SUBSTATION LEVEL STATE ESTIMATION AND TOPOLOGY ERROR PROCESSING

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ABSTRACT

SUBSTATION LEVEL STATE ESTIMATION AND TOPOLOGY ERROR PROCESSING

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The Phasor Measurement Units (PMUs) are recently utilized in the real-time monitoring, control and protection applications in electrical power systems. PMUs contribute the better understanding of modern power systems by rendering time synchronized voltage and current measurements thanks to their high-resolution and high-precision compared to the conventional SCADA measurements.

State estimation is one of the most important monitoring means in power systems. State estimation can be performed solely at substation level by utilization of synchrophasor PMU measurements. By substation level state estimation, erroneous measurements can be filtered at substation level and the computational burden of control centers may be reduced.

Topological errors cause biased state estimates, which may have catastrophic results for power system operation. Therefore, detection and identification of topological errors is critical. Despite its criticality, topological error processing has a significant computational burden for centralized control centers. Thus, performing topology error processing task at substation level can improve the computational performance. Performing state estimation and topology error processing tasks at substation level will improve the monitoring capabilities and the situational awareness of electric power systems.

This thesis proposes a substation level state estimator and topology error processor. The proposed method relies on the presence of PMU measurements and solves the estimation problem with the well-known Weighted Least Squares (WLS) estimator. The proposed method is validated with real substation topologies. The method can provide accurate system state estimates, filter the bad data and detect topological inconsistencies at the substation.

Keywords: State Estimation, Substation, Bad Data Processing, Topological Error Processing, Smart Grids

ÖZ

TRAFO MERKEZİ DÜZEYİNDE DURUM KESTİRİMİ VE TOPOLOJİ HATASI İŞLEME

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Fazör Ölçüm Birimleri (PMU) son zamanlarda elektrik güç sistemlerinde gerçek zamanlı izleme, kontrol ve koruma uygulamalarında kullanılmaktadır. PMU'lar, geleneksel SCADA ölçümlerine kıyasla yüksek çözünürlük ve yüksek hassasiyetleri sayesinde zaman senkronize gerilim ve akım ölçümleri yaparak modern güç sistemlerinin daha iyi anlaşılmasına katkıda bulunur.

Durum kestirimi, güç sistemlerindeki en önemli izleme araçlarından biridir. Durum kestirimi, senkrofazör PMU ölçümleri kullanılarak yalnızca trafo merkezi düzeyinde gerçekleştirilebilir. Trafo merkezi seviyesinde durum kestirimi ile hatalı ölçümler trafo merkezi düzeyinde filtrelenebilir ve kontrol merkezlerinin hesaplama yükü azaltılabilir.

Topolojik hatalar, güç sisteminin çalışması için yıkıcı sonuçlara yol açabilecek yanlı sistem durumu tahminlerine neden olur. Bu nedenle, topolojik hataların tespiti ve teşhisi oldukça kritiktir. Topolojik hata işleme, kritikliğine rağmen merkezi kontrol merkezleri için önemli bir hesaplama yüküne sahiptir. Bu nedenle, trafo merkezi düzeyinde topoloji hata işleme fonksiyonunun gerçekleştirilmesi hesaplama performansını geliştirebilir. Trafo merkezi düzeyinde durum kestirimi ve topoloji hata işleme fonksiyonlarının gerçekleştirilmesi, elektrik güç sistemlerinin izleme yeteneklerini ve durumsal farkındalığını geliştirecektir.

Bu tez, trafo merkezi düzeyinde durum kestirimcisi ve topoloji hata işlemcisi önermektedir. Önerilen yöntem PMU ölçümlerinin varlığına dayanır ve iyi bilinen Ağırlıklı En Küçük Kareler (WLS) tahmincisi ile durum kestirimi problemini çözer. Önerilen yöntem, gerçek trafo merkezi topolojileri ile doğrulanmıştır. Yöntem, doğru sistem durumu tahminleri sağlayabilir, kötü verileri filtreleyebilir ve trafo merkezindeki topolojik tutarsızlıkları tespit edebilir.

Anahtar Kelimeler: Durum Kestirimi, Trafo Merkezi, Kötü Veri İşleme, Topolojik Hata İşleme, Akıllı Şebekeler

To my family

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ABBREVIATIONS	
BD	Bad Data
CB	Circuit Breaker
CT	Current Transformer
DS	Disconnecting Switch
EMS	Energy Management System
GPS	Global Positioning System
GSE	Generalized State Estimation
IED	Intelligent Electronic Device
KCL	Kirchhoff's Current Law
LAV	Least Absolute Value
MAE	Mean Absolute Error
PMU	Phasor Measurement Unit
RMS	Root Mean Square
RTU	Remote Terminal Unit
SCADA	Supervisory Control and Data Acquisition
TP	Topology Processor
TSO	Transmission System Operator
VT	Voltage Transformer
WLS	Weighted Least Square

CHAPTER 1

INTRODUCTION

State estimation (SE) is a process of estimating the state of the network based on the available measurements and on the assumed system model. State estimators give most possible system states by processing available measurements. Bus voltage magnitudes and bus voltage angles are the primary system states through which the electrical systems can be represented completely. In short, the state of the network in other words operating conditions of electrical systems are determined by state estimation applications [1].

A topology processor gathers status data of the circuit breakers and switching devices, and configures the one-line diagram of the electrical network. Later, this one-line diagram is utilized by a state estimator as a system connectivity. Since topology processors are based on the topological data in other words the statuses of switching devices, erroneous status of circuit breakers or switching devices can cause inaccurate system topology. Consequently, the state estimator utilizes incorrect system topology and gives inaccurate system estimates as output [1]. Topology error process is the method of detecting and identifying of topological errors. In other words, topology error processors can detect and identify erroneous switching device statuses.

State estimation was firstly performed at control centers at transmission level by using the measurements coming from power substations. Thus, bad data detection-identification and topology error processing tasks were all performed centrally. Initially, state estimation cannot be performed solely at substation level due to lack of measurement redundancy and absence of time synchronization between measurements. There were methods which conduct state estimation in two stage which are substation level stage and central level stage. At first stage, state estimation was performed at substation level. Later, estimates of substation level was combined at second stage [9-11]. The problem of these methods was that due to lack of time synchronization between measurements, every substation had their own reference angle. Thus, as stated earlier state estimation cannot be performed solely at substation level in the past. However, with the advent of PMU devices, redundancy and accuracy of substation level measurements have increased greatly, and the time synchronization issues between measurements are resolved [8]. PMU devices provide more accurate measurements compared to SCADA measurements, and the refresh rate of PMU measurements is much higher than SCADA measurements [28]. Since PMU measurements are time-stamped with GPS signals and they have improved the redundancy at substations, substation level state estimation is now possible.

The main motivation of this thesis is the utilization of state of art PMU devices and PMU measurements by performing state estimation and topology error process at substation level. State estimators determine the most possible system states by processing the available measurements and help system operators to determine the operating conditions of electrical power systems. In other words, state estimation applications increase the situational awareness of power systems. Since complexity of electric systems have increased substantially with the growth in the size of electric systems and the penetration of renewable energy sources, importance of state estimation as a monitoring tool has increased as well. On the other hand, smartness in electrical power systems are also growing just like increasing complexity of electric systems. Since most of control actions and protective decisions are taken at power substations, and electrical quantities are measured at power substations through RTUs, IEDs and PMUs, it can be stated that most of the smartness of electrical systems exists at power substations [7]. Thus, secure and reliable operation of power substations have great importance. States of electrical networks are estimated by state estimation, similarly operating conditions and system states at substations can be determined by state estimation. Just like central state estimation applications, implementation of state estimation procedure to power substations will improve the situational awareness of substations which are one of the most important parts of electrical grids. Central state estimators utilize the measurements coming from power substations. Thus, by performing state estimation at substation level inconsistencies in analog measurements and substation topology can be eliminated at substation level, and filtered and corrected measurement sets can be transmitted to control centers for central state estimation [11]. Moreover, refresh rates of PMU devices are higher compared to conventional SCADA measurements, therefore central state estimators have to run much more frequently in the presence of PMU measurements. In addition, amount of data and redundancy in the presence of PMU measurements are also much higher than SCADA only systems. Thus, computational burden of central state estimators is also much higher in the presence of PMUs. Performing state estimation at substation level can also decrease the computational and communicational burden of central control centers and central state estimators. Similar to substation level state estimation process, topology error process has crucial importance for improving substation level awareness and power system monitoring tasks. Nowadays, much more control actions take place at power substations due to the increased complexity of power systems. Thus, possibility of topological errors is increasing as well. To handle this problem, power systems have to be monitored in a better way through measurement devices. However, most of electrical grids are deprived of advanced monitoring capabilities. Topology error processors can detect and identify topological inconsistencies at substations by utilizing redundant measurements and statuses of switching devices, and with that improve the monitoring capabilities of electrical power systems.

In literature, substation level state estimation process and topology error process are handled separately with different algorithms. In this thesis, both substation level state estimation process and topology error process are solved with same proposed Weighted Least Squares based algorithm. Performing substation level state estimation and topology error process together by utilization of PMUs constitutes the main contribution of this thesis to the literature.

1.1 Power System State Estimation

The idea of state estimation in power systems were firstly proposed by Fred Schweppe at the late of 1960s. Power system state estimation is matured in the last five decades. In the 1970s, state estimation was just a mathematical curiosity, in the 1980s its usage increased but compared to today's wide application area of state estimation it was still quite limited. In the 1990s, the role of state estimation in the power systems increased but the role was not a central role as today [1]. In 2000s and 2010s, application area of state estimation expanded from transmission level to distribution and substation levels with the advances in power system technology and the increased redundancy in all levels of power systems owing to new measurement devices and increase in the number of measurement devices.

State estimation provides optimal estimates or most possible system states based on the available measurements and on the assumed system model [1]. A power system can be fully described by system states electrically. In other words, if a power system is considered as a function, the system states are the variables of that function. Just like functions are represented by their variables, power systems can be fully represented by system states. Voltage magnitudes and voltage angles constitute the fundamental system states in power networks. If the voltage phasors (voltage magnitudes and voltage angles) of every bus in the system, the system model (system parameters; resistance values, impedance values, transformer taps etc.) and the system connectivity are known, all other electrical values such as power flows between buses, power injections at buses, current flows on lines etc. can be easily found.

Operating conditions of a power system, which are normal (secure/insecure), emergency and restorative states, have fundamental importance in terms of power system security and reliability. Operating conditions of a power system are determined based on the system model and system states. Thus, system states have crucial importance for determination of operating conditions. The biggest potential failure in a power system area is blackout which is the complete loss of power in electrical systems. After blackouts, brownouts and regional power outages come as biggest threat to secure operation of a power system [19]. In power system history, even though occurrence of major power outages is quite rare, it still constitutes one of the major threats to the operation of power systems both electrically and economically. Those power outages leave millions of people powerless and cause damage in power system equipment and loss of billions of dollars. One of the most important causes of those outages is incorrect operating conditions which means that incorrect information about the power networks or erroneous systems states. This fact makes state estimation which gives most accurate system states quite important for reliability and security of power system operations [20].

Power system operators manage power systems from the power system control center. The main task of the operator is to maintain the power system in the normal secure operating states for changes in the daily characteristics and operating conditions of power systems. System operators continuously monitor system operating conditions, and for this task determine system states and in case of normal insecure, emergency and restorative operating conditions take necessary precautions and actions. All these tasks constitute the security analysis function of the power system. Since operating conditions of power systems are determined based on system states, it can be said that state estimators are in the core of online security analysis of power systems [1].

Power system operators generally have deep experience, instinct and understanding about the nature and the operation of power systems. But as the need for electricity ramp up with increasing populations and growing economies, power systems as a whole become more complex and hard to operate. This make manual operation and monitoring of power systems more difficult task to accomplish. Power system state estimators take part in the center of the solution of those challenges. Most possible system states, which give information about the operating conditions of power systems, are determined by the state estimator in the power system. Thus, power system state estimators are among the fundamental building blocks of modern control centers and are found almost at every power system control centers.

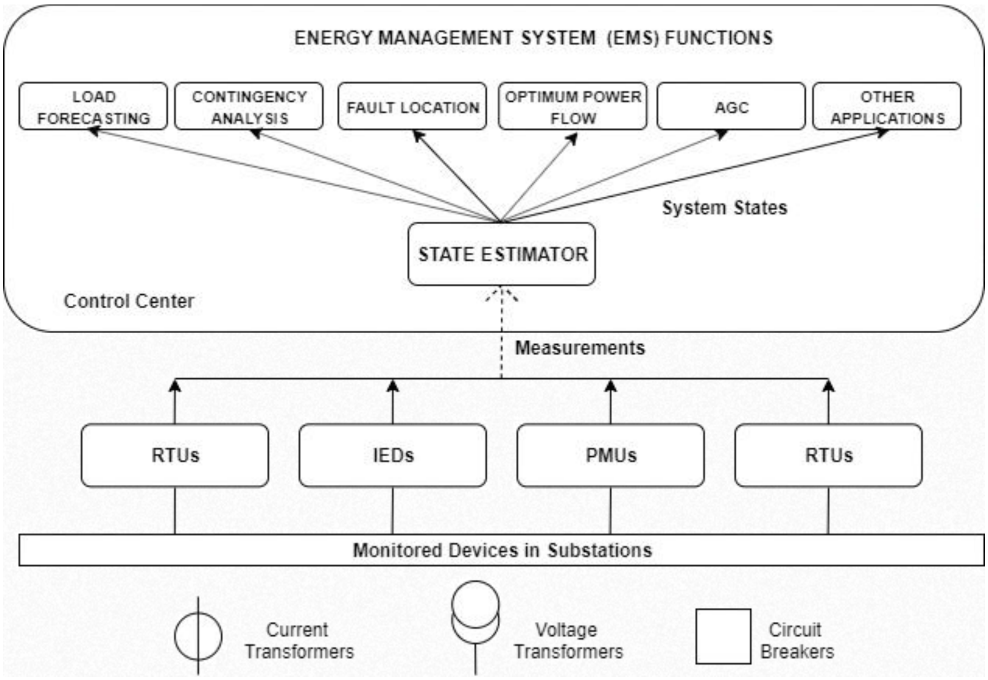

Figure 1.1. The Fundamental EMS System Structure

State estimators take raw measurement data, which are analog measurements and digital measurements (switching device statuses), and system model as input, process them and give most possible system states as output. In conventional power systems, raw measurement data are acquired by remote terminal units (RTU) which are devices that collect measurements at the substation and transmit them to the control center. Nowadays, in addition to RTUs, usage of Intelligent Electronic Devices (IEDs) and Phasor Measurement Units (PMUs) getting more popular. In conventional power system structures, data are collected by current transformers, voltage transformers etc. through RTUs and IEDs at substations. RTUs and IEDS transmit collected data to control centers via a local area network (LAN) through SCADA front end computers. In Figure 1.1, a typical conventional EMS structure is shown. Conventional state estimators at control centers are the core of Energy Management Systems. Energy management systems (EMS) are automation systems that collect measurement data from the field and making it available to users through graphics, online monitoring tools, and energy quality analyzers, thus enabling the management of energy resources [2]. Contingency analysis, automatic generation control, load forecasting, fault location and optimal power flow are some of the important EMS functions. All these functions use system states as their input and perform their task based on that system states. State estimators process available data and filter measurement noise and bad data in the measurements, and give most accurate system states to EMSs. In brief, as being the cornerstone of modern control centers, taking part in the core of online security analysis functions and in the core of the EMSs functions, state estimation makes operation of major power markets possible [1].

In conventional state estimation methods, measurements in substations are collected by RTUs and then those measurements are transmitted to central control centers via SCADA system infrastructure. At the central control center, the state estimation is performed centrally especially at transmission level by using measurements coming from substations and system model. Filtering and processing of raw data by state estimation through bad data and topology error processing procedures are all performed centrally. Although conventional state estimation approach made a breakthrough in the past for monitoring and control of power systems by providing true system states to EMS functions, now conventional state estimation has some drawbacks. Conventional state estimators cannot satisfy the requirements of modern power system operations. Firstly, number and type of measurements, and redundancy at substation level have increased enormously. Transmitting those huge amount of data can create communicational and computational problems at central level state estimation process [9]. Secondly, not all the measurements at substations are sent to the central level due to above constraints. In other words, variety and abundance of measurements at substations are higher than the central level [7]. Moreover, central level state estimators take substations as just a node which causes the lack of utilization of the overall information at the substation level [27]. Furthermore, bad data in the power systems are generally found at substations, thus performing bad data detection-identification and topology error processing tasks at substation level can give better results for system reliability [6]. Finally, in addition to PMUs which provide GPS synchronized phasor measurements, the advent of advanced communication protocols and standards (such as IEC 61850) which facilitates data exchange and integration within substation systems and introduction of smart grid concept are the other factors which make state estimation solely at substation level possible.

This thesis facilitates advances in the power systems technology and structures especially at substation level improvements and proposes a method for substation level state estimation which performs bad data detection-identification and topology error detection tasks by using a nonlinear weighted least squares method.

1.2 Literature Review

The advent of Intelligent Electronic Devices (IEDs), Phasor Measurement Units (PMUs), new generation of Remote Terminal Units (RTUs), etc., give rise to availability of huge amount of measurements at the substation level. Although increasing the amount of measurements at the substation level improves the redundancy of substations, formidable amount of measurements also brings computational and communicational burden to control centers. These issues are tackled by the introduction of the global communication standards for substation automation systems such as IEC61850. Improvements in measurement redundancy and communicational standards call for the implementation of a substation level state estimator. In recent years, research and application interests on substation level state estimation have increased dramatically and those applications have been proposed in [3–12].

One of the most important properties of smart grids is the fitting of various digital devices capable of communicating with each other and/or with a control center. At the transmission level this smartness exists almost entirely at substations [7]. Thus, for improving the transmission level state estimation, the redundant data available at substation level have to be utilized. In the literature, there are two different applications in which substation level state estimation is implemented which are single stage substation state estimation and hierarchical two-stage state estimation. Both of these approaches fundamentally aim to give more reliable system states to

EMS functions. In [3-8], single stage substation state estimation implementations are presented. In [9-11], hierarchical two-stage state estimation applications are presented.

The problem of including detailed substation models in state estimation at the least possible cost was analyzed in [3]. At that implementation bad data and topological error processing were carried out simultaneously by using the generalized state estimation (GSE) approach. In generalized state estimation algorithm, in order to estimate CB statuses, the modelling involves detailed physical modelling of whole substation which is called breaker-oriented modelling. In GSE, in addition to voltage magnitudes and voltage angles of buses at the substation, power flows on CBs are also taken as system state variables. To compensate this extra states, null power flow/voltage drop equality constraints are taken into account by using information of open/closed statuses of CBs. Moreover, zero-injection constraints are also taken into consideration at the substation level state estimation.

Implementation of a system that simulates collecting and processing of data at the substation level was presented in [4]. This implementation is called Substation State Estimator. IEDs facilitate collection and sharing of data within the substation, such as analog and digital measurements. This easiness and increased redundancy in the substation makes that implementation possible. Although it is called substation state estimator, its core algorithm is different than other implementations. There is no mathematical algorithm, weighted least squares (WLS), generalized state estimation etc. beneath it. Instead of mathematical concepts, the algorithm includes some consistency checking methods. In spite of that feature, this substation state estimator still can do data collection and processing tasks like [3]. Processed data by the substation state estimator may be used locally and/or delivered to remote sites (neighboring sites and/or control centers).

A local three-phase generalized state estimator which performs substation data validation task was presented in [5]. That application locally processes and filters huge amount of data available at substations and transmits the processed data to

Energy Management System. Many substation level state estimators are single phase and takes only positive sequence components of voltage magnitudes and voltage angles as state variables. Single phase applications exclude inconsistencies and unbalances between phases and accept the network as balanced. Implementation performed in [5], overcomes that deficiency of single phase estimators. Moreover, in that application, substation topology is also checked by using ideas recently introduced by GSE, which includes modelling of switching elements in detail. Being a three phase estimator and using ideas introduced by generalized state estimation approach brings large amount of data and needs great processing and communication capability. These issues are tackled by improvements in IEDs and increased computational capacities of modern computers. Bad data and topology error detection and identification tasks, which validate both analog measurements and CB statuses, were also performed in that application.

Papers in [3-5] were written at the beginning of 2000s. Usage of PMUs at power substations is still too low compared to widespread usage of RTUs. Thus, these applications could only utilize data coming from RTUs and IEDs which are not GPS synchronized. On the other hand, in [6] measurements coming from both RTU and PMU are utilized in the estimation process. Usage of PMUs at substation level improves local redundancy and accuracy enormously due to the GPS synchronized more precise phasor measurements provided by PMUs. In that application, substation state estimation was carried out on three-phase breaker oriented model using Kirchhoff's Current Law (KCL). Measurement functions are established according to KCL for zero impedance branches. In the application, bad data and topology error identification were decoupled. Since the application is based on three-phase state estimation, it provides real-time three-phase unbalanced degree monitoring at substation level. Like other existing applications, by removing analogy and topology errors at substation level this implementation also provides more accurate data for EMS functions at control centers.

With the advent of IEDs, local redundancy at substation level has been increased significantly. This increased redundancy also brings formidable amount of data as well. In order to deal with this huge amount of data available at substations, new system architectures have to be proposed. This problem was overcome by usage of local area network-based systems which use advanced IEDs instead of usage of centralized systems which are based on RTUs [7]. The global communication standard for substation automation system (IEC 61850) defines the communication rules between IEDs and specifies other system requirements.

Smart grids and also EMSs require fast, secure and error free high quality data for reliable system operation. Bad data on measurements is one of the biggest threats for secure system operation. From its earliest days, bad data detection is one of the most researched topic of state estimation. Although most of bad data detection algorithms are applied at central level, bad data in power systems generally exists at substation level. Centralized state estimators cannot eliminate overall the bad data exist at substation level. With the introduction of IEC 61850, data sharing within substation become more flexible and transparent allowing more sophisticated management of data quality [8]. In that paper, a substation level bad data detection method which uses linear WLS state estimation algorithm was presented. By that method bad data from failing current transformers (CT) can be detected. This method takes advantage of IEC 61850 standard and GPS synchronized IEDs such as PMUs.

In [9-11], two-level hierarchical state estimation methods are presented. The two-stage substation level state estimation methods resemble the classical multi-area state estimation problem, oriented to the regional or multi-TSO case. A two-level PMU-based linear state estimator was presented in [9]. The main contribution of that paper is the application of topology processing and bad data detection-identification functions at each substation rather than the control center. As stated in the paper, if all analog data were synchronized complex current and voltage measurements, then the state estimation would be linear and there will be no convergence issue. To meet that increasing redundancy level, in addition to RTUs, installation of more IEDS and PMUs are required. At that implementation, substation and control center level state estimators are linear. In some regions of China, higher penetration of PMU technologies are already available today. Thus, that application is specific to those regions only. In short, topology processing and bad data detection-identification tasks are performed locally, then processed more accurate data transmitted to control centers. The first level of this estimator is called Substation Level State Estimator or Zero Impedance Estimator.

A two-level state estimation with local measurement pre-processing methodology is presented in [10]. Raw measurements at substations are processed and filtered locally at the first level (local state estimator) and then only a manageable set of measurements are handled at the second level (conventional state estimator). In that application, each area reduces to a single electrical bus and no impedances are handled by local state estimator. Thus, the first level state estimator is linear. On the other hand, the second level state estimator is nonlinear. Application of a two-level state estimator which locally processes the raw measurements and uses only a manageable amount of data at the second level not only improves the reliability of state estimation of the whole system but also reduces the communication bandwidth.

A hierarchical state estimation based on state and topology co-estimation at substation level are presented in [11]. This paper introduces a hierarchical decentralized state estimation architecture in which lower level estimation is performed at each substation. At this local level, both state variables and substation topology are estimated together, and this processed data are delivered to regional control centers. In the higher level, utilization of locally processed data and tie line power flows between substations are carried out. As a result of higher level state estimation, system wide state estimates can be obtained. This proposed algorithm, reduces the deployment of huge amount of data from substations to control centers and like other substation level state estimators improves the system reliability.

A method of supervisory monitoring of substations which uses state estimation is presented in [12]. In that paper, a state estimation method is applied to double bus double breaker distribution substations which are common in the Korean power system. The supervisory monitoring consists of topology processing and normal state estimation. In topology processing process, errors in the switching elements are detected, after that connectivity matrix is constructed with that error free topology information. In state estimation part, conventional WLS algorithm is applied and bad data are detected by using Chi squares test. Results of bad data detection-identification processes are used to detect the degradation or malfunction of various analog sensors. Although there are enormous developments in sensors technology and measurement devices, it is still hard to detect anomalies on those devices automatically in the supervisory monitoring system. Thus, unlike other common state estimation applications, the object of this application is not mainly state estimation, but the supervisory detection of malfunction or degradation of the electrical devices.

The need for topology error processing was first proposed in 1980 [21]. In this paper Lugtu et al suggested the approach of using state estimation results for topology error detection. Since this time numerous methods have been proposed for detection and identification topological errors in power systems. Tree search algorithm [22, 23], sequential search method through the network graph [24], Bayesian-based hypothesis testing [25] etc. constitute some of the implemented topology error processing methods. Moreover, GSE and LAV based topology error processors are amongst the commonly used methods. Both of these methods explicitly model switching elements and bus configurations in the model used by state estimation process [26].

In addition to above topology error processing methods, results of normalized residual test (r^N) for bad data in state estimation is used for the detection of topology errors [13]. State estimation algorithm implements the electrical model provided by the topology processor. Some of the state estimation algorithms, like conventional WLS algorithms, accept topology of the examined system is correct and estimation process is carried out with this assumption. Thus, errors in switching status of breakers not only results in errors in the output of topology processor but also errors in state estimation outputs. In this paper, use of normalized residuals, which are results of the state estimation process, utilized for the detection of topology errors. The r^N (normalized residual) test for bad data processing is used for the detection of topology errors from the measurement data of the breaker statuses [13]. Moreover, the sensitivity matrix relating the normalized residuals and branch flows is derived for the identification of topology errors.

A method which carries out state estimation of voltage and phase-shift transformer tap settings are presented in [14]. As stated in that paper, state estimation algorithms have treated each transformer tap setting (voltage transformer turns ratio or phase-shift transformer angle) as a fixed parameter of the network, even though the real time measurement may be in error or non-existent. This approach can lead to errors in state estimation applications. In that paper, a transformer tap estimation technique is presented which takes turn ratios and phase angle values as measurements and each transformer tap setting as an independent system state variable.

1.3 Scope and Contribution of the Thesis

The main objective of this thesis is developing a substation level state estimator and a topology error processor which work together. Execution of state estimation process and topology error process simultaneously at the substation level constitutes the main contribution of this thesis to the literature. There are substation level state estimators already implemented in the literature, however those implementations do not perform topology error processing tasks at the same time, they only perform state estimation process. Topology error processing task is handled separately on applications in the literature. Moreover, most of the implemented substation level state estimators are part of two-stage or hierarchical state estimators. On those applications at first stage, the system states are estimated with respect to the reference angles of each substation due to lack of time synchronization between measurements. Later, at second stage the system states are calculated with respect to single reference angle. On the other hand, there are state estimators in the literature that perform state estimation solely at the substation level. Time-synchronized PMU devices and PMU measurements make independent state estimation solely at substation level possible.

The substation level state estimator proposed in this thesis also utilizes the PMU measurements.

In order for better understanding of contribution of this thesis to the literature, differences between state of art PMU measurements and conventional SCADA measurements have to be stated clearly. Before the advent of PMU measurements, only SCADA measurements were available as measurement sets for state estimators. PMU based measurement technology is a younger technology compared to SCADA based measurement technology. PMU device technology exists in the electricity market since 1988, however the history of SCADA systems is much older. Although, PMU devices are used in electrical grids more than three decades, their implementation rates were low due to their expensive cost. However, with the developing technology prices of PMUs decrease. Moreover, as power systems are becoming more complex, the need for PMU devices increases and as a result deployment rates of PMU devices are growing as well. PMU devices provide high-precision and high-resolution measurements compared to SCADA measurements. In other words, accuracy and refresh rate of PMU measurements are higher than SCADA measurements. Unlike SCADA measurements, PMU devices provide time synchronized phasor measurements. Synchrophasors measurements represent both the magnitude and phase angle of voltage and current measurements which are time synchronized. In addition to supplying measurements having better accuracy and increased redundancy, providing time synchronized phasor measurements is the most important feature of PMU devices. Before the advent of PMUs, due to lack of time synchronization between measurements solely substation level state estimation was not possible. But with the synchrophasor measurement supply capability of PMUs, independent substation level state estimation has become possible.

In Turkish Electric Systems, deployment rate of PMUs are increasing for improving the monitoring, control and protection capabilities of the national electric grid. By implementation of a sophisticated state estimator, situational awareness of the grid can be improved too. In this thesis, a Weighted Least Squares based substation level state estimation algorithm is proposed by the utilization of PMU measurements. In addition to proposition of substation level state estimation process, proposed algorithm can also perform topology error process task. Topology error processor can detect topological inconsistencies and errors by utilization of statuses of switching devices. With the simultaneous implementation of substation level state estimation process and topology error process which is the main contribution of this thesis to the literature, situational awareness and monitoring capabilities of Turkish national grid can be enhanced greatly.

1.4 Thesis Outline

This thesis consists of five chapters. In the first chapter, i.e. introduction chapter, power system state estimation problem is presented and the necessity of a substation level state estimator and topology error processor is justified. Moreover, literature review of substation level state estimation and topology error processing, and the scope of this thesis are explained in detail as well.

Chapter 2 provides background information about power substations, power system state estimation, bad data processing and topology error processing subjects. Importance of power substations for power systems, substation components and configurations are explained. Moreover, substation layouts in power systems and implemented substation layouts in Turkish Electric System are given. Local measurement redundancy at substations and importance of utilization of PMUs, which give time synchronized phasor measurements, in terms of substation level state estimation are presented too. In order to provide background for readers, power systems state estimation and WLS method which is the applied state estimation solution method in this thesis is represented in this chapter. In addition, mathematical fundamentals of WLS method, important functions of that method such as the measurement function and the measurement Jacobian are stated. Then, mathematical fundamentals of bad data detection and identification tasks in WLS state estimation method is presented. Finally, the methodology of the applied topology error processor is explained.

In Chapter 3, proposed substation level state estimation and topology error processing method is explained in detail. Substation measurements and system states which are fundamental inputs and outputs of the substation level state estimation algorithm are stated. Then, building blocks of the proposed substation level WLS state estimation algorithm and their formulations are presented. Topology processor, observability analysis function, state estimation solver, bad data processing function and topology error processing function constitute the building blocks of the proposed substation level state estimation method given in this thesis.

In Chapter 4, performed simulations and their results are presented. Substation level state estimation and topology error processing method is applied for various substations for different test cases. The proposed substation level state estimation and topology processing method is numerically validated with the generated test cases by examining the performance metrics and simulation graphs.

Chapter 5 summarizes the main contributions of proposed substation level state estimation and topology error processing method to the literature and to the monitoring capabilities of Turkish Electric System.

CHAPTER 2

BACKGROUND REVIEW

In the first chapter, power system state estimation concept and the importance of state estimators and topology error processors with regard to power system operation is explained. Then, literature review about substation level state estimators and topology error processors are represented. Later, the scope and the contribution of the thesis is stated. Finally, thesis outline is given. This chapter introduces the technical background of the proposed algorithm, which will lead the reader to understand the presented study. Firstly, the importance of power substations for power systems, power substation components and configurations are explained. Then, substation layouts in power systems and implemented substation layouts in Turkish Electric System are given. In addition, local measurement redundancy at substations and importance of utilization of PMUs, which give time synchronized phasor measurements, in terms of substation level state estimation are presented. Secondly, mathematical basis and solution procedure of WLS algorithm, which is the applied state estimation solution methodology in this thesis, are presented. In third and fourth parts of the chapter, fundamentals of the bad data detection-identification function in WLS and topology error processing function in WLS are expressed respectively.

2.1 Power Substations

Substations are the points in the power network where transmission lines and distribution feeders are connected together through circuit breakers or switches via busbars and transformers [15]. In other words, they are junction points in a distribution or transmission system. Substations in power network are used to [16]:

- Switch circuit to control power flow
- Switch circuit for maintenance purposes
- Isolate faulty sections of the system
- Split the system to maintain fault levels
- Provide system flexibility

In addition to the above items, substations are also centers where the measurement data are collected and some control actions are taken. In central state estimator concept, collected data at substations are directly sent to central control centers. Advancements in substation technology, advents of IEDs and PMUs, and also introduction of advanced communication protocols and standards make state estimation solely at substation level possible. As a result, data obtained at the substation are processed within the substation, and then filtered data are sent to regional control centers or central control centers.

2.1.1 Substation Components

Substations are connections points in the electrical grid in which generation, transmission and distribution systems are connected. Moreover, since substations have many functions in power networks, they have switching, control and protection equipment. In Figure 2.1, elements within a substation are shown in detail.

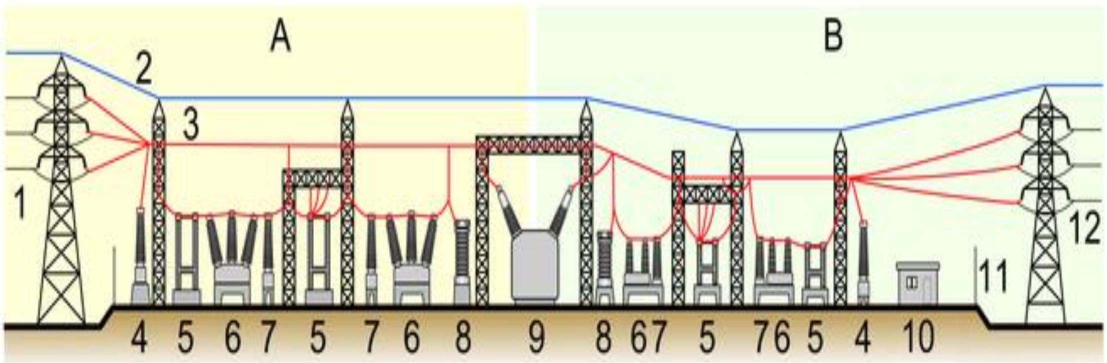

Figure 2.1. Elements of a Power Substation [17]

A: Primary power lines' side B: Secondary power lines' side

1. Primary power lines 2. Ground wire 3. Overhead lines 4. Voltage transformer

5. Disconnect switch 6. Circuit breaker 7. Current transformer 8. Lightning arrester

9. Main transformer 10. Control building 11. Security fence 12. Secondary power lines

Feeders or circuits at substations are connected to busbars through circuit breakers and disconnecting switches. Substations are the junction points in electrical power networks, similarly busbars are the junction points at substations. Power or current at a substation is carried from circuit to circuit through busbars since they have many connections with the circuits at a substation.

Circuit breakers are also one of the most important substation elements. They have three main functions at power substations which are related to protection, maintenance and control of power flow issues. Circuit breakers can interrupt current under short circuit conditions. Thus, if a fault occurs at the substation, the circuit breaker on the faulty path opens automatically and isolate faults from the rest of the power grid. If the maintenance will be carried out in a feeder, circuit breakers can be opened with disconnecting switches and isolate this feeder from the rest of the power network at the substation. Disconnecting switches are also switching elements at substations. Unlike CBs, disconnecting switches cannot interrupt current under short circuit conditions but they provide visual isolation for technical personnel at a substation for maintenance issues and faulty operations. Furthermore, by changing switching configuration of CBs, power flow in a substation can be controlled. Substation connectivity in other words substation topology are determined with respect to circuit breaker statuses which makes circuit breakers quite crucial in substation level state estimation.

Power transformers connect different voltage level equipment and feeders at a substation. Furthermore, in generation systems, transformers connect generators to transmission systems. In state estimation aspects, they bring nonlinearity to substation level state estimation procedure. Transformers taps are used for voltage control in other words reactive power control in power systems. Just like circuit breaker statuses, transformer tap positon data can be erroneous and this problem can be overcome by taking transformer tap positions as system state variables in substation level state estimation.

Instrument transformers, current and voltage transformers, are also quite important components of power substations. They measure currents and voltages at the substation and these measured values are used at substations for control actions and are also sent to control centers. In addition to instrument transformers, PMUs are also used for measurement purposes. Since these measurement devices provide measurement data to the state estimation function, they will be explained in detail in following sections.

2.1.2 Substation Layouts

There are several configurations in which switching equipment and busbars can be connected at substations. The selection of configurations depends on the following [16]:

- The degree of flexibility required.
- Importance of loads.
- Economic considerations, including availability and cost.
- Provision of extension.
- Protective zones.
- Maintenance and safety of personnel.

In this section, some substation configurations, in other words substation layouts will be briefly explained. Layouts will be compared in terms of the reliability, flexibility, complexity, maintenance and cost aspects.

2.1.2.1 Single Busbar Configuration

This is the simplest busbar layout in power networks. Feeders or circuits in a substation are connected to a single busbar through a single circuit breaker in this configuration as shown in Figure 2.2. In addition to being the most economical layout, it is also the least secure and the least reliable configuration as well. Any faults on the busbar will leave all feeders and connected networks to that feeders powerless. Moreover, total shutdown is required for any maintenance situation. Because of these reasons, this configuration type is not common in power networks.

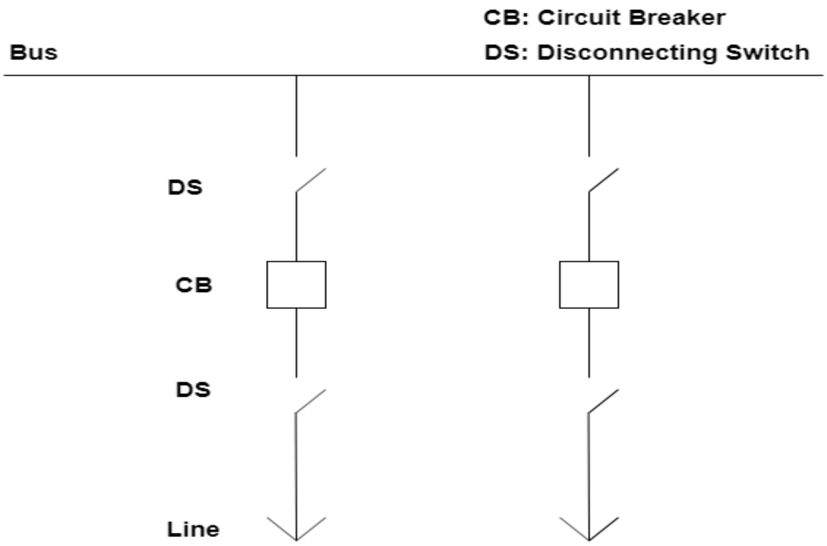

Figure 2.2. Single Busbar Configuration

2.1.2.2 Double Busbar Single Circuit Breaker Configuration

In this layout, each circuits are connected to two busbars through one circuit breaker. As seen in Figure 2.3, upper busbar is called main busbar and the below one is called reserve or transfer busbar. Bus coupler or coupling feeder connects main and transfer buses. Since there is one more busbar in the layout, it is more expensive than single busbar configuration. Moreover, addition of transfer bus also makes this layout more reliable in possible faulty operations and in any possible maintenance situations. It is one of the most commonly used layouts in power networks.

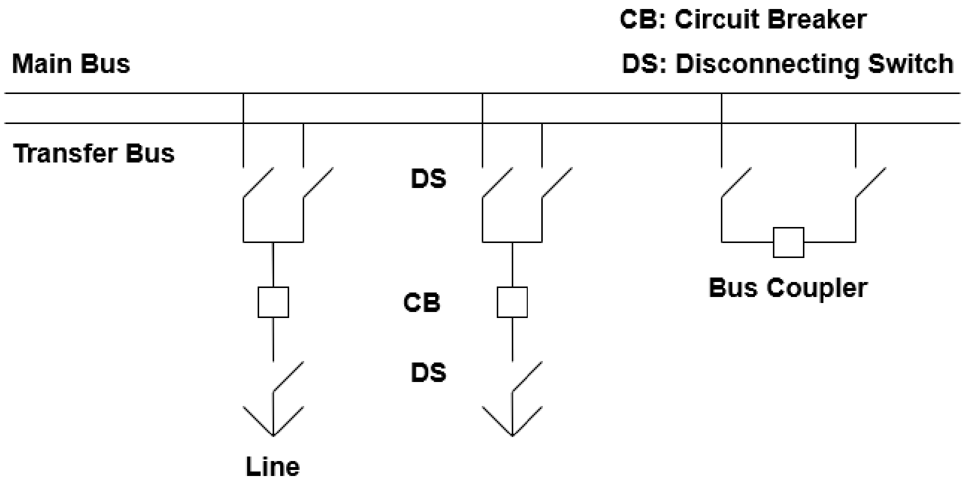

Figure 2.3. Double Busbar Single Circuit Breaker Configuration

2.1.2.3 One and a Half Breaker Configuration

In this layout, two circuits are connected to two busbars through three circuit breakers, in other words each circuit has one and a half circuit breakers as shown in Figure 2.4. This layout is more expensive and reliable than single busbar and double busbar one circuit breaker configurations. Thus, it is used in more important high voltage substations.

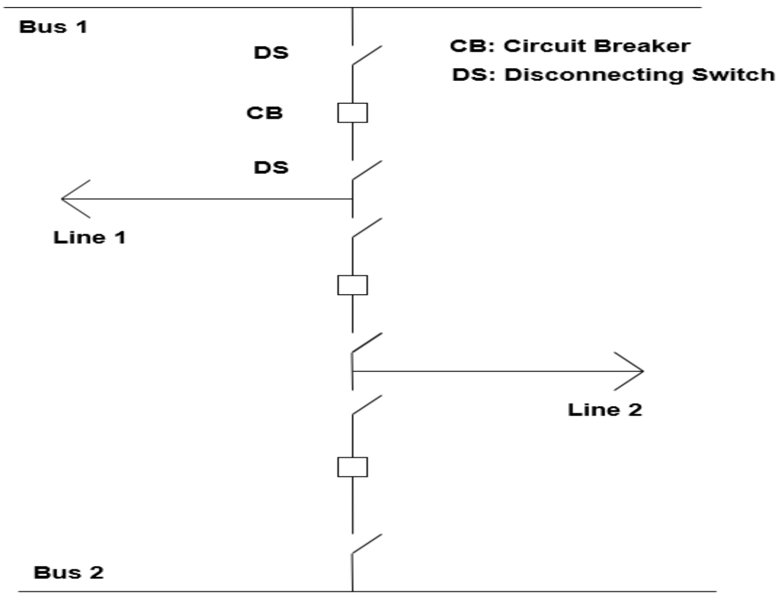

Figure 2.4. One and Half Breaker Configuration

2.1.2.4 Double Busbar Double Circuit Breaker Configuration

In this layout, each circuit has two circuit breakers and each circuit is connected to two busbars through these two circuit breakers as shown in Figure 2.5. This configuration is again more expensive and more reliable than above layouts. Thus, it is used for substantially important substations. Maintenance issues and faulty conditions are easily handled in this configuration. This configuration is also one of the most popular substation layouts in power networks.

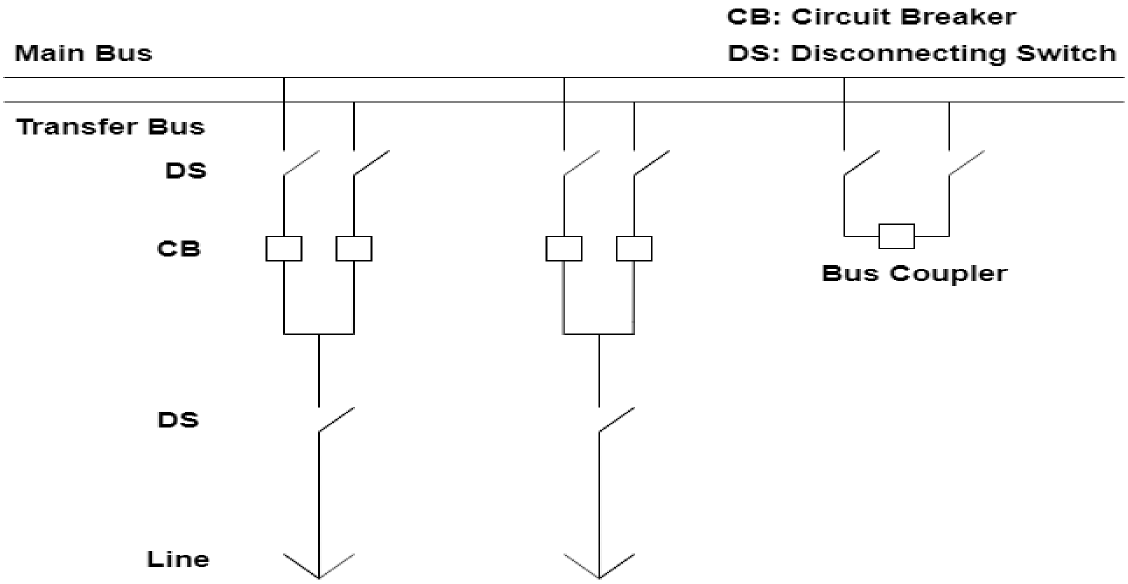

Figure 2.5. Double Busbar Double Breaker Configuration

2.1.2.5 Ring Busbar Configuration

Ring busbar configuration provides more operational flexibility and increased security. As seen in Figure 2.6, the power can flow through many routes which make this layout more flexible and secure for continuity of supply aspect. If a fault occurs, the faulty section can be separated from the rest of the network.

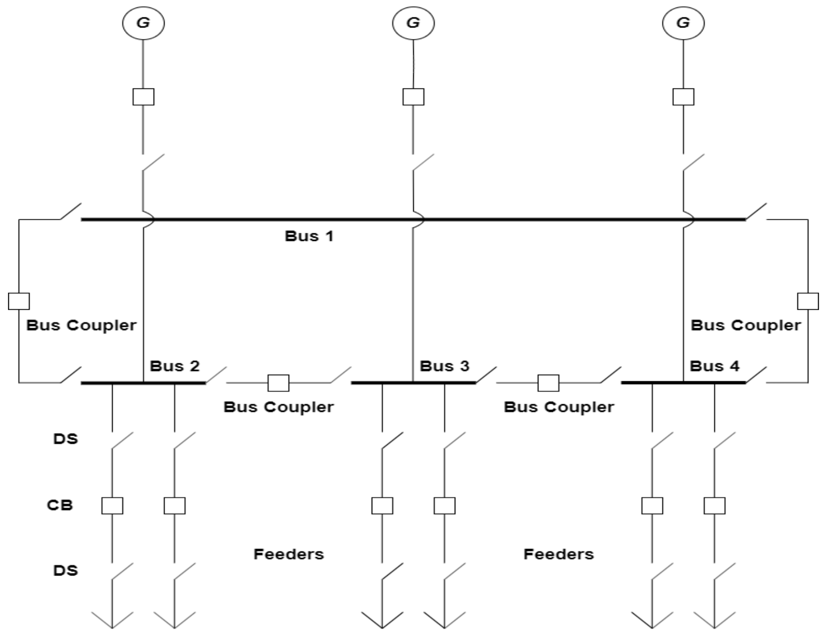

Figure 2.6. Ring Busbar Configuration

2.1.2.6 Interconnected Mesh Corners Configuration

Interconnected mesh corners layout provides maximum security against busbar faults. The structure of interconnected mesh corners layout is shown in Figure 2.7.

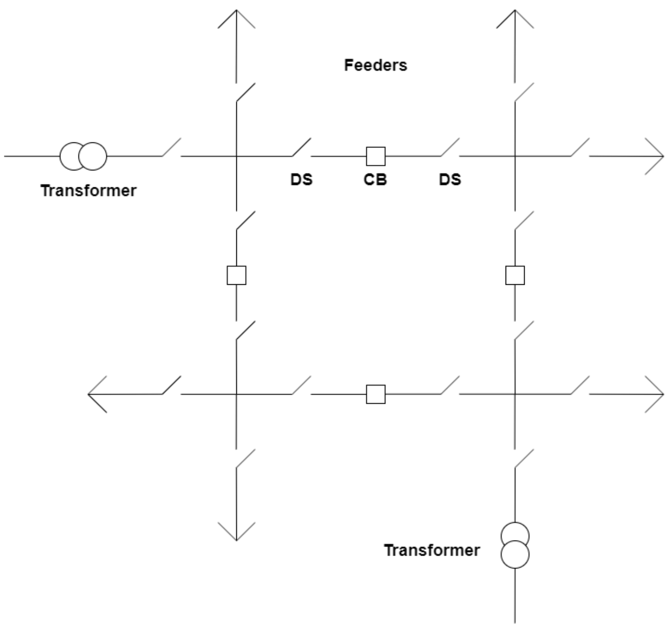

Figure 2.7. Mesh Configuration

2.1.3 Local Measurement Redundancy

Conventional state estimation is carried out based on analog measurements, digital measurements (switch statuses) and system connectivity data. In other words, those data are main inputs of state estimation. Analog measurements are captured remotely at substations and collected periodically by SCADA systems via Remote Terminal Units (RTUs). On the other hand, measurements that are transmitted to the central state estimator do not contain all the data that exist at power substations [4]. Moreover, the advent of IEDs, PMUs, new generation RTUs and smart grid concept give rise to huge amount of data at power substations. This huge amount of data and advanced communication protocols facilitate the implementation of substation state estimation. In short, the increasing local redundancy is the main motivation behind substation level state estimation applications.

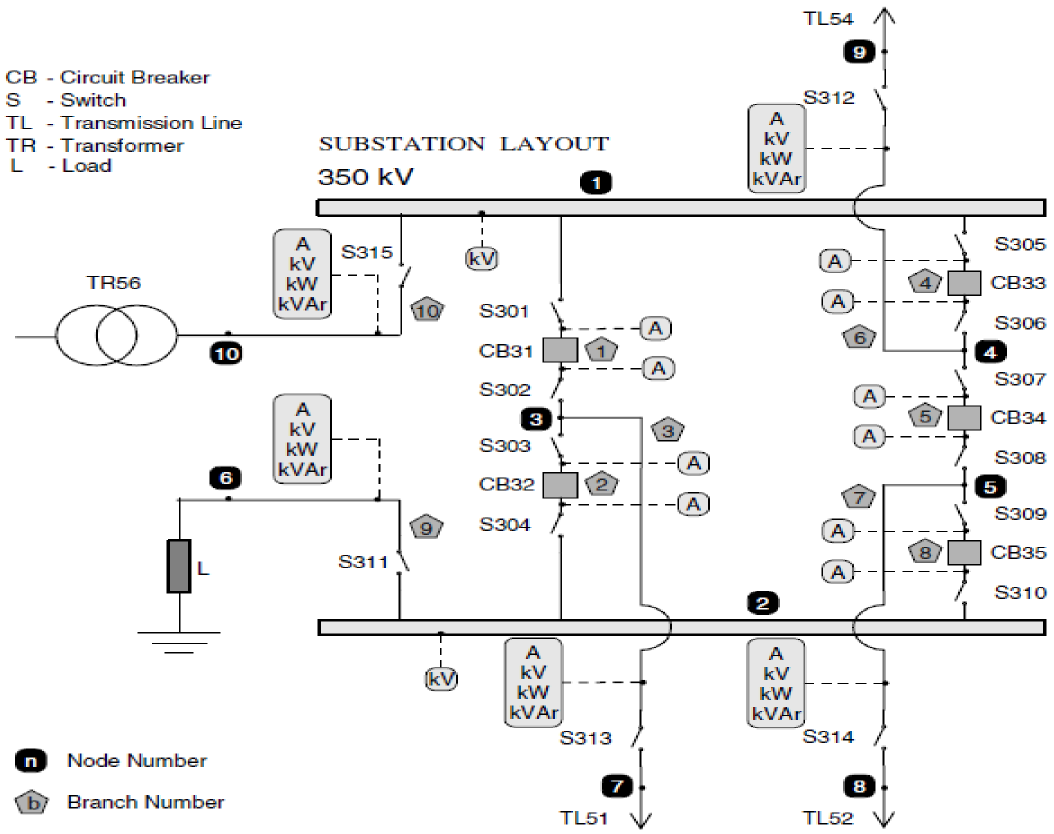

Figure 2.8. One-line diagram of a typical substation layout with measurement device allocation [4]

In modern substation architectures as seen in Figure 2.8, number of measurement points is numerous and the achieved redundancy level is also quite obvious. Current and voltage values at a substation can be measured by multiple devices. For example, current values on a feeder can be measured by both measurement current transformer and protective current transformer. In addition to measurements obtained from instrument transformers, IEDs and PMUs also provide measurements at the substation. PMU measurements include both magnitude and angle values of voltage and current measurements.

If all the redundant data at substations can be successfully integrated to the substation state estimator, bad data in analog measurements and erroneous circuit breaker statuses can easily be detected and identified. Moreover, malfunction in instrument transformers, circuit breakers, etc. can be detected as well. All those tasks are the main motivation behind substation level state estimation applications.

In addition to increased redundancy, the huge amount of data available at power substations cause several problems in the implementation of substation data integration. Those problems are listed below [4]:

- Great variety of devices for measurement and data acquisition tasks. Different measurement devices give different type of outputs which can be RMS values, peak values and phasors.

- Synchronization problems due to differences in frequency of data arrivals.

- Correlation between measurements makes state estimation and bad data identification difficult.

There are various solution methods for the above problems in power system literature. Output differences of measurement devices can be handled locally at substation level by appropriate pre-processing algorithms. The synchronization problem especially exists between SCADA and PMU measurements. PMUs measurements are updated 30–60 times a second, SCADA measurements are updated once in every few seconds. Hybrid state estimators, which employs pseudo-injection measurements during this unobservable duration exist in literature. Since those challenges are beyond the scope of this thesis, further details have been intentionally left out to the readers.

2.1.4 Substation Layouts in Turkish Electric System

In the above sections, possible substation layouts in power systems are shown. They are compared with respect to their reliability, flexibility, complexity, maintenance and cost aspects. Not all the substation layouts in practice exist in Turkey. Single busbar, double busbar single CB and double busbar double breaker configurations are the most implemented substation configurations in Turkey. Especially, double busbar single CB and double busbar double breaker configurations and their derivatives are the most applied ones in Turkish electrical power networks. In Turkish Electric System, substation layouts can be grouped more specifically unlike the above classification. There are four main substation layouts in operation in Turkish electrical power networks. Although more detailed grouping is possible based on the number of buses, number of circuit breakers and number of earthing switches, these four substation configurations are sufficient for representing the substation structures in Turkish Electric System.

1. Single Busbar Configuration

2. A Main Bus and A Transfer Bus Configuration

3. Two Main Buses Configuration

4. Two Main Buses and A Transfer Bus Configuration

The examples of the implementations of those layouts are shown below.

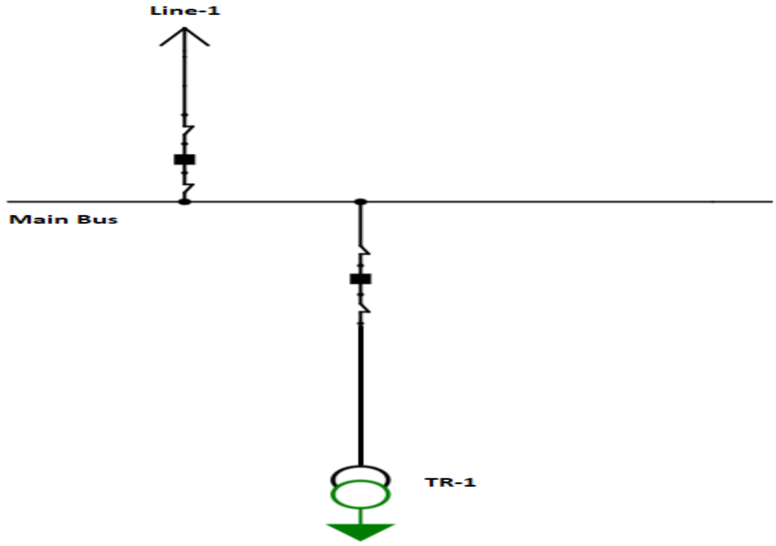

Figure 2.9. A Single Busbar Configuration Example

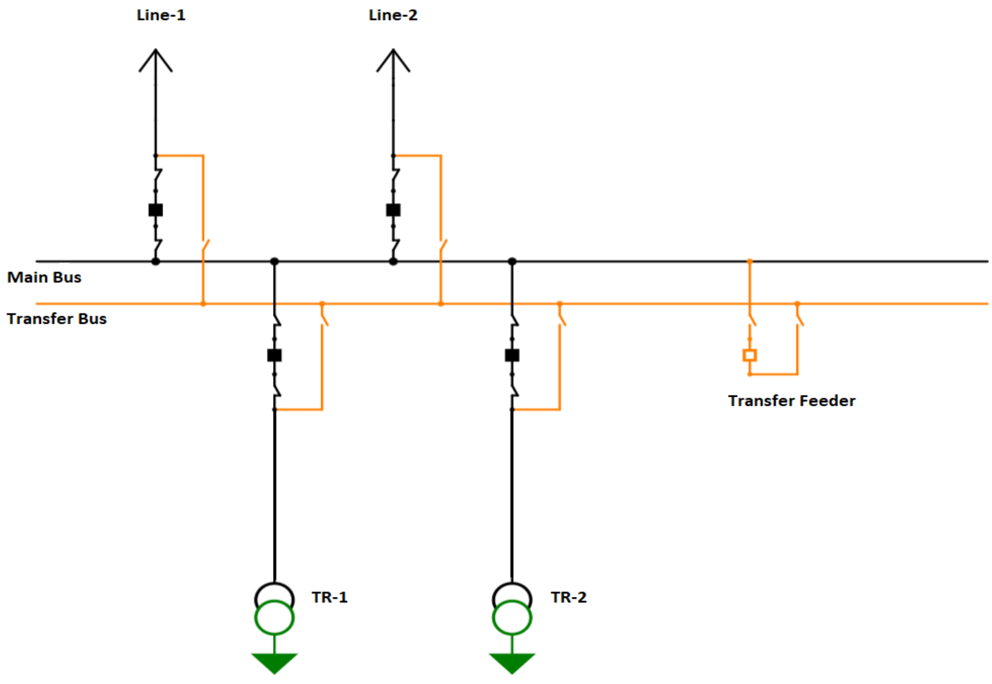

Figure 2.10. A Main Bus and a Transfer Bus Configuration Example

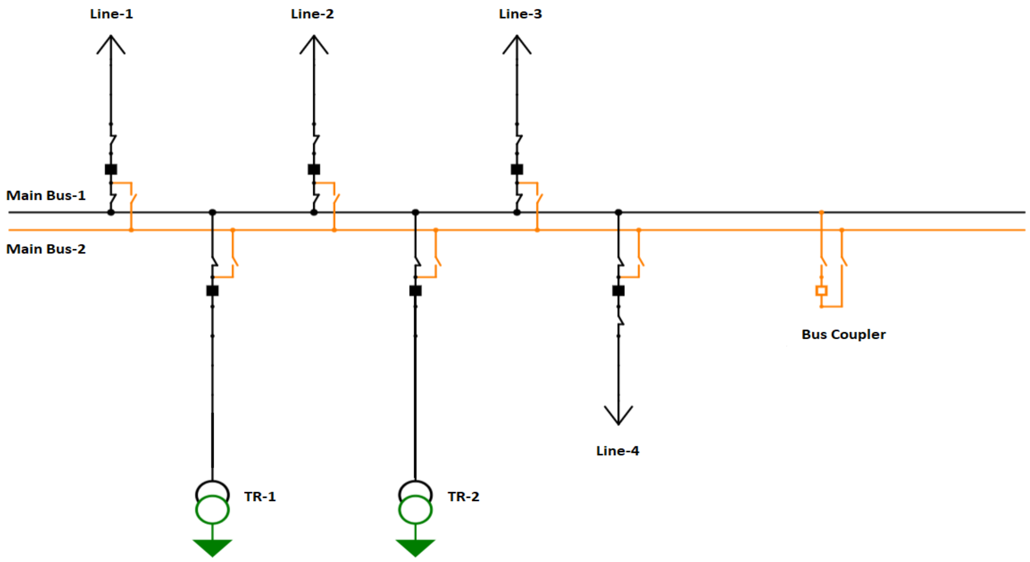

Figure 2.11. A Two Main Buses Configuration Example

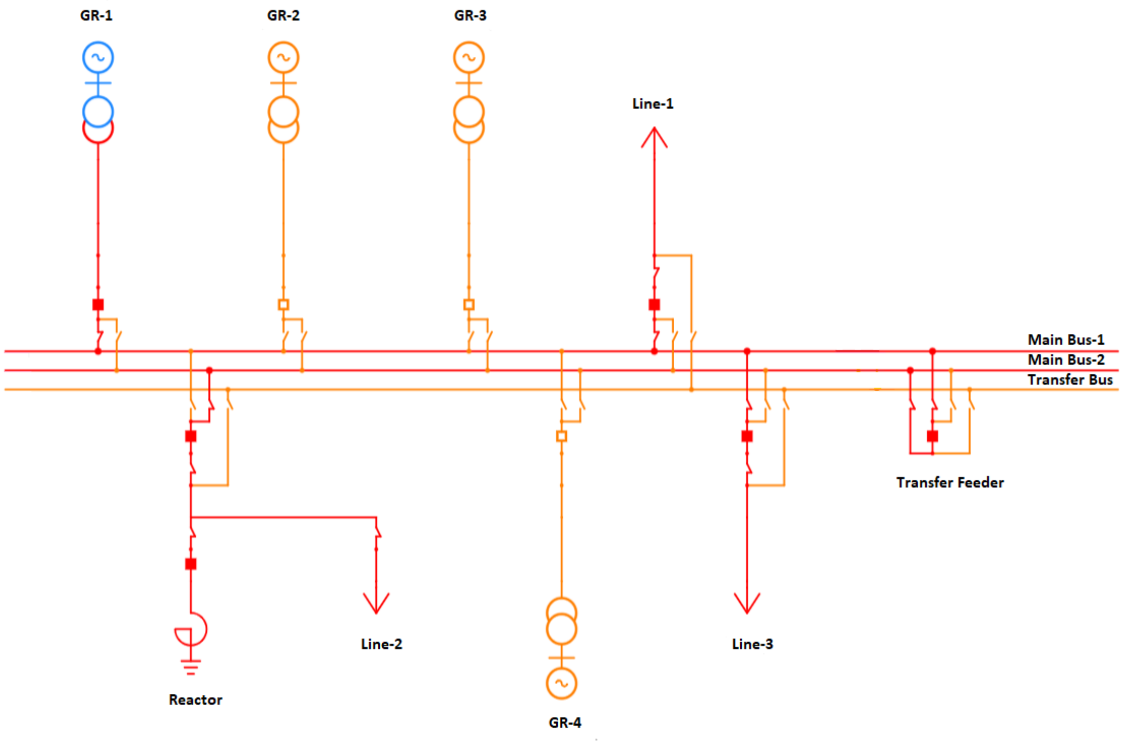

Figure 2.12. A Two Main Buses and a Transfer Bus Configuration Example

2.2 WLS Based State Estimation Algorithm

There are several state estimation methods in the literature such as Weighted Least Squares (WLS) based estimators, LAV (Least Absolute Value) based estimators and Kalman Filter based estimators, etc. In this thesis, the scope of state estimation is limited to the substation level state estimation. Detailed modelling of substation equipment and topology increases the computational burden and this task is more complex than the transmission level state estimation. After a careful survey, it is found that WLS method is the most suitable state estimation method for power substations. WLS method is the most common state estimation solution method in the literature. It is simple to implement and its computational burden is low. Thus, it is a fast method. Moreover, WLS gives unbiased estimates in the presence of Gaussian errors.

Power system measurements can be represented in terms of system states by measurement function, h with certain measurement residual. Weighted Least Squares method is the optimization method which estimates the system states by minimizing the weighted sum of squares of the measurement residuals. This procedure can be expressed as the solution of the below optimization problem for the state vector *x*:

$$\text{minimize} \sum_{i=1}^{m} W_{ii}\, r_i^2 \tag{2.1}$$

$$\text{subject to } z_i = h_i(x) + r_i, \quad i = 1, \dots, m \tag{2.2}$$

where:

z_i : *ith* measurement

x^T : $[x_1, x_2, \dots, x_n]$ is the system state vector

$h(x)$ is the nonlinear measurement function which relates measurement *i* to state vector x

r_i: residual value of measurement *i*

W_{ii}: *ith* diagonal entry of the weighting matrix

m : number of measurements

In the following sections, mathematical basis and implemented assumptions are given for constructing a WLS based state estimator.

2.2.1 Mathematical Basis of WLS Estimators

The relation between the measurement vector, the system state vector and the measurement error vector can be written as shown below.

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \cdot \\ \cdot \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2, \dots, x_n) \\ h_2(x_1, x_2, \dots, x_n) \\ \cdot \\ \cdot \\ h_m(x_1, x_2, \dots, x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \cdot \\ \cdot \\ e_m \end{bmatrix} = h(x) + e \qquad (2.3)$$

where e^T : $[e_1, e_2, \dots, e_n]$ is the measurement error vector

Expected value of measurement errors is assumed to be zero. Moreover, measurement errors are assumed to be independent. These assumptions are shown mathematically as below.

$\mathrm{E}(e_i) = 0 \quad \& \quad \mathrm{E}\left[e_i e_j\right] = 0 \quad i = 1, 2 \dots m$

Thus, $Cov(e) = \mathrm{E}[ee^T] = \mathrm{R} = \{\sigma_1^2, \sigma_2^2, \dots, \sigma_m^2\}$

where:

R: measurement error covariance matrix

The standard deviation σ_i of each measurement i reflects the expected accuracy of the corresponding measurement.

Weighted Least Squares based estimators minimize the objective function below:

$$J(x) = \sum_{i=1}^{m} {(z_i - h_i(x))^2}\Big/{R_{ii}} \tag{2.4}$$

$$J(x) = [z - h(x)]^T [R]^{-1} [z - h(x)] \tag{2.5}$$

The derivative of the objective function, which is denoted by $g(x)$, should be set to zero since the first-order optimality conditions have to be satisfied at the minimum.

$$g(x) = \frac{\partial J(x)}{\partial x} = -H^T R^{-1} [z - h(x)] = 0 \tag{2.6}$$

where $H(x) = \left[\frac{\partial h(x)}{\partial x}\right]$

The matrix, $H(x)$ is the measurement Jacobian matrix. As seen in the above equation, $H(x)$ is calculated based on the derivatives of measurement function with respect to system states.

Firstly, the non-linear function $g(x)$ is expanded to its Taylor series around the state vector x^k.

$$g(x) = g(x^k) + G(x^k)\,(x - x^k) + \cdots = 0$$

Then, neglecting the higher order terms in the above series leads to Gauss-Newton method which is an iterative solution method.

$$g(x) = g(x^k) + G(x^k)\,(x - x^k) = 0$$

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

$$\text{where } k\text{: } iteration\ index$$

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

$$G(x^k) = \frac{\partial g(x^k)}{\partial x} = H^T\,(x^k).R^{-1}.H(x^k) \tag{2.7}$$

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

The gain matrix, $G(x^k)$, is a sparse and symmetric matrix. It is generally a non-negative definite matrix, and positive definite if the system is fully observable. Although the gain matrix is a sparse matrix, its inverse is generally a full matrix. Thus, this matrix is generally not inverted. Instead of inversion process, triangular factorization method is used at each iteration *k*:

$$G(x^k)\Delta x^{k+1} = H^T\,(x^k).R^{-1}.[z - h(x^k)] \tag{2.8}$$

where $\Delta x^{k+1} = x^{k+1} - x^k$. This value represents the change in the state vector between consecutive iterations. The set of equations given by Equation (2.8) is referred as the Normal Equations.

2.2.2 WLS State Estimation Algorithm

WLS state estimation method is an iterative solution method and it utilizes Normal Equations shown in Equation (2.8). The solution procedure starts with an initial guess of the state vector x^0. In this initial guess, bus voltages are assumed to be 1.0 per unit and the bus voltage angles are in phase with each other.

The iterative solution procedure of the WLS state estimation method can be outlined as below [1]:

1. Initiate iterations with the iteration number $k = 0$.

2. Initialize the state vector x^k (flat start).

3. Write the measurements in terms of system states in $h(x)$.

4. Calculate the measurement Jacobian, $H(x)$ by taking derivatives of each measurements with respect to each system states.

5. Calculate the gain matrix, $G(x^k)$.

6. Calculate the right hand side $t^k = H(x^k)R^{-1}(z - h(x^k))$.

7. Solve Normal Equation as given in Equation (2.8) for Δx^k.

8. Test for convergence, max $\{\Delta x^k\} \leq \varepsilon$?

9. If no, update $x^{k+1} = x^k + \Delta x^k$; $k = k+1$ and go to step 3. Else, stop.

Construction of the measurement function $h(x^k)$, the measurement Jacobian matrix $H(x^k)$ and gain matrix $G(x^k)$ will be presented in the explanation section of the Chapter 3 which is about the proposed WLS based substation level state estimation and topology error processing application.

2.3 Bad Data Detection and Identification in WLS

Bad data detection and identification functions are one of the most important tasks of state estimation. Measurements can be erroneous due to different reasons such as limited accuracies of measurement devices, telemetry problems, incorrect wiring of measurement devices, malfunction in devices, etc. Since measurements are main inputs of state estimation, erroneous measurements can lead to large deviations in the estimated system states. If the measurement set is redundant enough, bad data can be detected, and if possible identified and eliminated.

Some bad data in measurement sets can be quite obvious. Negative voltage and current measurements due to incorrect wiring, measurements that are quite smaller or larger than expected values, large differences between incoming and leaving measurements at a connection node are some examples of obvious bad data. Those bad data can be detected and eliminated by pre-processing techniques, in other words, by simple consistency or plausibility checks. On the other hand, not all bad data types are simple to handle. Thus, in addition to simple plausibility checks, more advanced bad data detection and identification functions are accompanied to state estimators.

The structure of bad data detection and identification functions depend on which state estimation method is applied. Since proposed substation level state estimation and topology error processing method is conducted based on WLS based algorithm, bad data detection and identification procedures for WLS method are explained in this section.

Bad data detection and identification functions in the WLS estimation methods are performed after the state estimation process by processing the measurement residuals. Bad data detection and identification functions are fundamentally based on the properties of measurement residuals.

The classification of bad data depends on the type, the location and the number of measurements that are in error. There are two main types of bad data which are single bad data and multiple bad data [1].

1. Single bad data: Only one measurement has gross error in a measurement set.

2. Multiple bad data: More than one measurement has gross error in a measurement set.

Detection of multiple bad data is more difficult compared to detection of single bad data due to appearance of errors in more than one measurement. Depending on whether the residuals of erroneous measurements are correlated and conforming, multiple bad data can be classified into three types.

1. Multiple non-interacting bad data: Measurement residuals of multiple bad data are weakly correlated.

2. Multiple interacting but non-conforming bad data: Measurement residuals of multiple bad data are strongly correlated and their errors are not consistent with each other.

3. Multiple interacting and conforming bad data: Measurement residuals of multiple bad data are strongly correlated and their errors consistent with each other.

The interaction between measurements and analysis of errors can be performed based on sensitivities of measurement residuals to measurement errors. Thus, classification of measurements and also properties of measurement residuals for WLS state estimation method are reviewed below.

2.3.1 Classification of Measurements

Power systems include different kinds of measurements. These measurements will show different properties and affect the outcome of the state estimation accordingly, depending upon not only their values but also their location. Thus, measurements are categorized as below [18]:

Critical measurement: A measurement whose elimination from measurement sets makes system unobservable is called critical measurement. The measurement residual of a critical measurement is always zero. Moreover, the column of the residual covariance matrix Ω, corresponding to a critical measurement is also zero.

Redundant measurement: A measurement which is not critical is called as redundant measurement. Only redundant measurements may have nonzero measurement residuals.

Critical pair: Two redundant measurement whose simultaneous removal from the measurement set make the system unobservable.

Critical k-tuple: It contains k redundant measurements, where removal of all of them make the system unobservable. None of these k measurements belong to a critical tuple of lower order. Those k columns of the residual covariance matrix Ω, corresponding to the elements of this critical k-tuple are linearly dependent.

2.3.2 Bad Data Detection and Identification

Bad data detection refers to determination of whether or not measurement set contains any bad data. Identification refers to the determination of which specific measurements contains bad data. Bad data detection and identification capabilities depend on the configuration of the overall measurement set in a given power system.

Bad data can be detected if removal of the corresponding measurement does not make the system unobservable. In other words, bad data appearing in critical measurements cannot be detected.

A single measurement containing bad data can be detected and identified if and only if:

- it is not critical
- it does not belong to critical pair or critical k-tuple.

2.3.3 Properties of Measurement Residuals

Below equations will be performed based on linearized measurement equations:

$$\Delta z = Hx + e \tag{2.9}$$

where E(e) = 0 and Cov(e) = R, which is a diagonal matrix based on the assumption that measurement errors are not correlated. On the other hand, measurement residuals can be correlated even if the measurement errors are independent.

The estimated state vector is given by the below formula:

$$\begin{aligned} \Delta\hat{x} &= (H^T R^{-1} H)^{-1} H^T R^{-1} \Delta z \\ &= G^{-1} H^T R^{-1} \Delta z \end{aligned} \tag{2.10}$$

and the estimated measurement vector Δz:

$$\Delta\hat{z} = H\hat{x} = K\Delta z \tag{2.11}$$

where K = $HG^{-1}H^T R^{-1}$ and it is called *hat matrix* for putting a hat on Δz.

A rough idea about the measurement redundancy of a meter can be deduced by using K matrix. If a diagonal entry in a row is larger than off diagonal elements in the same row, the corresponding measurement estimate to that raw is mainly estimated by that measurement value. In other words, local redundancy is poor for that measurement point. Measurement residuals and residual sensitivity matrix are found by the help of K matrix; therefore, properties of K matrix are shown below.

$$K.K.K \dots K = K \tag{2.12}$$

$$K.H = H \tag{2.13}$$

$$(I - K)H = 0 \tag{2.14}$$

Now, an expression for measurement residuals can be found.

$$\begin{aligned} r &= \Delta z - \Delta \hat{z} \\ &= (I - K)\Delta z \\ &= (I - K)(H\Delta x + e) \\ &= (I - K)e \\ &= Se \end{aligned} \tag{2.15}$$

S matrix is called residual sensitivity matrix and represents sensitivity of measurement residuals to measurement errors. Measurement residual covariance matrix are calculated using S. Thus, properties of S matrix are given below.

- It is not a symmetric matrix unless the covariance of errors or standard deviation of measurements are same, i.e. $R = kI$, where k is any scalar.
- $S.S.S \dots S = S$
- $SRS^T = SR$

In WLS estimation, measurement errors are assumed distributed in Gaussian distribution as given below:

$$e_i \sim N(0, R_{ii}) \text{ for all } i$$

Using the relation between measurement residuals and measurement errors, the mean, the covariance, and thus the probability distribution of measurement residuals can be found as below:

$$E(r) = E(Se) = S.E(e) = 0 \tag{2.16}$$

$$Cov(r) = \Omega = E(rr^T)$$

$$\Omega = SE(ee^T)S^T$$

$$\Omega = SRS^T \quad where\ \left(R = E(ee^T)\right)$$

$$\Omega = SR \tag{2.17}$$

We get mean and covariance of measurement residuals formulas, hence we can obtain the probability distribution of measurement residuals as shown below.

$$r \sim N(0, \Omega\ )$$

In this section, formulas of measurement residual, sensitivity and covariance matrices of measurement residuals are found. Those formulas and matrices are quite important for detection and identification of bad data in measurement sets.

2.3.4 Bad Data Detection

The first step of bad data detection and identification function is the detection of bad data in measurement sets. Firstly, bad data are detected, then it is identified and eliminated or corrected for obtaining unbiased system states. In this part, bad data detection methods and their mathematical background are reviewed. Chi-squares distribution and normalized residuals are the two mathematical means for detection of bad data.

2.3.4.1 Chi-squares x^2 Distribution

Consider a set of N independent random variables each is distributed in Standard Normal Distribution:

$$X_i \sim N(0,1)$$

Now, a new random variable Y can be defined by:

$$Y = \sum_{i=1}^{N} X_i^2$$

have a x^2 distribution with N degrees of freedom, i.e.

$$Y \sim X_N^2$$

The degrees of freedom represent the number of linearly independent variables in the sum of squares.

The function *f(x),* represented in terms of measurement errors.

$$f(x) = \sum_{i=1}^{m} R_{ii}^{-1} e_i^2 = \sum_{i=1}^{m} (\frac{e_i}{\sqrt{R_{ii}}})^2 = \sum_{i=1}^{m} (e_i^N)^2 \qquad (2.18)$$

e_i is the *ith* measurement error, R_{ii} is variance of the *ith* measurement error and *m* is the number of measurements. If just like X_i, e_i are normally distributed random variables with zero mean and R_{ii} variance, e_i^N will have a Standard Normal Distribution as below.

$$e_i^N \sim N(0,1)$$

Then, just like Y *f(x)* will have a x^2 distribution with at most *(m-n)* degrees of freedom. Since at least *n* measurements have to satisfy the power balance equations in a power system, at most *(m-n)* errors will be linearly independent. Thus, the largest degree of freedom can be *(m-n)* where *m* is the number of measurements and *n* is the number of system states.

2.3.4.2 Use of X^2 Distribution for Bad Data Detection

A x^2 probability density function (p.d.f.) example is shown in Figure 2.13. The area under the curve represents the probability of finding random variable X in a specified region by below formula:

$$P_r\{X \geq x_t\} = \int_{x_t}^{\infty} x^2\,(u).\,du \tag{2.19}$$

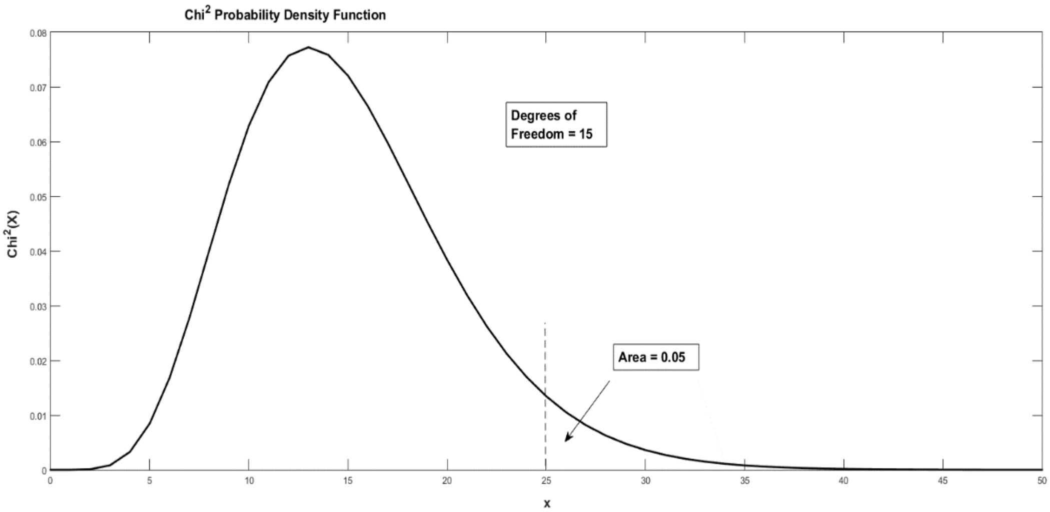

Figure 2.13. x^2 Probability Density Function

This formula represents the probability of X being larger than a specified x_t threshold. As x_t increases, the area between x_t and curve in other words probability of X being larger than threshold x_t decreases. If a probability of error is chosen as 0.05, x_t threshold can be set such that:

$$P_r\{X \geq x_t\} = 0.05$$

For 0.05 probability error, x_t is found as 25 which is shown in the Figure 2.13. In state estimation context, x_t represents the largest acceptable value for X that does not have any bad data. If X value is greater than, x_t with 0.95 probability, X value does not have a x^2distribution in other words X value can be erroneous.

In this thesis, Chi-squares x^2 values for different degrees of freedom are found by Matlab's statistical toolbox.

2.3.4.3 x^2 Test for Detecting Bad Data in WLS State Estimation

The WLS state estimation objective function *J(x)* can be approximated to *f(x)* function given above. After that bad data detection process can be performed by Chi squares test.

Chi squares based bad data detection process is given below:

1. Solve the WLS state estimation problem and calculate $J(\hat{x})$.

$$J(\hat{x}) = \frac{(z_i - h_i(\hat{x}))^2}{\sigma_i^2}$$

where:

$\hat{x}$: estimated state vector.

$h_i(\hat{x})$: estimated measurement i.

z_i : measured value of measurement i.

σ_i^2: R_{ii} : variance of the error in measurement i.

m : number of measurements

2. Calculate the detection confidence probability p (e.g. 95%) for (m-n) degrees of freedom which is represented by $x^2_{(m-n),p}$.

$$p = \mathrm{P_r}(J(\hat{x}) \leq x^2_{(m-n),p})$$

3. If $J(\hat{x}) \geq x^2_{(m-n),p}$, the measurement set can involve bad data. Else, measurement set does not involve bad data.

2.3.4.4 Use of Normalized Residuals for Bad Data Detection

x^2 test is not quite accurate due to the approximation of errors in equation 2.10. In some cases, it could not detect existence of bad data. A more accurate method of bad data detection function utilizes the normalized residuals. Similar to the measurement error, normalized residual value of a measurement can be found by dividing the absolute value of residual to corresponding diagonal entry of residual covariance matrix:

$$r_i^N = \frac{|r_i|}{\sqrt{\Omega_{ii}}} = \frac{|r_i|}{\sqrt{R_{ii}S_{ii}}} \tag{2.20}$$

Now, normalized residual vector have a Standard Normal distribution, i.e.

$$r_i^N \sim N(0,1)$$

Then, largest element r^N in can be compared with a specified threshold for detection of existence of bad data. This threshold can be selected for the desired level of detection accuracy.

2.3.5 Bad Data Identification

Bad data in measurement sets are identified by processing measurement residuals just like bad data detection methods. There are various identification methods in literature such as Largest Normalized Residual (r_{max}^N) Test, Hypothesis Testing Identification (HTI) method, etc. Since in this thesis normalized residuals test is applied, it will be described below.

2.3.5.1 Largest Normalized Residual (r_{max}^N) Test

Largest normalized residual test method identifies the bad data in a measurement set by using properties of normalized residuals. Identification process of a single bad data is shown below. If there is more than one single data in the measurement set, each one can be identified subsequently at a time.

1. Solve the WLS estimation and get the measurement residual vector:

$$r_i = z_i - h_i(\hat{x}), \qquad i = 1, \dots, m$$

2. Then, calculate the normalized residuals with below formula:

$$r_i^N = \frac{|r_i|}{\sqrt{\Omega_{ii}}} \qquad i = 1, \dots, m$$

3. Find largest normalized value r_k^N corresponding to *k-th* measurement.

4. If the largest normalized residual is greater than specified identification threshold ($r_k^N > c$), *k-th* measurement can be erroneous. Else, there is no bad data in the measurement set. In this thesis identification threshold c is set as 3.

5. If *k-th* measurement is erroneous, eliminate the erroneous measurement or remove bad data from that measurement. Then, go to step 1.

2.3.5.2 Removal of the Identified Bad Data

After identification of bad data, erroneous measurement can be extracted from measurement set or it can be corrected. Complete removal of erroneous measurement can damage the redundancy of measurement set. Thus, in this thesis erroneous measurement are corrected by subtracting the estimated error from the erroneous measurement as described below.

Assume that measurement *i* is erroneous and can be represented as below:

$$z_i + e_i = z_i^{bad} \tag{2.21}$$

where z_i is the true measurement value, z_i^{bad} is the erroneous measurement and e_i is the gross error of measurement *i*. Then, by using the linear relation between measurement residuals and measurement errors shown in (2.7), measurement residuals can be approximated as below:

$$z_i^{bad} - h_i(\hat{x}) = r_i^{bad} \approx S_{ii} e_i \tag{2.22}$$

where is $\hat{x}$ the estimated system states computed based on the measurement set which includes erroneous measurement. Thus, only an approximated value can be found for the error e_i.

$$z_i \approx z_i^{bad} - \frac{R_{ii}}{\Omega_{ii}} r_i^{bad}$$

2.4 Topology Error Processing in WLS

Topology processor configures the one-line diagram of the electrical network by utilizing the status data of circuit breakers and disconnecting switches. Topology processors convert detailed node-breaker models to compact and more useful bus-branch models, and this bus-branch model is used by other functions such as state estimation, observability analysis process, load flow studies etc. Moreover, topology processors are responsible for the allocation of analog measurements to the bus-branch model [27].

State estimators give most possible system states by processing available measurements and the system model provided by topology processors. State estimators utilize outputs of topology processors in their calculations and assume that the network topology and parameters are perfectly known. Thus, well-implemented and well-functioning topology processor are quite important in terms of state estimation process. Topology processors constitute network connectivity or network topology incorrectly due to erroneous circuit breaker statuses. As a result, system connectivity and allocation of measurements to system model will contain inconsistencies. Since state estimators utilizes output of topology processor, erroneous CB statuses will distort the output of state estimators in other words system states and state estimators will give incorrect or biased results.

The most of the time of system operation, breaker statuses are correctly known. However, in some rare cases, CB statuses can be erroneous. The reasons for incorrect breaker statuses are manifold such as telemetry problems, operator entry errors, malfunction in devices, mechanical failure of signaling devices etc. Although, occurrence of CB status errors is rare, topology errors severely effect state estimation results. Since EMS functions use the system states as their input, topological errors effect the functioning of all EMS functions poorly. In order to overcome the potential problems arising from erroneous CB statuses, topological errors have to be detected and identified. Topology error processing function perform this task and it is one of the most important tasks of state estimation process.

The structure and the methodology of topology error processing functions depend on which state estimation method is applied. In this thesis substation level state estimation is conducted based on WLS based algorithm, thus just like bad data detection functions topology error processing function is determined conveniently with WLS estimation methodology.

The proposed substation level state estimation application uses breaker oriented model and utilizes circuit breaker statuses at the substation. Based on substation topology and breaker statuses, virtual voltage and virtual current measurements are generated and those measurements also used by state estimation solver. Topology error processor can detect topological errors by utilizing results of largest normalized residuals test function just like bad data processor function and it is performed after the state estimation process by processing the measurement residuals. If there is a topological inconsistency at a substation, the measurement residual value of corresponding virtual measurements, which is related to topological error point, will be larger than other measurements. As a result of normalized test, topological errors at power substations can be detected. Implementation details of topology error processing function are given in the next chapter.

2.5 Chapter Summary and Comments

In this chapter, technical background of this thesis is constituted. Firstly, the importance and functionality of power substations with regard to the power system operation is expressed. Then, local measurement redundancy at substations and importance of utilization of PMUs, which give time synchronized phasor measurements, are examined in terms of their contribution to substation level state estimation applications. In the following parts of this chapter, mathematical fundamentals of the proposed power system state estimation and topology error processing methodology are presented. Firstly, mathematical basis of state estimation solver which is based on WLS method and its solution procedure is given. Then, fundamentals of the bad data detection-identification function in WLS and topology error processing function in WLS are expressed respectively. The implementation details of proposed substation level state estimation and topology error processing method are presented in the next chapter.

CHAPTER 3

SUBSTATION LEVEL STATE ESTIMATION AND TOPOLOGY ERROR PROCESSING

The general introduction and the literature review of the proposed substation level state estimation and topology error processing method is presented in the first chapter. Then, the required technical background for helping the reader to understand the concept is reviewed in the second chapter. In this chapter, the methodology and the implementation details of the proposed substation level state estimation and topology error processing method is explained in detail. Firstly, the substation measurements and the system states which are fundamental inputs and outputs of the substation level state estimation algorithm are stated. Then, the building blocks of the proposed substation level WLS state estimation and topology error processing algorithm and their formulations are presented in their execution order. Topology processor, observability analysis function, state estimation solver, bad data processing function and topology error processing function constitute the building blocks of the proposed substation level state estimation and topology error processing method.

3.1 Introduction

The complexity of electric power systems has increased enormously due to the advent of smart grid concept, the introduction and the continuous growth of renewable energy sources to the power systems. In parallel to the increased complexity, intelligence in power system has also increased too. Most of this intelligence exists at power substations. Thus, most of monitoring, control and protection actions are taken at power substations for reliability and security of power systems. Increased importance of substations in the power systems increases the attention to power substations. For these reasons, control actions taken at substations have more importance in terms of operation of power systems. Just like truly knowing the operating conditions of power systems, accurate knowledge of the measurements and the topology of the substations are quite important for reliable operation of power systems. Thus, we have to accurately know the operating conditions and the topology of power substations.

Measurements collected at substations are transmitted to the transformer stations and to the regional/central control centers. System states are determined by the state estimators exist at control centers based on measurements received from substations and system model. Those system states are given to EMSs and many EMSs functions, which are substantially important for the control of power system operations, are performed based on system states, i.e., indirectly based on substations measurements. Thus, the correctness of substation measurements is quite important both for the operation of substations, and reliable and secure operation of whole power networks. In order to attain accurate substation measurements, a filtration process is quite crucial. There are some consistency checking or plausibility checking methods in the literature for correction of substation measurements. In addition to those methods, state estimation can be applied at substation level for measurement filtration, checking the topology of substation and getting system states at substations correctly. Before going into more details about the substation level estimation, explaining substation configurations, available measurements at substations and topology of substations will provide better understanding to readers.

3.1.1 The Measurements

Substations are the connection points in the electric power systems. Transmission lines and feeders which have different or same voltage levels are connected via busbars through transformers, protection and measurement devices. Generator outputs, loads, busbar voltages and busbar voltage angles, active and reactive power flows on feeders, current magnitudes and current angles on feeders, statuses of switching devices (CBs and DSs), transformer tap values are some of the available measurements at power substations which are measured by voltage transformers, current transformers, power quality analyzer, PMUs, etc. Those measurements are attained through communication channel at power substations and collected by RTUs and IEDs.

Voltages at substations are measured by voltage transformers which are connected to busbars. Current magnitudes, active and reactive power flows on transmission lines or feeders are measured by current transformers on them. Actually, active and reactive power flows are achieved by multiplication of busbar voltages and feeder currents.

In addition to analog measurements, digital measurements in other words statuses of CBs and DSs are also attained at the substation level. By using switching statuses of CBs and DSs, the topology and the connectivity of substations are determined. Those measurements are obtained manually and their refresh rate is slower compared to refresh rates of analog measurements.

Analog measurements at substations can be erroneous due to many reasons which can be malfunction in CTs, VTs and RTUs, incorrect wiring, telemetry failures etc. These erroneous measurements badly effect many functions and control actions both at substations and at upper levels such as distribution and transmission levels, and EMS functions, etc. In addition to analog measurements, statuses of switching devices namely digital measurements are also quite critical for control actions and functions in the power systems. Digital measurements can be incorrect and do not represent the actual system configuration due to slow refresh rate of switching devices and possible problems in the communication channels, etc.

Available measurements at substations are the main input of control actions at power substations. Moreover, they are one of the main inputs of EMS functions through state estimators at control centers. Since the beginning of the first implementations of transmission level state estimation, substation measurements are quite important part of state estimation. Nowadays, power systems are more dynamic with respect to past applications due to increased complexity in the power networks. In the future, applications of smart grid concept and penetrations of renewables in power networks will spread and as a result the complexity of power systems will proceed to increase. Due to complex operation of power systems and bilateral flow of power in power systems, more control actions will be taken at power substations. Thus, there will be more data at substations and control of power substations will be more complex. This complexity and availability of huge amount of data at substations will make substations more prone to occurrence of incorrect analog and digital measurements.

The smart grid concept, the increased penetration of renewable sources to power networks and the advanced communication opportunities in power networks are the main reason and the motivation of substation level smartness and intelligence. All these challenges and potentials presented by modern power systems allow for implementations of substation level state estimation and topology error processing applications for handling bad measurements and incorrect topological data at substation level.

3.1.2 The System States

Busbar voltage magnitudes, feeder current magnitudes, active and reactive power flows on feeders or between different substations are the main analog measurements at substations in SCADA systems. All these measurements are transmitted to the control centers. The state estimator at the control center, which is a transmission level state estimator, especially deal with substation voltages and power flows between substations. Thus, busbar voltage magnitudes and busbar voltage angles are chosen as system states in transmission level state estimators. By using the busbar voltage magnitudes and the busbar voltage angles, transmission system and its variables can be easily described.

At the substation level, busbar magnitudes, active and reactive power flows at high level and low level sides of transformers, current magnitudes of feeders, active and reactive power injections through the feeders are the main analog measurements. Active and reactive power flows between substations at the transmission systems are represented as active and reactive power injections at substation level since only one side of power flows exist at a substation and the other side of power flows exist at another substation. Since state estimation is performed at the substation level, active and reactive power injections at a substation cannot be represented by just the voltage magnitudes and the voltage angles. Thus, the current magnitudes of feeders and the current angles of feeders are also taken as systems states in order to represent active and reactive power injections at substation level. Moreover, the feeders are connected to the busbars via DSs and CBs through more than one branch. In case of a malfunction in a main busbar, the second bus or the transfer bus can feed the circuits connected to that feeder or sometimes two busbars can feed a feeder simultaneously. Two or three busbars having two or three branches feeding a feeder provide more secure and reliable system operation. Since the power can flow through all these branches, current flows on all these branches feeding the same feeder are taken as system states. Moreover, those current magnitude and current angle states will be quite beneficial for topological error detection tasks. In addition to current states, voltage magnitudes and voltage angles of the main and the transfer busbars are also taken as system states similar to the applications of conventional state estimators.

Just like capacitors and reactors, tap changing transformers are amongst voltage control equipment which control reactive power flow in the system by regulating voltages of busbars in the power systems. There are two different kinds of tap changing transformers which are voltage magnitude changer and voltage phase changer. In Turkish Electric System, there are no phase shifting transformers in operation. There is only voltage magnitude tap changer transformers in the system. Traditionally, most of the state estimation algorithms have treated each transformer tap setting as a fixed parameter, even though the real time measurement may be erroneous or non-existent. Since transformer taps are quite important for voltage control or reactive power control at the substations, an assumption which takes transformer taps as a fixed parameter can cause a solution which does not match the actual real time monitoring requirements. Thus, in order to overcome these problems and to improve the overall quality of substation level state estimation process, transformer tap values are also added to the system states.

In Turkish Electric System, installation rate of PMUs are increasing day by day in order to improve the monitoring capabilities, the reliability and the security of the national power network. PMUs provide GPS synchronized real time voltage and current phasor measurements. Therefore, system states are directly measured in a PMU installed substation and this increases the linearity and the speed of the estimation process. In order to use opportunities and measurement data given by PMU devices, proposed state estimation algorithm is designed to handle both PMU and SCADA measurements. Therefore, voltage and current states which were represented in polar form as magnitude and angle values are now represented in rectangular form as real and imaginary parts of voltage and current phasors. These changes facilitate the representation of measurements in terms of system states. Furthermore, by these state changes the linearity of the state estimation method increases and computational burden decreases which also accelerates the estimation process.

After above changes, real part of voltage phasors of busbars, imaginary part of voltage phasors of busbars, real part of current phasors of feeders, imaginary part of current phasors of feeders and transformers tap values constitute the system states. These system states are represented by x vector which is shown below.

$$x^T = [V_r^1 V_r^2 \dots V_r^N V_i^1 V_i^2 \dots V_i^N I_r^1 I_r^2 \dots I_r^M I_i^1 I_i^2 \dots I_i^M a_{mn}^1 a_{mn}^2 \dots a_{mn}^K]$$

V_r^k*:* Real part of voltage phasors of busbar *k*

V_i^k*:* Imaginary part of voltage phasors of busbar *k*

I_r^l*:* Real part of current phasors of feeder bay *l*

I_i^l*:* Imaginary part of current phasors of feeder bay *l*

a_{mn}*:* Transformer tap values of the transformer between node *m* and *n*

N*:* Number of busbars at the substation

M*:* Number of feeder bays connected to measured feeders at the substation

K*:* Number of transformers at the substation

3.2 WLS State Estimation Algorithm at Substation Level

In this thesis WLS state estimation method is selected as substation level state estimation solver due to its prevalence both in the literature and in the practice, the simplicity of implementation and its fastness which is the results of low computational burden. Moreover, measurement sets in power substations have Normal (Gaussian) error distribution and WLS gives unbiased estimates, in the presence of Gaussian errors.

State estimation process generally includes below functions [1].

- Topology processor
- Observability analysis
- State estimation solution
- Bad data processing
- Parameter and structural error processing

Firstly, based on the connectivity data and the statuses of CBs and DSs, the topology of the system is formed in the topology processor function. After that, whether the system is observable or not are determined by the observability analysis function. Observability tells that whether there is a full or partial solution for the entire system. State estimation solution is the core of state estimation process and gives most possible system states as output. The bad data processing function can detect and identify gross errors if there is sufficient measurement redundancy in the measurement sets. Finally, transformer taps, shunt reactor or capacitor parameters and erroneous breaker statuses are estimated by the parameter and structural error processing function if there is sufficient measurement redundancy.

State estimation functions listed above is applied to the substation level WLS state estimator proposed in this thesis. Firstly, the topology of the substation is formed by using the connectivity data and the statuses of CBs and DSs in the topology processor function. Later, the observability of the substation for state estimation process are determined by examining the rank of the Measurement Jacobian Matrix, H. Rank is the number of linearly independent column or row vectors of the matrix. Then, the state estimation solution, here WLS method, is performed at the substation level. Since WLS applications are not robust against the bad data in measurement sets, even a single bad measurement can bias the system estimates. Therefore, the bad data detection-identification tasks are performed after the completion of state estimation process. Finally, whether there is a topology error or not are determined by the properties of measurement residuals like in the bad data processing function. In addition, transformer tap values are also determined by the proposed substation level state estimation and topology error processing algorithm.

In Figure 3.1, the overall structure and the process of the proposed substation level state estimation and topology error processing algorithm is shown. In following sections, details of sub-functions of the proposed method are explained in detail.

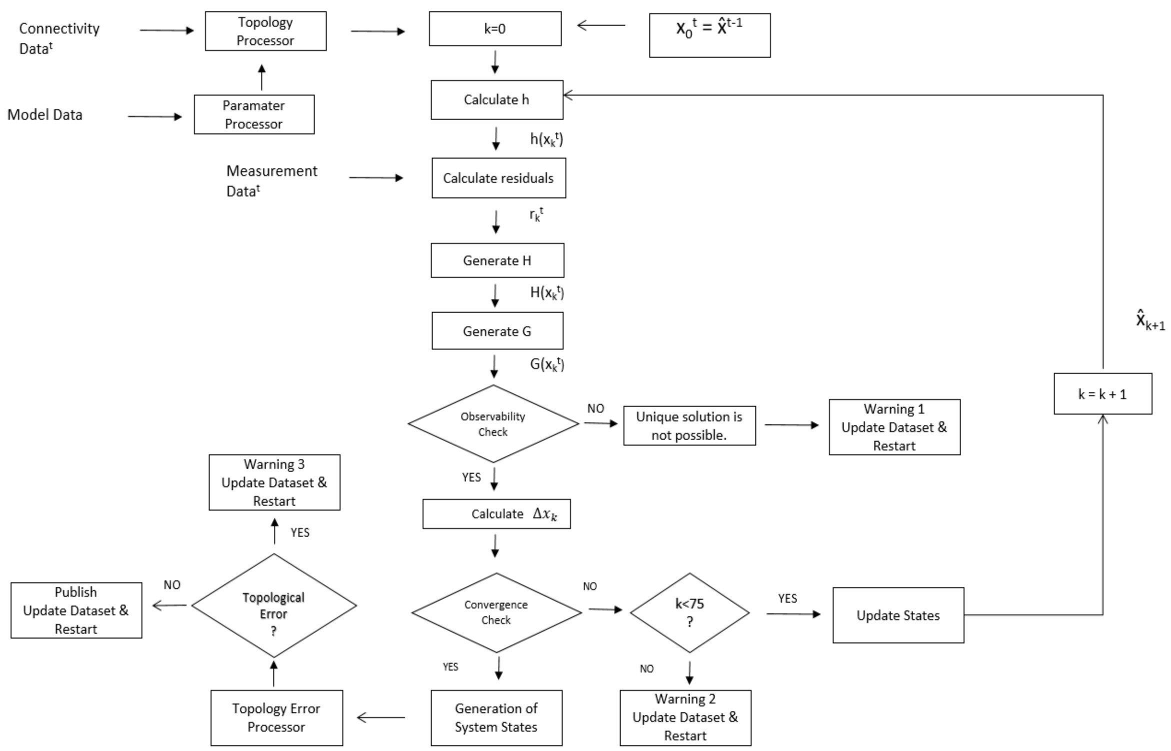

Figure 3.1. Substation Level State Estimation and Topology Error Processing Flow Chart

3.2.1 Topology Processor

There are three data sets which constitute inputs of the substation level state estimator. They are measurement data set, connectivity data set and model data set. The measurement data set includes three phase power measurements and standard deviation values of those measurements. The connectivity data set gives the type of branches, branch statuses and connection nodes of branches. The model data set gives nodes in the substation, their voltage zones and their types. In addition, the model data set includes necessary transformer and reactor data. The topology of a substation is formed by using the connectivity and the model data sets of that substation.

Transmission level state estimation methods use conventional bus-branch model which is generated by the topology processor. On the other hand, substation level state estimators use bus section-switch model, i.e., breaker oriented model, in which CBs are modeled in detail. Since the topology of substations is quite important and crucial for the estimation process, detailed modelling of substations is essential. Active and reactive power flows in a substation follow through busbars-feeder bays-feeders path. Active and reactive flow measurements in other words for substation level active and reactive power injection measurements are achieved by multiplication of current states on that feeder and the busbar voltage states of the busbar which that feeder connects. Thus, nodes at which active and reactive power injection measurements are taken in a substation, feeder bays or feeder branches reaching that nodes and the starting busbar nodes of feeder bays must be connected through a path. The topology processor performs this task and connects the busbar nodes, the feeder bays and the measurement nodes. TP connects measurements to system states by using connectivity data and CB/DS statuses and as a result creates breaker oriented model. The main busbars and the transfer busbars are connected by transfer feeder and coupling feeders. There is no analog measurement in the transfer and coupling feeders. There are only digital measurements (CB and DS statuses) of those feeders. In other words, there is no measurement redundancy for transfer and coupling feeders. CB and DS statuses of transfer and coupling feeders can be erroneous and due to lack of redundancy these errors cannot be detected and identified. In order to deal with this problem, TP generates the connectivity of transfer and coupling feeders separately. By the help of busbar voltage measurements, virtual voltage and current measurements, and created transfer and coupling feeder configurations, errors in transfer and coupling feeders can be detected. The topology error detection process proposed in this thesis will be explained in detail in the topology error processing section of this chapter. In short, TP creates topology of a substation in breaker oriented model by regarding CB statuses and this topology is used by the proposed substation level state estimator as input.

3.2.2 Observability Analysis

Observability analysis function tells that whether the system is fully observable or partial observable. In other words, the observability analysis function states that whether there is a unique solution or not as a result of the estimation process. There are two methods for observability analysis which are numerical observability analysis and topological observability analysis. If the system is unobservable, these methods give unobservable branches and observable islands. These islands have their own reference angles and the state estimation can be performed on these observable islands. Moreover, by measurement placement unobservable systems can be made observable too. Numerical observability analysis methods are suitable for large size power networks and topological observability analysis methods are suitable for small size power networks. Both of these methods are generally applied for transmission level power networks. Since substation level power networks are rather small compared to transmission level power networks and partial observability is not meaningful for substation level state estimation, both of those methods are not applied at substation level. Instead of usage of these methods, observability of a substation is determined by rank of Jacobian matrix, H of that substation. Rank is the number of linearly independent row or independent column vectors in a matrix. For the Jacobian matrix, H, rank is the number of linearly independent row vectors in the H matrix.

In a substation, if the number of system states is n, there should be n independent measurements for observability and for a unique system estimates. If the rank of the H matrix is smaller than the number of system states, the observed system is rank deficient in other words this system is unobservable. If the rank of the H matrix is equal to the number system states, it can be said that this system is an observable system and a unique system estimate can be found for this system. In short, the rank of the H matrix tells that whether the measurement set is redundant enough for the state estimation process. Thus, based on the result of the observability analysis function, it is determined that whether the state estimation can be performed. If the substation is not observable, i.e., rank deficient, state estimation in substation level cannot be performed. If the substation is fully observable, the state estimation at substation level can be performed.

The number of measurements is not directly related with observability. The type and the location of measurements, and the topology of the networks are quite important factors for the observability of power systems. Rather than the number of measurements, the number of linearly independent measurements are the determining metrics of the observability analysis function. The independency of the measurements is related with their type, location and topology of the power networks.

3.2.3 State Estimation Solution

State estimation solution determines most possible and accurate system states based on the system topology and the available measurements of the analyzed system. Moreover, the system measurements can be calculated and represented more precisely with obtained more accurate system states.

3.2.3.1 The Measurement Function, $h(x_k)$

Measurements can be of a variety of types. Most commonly used measurements are active and reactive line flows, bus power injections, bus voltage magnitudes and line current flow magnitudes. Since in this thesis, state estimation is performed at substation level, only the measurements in a single substation are used as a measurement set. In Turkish Electric System, most of the available measurements in the system are SCADA measurements and the implementation of PMUs as measurement units is still quite limited. However, the implementation of PMUs to the power substations is increasing gradually for better monitoring of the power substations and Turkish Electric System as a whole. Thus, the implemented substation level state estimator is designed to handle both SCADA only and SCADA/PMU measurements. For these reasons, in addition to SCADA measurements, PMU measurements are also involved in the used measurement data set. After the inclusion of PMU data set to SCADA based measurement data set, measurement data set consists of below listed measurements.

$|V|$: Busbar voltage magnitudes

θ : Busbar voltage phase angles

$|I|$: Feeder current magnitudes

δ : Feeder current phase angles

P_i : Three-phase active power injection measurements

Q_i : Three-phase reactive power injection measurements

P_{ij} : Three-phase active power flows through transformers in the substation

Q_{ij} : Three-phase reactive power flows through transformers in the substation

SCADA measurements do not involve the voltage angle measurements of busbars and the current angle measurements of feeders. Since PMU devices take the voltage and the current phasor measurements, the busbar voltage phase angle and the feeder current phase angle measurements are found in the PMU installed substations. Inclusion of those angle measurements to the measurement data set improves the substation level accuracy and redundancy enormously.

All these SCADA and PMU measurements can be expressed in terms of the state variables either using the rectangular or the polar coordinates.

The expressions for each of above types of measurements are given below.

- Real and imaginary parts of voltage phasor measurements at bus *m*:

$$V_r^m = V_r^k$$

$$V_i^m = V_i^k$$

- Real and active power injection at feeder *i*:

$$P_i = \sum_{k=1}^{t} (V_r^k * I_r^k + V_i^k * I_i^k) * S^k$$

$$Q_i = \sum_{k=1}^{t} (V_i^k * I_r^k - V_r^k * I_i^k) * S^k$$

where t is the number of branches feeding a feeder and S^k is the status of *kth* branch feeding the feeder.

- Real and active power flows through a transformer/transformers which is/are between bus *m* and bus *n*:

$$P_{flow} = \sum_{j=1}^{t} (V_i^m * V_r^n - V_r^m * V_i^n) * \frac{b}{x * c * a_{mn}}$$

$$Q_{flow} = \sum_{j=1}^{t} ((V_r^m)^2 + (V_i^m)^2) * \frac{b^2}{x * {a_{mn}}^2 * c^2} - (V_i^m * V_i^n + V_r^m * V_r^n) * \frac{b}{x * a_{mn} * c}$$

where:

t: the number of transformers between *mth* and *nth* nodes

x: per unit impedance value of the transformer which is between *mth* and *nth* nodes

b: low voltage side rated voltage value of transformer / low voltage side zone voltage

c: high voltage side rated voltage value of transformer / high voltage side zone voltage

V_r^k*:* Real part of voltage phasors of busbar *k*

V_i^k*:* Imaginary part of voltage phasors of busbar *k*

I_r^l: Real part of current phasors of feeder bay *l*

I_i^l: Imaginary part of current phasors of feeder bay *l*

a_{mn}: Transformer tap values of the transformer between node *m* and *n*

Above types of measurements are fundamental parts of the measurement function, *h* of the state estimation process. Since the substation level state estimation is based on the breaker-oriented model, utilization of breaker statuses for the state estimation procedure will improve capabilities of the substation level state estimator and the accuracy of system estimates. The measurements which are generated based on the statuses of breakers are called virtual measurements. There will be both current and voltage virtual measurement placements which will be explained in detail in below sections. In addition to breaker status related virtual measurements, by utilizing the KCL formula there will be KCL related measurement placement as well.

Before expressing the virtual current and voltage measurements, examining a small piece of a substation will be quite explanatory. The configuration and the detail of virtual measurements are shown below.

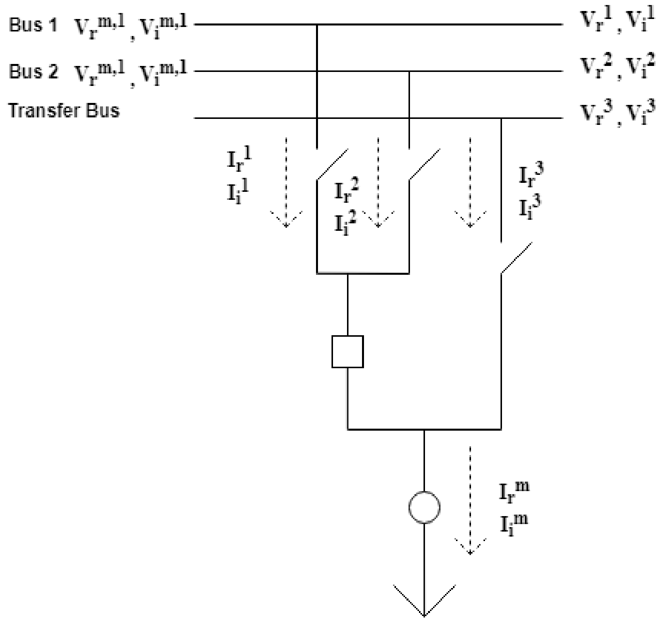

Figure 3.2. Current and Voltage States in a Substation

As shown in Figure 3.2, the current measurements at a substation are measured on the feeders through the current transformers. Moreover, there is no measurement on any feeder bays or branches that leaves buses and reaches feeders. Furthermore, the voltage measurements in a substation are measured by the voltage transformers located on the buses at the substation. In addition to the analog current and voltage measurements at a substation, the digital measurements (breaker statuses) are also available at the substation level.

- Virtual voltage measurements in feeder bays:

If there is a short circuit between the feeder bays in other words more than one disconnecting switches leaving buses are closed, the real and imaginary virtual voltage measurements for the buses of the closed feeder bays are generated. If there is a short circuit path between *mth* and *nth* buses, then the real and imaginary virtual voltage measurements added to the measurement function, *h* as shown below:

$$0 = V_r^m - V_r^n$$

$$0 = V_i^m - V_i^n$$

As shown in Figure 3.2, more than one feeder bays feed a feeder. Although there are no analog measurements on the feeder bays, the breaker statuses of feeder bays are known. Thus, those breaker statuses can be utilized by taking currents passing through branches on those feeder bays as system states. This assumption will improve the redundancy of power substations. Moreover, these virtual current measurements will help the detection of topological errors at the substations. Formulation and structure of generated real and imaginary virtual current measurements are shown below:

- Virtual current measurements in feeder bays:

$$I_r^m = \sum_{k=1}^{n} I_r^k * S^k$$

$$I_i^m = \sum_{k=1}^{n} I_i^k * S^k$$

$$\frac{I_r^m}{t} * S^k = I_r^k$$

$$\frac{I_i^m}{t} * S^k = I_i^k$$

where *n* is the number of branches feeding a feeder, t is the number of closed feeder bays and S^k is the status of *kth* branch feeding a feeder.

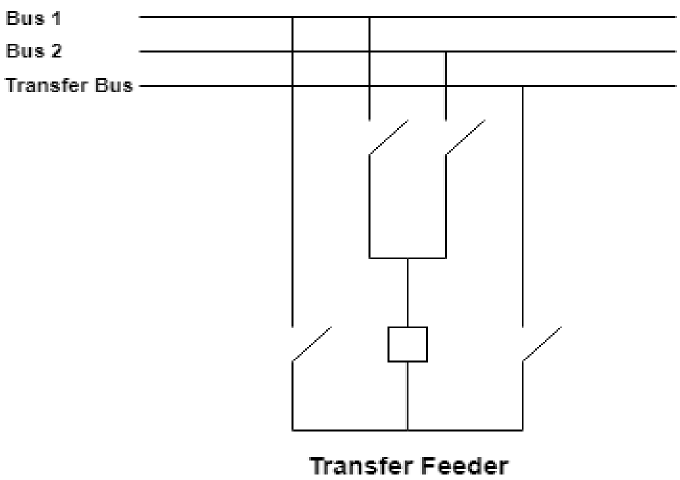

Figure 3.3. A Transfer Feeder Configuration in a Substation

In Figure 3.3, a transfer feeder configuration is shown as an example. Different buses at a substation are physically and electrically connected through transfer feeders and bus couplers. Like on feeder bays, there are no voltage and current measurements on transfer feeders and bus couplers. However, the statuses of breakers inside transfer feeders and bus couplers are available. Thus, by utilizing them we can add new virtual voltage measurements to the measurement function, *h*. The virtual voltage addition process is similar to the addition of virtual voltage measurements on feeder bays. If some of the buses are connected in transfer feeders or in bus couplers, a short circuit path is formed between those connected buses. Thus, voltage equality relations are generated both for real and imaginary parts of those buses as shown below.

- Virtual voltage measurements in transfer buses and bus couplers:

$$0 = V_r^m - V_r^n$$

$$0 = V_i^m - V_i^n$$

Kirchhoff's Current Law (KCL) states that the algebraic sum of the currents in a node in a network is zero. If there are current measurements on all feeders connected to the buses of the same voltage level, KCL formula can be utilized and based on this formula a real current measurement and an imaginary current measurement can be added to measurement function, *h* as shown below.

- KCL current measurement equations:

$$0 = \sum_{k=1}^{n} I_r^k$$

$$0 = \sum_{k=1}^{n} I_i^k$$

where n represents the number of feeders bays which are connected between measured feeders and buses having the same voltage level.

3.2.3.2 The Measurement Jacobian, *H*

The structure of the measurement Jacobian *H* will be as below:

$$H = \begin{bmatrix} \frac{\partial V_r}{\partial V_r} & 0 & 0 & 0 & 0 \\ 0 & \frac{\partial V_i}{\partial V_i} & 0 & 0 & 0 \\ 0 & 0 & \frac{\partial I_r}{\partial I_r} & 0 & 0 \\ 0 & 0 & 0 & \frac{\partial I_i}{\partial I_i} & 0 \\ \frac{\partial P_i}{\partial V_r} & \frac{\partial P_i}{\partial V_i} & \frac{\partial P_i}{\partial I_r} & \frac{\partial P_i}{\partial I_i} & 0 \\ \frac{\partial Q_i}{\partial V_r} & \frac{\partial Q_i}{\partial V_i} & \frac{\partial Q_i}{\partial I_r} & \frac{\partial Q_i}{\partial I_i} & 0 \\ \frac{\partial P_{flow}}{\partial V_r} & \frac{\partial P_{flow}}{\partial V_i} & 0 & 0 & \frac{\partial P_{flow}}{\partial a_{mn}} \\ \frac{\partial Q_{flow}}{\partial V_r} & \frac{\partial Q_{flow}}{\partial V_i} & 0 & 0 & \frac{\partial Q_{flow}}{\partial a_{mn}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \left.\vphantom{\begin{matrix} . \\ . \\ . \\ . \end{matrix}}\right\} \textbf{Virtual Measurements related elements}$$

The expressions for each partition are given below:

- Elements corresponding real part of bus voltage phasor measurements:

$$\frac{\partial V_r}{\partial V_r} = 1, \frac{\partial V_r}{\partial V_i} = 0, \frac{\partial V_r}{\partial I_r} = 0, \frac{\partial V_r}{\partial I_i} = 0, \frac{\partial V_r}{\partial a_{mn}} = 0$$

- Elements corresponding imaginary part of bus voltage phasor measurements:

$$\frac{\partial V_i}{\partial V_r} = 0, \frac{\partial V_i}{\partial V_i} = 1, \frac{\partial V_i}{\partial I_r} = 0, \frac{\partial V_i}{\partial I_i} = 0, \frac{\partial V_i}{\partial a_{mn}} = 0$$

- Elements corresponding real part of feeder current phasor measurements:

$$\frac{\partial I_r}{\partial V_r} = 0, \frac{\partial I_r}{\partial V_i} = 0, \frac{\partial I_r}{\partial I_r} = 1, \frac{\partial I_r}{\partial I_i} = 0, \frac{\partial I_r}{\partial a_{mn}} = 0$$

- Elements corresponding imaginary part of feeder current phasor measurements:

$$\frac{\partial I_i}{\partial V_r} = 0, \frac{\partial I_i}{\partial V_i} = 0, \frac{\partial I_i}{\partial I_r} = 0, \frac{\partial I_i}{\partial I_i} = 1, \frac{\partial I_i}{\partial a_{mn}} = 0$$

- Elements corresponding to active power injection at feeder *i*:

$$\frac{\partial P_i}{\partial V_r} = \sum_{k=1}^{t} I_r^k, \frac{\partial P_i}{\partial V_i} = \sum_{k=1}^{t} I_i^k, \frac{\partial P_i}{\partial I_r} = \sum_{k=1}^{t} V_r^k, \frac{\partial P_i}{\partial I_i} = \sum_{k=1}^{t} V_i^k, \frac{\partial P_i}{\partial a_{mn}} = 0$$

- Elements corresponding to reactive power injection at feeder *i*:

$$\frac{\partial Q_i}{\partial V_r} = \sum_{k=1}^{t} -I_i^k, \frac{\partial Q_i}{\partial V_i} = \sum_{k=1}^{t} I_r^k, \frac{\partial Q_i}{\partial I_r} = \sum_{k=1}^{t} V_i^k, \frac{\partial Q_i}{\partial I_i} = \sum_{k=1}^{t} -V_r^k, \frac{\partial Q_i}{\partial a_{mn}} = 0$$

where t is the number of feeder bays or branches that feeds the feeder i.

- Elements corresponding to active power flow through transformers:

$$\frac{\partial P_{flow}}{\partial V_r^m} = \sum_{k=1}^{t} (-V_i^n) * \frac{b}{x * c * a_{mn}}, \frac{\partial P_{flow}}{\partial V_i^m} = \sum_{k=1}^{t} (V_r^n) * \frac{b}{x * c * a_{mn}}$$

$$\frac{\partial P_{flow}}{\partial V_r^n} = \sum_{k=1}^{t} (V_i^m) * \frac{b}{x * c * a_{mn}}, \frac{\partial P_{flow}}{\partial V_i^n} = \sum_{k=1}^{t} (-V_r^m) * \frac{b}{x * c * a_{mn}}$$

$$\frac{\partial P_{flow}}{\partial I_r} = 0, \frac{\partial P_{flow}}{\partial I_i} = 0, \frac{\partial P_{flow}}{\partial a_{mn}} = \sum_{k=1}^{t} (V_i^m * V_r^n - V_r^m * V_i^n) * \frac{b}{x * c * a_{mn}}$$

- Elements corresponding to reactive power flow through transformers:

$$\frac{\partial Q_{flow}}{\partial V_r^m} = \sum_{k=1}^{t} 2V_r^m * \frac{b^2}{x * a_{mn}{}^2 * c^2} - V_r^n * \frac{b}{x * a_{mn} * c}$$

$$\frac{\partial Q_{flow}}{\partial V_i^m} = \sum_{k=1}^{t} 2V_i^m * \frac{b^2}{x * a_{mn}{}^2 * c^2} - V_i^n * \frac{b}{x * a_{mn} * c}$$

$$\frac{\partial Q_{flow}}{\partial V_r^n} = \sum_{k=1}^{t} - V_r^m * \frac{b}{x * a_{mn} * c}, \frac{\partial Q_{flow}}{\partial V_i^n} = \sum_{k=1}^{t} -V_i^m * \frac{b}{x * a_{mn} * c}$$

$$\frac{\partial Q_{flow}}{\partial I_r} = 0, \frac{\partial Q_{flow}}{\partial I_i} = 0, \frac{\partial Q_{flow}}{\partial a_{mn}} = \sum_{k=1}^{t} (V_i^m * V_i^n + V_r^m * V_r^n) * \frac{1}{(a_{mn}{}^k)^2}$$

where t is the number of transformers between *mth* and *nth* nodes.

- Elements corresponding virtual voltage measurements in feeder bays:

Instead of derivative of the virtual measurements, elements correspond to the virtual voltage measurements in the feeder bays and their corresponding matrix form will be shown by an example. In here, it is assumed that there is a short circuit path between the first and the second buses. Thus, real and imaginary voltages of that buses should be equal. Below matrices, show us this relationship in *H* matrix.

$$0 = \begin{bmatrix} 1 & -1 & 0 \end{bmatrix} * \begin{bmatrix} V_r^1 \\ V_r^2 \\ V_r^T \end{bmatrix}$$

$$0 = \begin{bmatrix} 1 & -1 & 0 \end{bmatrix} * \begin{bmatrix} V_i^1 \\ V_i^2 \\ V_i^T \end{bmatrix}$$

- Elements corresponding virtual current measurements in feeder bays:

Instead of derivative of virtual measurements, elements correspond to the virtual current measurements in the feeder bays and their corresponding matrix form will be shown by an example. As shown in Figure 3.2, more than one feeder bays feed a feeder. Hence, the sum of the real and the imaginary branch currents, which are taken as system states, should be equal to the real and the imaginary current measurements on that feeder. Moreover, the real and the imaginary parts of the feeder bay currents are taken as system states for improving the redundancy by utilizing the breaker statuses of those branches. Then, for the detection of topological errors, the virtual real and the imaginary current measurements are added to the measurement function, *h* for corresponding current system states. This relationship applied in *H* matrix is shown in the below matrices.

$$\begin{bmatrix} I_r^m \\ I_r^1 \\ I_r^2 \\ I_r^3 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} I_r^1 \\ I_r^2 \\ I_r^3 \end{bmatrix}$$

$$\begin{bmatrix} I_i^m \\ I_i^1 \\ I_i^2 \\ I_i^3 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} I_i^1 \\ I_i^2 \\ I_i^3 \end{bmatrix}$$

- Elements corresponding the virtual voltage measurements in transfer buses and in bus couplers:

Instead of derivative of virtual measurements, elements correspond to the virtual voltage measurements in transfer buses or bus couplers and their corresponding matrix form will be shown by an example. In here, it is assumed that there is a short circuit path between first bus and transfer bus. Thus, the real and the imaginary parts of the first bus and the transfer bus should be equal. This relationship applied in *H* matrix is shown in the below matrices.

$$0 = [1 \quad 0 \quad -1] * \begin{bmatrix} V_r^1 \\ V_r^2 \\ V_r^T \end{bmatrix}$$

$$0 = [1 \quad 0 \quad -1] * \begin{bmatrix} V_r^1 \\ V_r^2 \\ V_r^T \end{bmatrix}$$

- Elements corresponding KCL current measurement equations:

$$0 = [1 \quad \cdots \quad 1] * \begin{bmatrix} I_r^1 \\ \vdots \\ I_r^n \end{bmatrix}$$

$$0 = [1 \quad \cdots \quad 1] * \begin{bmatrix} I_i^1 \\ \vdots \\ I_i^n \end{bmatrix}$$

3.2.3.3 The Gain Matrix, G

The gain matrix is constructed using the measurement Jacobian H and the measurement error covariance matrix R. The measurement error covariance matrix R is assumed to be diagonal and its diagonal entries consist of measurement variances. Gain matrix is formed as a result of the below formula:

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

Gain matrix has following properties:

1. It is structurally and numerically symmetric.

2. It is sparse, yet less sparse compared to H.

3. It is generally a non-negative definite matrix and it is positive definite if the network is fully observable.

3.2.3.4 Solution of Normal Equations

The proposed state estimation solution methodology traces an iterative solution procedure due to the nonlinearity of transformers at the substations. Firstly, the iteration number is set as $k = 0$. Then, the state vector x^k is initialized with flat start. The real part of voltage and current states, and the transformer taps are initialized as 1. The imaginary part of voltage and current states are initialized as zero.

$V_r^T = [1 \quad \cdots \quad 1]_k$ *k*: number of busbars at a substation

$V_i^T = [0 \quad \cdots \quad 0]_k$

$I_r^T = [1 \quad \cdots \quad 1]_l$ *l*: number of feeder bays connected to measured feeders at a substation

$I_i^T = [0 \quad \cdots \quad 0]_l$

$a_{mn}^T = [1 \quad \cdots \quad 1]_t$ *t*: number of transformers at a substation

Measurements are expressed in terms of the system states by applying the formulas of each type of measurements stated in the measurement function, $h(x)$. Later, the measurement Jacobian, $H(x)$ is calculated by taking the derivatives of each measurements with respect to each system states. Then, the gain matrix is calculated based on the measurement Jacobian, $H(x)$ matrix and the measurement error covariance matrix, R. Now, every matrix is ready for the solution of the Normal Equations which is shown below once again for better understanding.

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

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

Solution of Normal Equations give the changes in the system states as output. Then, convergence of the change in system states are compared with the specified accuracy limit. If the convergence is reached, the state estimation solver part of the proposed algorithm stops and then the system estimates enter into bad data processing function. If the convergence is not reached, system states are updated and new iteration process starts from the calculation of measurement function, $h(x)$ and goes on as stated above.

3.2.4 Bad Data Processing

WLS based state estimators are vulnerable to the bad data exists in measurement sets. Thus, bad data processing functions of WLS based state estimators start after the completion of the state estimation procedure. Applied bad data processing function can detect and identify bad data in measurement sets if there is sufficient measurement redundancy in measurement sets. The methodology of the proposed bad data processor is shown in Figure 3.4.

Firstly, the system estimates are attained from the state estimation solution function. The estimated system states are processed firstly for the determination of existence of bad data in measurement sets through Chi Squares Test. Before performing this test, Chi Squares Test threshold value is calculated by chi2inv function of Matlab program. This Matlab function determines the threshold based on the desired accuracy level (0.95 in this application) and the differences between the number of measurements and the number of system states which is called degrees of freedom. In addition to the specified threshold, the objective function value of the system is calculated with the latest system estimates. If the objective function value is smaller than the specified threshold, then it is concluded that there is no bad data in the measurement set. If the objective function is greater than specified threshold, it is said that the measurement set may contain bad data. Since Chi Squares test is based on assumptions, it may fail to detect the bad data for certain cases. Thus, largest normalized residual test, which is a more accurate method, is also applied for the detection of bad data. If r_k^N is greater than chosen identification factor c (3 in this application), it is said that there is bad data in the measurement set. If r_k^N is smaller than chosen identification factor c, it is e said that there is no bad data in the measurement set. Furthermore, the bad data in the measurement set can be identified with that method by finding the index of the largest normalized residuals which is greater than identification factor, c. After the identification of bad data, the erroneous measurement can be corrected by subtracting the estimated error from the erroneous measurement or the erroneous measurement can be removed from the measurement set. After the removal of the bad data or correction of the erroneous measurement, WLS based state estimation procedure is started again and the estimation procedure is carried out with the corrected measurement data set.

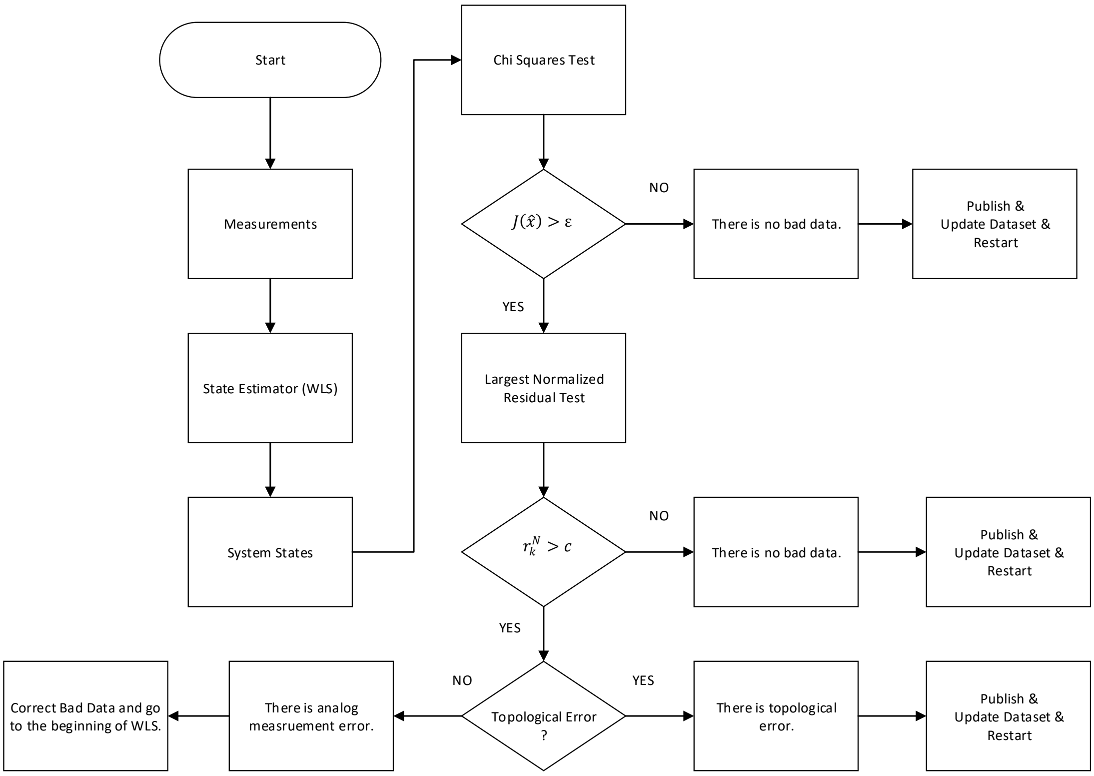

Figure 3.4. Flow Chart of the Bad Data Processor

3.2.5 Topology Error Processing

Topology processors constitute the one-line diagram of electrical networks based on the connectivity data and the circuit breaker statuses, and the generated network topology is used by state estimators as input. The occurrence of erroneous breaker statuses is rare and most of the time the breaker statuses are known correctly. However, in the presence of the circuit breakers having incorrect status data, topology processors will generate locally incorrect network topology and these topological errors cause the state estimate to be biased significantly. Thus, there is a need to develop effective methods intended to detect and identify the topological errors. Topology error processing functions perform these tasks [1].

In this thesis, substation level state estimation algorithm is proposed based on WLS estimation methodology. Since WLS based state estimators are vulnerable to both the topological errors and the bad data in analog measurement sets, topology error processing functions in WLS based state estimators start after the completion of the state estimation procedure just like the bad data processing functions in WLS based estimators.

Conventional SCADA measurements, synchrophasor PMU measurements and digital measurements (CB and disconnecting switch statuses) are all available at the substation level. By utilization of time synchronized PMU measurements, state estimation can be performed solely at substation level. Substation level state estimators can perform state estimation process by using more detailed substation models unlike centralized state estimators which utilize bus-branch model and can experience computational difficulties while implementing more detailed substation models. For complete utilization of substation level smartness and abundant measurement sets, the proposed substation level state estimation application uses breaker oriented substation model. In that node-breaker oriented model CB statuses are also utilized.

In this thesis, instead of using another topology error processing method, the results of the state estimation are used for the topology error processing task. The largest normalized residual test (r^N) which is used for the detection and identification of analog bad data is also utilized for the detection of topological errors. Thus, the digital measurements in other words CB statuses have to be utilized in the state estimation solver and measurements based on CB statuses have to be inserted into the measurement function (h) and the measurement Jacobian matrix (H). In order to perform this task, CB statuses and the connectivity based virtual measurements are formed. Four type of virtual measurements are created based on the substation configuration.

1. Virtual voltage measurements in feeder bays

2. Virtual current measurements in feeder bays

3. Virtual voltage measurements in transfer buses and bus couplers

4. KCL current measurement equations

Busbar voltage magnitudes and busbar voltage angles are the fundamental system states in state estimation applications. For the representation of active and reactive power measurements in terms of system states and for the utilization of CB statuses in the proposed substation level state estimation and topology error processing algorithm, current magnitude and current angle values on feeder bays feeding the same feeder are taken as system states. The second and the fourth virtual measurements listed above utilize CB statuses and form the virtual measurements related to the current magnitudes and the current angles. The first and the third virtual measurements listed above utilize CB statuses and form the virtual measurements related to the voltage magnitudes and the voltage angles.

In short, before the execution of topology error processing function based on the substation topology and breaker statuses, the virtual voltage and virtual current measurements are generated and then added to the measurement function, *h* and to the measurement Jacobian, *H*. Thus, the redundancy of the power substations is improved with this process. The indexes of the virtual measurements are stored separately for the detection of topological error. After the implementation of the virtual measurements in the state estimation solver and later on the execution of state estimation process, topology error processing function can be performed.

In this thesis, the topology error processing is performed by the utilization of largest normalized residual test. Thus, the topology error processing task is actually a part of the bad data processing function. Firstly, the virtual and the analog measurements are processed in the state estimation solver, then the system estimates are attained based on the measurements. Later, measurement residuals and the objective function (J) are calculated after the completion of the state estimation process. After that, the bad data processing function is started. Just like the analog measurements, the virtual measurements which are generated based on the CB statuses are processed in the bad data processing function. Firstly, the virtual and the analog measurements are processed in the Chi Squares Test for detection of the bad data. Later, all measurement set is processed by using the Largest Normalized Residual Test which is a more accurate test for the detection of bad data. If residuals of any measurement whether virtual or analog measurement are greater than identification factor c (3 in this application), it is said that there is bad data in the measurement set. Indexes of the analog measurements and the virtual measurements are kept separately for the differentiation of the bad data in the analog measurement sets and the topological errors. After the detection of the bad data in the complete measurement set, the index of the measurement which has the highest normalized residual value are checked for the determination of whether there is a bad data in the analog measurements or there is a CB status error in other words there is a topological error.

In brief, the topology error processor can detect topological errors by utilizing the results of the largest normalized residuals test function inside the bad data processor function. If there is a topological inconsistency at a substation, the measurement residual value of the corresponding virtual measurements will be larger than the other measurements. Since in this case, the index of the bad data amongst the indexes of virtual measurements, the algorithm states that there is a topology error in the system. Although the method can find that in which feeder there is a topological error, the exact location of topological error in other words openness/closeness information of which feeder bay is erroneous cannot be determined since virtual measurements on feeder bays behave similar to k-tuple critical measurements. Similar to k-tuple critical measurements, the detection of topological errors for virtual measurements is possible but the identification of topological errors for virtual measurements is not possible at substation level.

3.3 Chapter Summary and Comments

The details of the proposed WLS based substation level state estimation and topology error processing method is given in this chapter. Firstly, the importance and the necessity of substation level state estimators and topology error processors are reviewed briefly. Later, substation measurements and system states, which are the primary inputs and outputs of a state esimator, are stated. After that, the methodology of the applied WLS based substation level state estimation and topology error processing method is explained in detail. Topology processor, observability analyzer, state estimation solver, bad data detection-identification function and topology error processing function are the sub functions of the proposed method. In this chapter, formulas and details of sub functions of the proposed substation level state estimator and topology error processor are stated as well.

The proposed algorithm can perform the substation level state estimation task, the bad data detection and identification tasks, and the topology error detection task successfully. However, the algorithm cannot perform the topology error identification task exactly. The exact location of topological errors in other words erroneous circuit breaker statuses cannot be identified since virtual current and voltage measurements on normal feeder bays and transfer buses, bus couplers constitute a structure similar to the k-tuple critical measurements. Thus, although with the proposed method the topological inconsistencies can be detected and even in which feeder there is a topological inconsistency present can be stated, the identification of the exact location of topological errors is not possible similar to k-tuple critical measurements.

CHAPTER 4

NUMERICAL VALIDATION

In this chapter, performed simulations and their results are examined in terms of the proper functionality of the proposed method and the convenience of results to the determined performance metrics and the success criterion. For these reasons, substation level state estimation and topology error processing method was applied for various substation scenarios for different test cases. Two main substation test scenarios are formed which are called Large Scale Substation Scenario and Small Scale Substation Scenario. The generated test cases are implemented to these substation scenarios. The requirements and the design of the proposed algorithm are verified through results of test cases.

4.1 Simulation Scenarios

In the study of the algorithm, two main substation scenarios are generated for the test of events with general and special cases. They are called large scale substation scenario and small scale substation scenario. These scenarios are formed for the testing of performance and the functionality analysis of the proposed substation level state estimation and topology error processing method. The scenarios are based on a real substation configuration exists in Turkish Electric System which is one of the biggest substations in Turkish Electric System.

The single line diagram of the base substation in Turkish Electric System is shown in Figure 4.1. As seen in the figure, this substation is a big transmission level substation. It contains busbars having three different voltage levels which are 380 kV, 154 kV and 33 kV. Thus, there are autotransformers and transformers at the substation, and by modelling this equipment transformer tap values are estimated. Moreover, there are three busbars at 380 kV and 154 kV voltage levels, the first and second busbars are main busbars, and the third busbars at both levels are transfer busbars. Furthermore, there are transfer feeders which connect main busbars and transfer busbars at 380 kV and 154 kV voltage levels. By utilization of transfer feeders, the redundancy at substation level has increased and their models are used for bad data analysis and topology error processing tasks. As seen in the figure, current feeders are connected to all three busbars at 380 kV and 154 kV voltage levels through circuit breakers and disconnecting switches. All these branches connecting current feeders to busbars and statuses of CBs and DSs are utilized in the proposed algorithm for improving the redundancy and the detection of analog measurement errors and topological inconsistencies at the substation.

Large Scale Substation Scenario: This scenario was generated by drawing one of the largest substations in Turkish Electric System in the DIgSILENT PowerFactory program. The measurement set for this scenario was attained by utilizing the power flow solution function of DIgSILENT program. Connectivity and model information data are created manually.

Small Scale Substation Scenario: This scenario was generated by partially drawing one of the largest substations in Turkish Electric System in the DIgSILENT PowerFactory program. The measurement set for this scenario was attained by utilizing the power flow solution function of DIgSILENT program. Connectivity and model information data are created manually.

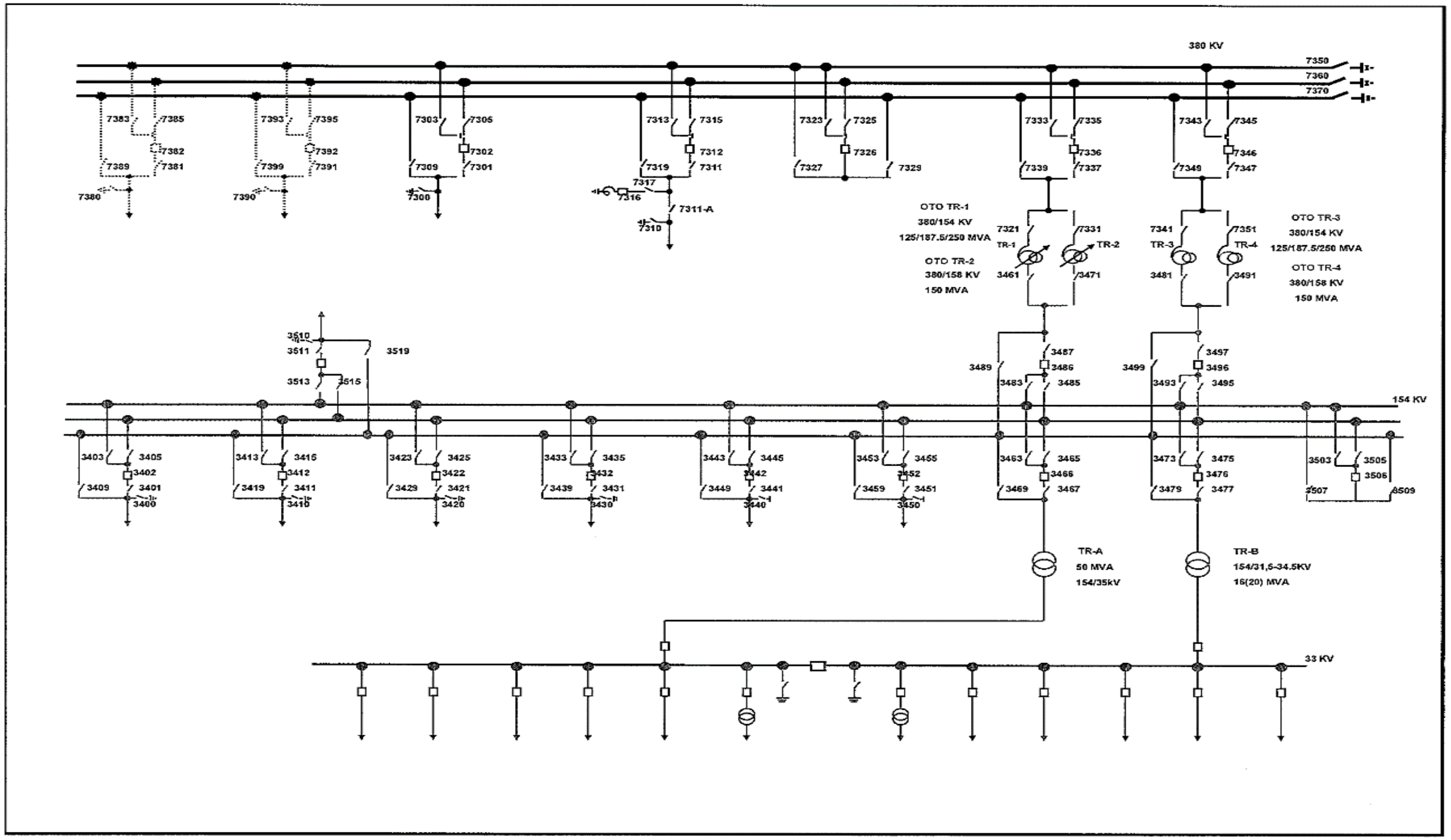

Figure 4.1. Base Substation Configuration

4.2 Test Cases and Results

Test scenarios are generated based on the validation of two different criteria which are proper functioning of algorithm functions and whether the algorithm performs the desired tasks within the expected performance accuracy. Through test cases whether the algorithm design is implemented properly and whether the algorithm meets the specified requirements and the accuracy of performance metrics are demonstrated.

In this section, the simulation graphs and results of test cases, which are implemented on large scale substation scenario and small scale substation scenario, are shown. The actual system states and estimated systems states are compared through graphs for different cases. Moreover, performance metrics are formed for the determination of system performance and the system accuracy. The performance metrics and their definitions are listed below.

1. Mean Absolute Error (MAE): State estimators give most possible system states by processing available measurements. The measurements can be many type and some system states can be measured directly such as voltage phasor values, current phasor values and transformer tap values. Thus, comparison of estimated system states with true system states in other words measured values of system states can give significant information about the performance and the accuracy of the applied state estimator. In statistics Mean Absolute Error (MAE) is a measure of error between the estimated and observed values. The utilization of MAE for system states as performance metric will assist the determination of the performance and the accuracy of the proposed substation level state estimation and topology error processing method. MAE metric is the sum of absolute differences between the true system states and the estimated system states divided by number of system states. Thus, as MAE of the system decreases, system states start to converge to true system states. In other words, small MAE for a system means that system states are closer to most possible system states with respect to the same system which has higher MAE value. The formula of this performance metric is shown below in Equation (4.1).

$$MAE = \frac{\sum_{i=1}^{N} |\hat{x}_i - x_i|}{N} \quad (4.1)$$

where:

$\hat{x}_i$: estimated system states

x_i : true system states

N : number of system states

2. Objective Function Value: As shown in Equations (2.1) and (2.2), the main aim of WLS algorithm is the minimization of the weighted sum of the squares of the residuals. Equation (4.2) shows this aim as a formula. Similar to MAE metric, small objective function value means more accurate system estimates.

$$J(\hat{x}) = \sum_{i=1}^{m} \frac{(r_i)^2}{R_{ii}} \qquad (4.2)$$

Algorithm performance metric results for base case error free large and small scale substation scenarios are given in Table 4.1. These performance metrics are calculated in the absence of bad data and topological inconsistencies. Thus, MAE and objective function values for both scenarios are remarkably small, in other words nearly zero. These facts mean that proposed substation level state estimation and topology error processing method operate properly in the desired accuracy.

Table 4.1. Algorithm Performance Metric Results for the Scenarios

Metrics	Small Scale Substation	Large Scale Substation
Mean Absolute Error	9.2465e-06	8.4923e-06
Objective Function Value	2.4436e-05	3.3322e-05

System states of the proposed substation level state estimation and topology error processing method consists of real part of voltage phasors of busbars, imaginary part of voltage phasors of busbars, real part of current phasors of feeders, imaginary part of current phasors of feeders and transformers tap values. The x axes of below graphs represent those system states. For distinguishing the system states and better understanding of the effects of bad data on related system states, the system states and corresponding system state numbers are explained in Table 4.2.

Table 4.2 System State Numbers and Corresponding System States Types for the Scenarios

System State Types	System State Numbers for Small Scale Scenario	System State Numbers Large Scale Scenario
Real part of busbar voltage phasors	1…7	1…7
Imaginary part of busbar voltage phasors	8…14	8…14
Real part of feeder current phasors	15…27	15…33
Imaginary part of feeder current phasors	28…40	34…52
Transformer tap values	41…43	53…55

The results of algorithm performance metrics are given in Table 4.1. These metrics, MAE and objective function values, give information about the general performance and the accuracy of the state estimator. The individual situation of the estimated system states compared to true system states and their deviations from the true system states cannot be achieved by just examining the proposed performance metrics. Thus, in order to perform this task, estimated system states and true system states, and their differences have to be compared and demonstrated individually. The estimate of each system states and their corresponding true values are compared in Figure 4.2 and in Figure 4.4, respectively for small scale substation and large scale substation scenarios. As shown in these figures, values of each system states and their corresponding true values are nearly the same. The differences between the estimate of each system states and their corresponding true values are shown in Figure 4.3 and in Figure 4.5, respectively for small scale substation and large scale substation scenarios. These figures give deeper insight about the comparison of true system states and estimated system states. If those figures are examined carefully, it is seen that the biggest differences between the true system states and the estimated system states exist among the transformer tap values. The reason for this fact is that the redundancy of transformer tap values are smaller compared to voltage and current system states, and there are only transformer active and reactive power measurements which are related to transformer tap values. Moreover, the differences between the true current related system states and the estimated current related system states are higher compared to voltage related system states, the reason for this situation is that higher standard deviation values are assigned to current measurements, as a result weight of current measurements are smaller than weight of voltage measurements in the measurement sets. Thus, current related measurements have smaller weight and as a results current related system states have higher deviation from the true system states. Although, there are differences between true system states and estimate of system states, once the below four figure are examined carefully, it is seen that true system states and estimated system states are nearly equal, and the differences between true system states and estimated system states are quite small, in other words almost zero for each system states. As a result, in consideration of above mentioned extractions and below figures, it can be said that proposed substation level state estimation and topology error processing method operate properly and with a quite well accuracy in fundamental bad data and topological error free base case for both scenarios. These results and conclusions comprehend the base test case, which is observable, bad data and topological error free case, and mainly related to proper functionality of the state estimation solver, which is the core of proposed algorithm. The proper functionality, simulation results and performance metrics of other functions of the proposed algorithm, which are topology processer function, observability analysis function, bad data processing function and topology error processing function, are analyzed and shown in the following sub-sections in detail.

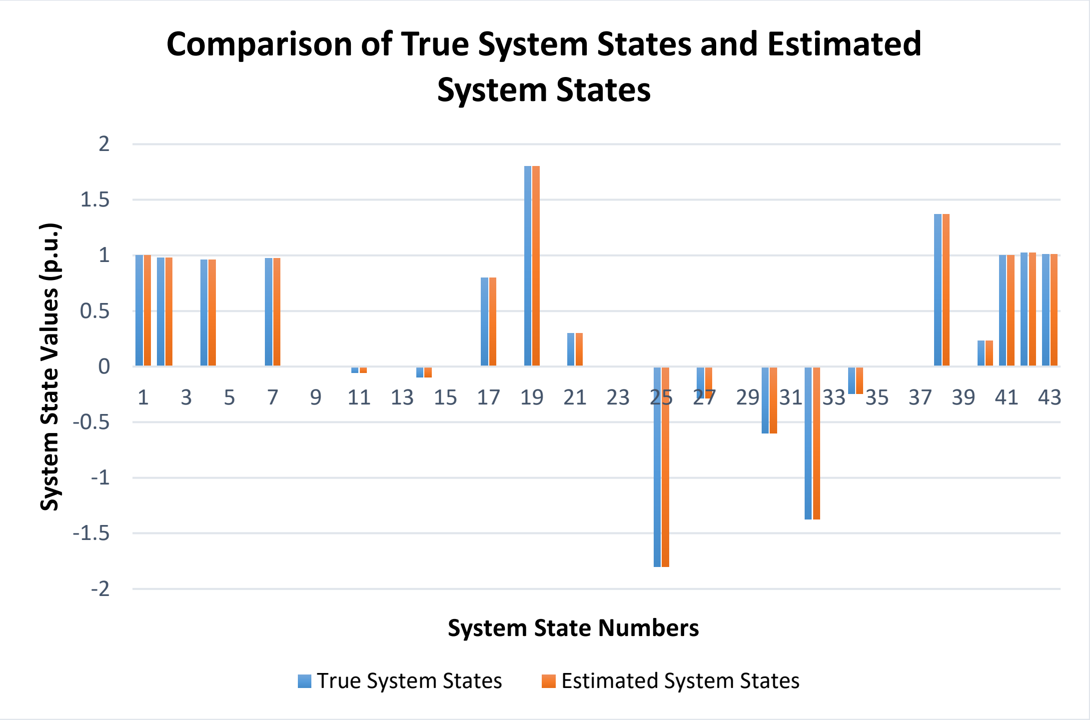

Figure 4.2 Small Scale Scenario Base Case - Comparison of True System States and Estimated System States

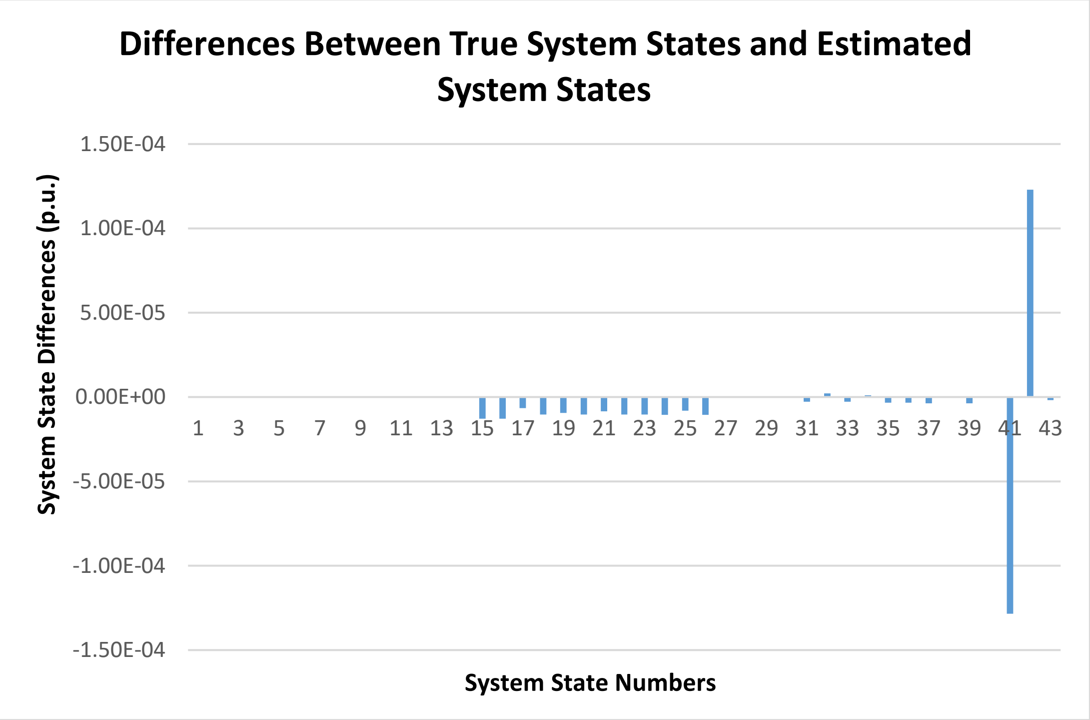

Figure 4.3 Small Scale Scenario Base Case - Differences Between True System States and Estimated System States

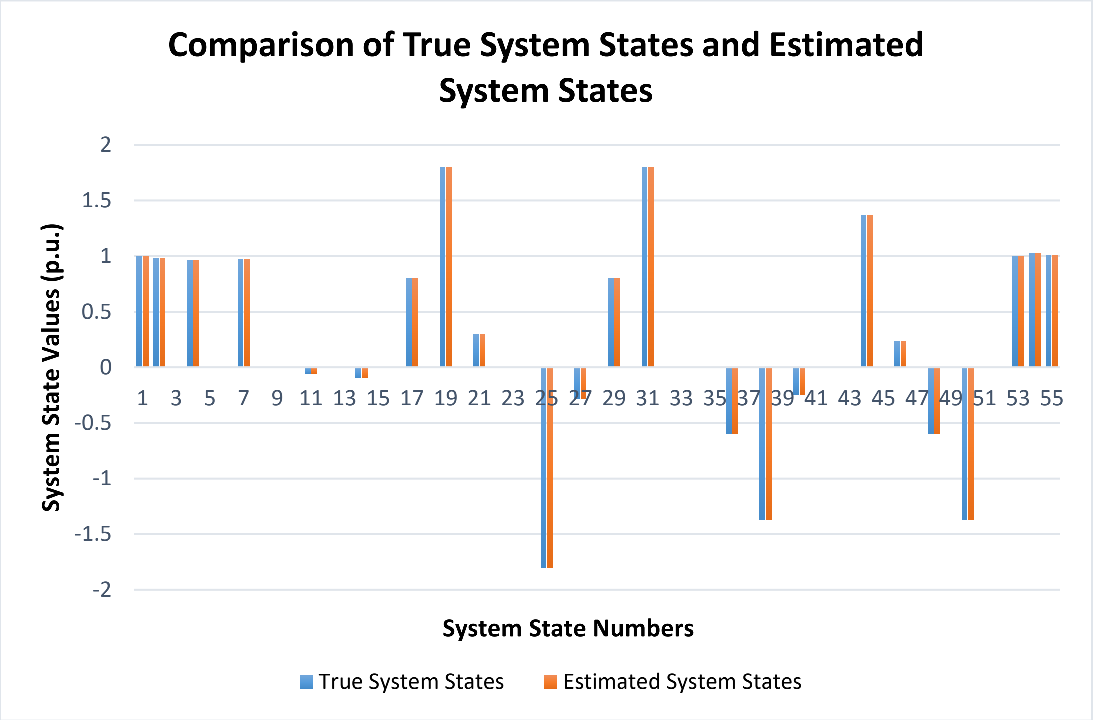

Figure 4.4 Large Scale Scenario Base Case - Comparison of True System States and Estimated System States

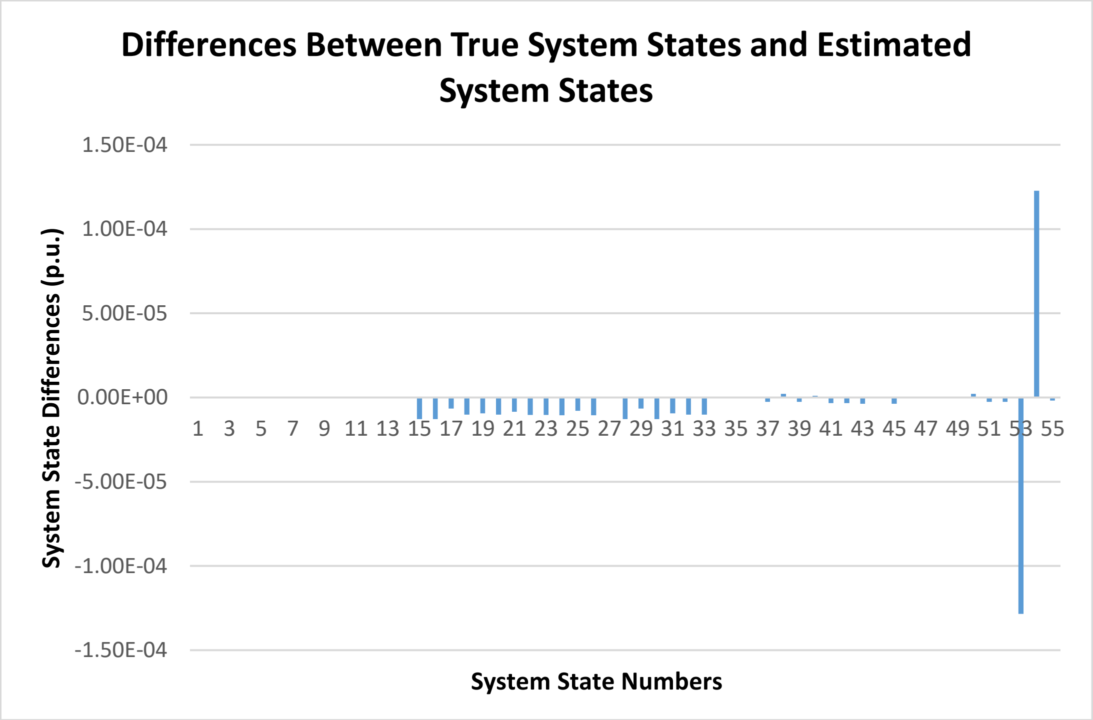

Figure 4.5 Large Scale Base Case - Scenario Differences Between True System States and Estimated System States

4.2.1 Topology Processor Correctness Test and Results

Proper functioning of the topology processor function of the proposed substation level state estimation and topology error processing method is controlled by Topology Processor Correctness Test. This test was carried out using the connectivity data of the large scale substation scenario and the small scale substation scenario. The output of the topology processor is compared with the single line diagrams of the large scale substation and the small scale substation scenarios.

Topology processor generates system topology by using the connectivity data of a substation. Substation level topology processer proposed in this thesis connects system states to system measurements. Feeders, feeder bays and busbars are connected together by topology processor. In this manner, system measurements and system states are processed in state estimation solver function. The output of the topology processor represents a modified single diagram of a substation in a matrix form. If this modified single diagram is compared with the single line diagrams of the large scale substation or the small scale substation scenarios, it can be seen that the algorithm can form the substation level system topology correctly.

4.2.2 Observability Analysis Test and Results

Observability analysis ability of the proposed substation level state estimation and topology error processing method is controlled by Observability Analysis Test. The test was performed by utilizing the redundant and irredundant measurement sets of the large scale substation scenario and the small scale substation scenarios as input to the proposed method.

Observability analysis function determines whether the system is fully observable or partially observable. In other words, this function express that whether there is a unique solution for state estimation process. This function performs observability analysis by using the rank of Jacobian matrix, H. The test was performed with the redundant and irredundant measurement sets for two scenarios. Rank of H matrix is equal to number of system states, n for redundant measurement sets which means that the system is observable. On the other hand, rank of *H* matrix is smaller than number of system states, n for irredundant measurement sets which means that the system is unobservable. As a result of these tests, it is seen that the algorithm determines the systems which do not have sufficient measurement redundancy, that is, the systems which are not observable.

4.2.3 Bad Data Detection-Identification Test and Results

Bad data analysis ability of the proposed substation level state estimation and topology processing method is controlled by Bad Data Detection-Identification Test. The test was performed by utilizing the measurement sets including bad data for the large scale substation scenario and the small scale substation scenario as input to the proposed method.

Bad data detection and identification function performs the detection of bad data and identification of bad data tasks if the system has sufficient measurement redundancy. Bad data appearing in critical measurements cannot be detected and identified. Moreover, bad data appearing in critical pair measurements and critical k-tuple measurements can be detected but cannot be identified. These are the detection and identification limits of the bad data analysis function. In this thesis, measurements sets of scenarios are intentionally disarranged and bad data involving measurement sets are generated. Many bad data including measurement combinations are formed and bad data detection-identification capabilities of the proposed algorithm were tested on those measurement sets for both scenarios.

Proposed substation level state estimation and topology error processing algorithm can detect and identify bad data if bad data is not in the critical, critical pair and critical k-tuple measurements. Moreover, after the detection and identification of bad data, proposed algorithm corrects the erroneous measurement by subtracting the estimated error from the erroneous measurement.

Bad data detection-identification function performs its task on many test cases. Some of the results of these tests are shown below. In that cases, one of the voltage measurements of both scenarios are intentionally corrupted. The true and the corrupted measurement values are shown in Table 4.3. The real part of voltage phasor measurement of the second main busbar at 380 kV level includes bad data at small scale substation scenario. On the other hand, the real part of voltage phasor measurement of the first main busbar at 380 kV level includes bad data at large scale substation scenario.

The state estimation is firstly operated for error free measurement sets for both scenarios. After that state estimation is carried out for measurement sets with bad data for both scenarios. Finally, the estimation process is completed with the measurement sets whose bad data are corrected for both scenarios. The results of the state estimation for error free measurement sets constitute reference points for the comparison of performance metrics for bad data including measurement sets. Performance metrics, MAE and objective function value, are calculated for all these three cases for determination and comparison of the system performance in the presence of bad data. Simulations of both scenarios and results of simulations are shown below.

Table 4.3. BD Analysis Test Case Erroneous Voltage Values for the Scenarios

Scenario	Real Part of Voltage Phasor Without Bad Data	Real Part of Voltage Phasor With Bad Data
Small Scale Substation	215.005	235.005
Large Scale Substation	219.393	249.393

4.2.3.1 Simulation Graphs for the Test Cases

In this part, simulation results of measurement sets including bad data and measurements sets with corrected bad data for both scenarios are compared with the true system states in order to evaluate the performance and the accuracy of the proposed method in the presence of bad data. The estimated system states for measurement set including bad data and measurement sets with corrected bad data are compared with true system states in Figure 4.6 and in Figure 4.8, respectively for small scale substation and large scale substation scenarios. The deviation of system states for measurement set including bad data and measurement sets with corrected bad data from the true system states are shown in Figure 4.7 and in Figure 4.9, respectively for small scale substation and large scale substation scenarios. As shown in the figures, values of each system states and their corresponding true values are nearly the same except from erroneous measurement related system states for measurement set including bad data and measurement sets with corrected bad data. As deviation of each system states from corresponding true system states are examined, the biggest deviations occurs at erroneous measurement related system states, which are second voltage system state for small scale scenario and first voltage system state for large scale scenario.

The system states, especially erroneous measurement related system states, diverge from true system states in the presence of bad data in the measurement sets, since weighted least squares method is not robust against bad data. In this thesis, this problem is tackled by the bad data correction process in which erroneous measurement are corrected by subtracting the estimated error from the erroneous measurement. The effect of bad data correction process can be seen from the below figures. After the correction of bad data all system states, including erroneous measurement related system states, converge to true system states and deviation of the estimated system states from the true system states decrease significantly.

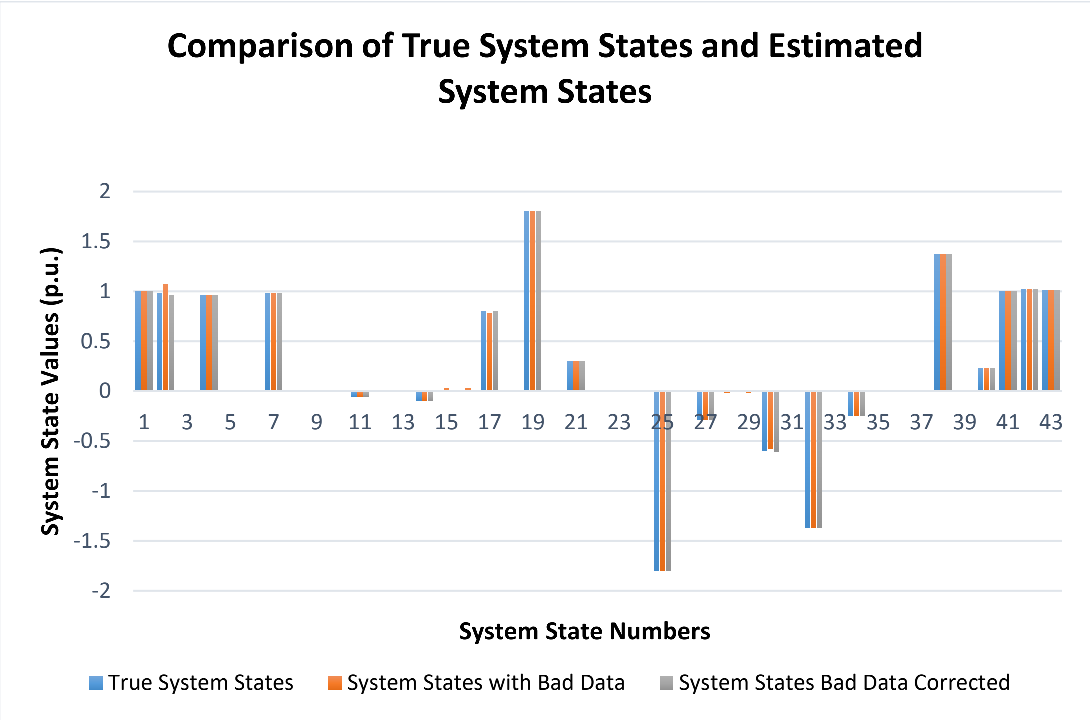

Figure 4.6. Small Scale Substation Scenario Bad Data Analysis - Comparison of System State Values

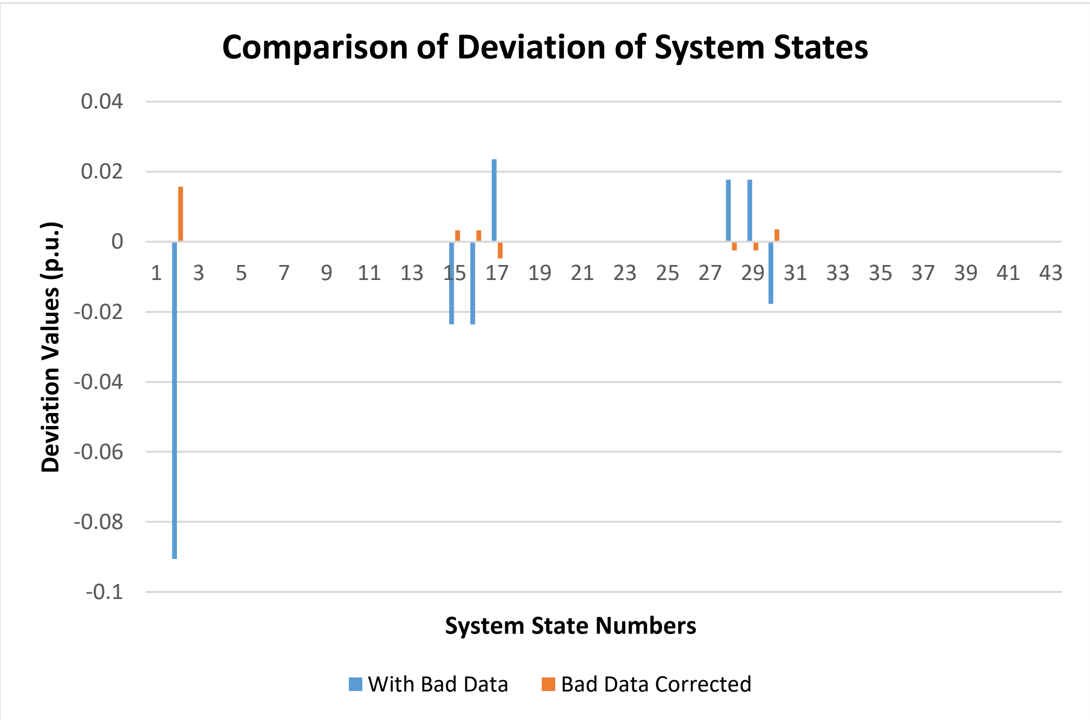

Figure 4.7. Small Scale Substation Scenario Bad Data Analysis - Comparison of Deviation of System States

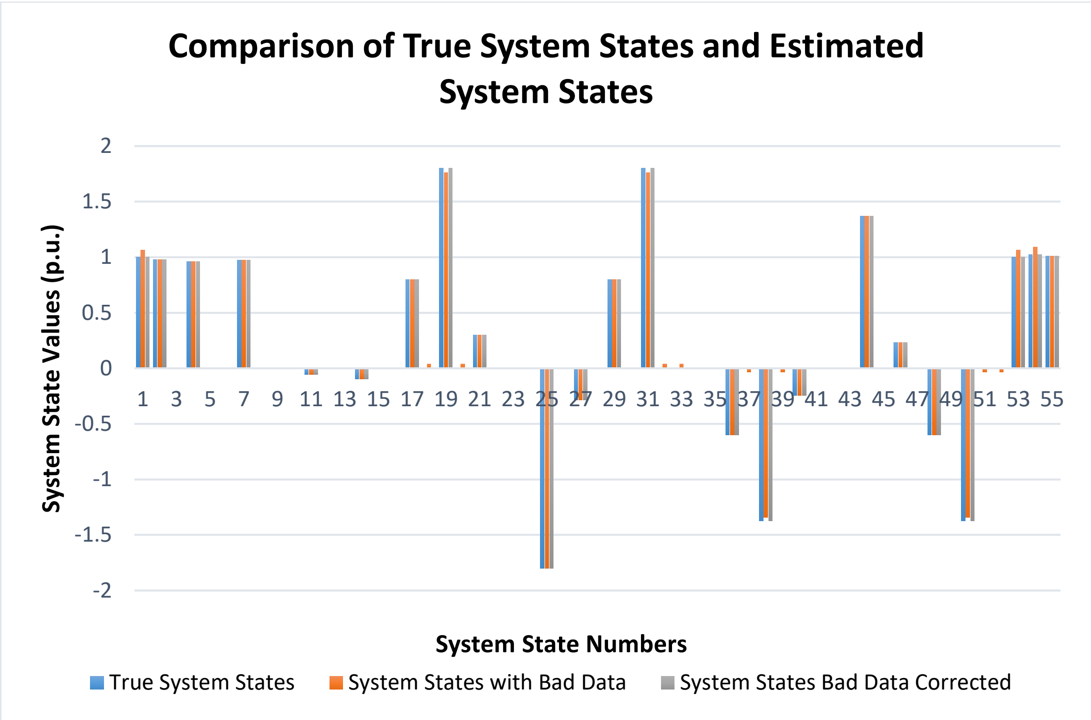

Figure 4.8. Large Scale Substation Scenario Bad Data Analysis - Comparison of System State Values

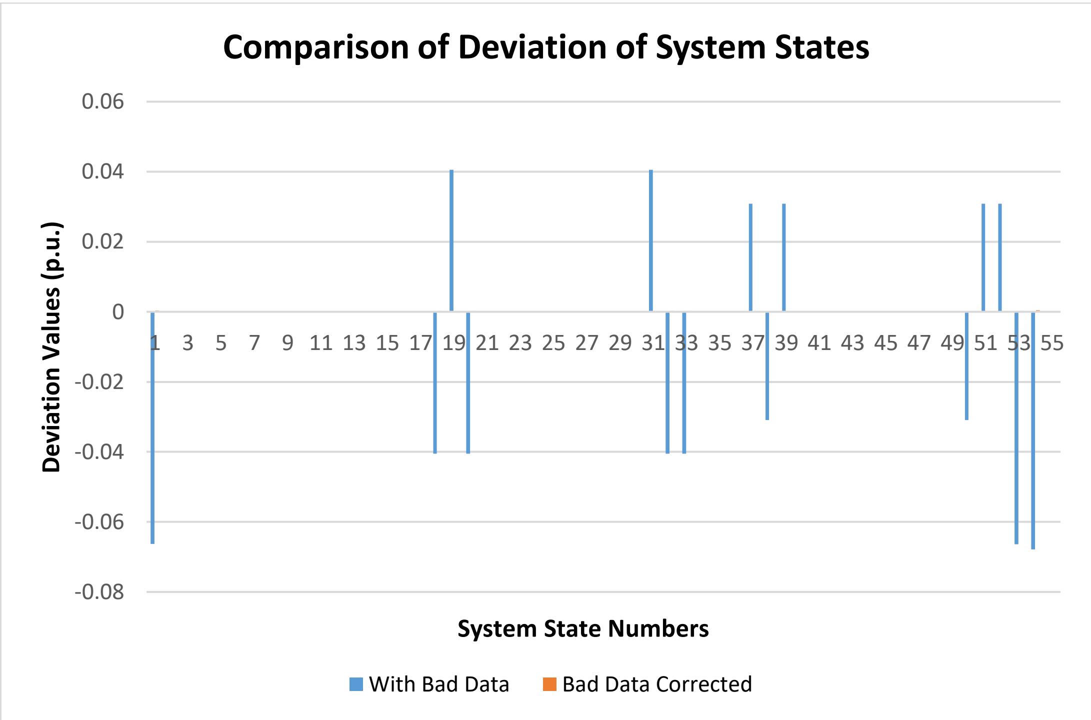

Figure 4.9. Large Scale Substation Scenario Bad Data Analysis - Comparison of Deviation of System States

4.2.3.2 Results of Performance Metrics

The performance and the accuracy of substation level state estimation and topology error processing method can be evaluated by examining the specified performance metrics. Performance metrics of scenarios and their values are shown in Table 4.4. As shown in the below table, MAE and objective function values for the error free case are quite small compared to other two cases, since system states are estimated quite accurately for error free case. If there is erroneous measurement in the measurement sets, MAE and objective function values increase enormously for both scenarios and estimated system states diverge from true system states. After the correction of bad data in the measurement sets, MAE and objective function values decrease compared to measurements including bad data case and estimated system states converge to true system states with relatively good accuracy. However, even after the correction of bad data from measurement sets, performance metric values are still quite bigger than error free measurement sets. As seen in performance metrics and simulation graphs of system states, bad data in measurement sets causes deviation from true system states and decreases the accuracy of estimation. This side effect is eliminated and decreased by the correction of bad data process as shown in the figures and below table.

Table 4.4. Bad Data Analysis Performance Metrics for the Scenarios

Scenarios	State of Bad Data	J (Objective Function Value)	MAE (Mean Absolute Error)
Large Scale Substation	Without Bad Data	3.3322e-05	8.4923e-06
	With Bad Data	9478.4	0.0114
	Bad Data Corrected	0.2506	5.7853e-05
Small Scale Substation	Without Bad Data	2.4436e-05	9.2465e-06
	With Bad Data	69.9713	0.0050
	Bad Data Corrected	2.0505	8.2831e-04

4.2.4 Topology Error Detection Test and Results

Topology error detection ability of the proposed substation level state estimation and topology error processing method is controlled by Topology Error Detection Test. The test was performed by utilizing the measurement sets including topological error and topological error free measurement sets of the large scale substation scenario as input to the proposed method.

Topology error detection function of the proposed substation level state estimation and topology error processing method detects the topological inconsistencies at a substation if the measurement set is redundant enough. In large scale substation scenario, first and second busbars at 380 kV level have two voltage magnitudes and two voltage angle measurements. On the other hand, in small scale substation scenario, the first and second busbars at 380 kV level have only one voltage magnitudes and one voltage angle measurements. If there are topological inconsistencies at the substation, virtual current or voltage related measurements are generated based on CB and DSs statuses. If there is only one topological error at the substation, virtual measurements will have two components which are real part and imaginary part of current or voltage virtual measurements. These virtual measurements are related to current or voltage related system states. In large scale scenario, number of analog measurements of first and second busbars at 380 kV level are twice the number of virtual measurements related to those busbars. In small scale scenario, number of analog measurements of first and second busbars at 380 kV level equal to the number of virtual measurements related to those busbars. Thus, redundancy of small scale substation scenario is less than large scale substation scenario. Since small scale substation scenario does not have sufficient measurement redundancy for topological error processing, topology error detection test is only performed on large scale substation scenario.

The generated virtual current and voltage measurements in the presence of topological error at the substation depend on more than one CB statuses. Virtual voltage measurements in feeder bays, virtual current measurements in feeder bays, virtual voltage measurements in transfer buses and bus couplers, and KCL current measurement equations all are created based the openness and closeness relation of at least two branches. In addition, CB statuses of these branches does not have different weights and weight of their statuses are equal. Thus, similar to k-tuple critical measurements, for virtual measurements the detection of topological errors is possible but the identification of topological errors is not possible due to coupling between CB statuses of at least two branches. These are the detection and identification limits of the topology error detection function.

In this thesis, different topological errors are generated for the determination of the performance of the topology error processing function of the proposed algorithm. Many topological error including measurement combinations are formed and topological error detection capabilities of proposed algorithm were tested on those measurement sets for large scale substation scenario. Some of the results of these tests are shown below. In that cases, some of the CB statuses are intentionally given as erroneous. Firstly, CB statuses of the transfer feeder at 380 kV level are given incorrectly. Secondly, CB statuses of one of the feeders at 380 kV level are given incorrectly. The true and the erroneous CB statuses of test cases are given in detail in Table 4.5.

Table 4.5 Topology Error Detection Analysis Topological Error Locations and Branch Statuses

Topological Error Location	True Statuses			Erroneous Statuses		
Transfer Feeder	From Node	To Node	Status	From Node	To Node	Status
	1	11	0	1	11	1
	2	11	0	2	11	1
	3	11	0	3	11	0
Feeder Bays	From Node	To Node	Status	From Node	To Node	Status
	1	6	0	1	4	0
	2	6	1	2	4	0
	3	6	0	3	6	0

The state estimation is firstly performed for topological error free measurement set for large scale substation scenario. Then, state estimation is carried out for above described topological error including measurement sets. The results of the state estimation for topological error free measurement sets constitute reference points for the comparison of performance metrics for topological error including measurement sets. Performance metrics, MAE and objective function value, are calculated for all these three test cases for determination and comparison of the system performance in the presence of topological error. Simulations of test cases for large scale substation scenario and results of simulations are shown below.

4.2.4.1 Simulation Graphs for the Test Cases

In this part, simulation results of measurement sets having topological errors at different locations are compared with the true system states in order to evaluate the performance and the accuracy of the proposed method in the presence of topological error. The estimated system states for measurement sets including erroneous CB statuses are compared with true system states in Figure 4.10 and in Figure 4.13, respectively for topological error at transfer feeder and topological error at feeder bays test cases. The deviation of system states for measurement sets including topological errors from the true system states are shown in Figure 4.11and in Figure 4.14, respectively for topological error at transfer feeder and topological error at feeder bays test cases. Finally, normalized residual values of measurements for test cases having topological error at transfer feeder and topological error at feeder bays test cases are show in Figure 4.12 and in Figure 4.15.

As shown in the figures, values of each system states and their corresponding true values are nearly the same except from topological error related system states for two topological error including test cases of large scale substation scenario. The first busbar and the second busbar at 380 kV level at large scale substation scenario have different voltage measurement values. Thus, their true states also have different values.

In the first test case, according to transfer feeder statuses which is given incorrectly, the real and imaginary part of voltage states of those busbars should be equal. In order to represent the topological data given in transfer feeder, virtual busbar voltage measurements equating specified busbars are generated based on the status data on the transfer feeder. Then, these virtual measurements are added to the measurement function, h and the measurement Jacobian, H. As shown in Figure 4.10 and in Figure 4.11, values of each system states and their corresponding true values are nearly the same and the biggest deviations from true system states occurs amongst topological error related system states, which are first and second system states representing the real part of busbar voltage of first and second busbars at 380 kV level, and transformer tap values related to those busbars. As shown in Figure 4.12, the measurement having the biggest normalized residual value is the 95th measurement which is the virtual measurement generated based on the equality in the transfer feeder.

In the second test case, according to feeder bay statuses which are given incorrectly, the real and imaginary part of voltage states of those busbars should be equal to zero. In order to represent the topological data given in feeder bays, virtual current feeder measurements are generated based on the status data on the feeder bays. Then, these virtual measurements are added to the measurement function, h and the measurement Jacobian, H. As shown in Figure 4.13 and in Figure 4.14, values of each system states and their corresponding true values are nearly the same and the biggest deviations from true system states occurs amongst topological error related system states, which are current states representing the real and imaginary part of feeder bay branch currents of the erroneous feeder bays. As shown in Figure 4.15, the measurements having the biggest normalized residual value are the 21th,28th, 29th and 30th measurements which are the virtual current measurements generated based on the statuses data of the feeder bays feeding the same feeder.

As a result, in consideration of above mentioned extractions and below figures, it can be said that the biggest deviation in system states occur at system states related to topological errors and the system states, especially erroneous measurement related system states, diverge from true system states in the presence of topological error in the measurement sets. The proposed algorithm can detect the topological errors by utilizing the virtual measurements and normalized residual test. As shown in the figures, the biggest normalized residuals values for each topology error including test cases correspond to the virtual measurements which are generated based on erroneous CB statuses. By the utilization of this fact and the normalized residual test, topological error in the test cases are detected and due to the specified structure of topological virtual measurements exact location of topological errors cannot be identified. Since the topological errors cannot be identified, topological inconsistencies in the measurement set cannot be removed or corrected.

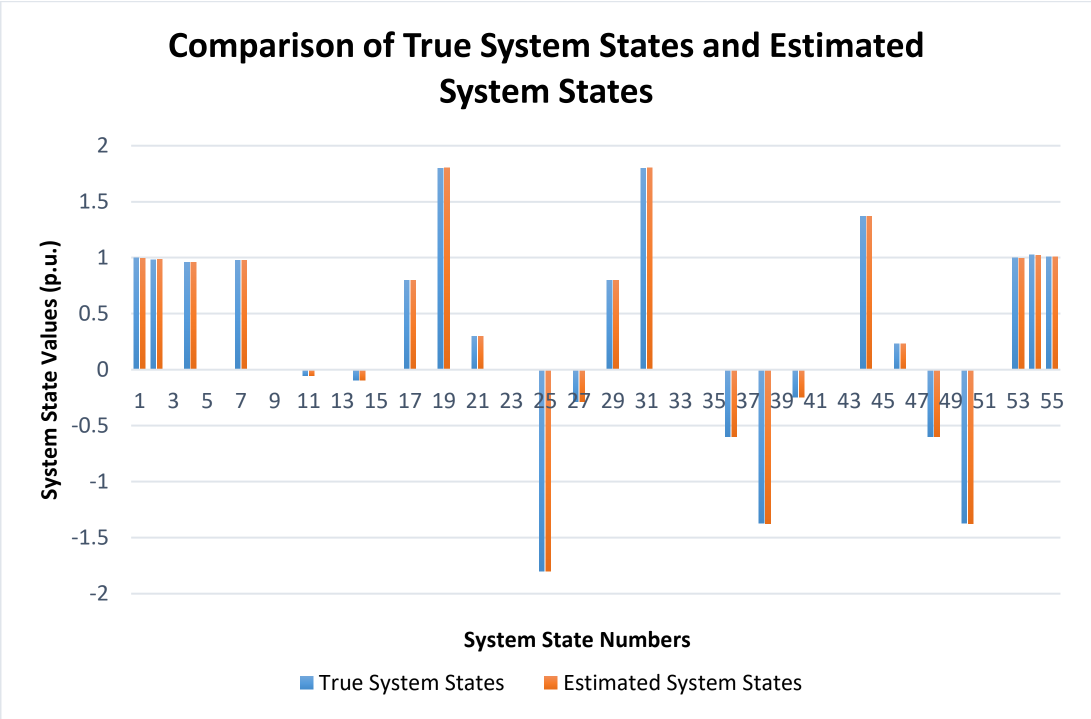

Figure 4.10 Large Scale Substation Scenario Topology Error Detection - Comparison of True System States and Estimated System States for Topological Error in Transfer Feeder

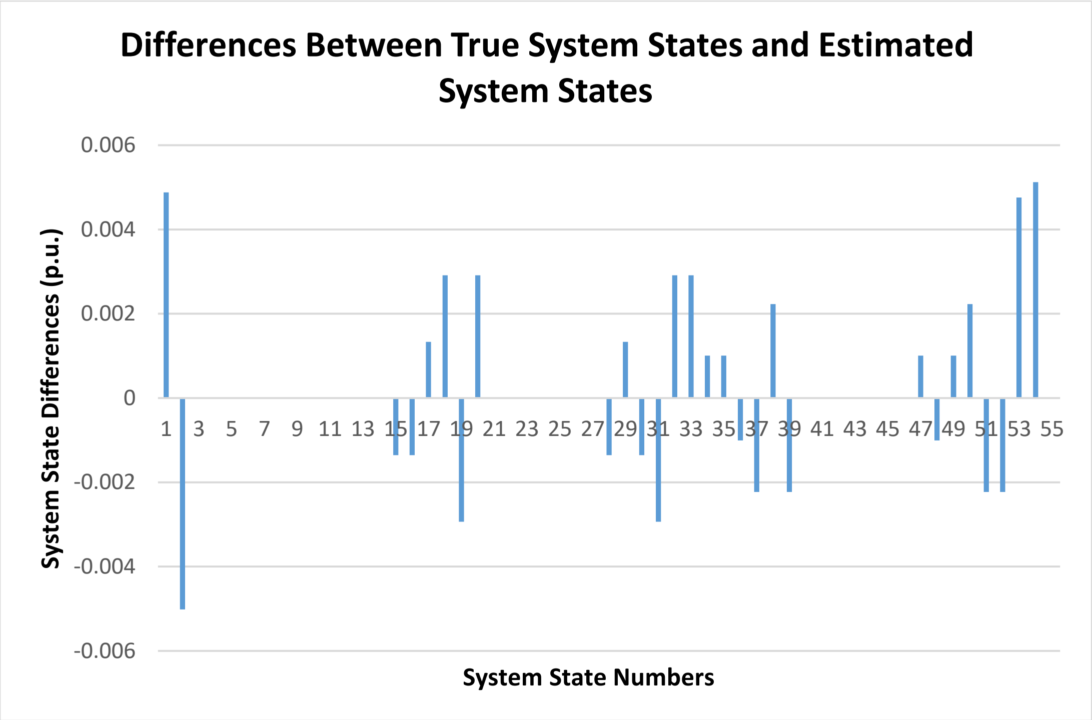

Figure 4.11 Large Scale Substation Scenario Topology Error Detection - Differences Between True System States and Estimated System States for Topological Error in Transfer Feeder

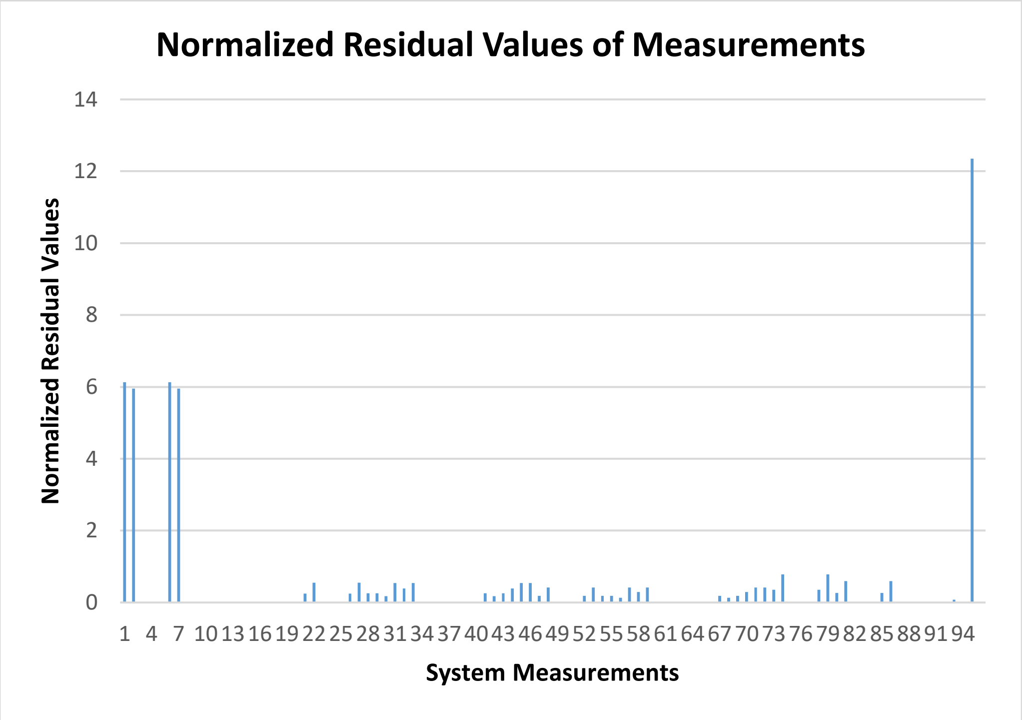

Figure 4.12 Large Scale Substation Scenario Topology Error Detection - Normalized Residual Values of Measurements for Topological Error in Transfer Feeder

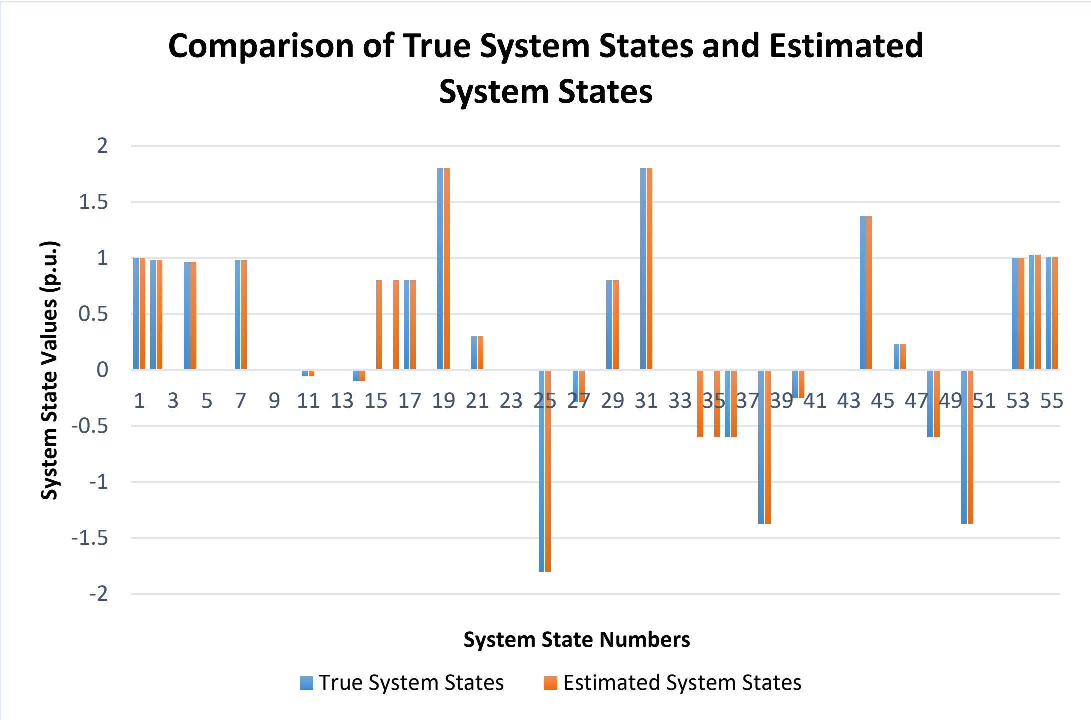

Figure 4.13 Large Scale Substation Scenario Topology Error Detection - Comparison of True System States and Estimated System States for Topological Error in Feeder Bays

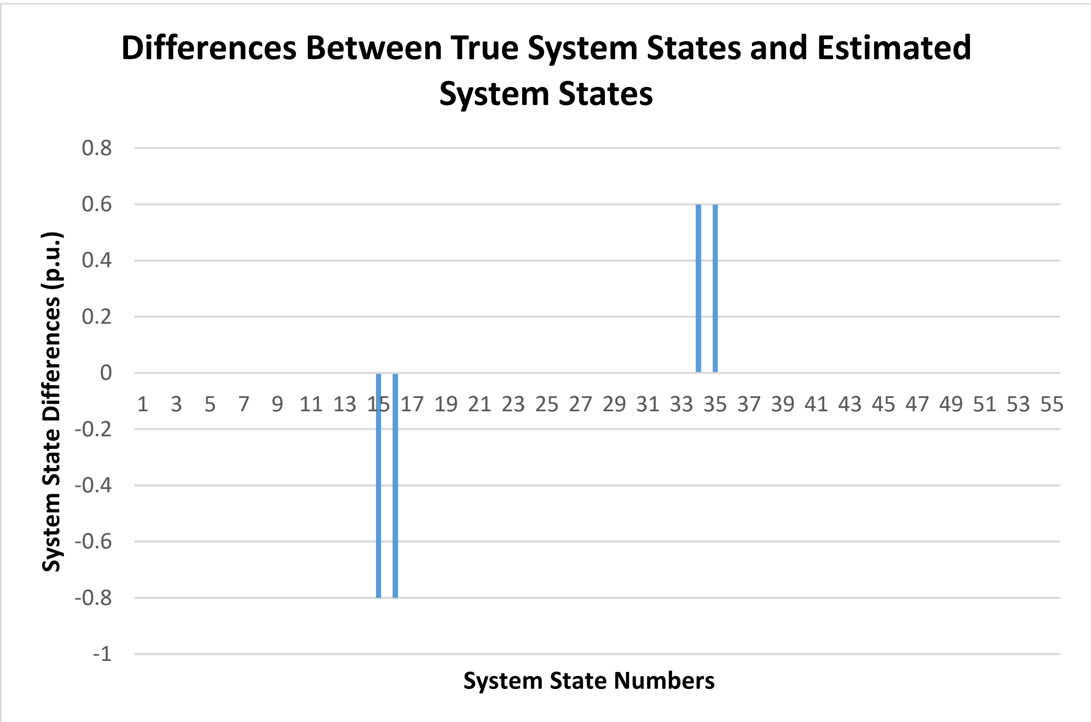

Figure 4.14 Large Scale Substation Scenario Topology Error Detection - Differences Between True System States and Estimated System States for Topological Error in Feeder Bays

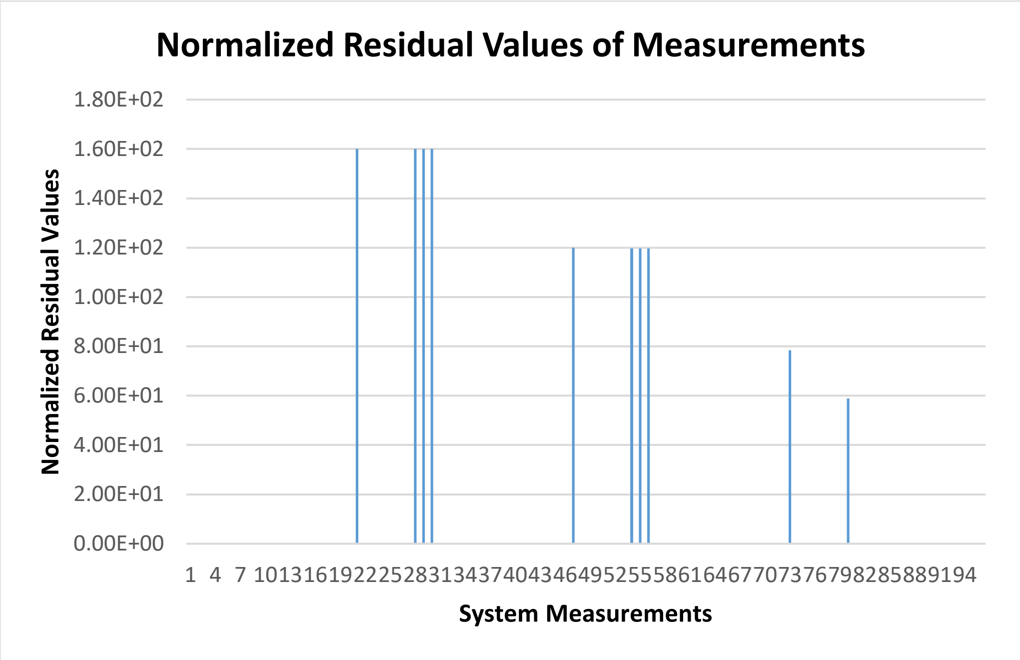

Figure 4.15 Large Scale Substation Scenario Topology Error Detection - Normalized Residual Values of Measurements for Topological Error in Feeder Bays

4.2.4.2 Results of Performance Metrics

The performance and the accuracy of substation level state estimation and topology error processing method can be evaluated by examining the specified performance metrics. The performance metric values for topology error processing test cases are shown in Table 4.6.

Table 4.6. Topology Error Detection Analysis Performance Metrics for the Test Cases

Topological Error Location	J (Objective Function Value)	MAE (Mean Absolute Error)
Topological Error Free	3.3322e-05	8.4923e-06
Topological Error in Transfer Feeder	202.6659	0.0012
Topological Error inside a Feeder	4.9576e+04	0.0763

As shown in the table, MAE and objective function values for the error free case are quite small compared to topological error including test cases, since system states are estimated quite accurately for topological error free case. If there is CB status error in the measurements, MAE and objective function values increase enormously for both topological error including test cases and the estimated system states diverge from true system states. As seen in performance metrics and simulation graphs of system states, topological error in measurement sets causes deviation from true system states and decreases the accuracy of estimation.

4.3 Chapter Summary and Comments

In this chapter, the proper functionality, the performance and the accuracy of the proposed substation level state estimation and topology error processing method are analyzed numerically by the utilization of different test cases on generated scenarios. The performance metrics, MAE (Mean Absolute Error) and J (Objective function value), are formed for the determination of system performance and the system accuracy. First of all, the algorithm performance metrics are calculated for bad data free and topological error free base test cases for both scenarios. The performance metrics for both scenarios are figured out as nearly zero. In addition to the performance metrics, true system states and estimated system states are nearly equal, and the differences between them are quite small, in other words almost zero for each system states. These facts mean that the state estimation solver of the proposed algorithm function properly with a quite well accuracy.

After the testing the proper functionality and the performance of the core of the proposed algorithm, the state estimation solver, with fundamental bad data and topological error free measurement sets for both scenarios, the proper functionality, simulation results and performance metrics of the sub functions of the proposed algorithm are analyzed and validated numerically.

Firstly, the topology processor function is tested by comparing of the output of this function, which is a modified single diagram of a substation in a matrix form, with the single line diagrams both scenarios.

Secondly, the observability analysis function is tested by utilization of the rank of Jacobian matrix, H to the redundant and irredundant measurement sets of both scenarios. Rank of H matrix is equal to number of system states, n for redundant measurement sets i.e., for observable systems and is smaller than number of system states, n for irredundant measurement sets i.e., for unobservable systems.

Thirdly, the bad data detection-identification function is tested by utilizing the measurement sets including bad data for both scenarios. This function performs the detection and identification of bad data tasks if the system has sufficient measurement redundancy. The proposed algorithm can detect and identify bad data if bad data is not in the critical, critical pair and critical k-tuple measurements. Moreover, the proposed algorithm corrects the erroneous measurement by subtracting the estimated error from the erroneous measurement. In the presence of bad data, the performance metric values grow and get worse, the deviations of estimated system states from true system states increase as well. In short, the estimated system states, especially bad data related system states, diverge from true system states and the substation level state estimator gives biased system estimates as output in the presence of bad data.

Lastly, the topology error detection function is tested by utilizing the measurement sets including topological error for the large scale substation scenario. This function performs the detection topology error task if the system has sufficient measurement redundancy. The exact location of topological errors cannot be identified since virtual measurements behave similar to k-tuple critical measurements. In the presence of topological error, the performance metric values grow and get worse, the deviations of estimated system states from true system states increase as well. In short, the estimated system states, especially topological error related system states, diverge from true system states and the substation level state estimator gives biased system estimates as output in the presence of CB status errors.

CHAPTER 5

CONCLUSION

State estimation has made online power system monitoring possible by instantaneously estimating the system states. State estimation applications obtain all system states based on solely at substation level computations was not possible in the past due to the lack of time synchronization between measurements. However, the time synchronization issue of measurements is overcome by the advent of PMUs.

This thesis proposes a substation level state estimator and topology error processor. The proposed method relies on the presence of PMU measurements and solves the estimation problem with the well-known Weighted Least Squares (WLS) estimator due to its prevalence in literature, simplicity in implementation, low computational burden and speed. WLS estimators give the most possible system states by minimizing the weighted sum of squares of the residuals.

In literature, substation level state estimation and topology error process are handled separately with different algorithms. In this thesis, both substation level state estimation process and topology error process are combined and solved with same WLS based algorithm. Performing substation level state estimation and topology error process together by utilization of PMUs constitutes the main contribution of this thesis to the literature.

The method utilizes both the synchrophasor PMU measurements and conventional SCADA measurements. In addition to analog measurements, digital measurements in other words breaker statuses are also utilized by the proposed method. Since PMU measurements are available at substation level and breaker statuses are utilized by the method, instead of voltage magnitude and voltage angles, real part of voltage phasors of busbars, imaginary part of voltage phasors of busbars, real part of current phasors of feeders, imaginary part of current phasors of feeders and transformers tap values are taken as system states. After that, the estimation problem is reformulated with respect to the utilized measurements and chosen system states. The method can provide accurate system state estimates, filter the bad data and detect topological inconsistencies. The method utilizes the largest normalized residual test for the bad data detection-identification and topology error processing tasks. Although the method can find that in which feeder there is a topological error, the exact location of topological error cannot be determined since virtual measurements on feeder bays behave similar to k-tuple critical measurements. Similar to k-tuple critical measurements, the detection of topological errors for virtual measurements is possible but the identification of topological errors for virtual measurements is not possible if the required measurement redundancy is not achieved.

The computational burden of control centers will be reduced thanks to the proposed method, since the topology error processing task which is computationally heavy for overall system is performed for each substation individually and the measurements which are transmitted to control centers are filtered at substation level. Since substation level filtered measurement data is transmitted to regional control centers and topological inconsistencies at substations are detected, with the proposed algorithm EMS functions will use more accurate data and as a result power system will operate better. Moreover, control actions taken in substations will be much more precise. As a result, mainly power substations in power systems and power systems as a whole will perform and operate better with the capabilities of the proposed WLS based substation level state estimation and topology error processing method.

Two level state estimation methods propose more reliable systems states than central transmission level state estimation methods since they utilize the substation level smartness and complete substation level data sets. For these reasons, a two level state estimation application which can estimate the power systems in transmission level can be utilized as future work. The first level of hierarchical state estimation is implemented in this thesis; later state estimation will be performed centrally for whole power system with the implementation of the second level of hierarchical state estimation as a future work.

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