VERY SHORT TERM LOAD FORECASTING AIDED HYBRID STATE ESTIMATOR WITH OPTIMALLY PLACED PSEUDO-MEASUREMENTS

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submitted by **BURAK ÖZSOY** in partial fulfillment of the requirements for the degree of **Master of Science in Electrical and Electronics Engineering Department, Middle East Technical University** by,

Prof. Dr. Gülbin Dural Ünver ______________
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Tolga Çiloğlu ______________
Head of Department, **Electrical and Electronics Engineering**

Assist. Prof. Dr. Murat Göl ______________
Supervisor, **Electrical and Electronics Eng. Dept., METU**

Examining Committee Members:

Prof. Dr. Ali Nezih Güven ______________
Electrical and Electronics Engineering Dept., METU

Assist. Prof. Dr. Murat Göl ______________
Electrical and Electronics Engineering Dept., METU

Assist. Prof. Dr. Ozan Keysan ______________
Electrical and Electronics Engineering Dept., METU

Assist. Prof. Dr. Ayşe Selin Kocaman ______________
Industrial Engineering Dept., Bilkent Uni.

Assist. Prof. Dr. Oğuzhan Ceylan ______________
Management Information Systems Dept., Kadir Has Uni.

Date: *19.01.2018*

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Burak ÖZSOY

Signature :

ABSTRACT

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ÖZSOY, Burak
M.S., Department of Electrical and Electronics Engineering
Supervisor : Assist. Prof. Dr. Murat Göl

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The use of PMUs in power grids have been increased with the development of GPS and computer-based technology. Unlike conventional SCADA measurements, PMUs obtain synchronized measurements with respect to the GPS. Moreover, PMU measurements are more qualified than conventional measurements thanks to having better accuracy and being updated with higher refresh rates. Nevertheless, it is unlikely that power system state estimator can be conducted with only PMUs instead of existing SCADA systems in large power systems in the near future due to the high cost of installation. Therefore, it seems more feasible to use both PMUs and SCADA in power system state estimation, namely hybrid state estimation. In the practical applications, the different resolutions of these measurements cause several problems. One of the major problems is that the system observability cannot be provided at the time instants between SCADA updates due to little number of PMUs for the system observability.

This thesis proposes a hybrid state estimation strategy, which uses pseudo-measurements to restore the system observability at time instants between adjacent SCADA updates. The pseudo-measurements are generated using statistical properties of the injection measurement data gathered in the most recent 60 days to include effects of climate and economy in power consumption. The derived statistical model of the injections is updated during the day via Kalman Filter based very short-term load forecasting. In order to minimize the bias because of the use of pseudo-measurements, minimum number of pseudo-measurements that restore system observability are selected among the candidate buses.

Keywords: Hybrid State Estimator, Kalman Filter, Optimal Pseudo-Measurement Placement, PMU.

ÖZ

OPTİMAL YERLEŞTİRİLMİŞ SANAL ÖLÇÜMLERİ KULLANAN ÇOK KISA DÖNEM YÜK TAHMİNİ DESTEKLİ HİBRİT DURUM KESTİRİMCİSİ

ÖZSOY, Burak
Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü
Tez Yöneticisi: Assist. Prof. Dr. Murat Göl

Ocak 2018, 83 sayfa

GPS (Küresel Konumlama Sistemi) ve bilgisayar tabanlı teknolojilerin gelişimiyle birlikte PMU'ların (Fazör Ölçüm Ünitesi) elektrik şebekelerinde kullanılımı artmıştır. PMU'lar, SCADA'dan farklı olarak GPS'i referans alarak birbirleriyle senkronize edilmiş ölçümler elde eder. Dahası, PMU ölçümleri, daha iyi doğrulukta olması ve daha yüksek yenileme hızlarıyla güncellenmesi nedeniyle konvansiyonel ölçümlerden daha niteliklidir. Bunlara rağmen, güç sistemi durum kestirimcisinin, mevcut SCADA sistemleri yerine sadece PMU'lar kullanılarak gerçekleştirilmesi PMU'ların yüksek maliyeti sebebiyle yakın gelecekte pek olası değildir. Bu nedenle, bu iki ölçümü de birlikte kullanan hibrid durum kestirimcisi çok daha uygulanabilir görülmektedir. Gerçek uygulamalarda, PMU ve SCADA ölçümlerinin farklı çözünürlüklere sahip olması çeşitli problemler ortaya çıkarmaktadır. En büyük sorunlardan biri, PMU'ların yetersiz sayıda olması nedeniyle SCADA güncellemeleri arasındaki zamanlarda sistemin gözlemlenebilirliğinin sağlanamamasıdır.

Tez, SCADA güncellemeleri arasındaki zamanlarda sistemin gözlenebilirliğini sağlamak için sanal güç enjeksiyonu ölçümleri kullanan bir hibrid durum tahmini

stratejisi önermektedir. Sanal güç enjeksiyonu ölçümleri, iklim ve ekonominin enerji tüketimine etkilerini içerecek şekilde geçmiş 60 günden toplanan güç enjeksiyonu ölçümlerinin istatistiksel özelliklerini kullanarak üretilir. Enjeksiyonların türetilmiş istatistiksel modeli, gün boyunca, Kalman Filtresi temelli çok kısa dönem yük tahmini kullanılarak güncellenmektedir. Sanal ölçümlerin kullanılması nedeniyle bu ölçümlerden kaynaklanacak sapmaları en aza indirgemek için, aday baralar arasından sistemin gözlemlenebilirliğini yeniden sağlayacak minimum sayıda sanal ölçüm seçilir.
Anahtar Kelimeler: Hibrid Durum Tahmincisi, Kalman Filtre, Sanal Ölçümlerin Optimum Yerleştirimi, Fazör Ölçüm Ünitesi.

To My Parents

And My Beloved Selen

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

Power system state estimation, which was proposed in 1968 by Schweppe, has always been a fundamental function in the Energy Management System (EMS) for accurate detection of the operating system state to take necessary precautions in time [1]. The complex voltages at every bus in the network, which are bus voltage magnitudes and angles, are computed as the set of system states in the solution by using the collected unsynchronized measurements supplied by the Supervisory Control and Data Acquisition (SCADA) system and synchronized measurements supplied by Phasor Measurement Units (PMUs) [2], [3].

In the beginning of the evolution of power industry, power systems were operated independently from each other in relatively small scales. The operators of power systems manually performed necessary regulations on the grid by observing the states of electric power components [4]. As expanding power systems in the world with investments become more complex, manual monitoring and controlling of power systems cannot provide the secure and reliable electricity supply to customers. Therefore, real-time state estimator plays a key role in reliable tracking and secure management of power systems [5]. The solution of state estimator determines the current operating state of the system, which is classified as a normal, emergency or restorative state.

In the past several decades, the SCADA architecture has been developed as a universal means of EMS in the electric power industry with collecting conventional data such as active and reactive powers, active and reactive current flows and voltage magnitudes to perform the centralized power system state estimation [1]. Due to the nonlinearity relationship between system states and conventional measurements, the states of the system can be found by using a state estimator such as weighted least-square method (WLS).

PMUs, which were firstly introduced by Phadke and Thorp in 1988, provide synchronized real-time voltage and current phasor measurements in high precision with time-stamp using Global Positioning System (GPS). Thanks to voltage phasors of buses received by PMUs, states of the buses on where PMUs are installed can be measured directly [6]. In addition, current phasors measured by PMUs make it possible to calculate the state of the neighbor buses where no PMUs are deployed [7]. Number of PMU channels determines number of measured current phasors by the PMU.

Widespread deployment of PMUs in power systems raised idea of including phasor measurements in power system state estimation. Because of their small refresh rate and higher accuracy compared to SCADA, those devices will enable EMSs to receive more accurate and reliable snapshots of the system to perform critical controls [8]. Despite the improvements of power system state estimation by PMU technology, it is unlikely that the traditional SCADA systems will be fully replaced by PMU-based systems in short term due to established infrastructure of SCADA system through many years in existing power systems [9]. Although the cost of PMUs has been decreased over the last several decades thanks to the improvements on computer-based technologies, cost of installation, which includes investments for security, communication and installation of PMUs to some feeders in the substations, has increased. Indeed, it is not expected that there would not be a large power system observed only by PMUs in near future. In contrast to PMUs, SCADA provides redundant measurements to observe the states of the system. Therefore, a hybrid state estimator combining SCADA and limited PMU measurements became a reasonable way for tracking the power system accurately in real-time.

1.1 LITERATURE REVIEW

Despite the increase in the performance of state estimator in terms of accuracy and robustness, combining unsynchronized conventional measurements by SCADA, and synchronized PMU measurements in power system state estimation have several challenges. The major challenge is the fact that PMU and SCADA measurements are received in different refresh rates, such that while phasor measurements are updated in the duration of few milliseconds, conventional measurements are updated in the duration of few seconds. Since there are insufficient number of PMUs for the observability of entire system, the states of the system cannot be obtained during refreshment of only PMU measurements. In addition to those, several issues on implementation of hybrid state estimation have already been stated and methods have been proposed in [6] – [24] to benefit from the opportunities of incorporation of synchronized phasor measurements along with SCADA measurements.

In the literature, there are mainly two different approaches in which hybrid state estimation is implemented as multistage and single stage. Both of these approaches aim to estimate reliable states using a mixed measurement set. The approaches can be processed by a centralized control center or by several distributed control centers. While PMUs can obtain the current and voltage phasors in the polar coordinates, SCADA can obtain the real and imaginary parts of power measurements in the rectangular coordinates. For single stage approach, phasor measurements are converted into rectangular coordinates in order to integrate phasor measurements into measurement Jacobian matrix [22]. In some multistage applications, the pre-estimated states obtained by nonlinear state estimation in the first stage and phasor measurements are solved by linear state estimation in the second stage to improve the accuracy of estimated states. In second stage, final results are obtained by solving linear measurement equations once a time unlike traditional power system state estimation. However, the resolution of estimation cannot keep up with the refresh rate of PMUs due to the necessity of new SCADA measurements in each first stage. Alternatively, linear state estimation is conducted at each PMU update as first stage considering that sufficient number of PMUs are installed in the system. Each SCADA measurements triggers to initialize second stage for solving nonlinear state estimation with the results of first stage [13].

In [11] – [15], hybrid power state estimator is accomplished in two stages in order to utilize PMU and SCADA measurements efficiently. In [12], a two-step algorithm is proposed, which fuses the estimated states of SCADA-based and PMU-based state estimators to obtain the optimal states of the system using Multi-sensor Data Fusion (MDF) theory, which can generate more reliable data set from the mixed data set received from different types of sensors with respect to that received from only one type of sensor. In [13], in the first stage, a linear state estimator is solved to estimate voltage phasors in rectangular form using only synchronized phasor measurements. In the second stage, the representation of estimated voltage phasors from the first stage are transformed from rectangular form to polar form and are combined with the SCADA measurements into non-linear estimator. According to the results of simulations in the report, if the number of installed PMUs in the system is increased, the performance of the two-stage state estimator is improved. In [15], the paper proposes an alternative approach of hybrid state estimator that combine synchronized phasor measurements in existing energy management system (EMS) without any changes of functions such as contingency analysis, optimal power flows, corrective actions, etc. in existing EMS. In this method, traditional state estimator is achieved using conventional measurements in existing EMS, and then, the estimated states in the traditional state estimator and the phasor measurements are incorporated to estimate the states of the entire system in post processing linear state estimator. Therefore, the proposed method provides an advantage of reducing executing burden with non-iterative solution of linear state estimator and increasing the accuracy and redundancy of measurements by PMUs without any modifications in existing traditional EMS software.

In contrast to multistage methods for hybrid state estimation, the proposed single stage strategies were employed by integrating synchronized measurements from PMUs and the conventional measurements from SCADA in [16] and [17]. M. Gol and A. Abur [16] propose a single stage hybrid state estimator that efficiently uses a limited number of PMU measurements, which do not observe the entire system, to increase the speed and accuracy of the state estimator. While WLS estimator as conventional is very slow, and vulnerable to bad data, least absolute value (LAV)-based state estimator is robust for only PMU-observable systems. Therefore, a conventional WLS estimator is employed when SCADA and PMUs are refreshed, and a robust weighted LAV estimator is employed with a minimum number of old SCADA measurements when only PMUs are refreshed. The proposed hybrid state estimator can track the changes of voltage described as momentary (30 cycles – 3 s) and temporary (3 s-1 min). In [17], when pseudo-measurements and zero injections recover the observability of the system at every update of PMU measurements, state estimator tracks the changes of the system states with a resolution of a few milliseconds.

In the last several decades, the authorities of the power systems have interconnected its own grid with the other grids for the aim of supplying more reliable and uninterrupted electricity. This evolution on the power industry leads to increase of computational burden and complexity on the real-time power system state estimation at the control center due to increasing the dimensions of matrices in the state estimation problem. In view of above problems, some novel methods have been proposed in [1], [18] – [20]. In these studies, the accumulation of computations in different control areas and the fusion of information about the state of boundaries are provided from the subsystems in a hierarchical structure or aggregation tree have been investigated.

Guo et al. [18] presents a new method that the power system state estimator finds the global optimal states of large power system composed of distributed observable and unobservable subsystems by PMUs using the linear relation between the linear model in PMU-observable zone and boundary states. In [19], the paper proposes a method that PMU measurements are used to assemble unsynchronized voltage phase angles, obtained by power system state estimation in subsystems. Firstly, the algorithm identifies the optimal placement of PMUs and the reference bus in each subsystem. Secondly, sensitivity analysis assembles the distributed solutions considering the state of boundary buses by which the subsystems interconnects with each other.

1.2 SCOPE AND CONTRIBUTION OF THE THESIS

The main objective of this thesis is to develop a hybrid state estimation strategy that can maintain observability between two SCADA updates and maximize the accuracy of the estimated states using minimum number of pseudo-measurements updated by Kalman Filter based very short-term load forecast. Because of theirs advantages compared to SCADA, PMU observable zones are expanding in the SCADA based power grids all over the worlds. In order to improve the redundancy of measurements for EMS applications, new methods have combined these in state estimation applications. In case that SCADA does not update for some PMU update instants, hybrid state estimation provides the entire observability with pseudo-measurements. In conventional methods, all injection measurements are selected as pseudo-measurements to merge the isolated observable islands. It is possible that the current system has different network topology and measurement configuration with respect to one in the most recent days. As a result of this, the daily characteristics of power injections may be very different compared to the trends of power injections in the most recent days. Therefore, the use of pseudo-measurements with big errors probably will bias the estimated states or result in the divergence of hybrid state estimation solution. The proposed method aims to use pseudo-measurements with best accuracies to minimize the bias on the power system state estimation. The selected pseudo-measurements are updated using the Kalman Filter Technique to reduce the uncertainty of the pseudo-measurements.

In this study, it is assumed that system model receives both SCADA and PMU measurements with different resolutions in order to detect the abnormal changes in the system. In this way, the necessary controls can be applied by operators and precautions can be taken before emergency situations occur. Conventional SCADA measurements are composed of power flows along transmission lines, injection powers, which can be supplied or demanded, and voltage magnitudes of buses. Due to low accuracy and low refresh rates of these measurements, system operator may not monitor temporary fluctuations on voltage and phase angles. Therefore, PMUs becomes inevitable for real-time power system state estimation in modern EMS because of receiving more accurate measurements with more refresh rates compared to SCADA.

For a large power system, it is known that sole use of PMUs is not enough to monitor all the system buses. Both SCADA and PMU measurements can be used for power system state estimation. However, it is known that, SCADA measurements are updated slower than PMUs, and once only PMU measurements exist at a time instant, the active and reactive power demands are calculated as pseudo-measurements instead of SCADA measurements in hybrid state estimation. Bus injections change depending on load demand and generation capacity on the bus. Many factors such as economy, climate, etc. affect the demand of electricity and hence generation. To involve those factors, the injection data corresponding to the most 60 days is used to calculate the pseudo-measurements.

In the proposed strategy, the system cannot be observable by only PMUs between SCADA updates in a hybrid state estimator. As a result of this, pseudo-measurements should be used to recover the observability in the absence of SCADA updates. Firstly, PMU-observable islands can be identified by grouping the buses in which PMUs are installed and buses adjacent to those buses considering current phasors measured by PMUs [25]. The unobservable buses by PMUs are considered as separate observable islands. If there are M observable islands, at least M-1 pseudo-measurements are incorporated to state estimator to recover the observability of the system [5].

In the first step of strategy, the pseudo measurements are selected optimally among the candidate of buses taking account of the standard deviation of those measurements, which is associated with error. In other words, the process of optimal pseudo measurement placement recovers the observability with minimum number of pseudo measurements, each of which has the highest accuracy, when only PMU measurements are updated. The selection of buses for pseudo-measurements is achieved using integer linear programming problem.

In the second step of strategy, SCADA measurements in the last update could be used as pseudo measurements between SCADA updates in conventional method. However, the result of state estimator is biased if the real and pseudo measurements are very different. To minimize the possibility of this miscalculation in the power system state estimation, the pseudo measurements are forecasted using Kalman Filter based on the most recent measurement data in every PMU scan. Finally, Weight Least Square (WLS) is performed because of general application in the modern EMS.

1.3 POWER SYSTEM STATE ESTIMATION

State Estimation is the process of determining the states of the system, which includes independent parameters, with assigning values using the known measurements collected in the system. The parameters drive the trend of changes indirectly or directly in physical manner. The process of estimation described as dynamic or static state estimation with respect to the behavior of the state variable. In Static State Estimation (SSE) it is assumed that the system is at steady state or quasi steady state, such that the state variables are constant with respect to time. In contrast to SSE, Dynamic State Estimation (DSE) can track the state changes on time varying system model using the transition vector of states and current measurements [35].

In power system state estimation, the voltage magnitudes and phase angles of buses in the system as state variables are computed using power network parameters and a set of measurements, which are conventional unsynchronized measurements by SCADA and synchronized phasor measurements by PMUs. The problem of power system state estimation is modeled as an optimization problem such that the difference between the estimated values and real ones is minimized when the redundant measurements are obtained from the remote terminal unit (RTU) in the EMS applications. If some redundant measurements have distorted data with gross error, it is likely that there would not be any equilibrium point to converge the derivations of all states to nearly zero. Therefore, bad data is identified and then eliminated from the measurement set [5].

There are mainly three different types of errors, which are topology errors by disturbance of equipment, and temporary maintenance; gross errors by measurement errors or telemetry failures; and parameter errors in the database. If a measurement has not sensitivity depending on changes of other measurements, the measurement is called as critical measurement [37]. In addition, the corresponding row of critical measurement represents to independent linear function in the Jacobian matrix. Therefore, elimination of critical bad data causes to decrease the rank of the Jacobian matrix H, and to be the system unobservable [38]. In case of being critical measurement, erroneous measurement cannot be identified and then eliminated. One of the proposed methods is that new redundant measurements are added to measurement set to identify the critical bad data [39].

The conventional power system state estimator is composed of four fundamental steps: topology processor, observability analysis, power system state estimation, and bad data processing. Topology processor identifies the true status of circuit-breakers. Observability analysis determines the unobservable branches, and the observable islands in the system. If the system has sufficient number of measurements for the redundancy, in the part of bad data processing the biased measurements are detected in the system, and then eliminated.

1.4 WEIGHTED LEAST SQUARES (WLS) BASED POWER SYSTEM STATE ESTIMATION

Since the development of power system state estimation, WLS has been used as traditional method for state estimator function in Wide Area and Monitoring Systems (WAMS). In this method, the load-flow-like calculations are implemented to determine the optimal value for the unknown system state in an iterative process because of non-linear functions of measurements with the system state variables. Indeed, some researchers have used Kalman Filter Technique to perform power system state estimation in [4], [33 – 35]. For a Kalman Filter based method, the covariance matrix of system error and state transition matrix must be known correctly to conduct the state estimation despite of decreasing the computational burden. Moreover, Least

Absolute Value (LAV) technique, which object to minimize the sum of absolute errors using integer linear programming, is alternative method because of being more robust compared to WLS method in case of only PMU observable system [16]. This method becomes inefficient when a large power system has measurement configuration including both PMU and SCADA measurements.

Weighted Least Squares (WLS) method aims to converge iteratively the system state to the real value in a specified limit with the purpose of minimizing the objective function. The measurement error covariance matrix is used to determine the weight of each of the measurements in WLS formulation. Therefore, the effect of each measurement on the solution of power system state estimation can be adjusted based on the accuracy. The below section explains the equations in the weighted least square problem and the structure of the system matrix including the measurement function matrix and measurement Jacobian matrix.

1.4.1 WLS Algorithm

In a power system with m measurements and N buses, the relationship between measurement vector denoted by z and state vector denoted by x are nonlinear function. If the system has only conventional measurements, the state vector is constructed by (2N-1) elements, N bus voltage magnitudes and (N-1) phase angles, where one of the phase angles is assigned as reference bus. For a hybrid measurement set, each phase angle obtained by voltage phasor can be assigned as reference angle because of each PMU being inherently synchronized with each other by GSP clock. Hence, states can be estimated without using reference angle. The state vector x is described as shown below if one of the PMU bus is selected as reference bus:

$$x = [\theta_1 \quad \theta_2 \quad \theta_3 \quad \ldots \quad \theta_N \quad V_1 \quad V_2 \quad \ldots \quad V_N] \tag{1.1}$$

When the measurement set is obtained from the system with no error, the nonlinear function would yield the true system state. However, these measurements include their own error (e), magnitude of which depends on the accuracy level of measurements. In other words, each of the measurements such as power flow, power injection, voltage magnitude, etc. has different error. In the mathematical formulation, the errors associated with these measurements are assumed to be independent of each other. The relation between the system state vector and the measurement vector can be written as shown below.

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \cdot \\ \cdot \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(\theta_2, \theta_3, \dots, \theta_N, V_1, V_2, \dots, V_N) \\ h_2(\theta_2, \theta_3, \dots, \theta_N, V_1, V_2, \dots, V_N) \\ \cdot \\ \cdot \\ h_m(\theta_2, \theta_3, \dots, \theta_N, V_1, V_2, \dots, V_N) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ \cdot \\ e_m \end{bmatrix} = h(x) + e \tag{1.2}$$

$where;$

$E(e_i) = 0 \quad \& \quad E[e_i e_j] = 0 \quad i = 1, 2 \dots m$

The following objective function in WLS estimator is iteratively minimized to obtain optimal state vector.

$$J(x) = \sum_{i=1}^{m} (z_i - h_i(x))^2 / R_{ii} \tag{1.3}$$

$where;$

$R = \begin{bmatrix} {\sigma_1}^2 & 0 & \cdots & 0 \\ 0 & {\sigma_2}^2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & {\sigma_m}^2 \end{bmatrix}$ is the measurement error covariance matrix, where σ_i is standard deviation of z_i

The squares of the measurement residuals weighted by their respective measurement error covariance are summed to obtain the value of objective function as shown below.

$$J(x) = [z - h(x)]^T [R]^{-1} [z - h(x)] \tag{1.4}$$

The derivative of the objective function, which is denoted by $g(x)$, should be set to zero to find the minimum point of this objective function in view of first-order optimality condition.

$$g(x) = \frac{dJ(x)}{dx} = -H^T R^{-1}[z - h(x)] = 0 \tag{1.5}$$

$$H(x) = \frac{dJ(x)}{dx}$$

The matrix, H(x), is called the measurement Jacobian matrix. The function of $g(x)$ can be written as an infinite sum of the terms of this function' derivatives about initial point with Taylor series expansion. The higher terms of derivatives in the equation are ignored to obtain an iterative solution known as the Gauss-Newton method.

$$g(x) = g(x^k) + G(x^k)\,(x - x^k) \; = 0 \tag{1.6}$$

$$x^{k+1} = x^k - G(x^k)^{-1}\,g(x^k) \tag{1.7}$$

$where\ k: iteration\ index$

$x^k \quad : solution\ vector\ at\ iteration\ k$

$G(x^k) = H^T\,(x^k) R^{-1} H(x^k)$

The gain matrix, $G(x^k)$, is sparse and symmetric matrix. It is generally a non-negative definite matrix, and positive definite if the system is fully observable.

In the first iteration, the initial point must be determined to solve the problem step by step. The initial point for the state vector is assumed as flat start where all the voltage magnitudes are 1.0 per unit and all the voltage angles are 0 degrees. The iteration is performed until the maximum value of the difference set between the estimated states for the step of k+1 and the states at the step of k is in a desired tolerance.

1.4.2 The Measurement Function

The common information about the current operating state of the system can be observed by the conventional measurements, which are the line power flows, bus power injections, bus voltage magnitudes and line current flow magnitudes. When the measurement functions are constructed with the system state variables, the two-port π model is assumed for network branches.

The mathematical representation of bus power injections at bus i, which are active and reactive power injections, can be written as the functions of the state vector and the parametric values of the network such as susceptance (B) and conductance (G). N is the total number of buses connected to bus i.

$$P_i = V_i \sum_{j=1}^{N} V_j \left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) \tag{1.8}$$

$$Q_i = V_i \sum_{j=1}^{N} V_j \left(G_{ij}sin\theta_{ij} + B_{ij}cos\theta_{ij}\right) \tag{1.9}$$

The mathematical representation of line power flows from bus i to bus j, which are active and reactive power flows, can be written as the functions of the state vector and the parametric values of the network such as susceptance (b_i), conductance (g_i) at bus i and susceptance (b_{ij}), conductance (g_{ij}) of the line between bus i and bus j.

$$P_{ij} = {V_i}^2\left(g_i + g_{ij}\right) - V_iV_j\left(g_{ij}cos\theta_{ij} + b_{ij}sin\theta_{ij}\right) \tag{1.10}$$

$$Q_{ij} = -{V_i}^2\left(b_i + b_{ij}\right) - V_iV_j\left(g_{ij}sin\theta_{ij} - b_{ij}cos\theta_{ij}\right) \tag{1.11}$$

The mathematical representation of the line current magnitude from bus i to bus j can be written as the functions of the voltage magnitude at bus i and the power flows from bus i to bus j as the following.

$$I_{ij} = \sqrt{{P_{ij}}^2 + {Q_{ij}}^2} \Big/ V_i = S_{ij} \big/ V_i \tag{1.12}$$

$where$;

V_i, θ_i $is\ the\ voltage\ magnitude\ and\ phase\ angles\ at\ bus\ i$

θ_{ij} $is\ the\ phase\ angle\ difference\ from\ bus\ i\ to\ bus\ j$

1.4.3 The Measurement Jacobian

The derivative of the six measurement types shown above seem to be complicated due to including both the partial derivatives with respect to the phase angle and voltage magnitude variables when the measurement Jacobian matrix is calculated. The basic formation of this matrix can be represented as the following general structure to become it more understandable for applications.

$$H = \begin{bmatrix} \frac{\partial P_{inj}}{\partial \theta} & \frac{\partial P_{inj}}{\partial V} \\ \frac{\partial P_{flow}}{\partial \theta} & \frac{\partial P_{flow}}{\partial V} \\ \frac{\partial Q_{inj}}{\partial \theta} & \frac{\partial Q_{inj}}{\partial V} \\ \frac{\partial P_{flow}}{\partial \theta} & \frac{\partial P_{flow}}{\partial V} \\ \frac{\partial I_{mag}}{\partial \theta} & \frac{\partial I_{mag}}{\partial V} \\ 0 & \frac{\partial V_{mag}}{\partial V} \end{bmatrix} \tag{1.13}$$

The partial derivatives of real power injection measurements with respect to phase angle and voltage magnitude of its buses and the adjacent buses connecting to its buses are represented by the mathematical expressions shown below.

$$\frac{\partial P_i}{\partial \theta_i} = \sum_{j=1}^{N} V_i V_j \left(-G_{ij} sin\theta_{ij} + B_{ij} cos\theta_{ij}\right) - {V_i}^2 B_{ii} \tag{1.14}$$

$$\frac{\partial P_i}{\partial \theta_j} = V_i V_j \left(G_{ij} sin\theta_{ij} - B_{ij} cos\theta_{ij} \right) \tag{1.15}$$

$$\frac{\partial P_i}{\partial V_i} = \sum_{j=1}^{N} V_j \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) + V_i G_{ii} \tag{1.16}$$

$$\frac{\partial P_i}{\partial V_j} = V_i \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) \tag{1.17}$$

The partial derivatives of reactive power injection measurements with respect to the phase angle and voltage magnitude of its buses and the adjacent buses connecting to its buses are represented by the mathematical expressions shown below.

$$\frac{\partial Q_i}{\partial \theta_i} = \sum_{j=1}^{N} V_i V_j \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) - {V_i}^2 G_{ii} \tag{1.18}$$

$$\frac{\partial Q_i}{\partial \theta_j} = V_i V_j \left(-G_{ij} cos\theta_{ij} - B_{ij} sin\theta_{ij} \right) \tag{1.19}$$

$$\frac{\partial Q_i}{\partial V_i} = \sum_{j=1}^{N} V_j \left(G_{ij} sin\theta_{ij} - B_{ij} cos\theta_{ij} \right) - V_i G_{ii} \tag{1.20}$$

$$\frac{\partial P_i}{\partial V_j} = V_i \left(G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) \tag{1.21}$$

The partial derivatives of real power flow measurements from bus i to bus j with respect to the phase angle and voltage magnitude of bus i-j are represented by the mathematical expressions shown below.

$$\frac{\partial P_{ij}}{\partial \theta_i} = V_i V_j \left(g_{ij} sin\theta_{ij} - b_{ij} cos\theta_{ij} \right) \tag{1.22}$$

$$\frac{\partial P_{ij}}{\partial \theta_j} = -V_i V_j \left(g_{ij} sin\theta_{ij} - b_{ij} cos\theta_{ij} \right) \tag{1.23}$$

$$\frac{\partial P_{ij}}{\partial V_i} = -V_j \left(g_{ij} cos\theta_{ij} + b_{ij} sin\theta_{ij} \right) + 2\left(g_{ij} + g_i \right) V_i \tag{1.24}$$

$$\frac{\partial P_{ij}}{\partial V_j} = -V_i \left(g_{ij} cos\theta_{ij} + b_{ij} sin\theta_{ij} \right) \tag{1.25}$$

The partial derivatives of reactive power flow measurements from bus i to bus j with respect to the phase angle and voltage magnitude of bus i-j are represented by the mathematical expressions shown below.

$$\frac{\partial Q_{ij}}{\partial \theta_i} = -V_i V_j \left(g_{ij} cos\theta_{ij} + b_{ij} sin\theta_{ij} \right) \tag{1.26}$$

$$\frac{\partial Q_{ij}}{\partial \theta_j} = V_i V_j \left(g_{ij} cos\theta_{ij} + b_{ij} sin\theta_{ij} \right) \tag{1.27}$$

$$\frac{\partial Q_{ij}}{\partial V_i} = -V_j \left(g_{ij} sin\theta_{ij} - b_{ij} cos\theta_{ij} \right) - 2\left(b_{ij} + b_i \right) V_i \tag{1.28}$$

$$\frac{\partial Q_{ij}}{\partial V_j} = -V_i \left(g_{ij} sin\theta_{ij} - b_{ij} cos\theta_{ij} \right) \tag{1.29}$$

The partial derivatives of voltage magnitude measurements of bus i with respect to the phase angle and voltage magnitude of bus i-j are represented by the mathematical expressions shown below.

$$\frac{\partial V_i}{\partial V_i} = 1, \frac{\partial V_i}{\partial V_j} = 0, \frac{\partial V_i}{\partial \theta_i} = 0, \frac{\partial V_i}{\partial \theta_j} = 0 \tag{1.30}$$

CHAPTER 2

PSEUDO-MEASUREMENT GENERATION

2.1 INTRODUCTION

This chapter will present the proposed pseudo-measurement generation method using historical data, which will be used to restore observability to the system between two consecutive SCADA updates. The method determines the accuracies of these pseudo-measurements to optimally utilize them in power system state estimation. Note that, most of the power grids have a limited number of PMUs in all over the world, hence the system cannot be observable by solely PMUs for the duration between two consecutive SCADA updates. Therefore, the generation of pseudo-measurements with the best accuracies can be one of the most reasonable way to observe the system states as accurately as possible.

Although recently PMUs have been increasingly installed on power grids, the sustainability of the system observability have become more difficult due to the integration of new investments such as generations, transmission lines, etc. Therefore, it is very reasonable that the pseudo-measurements based on historical data or priori measurements are incorporated to provide the measurement redundancy for the real-time tracking of the system considering that the deficiency of measurements may occur. In addition, the pseudo-measurements can interconnect observable islands with the appropriate placement of those measurements if the existing PMU measurements obtained from the grid can only observe several isolated islands. For this purpose, voltage magnitudes, power injections and power flows can be selected as pseudo-measurements to merge PMU observable islands into one island. The power injections on the buses of the power system seem to be more profitable than the other measurements in order to be utilized as pseudo-measurements because of including both the forecasted loads and scheduled generations.

This work uses power injection measurements updated by the Kalman Filter based very-short term load forecasting as pseudo-measurements. This proposed method assumes that EMS stores historical data including all the past generations and load demands with the topology of the network in the most recent days. Firstly, the daily load and generation profiles of the buses on the power system are summed to provide the daily profile of power injections and the daily profile of their standard deviations. Secondly, after the state estimator is carried out along an entire day, those profiles are updated once a day between the completion time of current day and the start time of next day by adding the daily injection profiles of completed day to historical data.

In Section 2.2, the details of the proposed pseudo-measurement generation method will be given. The influence of historical data on the accuracy of pseudo-measurements with respect to the days of the week will be examined to improve the accuracy of the generated pseudo-measurements. To achieve this goal, the classification of the past injection measurements will be applied to find the best procedure for determining the most realistic daily pseudo-measurement profiles, which compared with the daily actual power injections in two different methods. Finally, the classification of historical data based on the days of the week (Monday, Tuesday, etc.) will be determined as the best method according to the comparison of the results of these two methods.

2.2 THE PROPOSED METHOD

This section explains how to determine the power injection profiles of the buses in the system using historical data to generate pseudo-measurement. The injection profile of a bus is composed of generation and load demand profiles on the bus if there are generation units and medium-voltage transformers connected to the bus. The forecast of power generation on the bus has been a tough problem since the privatization of power generating companies (GENCOS) in electricity industry. However, the load demand curves of the power system changes with respect to some seasonal parameters such as humidity, temperature and as well as socio-economic parameters. This work models the power injection profile based on the standard deviation of and the mean of its associated past load demands at the considered bus.

Transmission System Operators (TSOs) receive active and reactive power injection measurements by RTUs and store these measurements in databases for planning purposes. In conventional power system state estimation, the long-time measurements are used as pseudo-measurements. It is assumed that the most recent data is more precise than dated data. In this study, the historical data belonging to the most recent 60 days are chosen to calculate the statistical characteristics of the past injection measurements, which will be used as pseudo-measurements. Use of the data corresponding to the most recent 60 days provides inclusion of some factors affecting load demand in pseudo-measurement generation automatically such as economic parameters and climate. The profile can be calculated as follows.

$$P_{d,t}{}^{ave} = \frac{1}{N_d}\sum_{j=1}^{N_d} P_{d,t,j} \tag{2.1}$$

$$\sigma_{d,t}{}^{2} = \frac{1}{N_d}\sum_{j=1}^{N_d} \left(P_{d,t,j} - P_{d,t}{}^{ave}\right)^2 \tag{2.2}$$

In (2.1) and (2.2), $P_{d,t}{}^{ave}$ is the mean of active power injections at the specific time instant t for day-d of week (Monday, Tuesday, etc.) using the number of measurements for day-d of week in the most recent 60 days (N_d). $P_{d,t,j}$ is the measured active power value at time instant t on the j-th day-d within the most recent 60 days. The reactive power injection characteristics can be modeled using (2.1) and (2.2) equations.

In Figure 2.1, hourly standard deviation characteristics of active power injections are calculated for each day-d of week using a historical data of most recent 60 days by taking the average of standard deviations of the active power injections on the buses in the system. As seen in Figure 2.1, the variance of power demands is not significant in the early hours of all days, while the uncertainty gets significant during afternoon hours, especially on Mondays and Tuesdays. The uncertain pseudo-measurements at these instants should be eliminated as much as possible with the appropriate selection strategy of pseudo-measurements to improve accuracy of the state estimator.

In Figure 2.2, the hourly active power injections are merged as weekdays (Monday, Tuesday, Wednesday, Thursday and Friday) and weekends (Saturday, Sunday) to compare two group of historical data in most recent 60 days. The hourly standard deviation characteristics of active power injection based on 1313-bus system indicate that the reliability of state estimator may decrease if all weekdays are combined as a single characteristic, rather than using separate characteristics for each day as in Figure 2.1. Note that, based on the system considered this conclusion may vary. Therefore, before implementing the proposed method, a through analysis of the measurements and load characteristics should be carried out. This work employs the characteristic behavior of Figure 2.1.

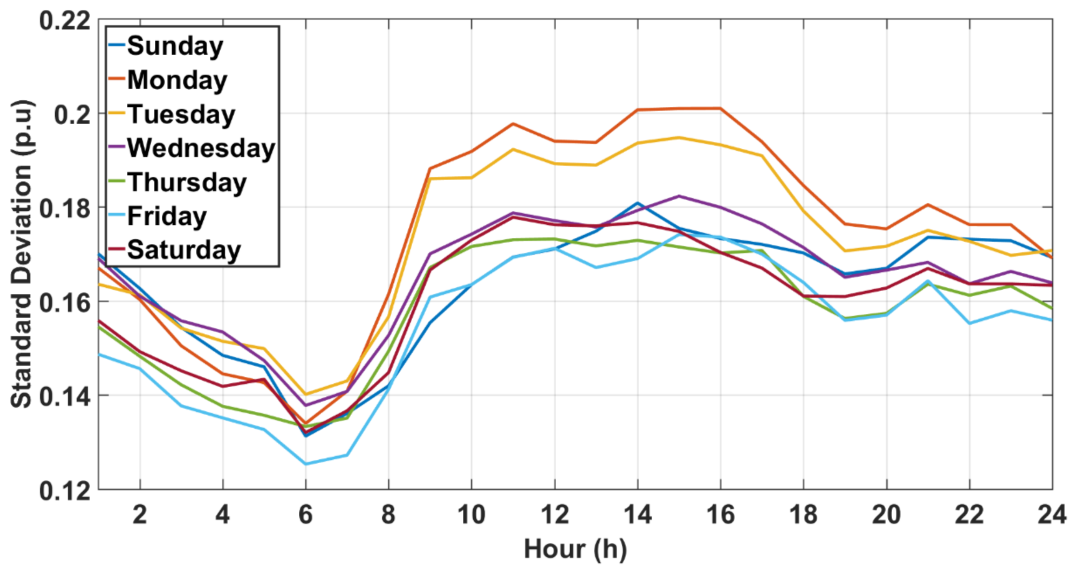

Figure 2.1. The Hourly Standard Deviation Characteristics of the Days of Week for Actual 1313-bus System

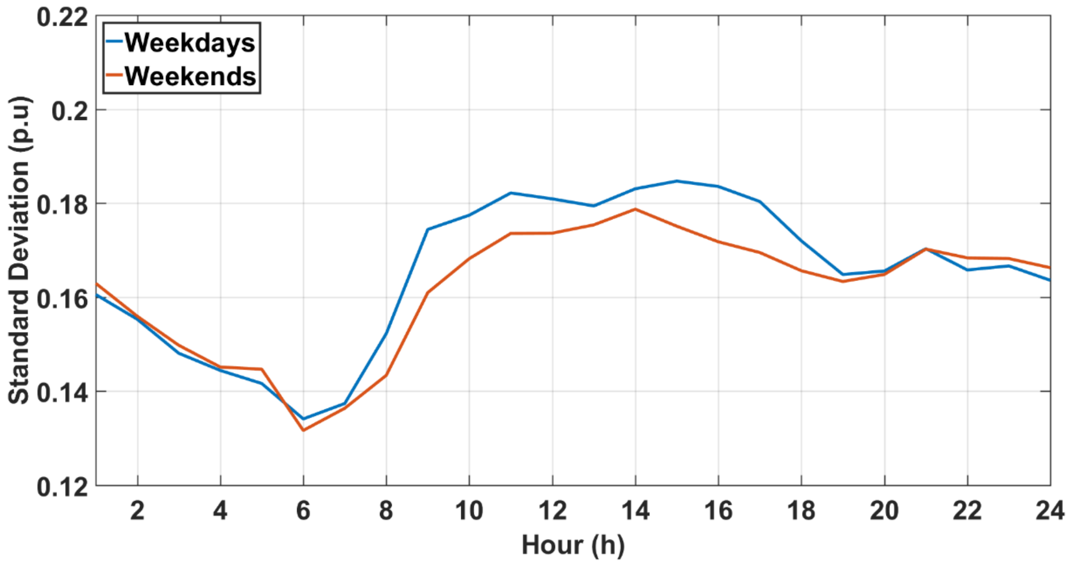

Figure 2.2. The Hourly Standard Deviation Characteristics of the Weekdays and Weekends for Actual 1313-bus System

2.3 SUMMARY AND COMMENTS

This chapter explains the proposed method that generates the pseudo-measurements by computing the statistical specifications of the past power injection measurements.

The hourly standard deviations and means of the past power injection measurements are calculated to generate pseudo-measurements. Since these pseudo-measurements are used in the power system state estimation, these measurements must be as close as possible to the real injection measurements. To generate reliable pseudo-measurements, both power generations and load demands are stored to be used as historical data. While GENCO changes its electricity generation depending on the electricity price due to the privatization of electricity industry, the load demand of electricity customer changes its electricity consumption depending on the some environmental effects such as climate, holidays, natural disasters, etc. Nevertheless, it is possible that hourly active and reactive power injections can be used to generate pseudo-measurements based on the standard deviation of and the mean of its associated past load demands at the considered bus.

In this section, hourly standard deviations characteristics of power injection measurements are computed to determine the best method of pseudo-measurement generation in two different classification of historical data. Firstly, pseudo-measurements are generated for each day-d of week using a historical data of most recent 60 days by taking the average of standard deviations of the active power injections on the buses in the system. Secondly, pseudo-measurements are generated separately for weekdays and weekends using a historical data of most recent 60 days by taking the average of standard deviations of the active power injections on the buses in the system. Considering these hourly standard deviation characteristics of two approaches, the accuracy of pseudo-measurements may be decrease in the second classification approach of historical data, especially for Mondays and Tuesdays. To sum up, pseudo-measurements should be generated as separate characteristics for each day using a historical data of most recent 60 days.

CHAPTER 3

HYBRID STATE ESTIMATION STRATEGY WITH OPTIMAL USE OF PSEUDO-MEASUREMENTS

3.1 INTRODUCTION

After presenting the methodology of generating the injection measurement profiles using historical data to create pseudo-measurement, this chapter will propose a hybrid state estimation strategy with optimal use of pseudo-measurements. In the study, it is assumed that PMUs update measurements at sequential instances between two consecutive SCADA updates as shown in Figure 3.1. Since only PMU measurements are obtained from the system between t and t+1, the system cannot be observed by limited number of phasor measurements. To recover the observability, both PMU and pseudo-measurements are incorporated to solve the state estimation between SCADA updates. The performance of WLS, which is employed as state estimator algorithm in the study, is affected seriously by bad data in measurement set. As mentioned in Chapter 2, some of the pseudo-measurements possibly include significant uncertainty since these are forecasted using historical data. Therefore, it is important to select minimum number of pseudo-measurements to filter out the biased measurements [26]. In the proposed strategy, the selection of pseudo-measurements is achieved via placing the minimum number of pseudo power injections to the selected candidate buses. In order to improve the performance of power system state estimation in view of quality, speed and reliability, the pseudo-measurements having the best accuracies, which are associated with their standard deviations, should be placed. Because of being critical measurements, the errors of the selected pseudo-measurements will be minimized on the estimated states of the individual islands, which were observed before the placement of these measurements. To improve the accuracy and minimize the bias, the pseudo-measurements are updated by Kalman Filter based very short-term load forecast using the pseudo-measurements and PMU measurements.

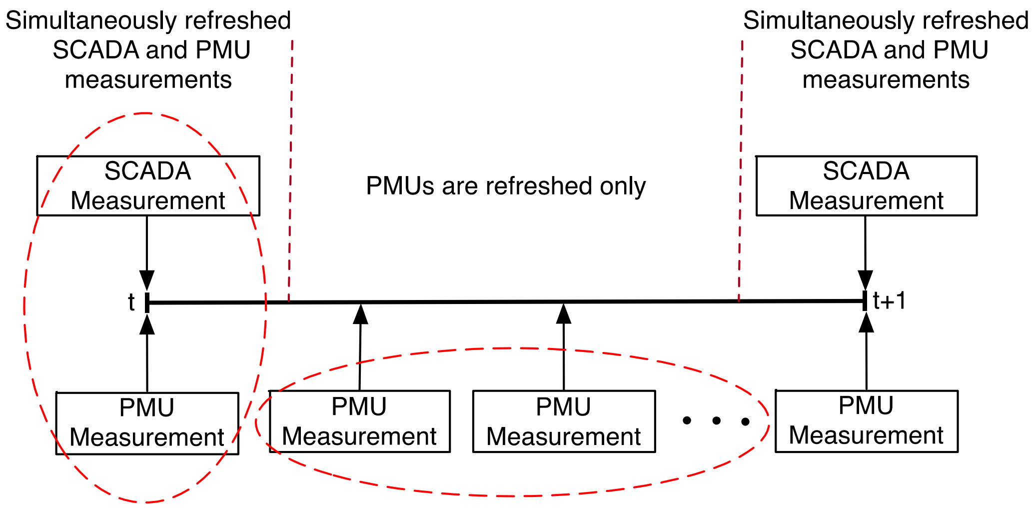

Figure 3.1. Measurement Updates of a Hybrid Measurement Set

In [26], the researchers present a novel pseudo-measurement placement method that make the system observable in case of measurement losses and topology changes. The decoupled Jacobian matrix is formed to the lower and upper matrices to identify the zero pivots of the upper matrix since the existence of zero pivot shows the system unobservable. To find the optimal placement of pseudo-measurements, linear optimization problem places iteratively new pseudo-measurements by adding their measurement functions to the Jacobian matrix until that there is no zero pivot in the upper matrix. In early study presented in [27], a novel algorithm for pseudo-measurement placement using numerical analysis method is proposed. The observable sub-networks are identified when the zero pivots of the gain matrix (G) are found using the Gaussian elimination. After that, the candidates for pseudo-measurements are selected as the boundary buses between the observable islands. The pseudo-measurements are added to the existing measurements one by one until the active power flows through all the branches in the system are zero by solving the DC state estimator. In [28] and [29], the pseudo-measurements are placed directly at the unobservable nodes, which are identified by factorizing the gain matrix (G) of the actual measurements. Major problem of these methods is the inefficiency of computational performance for large power grids due to the triangular decomposition. The work studied in [30] uses the power injections and bus voltages as pseudo-measurements to perform the power system state estimation with the internal states of one observable large island and the external network model. The states of this external system are estimated in the load flow analysis assigning the pseudo-measurements to the buses in the external system by keeping theirs values within specified limit of MVAR and voltage magnitude. The states of internal system and the solutions of load flow are harmonized by matching the power flows through the boundary buses. In [31], in order to provide observability, the selection of the optimum measurements is carried out using network graph theory, which is one of the topological approaches for the measurement placement. This work utilizes the method proposed in [26] for its computational efficiency.

In Section 3.2, the pseudo-measurement placement method is explained in detail. The Section also specifies how the PMUs are treated in the defined strategy. The iteration process used in this algorithm have three fundamental tasks, which are described as the identification of observable islands by PMUs, the determination of candidates for pseudo-measurements and the selection of optimal pseudo-measurements with their standard deviations using the integer linear programming. Section 3.3 describes how to update the pseudo-measurements with the standard deviation and mean profiles of past power injections using the Kalman Filter based very short-term forecasting. Moreover, Kalman Filter utilize the daily load curve of historical data and SCADA measurement at the time instant t in Figure 3.1 to track the disturbances on power injections dynamically. Finally, the proposed strategy for hybrid state estimation is evaluated according to the results of the simulations and explanations in Section 3.2 and 3.3.

3.2 PSEUDO-MEASUREMENT PLACEMENT

3.2.1 Identification of Observable Islands Formed by PMUs

For real applications in the power industry, PMUs have different number of channels, which measure the current phasors along the lines connected to the associated bus. In the literature, it is assumed that PMUs can measure the bus voltage phasor and the current phasors along all the lines connected to the bus. The voltage phasors of its neighbor buses are calculated by solving the equations of current flow measurements. Moreover, there could be zero injection buses, which have nor generators or loads, in the system. For a zero injection bus having n+1 branches, even if the current phasor measurements of its n branches are observed by PMUs, the current phasor along the unobservable line can be calculated according to Kirchhoff's current law.

The observable islands formed by PMUs can be determined in two consecutive steps. Firstly, the buses of PMUs and their neighbor buses are joined to construct the observable sub-networks or islands. Secondly, the individual observable sub-networks are considered as one island thanks to the synchronization GPS clock if there are some lines between the boundary buses of these sub-networks.

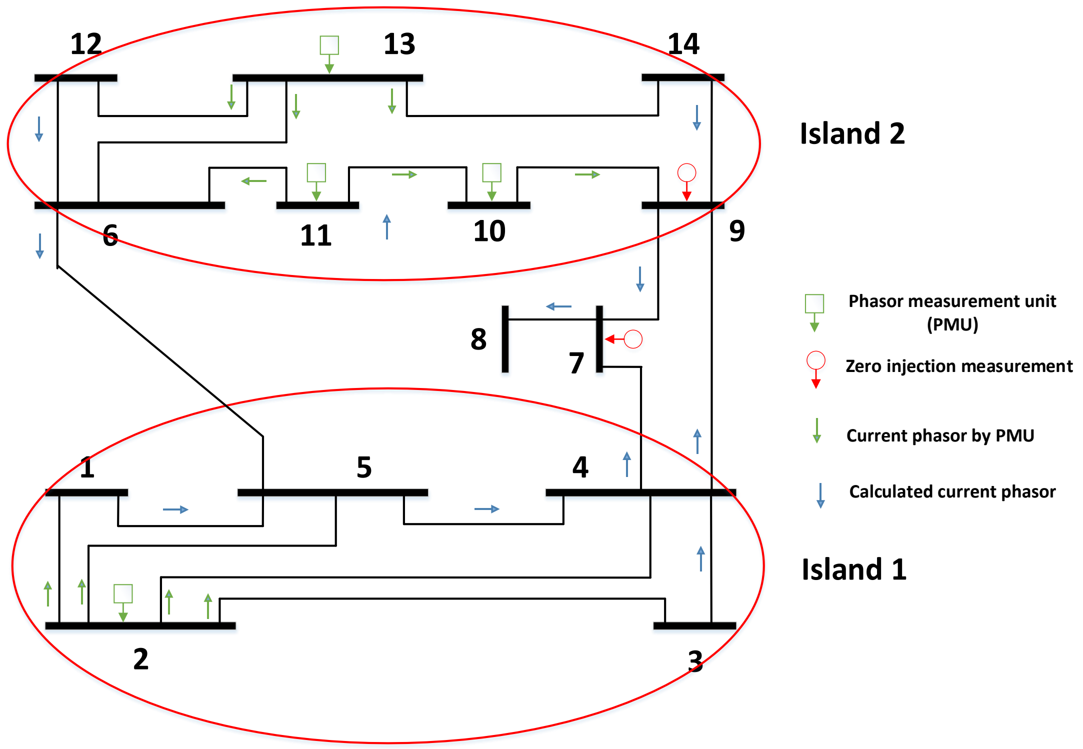

Figure 3.2. IEEE 14-bus System and Measurement Locations

For example, if PMUs are placed in the system given in Figure 3.2, Island 1, 2 are observed directly by the PMUs, which are installed at bus 2, and buses 10, 11 and 13, respectively. Since the power flows along the lines between Island 1 and 2 can be calculated using the synchronized voltage phasors of their boundary buses, Island 1 and 2 can be merged as one island. It is realized that the current flows along the lines 9-14, 9-10, 9-4 are known while the current flow between bus 9 and 7 are not known. Considering that the sum of current flows flowing into bus 9 should be equal to zero as zero injection bus, the voltage phasor of bus 7 can be calculated with the knowledge of the current phasor between bus 7 and 9. Similar to bus 7, bus 8 is added to the major island as being observable bus using Kirchhoff's current law. Although the system seems to be divided as two observable sub-networks in the beginning, those sub-networks in the system are merged as one island due to assigning one voltage phasor as reference. Note that, in order to minimize the placed pseudo-measurements, the zero-injection buses should be considered as in the example of Figure 3.2.

3.2.2 Optimal Pseudo-Measurement Placement

In the study, it is assumed that the system observability at time instant is directly dependent on the existence of SCADA measurements besides PMU measurements. In case that only insufficient number of PMU measurements are obtained at the instants between SCADA updates, pseudo measurements become more essential to substitute for SCADA measurements. For example, it is considered that the system is fully observable when the 6-bus system receives both conventional and PMU measurements shown in Figure 3.3. If the conventional measurements are omitted from the existing measurements, the sample system will be separated as three individual islands.

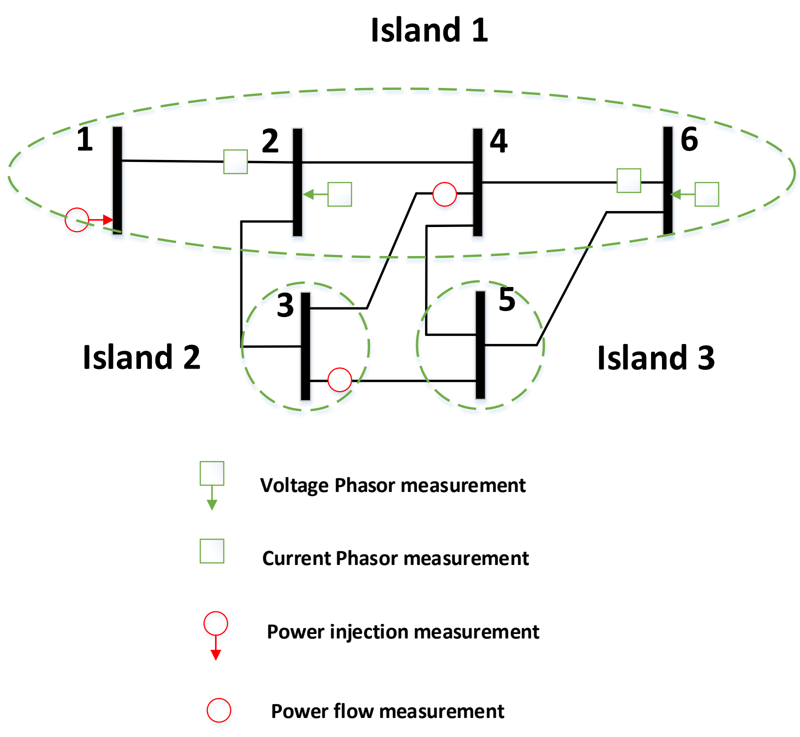

Figure 3.3. 6-bus Sample System

Power measurements are categorized in two types, which are essential and redundant. In order to group the existing measurements as essential and redundant, Gaussian elimination (LU decomposition) is applied to separate the measurement equations as the linearly independent and dependent rows in the measurement Jacobian matrix (H), respectively. For observable n-bus system having a slack bus, each of the n-1 buses should be associated with one measurement, which is called as essential. If there are remaining measurements in the system except the n-1 essential measurements, these measurements are described as redundant. In case that the number of rows being independent with each other is less than n-1 after the LU decomposition of H, the system can be stated as unobservable. Considering that each of the individual islands in the Figure 3.3 can be represented with one reference angle, the sample system is represented as 3 reference angles. Therefore, 2 pseudo-measurements should be placed to merge three observable islands using the known reference angles if these are essential measurements.

After the identification of observable islands, the candidate buses should be determined to select the optimal combination of buses to place the injection measurements as pseudo-measurements. In the proposed method, the boundary buses, which are the end buses of unobservable branches between observable islands, are selected as candidate buses in the beginning of the iteration in the algorithm [32]. In the literature, the measurement placement algorithm can be implemented to unite the observable islands with the minimum number of PMU measurements to improve the performance of state estimator. Although PMUs can be placed at any end buses of unobservable branches, the placement of PMUs at every boundary may not be affordable. Therefore, the most efficient and fastest technique for the optimal placement of pseudo-measurements is very important.

Since the measurement Jacobian matrix is sparse, recently some researchers in [28, 29] have implemented sparsity technique to separate the measurements as essential and redundant easily. Therefore, the redundant measurements can be removed from candidates because of having no impact on the system observability. The remaining measurements are selected as candidates for uniting individual islands. The proposed technique for optimal placement of pseudo-measurements need less computational time in comparison with different approaches, which place pseudo-measurements one by one in a repetitive algorithm. Because of using the sparsity technique, the method in this thesis can be implemented for large systems with transforming the measurement equations in appropriate time. However, the computational burden of the matrix decomposition may increase rapidly if a large power system has a lot of isolated islands observed by measurements in distinct zones.

In the section of 3.2.2.1, the formation of the measurement Jacobian matrix is described in detail using synchronized phasor measurements. In the part, the existing measurements are determined as insufficient for the system observability if zero diagonals exist in either L or U. In the section of 3.2.2.2, the procedure of selecting candidate measurements for adding these measurements to the existing measurements are explained if the system is unobservable. The section of 3.2.2.3 explains the utilization of integer programming problem to be solved based on standard deviations of historical data associated with these candidate measurements to identify optimal placement with minimum number of power injection measurements. Finally, the performance of the proposed method for optimal pseudo-measurement placement is tested for different cases in IEEE 14 bus system.

3.2.2.1 Formation of Measurement Jacobian Matrix with Synchronized Phasor Measurements

For a standard AC power system model, the measurement Jacobian matrix is composed of the derivatives of active and reactive power measurements with respect to the phase angles or voltage magnitudes of buses. Although the parametric values of the system components such as lines, transformers, etc. cannot affect the observability region of measurements, the network observability directly relates to the bus connectivity model of the system. Therefore, only the decoupled relation between active power measurements and the bus phase angles can be used to analyze the network observability by simplifying the measurement equations as DC model.

At some instants only synchronized phasor measurements are obtained from PMUs when the PMU measurements are incorporated with the existing conventional measurements to achieve hybrid state estimator. In these instants, measurement Jacobian matrix can be constructed with the measured voltage phasors in the PMU observable islands. For the system given in Figure 3.3, neglecting that the power injection at bus 1 and the power flows between buses 3-4 and buses 3-5, the measurement Jacobian matrix is written as follows.

$$z_{PMU} = H\theta$$

$$\downarrow$$

$$\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ z_5 \\ z_6 \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ 0 \\ \theta_4 \\ 0 \\ \theta_6 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \\ \theta_6 \end{bmatrix} \tag{3.1}$$

where

z is the measurement vector including the phase angles measured by PMUs

H is the decoupled Jacobian matrix

θ is the vector of phase angles

For conventional measurements, one bus in the system must be assigned as reference bus and its associated column are omitted from the Jacobian matrix. Therefore, Jacobian matrix is modified to new matrix using Gauss elimination to identify independent columns in the Jacobian matrix. In an n-bus system, n-1 independent columns in the modified matrix are sufficient to say that the measurement can provide the entire observability. For a system observed only by PMUs, since all the phasor measurements are referenced with a synchronization GPS clock, assigning a bus as slack becomes unnecessary. If the rank of Jacobian matrix is equal to the number of buses in the system, the system is defined as fully observable. The matrix equation given in (3.1) describes the Jacobian matrix for PMU measurements shown in Figure 3.3. For the measurement configuration, the rank of Jacobian matrix is 4 being less than the number of buses. Hence, it is obvious that the system given in Figure 3.3 is not observed fully by PMUs.

3.2.2.2 Selection of Candidate Buses for Pseudo-Measurements

When the existing measurements cannot provide the network observability, the pseudo-measurements should be incorporated into the available measurements to recover the observability. To achieve this goal, new rows, which are associated with candidate power injection measurements, are added to the measurement Jacobian matrix to achieve the full rank. The boundary buses between observable islands are chosen as candidate buses for pseudo-measurements. For an n-bus system having m measurements, n-1 measurements can provide the observability if the all of the measurements are essential. Moreover, the other measurements except the essential measurements are called as redundant. To place minimum number of pseudo-measurements having the best accuracy, the redundant measurements should be eliminated from the modified measurement set. Hence, the identification of redundant and essential measurements is carried out by examining the upper and lower matrices after the execution of LU decomposition.

For example, the three observable islands shown in Figure 3.3 interconnect with each other by five branches, along which the power flows cannot be computed. All the buses at two sides of these branches are defined as boundary buses as shown in Table 3.1. Therefore, all five buses except bus 1 of the system can be determined as candidate buses for placing the pseudo-measurements. The mathematical equation of the candidate measurements based on the DC measurement model can be written as below.

$$
\begin{aligned}
P_2 &= (\theta_2 - \theta_1) + (\theta_2 - \theta_3) + (\theta_2 - \theta_4) = 3\theta_2 - \theta_1 - \theta_3 - \theta_4 \\
P_3 &= (\theta_3 - \theta_2) + (\theta_3 - \theta_4) + (\theta_3 - \theta_5) = 3\theta_3 - \theta_2 - \theta_4 - \theta_5 \\
P_4 &= (\theta_4 - \theta_2) + (\theta_4 - \theta_3) + (\theta_4 - \theta_5) = 3\theta_4 - \theta_2 - \theta_3 - \theta_5 \\
P_5 &= (\theta_5 - \theta_3) + (\theta_5 - \theta_4) + (\theta_5 - \theta_6) = 3\theta_5 - \theta_3 - \theta_4 - \theta_6 \\
P_6 &= (\theta_6 - \theta_4) + (\theta_6 - \theta_5) = 2\theta_6 - \theta_4 - \theta_5
\end{aligned}
\tag{3.2}
$$

After the measurement equations of candidate measurements are added to Jacobian matrix, only the essential measurements are selected from the modified measurement set using sparse Gaussian elimination. Due to the problem of division by zero, the zero pivots become triangular decomposition insolvable without row pivoting. To make the Jacobian matrix solvable, the diagonals of Jacobian matrix associated with the zero pivots of U ought to be filled by 1's. Hence, Jacobian matrix is modified to a full rank matrix. Finally, the modified Jacobian matrix is created by concatenating the injection measurements at the boundary buses to the original Jacobian matrix formed by the existing PMU measurements and zero injections.

Table 3.1. Unobservable Connections & Boundary Buses between Observable islands

Unobservable Connection		Boundary Buses for Pseudo-Measurements
From Island	**To Island**	
Island 1	Island 2	Bus 2, 3, 4
Island 1	Island 3	Bus 4, 5, 6
Island 2	Island 3	Bus 3, 5

$$H_{con} = \begin{bmatrix} H_{mod} \\ ----- \\ H_{boundary} \end{bmatrix}$$

Zero pivots of U = **{3,5}** $\Downarrow$ LU Decomposition

$$L_{con} = \begin{bmatrix} L_{mod} \\ ---- \\ L_{boundary} \end{bmatrix} = \begin{array}{c} \begin{array}{cccccc} & & & \textbf{Pivot 1} & & \textbf{Pivot 2} \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ - & - & - & - & - & - \\ -1 & 3 & -1 & -1 & 0 & 0 \\ 0 & -1 & 3 & -1 & -1 & 0 \\ 0 & -1 & -1 & 4 & -1 & -1 \\ 0 & 0 & -1 & -1 & 3 & -1 \\ 0 & 0 & 0 & -1 & -1 & 2 \end{bmatrix} \end{array} \tag{3.3}$$

In the observability analysis, the isolated buses directly relate to the order number of zeros in the diagonals of U by factorizing Jacobian matrix with row pivoting. For the sample 6-bus system given in Figure 3.3, the order number of zero pivots in Jacobian matrix can prove bus 3 and bus 5 to be isolated. After the LU factorization of the concenated Jacobian matrix H_{con} is accomplished, the modified lower matrix L_{mod} as identity matrix and the lower matrix $L_{boundary}$ associating with injection measurements at the boundary buses are obtained. Moreover, each of the elements in the lower matrix L_{con} represents the observability relationship between buses and measurements with respect to its own column and row number, respectively. Hence, the intersection arrays of pivot columns into the lower matrix $L_{boundary}$ are used to select the optimal candidate measurements as pseudo-measurements to achieve the full observability. If one row of the lower matrix $L_{boundary}$ have at least one non-zero entry in the intersection arrays with the pivot columns, the corresponding boundary measurement can be selected as candidate measurement to merge the isolated islands.

Combining the non-zero arrays into $L_{boundary}$ for pivot columns, a binary matrix representing the relationship between the isolated islands and candidate measurements can be defined as follows [28].

$$\boldsymbol{A_{ij}} = \begin{array}{cc} \begin{array}{c} \mathbf{1.}\,\boldsymbol{pivot} \\ \mathbf{2.}\,\boldsymbol{pivot} \\ \vdots \\ \boldsymbol{i.\,pivot} \end{array} & \begin{bmatrix} \mathbf{0} & \mathbf{1} & \cdots & \mathbf{1} \\ \mathbf{1} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{1} & \mathbf{0} & \cdots & \mathbf{1} \end{bmatrix} \\ & \begin{array}{cccc} 1.\,candidate & 2.\,candidate & \cdots & j.\,candidate \end{array} \end{array} \tag{3.4}$$

3.2.2.3 The Optimal Placement of Pseudo-Measurements Using Integer Linear Programming

The solution of optimal pseudo-measurement placement is represented by a selection vector X, which includes 1's or 0's entries depending on whether selecting candidate injection measurement as pseudo-measurement or not, respectively. In the solution providing the constraints shown below, all the isolated islands must be observed by one candidate measurements at the least with minimum number of candidate measurements as pseudo-measurements. Since the candidate measurements are the injection measurements forecasted using the most recent data, some of these measurements may be biased. If the biased measurements are selected as pseudo-measurements through candidates, the performance of state estimator will be affected negatively in terms of robustness, reliability and accuracy. In the purpose of eliminating these biased measurements as many as possible for selecting the optimal measurements, the sum of standard deviations of candidates are defined as the linear cost function of the optimization problem shown below. Hence, the binary integer programming optimizes the solution of placement, which provides the observability constraints for the identified isolated islands with minimizing the sum of standard deviations for the placed pseudo-measurements.

$$
\begin{gathered}
minimize \quad \begin{bmatrix}\sigma_1 & \cdots & \sigma_j\end{bmatrix}\begin{bmatrix}X_1\\ \vdots\\ X_j\end{bmatrix}\\
\begin{bmatrix}A_{11} & \cdots & A_{1j}\\ \vdots & \ddots & \vdots\\ A_{i1} & \cdots & A_{ij}\end{bmatrix}\begin{bmatrix}X_1\\ \vdots\\ X_j\end{bmatrix} \geq \begin{bmatrix}b_1\\ \vdots\\ b_j\end{bmatrix} = I_{1Xj}
\end{gathered}
\tag{3.5}
$$

$where \quad j\ is\ the\ number\ of\ candidate\ measurements$

$\quad\quad i\ is\ the\ number\ of\ isolated\ buses$

$\quad\quad \sigma_j\ is\ the\ standard\ deviation\ of\ the\ jth\ candidate\ bus$

In the first iteration, the placement of selected injection measurements might not enough to merge the all the isolated islands. The processes in steps 2-7 given in Table 3.2 must be iteratively implemented by adding new selected measurements until the system is transformed to one observable island. In other words, the isolated islands are connected with each other using minimum number of injection measurements in every iteration. Since the placed pseudo-measurements are increased in every iteration, the number of zero diagonals will be decreased. If the zero diagonals are vanished, the added injection measurements until the last iteration give the optimal placement. The algorithm of the proposed placement method is proceeded step by step as shown in Table 3.2.

Table 3.2. The Steps of Algorithm for the Optimal Placement of Pseudo-Measurements

Step 1: Construction of lower and upper matrices for the available phasor measurements using the Jacobian matrix H
Step 2: Determination of zero pivots of U as the isolated islands & the boundary buses between observable islands if the system is unobservable
Step 3: Modification of H by replacing the zero pivots of H with 1's
Step 4: Formation of H_{con} by concatenating the Jacobian matrix of boundary injection measurements and the H_{mod} for the available PMU measurements
Step 5: Identification of the candidate measurements from the boundary injection measurements by accepting the nonzero rows of $L_{boundary}$
Step 6: Selection of the optimal pseudo-measurements from the candidates using binary integer programming
Step 7: Addition of the selected injection measurements to the existing measurements & Identification of zero pivots or isolated islands for the new measurement set
Step 8: Implementation Steps 2-7 repetitively until there is no more isolated islands

3.2.2.4 Performance Evaluation of the Proposed Method

In this section the performance of the proposed algorithm is evaluated for three cases, which have different number of placed PMU. In the first case, it is assumed that three PMUs are installed at buses 2, 6 and 7 as shown in Figure 3.4 when SCADA measurements cannot updated due to having slower refresh rates. In the second case, the change of the performance is investigated in terms of the consumed time and the number of iterations until the optimal solution is reached if the phasor measurements of PMU at bus 2 are lost. In the third case, the selection of pseudo-measurements is conducted considering that buses 1, 3, 10 have zero injection measurements with no generation units and loads.

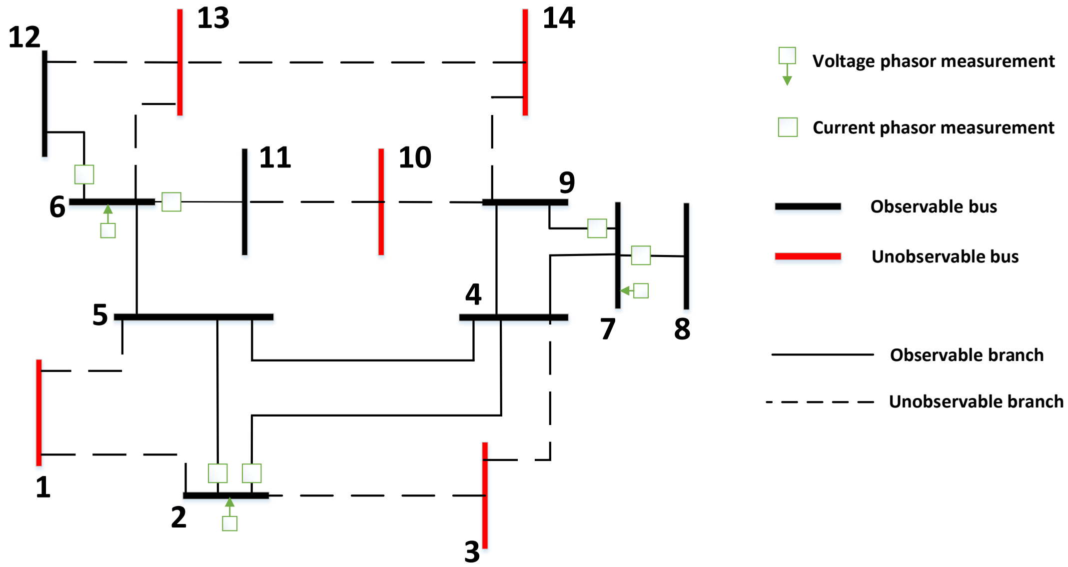

Figure 3.4. Placement of Phasor Measurements & Observability of the System

Table 3.3. Standard Deviations of All Pseudo-Measurements

Bus No	Case 1	Case 2	Case 3
1	0.2	0.2	0
2	0.02	0.02	0.02
3	0.5	0.5	0
4	0.003	0.003	0.003
5	0.001	0.001	0.001
6	0.04	0.04	0.04
7	0.05	0.05	0.05
8	0.035	0.035	0.035
9	0.042	0.042	0.042
10	0.37	0.37	0
11	0.015	0.015	0.015
12	0.03	0.03	0.03
13	0.1	0.1	0.1
14	1	1	1

Case 1: In Step 2, five isolated buses, which are bus 1, 3, 10, 13 and 14, are identified after the LU decomposition is carried out. Moreover, the unobservable branches between the isolated islands are presented as dash lines in Figure 3.4. In the real application, the standard deviations of injection measurements are computed using the daily power injection curves in the most recent 60 days. Considering that the installment of PMUs with their own channels and RTUs in the substations are not changed temporarily, the standard deviation of bus being measured by synchronized phasor measurement is assumed to be less than one by conventional measurement. Therefore, the weights of candidate buses given in Table 3.3 are used to determine the cost function of the optimization problem.

In the first iteration, the power injections at buses 4, 5, 9, 12, and 13 are selected as pseudo-measurements to compute the current phasors flowing along 3-4, 2-3, 1-5, 1-2, 12-13 and the voltage phasors of buses 1, 3, 13. Since there are six isolated islands at the first, at the least five pseudo-measurements have to be placed to merge these islands. Therefore, one more pseudo-measurement is placed at bus 13 in the second iteration.

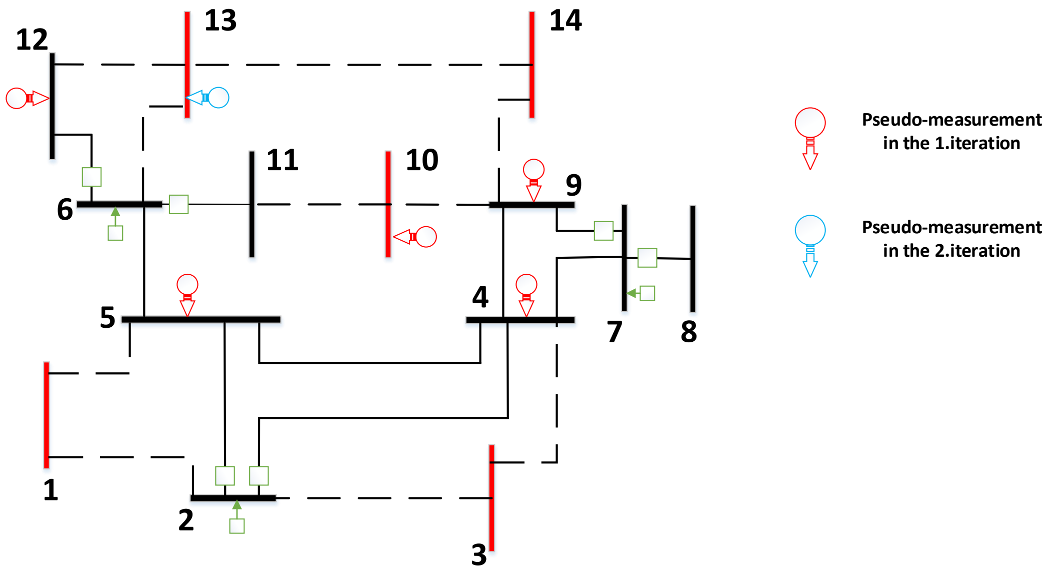

Figure 3.5. Pseudo-Measurement Placement for First Case

Case 2: To evaluate N-1 contingency of PMU, the measured voltage phasor at bus 2 and outgoing current phasors from bus 2 are removed. As a result of this, the buses 2, 4 and 5 return to isolated islands. Apart from the selected pseudo-measurements in the previous case, new three pseudo-measurements are added to the measurement configuration to observe the system with respect to only one reference angle. Due to the increment of buses having no connection with anchored island, it is expected that the algorithm should be iterated more time to attach these buses to the anchored island. Since the inverse formation is implemented in every iteration until the zero diagonals of upper triangular matrix are vanished completely, the loss of PMUs may cause to increase the computational time for the proposed algorithm.

For second case the placement of pseudo-measurements obtained after each iteration is completed is shown in Figure 3.6. In every iteration the first rank neighbors, which reach to the anchored island through only one branch in the shortest path, can be selected as the candidates for the pseudo-measurements. In the first iteration, the buses 1, 2, 3 are kept out of the optimization problem due to being the second rank neighbors. After the pseudo-measurements are placed at buses 4, 5, 9 and 12, these second rank neighbors are included to the algorithm as candidates. Since there are 8 isolated buses, the system become fully observable by placing 8 pseudo-measurements as shown in Figure 3.6, which have the best accuracy in the possible combination of locations.

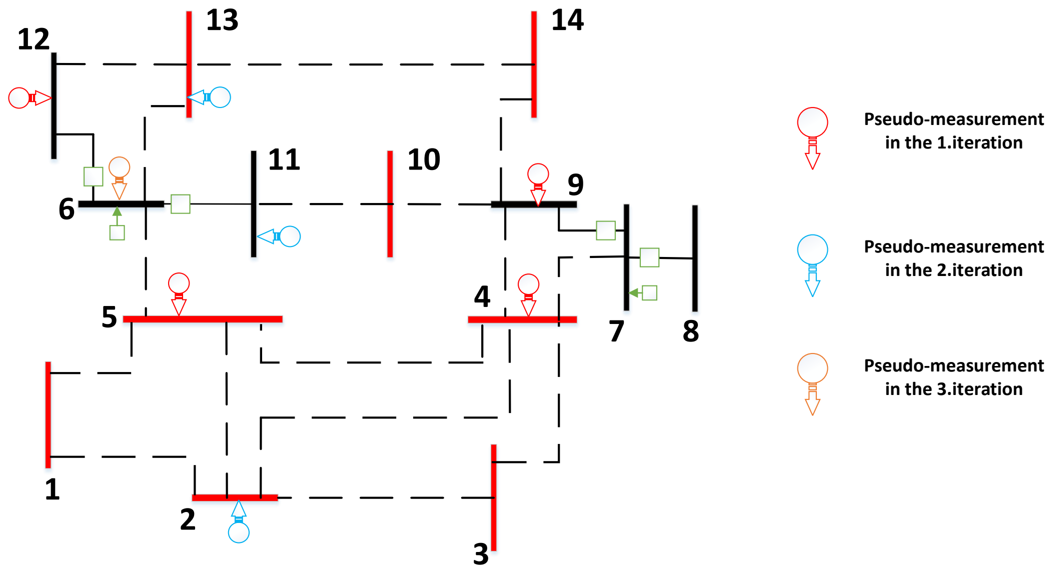

Figure 3.6. Pseudo-Measurement Placement for Second Case

Case 3: To evaluate the performance of the algorithm in case that the system includes zero injection buses. Since no generation or load is connected to these buses, the standard deviation of power measurement at zero injection bus is zero as buses 1, 3, 10 for case 3 given in Table 3.3. To minimize the cost function including the standard deviations of buses in the system, at first zero injection buses are selected for placing the power injection measurements, and then the remaining buses are selected in the integer linear programming. While assigning only one candidate measurement is enough for an isolated bus, to minimize the number of the selected measurements, redundant measurements may be placed in the case that there is more than one zero injection bus connecting to an isolated bus. Since the selection of a zero injection do not increase the result of cost function in the optimization problem. In case 3, 6 injection measurements are placed, 3 of which are zero-injections and 2 of which are pseudo-measurements, to merge 5 isolated buses and one PMU observable island shown in Figure 3.7.

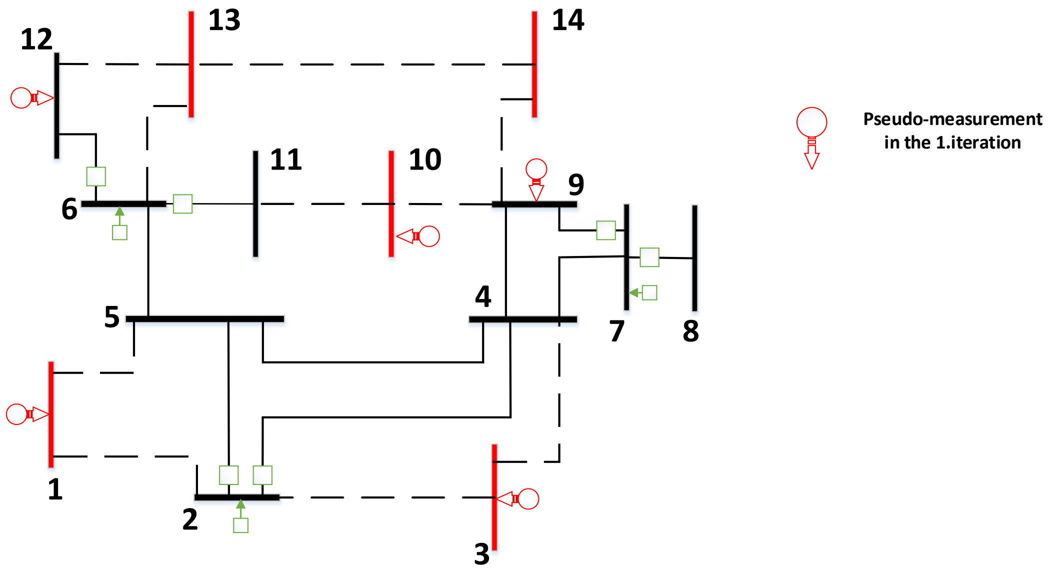

Figure 3.7. Pseudo-Measurement Placement for Third Case

Table 3.4. The Performance of Algorithm for Three Cases

	Placement of pseudo-measurements	The number of iteration	Computational time (s)
Case 1	4, 5, 9, 12, 13	2	0.018
Case 2	2, 4, 5, 6, 9, 11, 12, 13	3	0.030
Case 3	1, 3, 9, 10, 12	1	0.010

3.2.3 Updating Historical Data In Hybrid Power State Estimator

Recently hybrid state estimator has become preferred technique for the independent system operators of power grids to provide more reliable system operation and control by incorporating PMU and SCADA measurements. Moreover, synchronized phasor measurements obtained in high resolution enable state estimator to be performed in real-time applications. Due to having much less resolution than PMUs, SCADA cannot provide measurements in some instants while PMU measurements are updated.

Therefore, the system is divided to isolated islands being observed by PMUs. In order to merge the isolated islands, pseudo-measurements are generated using historical data and placed optimally to maximize the accuracy.

In the proposed hybrid state estimation strategy, active and reactive power injections are used as pseudo-measurements using the stored data in the most recent 60 days. The mean and standard deviation of the injection measurements are computed for each bus in the system. The power injection on a bus is the sum of power flows along its connected branches. Considering that it is likely that for some buses the power injection is measured by either using simultaneously SCADA and PMUs or only SCADA, the injection measurement of the bus cannot be computed at the instants between two consecutive SCADA updates. In order to solve this issue, the past injection measurements are stored in the resolution of SCADA to form the daily curve of mean and standard deviation for all of the system buses.

For the real-time application, it is aimed that the state estimator can track the sudden changes in the system snapshots with a resolution of milliseconds. To achieve this goal, pseudo-measurements have to be generated in the least amount of time and as accurate as possible. Therefore, the daily curve of mean and standard deviation is updated one time in each day. However, this work aims to improve those measurements using the online measurements of PMUs. Since the sample number of historical data is less than the resolution of state estimator as mentioned above, the values of power injections at such instants that there is no historical data are found by linearly interpolating the two points of the nearest SCADA updates. In fact, power injections are the nonlinear function with respect to the voltage magnitudes and angles of their associated buses. The power injections are computed again using the estimated states $x^k_{estimated}$ after the state estimator is conducted successfully. Due to being more precise than real measurements the estimated measurement values $z^k_{estimated}$ will be added to historical data to generate more reliable pseudo-measurements and standard deviations in the next days as shown in Figure 3.8. Therefore, historical data will include only the calculated power injections using the estimated states after the 60th day since hybrid state estimator is initialized.

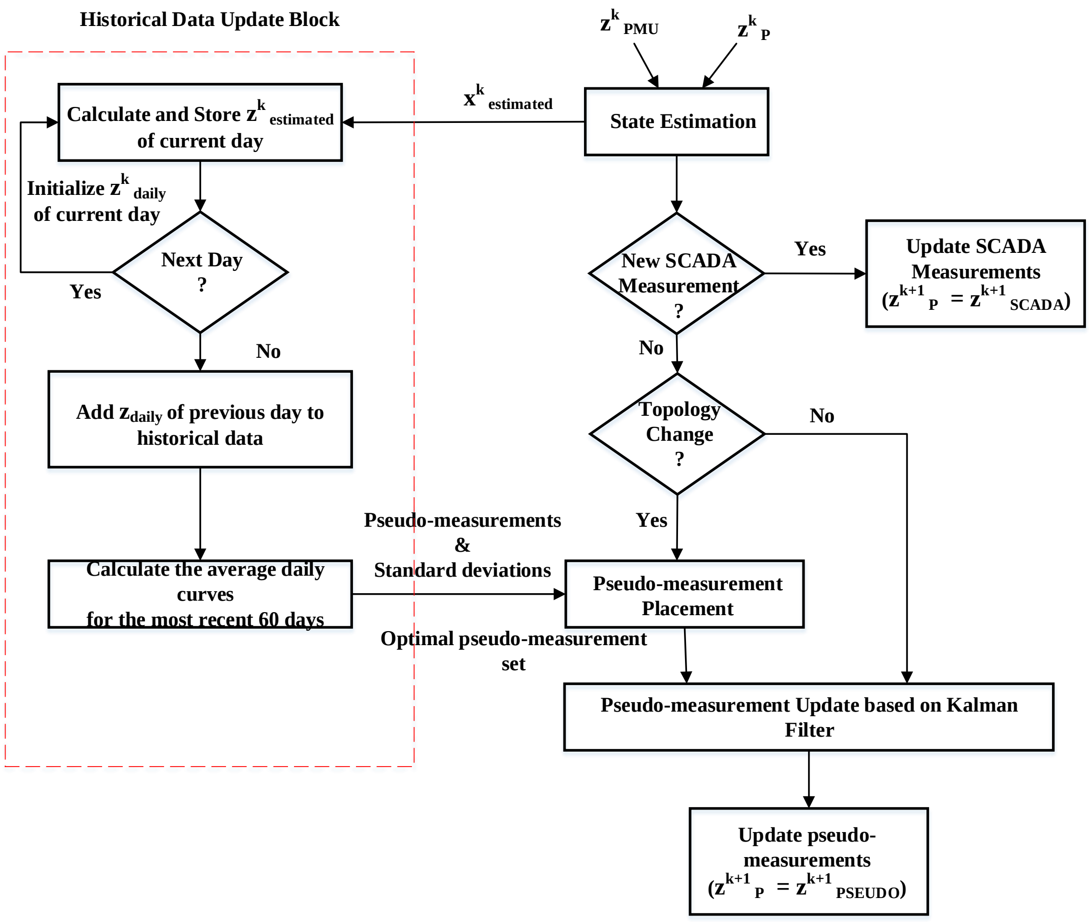

Figure 3.8. Flow Chart of the Proposed Strategy for Hybrid State Estimation

Although the mean of the daily power injection curves of the most recent 60 days represents several environmental factors affecting the load demands, special cases such as line contingency, equipment maintenance, etc. may not be represented by the pseudo-measurements. Due to these cases actual measurements may include temporary distortions during SCADA updates. Hence, Kalman filter technique is used to update the pseudo-measurements by fitting its daily curve between two sequential SCADA updates.

3.2.4 Kalman Filter Forecasting

Kalman filter is a dynamic state estimation technique that finds the changes of the system states receiving current measurement set and previous estimated states as input in a recursive algorithm. The technique was invented by R. E. Kalman [33] in 1960. In many decades traditional Kalman Filter has been used to observe and control some processes for some applications such as power systems, intelligence of vehicles, short-time forecast, navigation, etc. For the implementations in nonlinear system equations, “The Unscented Kalman Filter”, and “The Extended Kalman Filter” were improved by updating the traditional approach [34].

In order to implement Kalman Filter in a linear discrete-time system, the current state and the measurement equations with respect to previous state are written as:

$$x_k = A_k x_{k-1} + B_k A u_{k-1} + c_{k-1} \tag{3.6}$$

$$z_k = H_k x_k + e_k \tag{3.7}$$

where

x_k : current state vector at time k.

x_{k-1} : previous state vector at time k-1.

A_k : state transition matrix associated with the ratio of current state to previous state.

u_k : control vector.

z_k : measurement vector gathered at time k.

H_k : measurement matrix that gives the relation between the current states and measurements.

e_k : measurement noise vector with Gaussian distribution with zero mean and R_k covariance.

c_{k-1} : system error vector with Gaussian distribution with zero mean and Q_k covariance.

R and Q, which are called as the measurement noise covariance and the process noise covariance, are the symmetrical matrices shown above.

$$R = \begin{bmatrix} cov[e_1, e_1] & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & cov[e_k, e_k] \end{bmatrix} \tag{3.8}$$

$$Q = \begin{bmatrix} cov[c_1, c_1] & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & cov[c_k, c_k] \end{bmatrix} \tag{3.9}$$

It is assumed that the state vector is known at the initial time instant. The state vector and covariance matrix can be defined as follows:

$$E(x_0) = m \tag{3.10}$$

$$P_0 = E\left[\left(x_0 - E(x_0)\right)\left(x_0 - E(x_0)\right)^T\right] \tag{3.11}$$

To estimate current state accurately Kalman Filter is applied as two sequential steps, which are state prediction and correction, respectively. In the prediction stage, two equations shown in (3.12) and (3.13) is derived from the equation in (3.6) to find the predicted state x_k^- and the predicted covariance matrix P_k^-, respectively. Assuming that the system does not have any control input, the state prediction equations are written as:

$$x_k^- = A_k x_{k-1} + c_{k-1} \tag{3.12}$$

$$P_k^- = A_k P_{k-1} A_k^T + Q_k \tag{3.13}$$

In the state correction stage, the measurement error vector y_k is computed with respect to the actual measurement z_k using measurement equation as follows:

$$y_k = z_k - H_k x_k^- \tag{3.14}$$

Finally, the current state x_k is updated using Kalman Gain K_k and the measurement error vector y_k calculated in the correction stage with the following equations.

$$S_k = H_k P_k^{-} H_k^{T} + R_k \tag{3.15}$$

$$K_k = P_k^{-} H_k^{T} S_k^{-1} \tag{3.16}$$

$$x_k = x_k^{-} + K_k y_k \tag{3.17}$$

$$P_k = (I - K_k H_k) P_k^{-} \tag{3.18}$$

where

S_k : residual covariance matrix at time k

P_k : updated estimate covariance matrix for the state at time k

3.2.5 Kalman Filter Based Pseudo-Measurement Update

In the proposed hybrid state estimator, Kalman Filter is implemented at such instants that there are no SCADA measurements in order to update the placed pseudo-measurements as shown in Figure 3.9. In very short-term load forecasting, Kalman Filter may involve some environmental factors such as temperature, humidity, etc. as the states of load model to estimate load changes with high-resolution by using the determined state transition matrix with respect to the load demands of past days [35]. However, it is not possible to generate pseudo-measurements at each PMU updates between two consecutive SCADA updates in order to realize hybrid state estimator in the millisecond range using very-short term load forecasting due to lack of current measurements. In fact, the current pseudo-measurements at these PMU updates are generated as the mean of power injections for the same days of the week in the most recent 60 days before Kalman Filter based pseudo-measurement update in the study. The SCADA measurements trigger to initialize Kalman Filter to compute the posterior states for pseudo-measurements until new SCADA measurements arrive. For each time samples between two consecutive SCADA updates, Kalman Filter finds the predicted variables in the prediction stage, and then yields the Kalman Gain of pseudo-measurement using the equation given in (3.16). The final estimated value is obtained using Kalman Gain and priori estimated value for each pseudo-measurement by solving the equation given in (3.17). The updated estimate covariance matrix for the current time instant is computed to be used to find the predicted state covariance matrix of posterior pseudo-measurement in the next iteration. The flow chart of the Kalman Filter based pseudo-measurement update is given in Figure 3.9.

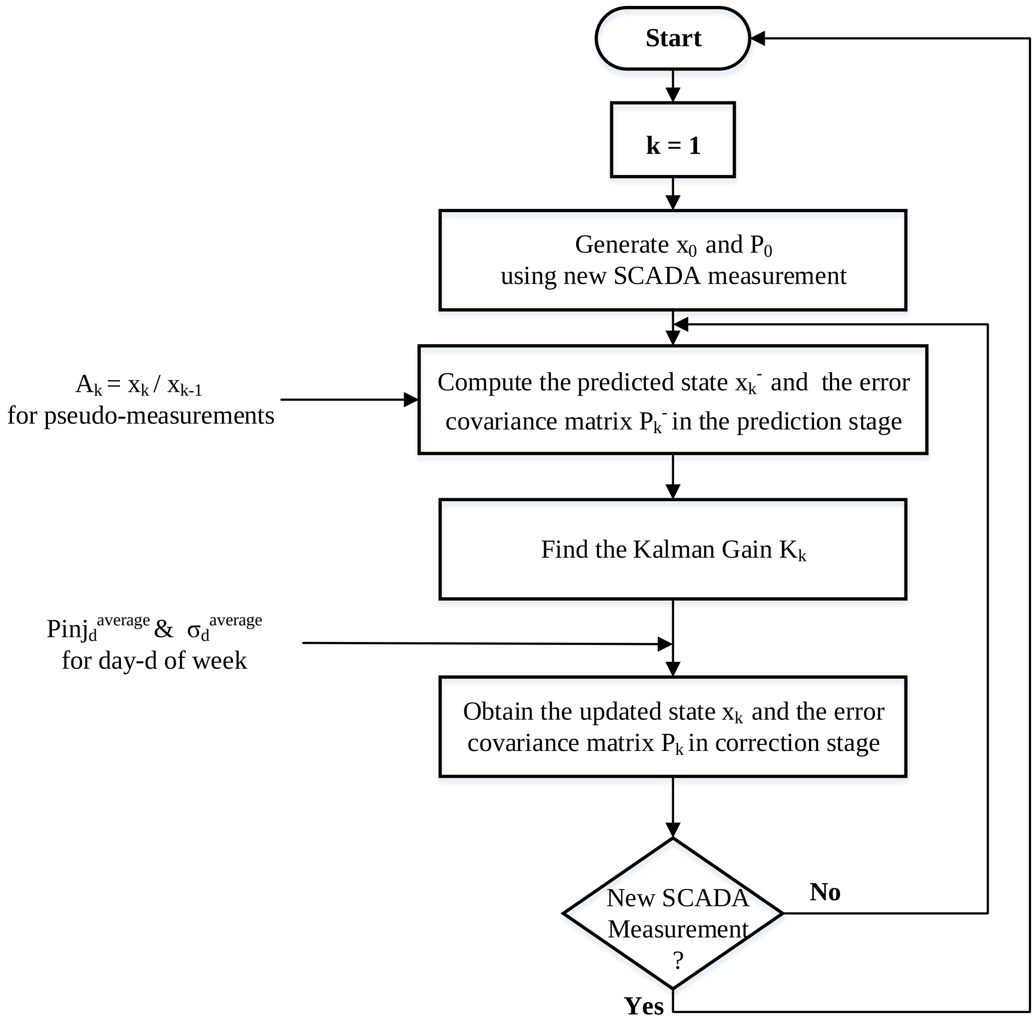

Figure 3.9. Flow chart of the Kalman Filter based Pseudo-Measurement Update

In the update of pseudo-measurements, the Kalman equations are applied as follows:

z_k : the generated pseudo-measurement at time k

H_k : taken as 1 because of updating pseudo-measurements with injection measurements

R_k : the standard deviation of the past injection measurements at time k

A_k : the transition ratio of the current pseudo-measurement to the previous pseudo-measurement

x_0 : the updated SCADA measurement at initial time instant

P_0 : the average of daily standard deviation characteristics of pseudo-measurement

$$x_k^- = A_k x_{k-1} \tag{3.19}$$

$$P_k^- = A_k P_{k-1} A_k^T \tag{3.20}$$

$$y_k = z_k - x_k^- \tag{3.21}$$

$$S_k = P_k^- + R_k \tag{3.22}$$

$$K_k = P_k^- S_k^{-1} \tag{3.23}$$

$$x_k = x_k^- + K_k y_k \tag{3.24}$$

$$P_k = (I - K_k) P_k^- \tag{3.25}$$

3.3 SUMMARY AND COMMENTS

This chapter explains the proposed strategy of hybrid state estimation as two main sections, which are optimal placement of pseudo-measurements, updating of pseudo-measurements using Kalman Filter.

The identification of PMU anchored islands is presented in an illustrative example. Considering one system is observed solely by PMUs during the absence of SCADA measurements, candidate buses for placement algorithm are selected in the boundary buses of individual islands. In order to recover the system observability in the unobservable duration between two consecutive SCADA updates, Integer Linear Programming based solution determines the optimal selection in the candidate buses considering its measurement accuracy to place the minimum number of pseudo-measurements. In the simulations, the robustness of the optimal placement algorithm is evaluated in both cases of PMU losses (Case 2) and the existence of zero injection bus (Case 3) with respect to Case 1, which considered as base case. It is observed that Case 2 needs little more computational time than base case because of the increment of unobservable islands and loop number of the execution. If the system has large complex connectivity, PMU losses will affect more seriously the performance of the placement algorithm. Since zero injection bus has zero standard deviation, redundant zero injection buses might be selected as pseudo-measurement location in the proposed method. Despite of having the best standard deviation as zero, the zero injection buses might reduce the quality of algorithm with increasing the number of loops in the execution of algorithm.

Pseudo-measurements may not capture instantaneous changes of power injections since these are computed using only the power injections of past days. Hence, Kalman Filter is used to update pseudo-measurements dynamically considering the relationship between the priori and posterior states in the estimation process to include the unexpected changes to pseudo-measurements as much as possible. It is possible that hybrid state estimator will give more unbiased estimated states due to having less erroneous pseudo-measurements by Kalman Filter based pseudo-measurement update.

CHAPTER 4

SIMULATIONS AND RESULTS

This chapter examines the performance of the proposed hybrid state estimation strategy in case of its implementation in real system. Firstly, numerical evaluation of the proposed algorithm is carried out in IEEE-14 bus test system in case that three determined cases occurs. Therefore, the simulations are performed to compare the results of the proposed method compared to conventional method. Secondly, hybrid state estimation is performed on a large power system model including 1289 buses in order to test the applicability of proposed method with increasing the complexity and size of system.

4.1 IEEE 14 BUS TEST SYSTEM

In this section, hybrid state estimation was conducted to implement the proposed strategy on IEEE 14-bus system in the MATLAB environment for three different cases. In order to observe the performance of proposed method in the real applications, three different measurement configurations were determined for these cases by placing generated pseudo-measurements based on actual data. Pseudo-measurements were classified as three accuracy class depending on their standard deviations. These accuracy classes are given in Table 4.1. In the first case, all the three types of pseudo-measurements were used in the system model. In the second case, there are only pseudo-measurements with accuracy class B in the system model. In the third case being as the worst case, the pseudo-measurements with accuracy class B, C are placed in the system model in order to observe the effect of bad pseudo-measurements on the accuracy of state estimation.

Table 4.1. Three Types of Pseudo-Measurement Accuracy Class

	Accuracy Class A	**Accuracy Class B**	**Accuracy Class C**
Standard deviation	σ < 0.01	0.01< σ < 0.5	0.5< σ

Table 4.2. Three Cases Based on Distribution of Pseudo-Measurements

	First Case	Second Case	Third Case
Pseudo-measurements with accuracy class A	✓	✗	✗
Pseudo-measurements with accuracy class B	✓	✓	✓
Pseudo-measurements with accuracy class C	✓	✗	✓

To generate three types of pseudo-measurements with accuracy class A, B and C, the daily standard deviation profiles of actual power injections and the daily average profiles of actual power injections were computed using the injection measurements of last days obtained from the substations supplying to residential, commercial, and industrial zones, respectively [36]. For example, the daily standard deviation profiles associated with three different actual measurements obtained from residential, commercial and industrial zones are shown in Figure 4.1. The daily average profiles represent only trend of daily curves associated with the pseudo-measurements by scaling the mean of the recent most days with respect to the peak of daily curve for day-d of week (Monday, Tuesday, etc.) in sequential specific 60 days using the equation (2.1) given in Chapter 2. The daily curves of loads were determined to perform real-time state estimator for three cases by using the trend of the daily curves in IEEE-14 bus system.

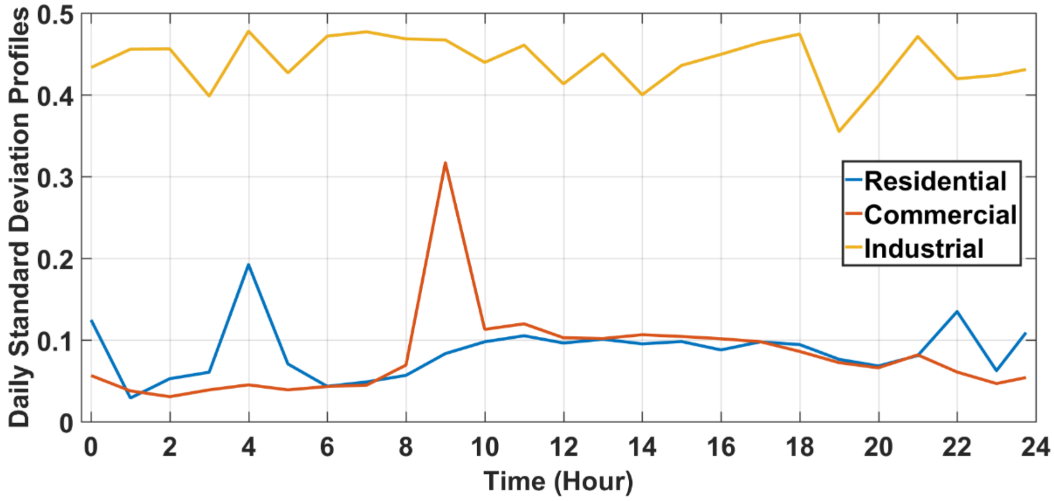

Figure 4.1. Three Different Daily Standard Deviation Profiles Associated with Actual Measurements

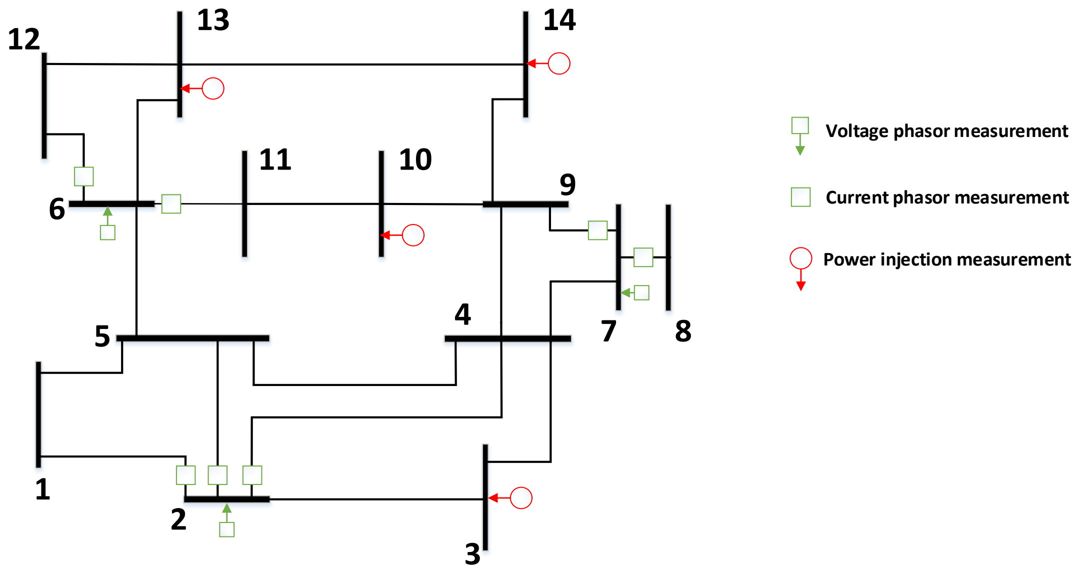

Figure 4.2. The Locations of Phasor and Conventional Measurements in IEEE-14 Bus System

4.1.1 Determination of Optimal Pseudo-Measurement Placement

In order to construct a system model with hybrid measurement configuration in the test model, it is assumed that there are insufficient number of PMUs and injection measurements being located as shown in Figure 4.2. With the purpose of determining the reliability of the pseudo-measurement placement algorithm, different pseudo-measurements with different standard deviations are placed in the system for three cases. The standard-deviations of pseudo-measurements for three cases are given in Table 4.3. While integer linear programming chooses the sets of boundary buses having the highest accuracy in each iteration of the placement algorithm, the critical buses providing entire observability with minimum number of pseudo-measurements is determined. There are four isolated buses and one PMU observable anchored island in three cases. Despite of the different locations of pseudo-measurements for three cases, four critical pseudo-measurements should be placed to merge isolated islands as given in Table 4.4. In according to the results of Case 1 given in Table 4.3, the placement algorithm selects the best pseudo-measurements with class A compared to the other candidate pseudo-measurements. The algorithm shows good performance in case 2 even if all of the pseudo-measurements have closely standard deviations. In case 3, all the pseudo-measurements with accuracy class C except one at bus 14 are eliminated from the measurement set with the improvement of measurement quality. Because of being critical measurement, state estimates will be biased at minimum even if some of these measurements have large standard deviation.

Table 4.3. Standard Deviations of Pseudo-Measurements

Bus No	Case 1		Case 2		Case 3	
	Standard deviation	Accuracy Class	Standard deviation	Accuracy Class	Standard deviation	Accuracy Class
1	0.009	A	0.11	B	0.11	B
2	1	C	0.18	B	1	C
3	2	C	0.40	B	2	C
4	**0.004**	**A**	**0.12**	**B**	0.15	B
5	0.12	B	0.21	B	0.17	B
6	0.32	B	0.32	B	0.51	C
7	0.13	B	0.30	B	0.60	C
8	0.15	B	0.15	B	0.90	C
9	**0.005**	**A**	**0.12**	**B**	0.20	B
10	**0.009**	**A**	**0.12**	**B**	0.51	C
11	0.13	B	0.13	B	0.13	B
12	0.51	C	0.45	B	0.57	C
13	**0.008**	**A**	0.17	B	0.55	C
14	0.51	C	**0.12**	**B**	0.51	C

Table 4.4. Selected Critical Buses for Pseudo-Measurement Placement

	Bus No. of Pseudo-Measurement placement
Case 1	4, 9, 10, 13
Case 2	4, 9, 10, 14
Case 3	4, 9, 11, 14

4.1.2 Pseudo-Measurements Update Based on Kalman Filter

In the simulation, PMU and SCADA measurements were created at one sample and 8 samples per second respectively using the power flow solution with DIgSILENT Power Factory. The power flow results of snapshots were used to obtain actual states at each time instant of PMU update. Gaussian errors were added to the results of the solution to obtain realistic PMU and SCADA measurements. It was assumed that the standard deviation of PMU measurements is much smaller than the standard deviation of SCADA measurements. Therefore, the effect of erroneous measurements on proposed method were observed by updating pseudo-measurements with the biased measurements.

In the proposed hybrid state estimation, the Kalman Filter technique updates regularly previously created pseudo measurements at the beginning of each second using current SCADA measurements. Pseudo-measurements are dynamically forecasted with previous forecasted pseudo-measurements for each PMU update until new SCADA is received. While measurement set involves current SCADA and PMU measurements at the beginning of each second such that new SCADA measurement is received, measurement set involves pseudo-measurements and PMU measurements at the time instants between two consecutive SCADA updates.

4.1.3 The Simulation Results for IEEE 14 Bus System

In this section, the numerical validation is done for the proposed hybrid state estimation by comparing estimated states and real states for three cases. In order to observe the effect of Kalman Filter based pseudo-measurement update on hybrid state estimator; power system state estimation is performed in two different ways, using and without using the Kalman Filter update block. The second mentioned method, which is based on not using the Kalman Filter update, is considered as conventional method. Mean absolute error (MAE) is calculated to determine the reliability of estimated voltage magnitudes and angles with respect to the real states using the following equation:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |(x_i{}^{estimated} - x_i{}^{true})| \tag{4.1}$$

Case 1: In this case, it is assumed that all the pseudo-measurements are determined as the accuracy class A. In other words, the standard deviations of the pseudo-measurements vary in the range between 0 and 0.01 p.u. In the system model, residential, commercial loads are used to generate these pseudo-measurements.

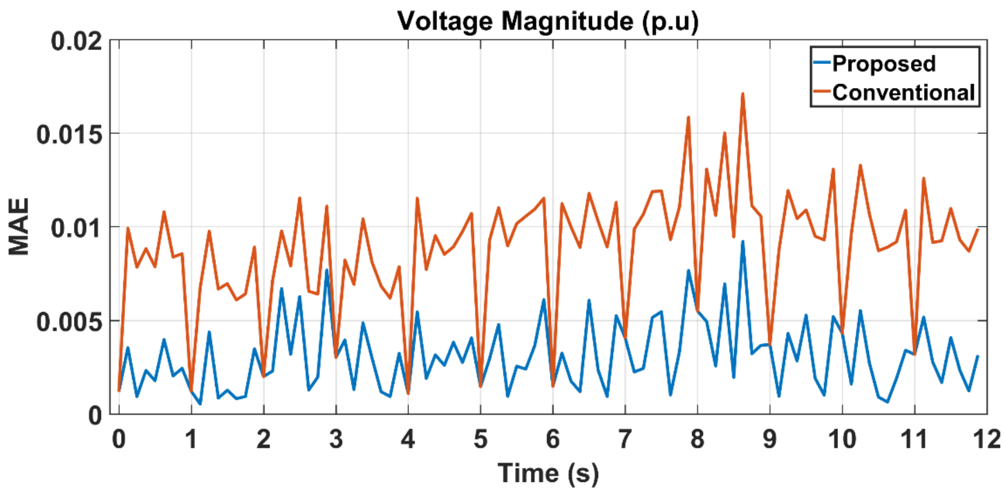

Figure 4.3. MAE of Voltage Magnitudes for Case 1

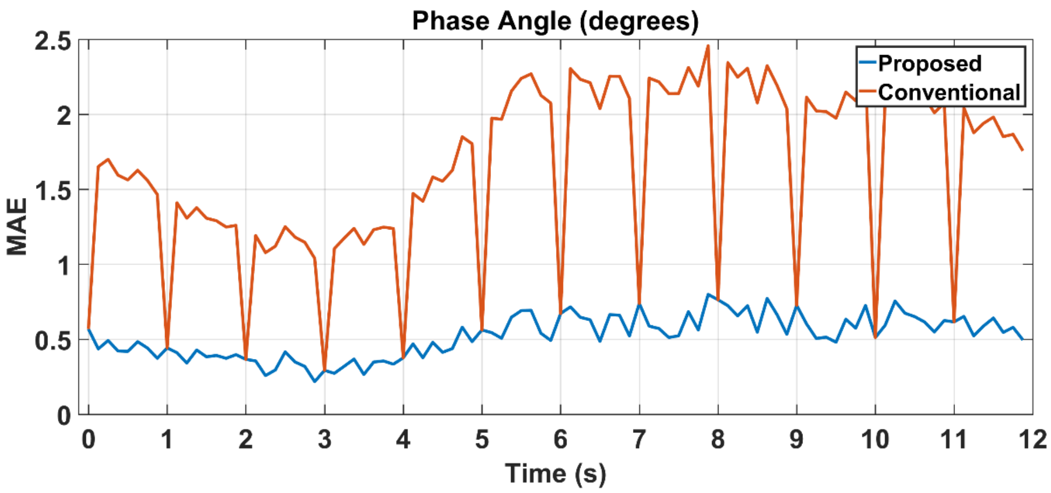

Figure 4.4. MAE of Phase Angles for Case 1

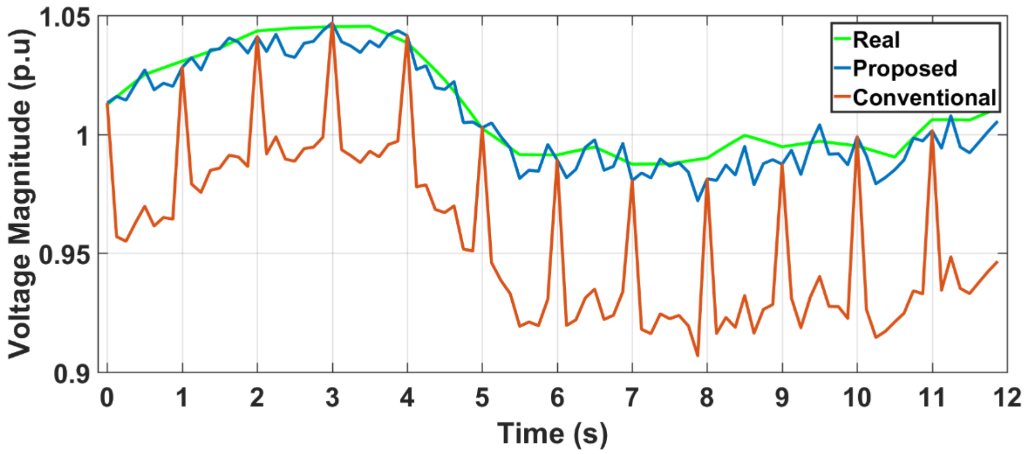

Figure 4.5. Estimated and Real Voltage Magnitudes for Case 1

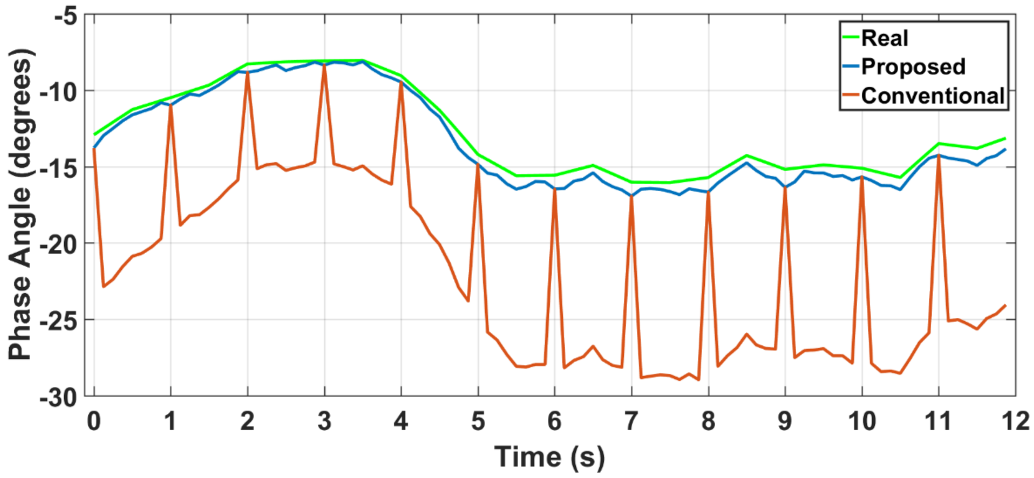

Figure 4.6. Estimated and Real Phase Angles for Case 1

Case 2: In this case, it is assumed that all the pseudo-measurements are determined as the accuracy class B. In other words, the standard deviations of the pseudo-measurements vary in the range between 0.01 and 0.5 p.u. In the system model, residential, commercial loads are used to generate these pseudo-measurements.

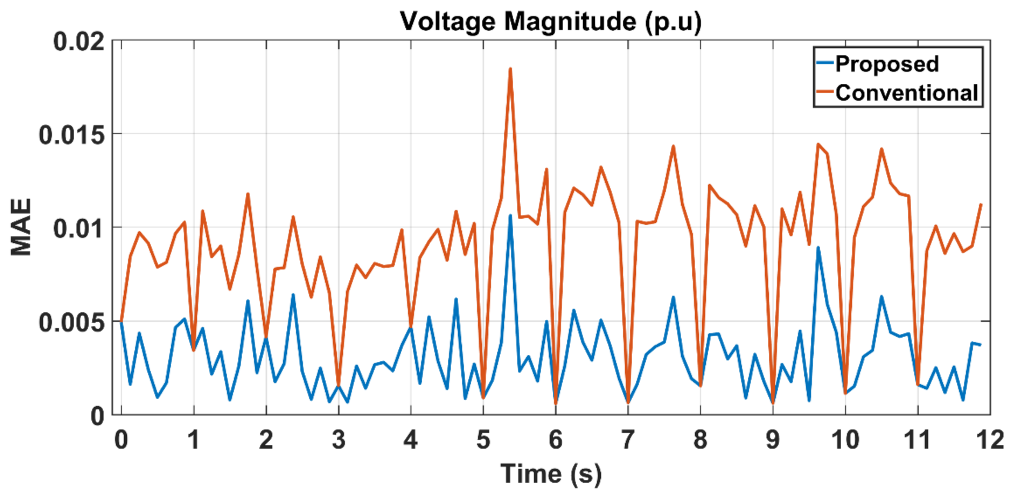

Figure 4.7. MAE of Voltage Magnitudes for Case 2

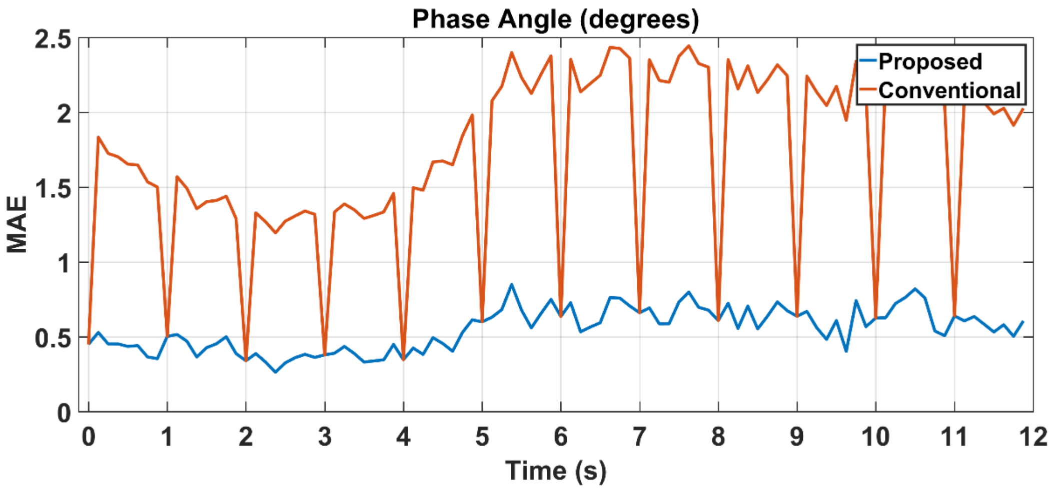

Figure 4.8. MAE of Phase Angles for Case 2

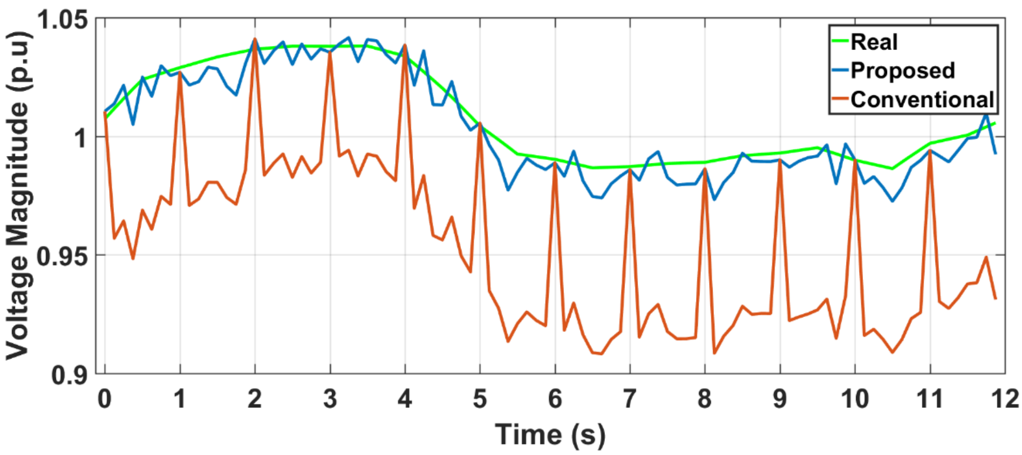

Figure 4.9. Estimated and Real Voltage Magnitudes for Case 2

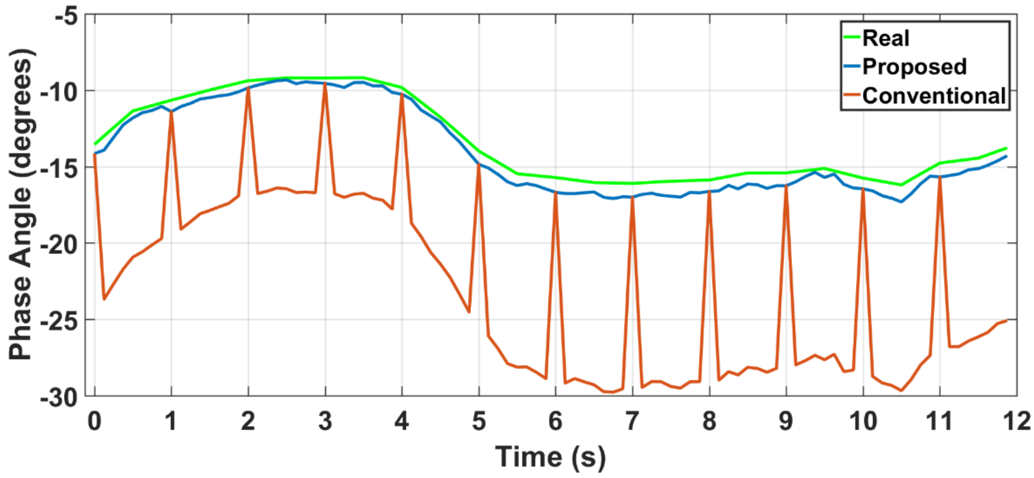

Figure 4.10. Estimated and Real Phase Angles for Case 2

Case 3: In this case, it is assumed that all the pseudo-measurements are determined as the accuracy classes B or C. In other words, the standard deviations of the pseudo-measurements must be larger than 0.01 p.u. In the system model, mostly industrial loads are used to generate these pseudo-measurements.

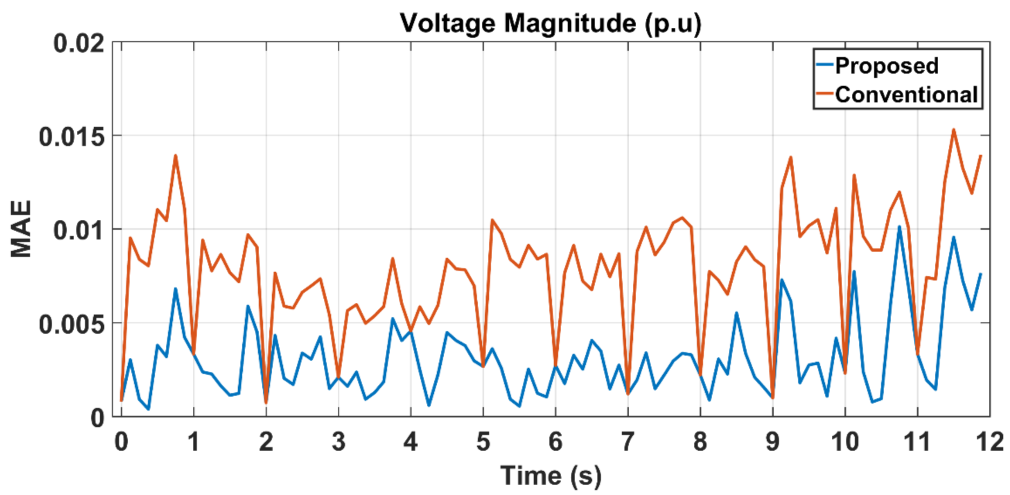

Figure 4.11. MAE of Voltage Magnitudes for Case 3

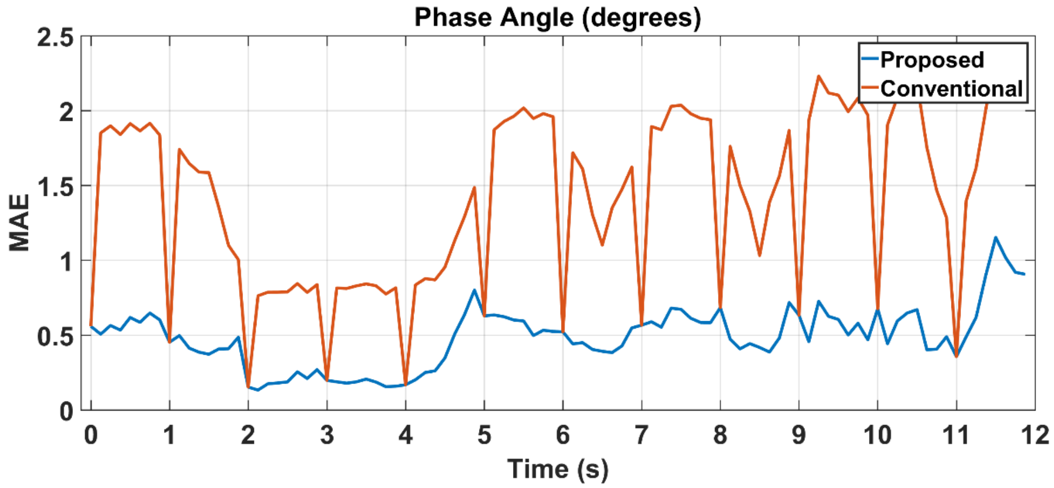

Figure 4.12. MAE of Phase Angles for Case 3

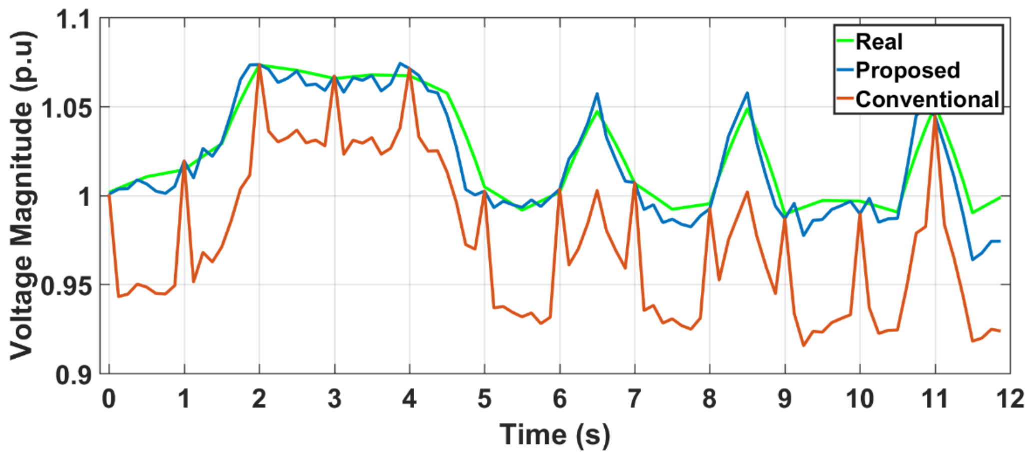

Figure 4.13. Estimated and Real Voltage Magnitudes for Case 3

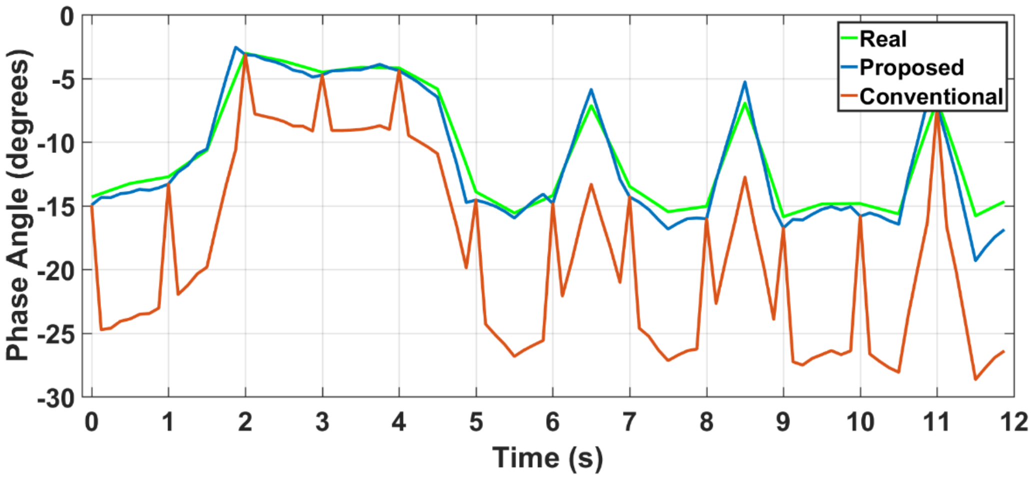

Figure 4.14. Estimated and Real Phase Angles for Case 3

4.2 1289 BUS ACTUAL SYSTEM

In this section, the proposed hybrid state estimator is performed on actual large power system model with 1289 buses. In the beginning of the study, a load flow analysis is solved for a snapshot of the system model with DIgSILENT Power Analysis Tool. To simulate the performance of the hybrid state estimator as a real-time application, a synthetic data is created using the daily profiles of injection measurements obtained from Turkish grid [36]. These daily injection profiles are used to determine the residential, commercial and industrial load demands in the system model. Since an industrial load have unexpected changes on the its waveform, the daily profile of industrial load has higher standard deviation compared to the others. Therefore, the accuracy of the pseudo-measurement related to an industrial load demand was considered as being worse compared to the accuracy of the pseudo-measurements related to residential and commercial load demands. In order to observe the effects of biased pseudo-measurements on the accuracy of estimated states, three cases, in which the accuracy classes of pseudo-measurements are different, are simulated. To evaluate the performance of the proposed method, both the proposed and conventional method are performed on the 1289 bus actual system for three cases.

4.2.1 The Simulation Results for 1289 Bus Actual System

In this study, 164 pseudo-measurements are optimally placed to merge the observable PMU islands with respect to the location of PMUs. The proposed method uses Kalman Filter to update the pseudo-measurements previously computed using the statistical data of the last measurements in the most recent 60 days. However, the conventional method uses directly the pseudo-measurements generated based on the statistical information.

Case 1: In this case, it is assumed that all the pseudo-measurements are determined as the accuracy class A. In other words, the standard deviations of the pseudo-measurements vary in the range between 0 and 0.01 p.u. In the Matlab Environment, the errors are generated as an array of normally distributed random numbers with a standard deviation of 0.01 for these pseudo-measurements.

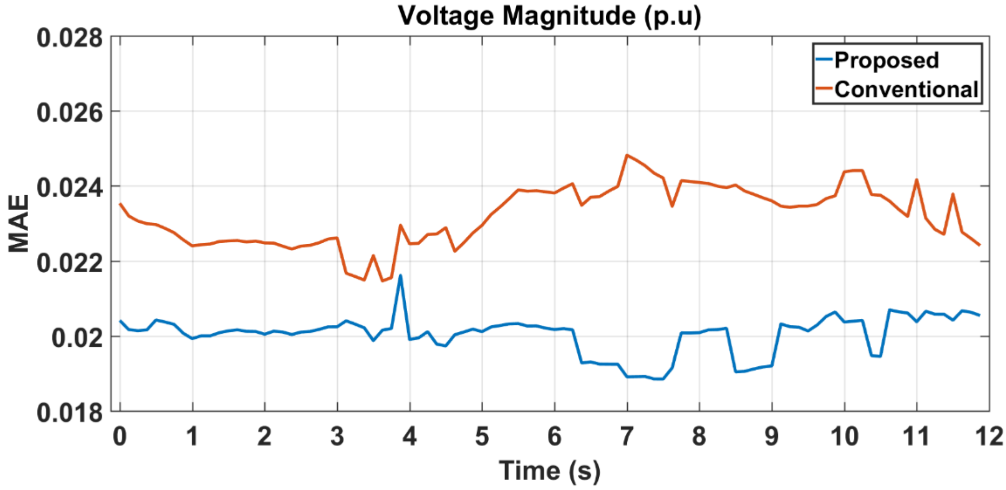

Figure 4.15. MAE of Voltage Magnitudes for Case 1

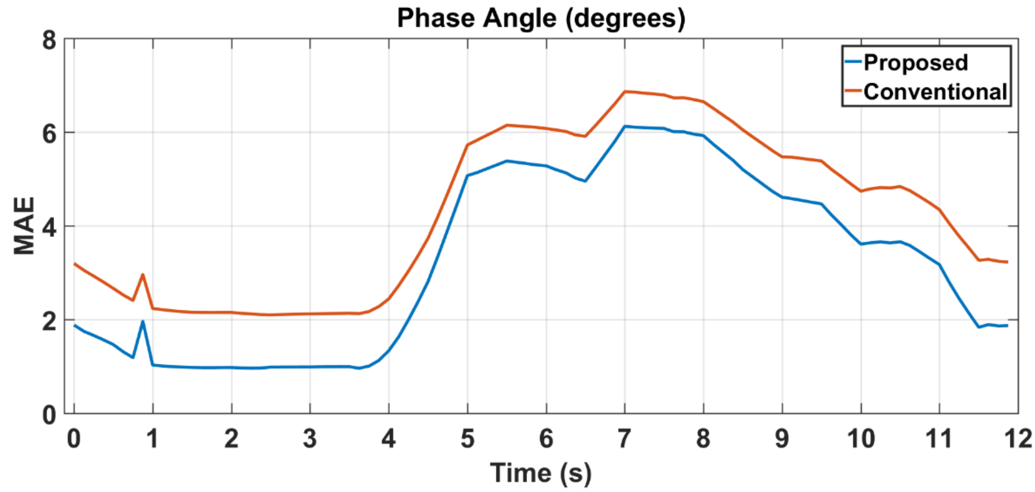

Figure 4.16. MAE of Phase Angles for Case 1

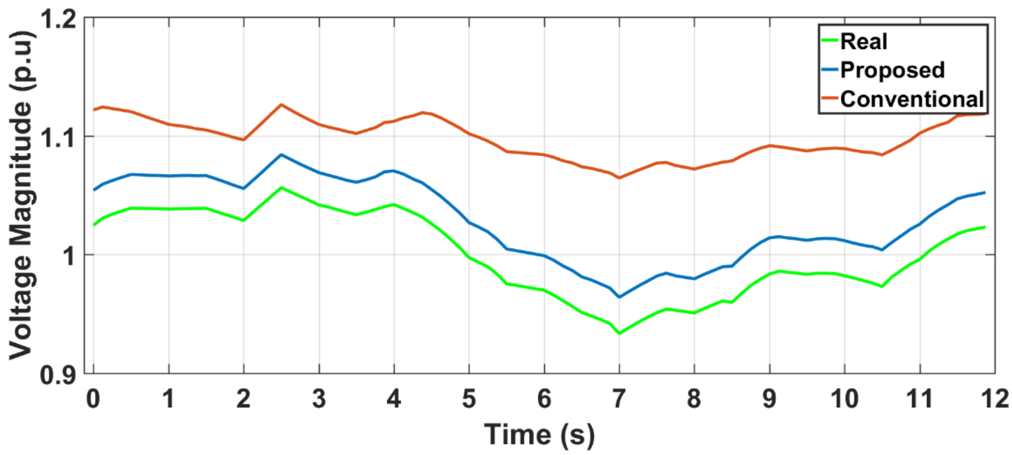

Figure 4.17. Estimated and Real Voltage Magnitudes for the Worst Estimated Voltage Magnitude of Conventional Method

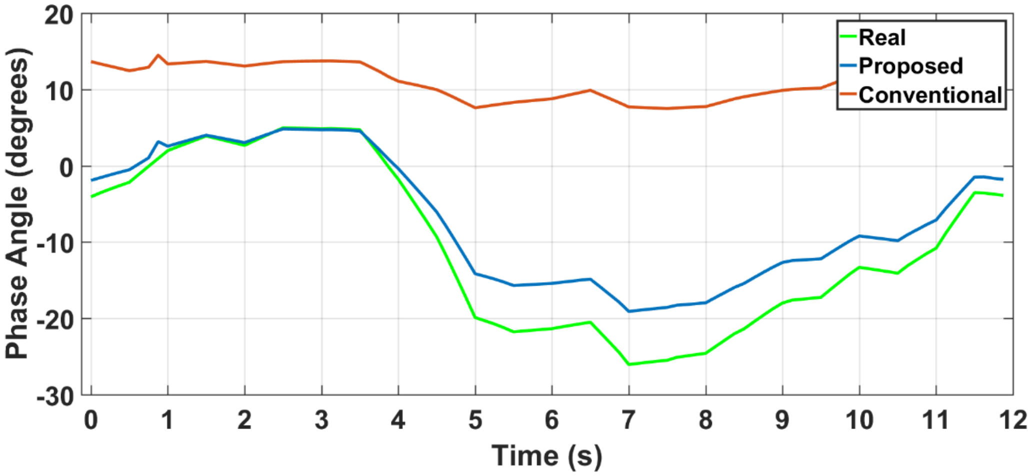

Figure 4.18. Estimated and Real Phase Angles for the Worst Estimated Phase Angle of Conventional Method

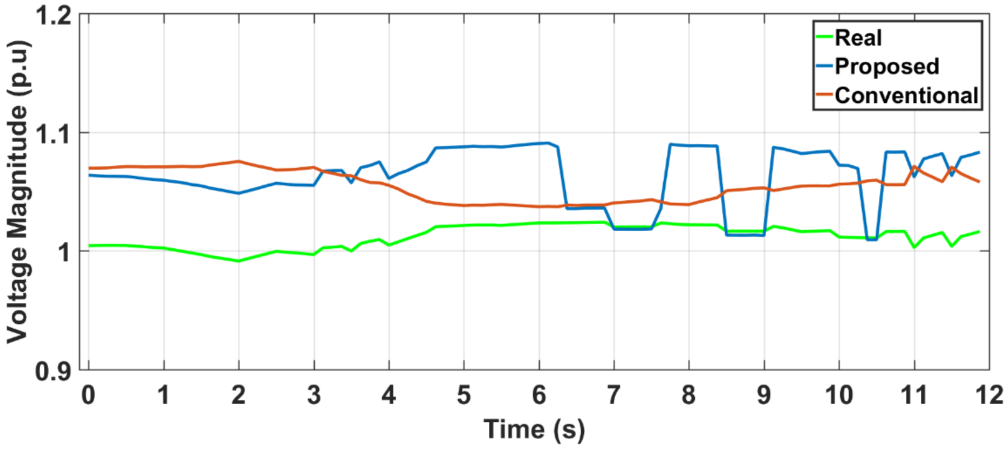

Figure 4.19. Estimated and Real Voltage Magnitudes for the Worst Estimated Voltage Magnitude of Proposed Method

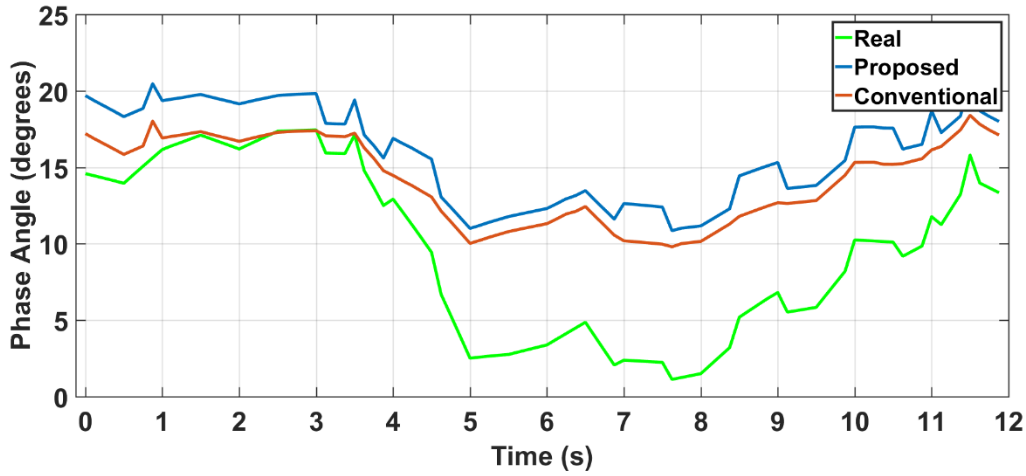

Figure 4.20. Estimated and Real Phase Angles for the Worst Estimated Phase Angle of Proposed Method

Case 2: In this case, it is assumed that there are both pseudo-measurements with the accuracy class A and with the accuracy class B. In other words, the standard deviations of the pseudo-measurements vary in the range between 0 and 0.5 p.u. In the Matlab Environment, the errors are generated as an array of normally distributed random numbers with a standard deviation of 0.5 for these pseudo-measurements.

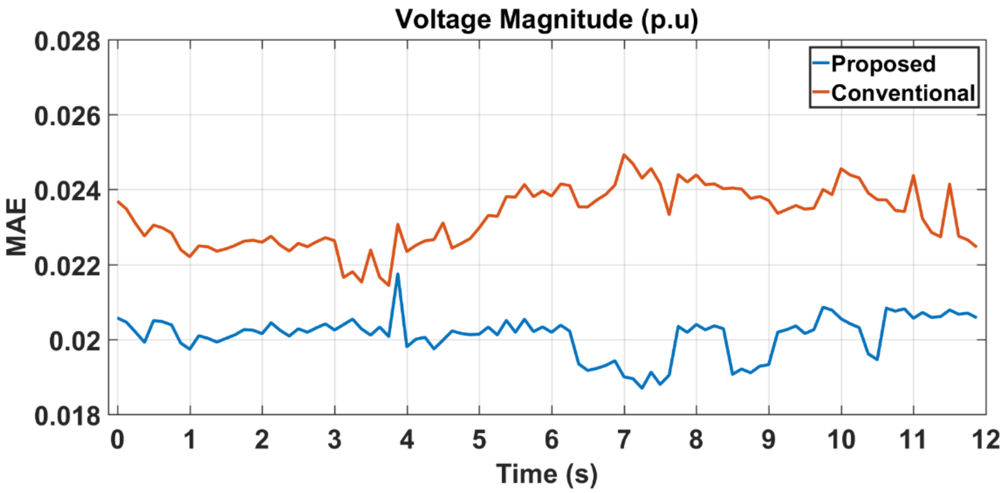

Figure 4.21. MAE of Voltage Magnitudes for Case 2

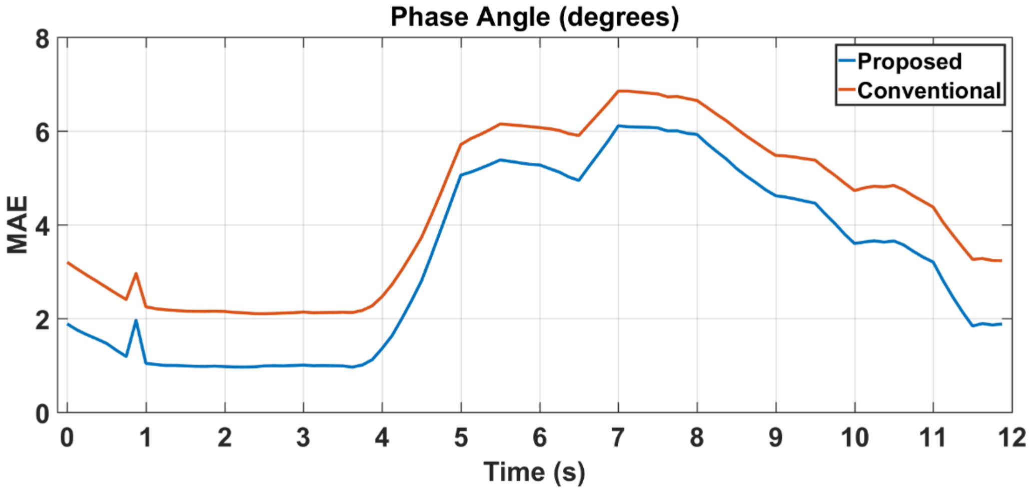

Figure 4.22. MAE of Phase Angles for Case 2

Case 3: In this case, there are pseudo-measurements with one of the three accuracy classes given in Table 4.2. Hence, the standard deviations of the pseudo-measurements are determined as being in the range between 0 and 1 p.u. Their errors are generated as an array of normally distributed random numbers with a standard deviation of 1.

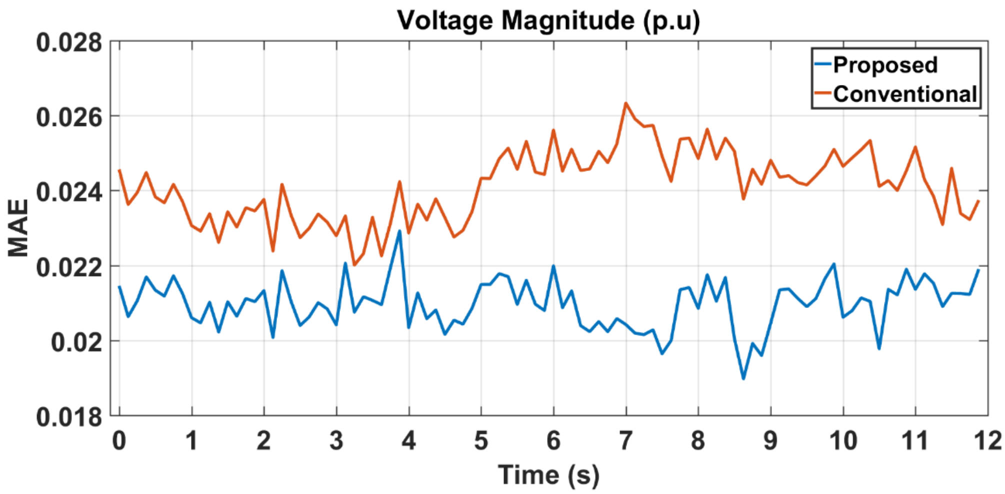

Figure 4.23. MAE of Voltage Magnitudes for Case 3

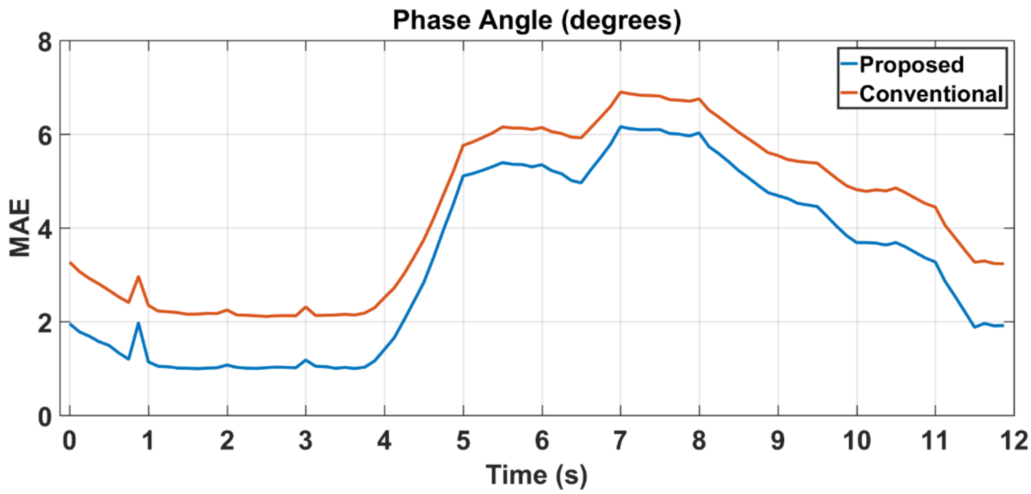

Figure 4.24. MAE of Phase Angles for Case 3

4.3 DISCUSSION AND COMPARISON OF THE RESULTS

- The simulation results of IEEE 14 bus test system are illustrated in Figure 4.3 -Figure 4.14. In according to these results, the accuracy class of pseudo-measurements is one of the most important factor that influences on the accuracy of the estimated states. In IEEE 14 bus system, three cases have different daily profile of real voltage magnitudes and real angles because of having different load profiles.

  In three cases, both the MAE of voltage magnitudes and the MAE of phase angles are decreased with respect to conventional method by using the proposed method. In other words, the sum of the difference between the real and estimated states are decreased by using the proposed method in the hybrid state estimator. For the results of three cases, the estimated states of bus 14 are detected as the worst estimated states with respect to their real values. Since bus 14 are isolated from the PMU anchored islands for the determined measurement configuration. According to these simulation results, the estimated states are the same for both the proposed method and the conventional method in each seconds when new SCADA measurements are received. At these instants, both the conventional method and the proposed method use the updated current SCADA measurements to perform the hybrid state estimator. However, the proposed method gives much better performance between two consecutive SCADA updates compared to the conventional method with respect to both the MAE of states and the waveforms of the estimated states of bus 14. Figure 4.11 - Figure 4.14 show that especially the pseudo-measurements with accuracy class C increases the MAE of the estimated states in case 3. In other words, these biased pseudo-measurements influence badly on the reliability of the state estimator. Even if the system includes mostly industrial loads with high standard deviation in case 3, the proposed method gives more reliable results compared to the conventional method.

- The simulation results of 1289 bus actual system are illustrated in Figure 4.15-Figure 4.24. In these simulations, three actual load profiles are used to represent as residential, commercial and industrial loads in the system model [36]. The characteristics of the network are taken from an actual power system including 1289 buses to test the proposed hybrid state estimator for the real applications. For three cases, the maximum limit of the standard deviations of pseudo-measurements are determined as 0.01, 0.5 and 1, respectively.

  In three cases, both the MAE of voltage magnitudes and the MAE of phase angles are decreased with respect to conventional method by using the proposed method. In other words, the sum of the difference between the real and estimated states are decreased by using the proposed method in the hybrid state estimator. For the results of three cases, the conventional method improves the performance of state estimator for the worst estimated states of the conventional method. According to these simulation results, the estimated states are the same for both the proposed method and the conventional method in each seconds when new SCADA measurements are received. At these instants, both the conventional method and the proposed method use the updated current SCADA measurements to perform the hybrid state estimator. However, the proposed method gives much better performance between two consecutive SCADA updates compared to the conventional method with respect to both the MAE of voltage magnitudes and phase angles. Figure 4.23 and Figure 4.24 show that especially the pseudo-measurements with accuracy class C increases the MAE of the estimated states in case 3. In other words, these biased pseudo-measurements influence badly on the reliability of the state estimator. Even if the system includes mostly industrial loads with high standard deviation in case 3, the proposed method gives more reliable results compared to the conventional method.

CHAPTER 5

CONCLUSION

In this thesis, a new strategy has been proposed to improve the robustness of hybrid state estimation using the updated pseudo-measurements considering that there are only PMU measurements between two consecutive SCADA updates. The study includes three main sections. In Chapter 2, hourly standard deviation characteristics of power injection measurements are calculated to investigate the uncertainty of the generated pseudo-measurements using the statistical information of historical data. According to these characteristics, it is resulted that the variance of power demands is not significant in the early hours of all days, while the uncertainty gets significant during afternoon hours, especially on Mondays and Tuesdays. Chapter 3, which have the most important section in the thesis, explains the hybrid state estimation strategy with optimal use of pseudo-measurements. Firstly, the determination of candidate buses is explained in detail. Boundary buses between observable islands are determined as the candidates for the placement of pseudo-measurements. Secondly, the proposed method of the optimal pseudo-measurement placement is explained in detail. It is noted that the standard deviations of pseudo-measurements, which are represented by their buses, are calculated using historical data once a day. Using these standard deviations, Integer linear programming method places the optimal pseudo-measurements with the selection of critical injection measurements with the best accuracies. Because of having no correlation with other measurements, these critical erroneous pseudo-measurements bias barely the results of state estimator. Thirdly, the hybrid state estimation strategy updates historical data by using the estimated states. The pseudo-measurements are generated using these updated historical data. Finally, Kalman Filter updates pseudo-measurements dynamically for each instants using the transition vector of pseudo-measurements and the most recent updated SCADA measurements until new SCADA measurements are received. Chapter 4 evaluates the performance of the proposed hybrid state estimation with respect to the conventional method for both IEEE 14 bus system and an actual system model with 1289 buses.

In the power systems, the changes of the network topology, measurement losses and the characteristic of load demand side have been the major factors that determine the accuracy of power injections in the system. It is very rough to detect bad data originating from the first two factors into injection measurement set because of being unexpected. Nevertheless, the standard deviation of injection measurement changes depending on the unsteadiness of load demand characteristic. This relationship motivates to place the optimal pseudo-measurements based on the standard deviation of pseudo-measurements to improve the quality of the pseudo-measurements used in hybrid state estimation. In addition, a corrupted pseudo-measurement may cause the states of the system to converge to different coordinate instead of the actual equilibrium point in the iterative computation of state estimator. Hence, these measurements can worsen the performance of state estimator when traditional method may use the incorrect priori measurement or the statistical data of past measurements as pseudo-measurement. To identify and eliminate the biased pseudo-measurements, the work presents main contributions, which are:

1) The pseudo-measurements can be grouped into the accuracy classes with their standard deviations of their past measurements using historical data in the most recent 60 days for the days of the week.
2) The minimum number of pseudo-measurements with the best accuracies are placed that all the measurements are critical, which are represented by independent row in the measurement Jacobian matrix, with respect to the configuration of PMUs in the network. Because of no correlation with other measurements, all the biased pseudo-measurements worse only directly related system states instead of all the state estimation.
3) In some cases, the pseudo-measurements with high accuracy may be very distorted compared to actual value. By fitting the curve of pseudo-measurement to the most recent SCADA measurements, the accuracy of pseudo-measurement is enhanced. The proposed method directs the daily curve

of pseudo-measurement along the most optimal path. To this purpose, Kalman Filter Technique updates the incorrect pseudo-measurement using its standard deviation based on its historical data and the last SCADA update.

4) The estimated states stored along the day are used to compute the most recent daily profile of injections, and then to incorporate this measurement set to the historical data once a day. Thus, the sample rate of pseudo-measurements is adapted to the resolution of state estimator in time.

The proposed strategy of hybrid state estimation was applied to both IEEE 14 bus test system and 1289 bus actual system. The residential, commercial and industrial loads were placed to different buses to generate three different cases having different pseudo-measurements with their determined accuracy classes. However, all the cases have the same measurement configuration for PMUs and conventional SCADA measurements. Firstly, the proposed placement method was used to select optimal pseudo-measurement with high accuracy using minimum number of pseudo-measurements for three cases. Secondly, Kalman Filter Technique was used to update the pseudo-measurements previously generated based on historical data for three cases. In addition, hybrid state estimation used the pseudo-measurements without updating, which is called as the conventional method. Finally, the estimated states of the conventional method and the proposed method were compared to evaluate the improvement of hybrid state estimator. The results of three cases show that the reliability of hybrid state estimator depends on the accuracy class of pseudo-measurements. Therefore, the higher the standard deviations of pseudo-measurements are, the less accurate the estimated states are. Nevertheless, the mean absolute errors of estimated states were less than compared to the conventional method for all the cases by using the proposed method.

It was observed that if the system has a large number of pseudo-measurements with high standard deviation such as industrial load demand, the difference between estimated states and real states are increased due to the increase of biases on the state estimator. As a result, it can be concluded that the proposed method is applicable to the selection of the pseudo-measurements with the best accuracies, and then to the enhancement of biased pseudo-measurements in order to improve the robustness of hybrid state estimator for a large power system when the deficiency of SCADA measurements occur.

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