Enhanced Power System State Estimation Techniques for the Incorporation of Variable Energy

By

Reshma Francy

A Thesis Presented to the Masdar Institute of Science and Technology in Partial Fulfillment of the Requirements for the Degree of Master of Science in Engineering Systems and Management

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Abstract

For many decades, state estimation has been a critical technology in the energy management systems utilized by transmission system operators. Over time, it has become a mature technology that provides an accurate representation of system state under fairly stable and well understood system operation. The integration of variable energy resources such as wind and solar generation, however, introduce new dynamics and uncertainties into the system. Along with increase in variability which needs real time monitoring, state estimation will be extended to the distribution networks which increase the size of the problem. Conventional solutions to this problem result in large problem sets being solved at a faster rate thereby becoming computationally intensive. This thesis builds upon the Weighted least Square approach to SE and enhances the approach to SE by combining the concepts of event triggering, tracking update mechanism and incorporation of weather information. The result of the thesis is a SE which can overcome the challenges of novelty or variability, complexity and weather events which threaten the reliability of the power grids.
This research was supported by the Government of Abu Dhabi to help fulfill the vision of the late President Sheikh Zayed Bin Sultan Al Nahyan for sustainable development and empowerment of the UAE and humankind.
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Reshma Francy, Masdar City, May 15, 2013.
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CHAPTER 1

Introduction

Every large complex system requires a monitoring system to provide the information necessary to ensure reliable operation. In power systems, the bus voltage and phase angles are identified as the state of the power system. Real time accurate estimates of the states enable the calculation of power flow between the branches, the power injections at the buses and other important parameters. The method of estimating the state is called state estimation (SE) and this forms the core of every Energy Management System (EMS) today. The advantage of the state estimator is that it provides a means to monitor all the parameters of the power system, with fewer real time measurements from the field. The state estimator, therefore, becomes the key component of the monitoring system used in power grids.

In this thesis, the existing techniques and practices in the field of SE are reviewed and built upon to arrive at new approaches to achieve real time system state updates. The remainder of this chapter provides the research motivation in Section 1.1, followed by the research objectives and questions in Section 1.2. Section 1.3 provides a brief description of the research approach adopted and Section 1.4 provides the scope of the research. Section 1.5 points out the novelty of the research contribution and lastly in Section 1.6 outlines the remainder of the thesis.

1.1 Research Motivation

In recent years, the power generation portfolio has expanded to include Variable Energy Resources (VERs) such as wind and solar generation to meet increasing energy demand and environmental objectives[19].
These sources inject uncertain amounts of power at time scales faster and generally dissimilar to that previously found in typical load profiles [19]. As a result, in order to keep the balance of load and generation, the state of all power system buses becomes highly variable. Under these conditions conventional measurement and state estimation (SE) techniques which perform the update of the states only at regular intervals [19] may introduce errors which may impede the acquisition of an accurate picture of the system state; thus further impairing downstream situational awareness and decision making [19].

Traditionally, state estimation as a monitoring technique has only been implemented in the bulk electric or transmission system. VER penetration is likely to challenge this status quo. As a network, the transmission system is generally meshed in structure [28] and represents comparatively few nodes per geographic area. The distribution system on the other hand is extremely radial in structure and adds many nodes per geographic area. For example, Figure 1.1 shows a network diagram of the Western
Interconnection Electric grid of the U.S.A. Each red dot on the grid represents a node in the network. The size of the network increases dramatically with the inclusion of distribution systems at the periphery of the system. Unlike large scale thermal generation, VERs are often implemented as distributed generation (DG) near this periphery; thus motivating the need for a monitoring system that extends to include the distribution system.

Such an increase in the size of the network under observation increases the computational load on existing algorithms for SE. Meanwhile, the integration of VER to such complex networks demands real-time decision making which requires real-time monitoring. The conventional approach of decreasing the time interval between consecutive updates may not effectively address the real-time monitoring requirement. More computationally efficient solutions are necessary to avoid severe computational facilities.

The higher penetration of VER increases the vulnerability of the power systems to variability in the weather and events such as ramp of wind speed, cumulus clouds etc. The higher impact of the weather on the power grid requires improvements in the EMS as well. The work in this thesis aims to enhance the features of the EMS to incorporate features to improve operator’s awareness to such events.

1.2 Research Objectives and Questions

From the motivation presented in Section 1.1, the following research objective is outlined for the thesis:

Research Objective: To develop enhanced power system state estimation techniques that mitigate the challenges posed by the integration of VER into the power grid.

These challenges as previously described in the motivation include: novelty, complexity and abrupt weather phenomena.

- **Novelty**: The variability of the VER introduces considerable novelty in the system measurements.

- **Computational Complexity**: Expansion of the power system network which increases the problem size.

- **Weather Phenomena**: Higher penetration of VER in power grids leaves it vulnerable to weather phenomena.

Based on the challenges which are identified, research questions were created to address them:

**Research Question 1.** How can a Classical State Estimation (CSE) algorithm be enhanced to account for the novelty introduced by VER?
Research Question 2. How can a CSE be enhanced to reduce computational load when addressing large complex networks?

Research Question 3. How can CSE be enhanced with new weather based information to improve the operators awareness and reaction to weather events?

1.3 Research Approach

State Estimation is an iterative algorithm which uses principles of optimization to estimate the states from a measurement set which becomes the input to the SE. In this thesis, the CSE[64], which reflects the industrial practice is taken as a starting point. Further details on its formulation are provided in Chapter 2. It is then enhanced to address each of the research questions posed in Section 1.2. The different approaches corresponding to the research questions are as follows:

- **Event Triggered State Estimation (ETSE):** This approach introduces a triggering mechanism when there exists sufficient novelty in the power system measurements.

- **Event Triggered Tracking State Estimation (ETTSE):** This approach introduces a computationally efficient updating mechanism between successive state estimation triggers.

- **Weather Aided State Estimation (WASE):** This approach utilizes available weather forecasts to present operators with advance information on abrupt weather events.

Throughout the thesis, a Fast State Estimator (FSE) is defined as an ideal case, where the updates are performed for every instant that the measurements are received. The remaining approaches are compared to the FSE to measure their performance and advantages.

1.4 Research Scope

The focus of this research is to enhance the SE approaches by taking the inputs to be the same as found in literature, with the exception of the WASE. The scope of the work in this thesis is limited to the SE which is placed within the EMS as shown in the Figure 1.2.
The following assumptions are made which dictates the boundary of the research:

- **Observability**: This defines the case when the available measurement sets are sufficient to determine the states of the entire network. Several methods are being developed to ensure state of the art algorithms that can identify the complete measurement set and ensure the success of the state estimation which is carried out. In this thesis the measurement set adopted is tested to ensure observability, as described in Chapter 2 and no additional work is done for the same.

- **Bad Data Analysis**: This step is performed to determine the accuracy of the estimates. In reality, the SCADA (Supervisory Control And Data Acquisition) measurements brought to the SE can be erroneous or time skewed. In any application of SE it is essential to check the estimates before being sent for decision making. In this work the SCADA measurements are provided with a Gaussian distribution error and therefore does not require Bad Data Analysis.
• **Weather forecast:** The weather information used in WASE is added to the system as an input. There was no work performed on the forecast techniques, the thesis assumes that weather forecast variables such as temperature, wind speed, irradiance etc. is a time varying spatial map.

### 1.5 Novelty and Contribution

This thesis represents a novel contribution in regards to all three research questions.

- **Trigger Criteria:** The Event Triggered State Estimation derives inspiration from the work in [36] and introduces the trigger criteria which is based on the Western Electric Rules [74]. This specific trigger criteria is new to literature [24]

- **Combination of Trigger Criteria and Tracking:** The work of Fred Schweppe in [63] is expanded to the trigger criteria introduced in this thesis. The combination of the two ensures faithful tracking of the states without expensive computation [25]

- **Implementation of Weather Aided ETTSE:** The incorporation of a weather information into state estimation also represents a novel contribution. It can run online and in parallel to the ETTSE to enhance the situational awareness of the operators. The emphasis is on the benefits to the control centers if there is sufficient sharing of information between the meteorological department and the power control centers.

### 1.6 Thesis Organization

The thesis is explained over the remaining 6 chapters:

- Chapter 2 gives the necessary background information about the field of SE. The literature gap is identified to support the work done in the remaining chapters.

- Chapter 3 presents the implementation of an Event Triggered State Estimation (ETSE) for power networks incorporating VER. The proposed framework represents an improvement over Classical State Estimation (CSE) as it captures the variability associated with the VER while maintaining a high fidelity of the power network states. The efficacy of the ETSE is demonstrated as compared to existing CSE on a standard IEEE 14 bus system.

- Chapter 4 builds upon the work of event-triggering in Chapter 3. Specifically, the concept of tracking saves significant computational effort at minimal expense of error by allowing for the
update of system state between two consecutive triggered instances. The new event-triggered tracking state estimator (ETTSE) is demonstrated on the standard IEEE 14-bus system and the results are observed for an arbitrarily chosen bus. Finally, the update provided by the ETTSE, at each step is observed to highlight the benefit of the new scheme.

• Chapter 5 introduces the concept of bringing together the area of weather forecast and communication of weather events to the SE algorithms. The incorporation of The Weather Aided State Estimator (WASE) is run in parallel to the ETTSE to provide warnings or alerts to the operators to enhance their reaction to weather events. The WASE is used to augment the performance of the ETTSE by determining the instances to trigger based on the forecasted data.

• Chapter 6 provides the conclusions drawn from the work presented in the thesis along with the area of future work.
This chapter provides the literature upon which the work presented in this thesis is developed in four parts. First, the complimentary measurement system which provides the input to the SE is described in Section 2.1.1. Next, Section 2.2 provides the classification of SE approaches found in the literature. The area of SE has been widely researched since the introduction of the idea to power systems by Fred Schweppe. In order to put in context the contribution of this thesis, it is important to describe the several versions of SE that have emerged from years of research in this field. Thirdly, Section 2.3 illustrates the VER model which is adopted in later in the case study simulation. Finally, the tools used for building the three flavours of SE presented in this thesis are presented in Section 2.4. The concept of Event Triggered State estimation from existing literature is provided in Section 2.4.2 along with the brief overview of the WER and the application of the same is presented in 2.4.3. The concept of tracking is introduced in Section 2.4.4.

### 2.1 Evolving Measurement & Communication Technologies in Power Grids

For decades the field of monitoring and control for power grids has been dominated by SCADA systems[39]. The deregulation of the power grids along with the integration of VER has triggered improvements in the SCADA design. The changing needs of the power grid monitoring systems have given rise to new technology such as synchrophasor devices [17].
2.1.1 Supervisory Control & Data Acquisition

Power grids are large complex infrastructure systems and have buses which are geographically distributed which require measurements to be centralized from remote points to the central control center. The measurements collected are used as inputs to the SE algorithm. The system responsible for this task is called SCADA: Supervisory Control And Data Acquisition[1]. The main components of the SCADA system are as follows:

- Remote Terminal Units: Collect the data from the remote locations.
- Communication Network: Allows the half duplex communication between the various devices in the system at the different levels.
- Master Terminal Unit: Processes the information from the remote location and produce information to display.
- Operator Console: Delivers the information to the operator.

RTUs and MTUs are data processing units which can communicate with one another through the communication network of the SCADA. The processed information is provided to the operator through the operator console. In the context of the application of SCADA to SE, the RTU collects the data from the sensors on the field and relays the data to the MTU through the communication network. The MTU provides the necessary data to the SE algorithm. The output which is the state vector is provided to the display units at the operator console. The block diagram depicting the application is provided in Figure 2.1.

Figure 2.1: Outline of the SCADA application in Power Grid monitoring

Despite the heavy reliance on SCADA as a mature and extensively adopted technology, they do suffer from some technical limitations especially in legacy implementations[38]. The data relayed through SCADA suffer from unsynchronized data, data loss and measurement error. Also, there is a need to have faster control and protection systems which cannot be supported by the current SCADA design [72].
2.1.2 Enhanced Measurement Devices

The recent development in the area of power system measurement is the Phasor Measurement Unit (PMU) which is based on synchrophasor technology[17]. Synchrophasor technology makes use of time synchronizing techniques, coupled with the computer-based measurement technique, to measure the magnitude and phase angle differences in real time [58] [71]. The PMU provides time stamped data sampled at the rate of 60 samples per second which provides real time monitoring of the parameter being measured. The PMU has a positive effect on the accuracy of SE algorithms, several SE algorithms which take into account the data provided by the PMU [59] have been developed. The other applications of PMU which include fault detection [16], line outage detection [70], overall stability monitoring [48].

The PMU has several advantages while at the same time faces challenges which prevent the large scale implementation in the power grid. Though the PMU provides synchronized data, the amount of data which is produced due to its higher sampling time results in communication overheads and communication networks have to be updated to handle the extra flow of information [32]. The other factors such as calibration of the equipment and developing testing methods are still in the nascent phase and also inhibit the implementation of PMU in the grid [69].

2.1.3 Enhanced Communication Technologies

The concept of SMART grids is placing new demands on the information and communication technologies applied in power systems The dominance of SCADA is being replaced by a heterogeneous landscape of communication technologies which enable faster communication and reduce the latency[77]. The communication network and protocols are being updated to include communication over power lines [21], fiber optics [68], wireless communication [8] and cognitive radio among others [30].

Also, the needs of two way communication and automation of the controls have resulted in the replacement of the SCADA architecture with Advanced Metering Infrastructure (AMI)[3]. This addresses the key concerns of implementing demand side management and faster automated control actions which is limited in SCADA [65].

The improvements in the measurement technologies supported by the improvements in communication enable collection of large amounts of data which calls for enhanced data processing.
2.1.4 Enhanced Data Processing

The new landscape of measurement and communication technologies have resulted in enhancements in the data processing involved to produce useful information. The main function of the ICT enabled in the EMS of the power system is to ensure the reliable operation of the grid. Therefore the conversion of the large volumes of data into useful information to aid the operators actions is an essential part of the EMS.

The need for enhanced data processing due to the enhancements in ICT has led to the work in the field of Wide Area and Monitoring Systems (WAMS) [61]. The WAMS complements the SCADA to enable faster processing of the data[12] [76]. Also, the Real Time Dynamics Monitoring System is another platform created to enhance the visibility of the power system with the help of the new metering devices [2].

2.2 Classification

The decades of research in the area of SE have resulted in the creation of a variety of SE algorithms and approaches. Literature reviews on the types of SE algorithms are presented in [66] [52] [73] and [23]. SE also has different approaches based on application of the algorithms such as Conventional SE [52], Distributed SE or Multi Area State Estimation(MASE)[29]. SE algorithms are broadly classified into Static State Estimator (SSE) and Dynamic State Estimator (DSE). A brief overview of the two are provided below:

2.2.1 Static State Estimators

Static state estimation assumes the power system to be quasi-static, which implies the system state stays constant between the two consecutive updates of the state vector. Therefore, to improve real time monitoring of the grid the updates need to be performed within shorter intervals. The most widely used form of SSE in industry is the weighted least square (WLS) method [73]. It is formulated as an optimization problem which attempts to reduce the least square error between the measurement set and the estimate calculated using the corresponding power flow equations. The WLS uses the Newton-Raphson algorithm to arrive at the state estimates and is elaborated further in Section 2.4.1.

The literature does provide variations of the WLS, each trying to improve specific aspects of the WLS. The Fast Decoupled State Estimator [31][26] is one such variation in which the voltage and phase angles are processed separately. The voltage values are concerned with the reactive measurements such
as the reactive power injection and reactive power flow. On the other hand, phase angles are related to 
the active power injection and active power flow. The algorithm enables parallel processing which can 
improve computation time. The Regularized Least Square for power systems proposed in [15] proposes 
a variation of the WLS which addresses the issue of observability and is able to function in the case of 
partial observability. Static SE also includes the Sequential SE which has the advantage of being able 
to perform updates with partial measurement set. These sequential SE addresses the problem with bad 
data and loss of data.

Algorithms other than the Newton Raphson are also used to solve the WLS. In [37] the Levenberg MarquardtLM algorithm is used to solve the WLS representation of the problem for ill conditioned 
systems or in other words systems which do not have complete observability.

The work presented in this thesis adopts the work presented in [64] [62] where WLS is used to 
represent the estimation as a least square optimization solved using Newton Raphson method [29]. Also 
the Static SE that performs the update at regular intervals is modified and the emphasis is on how the 
triggering mechanism is performed.

2.2.2 Dynamic State Estimation

Dynamic State Estimation (DSE) is a step closer to real time monitoring when compared to SSE. There 
are two parts to the DSE: Prediction and Filtering [66]. The prediction of the state variables involves the 
modeling of the power system behavior. The prediction is calculated based on a mathematical model 
which takes into account the nonlinearities of the measurement functions unlike in SSE where a linear 
model is developed for the ease of computation [45]. The power system incorporating nonlinearity of 
the power flow equations increases the computational expense of the DSE and therefore is not widely 
implemented in reality [80].

The algorithms used to perform the prediction include Artificial Neural networks [67] and Fuzzy logic 
[43] which are also computationally complex. However, their accuracy is questionable when there are 
random events such as in the case of VER or load fluctuations[55].

The second part of a DSE includes the filters used to filter out the bad data by combining the pre-
dicted information along with the actual measurements on arrival. The Extended Kalman Filter is widely 
used to perform this filtering [79]. There are several other methods which are provided in literature. The 
DS is well suited when the dynamics of the power system are smooth and follow the historical trend. 
The variations which are stochastic such as fluctuations by VERs, weather related load fluctuations, fluc-
tuations caused by charging of electric vehicles etc. are not easily addressed. Therefore, in this thesis
the theory of SSE is adopted and enhanced to fit the challenges outlined in Chapter 1.

2.3 VER systems

The variability introduced by solar and wind generation necessitates the need for improved real-time monitoring so as to improve situational awareness, decision-making and automatic control[19]. These sources are called variable because of two complimentary characteristics: uncertainty and intermittency. They are uncertain in that their inputs of solar irradiance and wind speed are stochastic in nature and hence require prediction. Forecast model accuracy for wind or solar energy has improved in recent years and remains as a field of active research [53][14]. VERs are intermittent in the sense that they are not dispatch able like conventional generators and hence introduce a new set of dynamics into the power grid.

In order to incorporate VERs into studies on SE, a stochastic input-to-output model of the VER is required. This paper presents a model for wind generation although a similar approach may be taken for solar generation. In-built controllers can reduce the variability in the wind power output, but wind speed ramps or sudden gusts may still cause significant fluctuations.

The model used within this work is as follows. The power output of a wind turbine is related to the wind velocity via [35]

\[ P_w(v) = \frac{1}{2} \times \mu A v^3 \]  

(2.1)

Here, \( P_w(v) \) is the wind power; \( \mu \) is the air density; \( A \) the area of cross section of the flow tube. The wind power is related to the mechanical power \( P_m \) from the turbine through the following [35]:

\[ P_m = C_v \times P_w(v) \]  

(2.2)

The turbine coefficient \( C_v \) depends on the turbine design and could be modeled as non-linear algebraic equation [50] [44]. The electrical power output is proportional to the mechanical power of the turbine through :

\[ P_e = \eta \times P_m \]  

(2.3)

where \( \eta \) is the generator efficiency and it varies with the choice of generator [5].

Any change in the active power injection at a bus will affect the state variables throughout the system. In [4], the effect of wind generation on the phase angle is established using field data from an experi-
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Figure 2.2: Variation in phase angle in Texas Independent Synchrophasor Network on April 4, 2009

mental work. Figure 2.2 shows the variation in phase angles in the Texas Independent Synchrophasor Network on April 4, 2009 due to wind generation as measured from the McDonald observatory in Ft. Davis.

The work in [4] shows a high correlation between the active power injection at a bus with VER and the system states, which is one of the main challenges the work in this thesis addresses.

2.4 Relevant Tools Used

In this section, the relevant tools from the literature used in this thesis are elaborated. First, the WLS algorithm is described. As mentioned in Section 2.2.1, it is the most widely used algorithm in industry and is used at the core of this work. The WLS is used to build the Classical State Estimator (CSE). Later, layers of complexity are added to it to enhance its performance as part of the original contribution. Second, the concept of event triggering as presented in the literature is provided in Section 2.4.2. Then, Section 2.4.3 introduces the western electric rules (WER) used in stochastic process control as a new triggering criteria to be incorporated in event-triggered state estimation. Finally, Section 2.4.4 recalls
the tracking state estimation formulation adopted from [63] for later use in the event-triggered tracking state estimator in Chapter 4.

### 2.4.1 WLS Algorithm

Classical state estimation as applied to power systems was originally introduced in [64]. Since then, it has gained widespread adoption in industry and has received much developmental attention in the literature [66] [73]. Here, the classical variant of the power system state estimation is presented as a weighted least square (WLS) problem solved by the common method of normal equations.

Given an N bus network, the state vector at time $k$ is $x(k) = [\theta_1 \ldots \theta_N, V_1 \ldots V_N]$ where $\theta_i$ and $V_i$ are the phase angle and voltage respectively at the $i^{th}$ bus. The state vector $x(k)$ is derived from a measurement set $z(k)$ of length $M$ which is obtained from the network through the SCADA system. The measurements obtained may be of many types. These include the active power injection $P_i$ and reactive power injection $Q_i$ at a bus $i$, the active power flow $P_{ij}$ and the reactive power flow $Q_{ij}$ between buses $i$ and $j$, voltage measurements $V_i$ or time stamped measurements from the phasor measurement units (PMUs) $[V_i, \theta_i]$.

The measurement vector $z(k)$ is related to the state vector $x(k)$ through the following [64]:

$$z(k) = h(x(k)) + \varepsilon(k) \quad (2.4)$$

where $\varepsilon(k)$ is the measurement error at time $k$ and it is assumed to be normally distributed such that a weighting matrix may be constructed for the individual measurement error variances $\sigma^2$ as:

$$W = diag(\sigma_1^{-2}, \sigma_2^{-2} \ldots \sigma_M^{-2}) \quad (2.5)$$

$h(x(k))$ is the function vector of length $M$ that consists of the power flow equations that define power injections into buses and flows within branches. Explicitly, they are:

$$P_i = |V_i| \sum_{j=0}^{n} |V_j| (G_{ij}cos(\theta_i - \theta_j) + B_{ij}sin(\theta_i - \theta_j)) \quad (2.6)$$

$$Q_i = |V_i| \sum_{j=0}^{n} |V_j| (G_{ij}sin(\theta_i - \theta_j) - B_{ij}cos(\theta_i - \theta_j)) \quad (2.7)$$

$$P_{ij} = |V_i||V_j|(G_{ij}cos(\theta_i - \theta_j) + B_{ij}sin(\theta_i - \theta_j)) - Gi|V_i|^2 \quad (2.8)$$

$$Q_{ij} = |V_i||V_j|(G_{ij}sin(\theta_i - \theta_j) - B_{ij}cos(\theta_i - \theta_j)) + Bi|V_i|^2 \quad (2.9)$$
CHAPTER 2. BACKGROUND

from which an $M \times 2N$ Jacobian matrix $H(x)$ and a gain matrix $G$ can be defined:

$$H(x) = \frac{\partial h(x)}{\partial x}$$ (2.10)

$$G(x^c) = H^T WH(x)$$ (2.11)

Prior to presenting CSE as solved by the method of normal equations, care must be taken to ensure that the measurement set yields full observability of the network [13] [56]. The measurement set must include a set of independent measurements of size greater than the length of the state vector i.e. $M \geq N$ [6]. This ensures that the matrix $(H^T WH)$ is non-singular.

The WLS formulation of CSE is then presented as a minimization of the square error:

$$\min : f = \left[ z(k) - h(\hat{x}(k)) \right]$$ (2.12)

$$s.t. z_i(k) = h_i(x(k)) + \epsilon_i(k)$$ (2.13)

CSE is executed and the state vector is updated at regular intervals. The iterative Newton-Raphson procedure used to solve for the state estimate $\hat{x}(k)$, by normal equations is presented in Algorithm 1 [6].

**Algorithm 1**

1. Receive $z$ from SCADA
2. Initialise state vector $x = x^c$ and iteration counter $c$
3. Compute the measurement residual $r^c = z - h(x^c)$
4. Obtain $H(x^c)$ and $G(x^c)$;
5. Solve for the linear system $G(x^c) \ \delta x^c = H^T W[z-h(x^c)]$
6. Update the state vector and the iteration counter $x^{c+1} + \delta x^c; c = c+1$
7. Check stopping criterion at a maximum count $c_{max}$
8. If stopping criterion is satisfied: $\hat{x} = x^c$

For the above described algorithm to converge to the optimal solution full observability of the system should be guaranteed. The literature has shown that the condition for full observability require for the Gain Matrix $G(x^c)$ to be nonsingular [7] [22]. This simultaneously requires that the no. of measurements is greater than the number of state variables to be estimated.
2.4.2 Event Triggering

The concept of event triggered state estimation has been in existence in several feedback based control systems which have highly networked communication systems [41]. The primary goal of event-triggered state estimation in communication networks of control systems is to reduce the communication overheads [46]. However, in this thesis the concept of identifying the novelty in the measurement in used to identify the events in the weather conditions which can cause considerable change in the state variables in a power system with high penetration of VER.

The application of event triggering in the field of state estimation for power systems is relatively new and is presented in [36]. Here, the SE is performed using the WLS algorithm only when there is considerable novelty in the measurement. The authors [36] apply the set membership adaptive filtering (SMAF) estimator and the trigger is set based on the novelty in the measurements. When the error identified is higher than the predefined threshold the algorithm performs an update of the state vector using the process of SMAF. The approach described in [36] is applied to a MASE and the results show reduced communication overheads.

In this thesis, the approach to state estimation provided in [36] is adopted and applied to the WLS estimation algorithm. The CSE based on WLS is enhanced to ETSE using the concept of triggering only when an event occurs. The event triggered approach to SE is tested in a central state estimation scheme in the presence of VER. Also, the criteria for identifying the events differs from the work in [36]. In this thesis, the WER is implemented as the trigger criteria which is described in the following section.

2.4.3 Western Electric Rules

The Western Electric Rules (WER) are used in the analysis of control charts to monitor statistical process control [74]. The rules are formulated to pick up non-random variations or trends in the process output so that necessary control action can be implemented. The rules are defined with respect to a central limit and the distance of recent measurements from the central limit. In stochastic process monitoring, the central limit $\mu$ is taken as the average of the measurement over a period of time or the expected value of the measurement. The WER are:

**Western Electric Rules**

1. If the measurement point lies outside $\mu \pm 3\sigma_i$
2. If the measurement point lies outside $\mu \pm 2\sigma_i$
3. If the measurement point lies outside $\mu \pm \sigma_i$
4. If the measurement point lies outside $\mu$

Where, $\sigma_i$ is the standard deviation of the measurements in a given observation window. The above given rules are modified to observe the output of the VER and used as a trigger in the ETSE proposed in Chapter 3.

2.4.4 Tracking

The concept of tracking was first introduced in [63] where they provide an update mechanism for the state vector in between consecutive executions of the entire WLS algorithm. The tracking mechanism is added to the ETSE created in Chapter 1 to provide a new Event Triggered Tracking SE- ETTSE algorithm. The advantage of applying tracking to a SE used in a power system with VER integrated to it is shown in Chapter 4.

The tracking method utilizes the available state estimate $\hat{x}(k-1)$ and current measurement set $z(k)$ to evaluate the update $\delta x$ which should be added to the state estimate $\hat{x}(k-1)$ to obtain $\hat{x}(k)$.

$$\hat{x}(k) = \hat{x}(k-1) + \delta x$$

(2.14)

The $\delta x$ is obtained by solving the following:

$$\delta x = G^{-1}(\hat{x}_t)H(\hat{x}_t)(W(z - h(\hat{x}(k))))$$

(2.15)

Where $\hat{x}_t$ is the state vector which is obtained from executing the WLS at time $t$ when the trigger is set. The inverse matrix $G^{-1}$ also known as the gain matrix and the Jacobian $H(\hat{x}_t)$ is calculated only when the trigger is set and is estimated using the Algorithm 1. The Gain matrix and the Jacobian matrix once calculated retain their value till the next event is identified. The method of tracking is computationally less intensive as the Gain matrix is not computed for each update. The combination of triggering and tracking provide a near real time monitoring without significant computational overheads and is illustrated in Chapter 4.

2.5 Chapter Summary

The chapter provided an overview of the literature upon which this thesis i developed. The complimentary measurement system SCADA described in The Section 2.1.1 provided the outline of the complimentary measurement system also highlighted the problems faced. The new synchrophasor technology
which is incorporated into the SCADA and the improvements in the communication and do not completely solve the problem of real time monitoring. Despite the improvements available in the physical components of the monitoring systems there is a need to develop algorithms to process the large amounts of data and convert them into useful information and address the issues of variability introduced by VERs.

The chapter also highlights the two main types of SE which is presented in literature. Since the thesis is aimed at providing practical and simple approach to the needs of the power systems the simple SSE is adopted. The SSE is further enhanced with features such as event triggering and tracking which were described in Section 2.4.
In this Chapter existing state estimation techniques are enhanced by building upon the recent work on event triggered state estimation (ETSE)[36]. Conventionally, the computation of classical SE occurs at fixed intervals whereas the recently published ETSE algorithm has a varying time interval. In the presence of VER, the regular interval based conventional SE algorithms may be unable to track the variability associated with such VER. At the same time, reducing the interval and computing the SE more times than required is a computationally intensive process. The concept of ETSE is to perform state estimation only when triggered by considerable novelty” in the measurements from the field. The ETSE algorithm in [36] addressed novelty purely on the basis of the distance between the measured and previously estimated state. Such triggering ensures that the computational overheads are reduced and while the dynamics of the system states are closely followed.

The remainder of the chapter develops into three sections. Section 3.1 covers the formulation of the event-triggered state estimator while the simulation methodology is presented in Section 3.2 Section 3.3 presents the results using the IEEE 14 bus benchmark example but with VER integrated into two of the buses. Results from the ETSE are compared against two CSE implementations of relatively slow and fast computation intervals.
CHAPTER 3. IMPLEMENTATION OF EVENT TRIGGERED STATE ESTIMATION

3.1 Triggering Criterion

The concept of event triggered state estimation was first introduced as a technique to reduce communication overheads in distributed state estimators[36]. In contrast, in this thesis the focus is on the inclusion of an event criterion to trigger when there is considerable novelty in the wind power output.

A number of triggering criteria can be used to capture the variability in the VER. In [36], the trigger is set by the square root error of the current measurement and the previous estimate. Here, the event is characterized as a considerable variation in the active power injection at the VER buses as considered by the Western Electric Rules [74] as explained in Section 2.4.3.

Here, the rules are applied to observe the active power injection at the buses with wind generation over a window that grows in size until the conditions of the triggering criterion are met; at which point it is reset back to a size of two.

Let the active wind power injection at time $k$ at bus $i$ be $P_{wi}(k)$ and $\mu = \bar{P}_{wi}(k)$ be the average of the measurements within a given observation window of size defined as $S_i(k)$;

$$S_i(k) = \begin{cases} 2 & \tau(k-1) = 1 \\ S_i(k-1) + 1 & \tau(k-1) = 0 \end{cases}$$  \hspace{1cm} (3.1)

$$\bar{P}_{wi}(k) = \frac{\sum_{j=1}^{S_i(k)} P_{wi}(k-j)}{S_i(k)}$$  \hspace{1cm} (3.2)

where $\tau(k)$ is a boolean trigger which decides whether to perform state estimation upon receiving $P_{wi}(k)$. The value of the previous trigger is used to update the window size.

The Western Electric Rules (WER) recognizes events such as ramps but cannot pick up random events such as gusts which may result in sudden spikes. In order to capture such an event, an additional criterion is introduced as follows:

$$|\bar{P}_{wi}(k) - \bar{P}_{wi}(k-1)| \geq \alpha \times P_{wi}(k-j)$$  \hspace{1cm} (3.3)
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The algorithm for the ETSE is as follows:

1. Receive active power measurement $P_{wi}(k)$ from all the buses with wind generation

2. Update $S_i(k)$ and compute $\overline{P}_{wi}(k)$

3. Update $\tau(k)$

4. If $\tau(k) = 1$ receive measurement set of the entire network and perform SE using Algorithm 1

5. Else if $\tau(k) = 0$ then $\hat{x}(k) = \hat{x}(k-1)$

6. Wait for $P_{wi}(k)$

3.2 Simulation Methodology

In Section 3.1, the performance of the ETSE is studied relative to CSE by evaluating three different SE approaches:

- The fast SE (FSE) which runs Algorithm-1 for every instant the measurement set is available (2s).
- The new ETSE which executes Algorithm-2.
- The CSE which executes Algorithm-1 every 10s.

The FSE is to mimic the real time SE and is used as a benchmark to compare the new ETSE and CSE. The CSE is implemented to reflect the current practice in SE in energy management systems.

In each case, the wind speed follows the composite wind speed model presented in [50]. This is taken as a stochastic input to the DFIG wind turbine model provided in SimPower [47]. These results are
CHAPTER 3. IMPLEMENTATION OF EVENT TRIGGERED STATE ESTIMATION

Figure 3.1: IEEE 14 bus system
integrated into the IEEE 14-bus system [49] as shown in Figure 3.1. The three SE approaches are tested for two levels of VER penetration:

- when Bus 2 has VER connected,
- when Bus 2 and Bus 6 are replaced with VER.

The measurement set is obtained from the power flow analysis performed in PSAT. The measurement set is defined such that the system is observable. A normally distributed measurement error of standard deviation 0.2 and mean 0.5 is introduced to the measurement set before executing the SE. The tuning parameter $\alpha$ is set to 0.25. The entire simulation is conducted within a Matlab environment on a Windows 7 HP laptop with an Intel Core i5 CPU running at 2.27Ghz.

The results of the simulations are assessed on the basis of both computation time and relative error. The computation time for the three SE approaches and two VER penetration levels is recorded for a simulation interval of [2s, 400s]. Relative error is assessed on the basis of the norm of the deviation of the CSE and ETSE approaches relative to the FSE which records the state vector. The phase angle at Bus 4 is arbitrarily chosen for inspection.

$$\text{norm}(\text{err}) = \sqrt{\sum_{j=0}^{n} \text{err}_j^2}$$

### 3.3 Results

This section presents the results of the simulation methodology explained in the previous section. The simulation results include the graph of the variation in phase angle at Bus 4 which is observed by the various SE approaches. The computation time as well as the relative error is also recorded for the different SE approaches.

The Figure 3.2 shows the variations of the phase angle at Bus 4 for the three different SE approaches. The ETSE algorithm has a variable time interval between consecutive updates while the CSE on the other hand, has a fixed time interval of 10s. The variable time interval in the ETSE is able to detect the drop in phase angle at $t=204s$, but this is missed by the CSE.

The Figure 3.3 shows the variability in phase angle at Bus 4 with VER connected at Bus 2 and Bus 6. The ETSE captures the drop in the phase angle at $t=204s$ and $t=208s$ which is missed by the CSE.

As seen in Table 3.1, the computation time taken for FSE is the highest since it invokes the optimization Algorithm 1 for every instant the new measurement is obtained. There is a significant reduction in
Figure 3.2: Variation in phase angle at Bus 4 when Bus 2 has VER connected

Figure 3.3: Variation in phase angle at Bus 4 when Bus 2 and Bus 6 have VER connected
CHAPTER 3. IMPLEMENTATION OF EVENT TRIGGERED STATE ESTIMATION

<table>
<thead>
<tr>
<th>Approaches</th>
<th>FSE(s)</th>
<th>ETSE(s)</th>
<th>CSE(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing Time-bus2</td>
<td>109.618</td>
<td>53.69</td>
<td>20.148</td>
</tr>
<tr>
<td>Processing Time-bus2 and bus4</td>
<td>211.25</td>
<td>64.273</td>
<td>20.19</td>
</tr>
</tbody>
</table>

Table 3.1: Computation time of the three SE approaches

<table>
<thead>
<tr>
<th>Approaches</th>
<th>ETSE</th>
<th>CSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure of error at bus 4-1 WIND GEN</td>
<td>1.01e-2</td>
<td>5.04e-2</td>
</tr>
<tr>
<td>Measure of error at bus 4-2 WIND GEN</td>
<td>2.4e-2</td>
<td>1.748e-1</td>
</tr>
</tbody>
</table>

Table 3.2: Relative error of the two SE approaches compared to FSE

the computation time in the CSE followed by the ETSE.

The Table 3.2 shows the relative error for the phase angle at Bus 4 for the new ETSE and the CSE. In both the scenarios of wind integration the ETSE has less error than the CSE. The relative error is used to compare the fidelity of the ETSE and CSE approaches.

3.4 Chapter Summary

The numerical as well as graphical results presented in this chapter have highlighted how ETSE is a better choice over the CSE and FSE. The combination of WER to create the trigger criteria in the application of SE is unique and the improvements in computational time and relative error in comparison to the FSE and CSE establishes the same. The ETSE successfully incorporates the variability exhibited in the power systems, in the operation of the SE.
Implementation of Event Triggered Tracking State Estimation

In Chapter 3 the concept of ETSE using the variability in the wind is introduced. In the ETSE the WLS is performed only when triggered. The ETSE addresses the problem of variability introduced in the system due to integration of VER. Along with increase in variability which needs real time monitoring, state estimation will be extended to the distribution networks which increase the size of the problem as highlighted in Chapter 1. Conventional solutions to this problem result in large problem sets being solved at a faster rate thereby becoming computationally intensive. This chapter builds upon the contribution presented in Chapter 3 where SE is only called in the case of considerable novelty in the evolution of the system state. Specifically, the concept of tracking saves significant computational effort at minimal expense of error by allowing for the update of system state between two consecutive triggered instances.

The remainder of the chapter develops into three sections. The Section 4.1 provides the algorithm which combines the triggering criterion and the formula for tracking[63]. The methodology and the results using an IEEE 14 bus system are outlined in Section 4.2.

4.1 ETTSE Algorithm

Although SE has traditionally only been used in transmission EMS, the incorporation of Distribution Generation (DG) has now let to SE methods to be included in Distribution Management System (DMS) [ref]. Distribution systems are characterized by more buses per unit area thereby dramatically increasing the problem size. The resulting computational expense, restricts the ability to sample at a higher speed
to improve monitoring. The increase in network size, the increase in variability and the limitations on computational capability together are the motivation of this chapter to look into different state estimation approaches to enhance real-time monitoring.

Traditionally, CSE executes the WLS algorithm at regular but relatively slow intervals (10-30s) under the assumption that the power system under observation evolves quasi-statically between consecutive executions of the WLS. The increasing penetration of VER in recent years has introduced greater dynamics thus potentially violating this assumption. To keep up with the variation in the states, reductions in the CSE execution interval has been proposed as a solution. Here, the concept of tracking in Chapter 2 and triggering in Chapter 3 are now combined to give a more computationally efficient ETTSE algorithm with improved real-time monitoring capability as an alternative solution.

Algorithm 3

1. Receive active power measurement $P_{wi}(k)$ from all the buses with wind generation

2. Update $S_i(k)$ and compute $P_{wi}(k)$ using Equation 3.1 and Equation 3.2

3. Update $\tau(k)$ using Equation 3.4

4. If $\tau(k) = 1$ receive measurement set of the entire network and perform SE using Algorithm 1

5. Else if $\tau(k) = 0$ then update $\delta x$ using Equation [from background] and $\hat{x}(k)$ using Equation from background

6. Wait for $P_{wi}(k)$

The Algorithm 1 which executes the gain matrix is only performed when the trigger is set. The remaining step to update the state vector is performed using Equation [from background] and [from background]. The results of this new approach are studied in a case study in the following section.

4.2 Methodology and Results

4.2.1 Methodology

The standard IEEE 14 bus system[50] is used to illustrate the scheme proposed in this chapter. The measurement set is predefined to be: Voltage measurement at Bus 1, Power injection (active and reactive) at Bus 2, 3, 7, 8, 10, 11, 12 and 14 and Power flow (active and reactive) on branches between the following buses 1-2; 2-3; 2-4; 2-5; 4-5; 4-7; 4-9; 5-6; 6-11; 6-13; 7-9 and 12-13.
Standard methods of observability[3] are applied to assure that the measurement set results in a full column rank of \( H \) given by Equation (6). The tuning parameter \( \alpha \) in Equation 3.4 is set to 0.25. The following 3 scenarios are observed and compared against each other:

1. Execute Algorithm 1 every 2s interval which is Fast SE (FSE)

2. Perform Event Triggered State Estimation(ETSE) using Algorithm 2

3. Perform Event triggered Tracking State Estimator (ETTSE) using Algorithm 3

The FSE is the ideal scenario which is used as the benchmark to assess the ETTSE. In each case, the wind speed follows the composite wind speed model presented in [49]. This is taken as a stochastic input to the DFIG wind turbine model provided in SimPower[47] to obtain the variability in power injection at Bus 2. These results are integrated into the IEEE 14-bus system. MATPOWER is used to obtain the power flow measurements for variation in the power injection. Two different wind profiles are used to test the three scenarios.

A normally distributed measurement error of standard deviation 0.07 per unit (p.u) and mean 0.06 p.u is introduced

The results of the simulations are assessed on the basis of the relative error. Relative error is assessed on the basis of the norm using Equation 3.5.

### 4.2.2 Results

The results in the variation of the phase angle at Bus 5 for two different wind profiles are studied. Case 1 represents a spike in the wind power injection and in Case 2 there are ramp events and higher variability. Also, the \( \delta x \) is observed and compared to the difference between the real update obtained from the FSE.

<table>
<thead>
<tr>
<th>Case</th>
<th>ETSE</th>
<th>ETTSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>1.04x10^{-2}</td>
<td>3.9x10^{-4}</td>
</tr>
<tr>
<td>Case 2</td>
<td>2.9x10^{-2}</td>
<td>1.2x10^{-3}</td>
</tr>
</tbody>
</table>

Table 4.1: Relative error of the two SE approaches compared to FSE

<table>
<thead>
<tr>
<th>Approaches</th>
<th>FSE(s)</th>
<th>ETTSE(s)</th>
<th>ETSE(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing Time-Case 1</td>
<td>218.71</td>
<td>29.19</td>
<td>28.96</td>
</tr>
<tr>
<td>Processing Time-Case 2</td>
<td>268.83</td>
<td>33.95</td>
<td>32.44</td>
</tr>
</tbody>
</table>

Table 4.2: Computation time of the three SE approaches
CHAPTER 4. IMPLEMENTATION OF EVENT TRIGGERED TRACKING STATE ESTIMATION

Figure 4.1: Variation in the phase angle at Bus 5 presented by the different SE approaches for Case 1

Figure 4.2: Variation in the phase angle at Bus 5 presented by the different SE approaches for Case 2

Figure 4.3: Variation in the update provided by ETTSE compared to the update provided by FSE for wind profile in Case 1
CHAPTER 4. IMPLEMENTATION OF EVENT TRIGGERED TRACKING STATE ESTIMATION

As can be seen in Figure 4.1 and Figure 4.2 the modulation in the phase angle for the different wind profiles have been faithfully captured by the ETTSE. The Table 4.1 shows the relative error for the phase angle at Bus 5 for the new ETSE and the ETTSE. In both cases of wind power injection profile the ETTSE has less error than the ETSE. The relative error is used to compare the fidelity of the ETSE and ETTSE approaches.

The difference \( \hat{x}(k) - \hat{x}(k-1) \) for the phase angle estimate at Bus 5 is recorded for the FSE and compared to the \( \delta x \) calculated at every update using the equation (15), for the corresponding state variable. Fig 4. observes that the ETTSE method is able to provide accurate update of the state variables at the same time the update mechanism in ETTSE represented by Equation [from background] is not complex compared to the computation of the WLS in Algorithm 1.

The Table 4.2 provides the computation time of the three SE approaches. The computation time for the FSE is certainly much higher than the ETTSE and ETSE. Though the ETTSE has a higher computation time than ETSE, the difference is negligible.

4.3 Chapter Summary

The ETTSE is an improvement to the ETSE described in Chapter 3, and provides a better reflection of the variability in the system states. The computational time of the ETTSE is comparable to the ETSE and is significantly lower than the FSE, at the same time the relative error is also well below ETSE. The combination of the computationally less intensive method to achieve tracking between consecutive triggers is a good combination for large power systems with higher penetration of VER.
In this chapter, the concept of SE from Chapter 2 is expanded to include meteorological information. In the Weather Aided State Estimator (WASE), short term forecasted data is used to identify different weather phenomena. The WASE creates an early warning system which can improve the situational awareness of the operators and can provide the information necessary to take appropriate action before the weather phenomena affects the power grid operation. The WASE is an algorithm which runs in parallel to an ETSE or ETTSE and alerts the operator of the upcoming weather events. The simulation emphasizes the need to introduce appropriate policy for information sharing between the weather stations and the power grid control centers as highlighted in [19] and the importance of developing short term forecasts to aid SE algorithms in the future.

The remainder of the chapter develops into four sections. The Section 5.1 provides the motivation for WASE. The methodology is provided in Section 5.2 and the modelling is provided in Section 5.3, followed by results in Section 5.4.

5.1 Motivation

The share of renewable energy in the generation mix is set to increase over the coming years to meet the growing energy demand and at the same time address the issues of climate change and carbon emissions [19]. Currently the power grids are subjected to fluctuations in load and in the future will be affected by the fluctuations in generation due to the increase in the presence of VER [40]. The higher penetration of
the VER in the power grids increases the vulnerability of the system towards weather phenomena such as wind gusts, cumulus clouds, ramp events etc. In order to maintain the reliability of the power grid operation it is necessary to improve the monitoring and control systems[20] to capture the effect of the weather on the power grids.

The WASE aims to aid the operator with the prediction of the system states to ensure that the three main operations listed below can be improved in the presence of fluctuations introduced by the VER. The power system operator is mainly concerned with the following three responsibilities:

- Balancing generation and load which is performed by ensuring frequency stability.
- Maintain voltage stability.
- Maintain thermal limits which includes monitoring the power flow through the tie lines.

The Figure 5.1 shows the block diagram of the integration of WASE into the current structure used in EMS.

![Figure 5.1: Block diagram of integration of WASE](image)

The market layer takes into consideration the weather forecasts and the load forecasts to perform economic dispatch, but the results from the economic dispatch are refreshed at a much slower rate than desired. The time scale of this operation ranges from 5min to 1hour. The low frequency of operation of the market layer will not be able to capture the sudden events in the weather and thus does not improve the operator’s situational awareness. Moreover the markets perform a security constraint economic dispatch [78] which is merely an approximation of the power system states.
The WASE proposed in this chapter aims to combine the advantages of short term forecasts with power flow analysis. The results of the WASE can be used directly to aid the operator in making decisions when a weather phenomena occurs. The WASE is an online tool which generates forecasted state values based on forecasted weather information.

Several surveys and studies have highlighted the need to include weather forecasts in the EMS to equip the operators to manage weather events which can affect the power grids. In [60] the authors highlight the need for improving the information available on renewable energy generation to enhance the operation of the SMART grids of tomorrow. The successful integration of VERs is supported by the use of operating reserves, the management of these reserves can be improved with the aid of forecasts. In [34] the need to develop special operating procedures to perform balancing when dealing with VERs is discussed. The recommendations provided in [33] to update the power system monitoring include improvements in the operator procedures to handle the events which arise in the power grid due to weather phenomena. The inclusion of forecasts specifically of ramp forecasts and relaying the information to the operator is highlighted as an important step to enhance situational awareness which can improve the operator’s reaction to a problem. The literature survey conducted in [34], [33] and [60] have concluded that there is a need to enhance the operational procedures by providing forecast and that methodologies to enable that needs to be developed.

The years of research on SE have been extensive and have been successful in implementing algorithms which cover issues such as observability [42][71], bad data analysis [9], computational time and complexity [75]. Recent developments in DSE have included load forecasts, which are based on priori information to build the time varying model of the power systems [10].

The work presented in this chapter is in line with the concerns highlighted in literature and a step towards the future of SE. A methodology is provided to include the forecasted weather information to enhance the operators understanding of the power system conditions when subjected to sudden changes in the weather which affects the power grid with higher penetration of VER.

5.2 Methodology

In this section the methodology for implementing the WASE is discussed. The high level objection of the WASE is to provide a foresight into the power system stability by using the steady state model.

The WASE methodology provided in Figure 5.2 can be divided to the five separate stages:

1. Collect weather data
2. Process weather information

3. Execute power generation/consumption function

4. Perform Power flow analysis

5. Process the results of the Power Flow Analysis

The function of each stage and how it eventually aids the operator’s situational awareness is elaborated in the remainder of this section.

5.2.1 Collect Weather Data

The weather information which is an input to the system can be collected from several sources. The developments in the field of communication, weather forecasting and meteorological sciences has resulted in vast amounts data which can be utilized by the WASE. The average time taken by the operator to react to any event is 15min, thus a 15min look ahead time should be achieved with the WASE to benefit the operators. Therefore, the forecast models are required to be short term forecasts of the order of 15 -30min [53]. Also an important feature required in the forecasts, are ramp and variability forecasts [27] which are identified as events that cause significant shift in the power generation of the VERs. The information from the weather stations can also be combined with the historical data to understand the evolution of the weather over a given period of time. Also, satellite imaging or Geographical Information Systems(GIS) can be used to enhance the weather data collection techniques [51]. The performance of the WASE is dependent on the availability and accuracy of the weather data, this is bound to improve with the further
CHAPTER 5. WEATHER AIDED STATE ESTIMATION

developments in communication and improvement in the accuracy of the forecast models.

Figure 5.3: Collection of weather data

5.2.2 Process Weather Information

The data collected from the several sources discussed in the previous section should be compiled to suit the power system analysis. The data is used to build a time varying spatial map for a given time frame of the weather variables $W_k(x,y)$. The map provides the weather data $W$ at time $k$ for the geographical locations given by coordinates $(x,y)$. The power system buses should have coordinates which correspond to their physical location and can be used to identify the weather variable at each bus. Therefore the geographical mapping of the grid is essential prerequisite for the implementation of this scheme.

5.2.3 Execute Power Generation/Consumption Function

Once the time varying spatial map of the weather variable is obtained for a given period into the future, it is used to forecast the power injection at the buses affected by the weather variables. The VER can include wind farms with the power function directly proportional to the wind speed, solar PV farms which have a power function directly proportional to the solar irradiance. Similarly, buildings which represent the load buses can have power consumption functions which have a direct correlation to the weather variables as well. Due to the heterogeneity of such building models such power functions do not exist, but a future development of such models can also be incorporated to the WASE.
Figure 5.4: The power function which can be adopted to generate the power injection profile

This step connects the weather data to the power system by generating the forecasted power generation profile. The output from the power generation function is used in the following step for power flow analysis.

### 5.2.4 Power Flow Analysis

The power flow analysis is performed for the variation in the power injection forecasted corresponding to the variability in the weather variables. The Equation 2.6 and 2.7 are solved to obtain the full list of the system states.

For each forecasted value the power flow analysis is executed. The results of the power flow analysis provides the values for the system states \( \hat{x}(k) \), corresponding to each instant \( k \) into the future. The power flow analysis performed using the steady state equations can also be replaced with dynamic frequency modelling of the power grid.

### 5.2.5 Process the Results of the Power Flow Analysis

The power flow analysis provides more information than the state vector. The state vector can be used to calculate the power flow between the buses using the Equations 2.8 and Equation 2.9.

The various results obtained from the power flow analysis are able to aid the three main responsibilities of the operator provided in Section 5.1. The system states provide the voltage and phase angles which are used for monitoring both voltage stability as well as frequency stability. The power generation and the power consumption information provided by the power injection values along with the Area Control
Error(ACE)[54] are calculated and used to ensure balancing of the load and generation. The thermal limits are monitored with the help of the power flow values which are calculated. With the help of the information obtained from this step, the operator is able have a better understanding of how the system will behave in the future when subjected to the changes in the weather.

![Power Flow Simulation](image)

Figure 5.5: Processing of the powerflow results

The better awareness of the system parameters and their evolution over a time frame into the future will be able to improve the reaction of the operators to weather events.

5.3 Modelling

The meteorological models distinguish between areas of constant weather variables with lines. Isobars for wind speed specifically and similar approaches can be done for the other VERs. Therefore, it is necessary to model the evolution of these lines of constant temperature, solar radiation, and wind speed to develop the varying weather map. In this section the model of a wind speed map is explained using the concept of a moving isobar.

Consider an arbitrary scalar field P which represents the air pressure. The \( \vec{\mathbf{W}} = \nabla P \) is a vector field that represents air speed/wind speed.

\[
\vec{W}(x,y) = W_x(x,y)\hat{i} + W_y(x,y)\hat{j}
\]  

(5.1)

The lines of equal wind speed are the same as lines of equal pressure isobars, which are perpendicular to the motion of wind. The isobars are described by \( P(x,y) = c \). Let the wind speed on one side of the isobar be \( \vec{A}_1 \) and the wind speed on the other side of the isobar is \( \vec{A}_0 \).

The isobar can be represented as a parametric equation in u:

\[
R(u) = R_x(u)\hat{i} + R_y(u)\hat{j}
\]  

(5.2)
If the isobar $R(u,t)$ is moving with a velocity $\vec{V} = V_x \hat{i} + V_y \hat{j}$, the evolution of $R(u,t)$ over a given period can be postulated as follows:

$$\vec{R}(u,t) = [R_x(u) + V_x t] \hat{i} + [R_y(u) + V_y t] \hat{j}$$  \hspace{1cm} (5.3)

The wind speed at a point $(x,y)$ is also a function of time and it is represented as:

$$\vec{W}(x,y,t) = W_x(x,y,t) \hat{i} + W_y(x,y,t) \hat{j}$$  \hspace{1cm} (5.4)

The vector $\vec{W}(x,y,t)$ is updated with respect to $\vec{R}(u,t)$.  

$$W_x(x,y,t) = \begin{cases} A_{1x} & \text{if } x < R_x(u,t) \\ A_{0x} & \text{if } x > R_x(u,t) \end{cases}$$ \hspace{1cm} (5.5)

$$W_y(x,y,t) = \begin{cases} A_{1y} & \text{if } y < R_y(u,t) \\ A_{0y} & \text{if } y > R_y(u,t) \end{cases}$$ \hspace{1cm} (5.6)
The energy from the wind speed \( \vec{W}(x,y,t) \) which is harnessed by the turbine along the direction \( \hat{s} = s_i \hat{i} + s_j \hat{j} \) is given by \( \vec{W}_e(t) = \hat{s}.\vec{W}(x,y,t) \).

The IEEE 14 bus system [50] is used as the test case. In this chapter the VER adopted is a wind generator with a power generation function given by Equation 5.7 and the simulation is performed within a Matlab environment.

\[
P_i = \frac{1}{2} \times \mu Av^3 \times C_P
\]  

(5.7)

Where \( C_P \) is the coefficient of performance for the turbine which considers the efficiency and the turbine coefficient together and in this example is given the value 0.59. The area of the turbine is set to 3848 m\(^2\) and \( \mu \) which is the density of air is 1.2 kg/m\(^3\).

5.4 Results

The Bus 2 in the IEEE 14 bus system is a generator bus and is substituted with the VER. The wind data is forecasted and assumed to be collected from the sources which are mentioned in Section 5.2. In this simulation a moving wind front along the horizontal direction is modelled.

The wind farm is provided with coordinates \( (x_{\text{turbine}}, y_{\text{turbine}}) \). The wind speed corresponding to the point \( \vec{W}_e(x_{\text{turbine}}, y_{\text{turbine}}, t) \) is used to calculate the \( P_i \).

The steady state power flow analysis is performed by MATPOWER within the Matlab environment [49]. The change in the wind speed over the geographical area of the grid is reflected in the power injection at the Bus 2. The predicted power injection profile results in a spike in the power injection and the power flow analysis is performed for the time frame in the future.

The time frame of the predicted power generation profile is 2min. The predicted power generation profile shown in Figure 5.7 is used as an input at Bus 2 of the IEEE 14 bus system.

The power flow analysis performed for the forecasted power generation and the results are highlighted to understand the behaviour of the system when subjected to changing wind speeds. In the Figure 5.9 the maximum and minimum values of the voltage and phase angle for the time frame can be observed. This allows the operator to maintain the voltage stability and frequency stability. Also the generator parameters [50] can be extracted and provided to the operators as shown in Figure 5.8, which can aid in taking decisions related to balancing.

The results of the power flow analysis provides more information that necessary to the operators. The operators require concise information about the essential parameters to make clear and quick de-
cisions. The development of Graphical User Interface (GUI) for conveying the critical information to the operators is a crucial part of the EMS [57][11]. A simple illustration of the necessary information is provided in Figure 5.10.
Figure 5.9: Collection of voltage and phase angle from the power flow analysis

<table>
<thead>
<tr>
<th>Bus</th>
<th>$V_{\text{max}}$</th>
<th>$V_{\text{min}}$</th>
<th>Bus</th>
<th>Phase $\text{Max}$</th>
<th>Phase $\text{Min}$</th>
<th>Phase $\text{Difference}$</th>
</tr>
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<tr>
<td>1</td>
<td>1.06</td>
<td>1.06</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1.05</td>
<td>1.05</td>
<td>2</td>
<td>-3.53</td>
<td>-6.16</td>
<td>2.63</td>
</tr>
<tr>
<td>3</td>
<td>1.01</td>
<td>1.01</td>
<td>3</td>
<td>-11.42</td>
<td>-13.77</td>
<td>2.35</td>
</tr>
<tr>
<td>4</td>
<td>1.02</td>
<td>1.02</td>
<td>4</td>
<td>-9.16</td>
<td>-11.24</td>
<td>2.08</td>
</tr>
<tr>
<td>5</td>
<td>1.02</td>
<td>1.02</td>
<td>5</td>
<td>-7.72</td>
<td>-9.62</td>
<td>1.90</td>
</tr>
<tr>
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<td>1.07</td>
<td>1.07</td>
<td>6</td>
<td>-13.14</td>
<td>-15.09</td>
<td>1.96</td>
</tr>
<tr>
<td>7</td>
<td>1.06</td>
<td>1.06</td>
<td>7</td>
<td>-12.22</td>
<td>-14.28</td>
<td>2.05</td>
</tr>
<tr>
<td>8</td>
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<td>1.09</td>
<td>8</td>
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<td>-15.85</td>
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</tr>
<tr>
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<td>1.05</td>
<td>10</td>
<td>-13.98</td>
<td>-16.00</td>
<td>2.02</td>
</tr>
<tr>
<td>11</td>
<td>1.06</td>
<td>1.06</td>
<td>11</td>
<td>-13.69</td>
<td>-15.68</td>
<td>1.99</td>
</tr>
<tr>
<td>12</td>
<td>1.06</td>
<td>1.06</td>
<td>12</td>
<td>-13.99</td>
<td>-15.95</td>
<td>1.96</td>
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<td>1.05</td>
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<td>-16.03</td>
<td>1.97</td>
</tr>
<tr>
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<td>1.04</td>
<td>14</td>
<td>-14.92</td>
<td>-16.93</td>
<td>2.01</td>
</tr>
</tbody>
</table>

Figure 5.10: List of essential parameters of critical buses and tie lines
If the $P_{\text{max}}$ for the line between the buses 1 - 2 is calculated as 1.8p.u, from the Figure 5.10 it can be observed that there is a violation of the thermal limit and the operator can take the necessary action to prevent the same. Similar GUI along with visualization tools can be developed to exploit the WASE and improve the operator’s understanding of the power grid when subjected to various weather conditions[18].

5.5 Chapter Summary

The work in this chapter proposes a methodology to enhance the SE which is a key source of data for decision making in the EMS. The proposed combination of weather data to enhance the SE is able to improve the operator’s situational awareness in power systems with high VER penetration. The modelling approach to represent time varying map of wind speed can be expanded to represent other sources utilized by VERs. The results simulated a spike in the power injection and displayed the several parameters which are obtained as part of the power flow analysis. The WASE supported by a strong GUI which can relay the evolution of critical information in the future will be able to support the operator in making clear and quick decisions when faced with sudden changes in the weather variables. The WASE running in parallel with a regular SE will be able to improve the EMS and capture the weather related changes in the power systems.
In this chapter the conclusions derived from the work in this thesis are presented. Also, the possibilities of future work are outlined.

6.1 Conclusions

The work in this thesis has surveyed the existing literature to identify the challenges faced by the power grids of today and which of those can be solved by enhancing the SE which forms a key part of the EMS. The triggering criteria developed based on the WER along with the tracking update formulated by F. Scheppe proved to be a solution to the problem posed by the VER penetration in large power systems. The impact of the higher penetration of VER is a widely discussed topic in the surveys on future of the grid and the work on WASE tries to outline an approach to cater to the impacts of weather on power grids. The thesis has attempted to fill in the gaps in literature to address the key problems of novelty, complexity and weather events, in power grids with Variable Energy Resources.

6.1.1 Objectives Achieved

How can a Classical State Estimation (CSE) algorithm be enhanced to account for the novelty introduced by VER?

SE Approach 1. The CSE is enhanced to an Event Triggered SE (ETSE) as shown in Chapter 3, to capture the novelty and execute the SE only when necessary.
How can a CSE be enhanced to reduce computational load when addressing large complex networks?

**SE Approach 2.** The CSE is enhanced to include tracking: ETTSE as described in Chapter 4 to reduce the computational load when dealing with large complex networks and at the same time achieve real time monitoring.

How can CSE be enhanced with new weather based information to improve the operators awareness and reaction to weather events?

**SE Approach 3.** The WASE explained in Chapter 5 is placed in parallel to the CSE to enhance the performance with forecasted data to improve operator’s awareness.

### 6.1.2 Novel Contributions

**Trigger Criteria:** The new ETSE algorithm proposed in Chapter 3 created a trigger criterion based on the power output of the VER in the network which is a new approach to event triggering in SE. The trigger criterion included the historical data of the power output and the used concepts of WER outlined in Section 2.4.3, to identify the events such as ramps and surge in the power output. The testing of the ETSE algorithm show that the ETSE compared to the CSE relative to the FSE show higher fidelity of the state. The computation time of the new ETSE is higher than the CSE but is significantly lower than the FSE.

**Combination of Trigger and Tracking for VER:** The work presented in Chapter 4 is to solve the issue with the variability combined with the expanding size of the power grids. The problem of computational complexity is addressed by combining tracking with the triggering mechanism in Chapter 3 resulting in the ETTSE. This new combination is tested and the results of the ETTSE show that the approach is able to incorporate the variability introduced by the VER and meet the real time monitoring demands of a dynamic power grid with reduced computational overheads.

**Methodology for using Forecasted Weather Information in SE:** The third challenge which is identified in Chapter 1 is addressed by the methodology proposed in Chapter 5. The methodology is illustrated with a simple example, to show how the situational awareness of the operators can be improved to manage higher penetration of VER in the power grids. The work in Chapter 5 describes how the combination of GUI and WASE can enable faster decision making when dealing with power systems with higher penetration of VERs.
6.2 Future Work

6.2.1 Future Academic Work

The recent changes in the power system have The research in the field of SE mainly provides the improvements in algorithms and aims to achieve improvements in computational time and expense. The new era of computation and communication is able to provide the platform necessary to run complex algorithms, collect time stamped data from remote locations and process large amounts of data. The future work in the area of SE should include further work on the WASE which can combine the technology of today with algorithms to produce better decision making tools.

The WASE can be refined to include a robust forecast model which uses the data from weather stations to determine the evolution of the weather variables over a given time period. The inclusion of the forecast model to the SE will be able to move the SE methodology into the realm of DSE.

6.2.2 Industrial Application

Also, the work in this thesis has produced an SE which falls into the category of static state estimators at the same time achieved real time monitoring. The results were based on IEEE test cases and therefore the application of the ETTSE to an existing power grid with VERs and analysis of its performance under real conditions will be interesting to look into.


