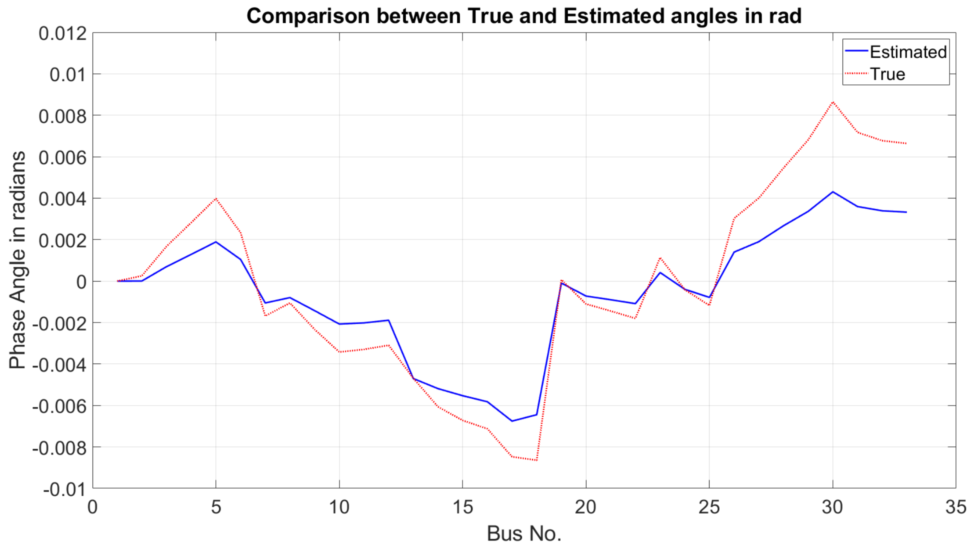

Figure 5.8: FASE output for voltage angles with smart-meter measurements

ing into consideration pseudo-measurements, demonstrating the importance of correctly forecasted measurements in FASE.

Chapter 6

Future Work

Future work includes the following:

- FASE is run individually for μPMU, RTU, and smart meter data. However, a practical system might incorporate μPMU, RTU, and smart meters together instead of having only one type of device throughout the entire system. All three measures must be taken into account on the same FASE in order to mimic this real-time scenario.
- Full observability does not imply a measurement device on every bus, hence the estimating technique needs to be enhanced to address this real-time condition.
- The viability of the approach should be verified against cyberattacks following the completion of FASE, which takes into account the majority of real-world situations

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