DISTRIBUTED STATE ESTIMATION OF SMART GRID

A project Report submitted in partial fulfillment

of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

By

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CERTIFICATE

This is to certify that the project report entitled "**Distributed State Estimation of Smart Grid**" submitted by **Mude Abhilash Naik (EE10B021**) is a bonafied record work carried out by him at power systems Laboratory**,** Department of Electrical Engineering, Indian Institute of Technology Madras, in partial fulfilment for the award of degree **BACHELOR OF TECHNOLOGY** in Electrical Engineering. The contents of this report have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

As the size of electric power systems are increasing, the techniques to protect, monitor and control them are becoming more sophisticated. Government, utilities and various organizations are striving to have a more reliable power grid. Various research projects are working to minimize risks on the grid. One of the goals of this research is to discuss a robust and accurate state estimation (SE) of the power grid. Utilities are encouraging teams to change the conventional way of state estimation to real time state estimation. Currently most of the utilities use traditional centralized SE algorithms for transmission systems.

Although the traditional methods have been enhanced with advancement in technologies, including PMUs, most of these advances have remained localized with individual utility state estimation. There is an opportunity to establish a coordinated SE approach integration using PMU data across a system, including multiple utilities and this is using Distributed State Estimation (DSE). This coordination will minimize cascading effects on the power system. DSE could be one of the best options to minimize the required communication time and to provide accurate data to the operators. This project will introduce DSE techniques with the help of PMU data for a system snapshot. The proposed DSE algorithm will split the traditional central state estimation into multiple local state estimations and show how to reduce calculation time compared with centralized state estimation. Additionally these techniques can be implemented in micro-grid or islanded system.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Traditional State Estimation Techniques

It is often taken for granted that at a flick of a switch, there will always be a reliable and uninterrupted source of electrical power. This was not the case, however, during the Northeast American power blackout of 2003 which left over 50 million consumers without power for more than 48 hours. The blackout claimed 10 lives and caused countless injuries, while also totaling an economic loss of approximately 6 billion dollars. The Northeast blackout ranks as the largest blackout faced by the North American people and the seventh largest on a worldwide scale

In the aftermath of the blackout, the IEEE Power Engineering Society set up a committee to understand the major causes of the system failure and provide recommendations for preventing blackouts in the future [1]. It was found that the starting point of the power outage was an incidental contact between a major high voltage transmission line and unmaintained tree branches which had grown beyond municipal city limits. The contact caused the line to fault. System operators of the EPG are usually notified of such abnormal events by a locally installed Energy Management System (EMS). In particular, the EMS provides a tool termed as State Estimation (SE), which continually monitors the state and security of the grid. However, at the time of the incident, the SE module of the EMS was inactive due to a software bug and thus the information of the faulted line was not relayed to the system operator. If a robust, efficient and accurate state estimator was in place, the damage caused by the blackout could have been greatly limited.

Furthermore, the infrastructure of the EPG has a number of fundamental issues which include: fossil fuel based power plants which emit massive carbon emissions into the atmosphere, ageing technology which will soon not be able to keep up with increasing

power demand, as well as a centralized, hierarchical infrastructure, which does not align well with the current deregulated electricity market sector. Driven by the urgent need to develop cheaper, cleaner, efficient and sustainable electric power grids, the electric power industry is currently undergoing a profound paradigm change towards a smarter grid setup. A smart grid represents a vision for digital upgrades of electric power transmission and distribution. The key to the smart grid utilization is enabling advanced control, communication, computing and monitoring technologies for shuttling numerous amounts of information back and forth between the electric utility sector and its customers. The distributed nature of restructured power systems and the new applications of monitoring and control techniques introduce a different set of indices for measuring the reliability of electric power systems.

1.1 OBJECTIVE AND SCOPE OF THE PROJECT

The focus of this thesis is to discuss the background information on the topic of state estimation and PMUs. Then it is, followed by the presentation of the traditional state estimation and the system state estimation with and without PMU. It continues with the discussion of distributed state estimation utilizing phasor measurements to obtain system snapshot, and finally conclude by providing a summary of the report

1.2 THESIS STRUCTURE

Chapter 2 presents the mathematical formulation of the algorithm employed by traditional state estimation techniques. It explores system component modeling, maximum likelihood estimation, weighted least squares (WLS) estimation (including the WLS algorithm and matrix formulation), and a brief discussion concerning statistical robustness of the weighted least squares estimator.

Chapter 3 will discuss the application of PMUs in state estimation. It will present some reasons for the paradigm change from traditional state estimation to linear methods using the PMU data.

Chapter 4 will represent the body of the project research and will show the benefits of Distributed state estimation over traditional state estimation. It will include the use of phasor measurement units to optimize the distributed state estimation, and cover how DSE can be applied to provide a bulk power system snapshot. And finally a summary of numerical test results and conclusion are provided.

CHAPTER 2

TRADITIONAL STATE ESTIMATION

State estimation is the process of computing a state variable of a system from known measurements of a system. In power systems, state estimation refers to the collection of enough measurements from the buses around the power system and computing a state vector of the voltage at each observed bus. Although no breakthroughs in the fundamental concept of state estimation have occurred, the state estimator analysis has improved a lot over the past few years. The first step is to collect the non-linear measurements and then perform iteration to evaluate the close value of the state variable. This chapter presents the mathematical basis for traditional state estimation techniques.

2.1 Traditional State Estimation Techniques

The power system state parameters under consideration are real power flow, reactive power flow, current injections, voltages, resistance, reactance, and shunt susceptance [2]. Field measurements need to be sent periodically into the control center over a SCADA network in traditional state estimation. The real system and the model should be closely related to each other. To achieve this, careful construction of transmission line parameter and physical system model is required. The rest of this chapter will present how to construct the system model in applying traditional state estimation.

2.2 Model Design

In power flow analysis the general parameters of importance are transmission line, transformers, shunt capacitors or reactors. Since state estimation calculation in the power system is the same into the power flow calculation, the parameters used in power flow are also used in state estimation calculations [13]. Knowledge of the overall topological structure of the power system network is essential in analyzing state estimation of the wide area network.

2.2.1. Transmission Line Component Modeling

The two-port π-model, equivalent of the transmission line, is used for analysis of state estimation purposes. The model, in Fig 2.1, has four parameters and is widely used in power flow calculation and most state estimation techniques.

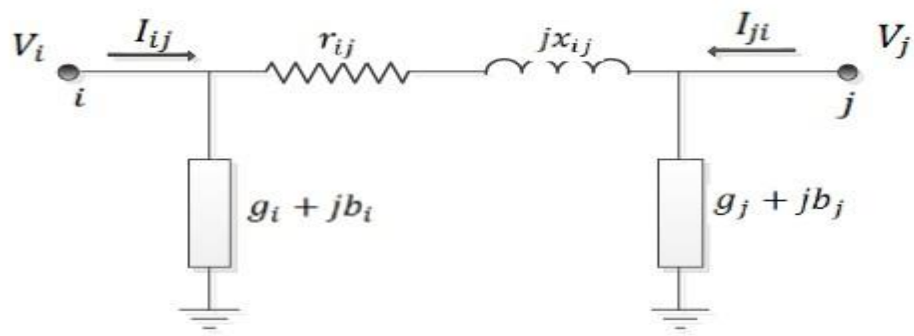

Fig 2.1 Two-port π-model

In this two port π-model, the losses in the transmission line and the energy stored around the conductors as a magnetic field and line charging are represented by resistance, inductor models and shunt impedance respectively.All the models parameters are in per unit.

2.2.2 Transformer Modeling

Below figure shows a transformer Branch model

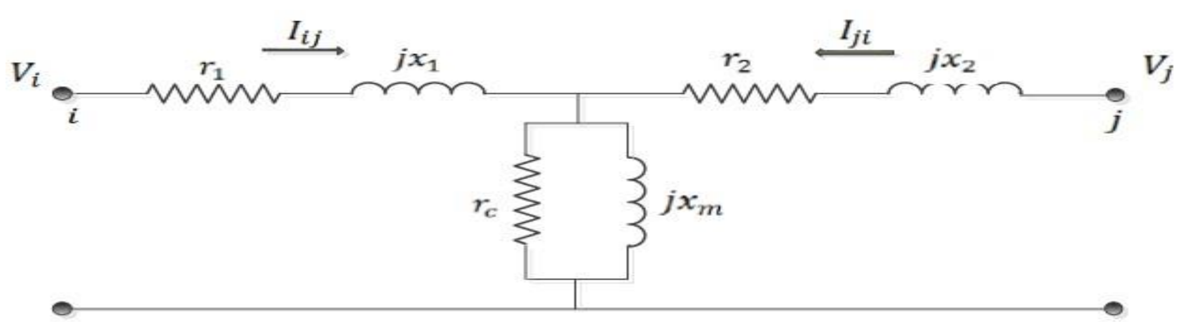

Fig 2.2 Transformer Model

As can be seen the transformer has series impedance and shunt impedance. The real and imaginary parts of the shut impedance are due to eddy current losses and hysteresis losses respectively. The inductance is produced from the way the conductors are arranged in a coil and the resistance represents the real losses in the coils. The transmission line and transformer are connected through at their ends with other parts of the network. Tap changing transformer, Fig 2.3., is modeled using series impedance in series with the transformer model.

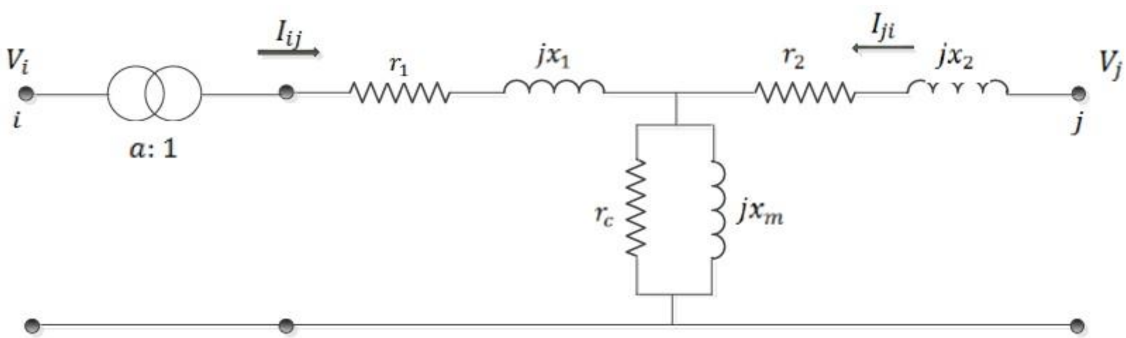

Fig 2.3 Tap Changing Transformer

2.2.3 Shunt Capacitor and Reactor Modeling

Modeling of other parameters is crucial to achieve a reliable and controllable power system. These parameters are shunt capacitors and reactors. They are used as reactive power backups and voltage control. They are installed at specific buses which significantly impact the power flow [2].

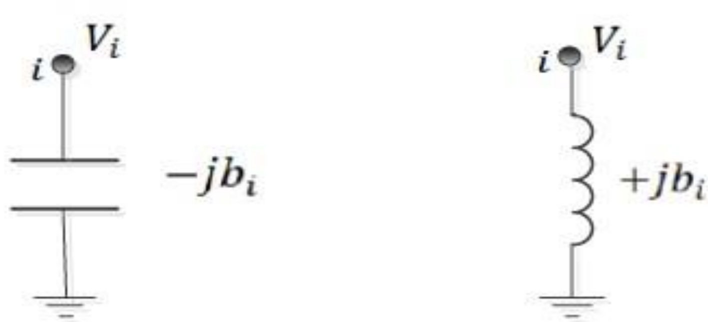

Fig 2.4 Shunt capacitor and reactor

2.3 The Bus-Admittance Matrix

To build the network model, transmission line series and shunt impedance, transformer impedance, and shunt capacitors and reactors should be defined. Then they can be combined together to construct a model of the system. The model is usually named as the admittance matrix or the Y-Bus of the power system. Traditionally, a Y-Bus matrix is used because of its advantage over an impedance matrix. The Y-Bus takes the following form:

$$I = \begin{bmatrix} i_1 \\ i_2 \\ \vdots \\ i_n \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1N} \\ Y_{21} & Y_{22} & \cdots & Y_{2N} \\ Y_{31} & Y_{32} & \ddots & \vdots \\ Y_{N1} & Y_{N2} & \cdots & Y_{NN} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_N \end{bmatrix} = Y * V$$

To construct the admittance matrix usually Kirchoff's current law is used. The ii^{th}element of the admittance matrix is the sum of the admittances of all of the lines connected to bus i and the element of the admittance matrix is the negative of the admittance between bus i and bus j [2].

2.4 Weighted Least Squares State Estimation Algorithm

As mentioned in the earlier sections power system state estimators use a set of redundant measurements taken from the power system to determine the closest system state for the given information and assumptions. These measurements help to get the best estimation through multiple iterations. The state estimator becomes a weighted least squares estimator with the inclusion of the measurement error covariance matrix. The measurement error covariance is used to weight the accuracy of each of the measurements. The mathematical formulation for the WLS estimator is expressed in several texts and in [2, 4, and 5]. Let's assume a measurement vector denoted by z containing 'm' number of measurements and a state vector denoted by 'x' containing 'n' number of state variables.

$$[\mathrm{z}] = \begin{bmatrix} \mathrm{z}_1 \\ \mathrm{z}_2 \\ \mathrm{z}_3 \\ \vdots \\ \mathrm{z}_\mathrm{m} \end{bmatrix} \qquad [\mathrm{x}] = \begin{bmatrix} \mathrm{x}_1 \\ \mathrm{x}_2 \\ \mathrm{x}_3 \\ \vdots \\ \mathrm{x}_\mathrm{n} \end{bmatrix} \tag{2.7}$$

The state vector will be organized such that the voltage phase angles will be listed first, followed by the voltage phase angles as shown below

$$x = (\theta_2 \quad \theta_3 \quad \cdots \quad \theta_N \quad |V_1| \quad |V_2| \quad \cdots \quad |V_N|)$$

Usually, traditional state estimation techniques use non-linear functions of the system state vector measurements. The vector forms of these functions are

$$[\mathrm{h(x)}] = \begin{bmatrix} \mathrm{h}_1(\mathrm{x}_1\ \mathrm{x}_2\ \mathrm{x}_3 \cdots \mathrm{x}_4) \\ \mathrm{h}_2(\mathrm{x}_1\ \mathrm{x}_2\ \mathrm{x}_3 \cdots \mathrm{x}_4) \\ \mathrm{h}_3(\mathrm{x}_1\ \mathrm{x}_2\ \mathrm{x}_3 \cdots \mathrm{x}_4) \\ \vdots \\ \mathrm{h}_\mathrm{m}(\mathrm{x}_1\ \mathrm{x}_2\ \mathrm{x}_3 \cdots \mathrm{x}_4) \end{bmatrix} \tag{2.8}$$

Where h(x) is a measurement function. Each measurement has its own unknown error$'e'$. The measurement errors, shown in Eq. (2.9) are assumed to be independent of one another and have an expected value of zero.

$$[e] = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ \vdots \\ e_m \end{bmatrix} \tag{2.9}$$

The state equation using non-linear functions can be written

$$[z] = [h(x)] + [e] \tag{2.10}$$

From the previous section, the solution to the state estimation problem can be formulated as a minimization of following objective function.

$$J(x) = \sum_{i=1}^{m} (z_i - h_i(x))^2 / R_{ii} \tag{2.11}$$

Where $'R'$ is the covariance matrix of the measurement errors and is diagonal in structure. This represents the summation of the squares of the measurement residuals weighted by their respective measurement error covariance. This can be redefined as-

$$J(x) = [z - h(x)]^T R^{-1} [z - h(x)] \tag{2.12}$$

To find the minimization of this objective function the derivative should be set to zero. The derivative of the objective function is represented by $g(x)$.

$$g(x) = \frac{\partial J(x)}{\partial x} = -\left[\frac{\partial h(x)}{\partial x}\right]^T R^{-1} [Z - h(x)] = 0 \tag{2.13}$$

Let

$$H(x) = [\frac{\partial h(x)}{\partial x}] \tag{2.14}$$

Where $H(x)$, is called the measurement Jacobian matrix. Ignoring the higher order terms of the Taylor series expansion of the derivative of the objective functions yields an iterative solution known as the Gauss-Newton method.

$$G(x^k) = \frac{\partial g(x^k)}{\partial x} = H^T(x^k).R^{-1}.H(x^k)$$

$$g(x^k) = -H^T(x^k).R^{-1}.\left(z - h(x)\right)$$

$$[G(x^k)]\Delta x^{k+1} = H^T(x^k).R^{-1}.[z - h(x^k)] \tag{2.15}$$

$$\Delta x^{k+1} = x^{k+1} - x^k$$

$$x^{k+1} = x^k - [G(x^k)]^{-1}. g(x^k)$$

$$\boldsymbol{x^{k+1} = x^k + [[H(x^k)]^T R^{-1} [H(x^k)]]^{-1} \left[[H(x^k)]^T R^{-1} [z - h(x^k)] \right]}$$

From the defined system models such as branch parameters, network topology and measurement locations, the measurement function and measurement Jacobian can be built. We know that the only information required to iteratively solve this optimization is the covariance matrix of measurement errors, R, and the measurement function, h(x).The error covariance matrix should also be constructed. In the first iteration of the optimization the measurement function and the measurement Jacobian should be evaluated at flat start. The reason of these values is that before we start any calculation slack bus with these values should be selected and all the other buses should be referenced to that bus. These values are the ideal values in power system power flow calculation. In combination with the measurements and results from the initial iterations, the next iteration of the state vector can be calculated until the required solution is obtained; finally the state of the system is determined. The flow chart of the iterative algorithm for WLS state estimation is shown in Fig 2.6. Initially set the iteration counter k=0, define the convergence tolerance e, and the iteration limit k_{limit} values. If k > k_{limit} then- terminate the iterations. Calculate the measurement function $h(x^k)$ the measurement Jacobian $H(x^k)$, and gain matrix $G(x^k) = H^T(x^k)R^{-1}H(x^k)$, then solve Δx^k from Equation 2.15. Then $if\ |\nabla x^k| > e$, then compute till $k < k_{limit}$ else, stop. Algorithm is converged to the required solution.

2.5 Power System Measurement Functions

The measurements in the power system include real and reactive power bus injections and flows, line current flow magnitude and bus voltage magnitudes. The two-port π-model is used to construct equations that relate the state vector measurement. The real and reactive injection powers to bus i are P_i and Q_i , and are computed as follows:

$$P_i = v_i \sum_{j+1}^{N} v_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \quad (2.16)$$

$$Q_i = v_i \sum_{j+1}^{N} v_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \quad (2.17)$$

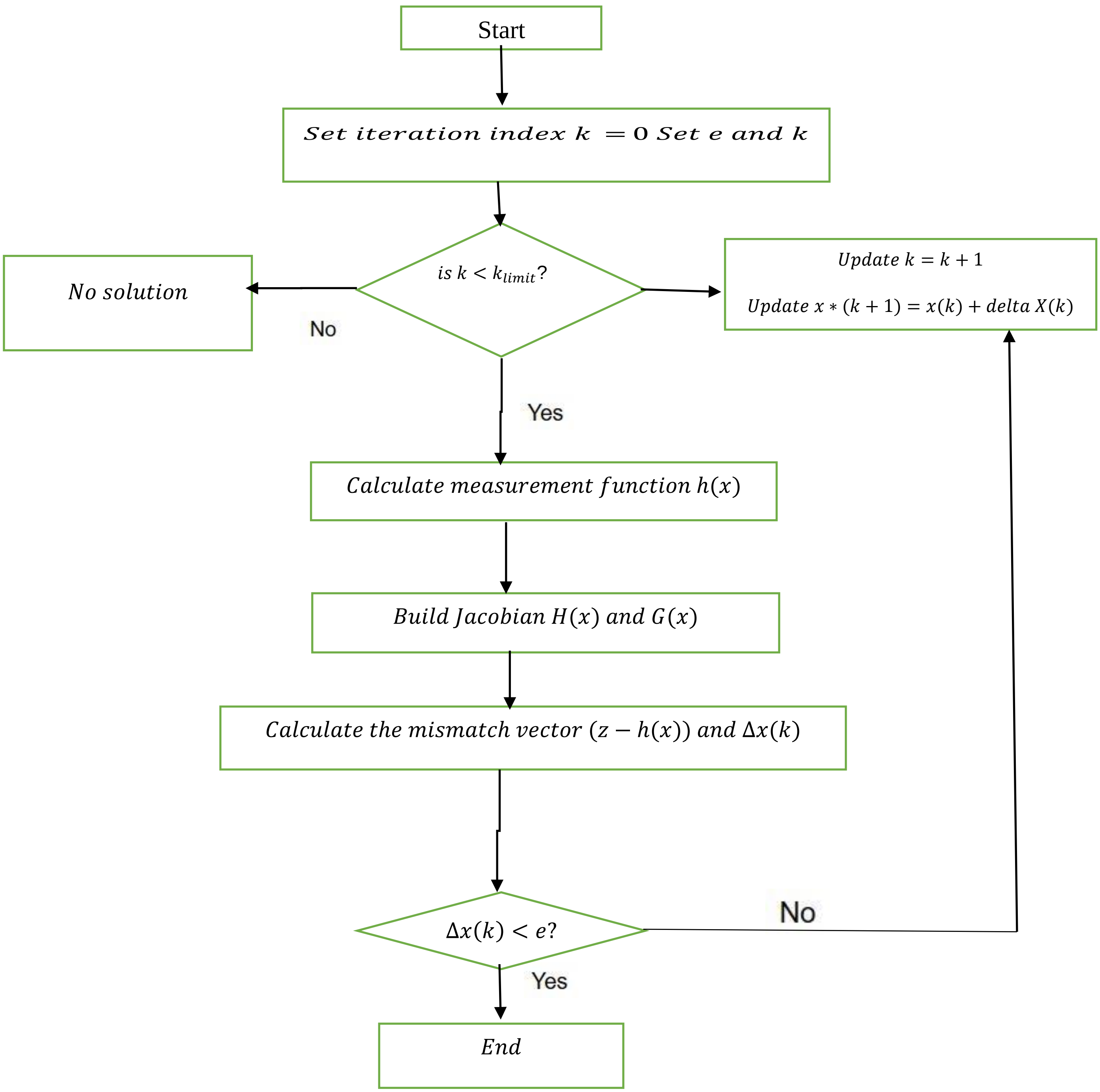

Fig 2.5 Flow chart for the WLS State estimation algorithm

The conductance and susceptance in the equations follows the notation of the two-port π- model. Similarly the real and reactive power flows between bus i and bus j are described as

$$P_{ij} = v_i^2(g_i + g_{ij}) - v_i v_j(g_{ij} \cos\theta_{ij} + b_{ij}\sin\theta_{ij}) \tag{2.18}$$

$$Q_{ij} = -v_i^2(b_i + b_{ij}) - v_i v_j(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}) \tag{2.19}$$

Additionally, the line current magnitude from bus i to bus j can be expressed as the following. S_{ij} is the complex power.

$$I_{ij} = \sqrt{(P_{ij}^2 + Q_{ij}^2)} \Big/ v_i = \frac{S_{ij}}{v_i} \tag{2.20}$$

2.6 Jacobian of Measurements

The measurement Jacobian is the derivative of the measurement function with respect to the state vector. The structure is seen in (2.21). The order of the rows and columns of the measurement function corresponds to the order of the measurement vector and the state vector respectively. Once constructed, the elements of the Jacobian matrix are non-linear functions of the state variable and are re-evaluated for each iteration of the estimation solution. The Jacobian measurement structure will be as follows [2].

$$[\mathrm{H}] = \begin{bmatrix} \frac{\partial |V|}{\partial \theta} & \frac{\partial |V|}{\partial v} \\ \frac{\partial P_i}{\partial \theta} & \frac{\partial P_i}{\partial v} \\ \frac{\partial Q_i}{\partial \theta} & \frac{\partial Q_i}{\partial v} \\ \frac{\partial P_f}{\partial \theta} & \frac{\partial P_f}{\partial v} \\ \frac{\partial Q_f}{\partial \theta} & \frac{\partial Q_f}{\partial v} \end{bmatrix} \tag{2.21}$$

The elements of the Jacobian matrix are computed as follows:

a) **Elements of Voltage magnitude measurements**.

Note that the voltage magnitude is not a function of voltage magnitude or angle at any bus besides its own

$$\frac{\partial v_i}{\partial v_i} = 1, \frac{\partial v_i}{\partial v_j} = 0, \frac{\partial v_i}{\partial \theta_i} = 0, \frac{\partial v_i}{\partial \theta_j} = 0 \qquad \text{(2.38, 2.39, 2.40, 2.4 respectively)}$$

b) Elements of Real power injection measurements.

$$\frac{\partial P_i}{\partial \theta_i} = \sum_{j=1}^{N} v_i\, v_j\left(-G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) - v_i^2 B_{ii} \qquad (2.22)$$

$$\frac{\partial P_j}{\partial \theta_j} = v_i v_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \qquad (2.23)$$

$$\frac{\partial P_i}{\partial v_i} = \sum_{j=1}^{N} v_j\left(G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) - v_i G_{ii} \qquad (2.24)$$

$$\frac{\partial P_i}{\partial v_j} = v_j\left(G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) \qquad (2.25)$$

c) Elements of Reactive power injection measurements

$$\frac{\partial Q_i}{\partial \theta_i} = \sum_{j=1}^{N} v_i\, v_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) - v_i^2 G_{ii} \qquad (2.26)$$

$$\frac{\partial Q_j}{\partial \theta_j} = -v_i v_j\left(G_{ij}\,\mathrm{Cos}\,\theta_{ij} + B_{ij}\,\mathrm{Sin}\,\theta_{ij}\right) \qquad (2.27)$$

$$\frac{\partial Q_i}{\partial v_i} = \sum_{j=1}^{N} v_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) - v_i^2 B_{ii} \quad (2.28)$$

$$\frac{\partial Q_i}{\partial \theta_j} = v_i\left(G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) \quad (2.29)$$

d) Elements of Real power flow measurements

$$\frac{\partial P_{ij}}{\partial \theta_i} = v_i v_j\left(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}\right) \quad (2.30)$$

$$\frac{\partial P_{ij}}{\partial \theta_j} = -v_i v_j\left(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}\right) \quad (2.31)$$

$$\frac{\partial P_{ij}}{\partial v_i} = -v_j\left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right) + 2(g_{ij} + g_i)v_i \quad (2.32)$$

$$\frac{\partial P_{ij}}{\partial v_j} = -v_j\left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right) \quad (2.33)$$

e) Elements of Reactive power flow measurements

$$\frac{\partial Q_{ij}}{\partial \theta_i} = -v_i v_j\left(g_{ij}\cos\theta_{ij} - b_{ij}\sin\theta_{ij}\right) \quad (2.34)$$

$$\frac{\partial Q_{ij}}{\partial \theta_j} = v_i v_j\left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right) \quad (2.35)$$

$$\frac{\partial Q_{ij}}{\partial v_i} = -v_j\left(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}\right) - 2(b_{ij} + b_i)v_i \quad (2.36)$$

$$\frac{\partial Q_{ij}}{\partial v_j} = -v_i\left(g_{ij}\sin\theta_{ij} + b_{ij}\cos\theta_{ij}\right) \quad (2.37)$$

The H matrix has rows at each measurement and columns at each variable. Most of the time, the H matrix contains more zero components and that’s why sparse matrix technique is used in constructing it. This chapter presented traditional state estimation techniques and the formulation of the weighted least squares solution of a non-linear state estimation algorithm. Regardless of its errors, WLS is the most widely used technique in electric utilities and has proven itself over several years. However, PMUs will provide a more accurate and time sensitive data, which helps in minimizing computational time in the state estimation technique therefore the inclusion of PMU data will provide additional advantage as we will see in the next chapter.

CHAPTER 3

PHASOR MEASUREMENT USAGE IN STATE ESTIMATION

Over the last decades, there have been several developments in traditional state estimation techniques; however, the fundamental concepts have not changed that much. The basic goal of state estimation is to estimate voltage magnitude and angle at each bus in the system based on the measurements and assumptions about the system. A state estimator requires ample measurements to find the best possible solution of an over-determined system of equations, whose best solution is given by minimizing mean square error. In the real world a linear system does not exist as almost everything is non-linear. The relationship between the voltages and the other electrical quantities is non-linear. The method that is commonly used to estimate the unknown variables in the power systems are iterative; we assume some initial values for the parameters that we are going to estimate.

As stated previously, in a maximum likelihood state estimation method, the PDF of measurements given parameters is required. Because we assume that noise measurements have Gaussian probability density function, the WLS method gives us the same result as the MLS. So, most of the time the traditional state estimators in power systems utilize the WLS approach, which converts the non-linear equations into the linear form by using first order Taylor's series expansion. Phasor technology, which measures the phase angle of a system, is evolving. With the growing use of this technology in substations, system operators have widely access to new types of measurements. The development of wide area monitoring system (WAMS) based on time-synchronized phasor measurement units (PMUs) has brought a new opportunity in estimating the state of a system. PMUs provide synchronized measurements of voltage phase angles to control system units. The signals from the satellite- based GPS system are used to synchronize PMUs.

The measurements obtained from PMU provide many advantages as compared to the Supervisory Control and Data Acquisition (SCADA) measurements. For example the measurements of voltage magnitude obtained from PMU are more accurate than the measurements from SCADA measurements and it has phase angle measurements that cannot

be obtained from RTUs. The other advantage of PMU is that its entire measurements can be synchronized and refreshed at every 20-50ms, which is much faster than the SCADA system.

We can say that PMUs are measuring the system state instead of indirectly estimating it. The idea is that the addition of synchronized phasor data as an input to a state estimator could improve the state estimation accuracy and reduce computational time. So, adding PMUs in a grid is a smart choice [6]. As we have seen in WLS, to obtain the required system state the estimator should execute many iterations and accordingly it needs more computational time. But in the case of PMU the state of system can be linearly expressed in terms of measurements which eliminate the need of iterative SE algorithms. However, such estimators do not use the existing traditional SCADA measurements, which reduce the measurement redundancy and are required to super pass the noise system. As mentioned in [7], a state estimator of multi-area for a wide system is working based on the assumption that only the boundary buses are affected from the neighboring utilities. The detailed information about the impact of internal buses on boundary buses will be explained in chapter 4. In [6], another method for state estimation that uses the phasor measurements in state estimation is suggested. In this method, phasor data is used in state estimation by keeping the traditional state estimator, because the cost to change the existing algorithm is expensive.

In the following sections we will see two methods of including phasor measurements into the traditional state estimator. The first technique is to mix the phasor measurements with the traditional measurements and solve as the same technique used in the traditional method. The second one is to use the phase measurements in the post-processing step of the traditional WLS state estimator.

3.1 Inclusion of PMU Data in Traditional State Estimation

When we employ PMUs in a power system, the measurement vector is augmented. Instead of containing only the voltage magnitude, power flows, and power injections provided by conventional measurements, it will also include the phase shifts and the real and reactive current flows throughout the system. The augmented measurement vector will take on the following form.

$$z = \left(P_{inj}^T \quad Q_{inj}^T \quad P_{flow}^T \quad Q_{flow}^T \quad V^T \quad \delta^T \quad C_{ij}^T \quad D_{ij}^T\right)^T$$

3.1.1 Integration of Phasor and Traditional measurements

The phasor measurements obtained from the available PMUs can be added to the existing SCADA measurements to increase the accuracy of the state estimation. The first method of adding these measurements to the state estimator comes from mixing real and reactive power flows of the traditional measurements, injections, and voltage and current magnitudes with complex voltage and current phasors. The next step is to follow the mentioned traditional state estimation method

PMU can measure not only the voltage phasor, but also the current phasors. It provides the following phasor measurements and their magnitudes.

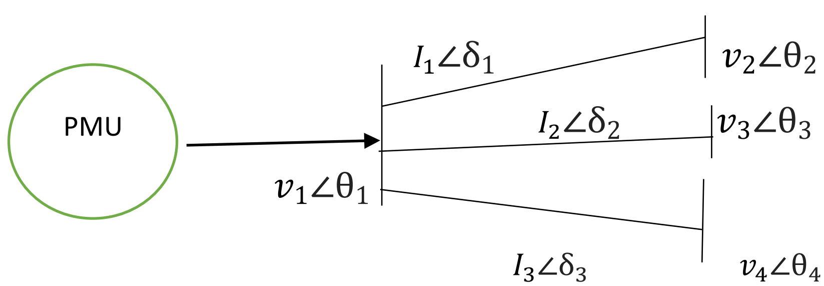

Fig 3.1 Simple PMU measurement model

The same way as we did in Section 2.6, the total Jacobian H can be computed, but now the measurement z will have voltage magnitude, power injections, power flows, phase angle, real line current and reactive line current measurements. PMUs have small variances compared to the Remote Terminal Units (RTUs) and hence have better accuracy. Let's assume there are two vector measurements vectors z_1 and z_2

$$[z_1] = \begin{bmatrix} z_{11} \\ z_{12} \\ z_{13} \\ \vdots \\ z_{1m} \end{bmatrix} \qquad [z_2] = \begin{bmatrix} z_{21} \\ z_{22} \\ z_{23} \\ \vdots \\ z_{2n} \end{bmatrix} \tag{3.1}$$

Where,

z_1= Traditional Measurement and

z_2= Phasor Measurements (Rectangular form)

S

We put these measurement vectors in one vector.

$$[z] = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} z_1 \\ v_{real} \\ v_{imag} \\ I_{real} \\ I_{imag} \end{bmatrix} \tag{3.2}$$

As we have seen in chapter two, the equality of optimization of the measurements becomes

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} h_1(x) \\ h_2(x) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \end{bmatrix} \tag{3.3}$$

Where,

$h_2(x) =$ A polar form vector of the non-linear function to the obtained phasor measurement . The measurements error covariance matrix will be

$$[R] = \begin{bmatrix} R_1 & 0 \\ 0 & R_2' \end{bmatrix} \tag{3.4}$$

Where,

$R_1 =$ Traditional measurements error covariance

$R_2' =$ Phasor measurements error covariance

The state vector is in polar form, and Jacobian matrix measurement will be

$$[H_1(x)] = \begin{bmatrix} H_1(x) \\ H_2(x) \end{bmatrix} = \begin{bmatrix} \frac{\partial h_1(x)}{\partial x} \\ \frac{\partial h_2(x)}{\partial x} \end{bmatrix} \tag{3.5}$$

Then the weighted square solution is formulated

$$[x^{k+1}] = [x^k + [G(x^k)][H_1^T R_1^{-1}][z_1 - h_1(x^k)] + [G(x^k)][H_2^T R_2'^{-1}][z_1 - h_2(x^k)]] \tag{3.6}$$

$$G(x^k) = [H_1^T(x^k) R_1^{-1} H_1(x^k) + H_2^T R_2'^{-1} H_2(x^k)]^2$$

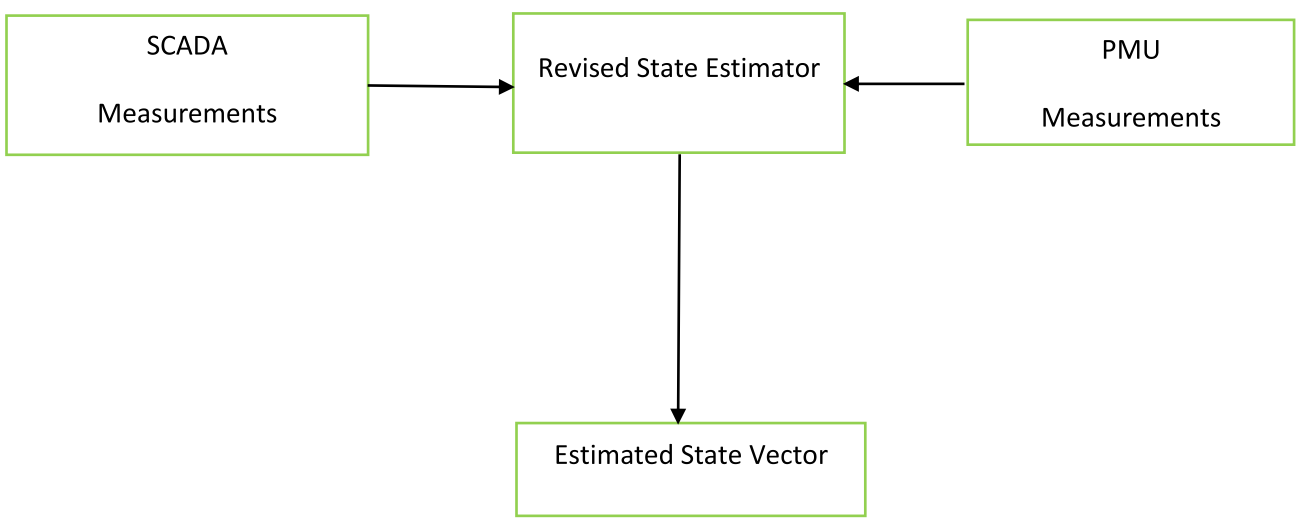

Fig 3.2 Block diagram of Non-Linear Iterative Method

The equations describing the rectangular components of the complex current flowing through the branch can be derived as:

$$C_{ij} = |V_i Y_{sj}| \cos(\delta_i + \theta_{si}) + |V_j Y_{ij}| \cos(\delta_j + \theta_{ij}) - |V_i V_{ij}| \cos(\delta_i + \theta_{ij})$$

$$D_{ij} = |V_i Y_{sj}| \sin(\delta_i + \theta_{si}) + |V_j Y_{ij}| \sin(\delta_j + \theta_{ij}) - |V_i V_{ij}| \sin(\delta_i + \theta_{ij})$$

When the Jacobian H matrix is formed, the following derivatives of C_{ij} and D_{ij} are used.

$$\frac{\partial C_{ij}}{\partial V_i} = |Y_{si}| \cos(\delta_i + \theta_{si}) - |Y_{ij}|\cos(\delta_i + \theta_{ij})$$

$$\frac{\partial C_{ij}}{\partial V_j} = \left|Y_{ij}\right| \cos\left(\delta_j + \theta_{ij}\right)$$

$$\frac{\partial C_{ij}}{\partial \delta_i} = -|V_i Y_{si}| \sin(\delta_i + \theta_{si}) + \left|V_i V_{ij}\right| \sin(\delta_i + \theta_{ij})$$

$$\frac{\partial C_{ij}}{\partial \delta_j} = \left|V_j Y_{ij}\right| \cos\left(\delta_j + \theta_{ij}\right)$$

$$\frac{\partial D_{ij}}{\partial V_i} = |Y_{si}| \sin\,(\delta_i + \theta_{si}) - |Y_{ij}|\sin(\delta_i + \theta_{ij})$$

$$\frac{\partial D_{ij}}{\partial V_j} = \left|Y_{ij}\right| \sin\,\left(\delta_j + \theta_{ij}\right)$$

$$\frac{\partial D_{ij}}{\partial \delta_i} = -|V_i Y_{si}| \sin(\delta_i + \theta_{si}) - \left|V_i V_{ij}\right| \sin(\delta_i + \theta_{ij})$$

$$\frac{\partial D_{ij}}{\partial \delta_j} = \left|V_j Y_{ij}\right| \cos\left(\delta_j + \theta_{ij}\right)$$

The SCADA measurements, PMU measurements, and Jacobian matrix are available, so the computation is the same as the traditional state estimation. Integrating phasor measurements into the existing state estimator techniques can result to some challenges. These challenges are because of the need to change the existing code, if integration of phasor measurement and the traditional measurements are required [17]. However, an alternate method of combining phasor measurements to the application of state estimation will be discussed below.

3.1.2 Inclusion of Phasor measurements into Post processing Technique

The technique that will be discussed is provided in [6] and does not change the traditional state estimation algorithm. The phasor measurements are not directly applied in the process of state estimation; instead, they are added in the linear post-processing step. Usually the traditional state estimation techniques follow steps to convert the non-linear functions into linear functions. In this scenario the first thing that the system should determine is to calculate the state of the system via traditional state estimator and then to mix it with the phasor measurements to improve the accuracy of the state estimation and the conversion of associated covariance matrix to rectangular coordinates is required.

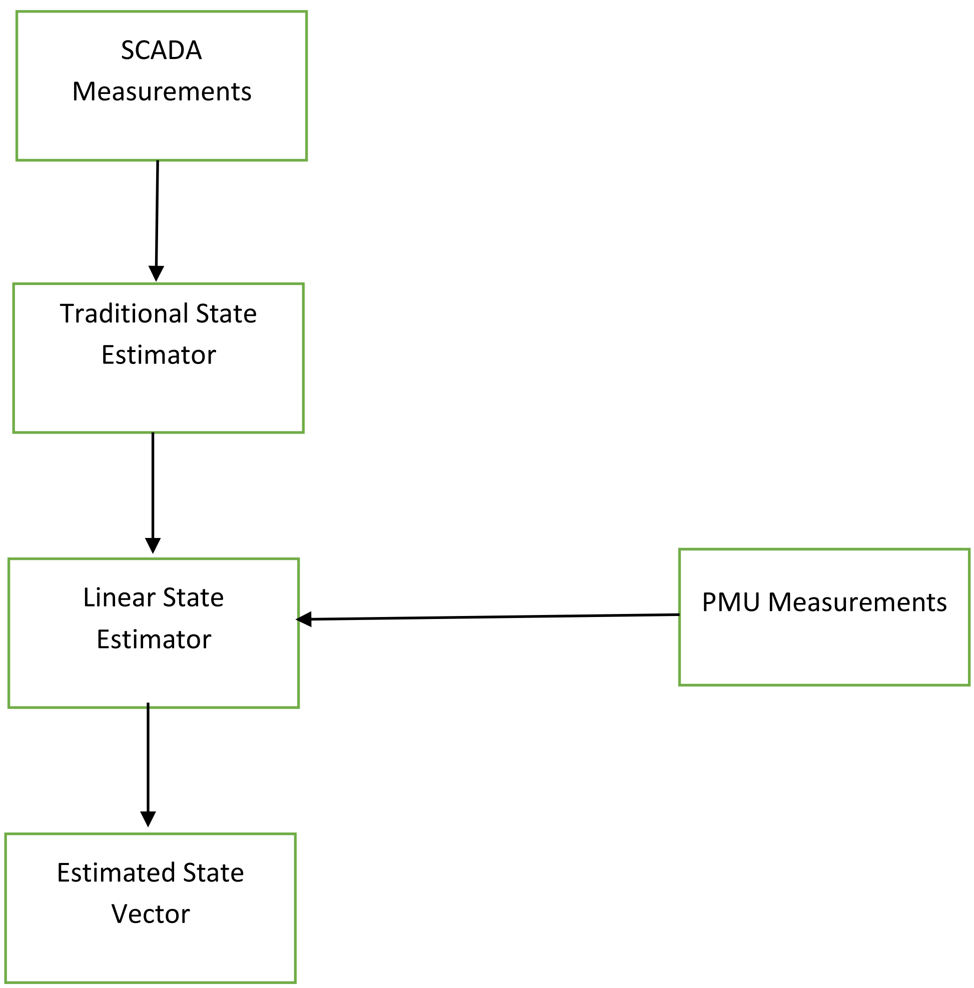

Fig 3.3 Post-Processing Linear Method

The following equation shows the formula:

$$cov([x])rec = [R'][cov([x])][W']^T = [R_1'] \quad (3.7)$$

Where, W=Rotation matrix.

Then the relationship of the calculated system state and the available phasor measurements should be as follows.

$$\begin{bmatrix} V'_{real} \\ V'_{imag} \\ V_{real} \\ V_{imag} \\ I_{real} \\ I_{imag} \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \\ I' & 0 \\ 0 & I' \\ C_1 & C_2 \\ C_{23} & C_4 \end{bmatrix} \begin{bmatrix} v_{real} \\ v_{imag} \end{bmatrix} = [A] \begin{bmatrix} V_{real} \\ V_{imag} \end{bmatrix} \quad (3.8)$$

In the above relationship, the identity matrix with a superscript is used to represent states without measurements and at the lower part of the relationship or measurement function there are system parameters that create a linear relationship of the system state to the line current phasor measurements in the measurement vector. The covariance matrix for both measurements is given below.

$$[R] = \begin{bmatrix} R_1' & 0 \\ 0 & R_2' \end{bmatrix} \quad (3.9)$$

Then the solution is

$$[x'] = [A^T R^{-1} A]^{-1} [R^{-1} A][z^1] \quad (3.10)$$

From the aforementioned techniques we can observe that PMU technology provides accurate and time-sensitive information for measurement collection. Therefore, the inclusion of PMU data in state estimation is advancement over the traditional state estimation. The following section will present a linear formulation of the state estimation problem using PMUs.

3.2 PMU DATA IN LINEARIZING STATE ESTIMATION

As it was discussed in the previous section, PMU measurements could be added in two different ways, which the addition of phasor measurements by a slightly different formulation of the traditional non-linear weighted least squares or the addition of the measurements after a preliminary system state has already been determined [6]. Even though it is not easy to implement PMUs in every substation due to different reasons, still a small number of these precise measurements can affect strongly the accuracy of the overall state of the system [4]. However, a true application of PMU technology to state estimation would include all the traditional measurements of real and reactive power injections and current and voltage magnitudes replaced by bus voltage phasors and line current phasors in the future.

Acceptance of the PMU technology by all utilities and their implementation in desired substations will force the state estimator to function with only PMU measurements. This avoids the problem that existed with traditional state estimator. Synchronization of PMUs with GPS has alleviated the problem of sending time. Once the shortening of sending time has been achieved, the only concern is the issue of time in the communication and computational delay between the collection of the measurements and the employment of useful information for decision-making by the operation and control applications.

The simple two-port π-model is used to figure out the difference between the measurements used in a traditional state estimator and the measurements used in a linear state estimator. In [4] the formulation of linear state estimation is shown clearly. The state variable of the system will be the voltage magnitude and angle at each end of the transmission line. Assuming a PMU at each end of a transmission line, all the measurements will be voltage phasors; however, because of the capacitance of the transmission lines the line current on each side of a single line will not be the same.

Consider the π-equivalent of a transmission line shown in the Fig 3.3 below. In this case consider all values rectangular [8].

This is what gives the state equation its linear property. The system state is then the following complex vector.

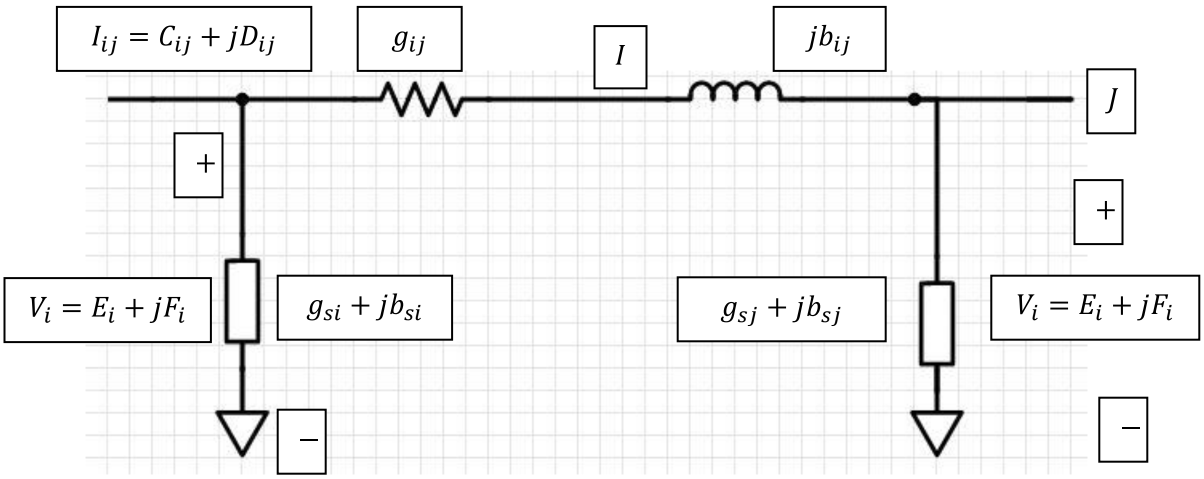

Fig 3.4 Two-Port π-Model of a Transmission Line

$$[\mathrm{X}] = \begin{bmatrix} \mathrm{V_i} \\ \mathrm{V_j} \end{bmatrix} \tag{3.11}$$

In the Fig 3.5 $(g_{ij} + b_{ij})$ is the series admittance of the line, and $(g_{si} + jb_{si})$ is the shunt admittance of the line and I_{ij} is line current flow. The measurement vector will be:

$$[z] = \begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} \tag{3.12}$$

From this measurement vector the system state and voltage measurement can clearly be related identically. However, the relationship between the system state and the line flows requires some work that is, first several quantities must be defined. Even though they will not be explained in detail, the series admittance and shunt susceptance of the transmission line are shown below.

$$y_{ij} = (g_{ij} + jb_{ij})^{-1} \tag{3.12}$$

$$y_{i0} = (g_{sj} + jb_{sj}) \tag{3.13}$$

$$y_{j0} = (g_{sj} + jb_{si}) \tag{3.14}$$

Sparing the derivation using Kirchoff's laws, the relationship of line current and system state is

$$\begin{bmatrix} I_{ij} \\ I_{ji} \end{bmatrix} = \begin{bmatrix} y_{ij} + y_{io} & -y_{ij} \\ -y_{ij} & y_{ij} + y_{io} \end{bmatrix} \begin{bmatrix} V_i \\ V_j \end{bmatrix} \tag{3.15}$$

$$I_{ij} = [(V_i - V_j)(g_{ii} + jb_{ij}) + V_i(g_{si} + jb_{sj})\ ]$$

And the complex State Equation is

$$\begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ y_{ij} + y_{i0} & -y_{ij} \\ -y_{ij} & y_{ij} + y_{i0} \end{bmatrix} \begin{bmatrix} V_i \\ V_j \end{bmatrix} \tag{3.16}$$

CHAPTER 4

DISTRIBUTED STATE ESTIMATION WITH PHASOR MEASUREMENT UNIT

4.1 Introduction

As the electrical power networks of the world continue to grow ever larger, there has been an increasing demand for a highly robust, computationally efficient state estimation algorithm. Initially, this goal was pursued by taking advantage of the innately sparse structure of the state estimation matrices. New algorithms were developed to deal with large, sparse matrices and the state estimators kept pace with the power grids for a time. Unfortunately, the gains provided by sparse matrix manipulation were limited, and eventually the size of the power networks required a new advance in state estimation algorithms.

This new advance came in the form of parallel processing. Instead of being limited to a single serial processor, the parallel state estimators break the large system down into smaller sub-systems which are solved simultaneously on multiple processors. The state estimation results from these individual areas are then sent to a second coordinating processor where they are combined into a single solution for the entire system.

4.2 Distributed State Estimation Algorithm and scheme

In any individual area in Distributed state estimation, there are three types of busses: internal, boundary, and external. Bus n of area i is considered to be internal if all of its neighboring busses also belong to area i .Bus n of area i is a boundary bus if at least one of its neighbors belongs to an area other than i. Finally, bus n will be an external bus of area i if it belongs to another area but has at least one connection to a boundary bus in area i . Any line running between two boundary busses of different areas, thus connecting the two areas, is known as a tie line. These four items are illustrated in the Figure 3 with busses 21, 22, and 23 being internal, boundary, and external busses to Area 1. There is a tie line running between busses 22 and 23 and another between 32 and 113.

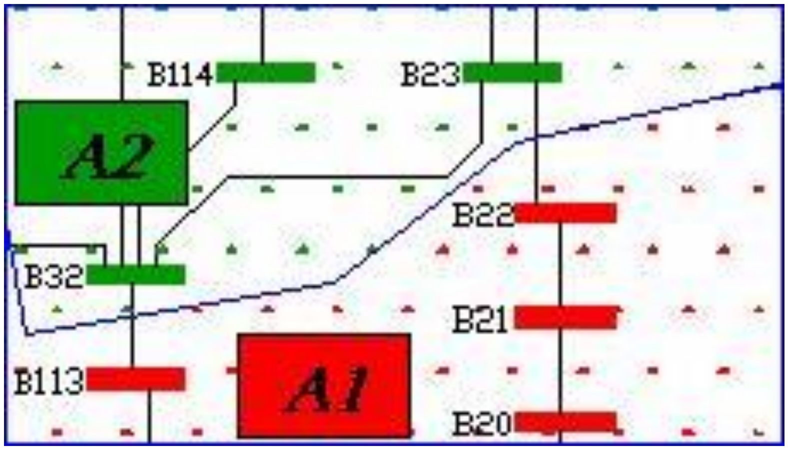

Fig 4.1 Distributed Multi-Area Bus Types

Since its inception, there have been many specific algorithms developed to carry out this parallel state estimation, some of the more successful ones have been detailed in [8]-[13]. In most cases, the first level state estimation is identical. The large system is broke down into smaller, more manageable areas and the standard state estimation algorithm is applied, as was shown in Chapter II. There is a great deal of confusion though about what to do from that point. Most of this confusion concerns what to do with the boundary measurements. Some algorithms insert a non-existent bus in between the boundary busses on tie lines [14]. Other methods based on the work in [15] break the system down into non-overlapping systems and then apply the model coordination method to come to a solution. More recently though, the work done in [4] and [16] has developed the algorithm which will be used in this thesis.

In [16] the author first decomposes the system into a group of overlapping subsystems. This is accomplished by including the boundary busses and external busses in both areas which they are associated with. Once the first stage of state estimation is complete, the state vectors for each area are organized in the following manner.

$$x_i = [x_i^{b^T} \quad x_i^{int^T} \quad x_i^{ext^T}]$$

For each area i, the components of the state vector x_i are organized by bus type. In the equation above, $x_i^{b^T}$ is the state vector composed of the voltage magnitude and phase angles at the boundary busses, $x_i^{int^T}$ is the state vector composed of the voltage magnitude and phase angles at the internal busses, and $x_i^{ext^T}$ is the state vector composed of the voltage magnitude and phase angles at the external busses. In each area, the phase angle of the slack bus will be removed from the appropriate vector

Once this first stage is complete, the estimation coordination must begin. The coordinating estimator is not only responsible for the coordinating of the individual area results, but must also carry out bad data detection and correction for the boundary measurements. The states used in this coordinating estimator include not only the states computed for each individual area, but also include the synchronized voltage phasors for the slack bus in each area. This state vector is defined in the following manner.

$$x_s = [x^{b^T} \quad u^T]^T$$

$$x^{b^T} = [x_1^{b^T} \quad x_2^{b^T} \quad \cdots \quad x_n^{b^T}]^T$$

$$u^T = [u_2 \quad u_3 \quad \cdots \quad u_n]^T$$

The voltage angle of the slack bus in each area measured with respect to the voltage angle of the slack bus in the first area is listed as u_i. The global reference bus among the individual area slack busses was chosen at random to be the slack bus in the first area, and could easily be any of the slack busses in the system. In this case, the u^T vector would start with u_1 and exclude the appropriate entry containing the slack reference bus.

At the second level of state estimation, the coordinating estimator will utilize a measurement vector with the following composition.

$$z = [z_u^T \quad z_{sp}^T \quad \overline{x}^{b^T} \quad \overline{x}^{ext^T}]^T$$

In the above measurement vector, z_u^T is the vector of boundary measurements, z_{sp}^T is the vector of synchronized phasor measurements, and $\overline{x}^{br}$ and $\overline{x}^{est}$ are the vectors of boundary and external state variables as estimated by the individual areas. This vector of states will then be treated as pseudo-measurements by the coordinating estimator .This leads us to the measurement model which will be used by the second level state estimator shown below.

$$z_s = h_s(x_s) + e_s$$

The covariance of these estimated measurements are obtained from the covariance matrix of the area from which they come. This covariance matrix is actually the inverse of the gain matrix of the area, as shown below.

$$cov(\overline{x}) = cov((H^T R^{-1} H^T)^{-1} H^T R^{-1} z))$$

$$cov(\overline{x}) = cov(G^{-1} H^T R^{-1} z)$$

$$cov(\overline{x}) = G^{-1} H^T R^{-1} cov(z) (G^{-1} H^T R^{-1})^T$$

$$cov(\overline{x}) = (G^{-1} H^T R^{-1}) R ((H^T R^{-1} H) H^T R^{-1})^{-1})^T$$

$$cov(\overline{x}) = (G^{-1} H^T R^{-1}) R \big((H^T R^{-1})^T ((H^T R^{-1} H)^{-1})\big)^T$$

$$cov(\overline{x}) = (G^{-1} H^T R^{-1}) R R^{-1} H H^{-1} R (H^T)^{-1}$$

$$Cov(\overline{x}) = G^{-1} H^T R^{-1} R (H^T)^{-1}$$

$$cov(\overline{x}) = G^{-1}$$

Once the coordinating estimator has reached a WLS solution for the entire area, residual testing may then take place, and any faulty measurements will be normalized. While this is an excellent procedure since it does not require the sharing of data between the areas, it can be improved upon still.

In [4], the author points out that the above technique simply uses the PMUs to measure the synchronized voltage angles among the areas and suggests the following. PMUs have the ability to measure the real and reactive current phasors. In fact, a single PMU may measure a bus voltage phasor and multiple current phasors simultaneously. As the measurements taken from PMUs have smaller variance than conventional measurements, the estimated state would benefit from the inclusion of these additional PMU current measurements.

The first level of state estimation with PMUs would follow the algorithm outlined in Chapter II. Once the states of the individual areas have been estimated though, the second level algorithm needs to be changed in order to accommodate the additional measurements provided by the PMUs. The new measurement vector of the second level state estimator will be of the following form.

$$z_s = [Z_u^T \quad z_{pmu}^T \quad \overline{x}^{b^T} \quad \overline{x}^{est^T}]^T$$

$$z_{pmu} = [z_{|v|}^T \quad Z_\theta^T \quad z_C^T \quad z_D^T]^T$$

$$z_s = [z_u^T \quad z_{|v|}^T \quad z_\theta^T \quad z_C^T \quad z_D^T \quad \overline{x}^{b^T} \quad \overline{x}^{ext^T}]^T$$

Above, Z_{pmu} is the measurement vector from a PMU. The overall measurement vector, z_s ,will contain twelve different types of measurements, four from conventional measurements, four from PMU measurements, and four pseudo- measurements from the first level of estimation. These twelve measurement types are detailed below

At this coordination level, the state vector contains the states from the boundary busses, as well as the states from the busses supporting a PMU and its neighboring busses.

$$x_s = [x^{b^T} \quad x_{pmu}^T]^T$$

Including this additional information does indeed increase the performance of the state estimator as shown in [4].

At this coordination level, the state vector contains the states from the boundary busses, as well as the states from the busses supporting a PMU and its neighboring busses.

$$x_s = [x^{b^T} \quad x_{pmu}^T]^T$$

Including this additional information does indeed increase the performance of the state estimator as shown in [4].

This chapter has laid out the basic theory behind multi-area state estimation, including the terminology, measurement types and measurement vector composition. In the following chapter, this algorithm will be tested and verified on the IEEE 118 bus test system. Its results shall not only be checked for accuracy with a standard state estimator, but its ability to detect bad data will also be put to the test.

4.3 Results

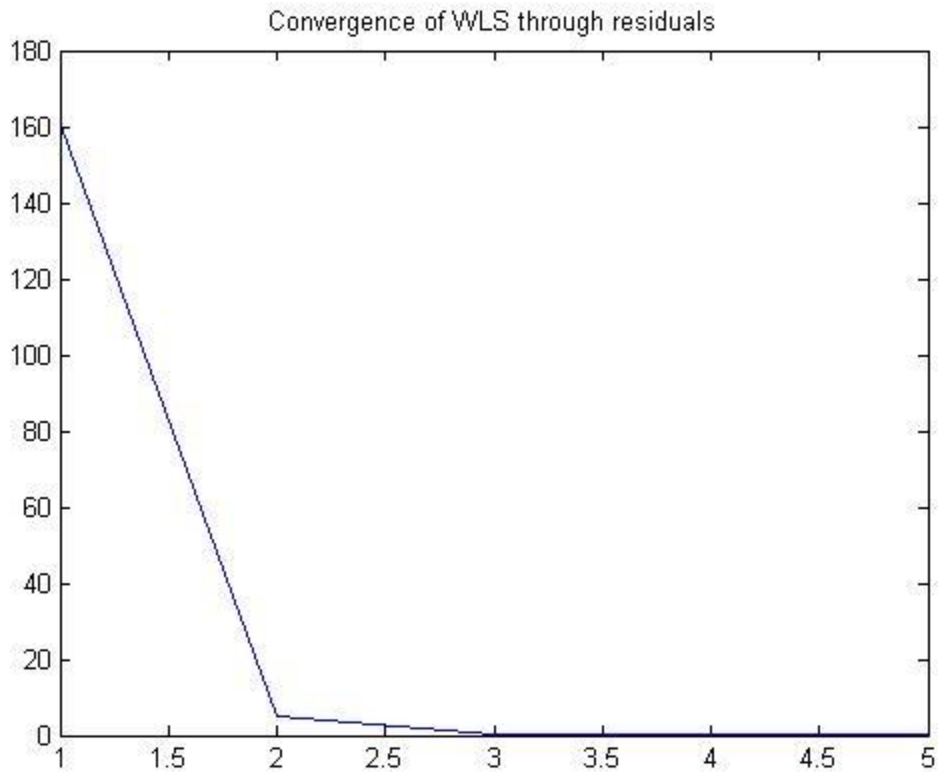

Fig 4.2 Plot of residuals vs iterations for IEEE-118 bus system using WLS Preprocessing

The residuals rapidly fall to zero with increasing iterations showing that the WLS estimator is working efficiently.

X-axis represents : Iteration cycle

Y-axis represents : $|V|^2$

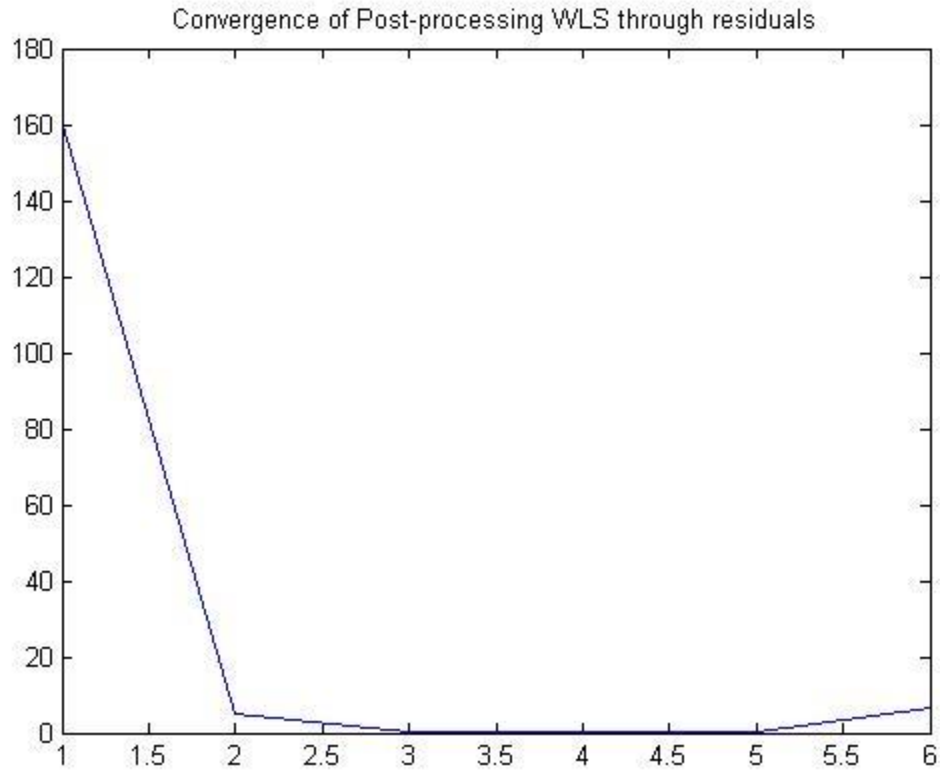

Fig 4.3 Plot of residuals vs iterations for IEEE-118 bus system using WLS Postprocessing

Preprocessing Algorithm converges the state estimate faster than post processing

X axis represents : Iteration cycle

Y axis represents : $|V|^2$

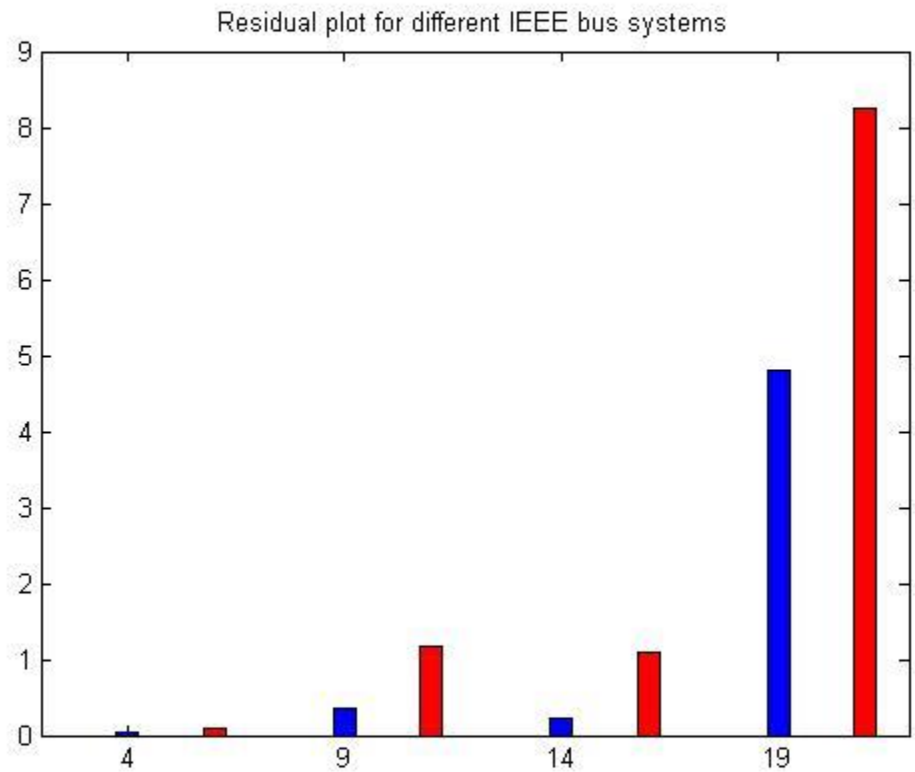

Fig 4.4 Plot of un-normalized residuals after one iteration cycle for Preprocessing and Post processing for IEEE 5, 14, 30 and 118 systems

Using PMU data in state estimation improves the accuracy of the estimation in fewer iteration cycles saving computational power and time.

Data : 4 - IEEE 5 Bus System
9 – IEEE 14 Bus System
14 – IEEE 30 Bus System
19 – IEEE 118 Bus System

Legend: Blue - Pre-processing
Red – Post-processing

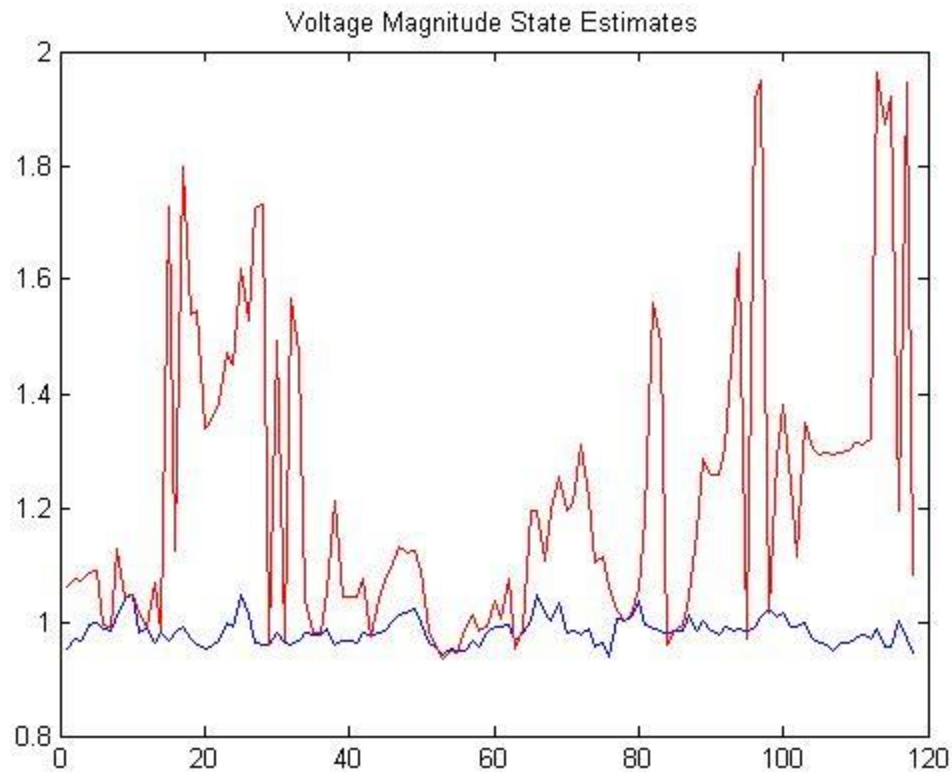

Fig 4.5 State Estimate for IEEE118 bus system after one iteration cycle

a) Distributed State Estimator- RED

b) Traditional WLS algorithm- BLUE

X axis represents: Bus number

Y axis represents: Voltage magnitude (V)

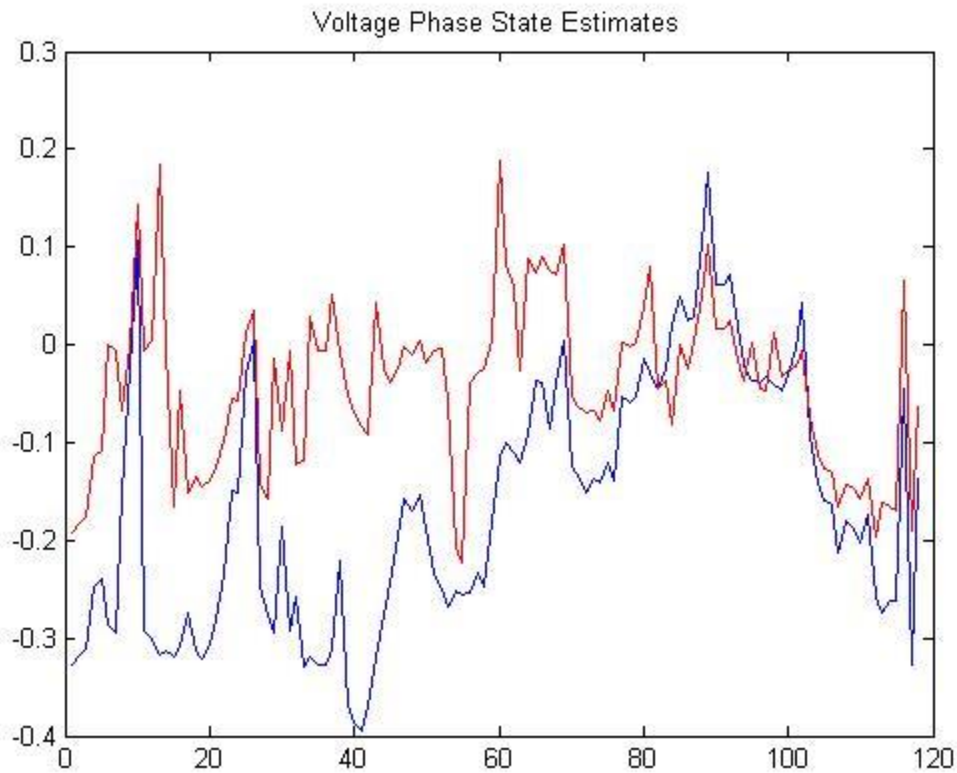

Fig 4.6 State Estimate for IEEE118 bus system after one iteration cycle

a) Distributed State Estimator- RED

b) Traditional WLS algorithm- BLUE

The distributed state estimator provides a state estimate which converges with the WLS estimate as expected in very few iteration cycles.

X axis represents: Bus number

Y axis represents: Volage Phase (radians)

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This report presents traditional state estimation techniques with and without PMUs and DSE algorithm utilizing synchronized phasor measurements. The goal was to discuss a technique that is replacing the centralized state estimation using a decentralized one to enhance the SE computation time and to get accurate data of the power system and finally to have a better system snapshot. The contribution of this research was just to discuss different techniques of SE and to determine the best possible technique. It includes the formulation of the distributed SE approach, development of an algorithm to locate PMUs, determination of the slack bus in each subsystem to coordinate the distributed SE solution, and the application of sensitivity analysis to determine the aggregation level SE measurement set to obtain an aggregated SE solution [50]. The tests were done on the IEEE 118 test case. The results obtained on the IEEE 118 bus test system demonstrate the efficacy of the proposed approach in significantly reducing the computational time and highlight the potential of the proposed approach in obtaining SE solutions for large interconnected areas. The results also show that the SE solution obtained by the proposed approach have the same accuracy as the integrated SE solution as demonstrated by the relative errors in the voltage magnitude and phase angle solutions obtained and the values of the performance index at the solution. Therefore, if the wide area network is decomposed to subsystems and if the optimal PMU placement is done properly based on the available algorithms a system snapshot could be available in almost real time and the system operators could monitor and control their system properly.

From this research project I have gained a valuable knowledge about state estimation and its importance in power system and the draw backs of the centralized state estimation due the increase in size of power system and the coming of new technologies. Most of the

blackouts could have been minimized if there was enough information exchange between the system operators; the main reason for that was the lack of real time information sharing among the utilities. Deregulation made the power system a more privately concerned system. The reason for that is the market situation. The customers got a chance to buy electricity from different utilities and this makes the utilities hide information from neighboring utilities. Even though there is development in technology such as implementation of PMU in power system the centralized type of state estimation needs to be replaced by distributed state estimation and in this section I learned a lot in how to use DSE. Distributed state estimation is used to estimate a state of a power system by sections. For example, an IEEE 118 bus system was assumed to decompose into three sub systems. The three sub systems estimate their value based on their own state estimator and the PMU is installed on the slack bus to coordinate the DSE solution from each system. From the results, when the DSE is used in the sub systems it is better than when it is used for the whole system.

Another thing I found is that, DSE can be applied to optimize the renewable energy. PMUs are intelligent electronic device which enable to provide real time data from the field into the control centers, so when DSE with the help of PMU is applied to different energy source the capability to monitor and control the systems is more effective. Say for example there is an integrated system of renewable energy, such as wind, solar as well as storage devices and the grid. If we use phasor measurement units to monitor and control the operation of the system, we have the privilege to control on a real time basis. If there is a fault in the wind farm or source we can avoid it by shedding a load or adding an additional generator to meet the available consumption. The other main point I have taken away is, the importance of smart grid. Our system is changing from time to time and currently researchers, utilities, governments and customers are more concerned about the importance of smart grid. The goal of smart grid is to make the power system operation more robust and to minimize or avoid faults from cascading. So the DSE with the help of PMU is one of the best options. The cost of phasor measurement units and other sensors and their cost of installation are very expensive, that is why ideas for implementing the PMUs phase by phase are valuable. When PMUs are installed to all the buses to monitor the wide area network, there will be no need

for state estimation except for the information required to identify the bad data in the system. Therefore the application of PMU is one of the greatest applications in power system especially in state estimation and it will play a great role in smart grid operation.

5.2 Future Scope

While this thesis was successful in verifying the accuracy of the multi-area state estimator, it was unable to see any time savings due to the implementation of said estimator. It has been said many times throughout this thesis that the shortened computation time was the impetus for the development of multi-area state estimation, and as such, this deserves further study. The next logical step would be to increase the size of the system and look for the promised reduction in computation time.

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