INCORPORATION OF PMUS IN POWER SYSTEM STATE ESTIMATION

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ABSTRACT

INCORPORATION OF PMUS IN POWER SYSTEM STATE ESTIMATION

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This dissertation describes new methods to efficiently incorporate PMUs in power system state estimation, which plays a key role in effective operation of power markets and enabling real-time security assessment of power systems.

The dissertation describes new observability and criticality analysis methods for power systems measured by both SCADA and PMU measurements. Prior to state estimation observability analysis needs to be performed to check if the system is observable with respect to the given measurement set, i.e. if the state estimation problem has a unique solution. Moreover, it is important to identify the critical measurements, whose removal causes unobservability. It should be noted that conventional observability and criticality analysis methods cannot be applied if there are PMUs in the system.

The dissertation then introduces an observability restoration method for unobservable power systems by optimally placing pseudo-measurements, such that they all will be strictly critical.

Another issue that is addressed by this dissertation is estimator's robustness. A Least Absolute Value (LAV) estimator is proposed and described for this purpose. It exploits

the fact that given sufficient number of PMUs to make the system observable, the state estimation problem becomes linear. It is shown that an LAV based estimator not only provides robustness but becomes computationally competitive with the existing WLS based estimators. Robustness of LAV estimator requires a certain level of measurement redundancy, which is achieved by an optimal PMU placement strategy developed in this work.

Next, a hybrid state estimator, which can utilize both SCADA and PMU measurements, is developed. Given the different refresh rates of SCADA and PMU measurements, the hybrid estimator switches between WLS and LAV estimators If only PMU measurements are updated, the LAV estimator provides best updates for the state estimates, while the WLS estimator is used when full set of PMU and SCADA measurements are updated.

Finally, a novel formulation of three-phase state estimation problem using modal decomposition is described. This is valid for general unbalanced system operation where there exists sufficient number of PMUs to make the three-phase system observable.

To Ebru

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CHAPTER 1

INTRODUCTION

Phasor Measurement Units (PMUs), which were introduced in 1988 by Phadke and Thorp at Virginia Polytechnic Institute and State University [1], provide voltage and current phasor measurements. These phasors are defined with respect to a reference signal obtained via the Global Positioning Satellite (GPS) System, which enables measurement synchronization for PMU measurements all around the world. Currently available PMUs can measure voltage and current phasors as fast as 30 times a second [1].

Widespread deployment of PMUs has been triggered by the Northeast Blackout of 2003. After the blackout, the U.S.-Canada Power System Outage Task Force released the final report in February 2004, which recommended the use of PMUs to provide real-time wide-area grid visibility [2]. Later, the U.S. Department of Energy sponsored multiple well-funded projects to deploy PMUs in power systems [3]. As a result, the number of PMUs installed in U.S. power grid has rapidly increased, such that while there were 166 installed PMUs in 2010, this number increased to 1126 in 2013 [3].

The work reported in this dissertation is primarily motivated by this rapid increase in installed PMUs. It proposes methods for incorporation of PMUs in power system state estimation, which is one of the crucial application functions of modern Energy Management Systems (EMS).

Power system state estimation, which was introduced and formulated by Schweppe in 1970 [4]-[6], determines the best estimates of voltage magnitudes and phase angles for all system buses, which are referred as system states. A state estimator uses all available measurements in the system in estimating the system state. These measurements have traditionally been the voltage magnitude, power injection and power flow measurements, which will be referred as conventional or SCADA (Supervisory Control And Data Acquisition) measurements throughout the dissertation.

State estimation plays a key role in secure operation of power systems. Using the state estimation solution operators can determine if the current operating state of the system belongs to a normal, emergency or restorative state. State estimators also provide accurate and efficient monitoring of operational constraints on quantities such as transmission line loadings and bus voltages [7].

This dissertation introduces new methods to incorporate PMUs in power system state estimation. These methods are designed not only for today's power systems, which are measured by both SCADA and PMU measurement, but also future systems, which will only include synchro-phasor measurements.

In order to perform state estimation, the considered system must be observable. A network is said to be observable, if for a given set of measurements and network topology, the entire system state vector can be uniquely calculated [7]. Therefore, one must perform network observability analysis, to check if the system is observable, before estimating the states. If the considered system is found to be unobservable, observable islands of the system should be identified as well.

Measurement criticality is also related to the measurement set and system topology as network observability. A critical measurement is a measurement that will make the system unobservable if it is removed from the measurement set [7], which creates vulnerability for state estimation process.

Conventional observability and criticality analysis methods are designed for physically connected power systems measured by conventional measurements [8]-[15], and cannot be readily applied to systems, whose measurement sets include phasor measurements. In an attempt to develop a general method that will work in all possible situations without making any assumptions, Chapter 2 develops methods for observability and criticality analyses for power systems measured by not only conventional measurements, but also PMUs. Furthermore, voltage magnitude measurements, which are commonly neglected in conventional observability and criticality analysis methods, are also taken into account.

Observability and measurement criticality analyses of the systems measured by PMUs have been studied recently [16]-[20]. Those studies developed methods for specific types of PMU configurations, rather than a general method applicable to all possibilities. Moreover criticality analysis and effect of voltage magnitude measurements were skipped in those studies. A more detailed literature review will be given in Chapter 2.

Power system state estimation can be performed only if the system is observable. If the system is found to be unobservable, the synchronized solution for all of the buses cannot be found. To restore observability, one can place pseudo-measurements to the system, which are statistics such as short-term load forecasts, scheduled generation dispatch, historical records, etc. [7].

Chapter 3 will present a method for pseudo-measurement placement to restore network observability by merging existing observable islands. Since pseudo-measurements are only approximations, using them in a redundant fashion will introduce unwanted errors, which will bias the estimated states. To avoid biased estimates, minimum number of pseudo-measurements will be placed, such that all of pseudo-measurements will be critical.

To restore observability, several pseudo-measurement placement methods have been proposed so far [21]-[26]. The method introduced in [21] proposed an iterative approach, which places one pseudo-measurement at a time by using the well-documented numerical observability analysis, and the methods introduced in [22]-[23] require computationally expensive matrix operations, such as inversion of triangular factors. The Procedure proposed in [24] depends on factorization of the Gramm matrix, which is computationally expensive if a large system with high number of observable islands is considered, due to the less-sparse structure of the Gramm matrix. Methods proposed in [25]-[26] are based on integer programming, which may solve the placement problem in an unacceptable long time for large-scale systems with large number of observable islands. All of the methods introduced are capable of solving the observability restoration problem, but computation times increase with the number of considered observable islands. The procedure proposed provides an efficient alternative, which can place the required set of critical pseudo-measurements in a computationally efficient way. The formerly proposed observability restoration methods will be discussed in detail in Chapter 3.

In power system state estimation, a measurement may contain gross error because of communication noise, incorrect sign convention or measurement device failure. These measurements are called bad measurements (data) and can lead to biased estimates. Therefore it is important to implement robust state estimators. Estimators with high breakdown points, which are the smallest amount of contamination that can cause an estimator to give an arbitrarily incorrect solution [27], have been investigated and developed by researchers [28], [29]. Some of these have also been applied to power system state estimation [30]-[33]. Among these robust estimators, the Least Absolute Value (LAV) estimator was shown to have desirable properties where its implementation can be made computationally efficient by taking advantage of power system's properties [34]-[36]. In Chapter 4, it is proposed to use LAV estimator for power systems measured by only PMUs.

Weighted Least Squares (WLS) estimator, which is the conventional state estimator used in today's power grid, will be non-iterative and fast, thanks to the linearity between the PMU measurements and the system states, once the system is measured by only PMUs. However, due to its non-robustness, bad-data analysis, which is computationally expensive, will still be necessary. On the other hand, LAV will be computationally competitive with WLS if the measurement set includes only phasor measurements [37], besides being robust. Furthermore, strategic scaling can eliminate leverage measurements, which cause deficiency in the performance of LAV, thanks to the linearity between PMU measurements and system states. Chapter 4 proposes the use of LAV state estimation if the considered system is measured solely by PMUs.

It is possible to eliminate leveraging effect of a measurement thanks to the linearity between the phasor measurements and state variables. However, the robustness of LAV is related to the measurement redundancy. Therefore, in Chapter 5, this dissertation proposes a method to place minimum number of PMUs to guarantee robustness of LAV estimator.

PMU placement has been a popular research topic in recent years [38]-[42]. Although many efficient and well-defined solutions have been proposed, those methods aim to find the minimum set of PMUs that makes the system observable, which results in a very low measurement redundancy. Therefore, this work introduces a PMU placement method, which places minimum number of PMUs for a robust measurement design, such that the resulting system will be observable and none of the measurements will be critical, in Chapter 5.

LAV estimator is proposed for the systems measured only by PMUs. However, most power grids are measured by mixed type of measurements, i.e. both SCADA and PMU measurements. Although the LAV estimator is robust and computationally efficient for

PMU-only systems, it is computationally expensive for today's power grids due to the non-linearity between the measurements and system states. Hence, in Chapter 6 a state estimator, which is designed to incorporate PMU measurements as well as SCADA measurements, will be introduced.

The significant difference between the refresh rates of SCADA and PMU measurements constitutes the major challenge in using mixed type of measurements. Typically, PMU measurements are updated 30 times a second, while SCADA updates vary from every 2 to 6 seconds. This difference causes unobservability, unless SCADA and PMU measurements are updated at the same instant.

In [43]-[45] multi-stage estimators, which require longer solution time than the conventional state estimation methods, were proposed. Although the method described in [46] is computationally efficient, since it is based on WLS estimator, it is vulnerable to bad data.

Chapter 6 proposes a state estimator, which uses both WLS and LAV estimation methods. Once PMUs and SCADAs are updated simultaneously, WLS estimator is used, because of its computational efficiency in the presence of SCADA measurements, which are non-linearly related to the system states. On the other hand, if only PMU measurements are updated a modified version of LAV estimator will be employed, thanks to the use of a linearization for the relation between the measurement set and system states. A detailed literature review and explanation of the method with reasoning will be given in Chapter 6.

Finally in Chapter 7, a modal components based decoupling method for three-phase state estimation will be introduced for PMU-only power systems. Although three-phase state estimation problem can be solved simply by using the full three-phase representation of the network and assigning the three-phase bus voltages as the system states [47], [48], this approach may be computationally costly due to the increased problem size. The proposed method uses modal components transformation, which is widely used in three-phase power system analysis. However, applying this transformation in state estimation has not had a computational advantage because of the power measurements. On the other hand, if the system is measured only by PMUs, the resulting system obtained after the transformation will consist of three decoupled sub-systems, namely positive, negative and zero sequence components, which will significantly decrease the size of the state estimation problem.

The following section will provide technical background, which will help the reader to understand the presented study. Firstly, WLS estimator, which is the commonly used state estimation method in today's power systems, will be explained. Following that, a detailed summary of conventional network observability and measurement criticality methods will be provided. Finally, LAV estimator, which is the proposed estimation approach for the future's power systems, will be introduced.

I. TECHNICAL BACKGROUND

A. WLS Based State Estimation

WLS estimator is the most common state estimation method used in today's power systems. In a power system with *m* measurements and *n* system states, measurement vector *z* is nonlinearly related to the system states as shown below.

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2, \cdots, x_n) \\ h_2(x_1, x_2, \cdots, x_n) \\ \vdots \\ h_m(x_1, x_2, \cdots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{bmatrix} = h(x) + e \tag{1.1}$$

where;

$$x^T = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}$$
$$h^T = \begin{bmatrix} h_1(x) & h_2(x) & \cdots & h_m(x) \end{bmatrix}$$
$$e^T = \begin{bmatrix} e_1 & e_2 & \cdots & e_m \end{bmatrix}$$

It is generally assumed that:

- $E(e_i) = 0 \quad i = 1, 2 \ldots m$
- Measurement errors are independent, i.e. $E\left[e_i e_j\right] = 0$

Therefore $Cov(e) = E\left[ee^T\right] = R = diag\left\{ \sigma_1^2 \quad \sigma_2^2 \quad \cdots \quad \sigma_m^2 \right\}$, where σ_i is the standard deviation of measurement *i*.

WLS estimator aims to minimize the following objective function.

$$\begin{aligned} J(x) &= \sum_{i=1}^{m} \left(z_i - h_i(x)\right)^2 / R_{ii} \\ &= \left[z - h(x)\right]^T R^{-1} \left[z - h(x)\right] \end{aligned} \tag{1.2}$$

At the minimum, the first-order optimality conditions, which are expressed below, have to be satisfied.

$$\begin{aligned} &g(x) = \frac{\partial J(x)}{\partial x} = -H^T R^{-1}\left[z - h(x)\right] = 0 \\ &\text{where } \mathrm{H}(x) = \frac{\partial h(x)}{\partial x} \end{aligned} \tag{1.3}$$

Expanding the non-linear function *g(x)* into its Taylor series around the state vector x^k yields:

$$g(x) = g\left(x^k\right) + G\left(x^k\right)\left(x - x^k\right) + \cancel{HOT} = 0 \tag{1.4}$$

Gauss-Newton method can be used to solve the estimation problem iteratively as shown by the following.

$$x^{k+1} = x^k - G\left(x^k\right)^{-1} g\left(x^k\right)$$

where k: iteration index

x^k: solution vector at iteration k

$$G\left(x^k\right) = \frac{\partial g\left(x^k\right)}{\partial x} = H^T\left(x^k\right) R^{-1} H\left(x^k\right) \quad (1.5)$$

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

G(x) is called the gain matrix, which is sparse, positive definite and symmetric provided that the system is fully observable.

B. Conventional Observability and Measurement Criticality Analyses

Power systems are measured traditionally by conventional measurements. Conventional measurements and system states are related via a nonlinear vector function, ***h*****,** as shown in (1.1). This relation can be represented simple as below;

$$z = h(x) + e \quad (1.6)$$

where z is the *mx1* measurement vector, x is the *nx1* state vector and e is the *mx1* measurement error vector, if m is the number of measurements and n is the number of system states. State vector x is composed of bus voltage magnitudes and phase angles as shown below.

$$x^T = \begin{bmatrix} V_1 & V_2 & \cdots & V_n & \theta_1 & \theta_2 & \cdots & \theta_n \end{bmatrix} \quad \theta_1 = 0$$

Note that bus-1 is arbitrarily assigned as the reference for phase angle calculations, since there is no global time reference in the absence of phasor measurements. This will no longer be necessary when there is at least one phasor measurement.

The classical numerical observability and criticality analysis methods are based on the decoupled Jacobian matrix, H_{PP}. For a power system, measured by conventional measurement devices, a decoupled measurement model can be easily obtained as:

$$\Delta z_P = H_{PP}\Delta\theta + e_P \tag{1.7}$$

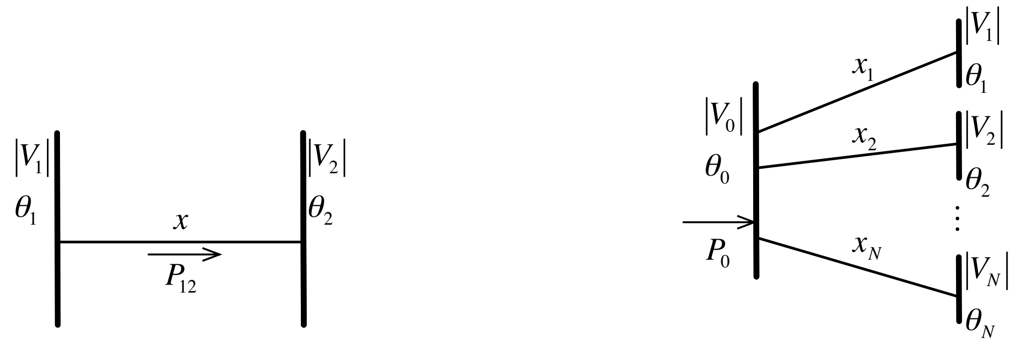
$$\Delta z_Q = H_{QQ}\Delta V + e_Q \tag{1.8}$$

$\Delta\theta$ and ΔV are the changes in the state vector's angle and magnitude rows respectively, while Δz_P and Δz_Q are the changes in the P-Q measurements respectively. In (1.7) and (1.8), e_P and e_Q represent the error in P and Q measurements respectively. H_{PP} and H_{QQ} are the decoupled Jacobian matrices, obtained by ignoring the coupling between V-P and θ-Q variables. For conventional measurements, P and Q measurements are considered in pairs, so only one of (1.7) and (1.8) is used for observability analysis.

Observability and criticality analysis methods are independent of network parameters and operating state of the system. Therefore, by neglecting all line resistances and shunt elements, assuming 1.0 p.u. reactances for all lines and 1.0 p.u. voltages at all buses, P flow from bus-k to bus-m can be expressed as:

$$P_{km} = \sin(\theta_k - \theta_m) \tag{1.9}$$

Applying the first order Taylor expansion around θ_{km}=0, where θ_{km} is the phase difference between buses k and m, (1.9) can be approximated to express power flow and injection measurements as shown in Fig. 1.1.



$$P_{12} = \theta_1 - \theta_2$$

$$P_0 = N\theta_0 - \theta_1 - \theta_2 - \ldots - \theta_N$$

a) P flow measurement

b) P injection measurement.

Fig 1.1. Measurement types and P-θ relations.

Decoupled measurement Jacobian, H_{PP} whose rows and columns correspond to P and θ, respectively can then be built. Observable islands in the system can be identified via the conventional observability analysis methods, which also determine the unobservable branches of the system. The unobservable branches are detected by factorizing the gain matrix, G, which is defined as the product $H^T H$ with modified version of Cholesky's method. Once the unobservable branches are removed, the observable islands are formed easily. Zero diagonal entries of the measurement sensitivity matrix, S can be used to identify critical measurements. Detailed explanation and derivation of the classical numerical observability and criticality analysis methods can be found in [7], [49]-[51].

Conventional methods are well developed and widely known, but they cannot be directly applied to phasor measurements. Although voltage phasor measurements can be decoupled trivially, it is not possible to decouple the current phasor measurements as it is done for power flow equations [52]-[54]. Magnitude and phase angle of the current phasor measured on the transmission line between bus k and m, with series admittance g_{km}-jb_{km} and shunt admittance jb_{kn}, will depend on both magnitude and phase angles of the sending and receiving end voltages of the line as shown below [7], where $|I_{km}|$ is the magnitude of I_{km}, current between buses k and m, and δ_{km} is phase angle of I_{km}. Therefore, the classical methods cannot be applied to current phasor measurements. Even if a full Jacobian is used, classical observability analysis methods will still be unable to handle some specific situations [16].

$$
\begin{aligned}
&|I_{km}| = \left[A|V_k|^2 + B|V_m|^2 - 2|V_k||V_m|\left(C\cos\theta_{km} - D\sin\theta_{km}\right)\right]^{1/2} \\
&\delta_{km} = \arctan\left(\frac{\left[g_{km}\left(V_k^i - V_m^i\right) - b_{km}\left(|V_k|\cos\theta_k - V_m^r\right) + b_{kn}V_k^r\right]}{\left[g_{km}\left(V_k^r - V_m^r\right) + b_{km}\left(V_k^i - V_m^i\right) - b_{kn}V_k^i\right]}\right)
\end{aligned}
\tag{1.10}
$$

$$
\begin{aligned}
&V_k^i = |V_k|\sin\theta_k \quad V_m^i = |V_m|\sin\theta_m \quad V_k^r = |V_k|\cos\theta_k \quad V_m^r = |V_m|\cos\theta_m \\
&A = g_{km}^2 + (b_{km} + b_{kn})^2 \quad B = g_{km}^2 + b_{km}^2 \\
&C = g_{km}^2 + b_{km}(b_{km} + b_{kn}) \quad D = g_{km}b_{kn}
\end{aligned}
$$

C. LAV Based State Estimation

Least Absolute Value (LAV) estimator is a robust M-estimator, which has an iterative solution if the measurement design includes conventional measurements. Objective function of LAV to be minimized is the sum of absolute values of measurement residuals. Objective function of LAV estimator is defined as below:

$$\sum_{i=1}^{2m} |r_i| = c^T |r| \tag{1.11}$$

where

$c^T = \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix}$ is a *1*x*m* vector of “1”s.

$r^T = \begin{bmatrix} r_1 & r_2 & \dots & r_m \end{bmatrix}$ is *1xm* residuals vector.

Measurement equations given in (1.6) can be re-written as below, if measurement residuals are considered instead of measurement errors, where z is the measurement vector and x is the system state vector.

$$z = h(x) + r \tag{1.12}$$

By using (1.11) and (1.12), the LAV estimation problem can be formulated as below:

$$\begin{aligned} &\min\ c^T \mid r \mid \\ &s.t.\ \ z - h(x) = r \end{aligned} \tag{1.13}$$

LAV optimization problem given in (1.13) can be expressed as an equivalent linear programming (LP) problem by re-arranging the equations and defining some new strictly non-negative variables [7], [30], [55] and [56], as formulated below.

$$\begin{aligned} &\min\ c^T y \\ &s.t.\ \ My = b \\ &\qquad y \geq 0 \\ \\ &c^T = [\ Z_n \quad O_m\ ] \\ &y = [\ \Delta X_a \quad \Delta X_b \quad U \quad V\ ]^T \\ &M = [\ H \quad -H \quad I \quad -I\ ] \\ &b = \Delta z \end{aligned} \tag{1.14}$$

Problem defined in (1.14) can be solved efficiently by using well-developed optimization tools. In (1.14), Z_n is the 1x$2n$ vector consisting of zeros and O_m is the 1x$2m$ vector consisting of ones. ΔX_a and ΔX_b are 1xn, and U and V are 1xm vectors where;

$$\begin{aligned} &\Delta x = \Delta X_a^T - \Delta X_b^T = x^{k+1} - x^k \\ &z - h(x^k) - H(x^k)\Delta x = \Delta z - H(x^k)\Delta x^k = U^k - V^k \end{aligned} \tag{1.15}$$

In (1.15) x^k is the solution vector at iteration k.

CHAPTER 2

OBSERVABILITY AND CRITICALITY ANALYSES FOR POWER SYSTEMS MEASURED BY PMUS

I. INTRODUCTION

After presenting the general introduction and technical background in Chapter 1, this chapter will introduce network observability and measurement criticality methods for systems measured by PMUs. As mention in Chapter 1, prior to the state estimation, one should perform observability and criticality analyses to evaluate the measurement design of the system. If the system is not observable, it is not possible to solve state estimation problem uniquely. Therefore, it is crucial to detect if a power system is observable or not. While observability analysis is about measurement design's capability of performing state estimation, criticality analysis is about the robustness of the measurement design. Criticality analysis aims to find the critical measurements of the system, which make the power system vulnerable against bad measurements. Moreover, absence of critical measurements causes loss of observability in the system. Hence, it is also important to detect the critical measurements. Although there are well-defined observability and criticality analysis methods for power systems measured by conventional measurements, those methods cannot be applied once PMUs are also present in the measurement set.

A PMU typically provides both voltage and current phasor measurements. However, in case of measurement loss or bad data, current phasors may be available without the corresponding voltage phasor at the sending end of the measured line. In an attempt to develop a general method that will work in all possible situations without making any assumptions, this work presents methods for observability and criticality analyses of power systems measured by PMUs as well as conventional power measurements. Furthermore, voltage magnitude measurements, which are commonly neglected in conventional observability and criticality analysis methods, are also taken into account.

New definitions should be introduced for observability analysis, before going any further to simplify the explanations given in this work. Observable islands are classified as *anchored* observable islands versus *floating* observable islands depending on whether voltage phase angles of the buses inside the observable island are synchronized to GPS or not, respectively. In addition to those definitions, PMUs are divided into two types according to the configuration of the current phasor measurements. Current phasor measurements can be placed in a power system with a voltage phasor measurement at its sending end (type-1) or voltage and current phasor measurements can be located at different buses (type-2). Note that, PMUs with configuration type-1 are branch PMUs, which measure a voltage and a current phasor. Any PMU, whose numbers of voltage and current phasor measurements do not match, should be considered as configuration type-2.

Observability and measurement criticality analysis of the systems measured by PMUs have been studied recently [16]-[18]. While [16] covered observability and criticality analyses for systems containing conventional measurements as well as PMUs with measurement configuration type-2, it neglected the effects of voltage magnitude measurements and boundary injection measurements on observability. In this work, these omissions are addressed along with extension of the method for observability and criticality analyses to systems including PMUs with measurement configuration type-1. Reference [17] proposes an integer-arithmetic algorithm for observability analysis of the systems measured by conventional measurements and PMUs with configuration type-1, but it does not cover a method for criticality analysis. Moreover, PMUs with configuration type-2 and voltage magnitude measurements are not studied in [17]. Another observability analysis method for systems measured only by PMUs with configuration type-1 is presented in [18].

This work introduces different observability and criticality analysis methods for two types of phasor measurement configurations. Conventional methods are modified for systems with measurement configuration type-1, while a new state estimation formulation and analysis procedure are introduced for systems with measurement configuration type-2. Moreover, voltage magnitude measurements, which have been neglected in observability and criticality analyses so far, are also taken into account in this work. In addition, the proposed method is also capable of detecting current phasor measurements, which yield multiple-solutions. Note that, the classical analysis methods do not consider the multiple solution possibility since measurement set consists of conventional measurements. Although, multiple solutions are quite possible even conventional measurements are used in state estimation due to the nonlinearity between measurements and system states, only one of those multiple solutions is reliable [7], as in power flow analysis. However, once current phasor measurements are available in the measurement set, it cannot be said that one solution is more reliable than other.

In Section-II, phasor measurements with configuration type-1 are represented as power flow measurements and then the proposed methods are given. Section-III formulates the observability problem for the measurement equations of phasor measurements with configuration type-2 to develop a revised observability and criticality analysis method. Once the proposed methods are introduced, simulations and results are given in Section-IV, followed by a summary in Section V.

II. PROPOSED METHOD FOR MEASUREMENT CONFIGURATION TYPE-1

A. Proposed Phasor Measurement Representation

A type-1 PMU consists of a voltage phasor measurement at the sending end bus of current phasor measurement. Having both voltage phasor at bus-k and current phasor from bus k to m, active and reactive power flow on line k-m can be expressed as below:

$$V_k I_{km}^* = P_{km} + jQ_{km} \tag{2.1}$$

It is evident from (2.1) that phasor measurements with configuration type-1 can be represented as a power flow measurement and a voltage phasor measurement. Since voltage phasor measurements can be decoupled easily, the decoupled Jacobian, H can be used for observability and criticality analyses by representing each current phasor measurement as a power flow measurement and by adding 1 to the column corresponding to the voltage phasor measurement bus.

B. Proposed Observability Analysis Method

Classical observability analysis method will declare a system as observable if the rank of decoupled Jacobian H, is $n-1$, where n is the number of the buses, and one bus is selected as the reference. On the other hand, having at least one phasor measurement eliminates the need for a reference bus. Therefore, the rank of H should be n, for an observable power system including phasor measurements.

It is proposed to use classical observability analysis method to detect observable islands of a power system when system is measured not only by conventional measurements but also by phasor measurements with configuration type-1. Conventional method detects zero pivots of the gain matrix, G (H^TH), and takes n_z-1 of them into account, where n_z is the number of zero pivots, to detect observable islands. If phasor measurements are considered, all of the zero pivots should be taken into account, since a full rank H is required for an observable power system. As done by the classical method, the unobservable branches of the system are identified after the zero pivots are determined.

At the end of the analysis, the anchored observable islands identified should be labeled as a single observable island or at the beginning of the procedure virtual lines should be located between all of voltage phasor measurements. These virtual lines, which will be labeled as observable branches by the classical method, represent the GPS synchronization between the phasor measurements.

C. Proposed Criticality Analysis Method

Conventional criticality analysis method can be applied to the power systems described in this section. Unlike the case of classical methods, due to the lack of a reference bus, none of the columns in H will be discarded in the proposed method. Thus, the sensitivity matrix S will be computed as described below, where I is a mxm identity matrix, m being the number of measurements, and its zero diagonals represent the critical measurements.

$$S = I - H(H^T H)^{-1} H^T \tag{2.2}$$

III. PROPOSED METHOD FOR MEASUREMENT CONFIGURATION TYPE-2

A. Proposed State Estimation Formulation

Conventional measurements are related to both voltage magnitude and phase angles in a non-linear manner. On the other hand, phasor measurements are related to the state variables linearly. This linearity can be seen if system states are assumed to be real and imaginary parts of the bus voltages. Once this change of system states is assumed, the bus voltage phasor measurement at bus-k can be expressed as the sum of the real and imaginary parts of the measured bus voltage as follows:

$$\begin{aligned} V_k &= \mathrm{Re}\{V_k\} + j\,\mathrm{Im}\{V_k\} \\ &= V_k \cos(\theta_k) + jV_k \sin(\theta_k) \end{aligned} \tag{2.3}$$

Current phasor measurements are proportional to the voltage difference between the sending and receiving end buses, where Z_{km} is the impedance between the buses k and m. Therefore, current phasor measurements can be represented as voltage drop measurements along the line k to m as:

$$\begin{aligned} \mathrm{Re}\{Z_{km} I_{km}\} &= \mathrm{Re}\{V_k\} - \mathrm{Re}\{V_m\} \\ &= V_k \cos(\theta_k) - V_m \cos(\theta_m) \\ \\ \mathrm{Im}\{Z_{km} I_{km}\} &= \mathrm{Im}\{V_k\} - \mathrm{Im}\{V_m\} \\ &= V_k \sin(\theta_k) - V_m \sin(\theta_m) \end{aligned} \tag{2.4}$$

Having (2.3) and (2.4), the following slightly modified formulation of the state estimation problem is proposed to be used:

$$Z = AX + e \tag{2.5}$$

$$X = \begin{bmatrix} |V_1|\cos(\theta_1) & |V_1|\sin(\theta_1) \\ |V_2|\cos(\theta_2) & |V_2|\sin(\theta_2) \\ \vdots & \\ |V_n|\cos(\theta_n) & |V_n|\sin(\theta_n) \end{bmatrix}$$

Z is the $m_p x2$ measurement matrix, where m_p is the number of phasor measurements and the columns correspond to the real and imaginary parts of measurements. X is the $nx2$ state matrix, where n is the number of buses and the columns correspond to the real and imaginary parts of the bus voltages. A is an $m_p xn$ matrix, which relates the states to measurements. Voltage phasor measurements are represented by a “1”, which is placed in the column corresponding to the bus measurement placed in A-matrix. Current phasor measurements are expressed with a “1” and a “-1” placed at the column corresponding to the sending and receiving ends of the measurement respectively.

The proposed formulation enables decoupling of the real and imaginary parts of the phasors automatically, since A is identical for real and imaginary parts. Observability and criticality analysis methods do not consider the solution, so the real parts of the states and measurements are employed to reduce the size of the analysis.

B. Proposed Observability Analysis Method

In this section, proposed observability analysis method for the systems including phasor measurements with configuration type-2 will be explained. The proposed method depends on the A-matrix; therefore, at the beginning of the procedure, classical observability analysis should be applied by disregarding phasor measurements. Once the observable islands are formed, it is assumed that there is at least one voltage magnitude measurement at each observable island. Observable islands will then be considered as super-nodes and non-processed phasor measurements are placed in the simplified system consisting of super-nodes. Thus, starting at this stage of the procedure, the proposed method is described only for phasor measurements. Fig. 2.1 presents the IEEE 14-bus system and corresponding measurements, which will be used as a tutorial example to describe the method. Once the proposed method is described, a way to incorporate the effect of voltage magnitude measurements will be presented.

Super-nodes of the system are found by disregarding all phasor measurements and applying the classical observability analysis method to the system considered. Super-nodes and the non-processed phasor measurements of the system given in Fig. 2.1 are shown in Fig. 2.2.

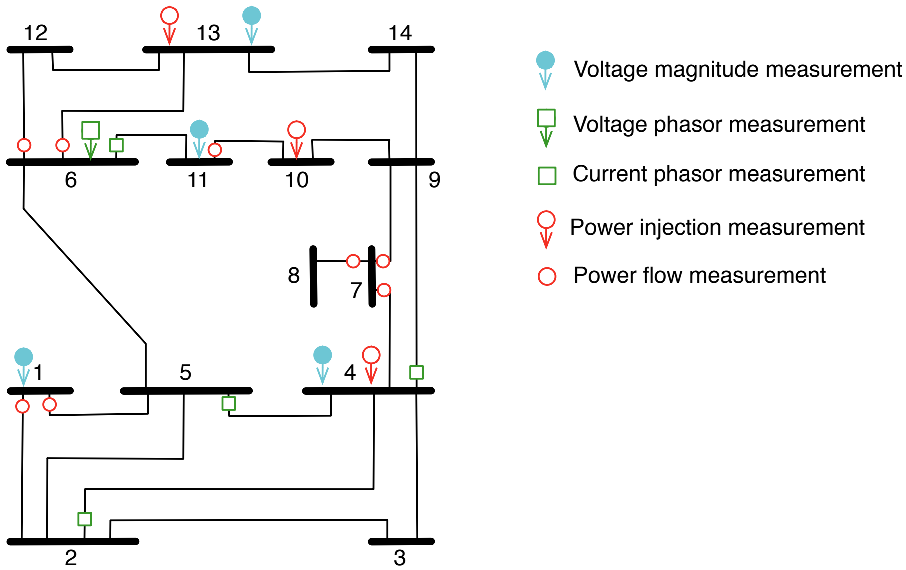


Fig. 2.1. IEEE 14-bus system and measurement placement. Note that the given legend for the measurements applies to all figures.

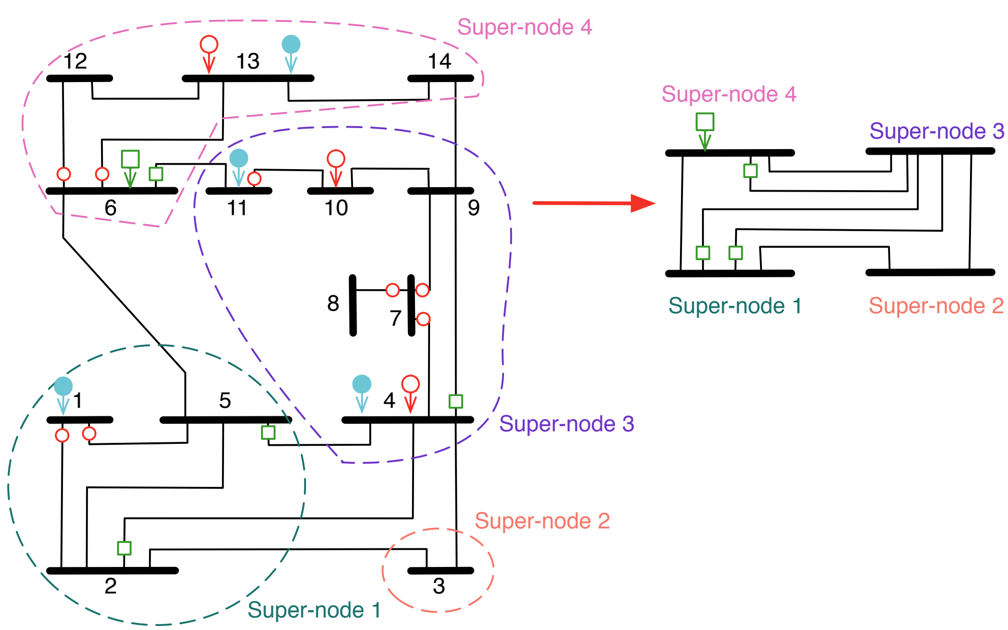


Fig. 2.2. Super-nodes and the non-processed phasor measurements of the studied system.

Once the super-nodes are formed, the *A*-matrix should be built as described in Section III-A by considering two special cases. First of those special cases is the parallel current phasor measurements between super-nodes. Current phasor measurements on lines 5-4 and 2-4 are examples for this special case. The relations between those measurements are expressed explicitly below. Note that, θ_{25} is known since buses 2 and 5 are in the same super-node:

$$
\begin{aligned}
\mathrm{Re}\{Z_{54}I_{54}\} &= |V_5|\cos(\theta_5) - |V_4|\cos(\theta_4) \\
\mathrm{Im}\{Z_{54}I_{54}\} &= |V_5|\sin(\theta_5) - |V_4|\sin(\theta_4) \\
\\
\mathrm{Re}\{Z_{24}I_{24}\} &= |V_2|\cos(\theta_2) - |V_4|\cos(\theta_4) \\
&= A_1|V_2|\cos(\theta_5) - A_2|V_2|\sin(\theta_5) - |V_4|\cos(\theta_4) \\
\mathrm{Im}\{Z_{24}I_{24}\} &= |V_2|\sin(\theta_2) - |V_4|\sin(\theta_4) \\
&= A_1|V_2|\sin(\theta_5) + A_2|V_2|\cos(\theta_5) - |V_4|\sin(\theta_4) \\
\\
A_1 &= \cos(\theta_{25}) \qquad A_2 = \sin(\theta_{25}) \\
\theta_{25} &= \theta_2 - \theta_5
\end{aligned}
\tag{2.6}
$$

As seen in (2.6), the two measurements give different information for the solution of the state estimation since they are linearly independent, so they should be expressed differently in the *A*-matrix for observability and criticality analysis, to reflect their effect on the solution. More generally, if sending and/or receiving ends of parallel current phasor measurements between two super-nodes are at different buses, then after indicating the first one as described in Section III-A, express the remaining ones with different numbers, such that a different number is assigned to each sending end super-node and to each receiving end super-node, to maintain the linearly independence between those measurements. For the case considered, measurements on lines 2-4 and 5-4 should be represented as follows:

$$
\begin{array}{lcc}
\text{Super-nodes} & & \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\
\text{Measurement} & \begin{array}{c} I_{24} \\ I_{54} \end{array} & \begin{bmatrix} 1 & 0 & -1 & 0 \\ 2 & 0 & -3 & 0 \end{bmatrix}
\end{array}
$$

The second special case covers current phasor measurements whose both ends are inside the same super-node. As an example to this case super-node 3 in Fig. 2.2 can be considered. Super-node 3 is an observable island so phase difference between buses 4 and 9, θ_{94}, is known. Thus, following relations can be directly derived:

$$
\begin{aligned}
\mathrm{Re}\{Z_{49}I_{49}\} &= |V_4|\cos(\theta_4) - |V_9|\cos(\theta_9) \\
&= |V_4|\cos(\theta_4) - |V_9|\cos(\theta_4 + \theta_{94}) \\
\mathrm{Im}\{Z_{49}I_{49}\} &= |V_4|\sin(\theta_4) - |V_9|\sin(\theta_9) \\
&= |V_4|\sin(\theta_4) - |V_9|\sin(\theta_4 + \theta_{94})
\end{aligned}
\tag{2.7}
$$

From the given relations, θ_4 can be solved, since voltage magnitudes and GPS-synchronized current phasor of line 4-9 are known. Therefore, the current phasor measurement on line 4-9 is equivalent to a voltage phasor measurement in terms of observability and should be represented in the A-matrix as shown below.

$$
\begin{array}{lcc}
\text{Super-nodes} & & \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\
\text{Measurement} & I_{49} & \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}
\end{array}
$$

Thus, current phasor measurements with both terminals in the same super-node are considered as voltage phasor measurements for the purposes of observability and criticality analysis.

Row reduced echelon form for the *A*-matrix is computed to identify the anchored super-nodes. Columns including “1”s, which are at linearly independent rows, represent the anchored super-nodes. For this example, super-nodes 1, 3 and 4 are found anchored as illustrated below:

$$
\begin{array}{c} \\ I_{54} \\ I_{24} \\ I_{49} \\ I_{611} \\ V_6 \end{array}
\begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 1 & 0 & -1 & 0 \\ 2 & 0 & -3 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array}
\Longrightarrow
\begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{array}
$$

Boundary injection measurements, which are at the boundary buses of observable islands, are irrelevant measurements since they do not have any impact on observability [11]. However, once phasor measurements are introduced, boundary injection measurements may become relevant for determining observable islands. Anchored super-nodes can be represented as a single super node, so once system is simplified the boundary injection measurements will have to be reconsidered for observability. In this example, the boundary injection measurement at bus-4 initially has no effect on forming super-nodes, but after identifying anchored super-nodes; it makes the floating super-node part of the system anchored as seen in Fig. 2.3. In Fig 2.3, the anchored and the floating observable islands of the system are shown, as well as the simplified model of the system. Therefore, the overall observability analysis procedure will apply the classical and the proposed *A*-matrix based methods alternatingly to the simplified systems until the number of observable islands no longer changes.

C. Proposed Handling of Voltage Magnitude Measurements

Conventional methods neglect voltage magnitude measurements while analyzing the observability. However, once current phasor measurements are introduced to the system, voltage magnitude measurements can affect observability analysis. This dissertation introduces a method to consider the voltage magnitude measurements in observability analysis. The main idea will be described using the system given in Fig. 2.4.a as an example.

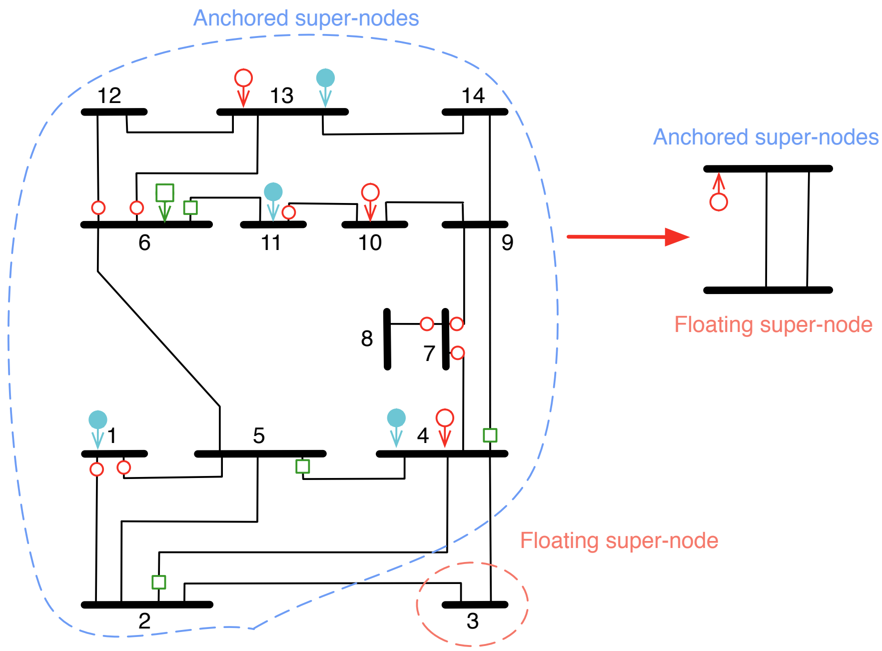
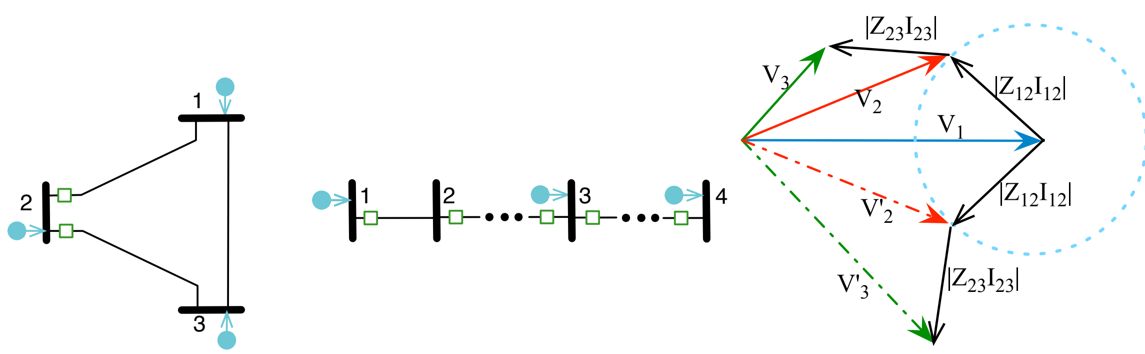


Fig. 2.3. Effect of boundary injection measurements.



a) 3-bus observable power system.

b) n-bus observable power system.

c) Phasor diagram of the 3-bus system

Fig. 2.4. Effect of voltage magnitude measurements.

Although phase angles of current phasors are known, there is no information about the voltage phase angles of the buses given in Fig. 2.4.a. By assuming that phase angle at bus-1 is zero, dotted circle in Fig. 2.4.c shows the infinitely many possibilities of bus-2 voltage. Thanks to the voltage magnitude measurement at bus-2, number of possibilities reduces to two, which are V_2 and V_2' as shown in Fig. 2.4.c. V_3 and V_3' are the two possible values of bus-3 voltage. They can be determined based on the known phase difference between the current phasors, thus their vector sum is obtained as shown in Fig. 2.4.c. Having the magnitude of bus-3 voltage, it is found that V_3 and V_2 are the bus voltages; given bus-1 voltage is V_1. Since current phase angles are determined with respect to GPS, actual voltage phase angles can be found easily. It can be concluded that, phase angles of a sub-system, which includes at least three voltage magnitude measurements connected via current phasor measurements as shown in Fig. 2.4.b, can be found with respect to GPS. To integrate this information to the proposed observability analysis method, a virtual voltage phasor measurement should be added to one of the buses with voltage magnitude measurements.

D. Proposed Criticality Analysis Method

This work proposes to apply classical criticality analysis method to detect the critical phasor measurements. Instead of using H, another matrix referred here as the A-matrix will be employed. Since critical measurements' residuals are equal to zero [7], the classical method flags the measurements corresponding to the zero-diagonal entries of sensitivity matrix S_A, as critical. S_A is defined below:

$$\begin{aligned} r &= z - AX \\ &= z - A[(A^T A)^{-1} A^T z] \\ &= z(I - A(A^T A)^{-1} A^T) \\ S_A &= I - A(A^T A)^{-1} A^T \end{aligned} \tag{2.8}$$

Proposed method is applied to the IEEE 14-bus system with the measurement design given in Fig. 2.5.

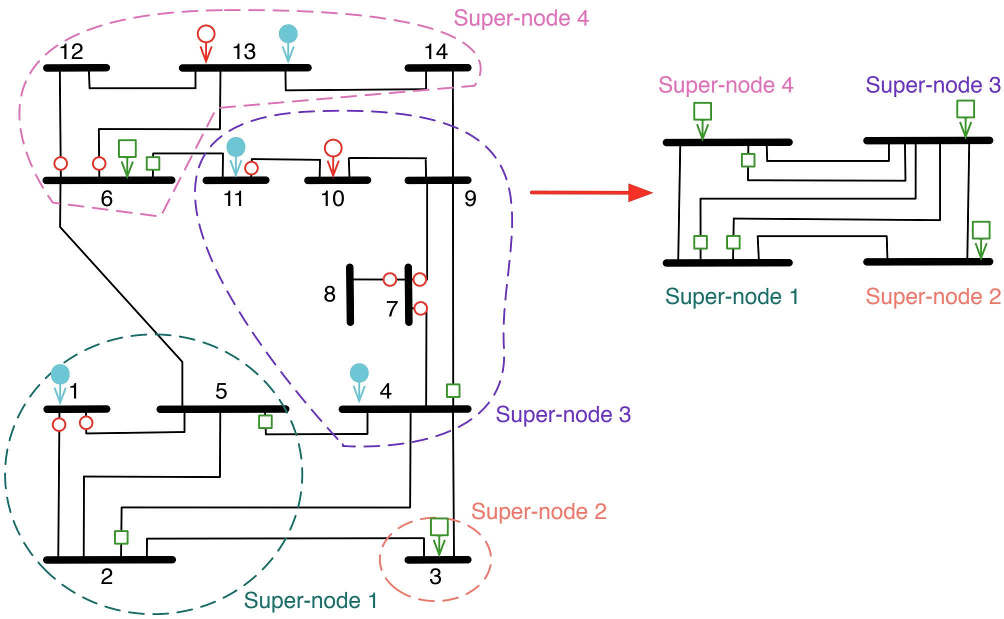


Fig. 2.5. IEEE 14-bus observable power system.

Once the A-matrix is formed and S_A is derived, the only critical measurement in Fig. 2.5 is found to be the voltage phasor measurement located at bus-3 as illustrated below. In S_A, n stands for non-zero terms.

$$A = \begin{array}{c} \\ V_6 \\ I_{49} \\ V_3 \\ I_{611} \\ I_{54} \\ I_{24} \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 1 \\ 1 & 0 & -1 & 0 \\ 2 & 0 & -3 & 0 \end{bmatrix} \end{array} \Rightarrow S_A = \begin{array}{c} \\ V_6 \\ I_{49} \\ V_3 \\ I_{611} \\ I_{54} \\ I_{24} \end{array} \begin{array}{c} \begin{array}{cccccc} V_6 & I_{49} & V_3 & I_{611} & I_{54} & I_{24} \end{array} \\ \begin{bmatrix} n & n & 0 & n & n & n \\ n & n & 0 & n & n & n \\ 0 & 0 & 0 & 0 & 0 & 0 \\ n & n & 0 & n & n & n \\ n & n & 0 & n & n & n \\ n & n & 0 & n & n & n \end{bmatrix} \end{array} \Rightarrow \begin{array}{c} \text{Voltage phasor meas.} \\ \text{at bus - 3 is critical} \end{array}$$

Note that, the proposed method allows identification of not only the measurements whose loss causes unobservability, but also the ones whose loss leads to the multiple-solutions. The latter cannot be detected directly when using classical methods.

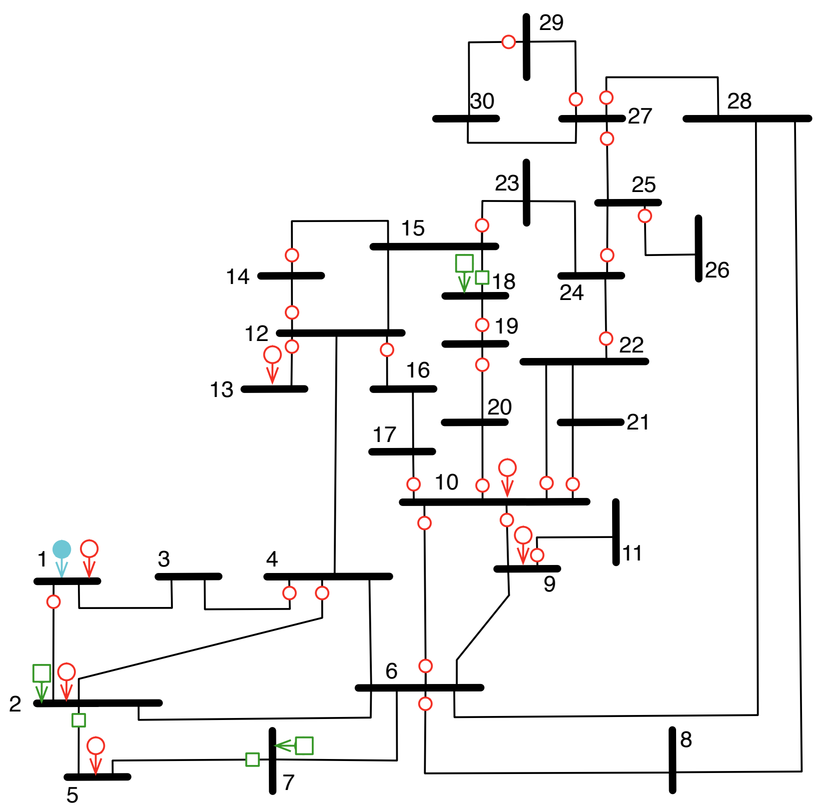
As explained earlier, effect of boundary injection measurements to observability cannot be detected before phasor measurements are considered. To see their effect, conventional analysis method should be conducted one more time on the reduced system. Since boundary injection measurements are neglected while forming the A-matrix, S_A cannot be used to identify critical measurements of the system. Thus, this approach is applicable to systems including no boundary injection measurements, once the super-nodes are formed.

IV. SIMULATIONS AND RESULTS

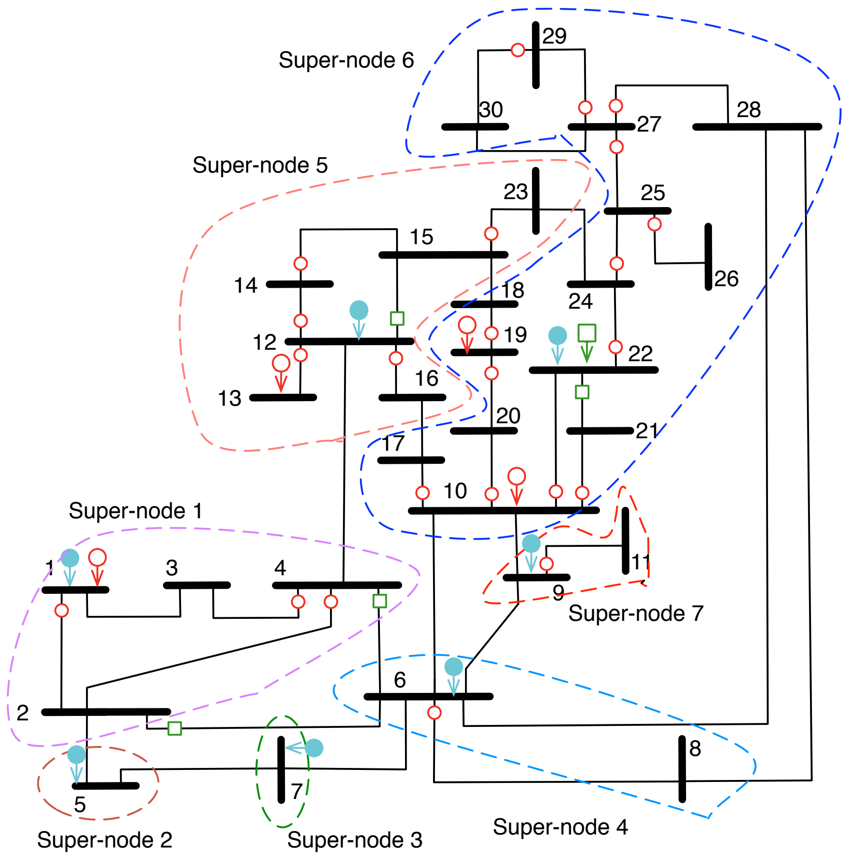
In this section three case studies are presented to illustrate the proposed methods. IEEE 30-bus system will be used in all cases. Measurement configurations for all cases will involve both conventional as well as phasor measurements. Phasor measurements in Case-1 are placed by using configuration type-1, while configuration type-2 is employed to place phasor measurements in Case-2 and Case-3. Fig. 2.6 presents measurement placement and super-nodes of the systems of all three cases.

In Case-1, type-1 phasor measurements are employed as well as conventional measurements. Once the proposed methods are applied, it is found that system is observable and voltage phasor measurement at bus-18 and current phasor measurement on line 18-15 are critical, as indicated in Tables 2.1 and 2.2.

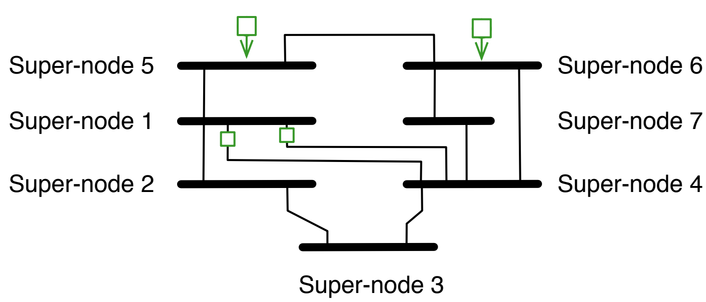
In Case-2, both ends of the line 12-15 are inside super-node 5. Therefore, the current phasor measurement placed on line 12-15 is treated as an equivalent voltage phasor measurement as explained in Section III-B. The same is correct for the current phasor measurement on line 21-22. The current phasor measurements on lines 2-6 and 4-6 are both from super-node 1 to super-node 4, hence they should be represented differently in the A-matrix as explained in Section III-B. Once the A-matrix is built by using the simplified system given in Fig. 2.6.c and the proposed method is applied, super-nodes 1, 4, 5 and 6 are flagged as anchored. By simplifying the system as given in Fig. 2.6.d and applying the conventional method one more time because of the boundary injection measurement at bus-10, it is found that super-node 7 is also anchored. Results of observability analysis are given in Table 2.1. Since the system is unobservable, criticality analysis cannot be applied.



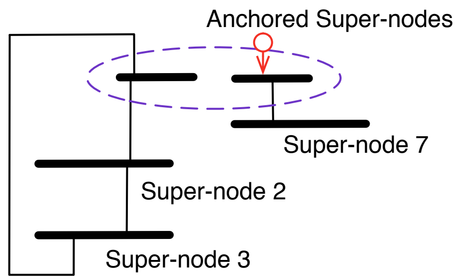
a) Case-1: IEEE 30-bus observable system with type-1 phasor measurements.



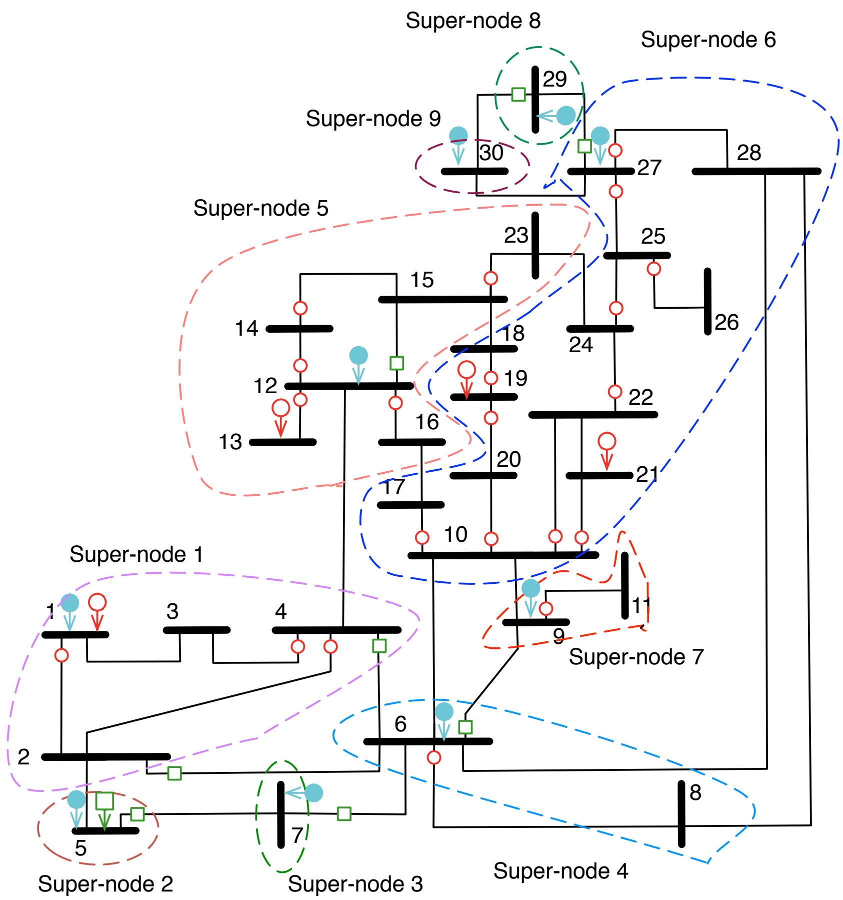
b) Case-2: IEEE 30-bus unobservable system with type-2 phasor measurements.



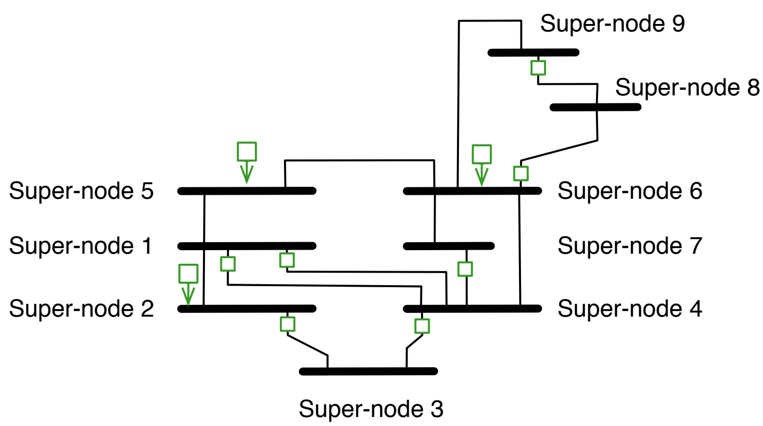
c) Super-nodes of system in Case-2 with phasor measurements.



d) Anchored and floating super-nodes of system in Case-2 with boundary injection measurements.



e) Case-3: IEEE 30-bus observable system with type-2 phasor measurements.



f) Super-nodes of system in Case-3 with phasor measurements.

Fig. 2.6. IEEE 30-bus system.

In Case-3, the buses 27, 29 and 30, each of which has a voltage magnitude measurement, are connected via the current phasor measurements on lines 29-30 and 27-29. Therefore, as explained in Section III-C, a voltage phasor measurement can be placed on one of the stated buses. Accordingly a voltage phasor measurement is added to super node 6 as shown in Fig. 2.6.f. The phasor measurements are represented in the *A*-matrix according the rules explained earlier. Once *A*-matrix is formed and proposed methods are applied, it is found that system is observable and current phasor measurements on lines 6-9, 15-16, 27-29 and 29-30 are critical as given in Tables 2.1 and 2.2. It is also found that voltage phasor measurement on super-node 6 is also critical, meaning that each of the voltage magnitude measurements on buses 27, 19 and 30 are critical.

TABLE 2.1. RESULTS OF THE SIMULATIONS FOR OBSERVABILITY ANALYSIS

	Case-1	***Case-2***	***Case-3***
Anchored buses	1, 2 … 30	1, 2, 3, 4, 6, 8 … 30	1, 2 … 30
Floating buses	-	5, 7	-
Observability	Observable	Unobservable	Observable

TABLE 2.2. RESULTS OF THE SIMULATIONS FOR CRITICALITY ANALYSIS

	Case-1	***Case-2***	***Case-3***
Critical voltage phasor measurements (bus number)	18	Not Available	-
Critical current phasor measurements (from-to bus)	18-15	Not Available	6-9, 15-16, 27-29, 29-30

V. SUMMARY AND COMMENTS

This chapter describes two procedures to analyze network observability and measurement criticality when using phasor measurements in addition to conventional measurements.

If all phasor measurements are of type-1, then modified versions of the classical observability and criticality analysis methods can be directly used. The proposed procedure for phasor measurements of type-2 depends on the newly defined *A*-matrix, which represents the linear relation between the state variables and measurements. The row reduced echelon form of *A*-matrix is formed considering the special cases for current phasor measurements, to identify the *anchored* and *floating* observable islands. Effect of voltage magnitude measurements on the observable islands is taken into account after phasor measurements are processed.

The methods described in this chapter can handle not only systems with only phasor measurements, but also the ones including both phasor measurements and conventional measurements. Furthermore, current phasor measurements which lead to multiple-solutions can be detected using the proposed methods.

CHAPTER 3

PSEUDO-MEASUREMENT PLACEMENT TO RESTORE NETWORK OBSERVABILITY

I. INTRODUCTION

Chapter 2 introduced observability and criticality analyses for power systems measured by PMUs. Chapter 3 will discuss observability restoration for unobservable power systems measured by PMUs. Power system state estimation can be performed only if the system is observable, as mentioned in Chapters 1 and 2. If a power system does not consist of a single observable island, the synchronized solution for all of the buses cannot be found; therefore, network observability needs to be restored. Network observability can be restored by placing pseudo-measurements at appropriate locations in the system. Pseudo-measurements typically consist of quantities such as short-term load forecasts, scheduled generation dispatch, historical records, etc. [7].

This work presents a method that is developed for pseudo-measurement placement in order to restore network observability by merging existing observable islands. The resulting measurement set consists of the already existing measurements and the pseudo-measurements all of which must be critical, i.e. their removal should lead to unobservable system, to avoid biased estimates. In this work, all considered pseudo-measurements are assumed to be net power injections at buses.

Several methods for pseudo-measurement placement have been proposed so far [21]-[26]. The method introduced in [21] is iterative and places one pseudo-measurement at a time by using the well-documented numerical observability analysis. A *candidate* *measurement* is placed and the resulting observable islands are identified at each iteration. Candidate measurements are the set of all pseudo-measurements available in the system. The process is repeated as many times as necessary until no more observable islands can be found. Methods introduced in [22]-[23] require computationally expensive matrix operations especially for larger systems, such as inversion of triangular factors. Procedure proposed in [24] is computationally fast for relatively small number of observable islands and uses Cholesky factorization of the Gramm matrix. However, calculating less sparse Gramm matrix and its zero-pivots bring extra work load if a large system with high number of observable islands is considered. Methods proposed in [25]-[26] are based on integer programming. The method proposed in [25] guarantees redundancy of all of the measurements at the system, since it also aims to keep observability in case of single line outages and single measurement losses. Method proposed in [26] is capable of placing just enough number of pseudo-measurements to the unobservable system with integer programming in an efficient way. However, for large-scale systems with large number of observable islands, the solution may again take an unacceptably long time, since solution method is based on binary integer programming.

All of the methods introduced are capable of solving the observability restoration problem, but computation times increase with the number of considered observable islands. The procedure proposed here provides an efficient alternative, which can place the required set of critical pseudo-measurements in a computationally efficient way. Since pseudo-measurements are only approximations, using them in a redundant fashion will introduce unwanted errors, which will bias the estimated state.

Consider (3.1) which represents the decoupled first order linear approximation (DC model) of the measurement equation, where z (vector with dimension $mx1$) is the real power measurement vector, H (matrix with dimension mxn) is the decoupled Jacobian matrix, x (vector with dimension $nx1$) is the voltage phase angle (state) vector and e (with dimension $mx1$) is the measurement error vector. m is the number of real power measurements and n is the number of buses.

$$z = Hx + e \tag{3.1}$$

In an observable power system measured by both conventional measurements and PMUs, where n is the number of buses the following must hold true:

$$rank(H) = n \tag{3.2}$$

$$nullity(H) = 0 \tag{3.3}$$

Therefore, the system is unobservable if;

$$nullity(H) > 0 \tag{3.4}$$

The nullity of the network with decoupled Jacobian matrix H is equal to the number of zero-pivots of gain matrix, G, which is defined as the product H^TH. Zero-pivots are the zero diagonal entries that are created during the factorization of the G matrix using a modified version of the Cholesky's method, as in the conventional observability analysis. The proposed method relies on the number of zero-pivots encountered during this factorization process.

The method introduced in this chapter provides a simple algorithm for pseudo-measurement placement, particularly suitable for systems with a large number of observable islands. The procedure will be described first, followed by a set of simulation results illustrating its application for large-scale power systems.

II. PROPOSED METHOD

The proposed method involves a five-step procedure. Before starting the measurement placement, the buses at the sending and receiving ends of zero-impedance branches, such as very short lines and circuit breakers, can be merged for computational simplicity assuming that voltage at those buses are identical, which is a reasonable assumption. Merging is shown in Fig. 3.1.

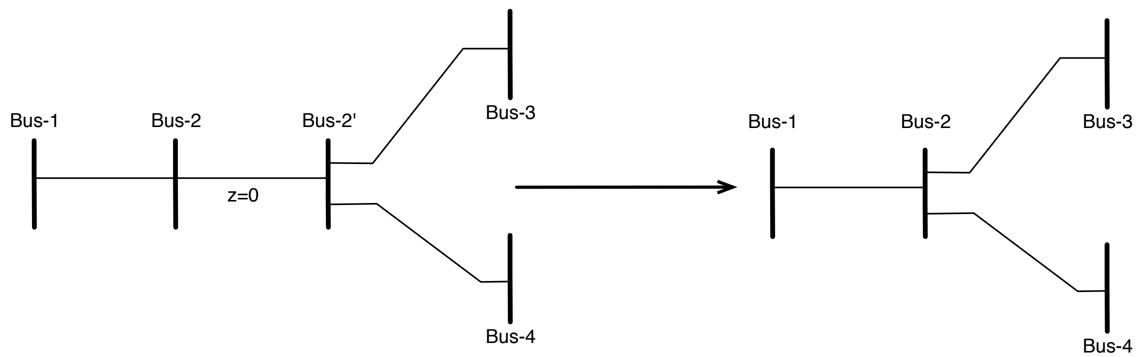


Fig 3.1. Merging buses at the ends of zero-impedance branches.

Candidate measurements are identified based on the available sources of pseudo-measurements. Since the objective is to avoid any redundant pseudo-measurements, they should strictly be placed at *boundary buses*, which are the sending and receiving ends of the unobservable branches. Placing pseudo-measurements at non-boundary buses may also affect observable islands according to the measurement distribution, but placing at boundary buses limits the size of search space significantly. Once the boundary buses are found, the ones with injection measurements should be disregarded. Proposed work assumes that pseudo-measurements are available for all buses; otherwise those buses with no pseudo-measurements can be eliminated from the candidate measurement set.

A. Step 1

The first step of the method forms the gain matrix *G*, which is the product $H^T H$. Measurement weights do not influence the observability analysis, so their incorporation in *G* is optional. Note that *G* is a square matrix with dimension *nxn* and each row/column of *G* corresponds to a bus of the system. By using Cholesky factorization the zero-pivots of *G* can be found [7]. Number of zero-pivots, *p* is equal to the nullity of the system, meaning that *p* pseudo-measurements are required to make system observable. Note that, if the measurement set of a power system includes PMUs, a reference bus should not be used, since phasor computations will be performed with respect to GPS reference signal. Therefore, a full rank *H* is required for network observability..

A pseudo-measurement is placed to each of the buses corresponding to a zero-pivot, which will be called zero-pivot buses, if it is also a candidate measurement. If pseudo-measurements are placed at all of the zero-pivot buses, then skip the rest of the steps and go directly to step 5.

Note that *G* is formed and zero-pivots are already identified as part of the network observability analysis, if all PMUs are type-1, hence this step in fact does not add any new computational burden.

B. Step 2

If there is only one unobservable branch connected to a bus, placing a pseudo-measurement at the mentioned bus makes the unobservable branch observable. Thus, pseudo-measurements are placed to those single-unobservable-branch connected buses in this step.

Note that, even if there is more than one unobservable branch between two observable islands, placing a pseudo-measurement to one of the single-unobservable-branch connected buses, merges those observable islands. In Fig. 3.2.a, by placing a pseudo-measurement at bus-1, two observable islands are merged, since the mentioned pseudo-measurements make the unobservable branch between buses 1 and 2 observable. Since buses 1 and 3, and 2 and 4 are in the same observable island, there is no need to add any other pseudo-measurements. Note that all of the buses shown in Fig. 3.2 are the boundary buses. Other buses in the observable islands are not considered and not shown in the figure.

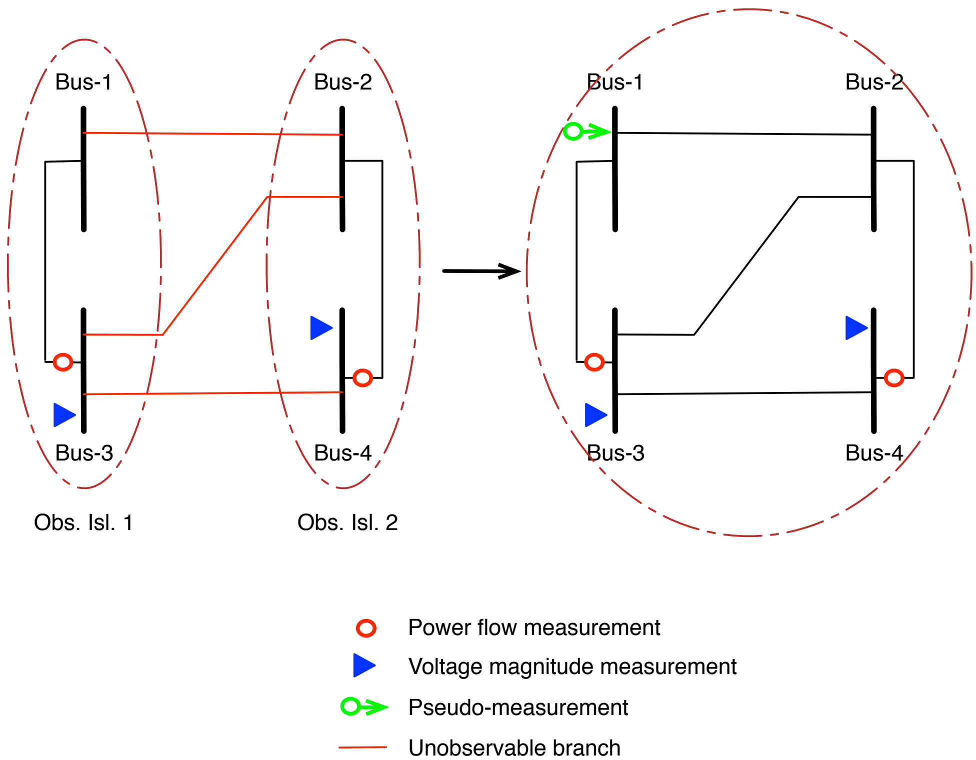
If two distinct observable islands are merged, the number of unobservable branches connected to the boundary buses in the mentioned observable islands decreases. Therefore, step 2 should be carried out recursively, by updating the number of unobservable islands connected to each boundary bus. For example, in Fig. 3.2.b note that by adding a pseudo-measurement at bus-1, not only observable islands 1 and 2 are merged but also number of unobservable branches connected to bus-2 is reduced to one. Similarly, by adding two more pseudo-measurements at buses 2 and 3, the entire system is merged into a single island as shown in Fig. 3.2.c.

C. Step 3

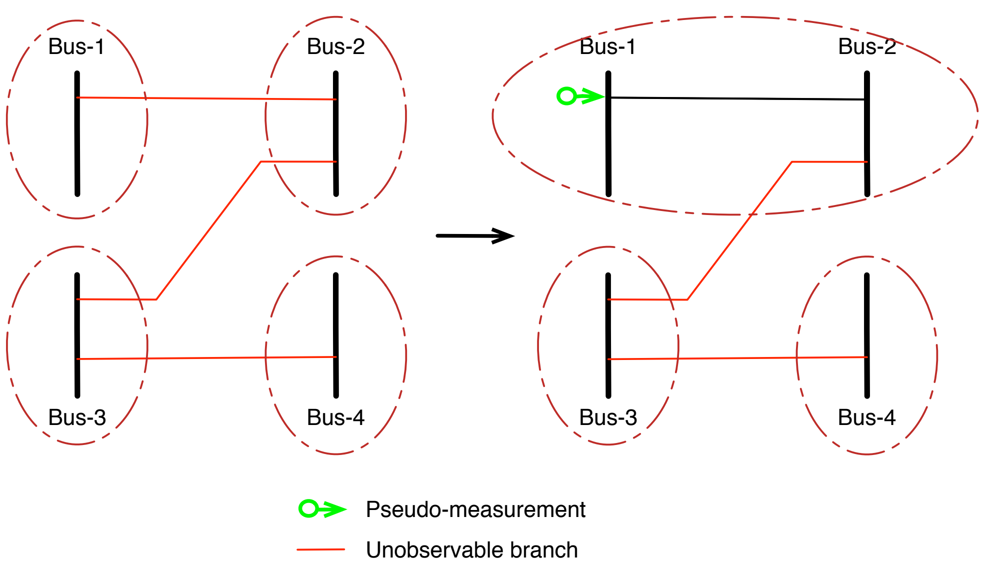
In this step, the zero-pivot buses, which are not boundary buses, are considered. First, the boundary buses connected to the considered zero-pivot bus are identified. Then a pseudo-measurement is placed at each of these buses, which are not in the same observable island with considered zero-pivot bus.

This step should satisfy two important requirements:

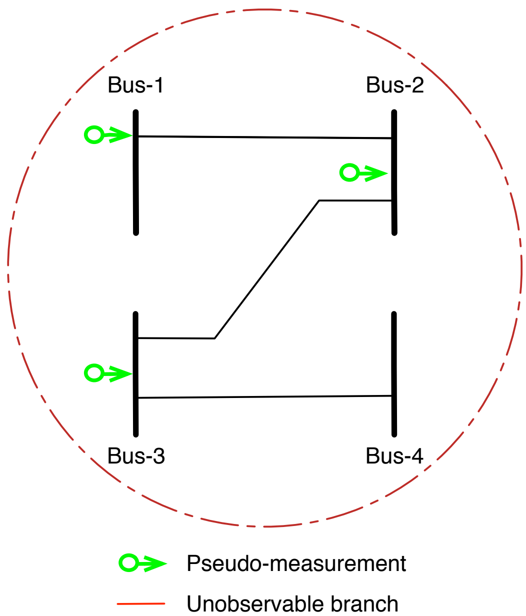
1. If there is more than one zero-pivot bus belonging to an observable island, only one of them will be considered in order to maintain their criticality.
2. Pseudo-measurements should be placed only in the observable islands with no prior pseudo-measurement assignments. This will ensure criticality of the pseudo-measurements.



a) Merging observable islands connected via multiple unobservable branches with single pseudo-measurement.



b) Merging observable islands by placing a pseudo-measurement to single-unobservable-branch-connected bus. It is assumed that there is voltage magnitude measurement at each observable island.



c) Unobservable power system given in Figure 2.b becomes observable by placing 3 pseudo-measurements.

Fig 3.2. Special cases for placing pseudo-measurements to single-unobservable-branch connected buses.

D. Step 4

If pseudo-measurements are placed at all of the boundary buses, the system becomes observable but some of the pseudo-measurements may be redundant. This step detects if there are any "not processed" observable islands, which have neither pseudo-measurements nor injection measurements at its boundary buses. At least one pseudo-measurement is assigned to all "processed" observable islands.

Boundary buses of "not processed" observable islands are considered buses at this step. After all of the pseudo-measurements found in steps 1-3 are added to system, corresponding candidate measurements are placed at the considered buses detected in this step one at a time. The number of zero-pivots of the system with new measurements is found at each iteration. Each placed measurement, which decreases the number of zero-pivots, is flagged as a pseudo-measurement. At the end of this step, the system will become fully observable.

Note that, this step is very similar to the method introduced in [21]. Instead of determining all of the observable islands, only the number of zero-pivots is considered in this work, which decreases the computational load. Moreover, the experiments have shown that there are very small number of observable islands and candidate measurements left at this step of the method, compared to initial state of the system. Therefore, this step does not significantly increase the computational burden.

E. Step 5

If the number of placed pseudo-measurements m_p is larger than the number of zero-pivots, p, then (m_p-p) redundant measurements should be removed. To identify those measurements, critical measurement detection method should be applied and one of the non-critical pseudo-measurements should be removed. This procedure is repeated until the number of pseudo-measurements becomes p.

Critical measurements can be detected and identified in several different ways. One of the simplest ones is to search for null diagonal entries of the measurement sensitivity matrix, S, which is defined in (2.2).

This step can also be used as a placement method itself for systems with small number of observable islands, since it will take long time for larger systems.

III. SIMULATIONS AND RESULTS

In this section some simulations and results are presented to show the performance of the proposed method with large-scale power systems. All of the simulations are conducted by using MATLAB R2010b on Mac Operating System Lion. The computer employed a processor of 2.3 GHz Intel Core i5 and memory of 4 GB 1333 MHz DDR3.

A large-scale utility system is considered for simulations. The circuit and measurement configuration of the five cases studied in this work are given in Table 3.1. Observable islands are formed, by applying the conventional methods to the simplified system. Candidate measurements are selected from boundary buses assuming that all have pseudo-measurements.

Applying the method proposed to the cases 1, 2 and 3 results in no extra pseudo-measurement at the end of step 4. All of the pseudo-measurements placed are critical and the execution times for each case are as given in Table 3.2.

In case 4, at the end of step 4, there is 1 and for case 5 there are 3 extra pseudo-measurements. Those extra ones are eliminated, by using step 5 introduced in Section III.

Note that, the method is capable of handling large-scale unobservable systems with high number of observable islands, even when the number of observable islands is comparable to the number of buses in the system.

TABLE 3.1. RESULTS OF SIMULATIONS FOR PSEUDO-MEASUREMENT PLACEMENT

Case No.	**No. of Buses**	**No. of Branches**	**No. of Obs. Islands**	**No. of Candidate Meas.**
1	3254	4786	1212	1450
2	3253	4785	1214	1452
3	3252	4785	1209	1444
4	3252	4783	1210	1448
5	3137	4645	1123	1372

IV. SUMMARY AND COMMENTS

This chapter introduces a hybrid method in order to place a minimum number of pseudo-measurements that will render the power system fully observable. The introduced method achieves its goal in a computationally efficient way, even for large-scale power systems with high number of small size observable islands. Since each of the pseudo-measurements placed is critical, their measurement errors do not bias the state estimate or propagate to other existing measurements in the system.

TABLE 3.2. RESULTS OF SIMULATIONS FOR PERFORMANCE

Case No.	No. of Pseudo-Meas.	Extra Pseudo-Meas. Found Initially	Solution Time (sec.)
1	1164	0	7.89
2	1168	0	8.26
3	1162	0	7.68
4	1162	1	10.46
5	1076	3	12.81

CHAPTER 4

ROBUST LEAST ABSOLUTE VALUE (LAV) ESTIMATION FOR SYSTEMS MEASURED BY PMUS

I. INTRODUCTION

Earlier chapters described observability and criticality analysis methods, and observability restoration for unobservable power systems. In this chapter a robust estimator, which can be used for power systems measured by only PMU measurements, will be proposed. This estimator will be implemented as a linear programming (LP) solution to a linear optimization problem. Today's power systems are measured by conventional measurements, and hence state estimation problem for those systems is solved iteratively by using WLS estimator, which is a widely used and well-investigated method. Despite being iterative, WLS estimator is quite fast due to the efficient sparse matrix methods used in its implementation. This is however true only for the main solution engine. As well known, WLS estimator is not robust and will breakdown (i.e. estimate will be biased) even in the presence of a single bad measurement. Hence, the solution is customarily followed by a bad data processor whose function is to detect, identify and correct any existing bad data. This is commonly accomplished by the largest normalized residual test. In this test, the main bottleneck is the computation of the residual covariance matrix, which requires calculation of a subset of the elements in the inverse of the sparse gain matrix. Even when highly efficient sparse inverse method [57]-[59] is employed, the computational complexity grows approximately proportional to the number of measurements. A practical alternative, which avoids this post-processing stage, is the use of re-weighted least squares method where measurement weights are modified based on their respective residuals during the iterative solution [7], [31], [60]-[61]. Despite its simplicity, this approach may lead to biased solutions especially when multiple interacting bad data are present.

Estimators with high breakdown points, which can be defined as the smallest amount of contamination (number of gross errors) that can cause an estimator to give an arbitrarily incorrect solution [27], have been investigated and developed by researchers in the past couple of decades [28], [29]. Some of these have also been applied to power system state estimation [30]-[33]. Among these robust estimators, the Least Absolute Value (LAV) estimator was shown to have desirable properties where its implementation can be made computationally efficient by taking advantage of power system's properties [34]-[36]. However, LAV estimator remains vulnerable against the so-called leverage measurements [31], [62]. This shortcoming along with the added computational burden brought on by the linear programming (or interior point) based problem formulation has so far made widespread implementation of LAV estimators non-viable.

In power system state estimation a measurement may be considered an outlier either because of its wrong value (it may contain a gross error) or because of the very large or very small entries (compared to the rest of the entries) of the measurement jacobian in the row corresponding to that measurement. In this study, the bad data refers to measurements with gross errors. The latter type of outlier will likely be a leverage measurement (this is what is referred as an outlier in this work). Note that a leverage measurement may or may not carry bad data. Leverage point is an observation (or measurement), which lies away from the rest of the measurements in the measurement space. In the special case of power system state estimation, a leverage point (or measurement) will have distinctly different values in the row of the measurement jacobian corresponding to this measurement. There are several ways to identify leverage measurements, which are well documented in [29]-[31].

As evident from the large number of publications on phasor measurements, their optimal deployment and utilization for a wide variety of power system control applications, phasor measurement units (PMUs) are expected to populate power systems in large numbers in a few short years. This chapter investigates the potential use of these phasor measurements in state estimation in a robust yet computationally efficient manner. While current power systems may not yet have sufficient number of PMU measurements to make the entire system observable, certain subsystems defined either by geography or voltage level can be fully observed by the existing set of strategically placed PMUs.

PMUs measure the bus voltages and line currents in a synchronized manner with respect to GPS. Phasor measurements are linearly related to system states as shown below:

$$\begin{aligned} V_k^m &= \mathrm{Re}\{V_k^m\} + j\,\mathrm{Im}\{V_k^m\} \\ &= |V_k|\cos\theta_k + j\,|V_k|\sin\theta_k \end{aligned} \tag{4.1}$$

$$\begin{aligned} I_{ij}^m &= \mathrm{Re}\{I_{ij}^m\} + j\,\mathrm{Im}\{I_{ij}^m\} \\ \mathrm{Re}\{I_{ij}^m\} &= G_{ij}(\mathrm{Re}\{V_i\} - \mathrm{Re}\{V_j\}) - B_{ij}(\mathrm{Im}\{V_i\} - \mathrm{Im}\{V_j\}) \\ \mathrm{Im}\{I_{ij}^m\} &= G_{ij}(\mathrm{Im}\{V_i\} - \mathrm{Im}\{V_j\}) + (B_{ij} + B_{ii})(\mathrm{Re}\{V_i\} - \mathrm{Re}\{V_j\}) \end{aligned} \tag{4.2}$$

In developing the problem formulation and implementing the solution the study will use rectangular coordinates, where the real and imaginary parts of bus voltage phasors will be used as the system states as shown in (4.1) and (4.2). Similarly, rectangular coordinate convention will also be used in representing the PMU measurements. In (4.2),

$G_{ij}+jB_{ij}$ is the series admittance of the branch connecting buses i and j and B_{ii} is the shunt admittance at bus-i. The superscript m is used to indicate that it is a measured value.

When there are sufficient PMU measurements to make the system observable, WLS estimation will be non-iterative and fast, thanks to the linearity between the PMU measurements and the system states. However, bad-data analysis, which is computationally expensive, will still be needed due to the non-robustness of WLS estimation. On the other hand, LAV will be computationally competitive with WLS if the measurement set includes only phasor measurements [37]. Moreover, biasing effect of leverage measurements can be eliminated by strategic scaling. This work proposes the use of LAV state estimation if the considered system is measured solely by PMUs. This subject was first discussed in [37] however performance comparisons were not comprehensively carried out. In this work, a thorough and detailed performance comparison between LAV and WLS estimators will be presented. Moreover, a realistic case study involving a large size power system will be shown.

In Section II LAV-based state estimator is explained in detail. Section III defines the concept of leverage measurements and how they can be transformed in systems measured only by PMUs. In Section IV performance comparison of WLS and LAV estimators is presented. Use of LAV is explained in an algorithmic manner in Section V. Simulation results are given in Section VI followed by a summary.

II. LAV Based State Estimation

WLS is a well-known and widely used method for state estimation [7]. The solution algorithm is iterative when conventional measurements are used. This algorithm simplifies and becomes non-iterative when only PMU measurements are used. Consider a system with n buses and measured by m phasor measurements. The measurement and WLS estimation equations will take the following form:

$$\begin{aligned} z &= H\hat{x} + r \\ \hat{x} &= (H^T R^{-1} H)^{-1} H^T R^{-1} z \end{aligned} \tag{4.3}$$

In (4.3), H is the measurement Jacobian with a dimension of $2m$x$2n$. Note that H is a constant matrix, i.e. not a function of system states, since the system is measured by PMUs. R is the measurement covariance matrix, which has a dimension of $2m$x$2m$. $\hat{x}$ and z represent the system state vector ($2n$x1) and measurement vector ($2m$x1), respectively.

Once WLS estimation is completed, post-processing of measurement residuals for bad-data analysis should be carried out. While the WLS estimation solution is obtained fast due to the direct linear solution, bad-data analysis will still require significant computation time. Hence, this study considers and investigates the viability of the more robust LAV estimator as an alternative.

LAV estimator aims to minimize the sum of absolute values of measurement residuals. Objective function of LAV estimator is defined as below:

$$\sum_{i=1}^{2m} |r_i| = c^T |r| \tag{4.4}$$

where $c^T = \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix}$ is a (1x$2m$) vector of "1"s.

$r^T = \begin{bmatrix} r_1^r & r_2^r & \dots & r_m^r & r_1^i & r_2^i & \dots & r_m^i \end{bmatrix}$, $r_i^r = z_i^{m,r} - \hat{z}_i^r$ and $r_i^i = z_i^{m,i} - \hat{z}_i^i$

r_i^r and r_i^i are real and imaginary parts of ith measurement residual, respectively,

$z_i^{m,r}$ and $z_i^{m,i}$ are real and imaginary parts of the ith measured value, respectively and

$\hat{z}_i^r$ and $\hat{z}_i^i$ are real and imaginary parts of the ith measurement value calculated with estimated states, respectively.

In compact form the measurement equations can be written as:

$$z = Hx + r \tag{4.5}$$

where n is the number of buses and:

$z^T = \lfloor z_1^r \quad z_2^r \quad \dots \quad z_m^r \quad z_1^i \quad z_2^i \quad \dots \quad z_m^i \rfloor$ and $x^T = [e_1 \quad e_2 \quad \dots \quad e_n \quad f_1 \quad f_2 \quad \dots \quad f_n]$

x is the estimated state vector, e_i and f_i are the real and imaginary parts of i[th] state variable, i.e. bus voltage phasor, respectively.

By using (4.4) and (4.5), the LAV estimation problem can be formulated as below:

$$\begin{aligned} &\min \mathrm{c}^T \mid r \mid \\ &s.t. \;\; z - Hx = r \end{aligned} \tag{4.6}$$

LAV optimization problem given in (4.6) can be expressed as an equivalent linear programming (LP) problem by re-arranging the equations and defining some new strictly non-negative variables [7], [30], [55] and [56], as formulated below.

$$\begin{aligned} &\min c^T y \\ &s.t. \;\; My = b \\ &\qquad \mathrm{y} \geq 0 \\ \\ &c^T = [Z_n \quad O_m] \\ &y = [X_a \quad X_b \quad U \quad V]^T \\ &M = [H \quad -H \quad I \quad -I] \\ &b = z \end{aligned} \tag{4.7}$$

Problem defined in (4.7) can be solved efficiently by using well-developed optimization tools. In (4.7), Z_n is the 1x$2n$ vector consisting of zeros and O_m is the 1x$2m$ vector consisting of ones. X_a and X_b are 1xn, and U and V are 1xm vectors where;

$$\begin{aligned} x &= X_a^T - X_b^T \\ r &= U^T - V^T \end{aligned} \tag{4.8}$$

III. LEVERAGE MEASUREMENTS AND SCALING

LAV estimator is known to be robust against measurement errors. It can automatically reject bad measurements during the estimation without any additional post-estimation processing, unless leverage measurements are present in the system.

A leverage point is an observation (x_k, y_k) where x_k lies far away from bulk of the observed x_i in the sample space [29], [37]. In power systems, a leverage measurement presents itself as an outlier, where its corresponding row in H includes very large or very small values compared to those in the remaining rows. Leverage measurements bias estimation results by forcing their residuals to be close to zero.

The following conditions are known to create leverage measurements in power systems measured by conventional measurements [34]:

- An injection measurement placed at a bus incident to large number of branches.
- An injection measurement placed at a bus incident to branches with very different impedances.
- Flow measurements on the lines with impedances, which are very different from the rest of the lines.
- Using a very large weight for a specific measurement.

In the special case of phasor-only LAV estimation, only the third condition will be relevant in the creation of leverage measurements, since PMUs are assumed to provide bus voltage and current flow phasor measurements but not bus phasor current injection measurements. Even when a PMU is used to measure the net injected current at a bus, which is in fact the current supplied by a generator or drawn by a load via a transformer, it can be represented as a flow measurement by adding an extra bus as shown in Fig. 4.1.

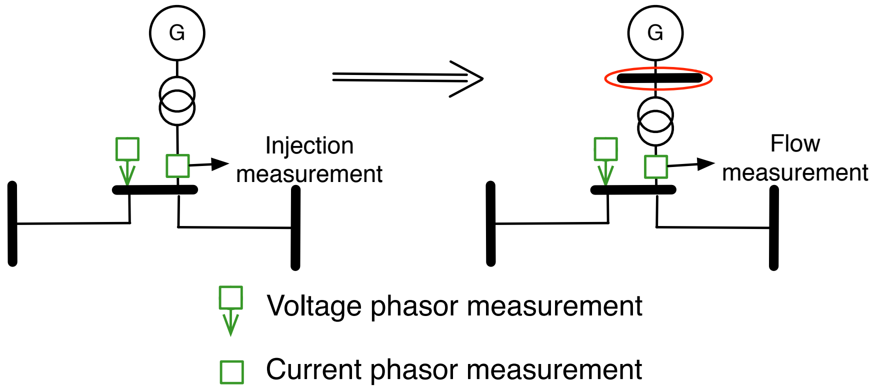


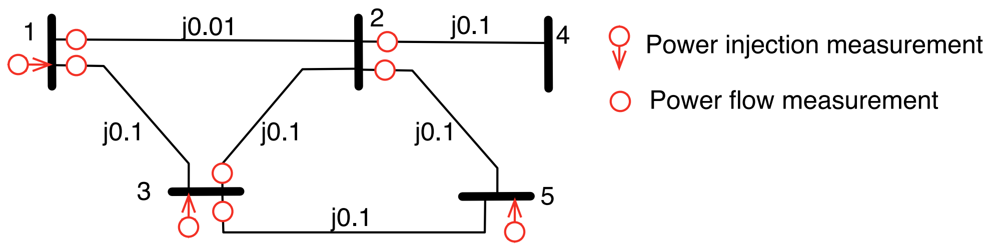
Fig. 4.1. Representing an injection measurement as a flow measurement.

Weights are not used to artificially enforce any measurements, since linear programming can easily incorporate equality constraints if such are needed.

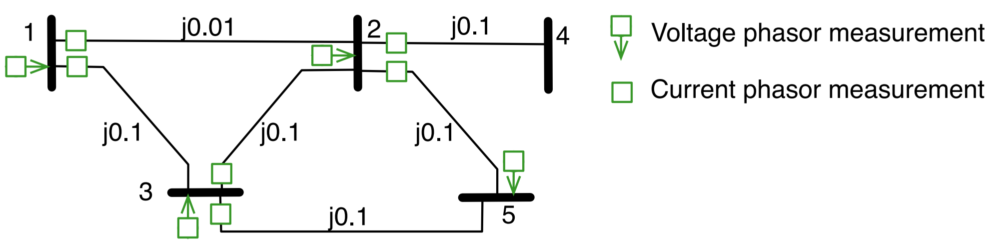
A current phasor measurement on a line having impedance which is very different from the rest of the lines can be identified as a leverage measurement by using leverage measurement identification methods [20], [63]. However, by scaling both sides of (4.5), the leveraging effect of the measurement can be eliminated. Scaling does not affect the results of the state estimation, thanks to the linearity between the states and the phasor measurements [64].

In literature, scaling is performed by dividing each column of Jacobian matrix, H, by the largest entry of that column, after which the same procedure is applied to the rows [64]. In order to illustrate the application of scaling, a simple 5-bus system shown in Fig. 4.2 is considered. The 5-bus system is measured by conventional measurements in Fig. 4.2.a, while it is measured by PMUs in Fig. 4.2.b. Line 1-2 has an impedance of j0.01, while other line impedances are set equal to j0.1. In this example, projection statistics [30] will be used to identify the leverage measurements.

Injection measurement at bus-1 and flow measurement on line 1-2 shown in Fig. 4.2.a are found to be leverage measurements as shown in Table 4.1. $\chi^2_{k,0975}$, which is the value that exceeds 97.5% of the samples from a chi-square distribution with *k* degrees of freedom, represents the detection limit for leverage measurements.



a) Sample system measured by conventional measurements.



b) Sample system measured by PMUs.

Fig. 4.2. 5-bus sample system.

TABLE 4.1. RESULTS FOR EXAMPLE 1-A

	PS	$\chi^2_{k,0975}$
$\mathbf{P_1}$	9.35	7.38
$\mathbf{P_3}$	0.84	9.35
$\mathbf{P_5}$	1.68	7.38
$\mathbf{P_{1\text{-}2}}$	8.80	7.38
$\mathbf{P_{1\text{-}3}}$	0.84	5.02
$\mathbf{P_{2\text{-}3}}$	0.42	5.02
$\mathbf{P_{2\text{-}4}}$	0.84	7.38
$\mathbf{P_{2\text{-}5}}$	0.84	7.38
$\mathbf{P_{3\text{-}5}}$	0.84	7.38

Table 4.2 lists the leverage measurements for the system given in Fig. 4.2.b. Note that, in Table 4.2 both scaled and original results are given. Although, current flow measurement on line 1-2 is identified as a leverage measurement, after scaling both the corresponding row of H and z, its leveraging effect is eliminated. Original and scaled Jacobian matrices of the system given in Fig. 4.2.b are shown below. Note that, scaling method described in [63] considers measurement weights. However, weights are disregarded in this study, so column wise scaling becomes redundant, and only row-wise scaling is employed.

$$H_{original} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 100 & -100 & 0 & 0 & 0 \\ 10 & 0 & -10 & 0 & 0 \\ 0 & -10 & 10 & 0 & 0 \\ 0 & 10 & 0 & -10 & 0 \\ 0 & 10 & 0 & 0 & -10 \\ 0 & 0 & 10 & 0 & -10 \end{bmatrix} \quad \mathrm{H}_{scaled} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & -1 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 & -1 \end{bmatrix}$$

TABLE 4.2. RESULT FOR EXAMPLE 1-B

	PS (original)	**PS (scaled)**	$\chi^2_{k,0975}$
$\mathbf{V_1}$	0.084	0.84	5.02
$\mathbf{V_2}$	0.084	0.84	5.02
$\mathbf{V_3}$	0.084	0.84	5.02
$\mathbf{V_5}$	0.084	0.84	5.02
$\mathbf{I_{1\text{-}2}}$	16.77	1.68	7.38
$\mathbf{I_{1\text{-}3}}$	1.68	1.68	7.38
$\mathbf{I_{3\text{-}2}}$	1.52	1.68	7.38
$\mathbf{I_{2\text{-}4}}$	1.68	1.68	7.38
$\mathbf{I_{2\text{-}5}}$	1.52	1.68	7.38
$\mathbf{I_{3\text{-}5}}$	1.68	1.68	7.38

IV. Performance Comparison of WLS and LAV

In this section performances of WLS and LAV estimators are compared. As explained in Section II, although WLS is an iterative estimator, it becomes non-iterative if the system is measured by PMUs, thanks to the linearity between the system states and phasor measurements.

State estimation problem given in (4.3) can be solved using WLS method in a single iteration, in a fast and computationally efficient way. However, once the estimation is completed, post-estimation procedure should be performed, in order to identify bad measurements and correct them. Bad-data analysis can be conducted by using two different approaches:

- **Re-weighting [61]:** This approach adjusts the measurement weights at each iteration based on the measurement residuals. If some of the residuals are higher than a threshold value, the weights of corresponding measurements are decreased to minimize the effect of those measurements on the estimate. When integrated in the WLS estimation solution, this method does not have significant computational cost and therefore commonly employed. However, it is not entirely reliable. Moreover, once the PMUs are considered, since the solution is non-iterative, iterative re-weighting will no longer be applicable.
- **Largest normalized residuals [65]:** This approach depends on the measurement residuals obtained after estimation, which are normalized using the corresponding residual covariance matrix. Residual covariance matrix, Ω, and normalized residuals are calculated as:

$$\begin{aligned} \Omega &= R - HG^{-1}H^T \\ G &= H^T R^{-1} H \end{aligned} \tag{4.9}$$

$$r_i^N = |r_i| \Big/ \sqrt{\Omega_{ii}} \tag{4.10}$$

If there are normalized residuals larger than a pre-determined threshold, e.g. 3.0, the largest one will correspond to the bad measurement. As seen from (4.9), inverse of the gain matrix G, which is $2n$x$2n$, should be computed. This introduces significant computational load, even when sparse inverse methods are employed, especially for large systems. Once the largest normalized residual is found, corresponding measurement is updated using [65]:

$$z_i^{new} = z_i^{bad} - R_{ii} \Big/ \Omega_{ii} \, r_i^{bad} \tag{4.11}$$

The states will then be recalculated using the updated measurements. Inverse of G is calculated once since it does not change significantly iteration to iteration. However, updating the measurements and states continues until all normalized residuals drop below the threshold. The computational complexity of this procedure is $2m$, which is the number of real and imaginary parts of the measurements, if the complexity of WLS is assumed to be *1* unit.

Hence, although WLS estimation is an efficient method, computation of normalized residuals carries a high computational burden especially in large-scale systems. Covariance calculation requires sparse inverse calculation, whose complexity grows linearly with the number of measurements.

The LP based solution of the LAV estimation problem will require several simplex iterations and therefore may be computationally more demanding than a WLS estimator, if the considered system is measured by conventional measurements. However, if the measurement set consists only of PMUs, LAV estimation will involve solution of a single LP problem whose dimension will be $2(m+n)$.

WLS estimation and post-estimation bad-data analysis have a complexity of $2m+1$ as explained in this section. On the other hand, complexity of LAV estimation is $2(m-n)$ with proper implementation of an LP solver [56]. Thus, it can be argued that LAV estimator will be computationally competitive with WLS estimator when using phasor measurements. Furthermore, recently released implementations of sparse LP solvers facilitate solution of this problem very efficiently. It is also noted that the structure of H is typically very sparse.

V. PROPOSED STATE ESTIMATION APPROACH

In Section IV, it is shown that LAV estimator is comparable to WLS estimator in terms of performance, once the considered system is measured only by PMUs. Moreover, thanks to scaling as shown in Section III, robustness deficiency of LAV estimation due to leverage measurements can be eliminated in a very simple way. In this section, results of applying LAV estimator to a large scale power system will be presented.

Although methods to identify leverage measurements are available in the literature [30], [63], it can be time consuming once the large-scale systems with changing topology and measurement configuration are considered. Therefore, it is proposed to scale all current phasor measurements with respect to the impedance of their associated branches. The complex scaling (scaling with a complex number) does not affect the solution and avoids a separate step of leverage measurement identification.

As an example of complex scaling, consider the following example, where $y_{k\text{-}m}$ is the admittance between buses k and m;

$$z = Hx$$

$$\begin{bmatrix} V_1 \\ V_3 \\ I_{1-2} \\ I_{1-4} \\ I_{3-2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ y_{1-2} & -y_{1-2} & 0 & 0 \\ y_{1-4} & 0 & 0 & -y_{1-4} \\ 0 & -y_{3-2} & y_{3-2} & 0 \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix}$$

Once the complex scaling is applied to the given equation, such that each measurement is scaled with the corresponding impedance, the following scaled set will be obtained:

$$\begin{bmatrix} V_1 \\ V_3 \\ I_{1-2}/y_{1-2} \\ I_{1-4}/y_{1-4} \\ I_{3-2}/y_{3-2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 \\ 0 & -1 & 1 & 0 \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix}$$

Note that shunt admittances of the lines are ignored for simplicity in the given example. If shunt admittances are included in measurement equations, as in reality, scaling is performed simply using the largest number in the corresponding row of *H*. After application of scaling, the LAV estimation problem can be solved by using an efficient linear programming problem solver.

VI. SIMULATIONS AND RESULTS

In this section two test systems will be used to test the performance of the LAV estimator. Simulations are carried out using a PC with 3GB RAM and Windows XP operating system. LP based LAV problem is solved using GUROBI version 5.0.1, while WLS estimation is solved in MATLAB R2011a environment.

Results of simulations for two cases will be presented. The first case is intended to illustrate the effect of scaling on the robustness of the LAV estimator for a 30-bus system, and the second case will comparatively present CPU performances of the WLS and LAV estimators for a realistic 3265-bus utility grid.

Case 1: Effect of Scaling

Consider the IEEE 30-bus system and its measurement configuration shown in Fig. 4.3. Here, the current phasor measurements on lines 1-2, 2-4 and 15-18, whose impedances are intentionally chosen as two orders of magnitude smaller than all the other lines in the system, will constitute leverage measurements.

Results of executing LAV estimation with and without scaling in the presence of bad leverage measurements are given in Table 4.3 to illustrate the effectiveness of scaling in maintaining robustness of the LAV estimator in the presence of leverage measurements. Three cases will be presented:

- Case 1.a: No bad data.
- Case 1.b: Current phasor measurements on lines 1-2, 2-4 and 15-18 are intentionally corrupted with bad data, such that those measurements were set to 0. However, no scaling is used in LAV estimation.
- Case 1.c: This is the same as case 1.b above except in this case the LAV estimator is executed by applying scaling.

The scaling factor is determined by using the method described in Section V. As evident in Table 4.3, when the three leverage measurements (flows through 1-2, 2-4 and 15-18) are corrupted with gross errors, the LAV estimator failed to recognize and automatically reject these bad data as can be seen from the wrong results of columns under case 1.b. However, once the scaling is applied, the leveraging effect of the current phasor measurements on lines 1-2, 2-4 and 15-18 are effectively eliminated and the LAV estimator converged to the correct solution as shown in columns under case 1.c.

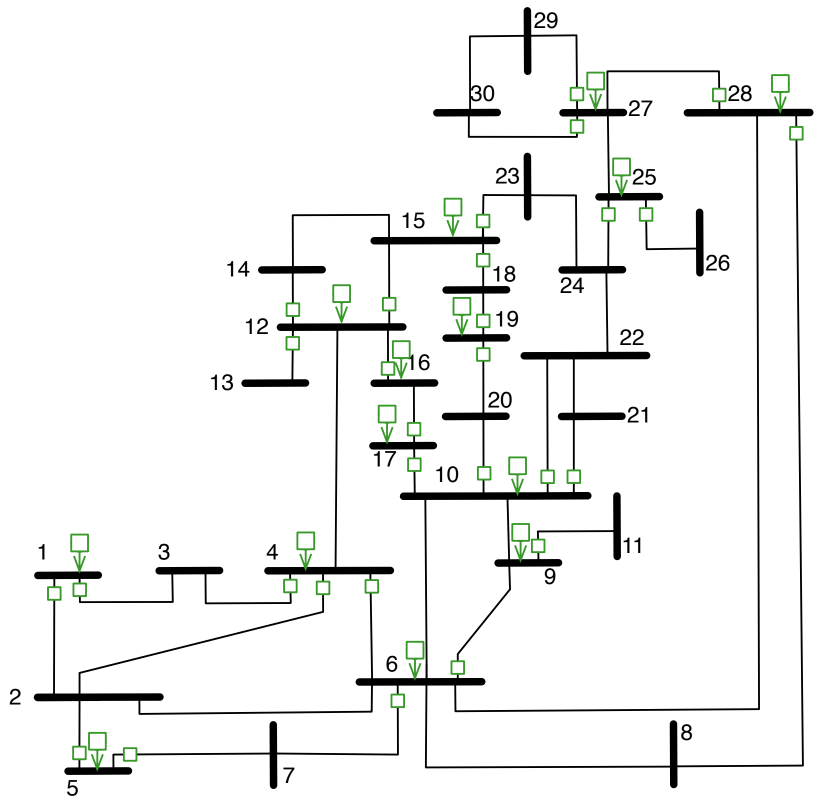


Fig. 4.3. IEEE 30-bus system.

Case 2: Performance of LAV estimator

A 3625-bus utility power system is used to compare the performance of the WLS versus LAV estimators. Measurement set is chosen such that 3800 branches are measured by phasor current and phasor voltage measurements taken at one end to make the system observable with reasonable redundancy. The redundant measurements are added to facilitate investigating effects of bad measurements on the performance of the LAV and WLS estimators.

Among the many cases tested, three representative cases will be discussed here. In these three cases, bad measurements are intentionally created in the following manner:

- Case 2.a: No bad measurement.
- Case 2.b: Single bad measurement.

- Case 2.c: Five bad measurements.

TABLE 4.3. RESULTS OF THE SIMULATIONS ON IEEE 30-BUS SYSTEM

	Case-1.a		**Case-1.b**		**Case-1.c**	
	V (pu)	**θ (deg)**	**V (pu)**	**θ (deg)**	**V (pu)**	**θ (deg)**
1	1	5.2	0.9999	-3.65	1	5.2
2	1	-3.74	1	-3.74	1	-3.74
3	0.9952	0.13	0.9818	1.12	0.9952	0.13
4	0.9992	-4.81	0.9999	-3.75	0.9992	-4.81
5	1	-9.02	1	-9.02	1	-9.02
6	0.9851	-7.41	0.9851	-7.41	0.9851	-7.41
7	0.9869	-8.88	0.9869	-8.88	0.9869	-8.88
8	0.9915	-8.89	0.9915	-8.89	0.9915	-8.89
9	0.9991	-8.10	0.9991	-8.10	0.9991	-8.10
10	0.9902	-8.81	0.9902	-8.81	0.9902	-8.81
11	1	-8.10	1	-8.10	1	-8.10
12	0.9547	-7.73	0.9547	-7.73	0.9547	-7.73
13	0.9793	-7.73	0.9793	-7.73	0.9793	-7.73
14	0.9553	-8.49	0.9553	-8.49	0.9553	-8.49
15	0.9577	-8.85	0.9577	-8.85	0.9577	-8.85
16	0.9633	-8.43	0.9633	-8.43	0.9633	-8.43
17	0.9737	-8.89	0.9737	-8.89	0.9737	-8.89
18	0.9631	-9.31	0.9578	-8.85	0.9631	-9.31
19	0.9696	-9.57	0.9642	-9.12	0.9696	-9.57
20	0.9795	-9.25	0.9742	-8.80	0.9795	-9.25
21	0.9782	-9.60	0.9782	-9.60	0.9782	-9.60
22	0.9778	-9.35	0.9778	-9.35	0.9778	-9.35
23	0.9605	-9.34	0.9605	-9.34	0.9605	-9.34
24	0.965	-9.64	0.965	-9.64	0.965	-9.64
25	0.9595	-9.69	0.9595	-9.69	0.9595	-9.69
26	0.9571	-9.91	0.9571	-9.91	0.9571	-9.91
27	0.9564	-9.53	0.9564	-9.53	0.9564	-9.53
28	0.9881	-8.61	0.9881	-8.61	0.9881	-8.61
29	0.9551	-9.85	0.9551	-9.85	0.9551	-9.85
30	0.9547	-10.02	0.9547	-10.02	0.9547	-10.02

In Case 2.b and 2.c, 100 runs were performed, and at each run bad measurements were assigned randomly. Both voltage and current phasor measurements were assigned as bad measurements in those 100 runs. In Case 2.b, the bad measurement was set as 0, and in Case 2.c three measurements were set to 0 and two measurements were set to the negative of the actual value of the corresponding measurement.

Table 4.4 provides a comparison of the performance of the two estimators for the above three cases. Table 4.4 presents the averages of the performance results of WLS and LAV estimators. Simulation CPU times include the sum of state estimation solution plus bad data processing times for the WLS estimator and the overall solution time for the LAV estimator. Note the increase in total processing time for the WLS estimator with increasing number of bad data versus the relatively fixed computation time for the LAV counterpart. While the actual CPU times naturally depend on the processor speed and implementation details (here sparse matrix methods are employed, but no effort is put towards code optimization), the trend will remain valid irrespective of these factors.

For both estimators Table 4.4 also shows the Mean Squared Error (MSE), which is calculated by:

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i^{estimated} - x_i^{true})^2} \tag{4.12}$$

TABLE 4.4. MEAN RESULTS OF THE SIMULATIONS ON 3625-BUS SYSTEM

Estimator	Case Number					
	2.a		2.b		2.c	
	CPU (second)	MSE ($\times 10^{-3}$)	CPU (second)	MSE ($\times 10^{-3}$)	CPU (second)	MSE ($\times 10^{-3}$)
LAV	3.33	0.74	4.80	0.77	4.74	1.4
WLS	2.32	0.73	9.31	0.95	15.81	2.9

VII. SUMMARY AND COMMENTS

This work presented in this chapter is motivated by the possibility that in the near future almost all power systems will be monitored exclusively by synchronized voltage and current phasor measurements. This possibility implies two important benefits: (i) state estimation problem will become linear; (ii) LAV estimation can be made truly robust by simple scaling. It is thus argued that the LAV estimator will then be a better choice for phasor measurement based static state estimation. When the errors have a Gaussian distribution, WLS estimator is known to be the best linear unbiased estimator. However, in the presence of bad data WLS estimator will require post-estimation bad data detection and elimination procedures. LAV estimator on the other hand will remain robust against bad data due to its automatic bad data rejection property. Robustness is a critical property due to the dire consequences of missing bad data. This study shows that a robust yet computationally competitive LAV estimator based on linear programming can be implemented when using phasor measurements.

CHAPTER 5

PMU PLACEMENT FOR ROBUST STATE ESTIMATION

I. INTRODUCTION

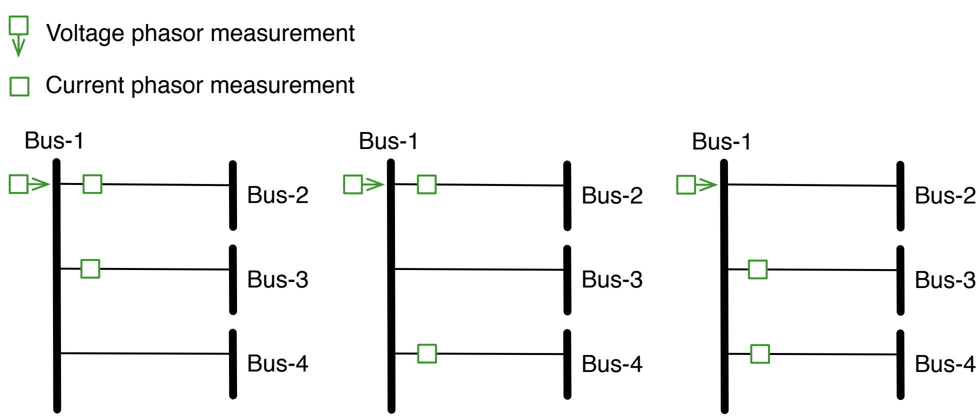
Chapter 4 proposed the use of LAV estimator if the measurement set consists of only PMUs, after the introduction of observability and criticality analysis, and observability restoration methods in Chapters 2 and 3 respectively. In this chapter measurement redundancy required for robustness of LAV estimator will be discussed. Rapid population of power grids by PMUs rekindled the idea of using LAV estimator in power systems measured by only PMUs. If the measurement set only consists of PMUs, besides robustness of LAV against bad data, the effect of leverage measurements can be eliminated through the use of simple scaling as demonstrated in Chapter 4 [37]. Although capability of eliminating leveraging effect of a measurement is directly related to the linearity between the phasor measurements and state variables, robustness of LAV estimator is related to the measurement redundancy. Therefore, this study proposes a method for redundant PMU placement to guarantee robustness of LAV estimators using a minimum number of PMUs.

PMU placement has been a popular research topic in recent years [38]-[42]. Although many efficient and well-defined solutions have been proposed, those methods aim to find the minimum set of PMUs that make the system observable. The resulting measurement redundancy will be very low in the solution set, if the only objective of the placement method is to restore observability. Moreover, most of the measurements are generally critical. On the other hand, the method defined in this chapter is developed in order to place a minimum number of PMUs to obtain a redundant enough measurement set, i.e. none of the placed measurements are critical and each bus is measured by at least a pre-determined number of measurement devices (voltage and current phasor measurements).

The chapter is organized as follows: In Section II general formulation of the proposed method is given. Section III defines the proposed method for commonly employed branch PMUs as a tutorial example. In Section IV, the proposed method is enhanced to obtain more feasible results. Simulations are given in Section V and finally a summary is presented in Section VI.

II. PROPOSED PMU PLACEMENT METHOD

In this work it is assumed that each PMU can provide a voltage phasor measurement and p current phasor measurements, and a "PMU configuration" is a possible assignment of those p current phasor measurements to the incident branches of the considered bus. As an example, consider the 4-bus system given in Fig. 5.1. There are 3 possible PMU configurations for a PMU with 2 current phasor measurements at bus-1. These are shown in Fig. 5.1 (a), (b) and (c).



a) PMU configuration 1 b) PMU configuration 2 c) PMU configuration 3

Fig. 5.1. PMU configurations for 4-bus system.

Consider a PMU placed at bus i that measures a voltage phasor and p current phasor measurements. There are k_i possible ways to assign those p current phasor measurements (PMU configurations) at bus i,

$$k_i = \binom{t_i}{p} = \frac{t_i!}{p!(t_i - p)!} \tag{5.1}$$

where t_i is the number of branches connected to bus i. Let us also define N as the total number of possible combinations for the entire system:

$$\begin{aligned} &N = \sum k_i \\ &i = 1,2 \ldots n \end{aligned} \tag{5.2}$$

The proposed PMU placement method will be based on the well-known linear programming (LP) formulation which can be compactly written as follows [38]:

$$\begin{aligned} &\min \mathrm{c}^T x \\ &s.t.\ \mathrm{A}x \geq b \end{aligned} \tag{5.3}$$

The solution ensures that each PMU is non-critical and LAV estimator is robust against bad measurements. In (5.3), c and x are $Nx1$ vectors, A is an nxN matrix and b is an nx1 vector. N is the number of possible PMU configurations for all buses and n is the number of buses. More details on these arrays are given below:

1) Cost vector [c]: Each entry corresponds to installation cost of a PMU configuration. All entries of c will be set equal to 1, if there are no PMUs already placed in the system and installation costs of all PMU configurations are the same. Otherwise, smaller costs can be assigned for the preferred PMU locations or configurations and zero (0) costs will be used for already installed PMUs.

2) Binary vector [x]: i^{th} entry is 1 or 0 depending on whether the corresponding PMU configuration is selected or not respectively.

3) PMU configurations matrix [A]: If a PMU, which can measure p current phasors, is placed at bus-i, i^{th} entry of the corresponding column of A equals to $p+1$, since $p+1$ measurements are taken at bus-i, such that there is 1 voltage phasor measurement and p current phasor measurements, located at bus-i. On the other hand, all of the buses at the receiving ends of those p current phasor measurements are monitored by 1 current phasor measurement. Therefore, entries corresponding to those buses are set equal to 1 and the remaining entries are equated to zero (0) at the corresponding row of A.

If the number of branches connected to bus-i, which is t_i, is smaller than p, it is assumed that a PMU, which can measure t_i current phasors, is connected at bus-i. Therefore, i^{th} entry of the corresponding column of A equals to t_i+1, instead of $p+1$.

4) Index vector [b]: This vector indicates the minimum number of measurements that should be located at each bus. In this work, minimum of 4 measurements are assumed to be located at each bus. If chosen index is less than 4, isolated bus groups, which are illustrated in Fig. 5.2, may appear in the system. Since the system states corresponding to those bus groups are independent of the measurements from the rest of the system, any bad measurement in this isolated group may lead to biased state estimates. Therefore, it is suggested that an index of 4 be used when placing PMUs. This will ensure that no isolated bus groups will be formed. Note that, the proposed method always satisfies system observability; even when the index is less than 4.

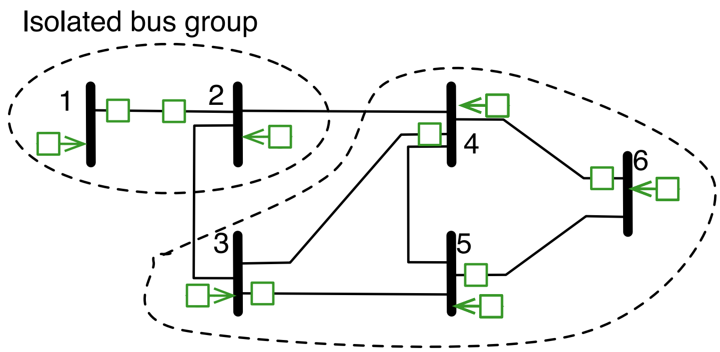


Fig. 5.2. Isolated bus groups if index is chosen to be 3.

Although, it is proposed to use an index of 4 for all buses, it is not possible to place 4 measurements if the considered bus has only one branch connected to it. In this case, at most 3 measurements can be placed, as shown in Fig. 5.3. In Fig. 5.3, voltage phasor measurement 1 and current phasor measurements 2 and 3 measure bus-1. Similarly, voltage phasor measurement 4 and current phasor measurements 2 and 3 measure bus-2.

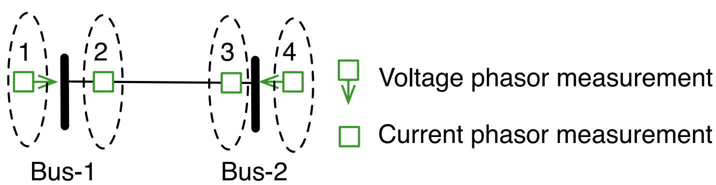


Fig. 5.3. Single branch connected buses.

In order to have a robust measurement design, a higher number of PMUs compared to the optimal (minimum) PMU placement problem, is required. Note also that zero injection buses can be considered in order to further reduce the required number of PMUs to be placed.

If a bus is a zero injection bus, sum of all currents from the considered bus to neighboring buses is equal to 0. This information can be treated as a virtual measurement (zero injection) taken at that bus. To take this pseudo-measurement into account, an extra column is added to A with a cost of 0. Entries of the new column corresponding to the zero injection and neighboring buses will be equal to 1 while remaining rows will all be zeros. If there are neighboring zero injection buses, instead expressing them separately in A, they should be combined in a single expression. For example, if both of buses 2 and 3 in Fig, 5.4 are zero injection buses, the corresponding combined zero injection equation should be as following, assuming branch impedance are unity and shunt elements are neglected.

$$\left.\begin{array}{l} 2V_2 - V_1 - V_3 = 0 \\ 2V_3 - V_2 - V_4 = 0 \end{array}\right\} V_3 + V_2 - V_4 - V_1 = 0 \tag{5.4}$$

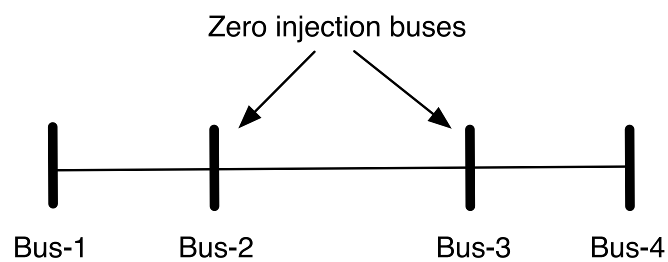


Fig. 5.4. Zero-injection buses on the sample 4-bus system.

Eq. (5.4) is a pseudo-measurement, which is also a combined zero injection equation, and it should be treated as zero injection measurements. If zero injection buses are also considered in the optimization problem, N should be defined as follows, where n_z is the number of combined zero injection equations;

$$\begin{array}{l} N = n_z + \sum k_i \\ i = 1,2 \ldots n \end{array} \tag{5.5}$$

III. Tutorial Example

In this section, the proposed method is applied to a 6-bus system with a branch PMU shown in Fig. 5.5, where bus-3 is a zero injection bus. The objective is to place a minimum number of branch PMUs and still maintain an observable system and a robust measurement design. A branch PMU can be defined as a PMU with one voltage phasor measurement and one current phasor measurement as illustrated in Fig. 5.5.

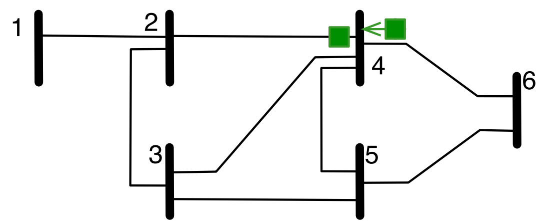


Fig. 5.5. Sample 6-bus system.

Considering Fig. 5.5, N is determined as follows, where k_i is the number of PMU configurations for bus-i;

$$\begin{aligned} N &= k_1 + k_2 + k_3 + k_4 + k_5 + k_6 + n_z \\ N &= \binom{1}{1} + \binom{3}{1} + \binom{3}{1} + \binom{4}{1} + \binom{3}{1} + \binom{2}{1} + 1 = 17 \end{aligned} \quad (5.6)$$

Consider bus-6, which is connected to buses 4 and 5. The columns of A corresponding to bus-6 are as follows;

$$A_6^T = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 2 \\ 0 & 0 & 0 & 0 & 1 & 2 \end{bmatrix} \quad (5.7)$$

Using (5.7), the complete A matrix for the system given in Fig. 5.5 will be built as follows;

$$A = \begin{array}{c} \begin{array}{ccccccccccccccccc} \scriptstyle bus-1 & \multicolumn{3}{c}{\scriptstyle bus-2} & \multicolumn{3}{c}{\scriptstyle bus-3} & \multicolumn{4}{c}{\scriptstyle bus-4} & \multicolumn{3}{c}{\scriptstyle bus-5} & \multicolumn{2}{c}{\scriptstyle bus-6} & \scriptstyle zero-inj. \end{array} \\ \begin{bmatrix} 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 2 & 2 & 2 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 2 & 2 & 2 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 2 & 2 & 2 & 2 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 2 & 2 & 2 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 2 & 2 & 0 \end{bmatrix} \end{array} \tag{5.8}$$

Once A is formed, Nx1 c vector can be defined. Since there is a zero injection bus, which corresponds to the 17th column, and the PMU seen in Fig. 5.5 is already available in the system, which corresponds to 8th column, c can be as defined as follows:

$$c^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{5.9}$$

Considering the system in Fig. 5.5, b vector will take the following form:

$$b^T = \begin{bmatrix} 3 & 4 & 4 & 4 & 4 & 4 \end{bmatrix} \tag{5.10}$$

Note that, since there is only one branch connected to bus-1, only 3 measurements can be connected, instead of 4.

Having (5.8), (5.9) and (5.10), (5.1) can be solved for x using a linear programming solver. It is found that 6 new PMUs are required for a robust measurement design. The placement of all the PMUs is shown in Fig. 5.6. Note that voltage and current phasor measurements are color coded, to show different PMUs.

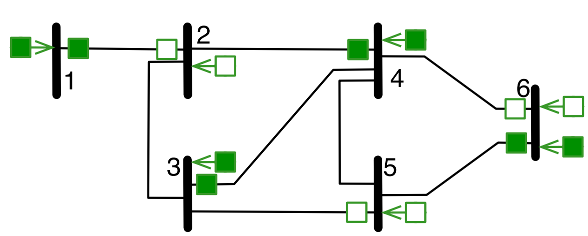
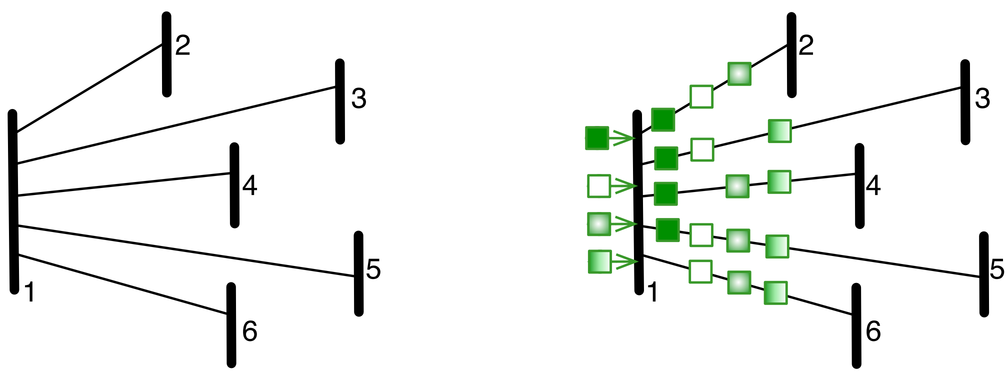


Fig. 5.6. PMU placement of 6-bus system.

IV. Enhanced Method

The proposed method places minimum number of PMUs for robust state estimation. However, resulting measurement placement may not be realistic and feasible. Consider the 6-bus system given in Fig. 5.7.a, which is the worst-case scenario of the PMU placement problem. If it is desired to obtain a robust measurement design by placing PMUs with 4 current phasor measurements, the resulting measurement placement will be as given in Fig. 5.7.b. Placing multiple PMUs at the same bus is not realistic since in this case same voltage transformer will be used for all PMUs at the considered bus, which will increase the risk of unobservability due to loss of a voltage transformer. Moreover using the same voltage transformer will introduce the same measurement error to all PMUs, which may bias the state estimates. In addition, it is preferred to take voltage phasor measurements from different buses to increase the measurement set quality. Therefore it is proposed to modify the proposed method to enhance the resulting PMU placement.



a) 6-bus system, worst-case study.

b) PMU placement result.

Fig. 5.7. PMU placement of 6-bus system.

In this section, it is proposed to modify the cost vector, *c*, to obtain more realistic placement designs. If number of current phasor measurement channels of a PMU is more than or equal to the number of branches connected to the considered bus, there is only one possible PMU placement strategy for that location. Therefore, it is assumed that this kind of PMU configurations has a unit cost. On the other hand, if the number of current phasor measurement channels is less than number of branches, there exist multiple PMU placement configurations at the considered bus. In this case, it is desired to place minimum number of PMUs at the same bus.

The enhanced method aims not to place two PMUs at the same bus, unless it is mandatory. Therefore, considering the system given in Fig. 5.7.a, cost of placing two PMUs at the same bus (bus-1) should be equal to the cost of placing single PMU at the considered bus (bus-1) and placing unity cost PMUs at the neighboring buses (buses 2-6). Hence the corresponding costs of those configurations are proposed to be $t_i/2$, where t_i is the number of branches connected to bus i. The proposed cost favors placement of PMUs at different buses.

V. SIMULATIONS AND RESULTS

In this section, IEEE 14-bus system is considered as the test system. The proposed method is applied three times for three different types of PMUs. It is assumed that there are neither zero injection buses nor PMUs already installed in the system. In Table 5.1, details of those three types of PMUs and numbers of each PMU type to obtain an observable and robust measurement design are presented. Fig. 5.8 presents the placement of each PMU type.

To test the robustness of the measurement designs shown in Fig. 5.8, following procedure is applied, where z is measurement vector consisting of voltage and current phasor measurements and m is the total number of those measurements.

for all $i = 1 : m/2$ do

$z(i) \to 0$

$z(i+m/2) \to -z(i+m/2)$

Solve state estimation problem

Plot estimated states

end for

TABLE 5.1. RESULTS OF SIMULATIONS FOR PMU PLACEMENT

	PMU Type		**Number of placed PMUs**
	Voltage Phasor Number	**Current Phasor Number**	
One-channel PMU	1	1	19
Two-channel PMU	1	2	12
Three-channel PMU	1	3	11

Results of robustness study are shown in Fig. 5.9. In Fig. 5.9, estimated states for every run are plotted on the same graph as the true states.

In Fig 5.10, estimates obtained using classical WLS based estimator and proposed LAV based estimator are compared. For this study two-channel PMUs are employed. Voltage phasor measurement at bus-5 and current phasor measurement between buses 9 and 10, which are shown in Fig. 5.8.b, are set as bad measurements.

As seen in Fig. 5.9 and 5.10, estimated states closely match the true states, although there are two bad measurements in the system. On the other hand, WLS based estimator gives biased results.

Finally, to evaluate the enhanced method, 140-bus NPCC system is considered. PMU placement is performed for 10 types of PMUs using both the enhanced and regular PMU placement methods. Results are presented in Table 5.2. Since maximum branch number connected to a bus is 9, as seen from Table 5.2, both methods give same results if a PMU has 9 or more current phasor measurement channels. The enhanced method does not place multiple PMUs at the same bus as seen from Table 5.2, unless number of current phasor measurement channels is less than four. There is not a significant difference between the methods, in the number of placed PMUs if one-channel or two-channel PMUs are used, because of the low number of current phasor measurements, it is mandatory to place multiple PMUs at a single bus to satisfy the constraints of the optimization problem. As a final remark, in the case of three-channel PMUs, although both methods places multiple PMUs at a single bus, total number of buses with PMUs is 81 for regular method, while this number increases to 106 if enhanced method is performed.

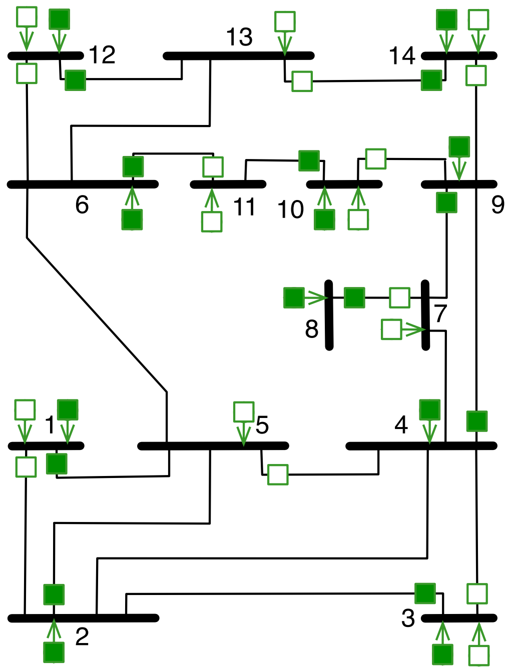
VI. SUMMARY AND COMMENTS

This chapter revisits the LAV estimator, which is shown to remain robust against gross measurement errors if PMUs are strategically placed in a power system. Such a strategic placement approach is proposed and implemented.

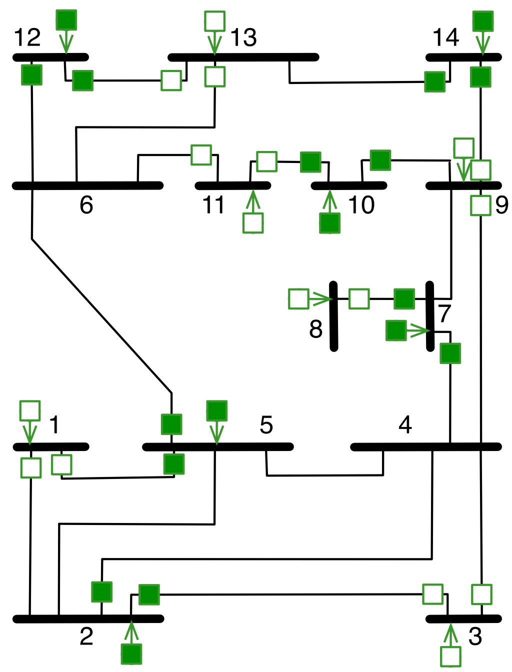
The proposed method also considers passive buses where zero injections are treated as virtual measurements with zero cost and they help reduce the number of required PMUs. Moreover, the approach incorporates all existing PMU locations to take advantage of already installed PMUs in an optimal manner. It is also shown that, by modifying the cost vector, more realistic and feasible measurement designs can be obtained.

TABLE 5.2. RESULTS OF THE METHOD COMPARISON

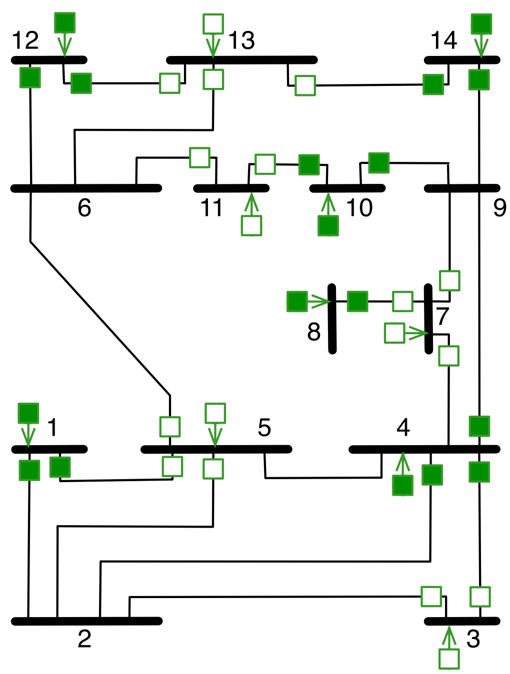
	PMU Number		Multiple PMUs at a single bus	
	Regular Method	**Enhanced Method**	**Regular Method**	**Enhanced Method**
One-channel PMU	184	186	Yes	Yes
Two-channel PMU	121	122	Yes	Yes
Three-channel PMU	100	108	Yes	Yes
Four-channel PMU	94	105	Yes	No
Five-channel PMU	98	103	Yes	No
Six-channel PMU	97	102	Yes	No
Seven-channel PMU	96	100	Yes	No
Eight-channel PMU	98	99	Yes	No
Nine-channel PMU	98	98	No	No
Ten-channel PMU	98	98	No	No



a) PMU placement for one-channel PMUs.

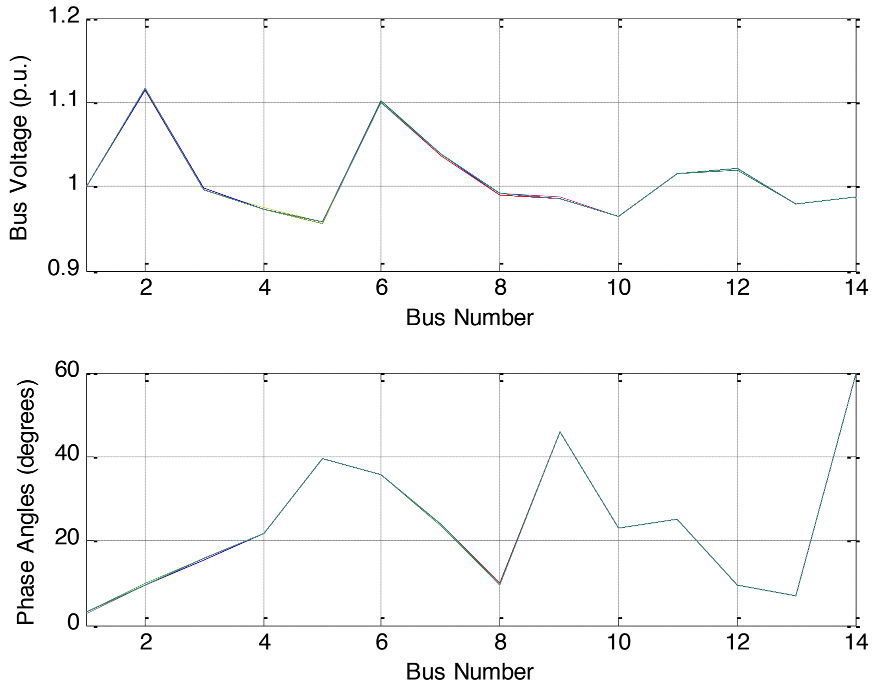


b) PMU placement for two-channel PMUs.

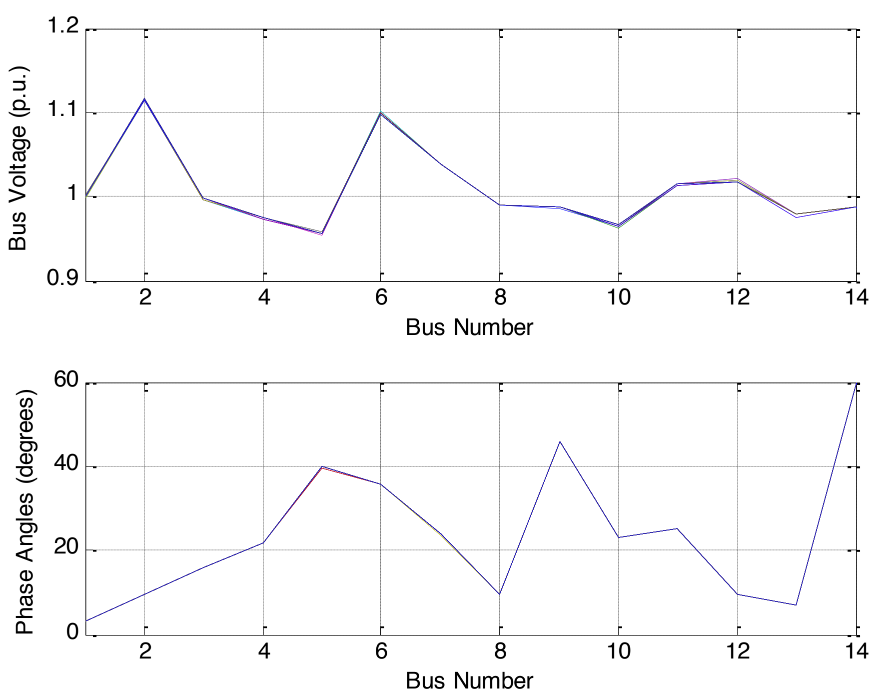


c) PMU placement for three-channel PMUs.

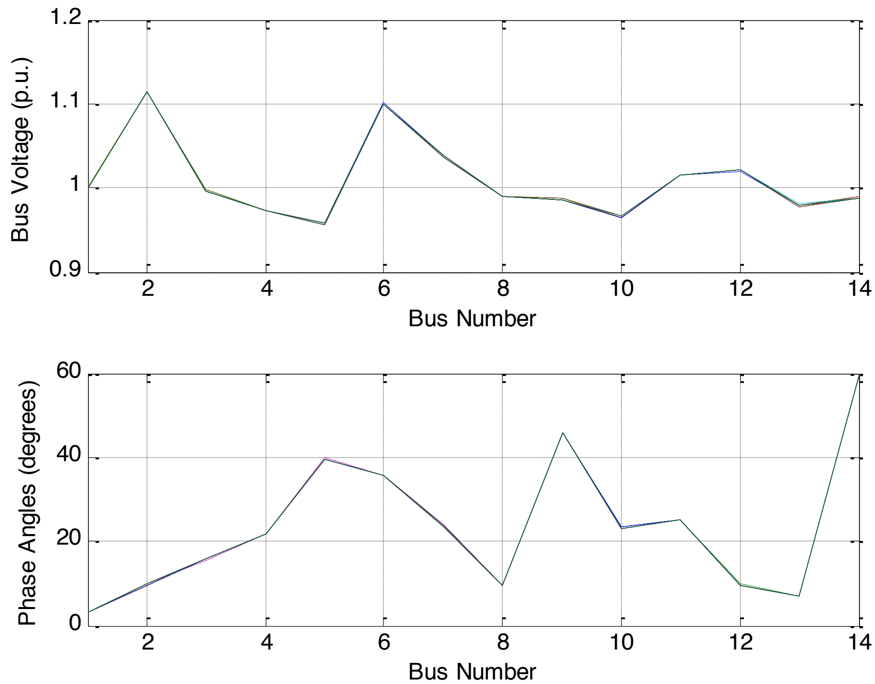
Fig. 5.8. PMU placement of IEEE 14-bus system.



a) True and estimated states with one-channel PMUs.

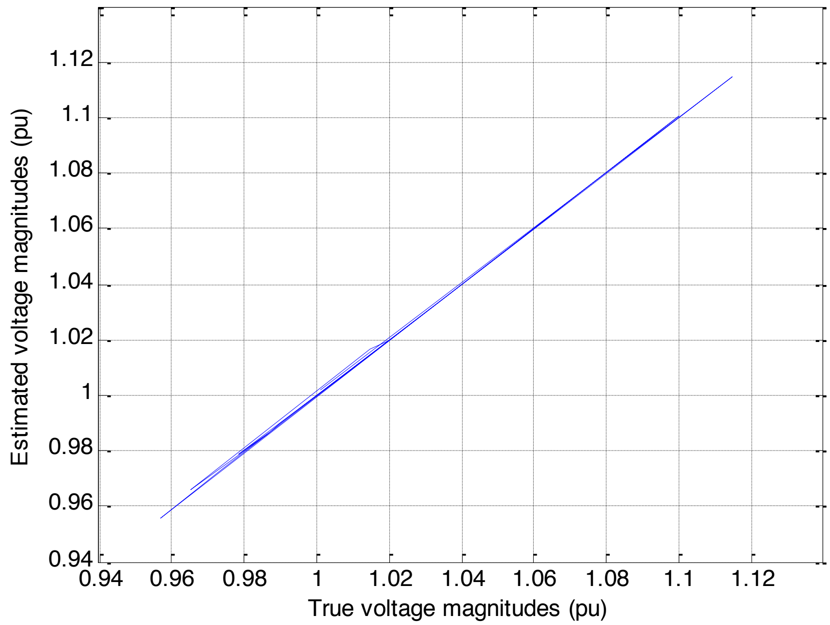


b) True and estimated states with two-channel PMUs.

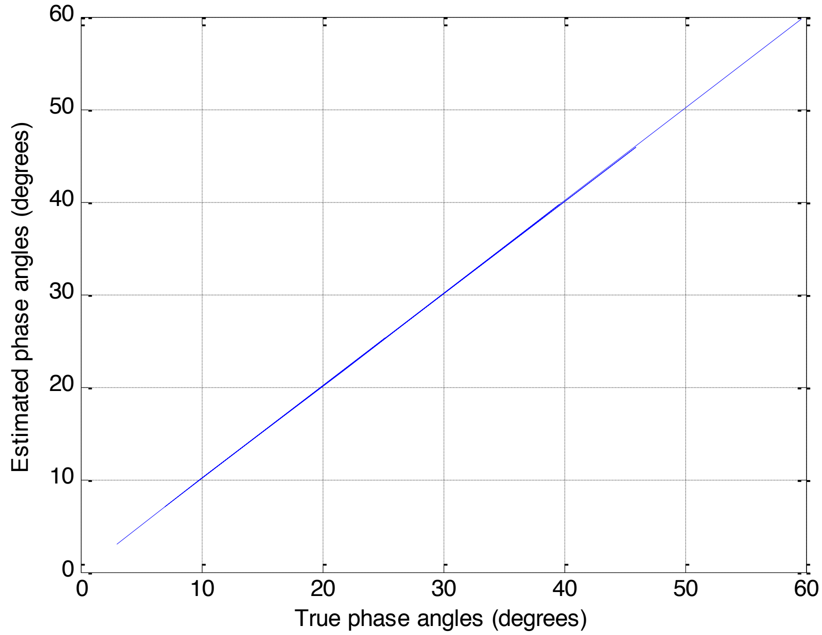


c) True and estimated states with three-channel PMUs.

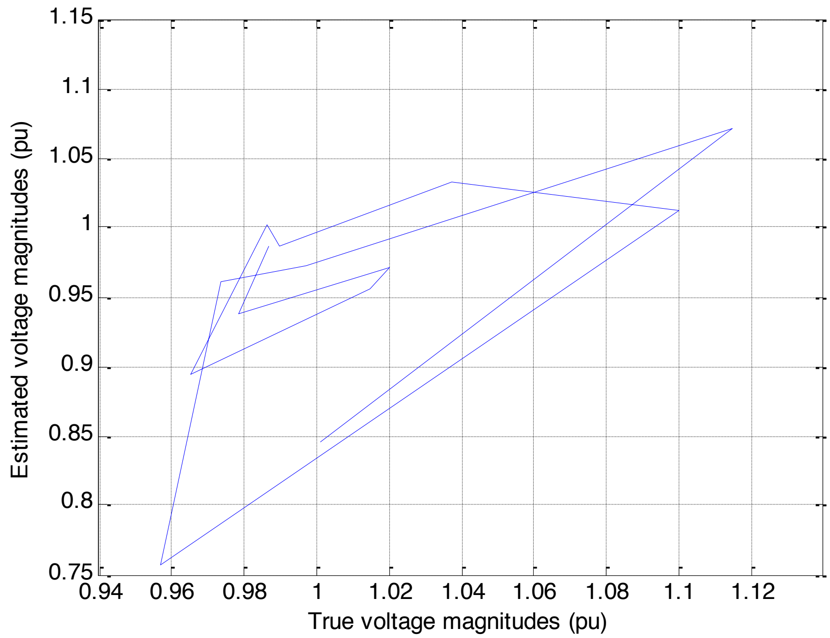
Fig. 5.9. Robustness study for IEEE 14-bus system.



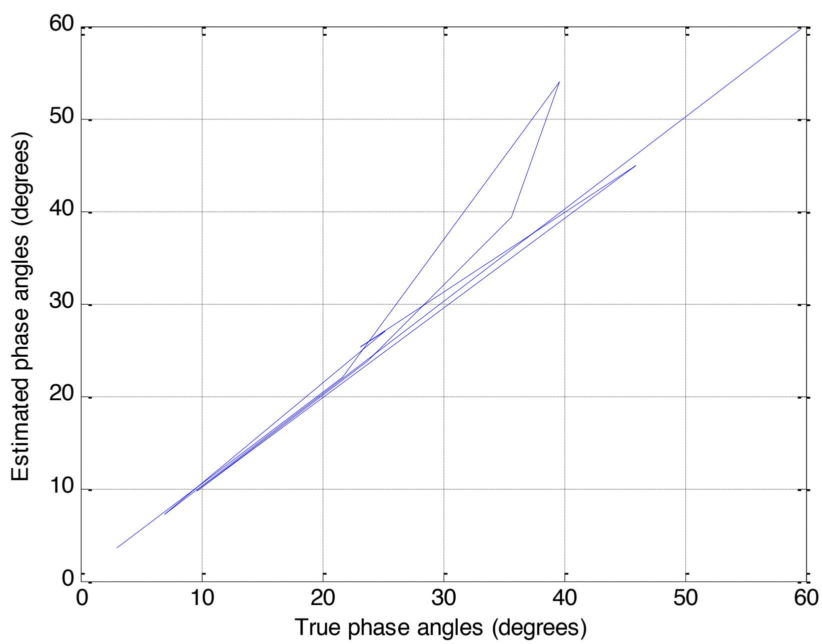
a) Estimated vs. true voltage magnitudes.



b) Estimated vs. true phase angles.



c) Estimated vs. true voltage magnitudes.



d) Estimated vs. true phase angles.

Fig. 5.10. Comparison of true states and estimates of LAV ((a) and (b)) and WLS ((c) and (d)) based method.

CHAPTER 6

STATE ESTIMATION FOR SYSTEMS MEASURED BY SCADA AND PMU MEASUREMENTS

I. INTRODUCTION

State estimation plays a key role in ensuring the secure operation of power systems [66]. It provides the optimal estimate of the current state of the power grid based on the received measurements and network topology [7]. In Chapter 4, LAV based robust state estimator was proposed for systems measured only by PMUs followed by Chapter 5, which introduced PMU placement for robust state estimation. The LAV based state estimation is robust and computationally efficient if the measurement set consists of only PMUs. However it is computationally expensive for today's power grids since the measurement sets consist of both conventional (SCADA) and PMU measurements. Therefore, there is a need to reconcile these two different categories of measurements and utilize both fully in order to monitor the system in the best possible way. This chapter will describe a novel approach, which handles the different update rates of PMU and SCADA measurements. This approach is seen as a good compromise between the use of slow rate SCADA measurements and fast rate phasor only linear estimation. It can provide benefits over SCADA only counterparts when monitoring events such as slow moving voltage sags, swells or collapses.

One of the main challenges in state estimation using both SCADA and PMU measurements is the different refresh rates of the measurements. Typically, PMU measurements are updated 30 times a second, while SCADA updates vary from every 2 to 6 seconds. Fig. 6.1 is a graphical illustration of this challenge where the different update rates of PMU and SCADA measurements lead to possibly unobservable configurations at instants when only PMU measurements are received and they are not sufficient to make the entire system observable. Commonly used WLS state estimator can process both types of synchronized PMU and SCADA measurements at time “t”, however there are several different ways the PMU measurements can be processed for the remaining instances until “t+1” as they become available.

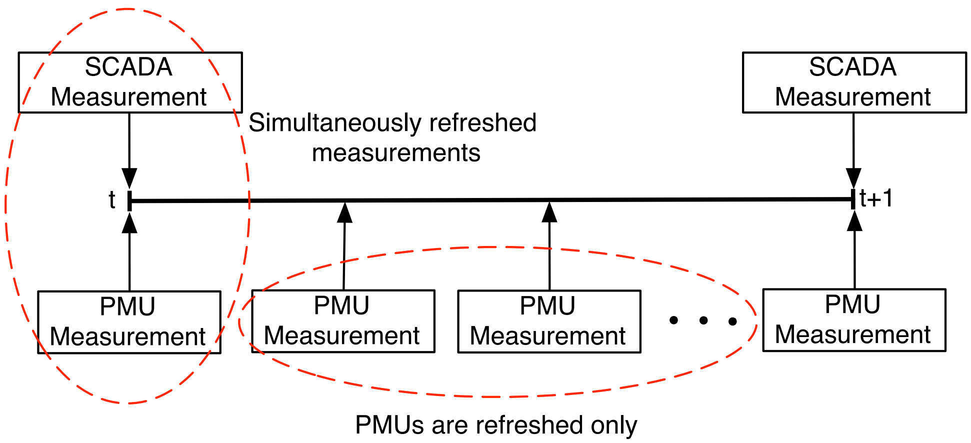


Fig. 6.1. SCADA and PMU measurements between time instants t and t+1.

In [43], [44] and [45] multi-stage estimators were introduced, which require longer solution time than the conventional state estimation methods. Multi-stage estimators handle SCADA and PMU measurements in different estimation steps.

More recently, a WLS based estimator, which handles intermediate PMU measurements in an efficient manner, is described in [46]. While this estimator performs well with PMU measurements having random errors, it remains non-robust or vulnerable against erroneous PMU measurements. Such errors may be due to communication or transducer failures and they may be caused by intentional tampering of selective PMUs by third parties.

It should be mentioned that in the long run, given enough PMU measurements, it may be possible to completely disregard SCADA measurements and carry out the estimation based only on PMU measurements. However, given today's systems, it is assumed that this is not the case and the existing PMUs constitute a small fraction of the set needed to make the entire system observable. Hence, one has to at least partially rely on SCADA measurements even during the intermediate instances between SCADA refresh points in order to maintain full observability.

This work proposes a single-stage and computationally efficient estimation algorithm, which can process both PMU and SCADA measurements simultaneously. At instances when both types of measurements are received (as at time "t" or "t+1" in Fig. 6.1) WLS estimator is used. WLS is a very fast estimator if the measurement set includes SCADA measurements, which are related to the system states non-linearly. Otherwise, it switches to a modified/scaled LAV based state estimator, which is shown to be robust against intentional or unintentional errors in measurements [37]. If the considered power system is PMU-observable, which means that SCADA measurements are not required to perform state estimation, the measurements become linearly related to system states and state estimation problem can be solved using only LAV estimator in a very efficient way [37].

The proposed method can be used as a complementary diagnosis tool to track the system voltage. Voltage collapses as well as voltage sags and swells can be monitored using the introduced method. Note that the proposed state estimation algorithm is not fast enough to detect any instantaneous events, such as transients.

The chapter is organized in four sections. The proposed method is explained in detail in Section II. Simulations are given in Section III, followed by summary and comments in Section IV.

II. PROPOSED METHOD

WLS state estimator is well known and documented as mentioned in Chapter 1. WLS estimator will be used at instances when both PMU and SCADA measurements are refreshed simultaneously, since it is a fast method once the measurements are related to the system states nonlinearly. Note that, SCADA measurements are not synchronized and therefore will carry the usual time-skew errors. At subsequent instances only the PMU measurements will be refreshed but regretfully their numbers will be insufficient to make the entire system observable. These measurements will be processed by a robust LAV estimator, which will also utilize a minimum required set of "old" SCADA measurements to maintain observability. Here, LAV estimator's data interpolation property will be exploited in order to ensure the best possible estimate to be obtained with the refreshed PMU measurements and a minimum number of "old" SCADA measurements. Details of LAV based state estimation were given in Chapter 4.

In compact form the measurement equations can be written as:

$$z = h(x) + e \tag{6.1}$$

where n is the number of buses, $h(.)$ is the linear and non-linear relations between the system states and measurements for PMU and SCADA measurements, respectively and:

z is (mx1) measurement vector,

x is (nx1) system state vector,

e is (mx1) measurement error vector.

Note that LAV based estimation is computationally costly if the system states are non-linearly related to the measurement set. Considering short duration between two PMU measurement updates and first order Taylor series expansion of (6.1), it is assumed that following relation is true:

$$\Delta z = H\Delta x + e \quad (6.2)$$

where H is the (mxn) Jacobian matrix and,

$\Delta z = z^k - h(x^k)$

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

x^k is the vector of estimates of system states at time instant k.

As shown in Fig. 6.1, SCADA measurements do not update every time PMU measurements are updated. Therefore, either the last updated SCADA measurements should be used or SCADA measurements should be updated artificially. In [46], it is proposed to update SCADA measurements every time estimation runs as defined below, until a new set of SCADA measurements is received.

$$z_{SCADA}^{k+1} = h_{SCADA}(x^k) \quad (6.3)$$

where;

z_{SCADA}^{k+1} is the vector of updated SCADA measurements at time instant k+1.

$h_{SCADA}(.)$ represents the non-linear relations between SCADA measurements and system states.

Flow-chart of the proposed method is presented in Fig. 6.2.

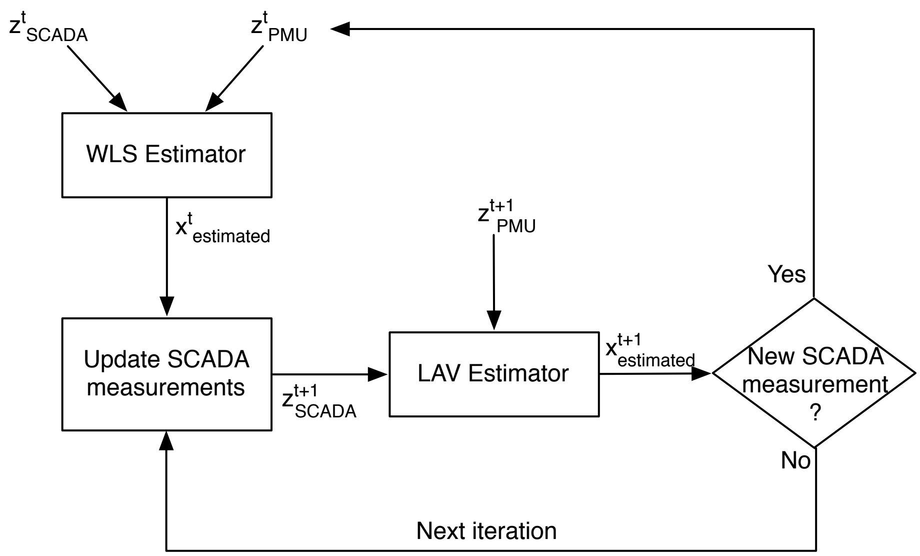


Fig. 6.2. Flow-chart of proposed method.

III. Simulations and Results

In this section two cases will be studied to check the validity of the proposed method. The first one compares estimation results of the proposed method with WLS based solution. In the second study, effect of placed PMU number is investigated. Simulations are carried out using a PC with 4GB RAM and MAC operating system. LP based LAV estimation problem is solved in MATLAB R2010b environment.

Case 1: The first study employs 57-bus IEEE test system with 32 power injection measurements and 32 power flow measurements, as well as 9 branch PMUs. The buses at which PMUs are placed are assumed to be strategically important. One line diagram of the system and measurement placement for SCADA and PMU measurements are provided in Fig. 6.3.

In the considered case, a voltage collapse with duration of 1 second occurs at bus-22. Neither a voltage nor a current phasor measurement is located at the stressed bus.

It is assumed that SCADA measurements are received every 2 seconds and PMU measurements are updated every 10 ms.

State estimation problem is solved using two different methods to show the validity of the proposed method:

1) WLS with updated SCADA measurements as defined in (6.4).

2) LAV with updated SCADA measurements as defined in (6.4) (the proposed method).

In Table 6.1, average duration of each estimation method is presented. Although the proposed method has a longer solution time, it is still competitive with WLS-based methods.

TABLE 6.1. PERFORMANCES OF WLS AND LAV BASED METHODS

	Method 1	**Method 2 (Proposed method)**
Average Run Time	4.5 ms	9.7 ms.

In Fig. 6.4 true values of bus-22 voltage magnitude are compared to the estimated values obtained using the two methods stated. Gaussian error is added to all measurements. Note that, initial conditions, measurement values and system considered are the same for both estimators.

In Fig. 6.5 deviation of the estimation results of the two methods from the true states is compared. Deviations are calculated for 10 time steps as defined below;

$$dev = \sqrt{\sum_{i=1}^{n} (x_i^{estimated} - x_i^{true})^2} \tag{6.8}$$

As seen in Fig. 6.5, the proposed method gives more accurate results than WLS based method. Furthermore, improvement increases with increased number of intermediate estimation instants.

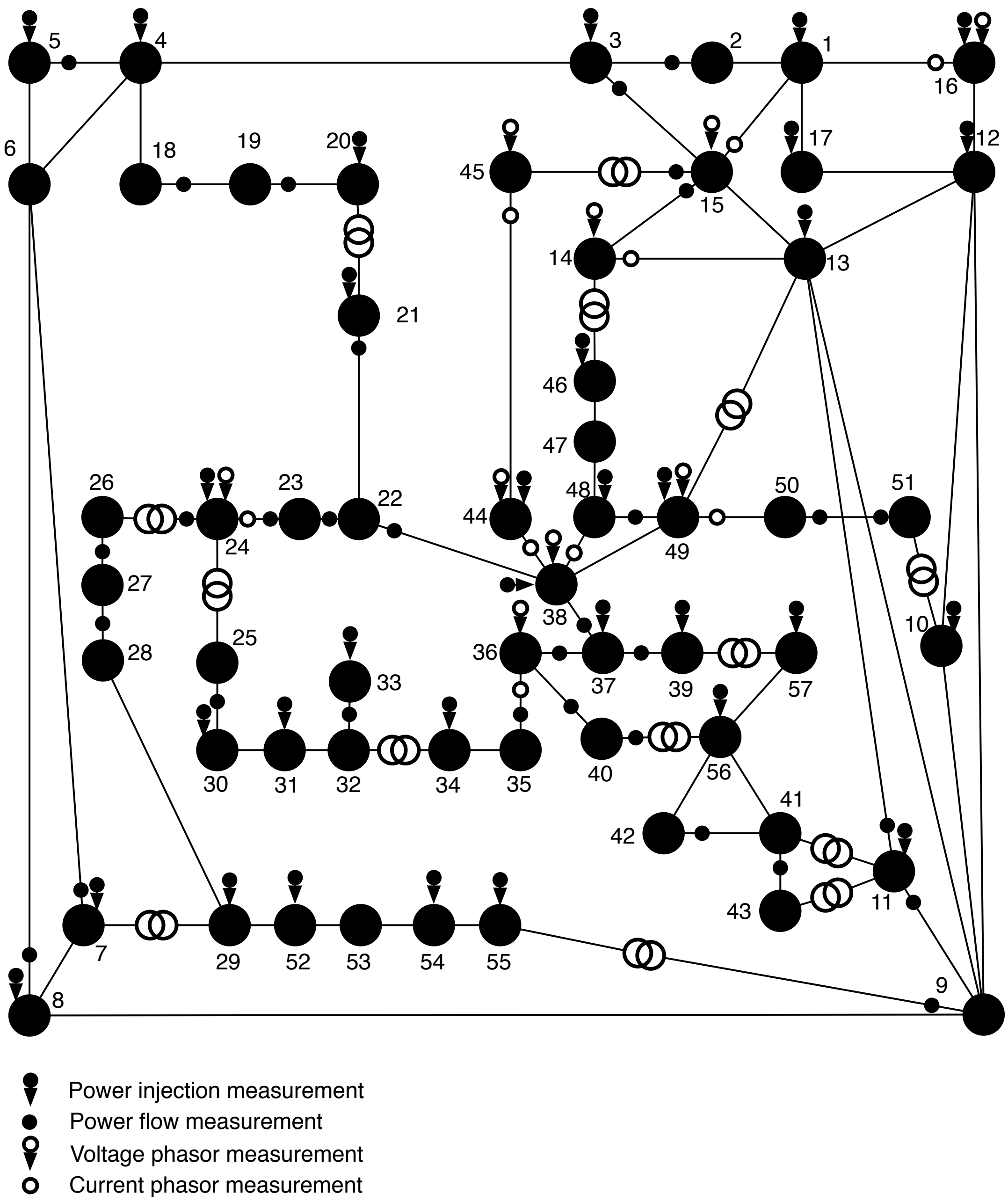


Fig. 6.3. One line diagram and measurement placement of IEEE 57-bus system.

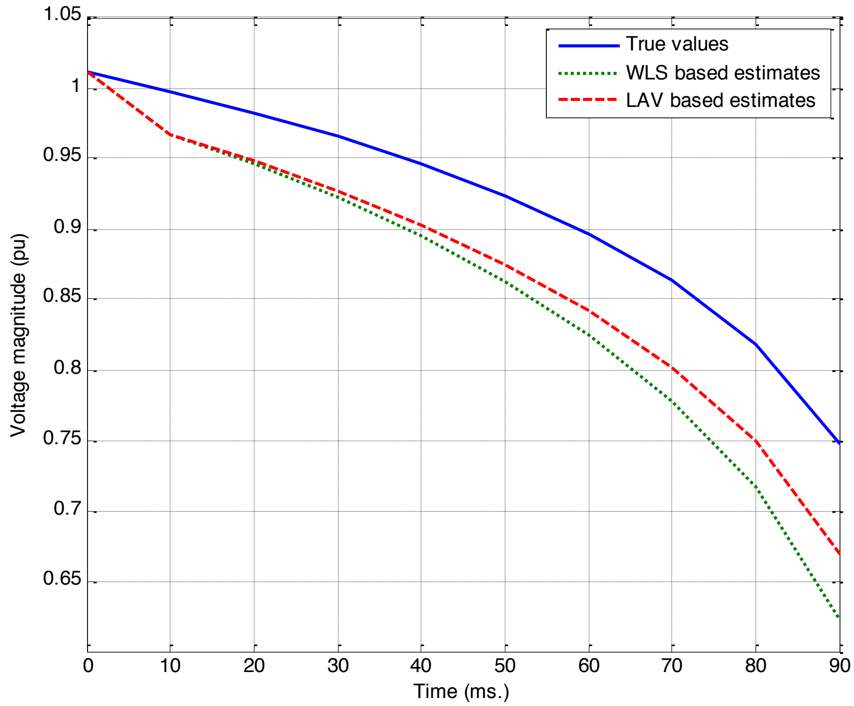


Fig. 6.4. Comparison of the bus-22 voltage magnitude estimates of the two estimators with the true states.

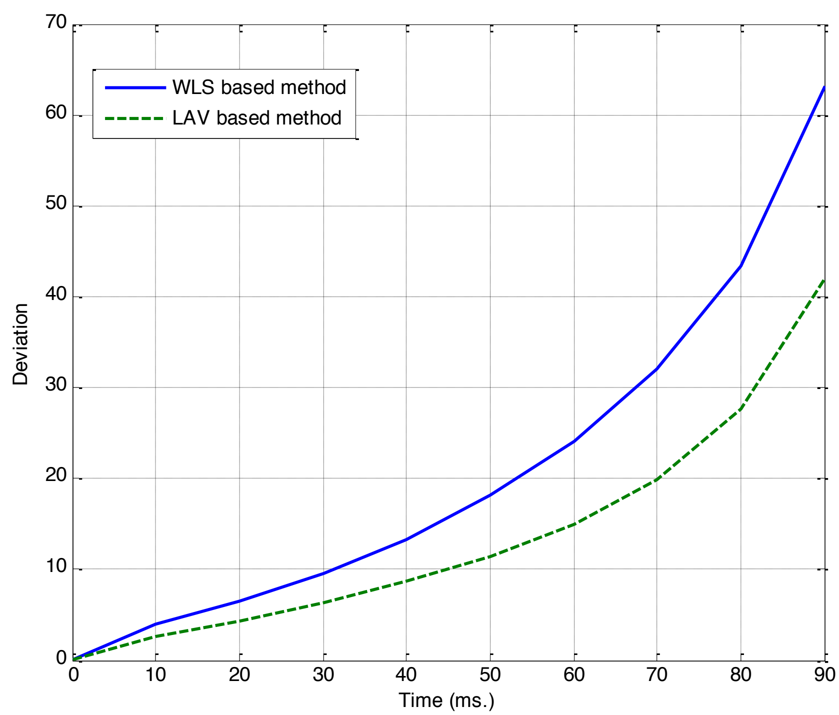
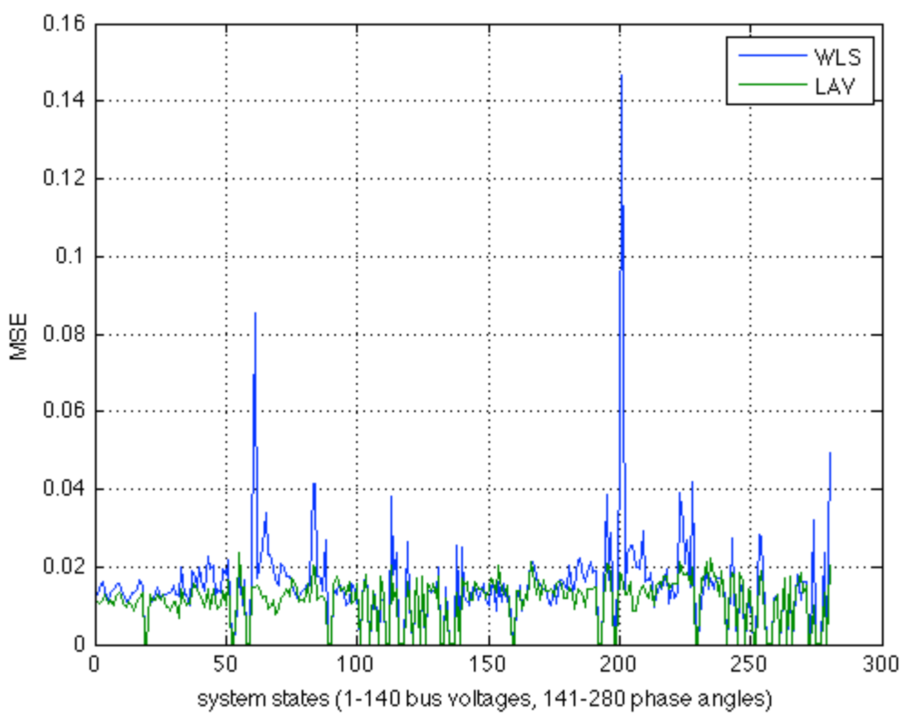
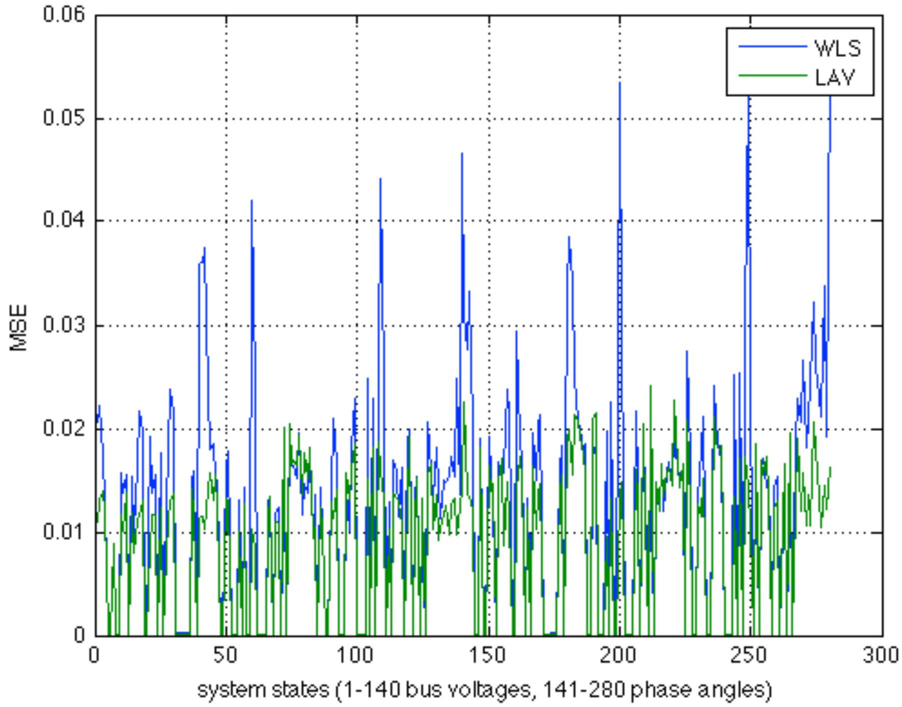


Fig. 6.5. Comparison of the deviations of two estimators' estimates from the true states.

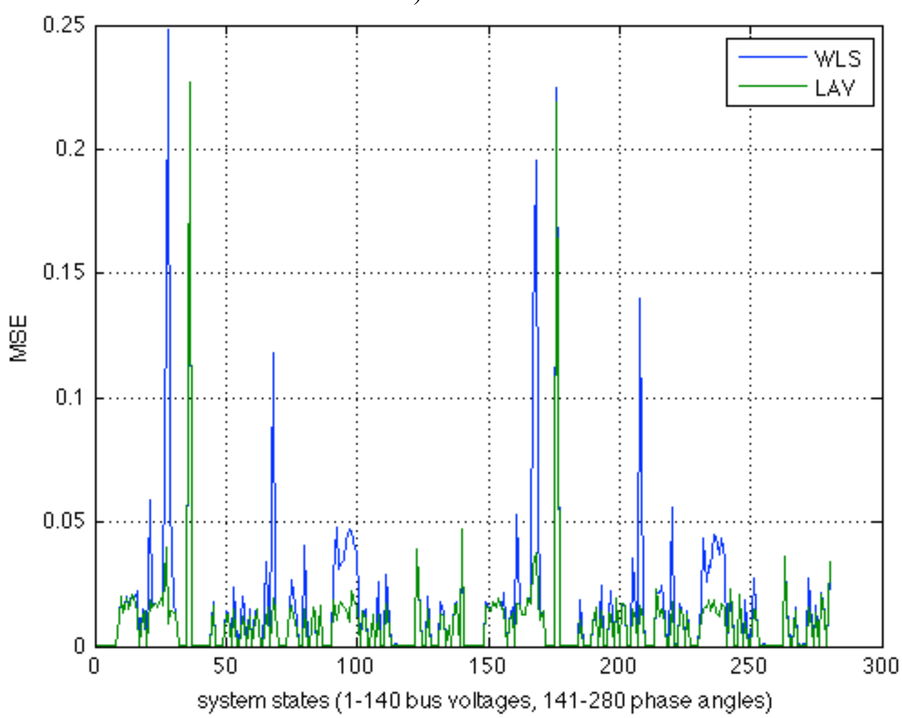
***Case 2*:** This study employs 140-bus, 233-branch Northeast Power Coordinating Council (NPCC) system. System is measured by 95 power injection and 205 power flow measurements. It is assumed that SCADA measurements are updated every 1 second and PMU measurements are updated 30 times a second. 10-second-long simulations were performed for different number of PMUs. Gaussian error is added to measurements. Fig. 6.6 shows MSE values for each system state for different number of PMUs. Note that as installed PMU number increases, more states are estimated accurately. Note that both WLS and LAV based estimation results are provided for further comparison between two estimators.



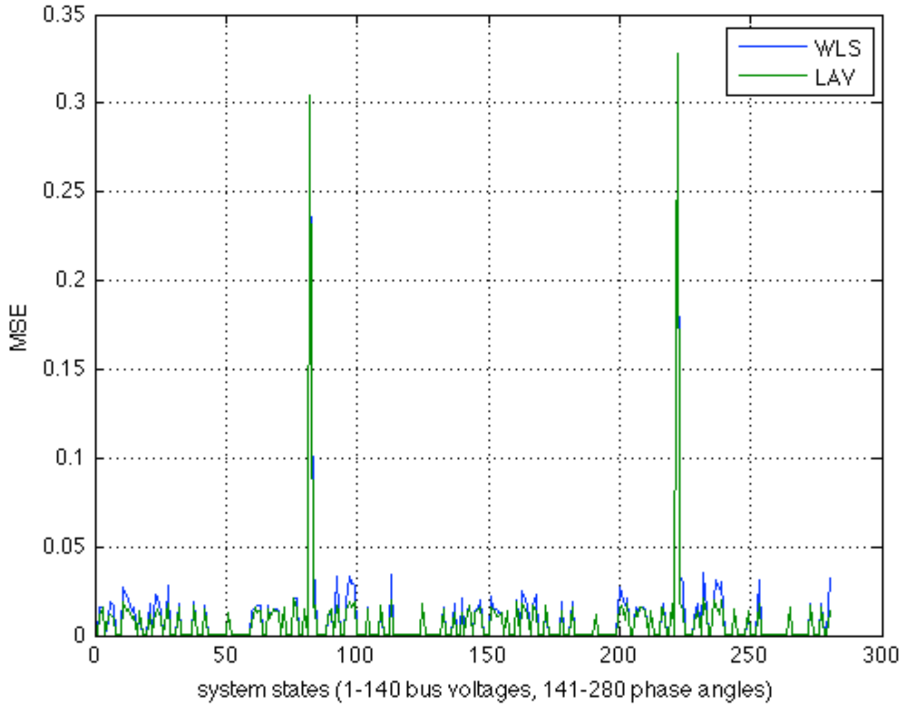
a) 14 PMUs



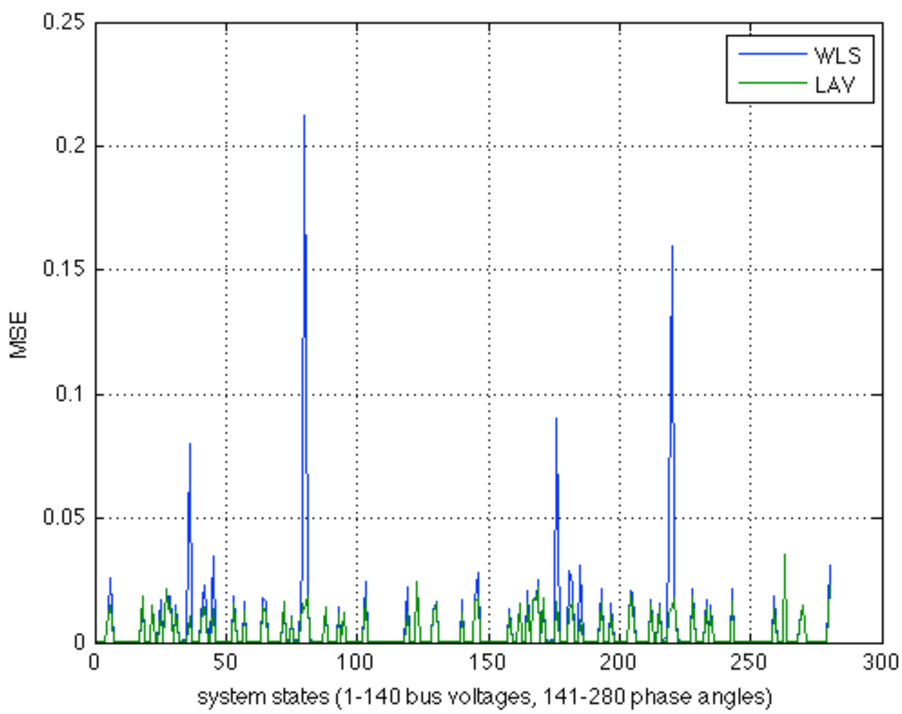
b) 30 PMUs



c) 50 PMUs

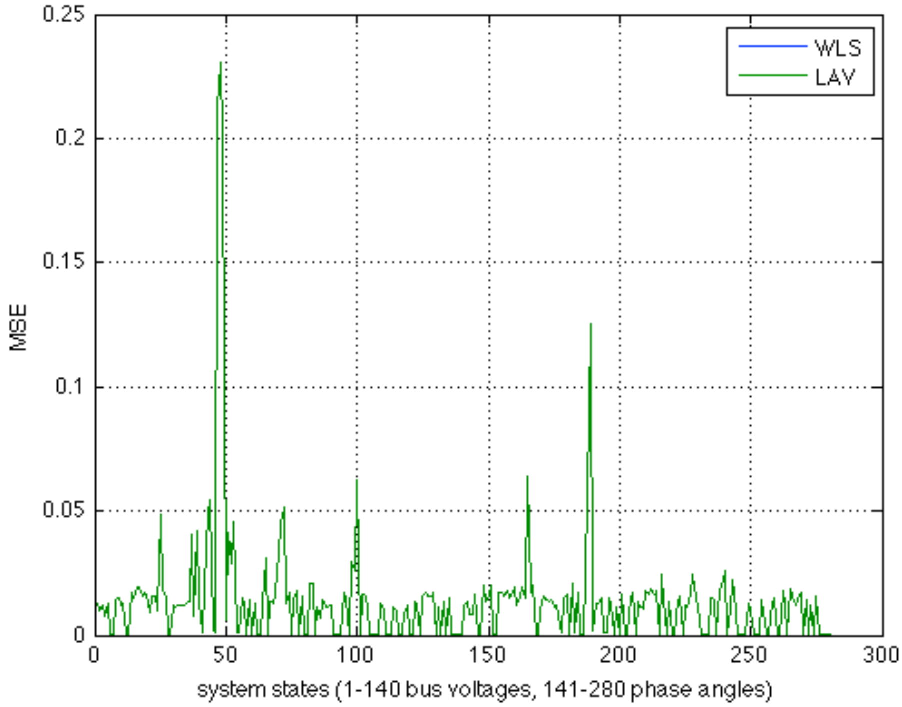


d) 70 PMUs

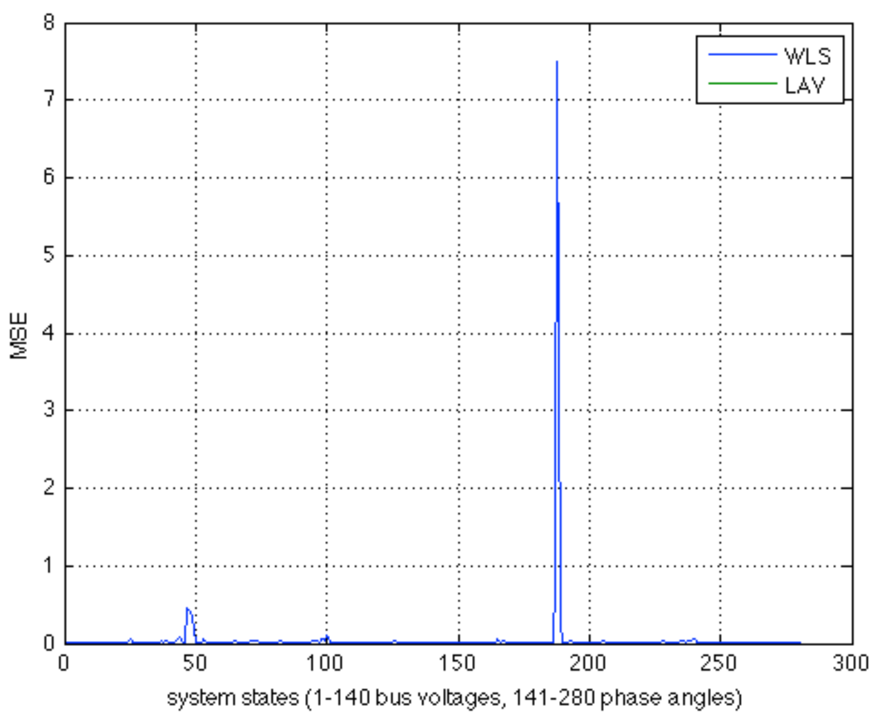


e) 90 PMUs

Fig. 6.6. Comparison of the MSEs of two estimators' estimates for NPCC system.



a) MSE values of LAV based estimator.



b) MSE values of WLS based estimator.

Fig. 6.7. Performance comparison between LAV and WLS based methods under bad data.

Finally, to check the performance of the proposed estimator under bad data conditions, current phasor measurements between buses 43 and 50, and 84 and 116 are set to 0. The NPCC system described is employed for the study, and 30 PMUs are placed. MSE values of the system states are provided in Fig. 6.7. Fig. 6.7.a presents the results for proposed LAV based estimator, while results for WLS based estimator are given in Fig. 6.7.b. As seen in Fig. 6.7, WLS estimator requires bad data process, because of the very high MSE values.

IV. SUMMARY AND COMMENTS

This chapter presents a state estimator, which can handle mixed type of PMU and SCADA measurements. The main contribution of this work is the incorporation of a LAV based robust alternative estimator to handle the PMU measurements at their refresh rates.

Because of the limited number of available PMUs, incorrect SCADA measurements need to be used to keep the system observable between two SCADA updates. Robustness of LAV helps improving the estimates between those two SCADA scans, since LAV selects only a minimum set of SCADA measurements that will make system observable. Note that, bad data analysis after each SCADA scan becomes unnecessary, if the system is measured only by PMUs with sufficient measurement redundancy and LAV estimator is employed.

In the case of slow moving voltage problems, the proposed method can be used as a complementary diagnosis tool in monitoring the system voltage. Especially voltage sags and swells can be better monitored. Note that the proposed method is not fast enough to detect any instantaneous events, such as transients. However, momentary (30 cycles-3 seconds) and temporary (3 seconds-1 minute) events can be detected, which would be missed by any estimator running at the scan rate of SCADA measurements.

As a final remark, note that estimated voltages will be less accurate if the stressed bus or area is far away from the majority of the PMUs. Hence, the effectiveness of this approach will increase as more PMUs are placed at strategic locations in the system.

CHAPTER: 7

A ROBUST PMU BASED THREE-PHASE STATE ESTIMATOR USING MODAL DECOUPLING

I. Introduction

Chapters 4 and 6 proposed state estimation methods for systems measured by only PMUs and by mixed measurements, i.e. SCADA and PMU measurements, respectively. In this section a three-phase state estimation method is proposed for systems measured by only PMUs. The increase in the number of the renewable energy sources connected to the power grid in the recent years necessitates effective incorporation of those sources into the network model monitored by the state estimator. Accurate representation of these remote sources may require modeling of the corresponding sub-transmission system, which commonly contains unbalanced loads. Moreover the validity of using positive sequence model is questioned even for transmission systems [67]. Therefore, future state estimators may have to account for imbalances in system operation. This can be achieved simply by switching to the full three-phase representation of the network and designating the set of three-phase bus voltages as the system states [47], [48]. However, this approach may be computationally costly because of the increased problem dimension.

Use of modal decomposition and the so-called sequence networks in analysis of various types of faults in unbalanced three phase systems is well known and documented. The same approach regretfully fails to decompose the problem when applied to power balance equations due to the nonlinearity of the power expressions. Recent proliferation of synchronous phasor measurements [68] in power systems however allows the measurement equations to be written as linear functions of the system states. The linearity between the phasor measurements and the system states is also the motivation of the work done towards development of a tracking three-phase state estimator, which uses phasor measurements as inputs [69].

This study proposes a decoupled solution based on the modal (symmetrical) components to address the computational complexity introduced by the coupled three-phase model. This will be true if sufficient number of well-placed PMUs make the system fully observable. The linearity between the system states and the measurements allows direct (non-iterative) solution of the state estimation problem [70]. Moreover, thanks to the PMUs, three-phase measurement equations can be decoupled using modal transformations, which will reduce the state estimation problem into three smaller size problems. Those three estimation problems can be solved separately and possibly in parallel if the required parallel processors are available. Note that this is not possible when using conventional measurements, namely power injection and flow measurements, due to their nonlinear dependence on system states.

WLS estimator is widely employed to solve the state estimation problem in today's power systems, which are commonly monitored by SCADA measurements. Despite being iterative, WLS estimator is quite fast thanks to the efficient sparse matrix methods used. However, since WLS estimator is non-robust and will be biased even in the presence of a single bad measurement, bad data need to be processed after convergence to a solution. The aim is to detect, identify and correct any existing bad data, which will be commonly achieved by applying the largest normalized residual test [65]. In this test, the computation of the residual covariance matrix constitutes the main computational bottleneck, since it requires calculation of a subset of the entries of the inverse of the sparse gain matrix. Even when highly efficient sparse inverse methods [57]-[59] are employed, computational complexity grows approximately proportional to the number of measurements. As a practical alternative to the largest normalized residuals test, measurement weights can be modified based on their respective residuals during the iterative solution, which is commonly referred as the re-weighted least squares solution [61]. Although it completely avoids the post-processing stage, re-weighted least squares method is not entirely reliable and may occasionally miss bad data leading to biased solutions. If the measurement set includes only PMUs, as explained in Chapter 4, LAV estimator can be employed since not only it becomes computationally competitive with WLS, but also effects of the leverage measurements on LAV can be eliminated with simple strategic scaling [37]. Although WLS estimation will be non-iterative and fast, bad-data analysis, which is computationally expensive, will still be needed due to the non-robustness of WLS estimation.

This chapter presents the development of a three-phase state estimation solution, which is based on modal components of a three-phase system. Furthermore, it uses the LAV estimation method making the proposed method robust against intentionally introduced or random bad data. Note that the proposed method does not introduce significant computational burden compared to the positive sequence counterpart.

Concept of decoupling three-phase measurements using modal transformation in power systems measured by only PMUs was first introduced in [71]. In this work, the preliminary ideas of [71] are further extended to address its lack of robustness against bad data via the introduction of the LAV alternative. Moreover a novel mechanism to handle current phasor measurements on un-transposed lines is developed and implemented in this work.

In Section II proposed modal transformation based decoupling method is introduced. Section III explains the procedure to handle the current phasor measurements on untransposed lines. Simulation results are given in Section IV followed by conclusions in Section VII.

II. PROPOSED DECOUPLED STATE ESTIMATION

PMU measurements are assumed to be the bus voltage and line current phasors, which are measured in a synchronized manner with respect to Global Positioning System (GPS). Those measurements are linearly related to system states as shown below:

$$V_k^m = \mathrm{Re}\{V_k^m\} + j\,\mathrm{Im}\{V_k^m\}$$
$$= |V_k|\cos\theta_k + j|V_k|\sin\theta_k + e^m$$

$$I_{ij}^m = \mathrm{Re}\{I_{ij}^m\} + j\,\mathrm{Im}\{I_{ij}^m\} \qquad (7.1)$$
$$\mathrm{Re}\{I_{ij}^m\} = G_{ij}(\mathrm{Re}\{V_i\} - \mathrm{Re}\{V_j\}) - B_{ij}(\mathrm{Im}\{V_i\} - \mathrm{Im}\{V_j\}) - B_{ii}\,\mathrm{Im}\{V_i\} + e^m$$
$$\mathrm{Im}\{I_{ij}^m\} = G_{ij}(\mathrm{Im}\{V_i\} - \mathrm{Im}\{V_j\}) + B_{ij}(\mathrm{Re}\{V_i\} - \mathrm{Re}\{V_j\}) + B_{ii}\,\mathrm{Re}\{V_i\} + e^m$$

In (7.1), $G_{ij}+jB_{ij}$ is the series admittance of the branch connecting buses i and j and B_{ii} is the shunt admittance at bus-i. The superscript m is used to indicate that it is a measured value. e^m represents the measurement error of corresponding measurement.

In this chapter all equations are derived using the linear relations given in (7.1) and assuming an observable power system, which is measured with only PMUs. Consider the measurement vector Z containing phasor measurements, which include three phase bus voltage phasors and branch current phasors as given below:

$$Z = HV + e \qquad (7.2)$$

H : $3m$x$3N$ measurement Jacobian matrix.

m : Number of three phase sets of phasor measurements. Therefore, the total number of individual phase phasor measurements will be 3m.

V : 3Nx1 system state vector, where states are the three phase bus voltage phasors.

N : Number of three phase buses in the system, thus the total number of states will be 3N.

e : $3mx$1 measurement error vector.

Form the measurement vector Z (3mx1) as follows:

$$Z^T = [Z_V^T Z_I^T] \tag{7.3}$$

Z_V^T: Vector of three phase voltage phasor measurements.

Z_I^T: Vector of three phase current phasor measurements.

Let [T] be the modal transformation matrix which relates the phase and modal domain voltage and current vectors as follows:

$$V_S = TV_P \tag{7.4}$$

$$I_S = TI_P \tag{7.5}$$

V_S and I_S are the 3x1 modal domain vectors.

V_P and I_P are the 3x1 phase domain vectors.

Let us then define matrix T_Z as follows, which is a 3mx3m block diagonal square matrix having 3x3 modal transformation matrices [T] on its diagonal.

$$T_Z = \begin{bmatrix} T & 0 & \cdots & 0 \\ 0 & T & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & T \end{bmatrix} \tag{7.6}$$

Following relation is obtained by multiplying both sides of (7.2) by T_Z from the left:

$$T_Z Z = T_Z HV + T_Z e \tag{7.7}$$

Voltage transformation matrix T_V can be defined as a 3Nx3N block diagonal square matrix having 3x3 modal transformation matrices $[T]^{-1}$ on its diagonal.

$$T_V = \begin{bmatrix} T^{-1} & 0 & \cdots & 0 \\ 0 & T^{-1} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & T^{-1} \end{bmatrix} \tag{7.8}$$

The three-phase bus voltage vector V in (7.7) can be expressed in terms of its 3Nx1 modal component vector V_M as shown below:

$$V = T_V V_M \tag{7.9}$$

If (7.9) is substituted in (7.7) the following relation can be obtained, which constitutes the proposed decoupled formulation.

$$Z_M = H_M V_M + e_M \tag{7.10}$$

where, $Z_M = T_Z Z$, $H_M = T_Z H T_V$ and $e_M = T_Z e$. $\mathrm{Z} = \mathrm{H} \cdot \mathrm{V} + \mathrm{e}$

In this paper [T] is chosen as the inverse of symmetrical components transformation matrix, which is given below.

$$T = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & e^{\frac{2}{3}\pi i} & e^{-\frac{2}{3}\pi i} \\ 1 & e^{-\frac{2}{3}\pi i} & e^{\frac{2}{3}\pi i} \end{bmatrix} \tag{7.11}$$

Equation in (7.10) can be expressed explicitly as follows:

$$\begin{bmatrix} Z_0 \\ Z_r^+ \\ Z_r^- \end{bmatrix} = \begin{bmatrix} H_0 & 0 & 0 \\ 0 & H_r & 0 \\ 0 & 0 & H_r \end{bmatrix} \begin{bmatrix} V_0 \\ V_r^+ \\ V_r^- \end{bmatrix} + \begin{bmatrix} e_0 \\ e_r^+ \\ e_r^- \end{bmatrix} \tag{7.12}$$

or as two sets of decoupled equations, one of which for the zero and the other for the positive/negative sequence components, as defined below.

$$Z_0 = H_0 V_0 + e_0 \tag{7.13}$$

$$Z_r^{+/-} = H_r V_r^{+/-} + e_r^{+/-} \tag{7.14}$$

where the subscripts "0" and "r" refer to zero and positive/negative sequence components respectively.

Note that [T] cannot decouple the flow measurements corresponding to untransposed lines. A simple way to address this limitation is developed and described in Section III below.

Once the estimated modal components are found by using the LAV estimator, which is explained in detail in Chapter 4, those estimates can be transformed back to phase domain by using the inverse of the transformation matrix [T].

III. TRANSFORMATION OF CURRENT PHASOR MEASUREMENTS ON UNTRANSPOSED LINES

The method defined so far can only be applied if all lines of a system are transposed. If the decoupling method introduced in Section II is applied to current phasor measurements on untransposed lines, the resulting symmetrical components will not be decoupled. Consider the admittance matrix given below, which is *H* of a three-phase current phasor measurement on untransposed lines with series admittance *Y*. Note that *M* represents the mutual admittance between the lines. A horizontal conductor configuration is assumed where phase b conductor lies in the middle and the other two at two sides equidistant from the middle one.

$$\overline{Y} = \begin{bmatrix} Y & M_1 & M_2 \\ M_1 & Y & M_1 \\ M_2 & M_1 & Y \end{bmatrix} \tag{7.15}$$

If the transformation method defined in Section II is applied to (7.15), the following matrix will be obtained.

$$H_Y = T_Z \overline{Y} T_V$$
$$H_Y = \frac{1}{3}\begin{bmatrix} A_1 & B_1^* & B_2^* \\ B_1 & A_2 & B_3^* \\ B_2 & B_3 & A_2 \end{bmatrix}$$
$$\begin{array}{ll} A_1 = 3Y + 4M_1 + 2M_2 & B_1 = M_1 e^{\frac{2}{3}\pi i} - M_2 e^{\frac{2}{3}\pi i} \\ A_2 = 3Y - 2M_1 - M_2 & B_2 = M_1 e^{-\frac{2}{3}\pi i} - M_2 e^{-\frac{2}{3}\pi i} \\ & B_3 = -2M_1 e^{\frac{2}{3}\pi i} + 2M_2 e^{\frac{2}{3}\pi i} \end{array} \tag{7.16}$$

As seen in (7.16), the symmetrical components are not independent of each other, which makes the direct decoupling impossible, if the measured lines are untransposed. Therefore, in this work a transformation method for the current phasor measurements on untransposed lines is introduced to make the decoupling possible [73]. Consider the following relation for a current phasor measurement on untransposed lines between buses 1 and 2.

$$\begin{bmatrix} I_A^{1-2} \\ I_B^{1-2} \\ I_C^{1-2} \end{bmatrix} = \begin{bmatrix} Y & M_1 & M_2 \\ M_1 & Y & M_1 \\ M_2 & M_1 & Y \end{bmatrix} \begin{bmatrix} V_A^{1-2} \\ V_B^{1-2} \\ V_C^{1-2} \end{bmatrix} \tag{7.17}$$

It is known that inverse of the admittance matrix defined in (7.15) exists. If both sides of (7.17) are multiplied by the impedance matrix, which is the inverse of admittance matrix, the following relation will be obtained.

$$\begin{bmatrix} Y & M_1 & M_2 \\ M_1 & Y & M_1 \\ M_2 & M_1 & Y \end{bmatrix}^{-1} \begin{bmatrix} I_A^{1-2} \\ I_B^{1-2} \\ I_C^{1-2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} V_A^{1-2} \\ V_B^{1-2} \\ V_C^{1-2} \end{bmatrix} \tag{7.18}$$

Current measurements in (7.18) are represented as voltage difference measurements, which can be decoupled easily as current phasor measurements on transposed lines. Since the same matrix scales both sides of the measurement equation, state estimation results will not be affected.

Shunt admittances of the untransposed lines are neglected so far. Consider following formulation

$$\overline{I} = \overline{Y}\overline{V}_1 - \overline{Y}\overline{V}_2 + \overline{B}\overline{V}_1 \tag{7.19}$$

where

$\overline{I}$ is the three-phase current vector,

$\overline{V}_1$ and $\overline{V}_2$ are the sending and receiving bus three-phase voltage vectors, respectively,

$\overline{Y}$ and $\overline{B}$ are the series and shunt admittance matrices, respectively. Using (7.19), following relation can be obtained easily:

$$
\begin{aligned}
\overline{Y}^{-1}\overline{I} &= \overline{Y}^{-1}\overline{Y}\overline{V}_1 - \overline{Y}^{-1}\overline{Y}\overline{V}_2 + \overline{Y}^{-1}\overline{B}\overline{V}_1 \\
\overline{Y}^{-1}\overline{I} &= \overline{V}_1 - \overline{V}_2 + \overline{Y}^{-1}\overline{B}\overline{V}_1
\end{aligned} \tag{7.20}
$$

Product of $\overline{Y}^{-1}\overline{B}$ can be written as follows, if it is assumed that outer lines are equally distanced from the centered one:

$$
\begin{gathered}
\overline{Y}^{-1}\overline{B} = \begin{bmatrix} Z & Z_{M1} & Z_{M2} \\ Z_{M1} & Z & Z_{M1} \\ Z_{M2} & Z_{M1} & Z \end{bmatrix} \begin{bmatrix} B & 0 & 0 \\ 0 & B & 0 \\ 0 & 0 & B \end{bmatrix} \\
\overline{Y}^{-1}\overline{B} = \begin{bmatrix} BZ & BZ_{M1} & BZ_{M2} \\ BZ_{M1} & BZ & BZ_{M1} \\ BZ_{M2} & BZ_{M1} & BZ \end{bmatrix}
\end{gathered} \tag{7.21}
$$

If the proposed transformation is applied to this product, the result will be in the form of (7.16). Note that A_1 is significantly larger than the rest of the entries, while B_1 and B_2 constitute negligibly small values. Off-diagonal entries of this coupled matrix can be neglected if B_3 is significantly smaller than A_2, which is the general case. Neglecting those off-diagonals does not create a significant difference in estimated states as simulated in Section IV.

If the off-diagonal entries are not small enough, neglecting those entries will make the considered current phasor measurement a bad measurement. However, the estimation results will be unbiased, if the current phasor measurement on the untransposed lines is not a critical one, thanks to the robust LAV estimator. It is proposed to solve state estimation problem with LAV estimator..

IV. SIMULATIONS AND RESULTS

In this section two studies will be carried out to illustrate the validity of the proposed method. Simulations are carried out using a PC with 3GB RAM and Windows XP operating system. LP based LAV problem is solved using GUROBI version 5.0.1, while required coding is implemented in MATLAB R2011a environment.

The first study is intended to show the validity of the proposed transformation of current phasor measurements on untransposed lines. The second study comparatively presents CPU performances of the conventional WLS and the proposed LAV-based three-phase estimators.

Case 1: Validation of Measurement Transformation

Consider the 15-bus system shown in Fig. 7.1. Lines between buses 9-10 and 14-15 are untransposed. All lines assumed to have a series impedance of *0.01+j0.1* and shunt admittance of *j0.1*. Mutual impedances for transposed lines are assumed to be *0.003+j0.03* and mutual impedances for untransposed lines are given in Table 7.1. Moreover, an unbalanced load is connected to bus-15. Note that no error is added to the measurement set to show the validity of the proposed method. Plots of true versus the estimated states given in Fig. 7.2 show the close agreement between them. For all three phases, Table 7.2 shows the Mean Square Error (MSE), which is calculated as given in (4.12).

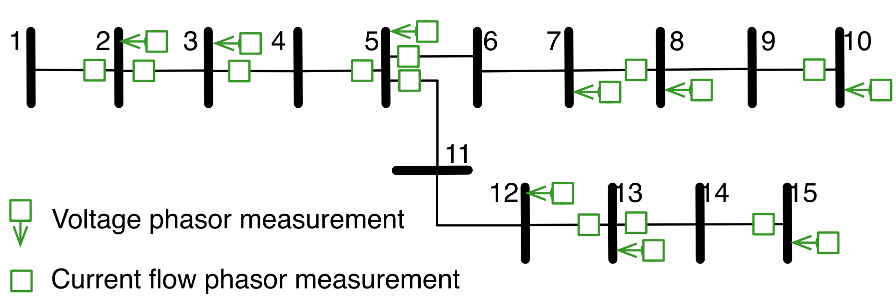


Fig. 7.1. 15-bus test system.

TABLE 7.1. MUTUAL IMPEDANCES OF THE UNTRANSPOSED LINES IN FIG. 7.1

	A-B		**B-C**		**A-C**	
Lines	**R**	**X**	**R**	**X**	**R**	**X**
9-10	0.003	0.03	0.003	0.03	0.003	0.025
14-15	0.003	0.03	0.003	0.03	0.003	0.025

TABLE 7.2. MSE FOR VOLTAGE MAGNITUDES AND PHASE ANGLES

	Phase-A		**Phase-B**		**Phase-C**	
	For |V|	**For θ**	**For |V|**	**For θ**	**For |V|**	**For θ**
MSE	0.00013	0.00019	0.00027	0	0.00013	0.0002

Case 2: Performance of the Proposed Method

A 3625-bus, 4836-branch utility power system is used to test the performance of the proposed estimation method. It is assumed that all lines are transposed. Measurement set is chosen such that 3800 branches are measured by phasor current and phasor voltage measurements taken at one end to make the system observable with reasonable redundancy. The redundant measurements are added to facilitate investigation of effects of bad measurements on the performance of the LAV estimator.

Among the many cases tested, three representative cases will be discussed here. In these three cases, bad measurements are intentionally created in the following manner:

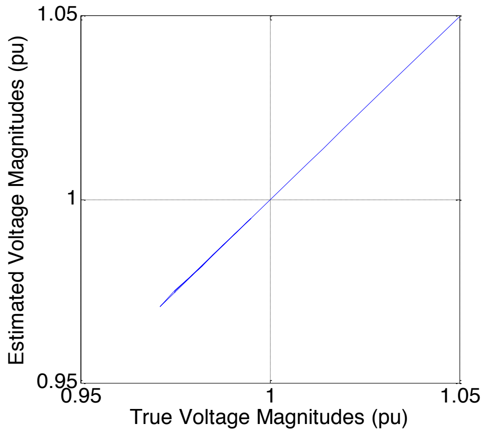
- Case 2.a: No bad measurement.
- Case 2.b: Single bad measurement.
- Case 2.c: Five bad measurements.

In Case 2.b and 2.c, 100 runs were performed, and both voltage and current phasor measurements were assigned as bad measurements. In Case 2.b, the bad measurement was set as 0, and in Case 2.c three measurements were set to 0 and two measurements were set to the negative of the actual value of the corresponding measurement.

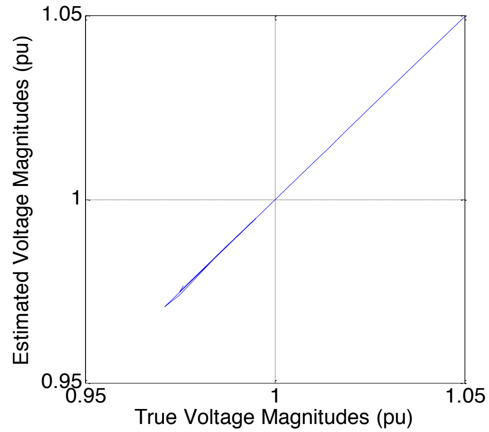
After applying the proposed decoupling method, all three cases were solved using LAV and WLS estimators. Simulation CPU times are compared in Table 7.3. CPU time for WLS estimator includes bad-data processing time as well as solution times of zero, positive and negative sequences. As seen in Table 7.3, WLS based estimator has a better performance if there are no bad measurements in the measurement set. However, the proposed LAV based estimator is significantly superior in terms of performance, in the presence of bad measurements. Note the relatively fixed computation time for the proposed estimator. Case 2.a is solved using WLS estimator without applying the proposed decoupling method. CPU time of solution time was found to be 35.9 seconds, which is not surprising, once the 9 times larger Jacobian matrix of the coupled three phase state estimation problem is considered. While the actual CPU times naturally depend on the processor speed and implementation details (here sparse matrix methods are employed, but no effort is put towards code optimization), the trend will remain valid irrespective of these factors. The differences between the MSE values calculated according to (29) for both estimators are found to be insignificant.

TABLE 7.3. RESULTS OF THE SIMULATIONS ON 3625-BUS THREE-PHASE SYSTEM

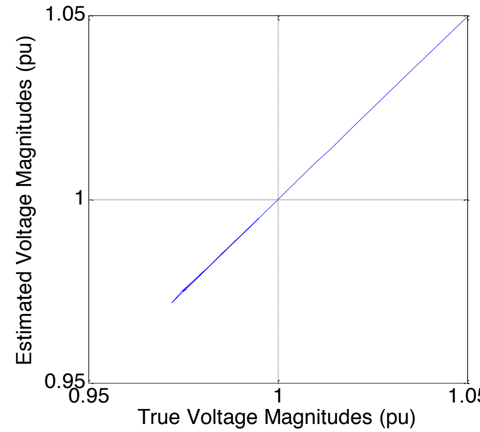
	Case 2.a		**Case 2.b**		**Case 2.c**	
	LAV	**WLS**	**LAV**	**WLS**	**LAV**	**WLS**
Zero Seq.	3.52 s.	2.32 s.	4.85 s.	9.35 s.	4.74 s.	15.81 s.
Positive Seq.	3.61 s.	2.62 s.	4.79 s.	10.41 s.	4.23 s.	16.02 s.
Negative Seq.	3.21 s.	2.22 s.	4.92 s.	8.51 s.	4.92 s.	15.32 s.



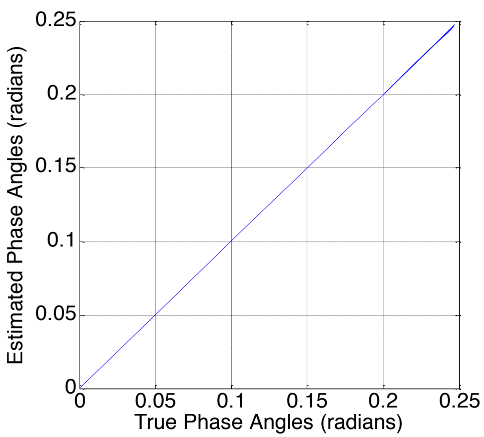
a) Bus voltage comparison for Phase-A



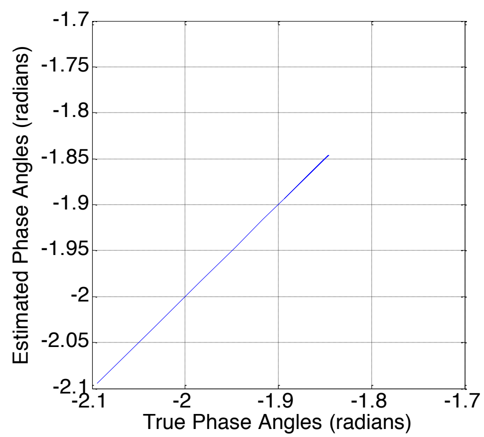
b) Bus voltage comparison for Phase-B



c) Bus voltage comparison for Phase-C



d) Phase angle comparison for Phase-A



e) Phase angle comparison for Phase-B

f) Phase angle comparison for Phase-C

Fig. 7.2. Comparison of estimated vs. true states.

V. SUMMARY AND COMMENTS

The motivation of this work is the expectation that PMUs will measure and observe entire power systems in the near future. If this possibility is realized, state estimation problem will become linear. Moreover, it will be possible to decouple three-phase measurements and perform three parallel state estimations for much smaller single phase modal equivalents. Existing positive sequence state estimators can be used to solve each modal equivalent simultaneously in parallel.

The developed tool is capable of solving state estimation problem for unbalanced three-phase systems, including both transposed and untransposed lines in a computationally efficient way by using robust LAV estimator. Note that, robustness of LAV estimator is highly related to measurement design and redundancy. A more detailed study on robustness of LAV estimator and corresponding measurement design requirements can be found in [37] and [72], respectively.

The proposed method is capable of handling unbalanced power systems. The only approximation of the method is introduced if one of the PMUs is placed on untransposed lines and the shunt admittances of those lines are not small enough to neglect. Otherwise, the proposed decoupling method can be applied any system without introducing any additional assumption or approximation. Moreover, in distribution system analysis the proposed method can be used without any additional approximation, since short transmission line model, which neglects shunt admittances of the lines, is employed for numerical analyses.

CHAPTER: 8

CONCLUSIONS AND FUTURE WORK

This dissertation introduces new methods for efficient incorporation of PMUs in power system state estimation. Chapter 2 describes network observability and measurement criticality analysis methods for power systems measured by both PMUs and conventional SCADA measurements. Following that, an observability restoration method that places a minimum number of pseudo-measurements is presented in Chapter 3. Chapter 4 introduces the robust LAV estimator for systems using only PMU measurements. . Chapter 5 proposes a PMU placement method, such that resulting measurement design satisfies network observability and guarantees the robustness of LAV estimator. After that, a state estimation method based on both WLS and LAV estimators for measurement sets consisting of both conventional and PMU measurements, is introduced in Chapter 6. Finally, a computationally efficient and robust three-phase state estimation approach for power systems measured by PMUs, which depends on the symmetrical components, is proposed in Chapter 7.

Rapidly increasing number of PMUs in recent years is the major motivation of this dissertation, because considering the number of installed PMUs, it is inevitable to deploy them in state estimation. Possibility that in the near future almost all power systems will be monitored exclusively by PMUs and efficiently implemented linear program solvers encouraged the use of LAV estimator. Besides that, increased CPU speed and decreased computer memory costs enabled LAV compete with WLS estimator in terms of computational efficiency.

In addition to the increase in PMU number and advances in computers, several technical needs in state estimation field also motivated this work. Robustness has a major importance in state estimation, since biased estimates may cause incorrect system operations and market pricing. Therefore to guarantee the robustness of LAV, a PMU placement method was developed. Although, three-phase state estimation was out of concern in the previous years, due to the increased renewable sources in the grid, need for three-phase state estimation has risen in recent years to monitor unbalanced operation.

The dissertation’s main contributions are:

1) The proposed observability and criticality analysis methods, which depend on the newly defined A-matrix, can be applied to any power system independent of the phasor measurement configuration.
2) The proposed observability analysis method can detect current phasor measurements leading to multiple-solutions, which was not possible with conventional methods.
3) The proposed observability analysis method considers conventional measurements and PMUs as well as voltage magnitude measurements, which were neglected in conventional observability analysis methods so far. Note that neglecting measurements may affect results of observability analysis, and may cause placement of redundant pseudo-measurements, which may result in biased state estimates.
4) The proposed observability restoration method operates in a computationally efficient manner, even for large-scaled systems with high number of observable islands.
5) It was shown that if measurement set only consists of PMUs, robust LAV estimator, which is also a computationally efficient linear programming based estimator, is a better estimator option compared to WLS estimator.

6) The proposed PMU placement method guarantees estimator robustness, which was not studied so far even though many methods to provide system observability had been proposed.
7) The single-stage state estimation method, which was developed for systems measured by both PMUs and conventional measurements, is shown to be competitive with the methods described in literature in terms of computational efficiency, besides giving better estimation results.
8) The proposed three-phase state estimation method makes it possible to perform three-phase state estimation in a computationally efficient way for unbalanced and balanced power systems, since three-phase measurements and system states are decoupled, and three parallel state estimation problems are solved for much smaller single-phase modal equivalents.

Despite the high number of installed PMUs in the grid, it is not possible to perform state estimation using only PMUs. Hence, it is important to expand the studies on state estimation using both SCADA and PMU measurements. As mentioned earlier, location and number of PMUs are especially important for accuracy of the state estimates, if both PMUs and SCADA measurements are employed in state estimation. Therefore, as a future work, a study on minimum number of PMUs and their locations for accurate enough state estimates can be conducted. In order to carry out such a study, a definition of ‘accurate enough’ should be developed in the first place. As a second future work, a PMU placement method, which can take PMUs with different number of channels into account, may be developed. The resulting measurement design may have less cost compared to the proposed one, since it may use less number of channels for the same measurement redundancy. Finally, a three-phase state estimator, which considers the coupling between two or more parallel three-phase lines may be implemented. This kind of coupling is generally neglected in power system analysis, except transient studies. However, to analyze how effective it is on state estimation, this study can be further extended to modal components due the coupling between parallel three-phase lines. Transformation matrices for such analyses have been presented in the literature. Those transformation matrices can be employed in the proposed method, instead of using symmetrical components transformation matrix.

REFERENCES

[1] A. G. Phadke, “Synchronized Phasor Measurements – A Historical Overview”, IEEE PES Transmission and Distribution Conference and Exhibition 2002: Asia Pacific, vol. 1, pp. 476-479, 6-10 October 2002.

[2] U.S.-Canada Power System Outage Task Force, “Final report on the August 14, 2003 Blackout in the United States and Canada: Causes and Recommendations”, *http://www.ferc.gov/industries/electric/indus-act/reliability/blackout/ch1-3.pdf*, February 2004.

[3] U.S. Department of Energy, Electricity Delivery and Reliability, “Synchrophasor Technologies and Their Deployment in the Recovery Act Smart Grid Programs”, August 2013.

[4] F. C. Schweppe and J. Wildes, "Power System Static-State Estimation, Part I: Exact Model", IEEE Transactions on Power Apparatus and Systems, Vol.PAS-89, pp. 120-125, January 1970.

[5] F. C. Schweppe and D. B. Rom, "Power System Static-State Estimation, Part II: Approximate Model", IEEE Transactions on Power Apparatus and Systems, Vol.PAS-89, pp.125-130, January 1970.

[6] F. C. Schweppe, "Power System Static-State Estimation, Part III: Implementation", IEEE Transactions on Power Apparatus and Systems, Vol.PAS-89, pp. 130-135, January 1970.

[7] A. Abur and A. Gomez-Exposito, “Power System State Estimation: Theory and Implementation”, book, Marcel Dekker, 2004.

[8] A. Gomez-Exposito and A. Abur, "Generalized Observability Analysis and Measurement Classification", IEEE Transactions on Power Systems, Vol. 13, Issue 3, pp. 1090-1095, 1998.

[9] B. Xu, and A. Abur, "Observability Analysis and Measurement Placement for Systems with PMUs," Power System Conference and Exposition, 10-13 October 2004.

[10] G. R. Krumpholtz, K.A. Clements and P. W. Davis, "Power System Observability: A Practical Algorithm Using Network Topology", IEEE Trans. On Power Apparatus and Systems, Vol. 101 (7), pp. 3044-3052, 1982.

[11] K.A. Clements, G. R. Krumpholtz and P. W. Davis, "Power System State Estimation with Measurement Deficiency: An Observability/ Measurement Placement Algorithm", IEEE Trans. On Power Apparatus and Systems, Vol. PAS-102, Issue: 7, pp. 2012-2020, July 1983.

[12] K.A. Clements, G. R. Krumpholtz and P. W. Davis, "Power System State Estimation with Measurement Deficiency: An Algorithm that Determines the Maximal Observable Sub-network", IEEE Trans. On Power Apparatus and Systems, Vol. 101 (7), pp. 3044-3052, 1982.

[13] V. H. Quintana, A. Simoes-Costa, A. Mandel, "Power System Topological Observability Using A Direct Graph-Theoretic Approach", IEEE Trans. On Power Apparatus and Systems, Vol. PAS-101, No. 3, pp. 617-626, March 1982.

[14] N. S. da Silva, A. Simoes-Costa, E. M. Lourenço, "A Numerical Method for Observability Analysis Based on Given Rotations", North American Power Symposium, 2011.

[15] G. N. Korres, “Observability and Criticality Analysis in State Estimation Using Integer-Preserving Gaussian Elimination”, European Transaction on Electric Power, 2012.

[16] M. Gol and A. Abur, “Observability Analysis and Critical Measurement Detection for Power Systems Measured by PMUs”, Innovative Smart Grid Technologies, IEEE PES, 16-20 Jan. 2012.

[17] G. N. Korres, “An Integer-Arithmetic Algorithm for Observability Analysis of Systems with SCADA and PMU Measurements”, Electric Power Systems Research, vol. 81, no. 7, pp. 1388-1402, July 2011.

[18] G. N. Korres and N. M. Manousakis, “State Estimation and Observability Analysis for Phasor Measurement Unit Measured Systems”, IET Generation, Transmission and Distribution, vol. 6, no. 9, pp. 902-913, Sep. 2012.

[19] M. Gol and A. Abur, “Observability Analysis of Systems Containing Phasor Measurements”, IEEE PES General Meeting, July 22-26 2012, San Diego, CA.

[20] M. Gol and A. Abur, “Observability and Criticality Analyses for Power Systems Measured by Phasor Measurements”, IEEE Transactions on Power Systems, vol. 28, no, 3, August 2013.

[21] A. Monticelli and F. F. Wu, “Network Observability: Identification of Observable Islands and Measurement Placement”, IEEE Trans. On Power App. Syst., vol. PAS-104, no. 5, pp. 1035-1041, May 1985.

[22] B. Gou and A. Abur, “A Direct Numerical Method for Observability Analysis”, IEEE Transactions on Power Systems, Vol. 15, No. 2, May 2000.

[23] B. Gou and A. Abur, “An Improved Measurement Placement Algorithm for Network Observability”, IEEE Transactions on Power Systems, Vol. 16, No. 4, November 2001.

[24] G. N. Korres, “A Gram Matrix-Based Method for Observability Restoration”, IEEE Transactions on Power Systems, Vol. 26, No. 4, November 2011.

[25] F. H. Magnago and A. Abur, “A Unified Approach to Robust Meter Placement Against Loss of Measurements and Branch Outages”, Transactions on Power Systems, Vol. 15, No. 3, August 2000.

[26] B. Donmez and A. Abur, “A Computationally Efficient Method to Place Critical Measurements”, IEEE Transactions on Power Systems, Vol. 26, No. 2, May 2001.

[27] D. L. Donoho, “Breakdown Properties of Multivariate Location Estimators,” Ph.D. Qualifying Paper, Harvard University, Statistics Department, 1982.

[28] F. R. Hampel, E. M. Ronchetti, P. J. Rousseeuw and W. A. Stahel, "Robust Statistics: The Approach Based on Influence Functions", Wiley Series in Probability and Mathematical Statistics, John Wiley &: Sons, 1986.

[29] P. J. Rousseeuw and A. M. Leroy, “Robust Regression and Outlier Detection”, book, John Wiley and Sons, 1987.

[30] L. Mili, M. G. Cheniae, N. S. Vichare and P. J. Rousseeuw, “Robust State Estimation of Power Systems”, IEEE Transactions on Circuits and Systems, Vol. 41, No. 5, pp. 349-358, May 1994.

[31] L. Mili, M. G. Cheniae, N. S. Vichare and P. J. Rousseeuw, “Robust State Estimation Based on Projection Statistics,” IEEE Transactions on Power Systems, vol. 11, no. 2, pp. 1118-1127, May 1996.

[32] R. Baldick, K. A. Clements, Z. Pinjo-Dzigal And P.W. Davis, “Implementing Non-quadratic Objective Functions for State Estimation and Bad Data Rejection” IEEE Transactions on Power Systems, Vol. 12, No. 1, pp. 376-382, February 1997.

[33] M. R. Irwing, R. C. Owen and M. J. H. Sterling, "Power System State Estimation Using Linear Programming", IEEE Proceedings, Part C, Vol. 125, No. 9, pp. 879-885, September 1978.

[34] M. K. Celik and A. Abur, "A Robust WLAV State Estimator Using Transformations", IEEE Transactions on Power Systems, Vol. 7, No. 1, pp. 106-113, February 1992.

[35] A. Abur and M. K. Celik, "A Fast Algorithm for the Weighted Least Absolute Value State Estimation", IEEE Transactions on Power Systems, Vol. 6, No. 2, pp. 1-8, February 1991.

[36] A. Abur and M. K. Celik, "Least Absolute Value State Estimation with Equality and Inequality Constraints", IEEE Transactions on Power Systems, Vol. 8, No. 2, pp. 680-688, May 1993.

[37] M. Gol and A. Abur, "PMU Based Robust State Estimation Using Scaling", North American Power Symposium, 9-11 September, 2012, Urbana-Champaign, IL, USA.

[38] R. Emami and A. Abur, "Robust Measurement Design by Placing Synchronized Phasor Measurements on Network Branches," IEEE Transactions on Power Systems, vol. 25, no. 1, pp. 38-43, February 2010.

[39] B. Gou, "Generalized Integer Linear Programming Formulation for Optimal PMU Placement", IEEE Transactions on Power Systems, vol. 23, issue 3, pp. 1099-1104, August 2008.

[40] N. M. Manousakis, G. N. Korres and P. S. Georgilakis, "Taxonamy of PMU Placement Methodologies", IEEE Transactions on Power Systems, vol. 27, issue 2, pp. 1070-1077, May 2012.

[41] M. Esmaili, K. Gharani and H. A. Shavanfar, "Redundant Observability PMU Placement in the Presence of Flow Measurements Considering Contingencies",

IEEE Transactions on Power Systems, vol. 28, issue 4, pp. 3765-3773, November 2013.

[42] M. H. F. Wen, Jin Xu and V. O. K. Li, “Optimal Multistage PMU Placement for Wide Area Mintoring”, IEEE Transactions on Power Systems, vol. 28, issue 4, pp. 4134-4143, November 2013.

[43] K. Jamuna and K. S. Swarup, “Two Stage State Estimator with Phasor Measurements”, Third International Conference on Power Systems, 27-29 December 2009, Kharagpur, India.

[44] R. Baltensperger, A. Loosli, H. Sauvain, M. Zima, G. Andersson, R. Nuqui, “An Implementation of Two-Stage Hybrid State Estimation with Limited Number of PMU”, 10th IET International Conference on Developments in Power System Protection, March 29-April 1 2010.

[45] A. S. Costa, A. Albuquerque and D. Bez, “An Estimation Fusion Method for Including Phasor Measurements into Power System Real-Time Modeling”, IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 1910-1920, May 2013.

[46] M. Glavic and T. Van Cutsem, “Reconstructing and Tracking Network State From a Limited Number of Synchrophasor Measurements”, IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 1921-1929, May 2013.

[47] C. W. Hansen and A. S. Debs, “Power System State Estimation Using Three-Phase Models”, IEEE Transactions on Power Systems, vol.10, no.2, May 1995, pp.818-824.

[48] H. Kim, and A. Abur, “State Estimation for Three Phase Power Networks”, Proceedings of the 26th Annual North American Power Symposium, pp. 210-220, Sep. 27-28, 1994, Manhattan, Kansas.

[49] A. Monticelli, “Electric Power System State Estimation”, Proceedings of the IEEE, Vol. 88, No 2, pp. 262-282, February 2000.

[50] F. F. Wu, “Power System State Estimation: A survey,” Int. J. Elect. Power Eng. Syst., vol. 12, pp. 80–87, Jan. 1990.

[51] A. Monticelli and F. F. Wu, “Network Observability: Theory”, IEEE Transaction on PAS, Vol. PAS-104, No 5, pp.1042-1048, May 1985.

[52] A. Abur and A. Gomez-Exposito, “Observability and Bad Data Identification When Using Ampere Measurements in State Estimation”, IEEE International Symposium on Circuits and Systems, 1993.

[53] A. Abur and A. Gomez-Exposito, “Bad Data Identification When Using Ampere Measurements”, IEEE Transactions on PWRS, vol. 12(2), pp. 831-836, May 1997.

[54] K. I. Geisler, “Ampere Magnitude Line Measurements for Power System State Estimation”, IEEE Transactions on PAS, Vol. PAS-103, No 8, pp. 1962-1969, August 1984.

[55] W. W. Kotiuga and M. Vidyasagar, “Bad Data Rejection Properties of Weighted Least Absolute Value Techniques Applied to Static State Estimation”, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-101, No. 4, pp. 844-851, April 1982.

[56] D. G. Luenberger, “Linear and Nonlinear Programming”, Addison-Wesley Publishing Co., 1984.

[57] F. Broussolle, “State Estimation in Power Systems: Detecting Bad Data Through the Sparse Inverse Matrix Method”, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-97, No. 3, pp. 678-682, May/June 1978.

[58] A. M. Erisman and W. F. Tinney, “On Computing Certain Elements of the Inverse of a Sparse Matrix”, Communications of the ACM, Vol. 18, Issue 3, pp. 177-179, March 1975.

[59] K. Takahashi, J. Fagan and M. Chen, “Formation of a Sparse Bus Impedance Matrix and Its Application to Short Circuit Study”, PICA Proceedings, pp. 63-69, May 1973.

[60] P. W. Holland and R. E. Welsch, “Robust Regression Using Iteratively Reweighted Least Squares,” Communications in Statistics, Theory and Methods, A6(9), 813-827, 1977.

[61] R. C. Pires, A. S. Costa and L. Mili, “Iteratively Reweighted Least-Squares State Estimation Through Givens Rotations”, IEEE Transactions on Power Systems, Vol. 14, No. 4, pp. 1499-1507, November 1999.

[62] A. Abur, “A Bad Data Identification Method for the Linear Programming State Estimation”, IEEE Transactions on Power Systems, Vol. 5, No. 3, pp. 894-901, August 1990.

[63] P. C. Mahalanobis, “On the Generalized Distance in Statistics”, Proceedings of the National Institute of Science of India 2 (1), pp. 49-55, 1936.

[64] M. K. Celik and A. Abur, “Use of Scaling in WLAV Estimation of Power System States”, Transactions on Power Systems, Vol. 7, No. 2, pp. 684-692, May 1992.

[65] A. Monticelli and A. Garcia, “Reliable Bad Data Processing for Real-Time State Estimation”, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-102, No. 5, pp. 1126-1139, May 1983.

[66] F.F. Wu, K. Moslehi, A. Bose, “Power System Control Centers: Past, Present and Future”, Proceedings of the IEEE (Special Issue on Power Technology and Public Policy: Forty Years After the 1965 Blackout), Nov. 2005.

[67] G. K. Stefopoulos, R. H. Alaileh, G. J. Cokkinides, and A. P. S. Meliopoulos, "On Three-Phase State Estimation in the Presence of GPS-Synchronized Phasor Measurements", Proceeding of the 39th North American Power Symposium, 2007, Atlanta, GA.

[68] A. G. Phadke, J. S. Thorp, R. F. Nuqui, & M. Zhou, "Recent Developments in State Estimation with Phasor Measurements", Proceedings of the IEEE/PES Power Systems Conference and Exposition, pp. 1-7, 2009.

[69] A. G. Phadke, "Synchrophasor Based Tracking Three Phase State Estimator and Its Applications", Virginia Tech, Blacksburg, VA. DOE 2010 Transmission Reliability Program Peer Review, October 19-20 2010.

[70] M. Zhou, V. A. Centeno, J. S. Thorp and A. G. Phadke, "An alternative for Including Phasor Measurements in State Estimator", IEEE Transactions on Power Systems, vol. 21, no. 4, pp. 1930-1937, Nov 2006.

[71] M. Gol and A. Abur "Synchro-Phasor Based Three Phase State Estimation Using Modal Components", IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies-Europe, 14-17 October 2012, Berlin, Germany.

[72] M. Gol and A. Abur "PMU Placement for Robust State Estimation", IEEE North American Power Symposium, 22-24 September, 2013.

[73] M. Gol and A. Abur "A Robust PMU Based Three-Phase State Estimator Using Modal Decoupling", IEEE Transactions on Power Systems, Early-Access.

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Research Interests

Power system state estimation

Phasor measurement units (PMUs)

Computational methods applied to power systems

Power system analysis

Smart grid

Power quality

Power system modeling

Education

PhD degree in Electrical and Computer Engineering, Northeastern University, Boston, MA, 2010-2014

Advisor: Prof. Ali Abur

Thesis: Incorporation of PMUs in Power System State Estimation

Courses Taken: Power system state estimation, Optimization methods, Analysis of unbalanced power grids, Modern signal processing, CURENT seminars.

MS in Electrical and Electronics Engineering, Middle East Technical University, Ankara, Turkey, 2007-2009

Advisor: Prof. Muammer Ermis

Co-Advisor: Asst. Prof. Özgül Salor

Thesis: A New Field-Data Based EAF Model Applied to Power Quality Studies

Courses Taken: Digital signal processing, Generalized electrical machine theory, Advanced static power conversion, Design of electrical machines, Stability theory of dynamical systems, Advanced high voltage techniques, Power quality.

BS in Electrical and Electronics Engineering, Middle East Technical University, Ankara, Turkey, 2003-2007

Experience

Research Assistant, Northeastern University, Department of Electrical and Computer Engineering

Development and implementation of Synchro-Phasor Assisted State Estimator (SPASE) as part of ENTERGY Smart Grid Investment Grant Phasor Project. (2010-present)

Researcher, TUBITAK-Uzay, Power Electronics Group

Participated in National Power Quality Project of Turkey. Modeling of industrial loads and FACTS. Power quality analysis of industrial loads.(2007-2010)

Awards, Honors

Student Success Scholarship, Middle East Technical University (2003-2007)

İş Bank Prize (2003)

Ranked 41st in University Entrance Exam in Turkey (2003)

Ranked 36th in High School Entrance Exam in Turkey (2000)

Professional Activities

Supervising undergraduate students in the National Science Foundation (NSF) Research Experience for Undergraduates

(REU) Program.

Reviewer of IEEE Transactions on Power Systems.

Reviewer of IEEE Transactions on Power Delivery.

Reviewer of IEEE Transactions on Smart Grid.

Organization Committee of North American Power Symposium (NAPS) 2011.

Organization Committee of IEEE PES Boston Chapter Distinguished Lecture at Northeastern University, October 2012.

Organization Committee of IEEE PES Boston Chapter Distinguished Lecture at Northeastern University, October 2013.

Affiliations and Leadership

IEEE PES at Northeastern University;

President, June 2013 – present

Vice-President, June 2012 – June 2013

CURENT (Center for Ultra-Wide-Area Resilient Electric Energy Transmission Networks) Student Leadership Council Representative at Northeastern University, April 2013 - present

IEEE, 2008 - present

IEEE Power and Energy Society, 2010 - present

Skills

Matlab, PowerWorld, PSCAD, C++

LIST OF PUBLICATIONS

Journal/Magazine Papers:

[1] M. Gol and A. Abur, "LAV Based Robust State Estimation for Systems Measured by PMUs," IEEE Transactions on Smart Grid, Accepted.

[2] M. Gol and A. Abur, "A Robust PMU Based Three-Phase State Estimator Using Modal Decoupling," IEEE Transactions on Power Systems, Accepted.

[3] M. Gol and A. Abur, "Observability and Criticality Analyses for Power Systems Measured by Phasor Measurements," IEEE Transactions on Power Systems, vol. 28, issue 3, pp. 3319-3326, August 2013.

[4] M. Gol and A. Abur, "Metrics for Success: Performance Metrics for Power System State Estimators and Measurement Designs**,"** IEEE Power and Energy Magazine, vol. 10, issue 5, pp. 50-57, September 2012.

[5] M. Gol, O. Salor and et. al., "A New Field-Data Based EAF Model for Power Quality Studies," IEEE Transactions on Industry Applications, vol. 46, issue 3, pp. 1230-1242, May 2010.

Peer-Reviewed Conference Proceedings:

[1] M. Gol, F. Galvan and A. Abur, "Rapid Tracking of Bus Voltages Using Synchro-Phasor Assisted State Estimator," IEEE Innovative Smart Grid Technologies (ISGT) Europe, October 2013.

[2] M. Gol and A. Abur, "PMU Placement for Robust State Estimation," IEEE North American Power Symposium (NAPS), September 2013.

[3] M. Gol and A. Abur, "Identifying Vulnerabilities of State Estimators Against Cyber-Attacks," PowerTech, June 2013.

[4] M. Gol and A. Abur, "Synchro-phasor Based Three Phase State Estimation Using Modal Components," IEEE Innovative Smart Grid Technologies (ISGT) Europe, October 2012.

[5] M. Gol and A. Abur, "PMU Based Robust State Estimation Using Scaling," IEEE North American Power Symposium (NAPS), September 2012.

[6] M. Gol and A. Abur, "Observability Analysis of Systems Containing Phasor Measurements**,"** IEEE PES General Meeting, July 2012.

[7] M. Gol and A. Abur, "Pseudo-Measurement Placement for Reliable State Estimation**,"** International Conference on Probabilistic Methods Applied to Power Systems, June 2012.

[8] M. Gol and A. Abur, "Observability Analysis and Critical Measurement Detection for Power Systems Measured by PMUs," IEEE Innovative Smart Grid Technologies (ISGT), January 2012.

[9] M. Gol, O. Salor, et. al., "A New Field-Data Based EAF Model for Power Quality Studies," IEEE Industry Applications Society Annual Meeting, October 2008.