Impact of input uncertainties on power system state estimation robustness

Incorporating PMU measurements

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Preface

This master thesis is a partial requirement for the Master of Science degree in Electric Engineering at KTH. This thesis project has been executed in collaboration with Svenska Kraftnät in Stockholm, Sweden and was supervised and approved by the Department of Industrial Information and Control Systems at KTH. During this five month of work, many precious experiences and knowledge relating to Power System State Estimation is gained by the author. Here, I would like to express my deep appreciation to my supervisors Tekn.Dr. Lars Nordström and Tekn.Lic. Lennart Ekstam, for their patient guidance and patronage. Also I would like to show my gratitude to Lennart Ekstam for sharing his valuable working experience with me. Last but not least, many thanks go to all the colleagues at Svenska Kraftnät for their kind support and accompany during this period.

Stockholm, June 2008

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Abstract

This report presents a study on the state estimation regarding the sensitivity of WLS estimator given uncertainties in inputs, and a feasibility investigation of incorporating PMU measured voltage angles in state estimation. As a project output, WLS State Estimation Algorithm has been implemented using the Nordic 32 power grid model. And a survey of the state of the art in this field has been conducted.

Before the simulation results are presented, a foundation is laid, explaining the involved state estimation algorithm and bad data detection method utilizing normalized residuals. The study also reveals that the involved bad data detection method is effective in identification and modification of non-correlated bad measurements dependent on the measurement redundancy.

The impact of topology information mismatch, biased measurements and measurements unavailability given as state estimation inputs to the estimation are simulated, together with the mitigation strategies from the Svenska Kraftnät in this report.

Two possible solutions of incorporating PMU measurements in the state estimation are presented here, aligned with an optimum placement method under the constraint of improving the quality of estimates with limited number of PMUs. The simulation results here are consistent with those tests carried out on other power system models from the previous researchers.

The simulation platform used in this study is developed by the author based on power system simulation software package MATPOWER 3.2 from Electrical Engineering department in Connell University, USA.

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Glossary

In this master thesis, the following abbreviations and terms are used:

ADS: Alternative Data Source. It is designed to be used as the reverse to the unavailable or deactivated measurements, which can be taken from previous estimations.

EMS: Energy Management System, which is used in the monitoring and control of the power generation and transmission.

GPS: Global Positioning System. A satellite based system for providing position and time. The accuracy of the GPS based clocks can be better than 1 microsecond.

MATPOWER 3.2: A software package in power system simulation, developed by the Electrical Engineering Department in Cornell University in the MATLAB environment.

Modified Nordic 32 Model: CIGRE Nordic 32 model is a condensed model of the power grid in Sweden and its neighboring counties, which originally contains 32 buses. This updated model contains 41 buses, which describes the Swedish power grid in a more detailed manner.

PMU: Phasor Measurement Unit, from which the voltage or current measurements are aligned with the GPS synchronized time stamps. Consequently, the phase angle differences of buses can be obtained by the comparison of phasor' zero passing time with the knowledge of power grid frequency.

Svenska Kraftänt: The Transmission System Operator in Sweden, who operates and manages the 400 kV and 220 kV level transmission network.

TSO: Transmission System Operator. A company owning and operating the backbone of the transmission grid whose responsibility is to balance the electricity market and secure operation of power grid.

WLS: Weighted Least Square state estimation algorithm. Commonly, this algorithm is based on the assumption that the measurement errors have normal distributed noises with known variances and zero means.

Chapter 1

Introduction

1.1 State Estimation Background

The core idea of state estimation is to calculate the immeasurable states from available measurement sets based on physical relationships between them or enhance the accuracy of the observable states utilizing mathematics.

State estimation is commonly considered as the “boarding ticket” to the other power system monitoring and control applications, which determines a best estimate of the current power system states usually including the voltage phasors, the tap positions and circuit breaker status based on the available SCADA measurements, power system model and information from other data sources.

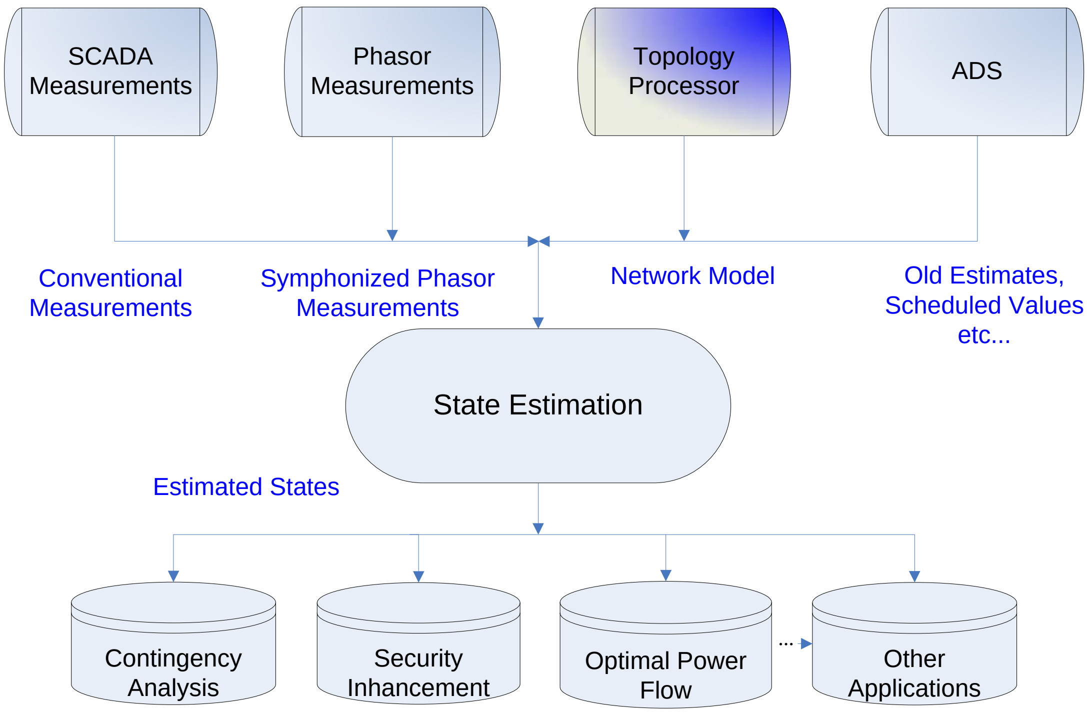

Figure 1.1: Roles of State Estimation in EMS

The state estimation concept is proposed initially by Schweppe at the 1970’s as a mathematical curiosity [1]. From its limited use during the 1980’s to its expanded but not yet central role in the operation of the system in 1990’s, recently state estimation has become nothing less than the cornerstone upon which a modern control center for a power system is built.

One of the major causes of the New York power outage of 1987 was ultimately traced back to incorrect information about the statues of a circuit in the system [2]. And the control and operation of the modern real time electricity market, such as the one between Nordic countries, is highly dependent on the real time information about power system states. State estimation stands in between the real time information and power system control and monitor applications, undoubtedly, it plays a crucial role in the real time power system control and operation.

1.2 Project Objective

One of the purposes of this master thesis project is to conduct a study regarding the sensitivity of an estimator based on WLS algorithm given uncertainties in inputs. A model development and implementation are conducted where the impact of biased measurements and the unavailability of measurements together with the topology error on the estimates accuracy can be demonstrated.

The prospects of using direct measurements of state variables have long intrigued state estimator vendors and users. With the advent of GPS synchronization, the precision of the voltage angle measurements are improved which, in turn, makes PMU measured voltage angles valuable inputs for state estimation. The incorporation of the voltage angle measurements from PMU to the state estimation is studied in this thesis. Also, a discussion of optimum PMU placement with the objective of improving the estimation accuracy is appended.

The third objective of this work is to perform a state of art study focusing on power system state estimation

1.3 Study Approach

The following figure presents the simulation procedure in this study:

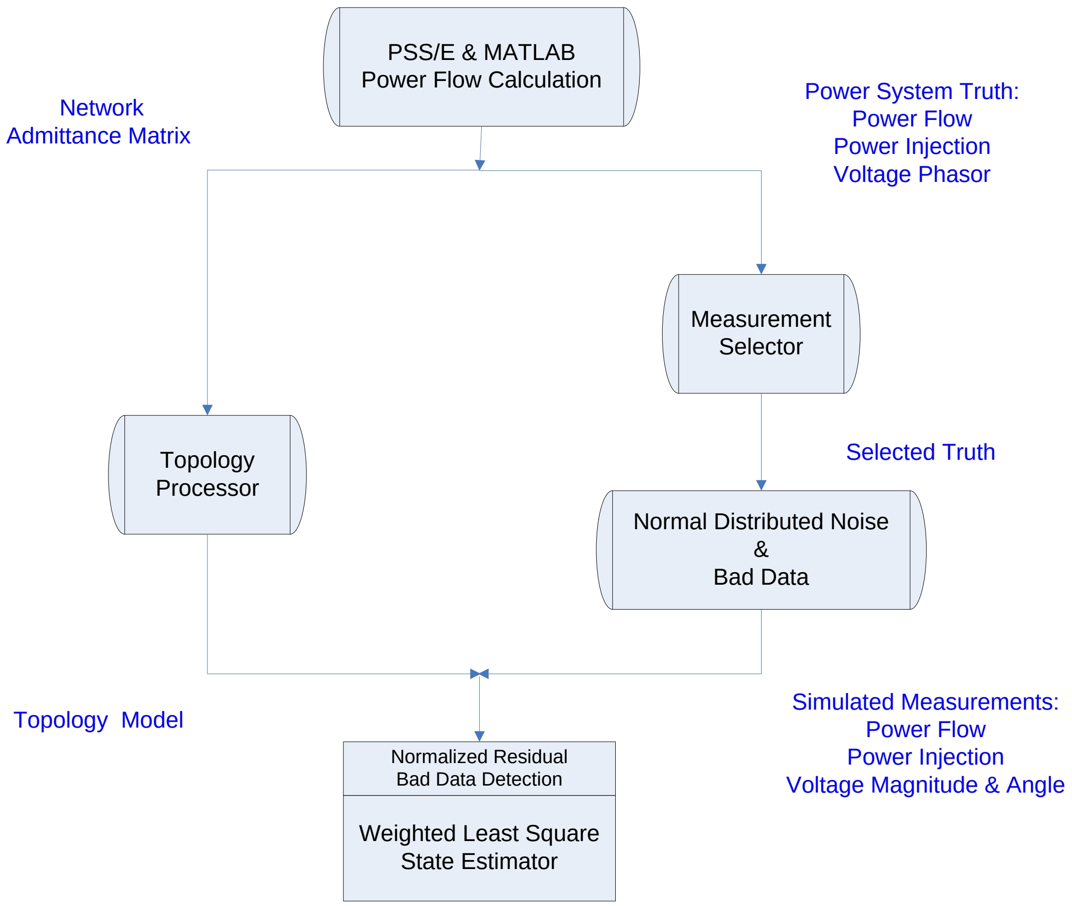

Figure 1.2: Simulation Procedure

The true power system states, the voltage phasors, together with the power flows of the entire network and the power injections at all buses are created from the power flow calculation which is conducted both in the MATLAB environment and PSS/E 2.8. The voltage magnitudes, power flows and power injections from the conventional transducer together with voltage angle measurements from the PMUs are simulated by implementing the normally distributed, zero mean measurement noises to this calculated power system truth. From the measurement selector, arbitrary measurement configuration can be created. And it is possible to perturb the measurement further by introducing errors, in this sense, a corrupted measurement is created.

Additionally, the admittance matrix used in the power flow calculation is interpreted as the true topology model. An assumption has to be stated here, the network parameters involved in calculation are free of errors. Network parameter estimation is out of the scope of this report.

1.4 Thesis Outline

Chapter 2

This chapter presents a common state estimation algorithm, WLS and a state estimation literature review. This chapter can be skipped by the readers whose focuses are on the utilization of the state estimator.

Chapter 3

This chapter presents a system description of the Nordic 32 model and a discussion relating to the measurement redundancy involved in this thesis.

Chapter 4

This chapter illustrates some problems encountered in the daily operation of the state estimator together with the mitigation strategies used in Svenska Kraftnät. In detail, impacts of the topology errors, the biased measurements and loss of measurements in certain areas are simulated respectively.

Chapter 5

Incorporating the PMU measurements in state estimation, two different methods of using PMU measured voltage phase angle are presented in this chapter. The PMU placement in this chapter follows the suggestions from PMU-Project prestudy done by Gothia Power.

Chapter 6

Optimum PMU placement with the object to improve the estimates accuracy is presented. And a comparison of the estimated results following the optimum placement with those obtained from the previous chapter is given.

Chapter 7

Overall conclusion and future work.

Chapter 2

State Estimation Algorithm

2.1 Weighted Least Square State Estimation

Presently, a common state estimation algorithm relies on the Least Square approach to minimize the sum of L_2 norm of the measurement residues. The calculation involved here is based on linearization of the power system equations.

Consider a SCADA measurement set z consisting non-synchronized data of power injections, S_{inj}, power flows through lines, S_{flow} and voltage magnitudes, V_{mag}. Vector x is assigned as power system states, which is composed by voltage magnitudes V^{mag} and voltage angles V^{ang} at every bus.

Their nonlinear relationship is expressed as:

$$z = h(x) + e \tag{2.1}$$

Where *h(x)* is the nonlinear function of the state *x*, and *e* is the normally distributed noise vector whose covariance composes the covariance matrix *R*. The assumptions that the measurement noises have zero mean and are independent to each other are commonly made in WLS algorithm, regarding the statistical properties of the measurement errors. Hence:

$$E(e_i) = 0 \quad i = 1, \dots, m$$
$$Cov(e) = E[e \cdot e^T] = R = diag\{\sigma_1^2, \sigma_2^2, \dots, \sigma_m^2\}$$

m represents the number of measurements and σ_i is the standard deviation of the SCADA measurement noises, which is an indication of the measurement accuracies of the corresponding meters.

The measurement Jacobian matrix *H* is the partial derivatives of *h(x)* with respect to *x*.

$$H = \left[\frac{\partial h(x)}{\partial x} \right] = \begin{bmatrix} \frac{\partial P_{inj}}{\partial V_{mag}} & \frac{\partial P_{inj}}{\partial V_{ang}} \\ \frac{\partial P_{flow}}{\partial V_{mag}} & \frac{\partial P_{flow}}{\partial V_{ang}} \\ \frac{\partial Q_{inj}}{\partial V_{mag}} & \frac{\partial Q_{inj}}{\partial V_{ang}} \\ \frac{\partial Q_{flow}}{\partial V_{mag}} & \frac{\partial Q_{flow}}{\partial V_{ang}} \\ \frac{\partial V}{\partial V_{mag}} & 0 \end{bmatrix} \tag{2.2}$$

The objective function to be minimized by the WLS algorithm is:

$$J(x) = \sum_{i=1}^{m} \frac{(z_i - h_i(x))^2}{R_{ii}} \tag{2.3}$$

Weighting are done following the principle enhancing the accurate measurements whereas de-emphasizing the less accurate ones. In WLS algorithm the weighting factor is the inversed square of measurement standard deviations.

The first-order optimality condition has to be satisfied. This gives rise to:

$$g(x) = \frac{\partial (J(x))}{\partial x} = -H^T(x) R^{-1} [z - h(x)] = 0 \tag{2.4}$$

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

$$g(x) = g(x^k) + G(x^k)(x - x^k) = 0 \tag{2.5}$$

From this equation, it can be shown:

$$x^{k+1} = x^k - [H^T(x^k) \cdot R^{-1} H(x^k)]^{-1} [-H^T(x^k) \cdot R^{-1} (z - h(x^k))] \tag{2.6}$$

WLS state estimation usually involves Newton iteration to solve this non-linear function given by equation 2.6. The initial states are commonly assumed to have a flat profile that means all the voltage phasors are of 1 p.u and in phase with each other.

The convergence constrains involved in this work are set as:

$$\max(\Delta x^k) \le \varepsilon_1$$

And

$$J^{k+1} - J^k \le \varepsilon_2$$

The second condition actually is the objective of the WLS algorithm that is set to ensure a minimum objective function. Commonly, such a condition is seldom used in real time operation due to the consideration of execution time [3]. The state estimation will be terminated, when the first convergence condition is reached.

2.2 State Estimation Literature Review

2.2.1 Static State Estimation

The primary disadvantage of full WLS algorithm is its time consuming requirement of having the gain matrix evaluated and factored at each iteration. A strong incentive of reducing the execution time leads to the utilization of a constant but approximate gain matrix in the calculation based on a general assumption that gain matrix elements tend to have minor changes during the iteration procedure together with the observation that real (reactive) power equations are insensitive to voltage magnitudes (angles) [2].

One advancement in the field of state estimation is the introduction of a weighting matrix to Least Square algorithm to increase the estimation accuracy. Weighting is considered as confidence indications of certain measurements which are time dependent, so overtime, the confidence in a measurement should change depending on the measurements. Consequently, some auto weight tuning methods are proposed. Since the weights are related to the measurement error variances, sample variances are estimated using historical data from previous measurement scans and the corresponding WLS estimation results. One approach that can be implemented as a one-time estimation function for off-line execution or as a recursive function for updating the measurement weights on-line is presented in [4].

The assumption that measurements have zero means is made for the WLS state estimation algorithm. However, it is challenged by the large scale utilization of the "sensor-less" technologies such as A/D converters. A suggestion towards this problem is to parallel the measurement calibration with state estimation based on the theory that calibration error will always be constant comparing normal distributed measurement error [5].

Another perquisite of Least Square estimation calculation is that system should be observable. Reference [6] and [7] laid a general foundation for observability analysis.

The commonly used Least Square state estimation is a process inherently aiming to suppress the normal distributed measurement noises. However, there are cases in reality that the measurements contain errors which will deviate estimation, so it is necessary to introduce an additional process where the erroneous data can be identified, eliminated or modified. One straightforward method is to compare the deviations of measurements with respect to their expected values with desired threshold values [8]. In literature [9], a hypothesis based method is also proposed.

2.2.2 Dynamic State Estimation

Dynamic state estimation is increasingly important in a modern EMS. Particularly, in view of new possibilities associated with open access and the operation of transmission networks, the patterns of power flows in a deregulated power system has become less predictable comparing to the vertically integrated systems [10]. Under such new situation, the need for the real-time network model is especially vital considering the operation performance, yet the quality of this model highly relies on the effectiveness of state estimators. With the utilization of the previous estimate of the state, a dynamic state estimator is able to forecast the state vector ahead. Thus, it contributes the system operator with a larger time margin in making control decisions such as economic dispatch, security assessment, and other related functions [11].

Dynamic State Estimation based on Extend Kalman Filter is proposed by Debs in the 1970s [12]. The concept of tracking state estimation is initially introduced by Masiello [13]. In the aim of improving model performance of state estimation tracking, invariant parameters exponential smoothing describing the state transition equations is used by Leite da Silva [14]. Utilizing the Fuzzy Control Theory, Sliding-Surface enhanced Fuzzy Control Extended Kalman Filtering for Dynamic State Estimation is discussed as the research goes further in [11]. A general framework for self-updating dynamic estimator can be found in [15].

2.2.3 Multi-area State Estimation

In multi-area power systems, a synchronous power grid is managed by several different organizational entities. Depending on location and tradition, these entities can be either national TSOs who own and operate the network as well as have system responsibility, or privately operated RTOs. Regardless of organizational setting, control of the synchronous system becomes a shared responsibility. Most of work done is related to distributed/hierarchical state estimation algorithm, for example [16].

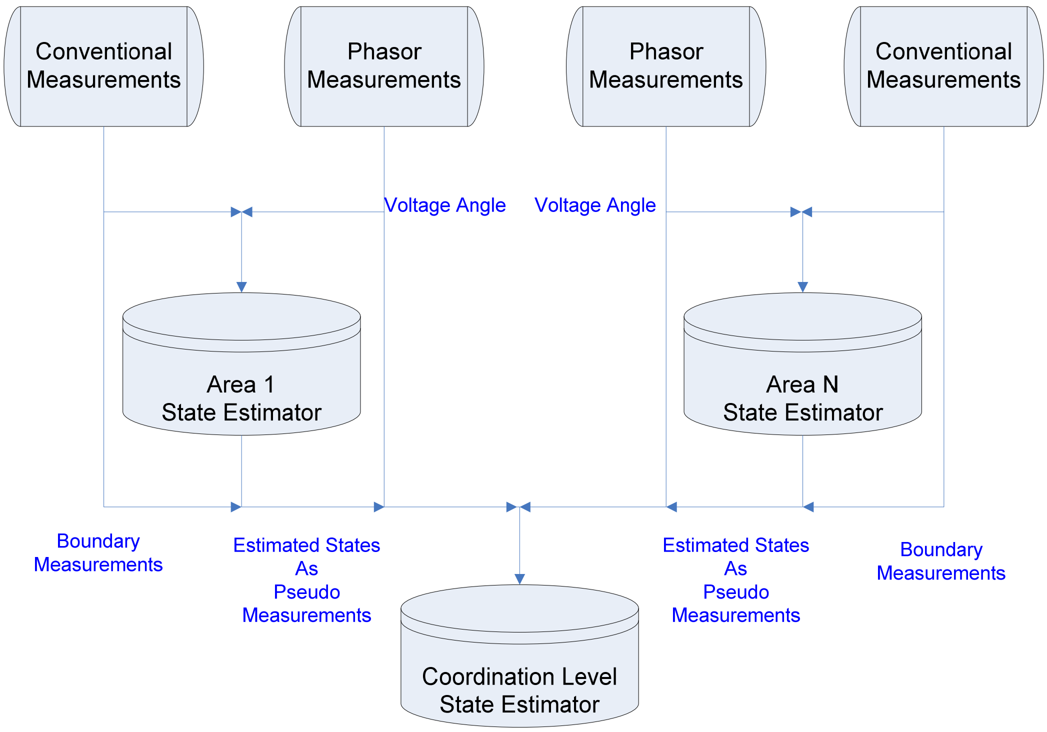

Figure 2.1: Process of Distribute/Hierarchical State Estimation

Some further researches have been done following this idea. In the local state estimation stage, the boundary measurements and the sensitive measurements from the neighboring area, together with the estimated local states used as pseudo measurements are combined as a second-level measurement set, and based on it the state estimation result is re-evaluated [17]. Two algorithms dealt with asynchronism of local state estimation results caused by heterogeneity, delay of arrival of state outputs and lose of state outputs are proposed in the paper [18].

And a distributed Static State Estimation algorithm acknowledging the utilization of the PMU enhancing the computation speed and numerical precision is presented in [17].

2.3 Conventional Metering Error Model

Regardless of state estimation formulation, the accuracy of the estimates is highly dependent on the quality of the measurement. The quality of data can be improved by using high accuracy metering devices together with communication channels which are of high transmission quality. The conventional measurements are assumed to have errors with Gaussian distribution with a standard deviation that consists of two components: one component is proportional to the full scale of the meter, f_s, and another one is proportional to the actual measured value, M [3].

$$\sigma_i = (0.02M + 0.0052 f_s)/3 \tag{2.7}$$

Where

$$M = \begin{array}{c} \sqrt{Pflow_i^{\,2} + Qflow_i^{\,2}} \\ \sqrt{Pinj_i^{\,2} + Qinj_i^{\,2}} \\ \left|V_i\right| \end{array}$$

The definition of σ_i indicates that it is necessary to update the weighting matrix in real time, since it is dependent on the measurement values. However, usually the power system states tend to change slowly, so that this matrix in this study is assumed as constant.

Chapter 3

Nordic 32 Model

3.1 Model Description

The modified Nordic 32 bus model (41 buses) is used in this thesis, which is a condensed model of the power grid in Sweden together with part of its neighboring counties. The electrical configuration is presented below in Figure 3.1.

The Swedish test system is fictitious but has dynamic properties that are similar to the transmission power grid in Sweden and other Nordic countries. Originally, this system is intended for the transient stability and long term dynamics analysis. The northern part of the system contains considerable amount of generation and the consumption is concentrated in the south, these two areas are linked by a long transmission corridor with large transmission capacity [19].

The main transmission system is designed for 400 kV and 220 kV. In this model, also some regional system at 130 kV is included. The regional network buses are assigned with green and the transmission voltage level buses are of black. The slack bus involved in power flow calculation is bright blue. The lines with the grey color are transmission lines with transformers and the blue lines represent the π-modeled transmission lines.

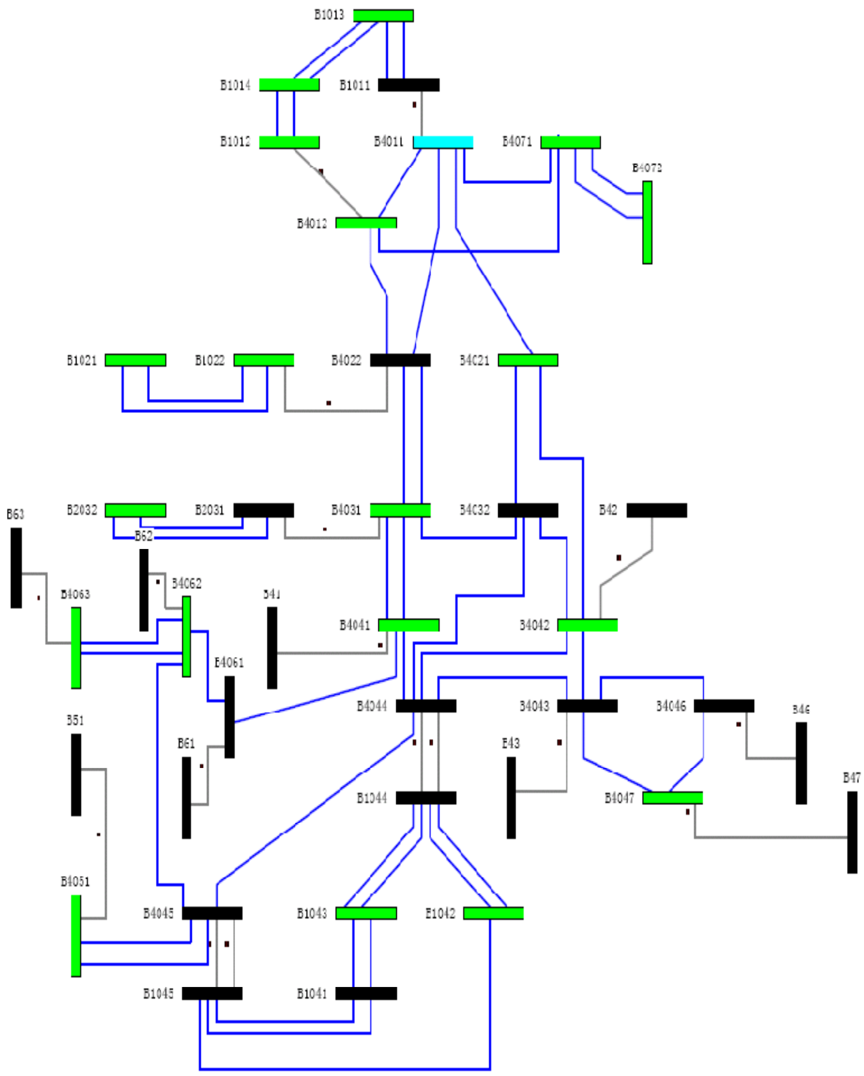

Figure 3.1: One-line Diagram of Nordic 32 Model

3.2 Measurement Configuration

Despite the fact that the accuracy of the estimates is highly dependent on the measurement quality and algorithm, the impact of measurement redundancy can not be neglected as well. A well designed measurement configuration is the prerequisite to ensure accurate and robust state estimation solutions. Since the observability analysis is out of the study scope of this work, an assumption that the measurement configuration involved in this study allows a unique solution for the states of the entire network is made here.

Three types of measurements are involved in this study: voltage magnitude measurements, power flow measurements and injected power measurements. For all the flow and injection measurements, active and reactive measurements appear as pairs. In this study, it is assigned that the transmission network of 400 kV has voltage magnitude measurement and power injection at each bus and 220 kV buses are equipped with voltage magnitude measurements, together with power flow measurements at two ends of the transmission lines. The regional network of the 130 kV has power flow measurements at both ends of the transmission lines and voltage magnitude measurement at each bus.

In the WLS algorithm, the cap matrix K is defined as:

$$\hat{z} = Kz \tag{3.1}$$

Where

$$K = H(H^T R^{-1} H) H^T R^{-1}$$

Geographically, the i-th diagonal entry of the cap matrix K, K_{ii}, gives an indication of the distance of the measurement factor of the corresponding i-th row of H from the bulk of the other remaining measurement factors. The diagonal elements are in the range from zero to one, a large value indicates a low local measurement redundancy.

It can be concluded from equation 3.1 that when K_{ii} equals to one, corresponding measurement decides its estimate autocratically. This type of measurements is cataloged as critical measurement whose elimination from the measurement set will result in an unobservable system. Another type of measurements is named as critical measurement pair whose simultaneous removal can destroy the system observability as well. it can be proved the critical measurements have the same K diagonal numbers [2]. Bad data can only be detected if removal of the corresponding measurements does not render the system unobservable. In other words, the bad data on critical measurements and measurement pairs can not be suppressed numerically. In the aim of laying a foundation for the coming bad data detection algorithm test, it is necessary to design the measurement configuration free of critical measurements and critical measurement pairs. Here the diagonal elements of the cap matrix K are calculated and used as indications to prove that these types of measurements do not exit, see Table 3.1.

0.314	0.4624	0.2369	0.3215	0.4292	0.2493	0.038
0.266	0.3279	0.4191	0.2739	0.3087	0.4211	0.0366
0.4336	0.3221	0.1171	0.434	0.298	0.0774	0.0323
0.4854	0.4229	0.158	0.3751	0.3962	0.1651	0.0364
0.4163	0.4034	0.2762	0.4118	0.3731	0.2804	0.0643
0.221	0.4276	0.3488	0.2123	0.4173	0.3202	0.0448
0.4146	0.3675	0.2582	0.3219	0.3652	0.2074	0.0672
0.0935	0.428	0.3755	0.0657	0.4207	0.3837	0.0721
0.3395	0.3092	0.4268	0.363	0.3108	0.4427	0.0759
0.4593	0.2966	0.3017	0.5041	0.2928	0.3102	0.0018
0.2653	0.426	0.284	0.2713	0.4134	0.2904	0.0052
0.0746	0.3314	0.4603	0.0695	0.3157	0.462	0.0213
0.0835	0.2798	0.3214	0.0683	0.2711	0.3287	0.022
0.1593	0.4424	0.3175	0.1666	0.4414	0.3184	0.2382
0.0886	0.4038	0.4185	0.075	0.5125	0.4254	0.0207
0.1272	0.4379	0.393	0.1322	0.4323	0.4111	0.0822
0.1084	0.2386	0.426	0.0915	0.2352	0.4284	0.2556
0.0584	0.4036	0.3672	0.0459	0.3169	0.3666	0.0662
0.1164	0.0872	0.428	0.0884	0.0716	0.4221	0.0292
0.1405	0.3686	0.3074	0.1341	0.3332	0.3139	0.0326
0.0977	0.4965	0.2947	0.0972	0.4725	0.2978	0.0294
0.0615	0.2686	0.4239	0.0548	0.2636	0.4258	0.0918
0.0337	0.0624	0.5154	0.0363	0.0693	0.4957	0.0277
0.1387	0.0775	0.5419	0.1359	0.0602	0.5373	0.0014
0.2846	0.1578	0.6181	0.2695	0.1429	0.6127	0.0278
0.134	0.0803	0.8517	0.1323	0.0701	0.851	0.0108
0.0933	0.1283	0.7518	0.092	0.1179	0.754	0.02
0.3387	0.1052	0.8249	0.3359	0.112	0.8222	0.0206
0.3	0.0489	0.8342	0.3051	0.0676	0.8353	0.0277
0.1409	0.1028	0.5972	0.1395	0.103	0.6151	0.0261
0.2403	0.1358	0.8409	0.2386	0.1402	0.8435	0.0269
0.3372	0.0887	0.882	0.3382	0.1079	0.8859	0.0258
0.1066	0.0522	0.8435	0.1098	0.0725	0.8451	0.0289
0.1554	0.0296	0.7758	0.1542	0.0401	0.7786	0.0287
0.2672	0.131	0.3067	0.274	0.1307	0.3153	0.0285
0.3489	0.267	0.4692	0.3671	0.2331	0.4725	0.038
0.2582	0.1279	0.742	0.3376	0.1359	0.7383	0.0509
0.3802	0.0898	0.552	0.3646	0.0922	0.5372	0.0531
0.4323	0.3353	0.3251	0.4144	0.3338	0.3263	0.0628
0.3083	0.3014	0.6094	0.2932	0.3072	0.6014	0.014
0.2905	0.1464	0.2582	0.271	0.1474	0.2074	0.0254

Table 3.1: The Diagonal Elements of the Cap Matrix corresponding to the given Measurement Configuration

It can be observed that there are no values equal to 1 or equal elements, so the numerical calculation here implies that the measurements are on a sufficient redundancy level and there is no critical measurement or critical measurement pairs in the measurement configuration involved in this report.

Chapter 4

Challenges for State Estimation

4.1 State Estimator in Svenska Kraftnät

In Svenska Kraftnät, one of the major uses of the output of state estimator is for "Spica", a voltage collapse supervision program determining the transmission capacity margin for specific network sections [20].

The model in Swedish estimator covers the national transmission grid, 400 and 220 kV and also most of the regional network, 130kV in Sweden. Also, it has the 400 kV national grid and part of 130kV network in east Denmark, together with fairly large portion of 400 kV network in Finland and Norway. In total, the estimator model contains about 1500 buses, 1300 lines and 250 generators. With an ambition to include the whole transmission grid in the neighboring countries, this system model is under extension.

The estimator used in Svenska Kraftnät defines network observability, estimates the power system states, filters and suppresses the measurements suffering gross errors, and estimates the step position on on-load-tap-changers by using power flows through the transformers, based on measuring bus voltage magnitudes, transmission line power flows, power flows at the generators and load injection and tap changer positions [20]. The algorithm used here is WLS and the bad data detection method is based on the comparison of normalized residuals. Estimator calculates the states once in every 5 minutes. In the near future, the estimator at Svenska Kraftnät will be upgraded with the ambition to run in an interval of 10 seconds which makes more network supervision applications possible.

4.2 Impact of Uncertainties in State Estimation Input

State estimation concept is proposed several decades ago and there are already some robust algorithms available in the market, however, nowadays, despite the estimator algorithms, a state estimator can still encounter many problems and it is always the case that guaranteeing estimates to an acceptable quality is at the cost of time and effort. All these can be traced back to the uncertainties given as the input to the estimators. The following simulations display the impacts of the errors in topology, biased measurements and unavailability of measurements in a certain area, together with experience based error locating method and mitigation strategies to bring the estimates back to an acceptable quality used by the operators.

4.2.1 Topology Error

Perhaps one of the greatest obstacles for achieving a reliable and accurate power system state estimation is the occurrence that the actual network topology differs from the assumed network model due to the inaccurate knowledge of the switch positions. Commonly, topology errors have more significant negative impact to the estimates comparing with errors in network parameters or measurement calibration errors.

In order to introduce a major impact to the power system estimates, a topology error is created at the lines between bus 4031 and 4041 at “Snitt 2”, which carries a significant real power transmission. The introduction of this error diverges the estimator solution at the default convergence setting. A simulation is conducted with convergence constraints set 100 times larger than the default ones, and the some estimates are collected below:

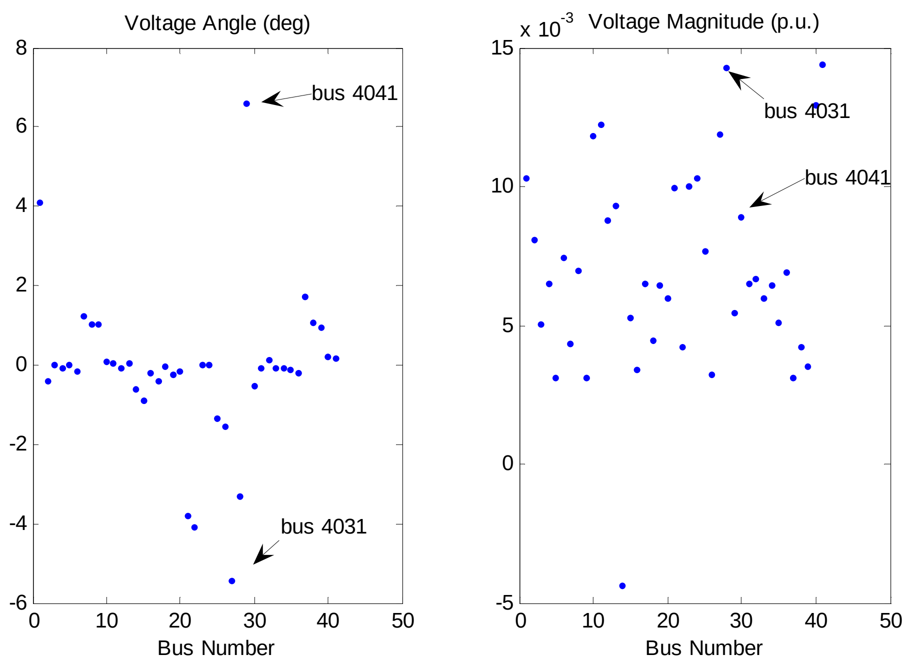

Figure 4.1: Voltage Residues with Topology Error

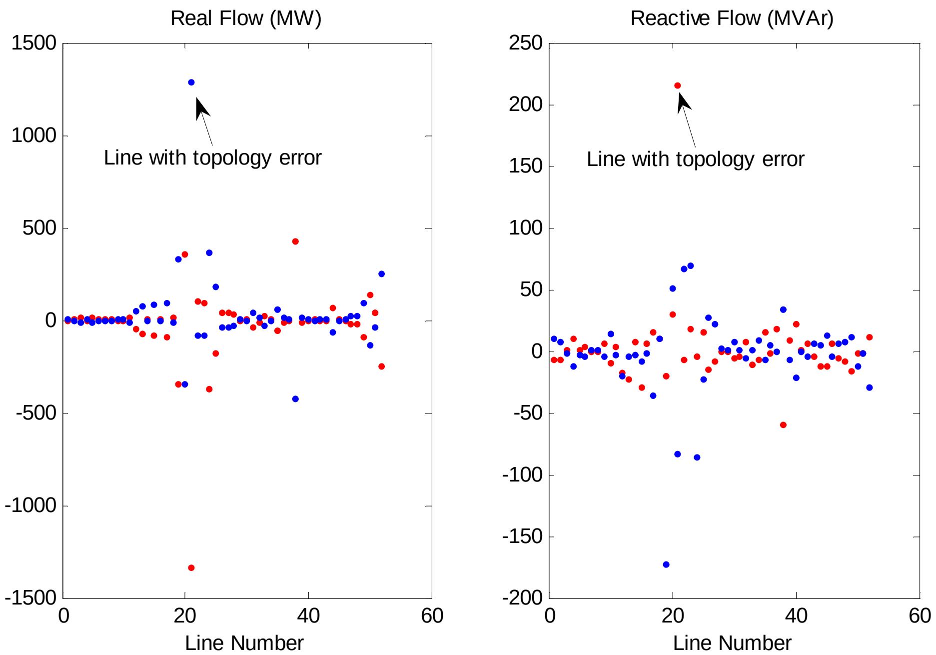

Figure 4.2: Power Flow Residues with Topology Error

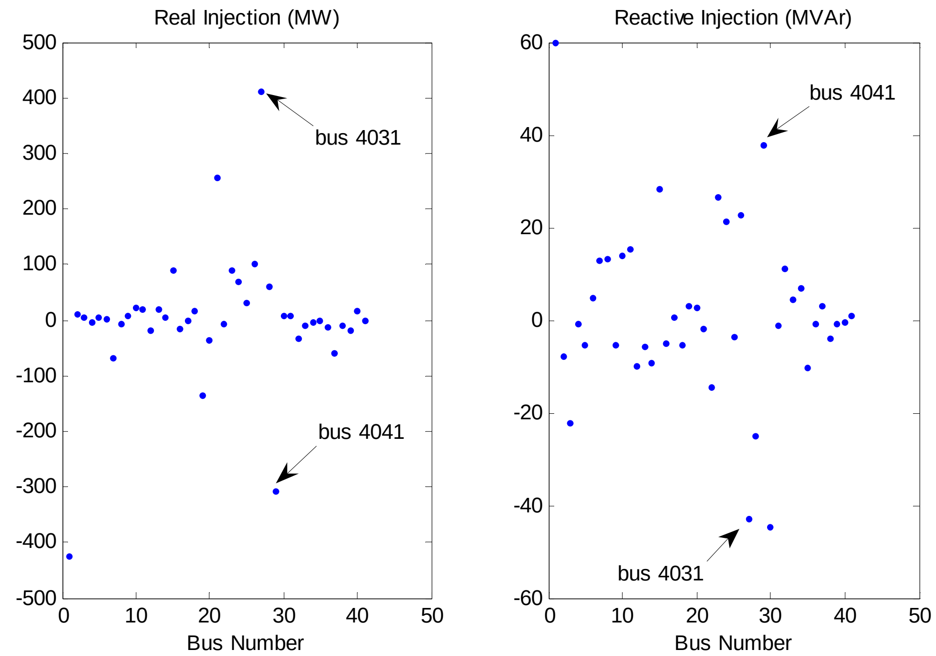

Figure 4.3: Power Injection with Topology Error

The state estimation results about the power flows on the line with topology error are expected to have large residues, which can usually be used as an indication of this error. Besides this, the nodes connected by this line have large residuals for power injection and voltage estimates and also it can be observed that the neighboring nodes have comparable large residues due to large amount of power flow mismatch. A detailed and more systematic analysis of this kind of topology errors can be found in [8], in which test results based on the WLS state estimation algorithm with a Normalized Largest Residual are presented

4.2.2 Biased Measurements

One of the most important attributes of a real-time state estimator is its ability to detect and identify gross errors in measurements. At an early stage in the development of state estimation, approach to detect the bad data is chi-square test, which is an indirect statistical method acknowledging that the index, $J(\hat{x})$ of WLS algorithm follows a Chi-square distribution. This method significantly suffers from its poor reliability for detecting the presence of measurement error in the range of 3 to 20 times standard deviation, alternatively a normalized residual based test has been proposed, which overcomes the drawback of the former [21].

The basic idea of this method is to compare the measurement z_i presenting the largest normalized residue with its corresponding estimated value $\hat{z}_k$ calculated by a new set of measurements in which the measurement z_i is excluded.

The residual covariance matrix is given as:

$$Cov(R) = R - H \times [H' \times R \times H]^{-1} \times H' \tag{4.1}$$

The diagonal elements of this matrix are assigned as ρ_{ii}^2 and normalized residual r_i^N are calculated as:

$$r_i^N = \frac{r_i}{\rho_{ii}^2} = \frac{z_i - h(\hat{x})_i}{\rho_{ii}^2} \tag{4.2}$$

Identifying largest normalized residual which is suspected as containing bad data, and then estimated measurement error is calculated as:

$$b_i = \frac{\sigma_i^2}{\rho_{ii}^2} r_i^N \tag{4.3}$$

From the normal distribution table, it is known that, for instance, 99.9999% of the measurements collected with meters should fall within the range $\pm 4\sigma_i$. The gross error threshold is set to 4 in this study.

When

$$|b_i| \geq 4$$

When the measurement is identified as bad and modification to this data is introduced as:

$$z_i^{new} = z_i - \frac{\sigma_i^2}{\rho_{ii}^2} r_i \tag{4.4}$$

Then z_i will be substituted by z_i^{new} and solving the state estimation problem again [21].

The bad data identification ability is dependent on the measurement redundancy, which is in turn decided by measurement configuration in the network, regardless of the algorithm itself. That means in order to assess the performance of one bad data detection method in one power grid model, it is necessary to analyze the errors on measurements with different redundancy level, respectively. The measurements involved in this study are cataloged as high redundancy, medium redundancy and low redundancy level according to the calculated diagonal elements of the cap matrix. In this report, one real power flow measurement, one reactive power injection measurement and one voltage magnitude measurement are analyzed to guarantee that all the study objectives cover all measurement types and span real and reactive power measurements. The measurement with the medium level redundancy is defined as the one who has the closest value regarding the average value of this measurement type.

Measurement Types	P^{flow}	Q^{inj}	V^{mag}
Low Redundancy	$P^{flow}_{1021-1022}$ 0.4854	Q^{inj}_{4044} 0.8859	V^{mag}_{4012} 0.0014
Medium Redundancy	$P^{flow}_{4032-4044}$ 0.2653	Q^{inj}_{4072} 0.6127	V^{mag}_{1042} 0.0448
High Redundancy	$P^{flow}_{4011-4012}$ 0.0037	Q^{inj}_{4021} 0.2074	V^{mag}_{51} 0.2556

Table 4.1: Selected Measurements and Corresponding Redundancy

Considering the test system in Figure 3.1, random normal distributed noises are implemented to the exact load flow solution to simulate the SCADA measurements. And gross errors with different magnitudes are added to the selected measurement candidates. The tests are repeated for 1000 times on measurements with different redundancy level respectively and the successful detection probability is recorded.

Gross Error $b_i\sigma_i$	$P^{flow}_{1021-1022}$	Q^{inj}_{4044}	V^{mag}_{4012}
11σ	100%	100%	100%
$10\sigma_i$	100%	90%	100%
$7\sigma_i$	99.4%	62.1%	100%
$5\sigma_i$	79.7%	47.8%	100%
$4\sigma_i$	45.2%	27.0%	100%
$-4\sigma_i$	48.3%	22.9%	99.6%
$-5\sigma_i$	68%	41.2%	100%
$-7\sigma_i$	100%	77.1%	100%
$-10\sigma_i$	100%	88.2%	100%
$-11\sigma_i$	100%	100%	100%

Table 4.2: Successful Bad Data Detection Probability Summary for Low Redundancy Measurements

Gross Error $b_i\sigma_i$	$P^{flow}_{4032-4044}$	Q^{inj}_{4072}	V^{mag}_{1042}
$7\sigma_i$	100%	99.9%	100%
$5\sigma_i$	100%	51.9%	99.7%
$4\sigma_i$	58.7%	33.2%	93.4%
$-4\sigma_i$	68.2%	40.1%	86.1%
$-5\sigma_i$	97.4%	60.1%	100%
$-7\sigma_i$	100%	97.5%	100%

Table 4.3: Successful Bad Data Detection Probability Summary for Medium Redundancy Measurements

Gross Error $b_i\sigma_i$	$P^{flow}_{4011-4012}$	Q^{inj}_{4021}	V^{mag}_{51}
$6\sigma_i$	100%	100%	100%
$5\sigma_i$	92.1%	66.3%	100%
$4\sigma_i$	59.2%	37.2%	100%
$-4\sigma_i$	71.5%	44.2%	99.8%
$-5\sigma_i$	94.2%	77.5%	100%
$-6\sigma_i$	100%	100%	100%

Table 4.4: Successful Bad Data Detection Probability Summary for High Redundancy Measurements

The study demonstrates that the detection capability is dependent on the measurement configuration in the network. According to the simulation records, this bad data detection method is very effective to identify the biased measurements with error magnitudes larger than $\pm 11\sigma_i$ given the measurement configuration used in this thesis.

4.2.3 Measurement Lost

State estimation is a common concern between the TSOs and their counterparts who share the joint responsibility of power system operation and control. In Sweden, Svenska Kraftnät is in charge of state estimation based on bilateral agreements with distribution companies here. The distribution companies send measurements on their own network upstream to Svenska Kraftnät and receive estimated states of the whole Swedish network in PSS/E format back. This approach is beneficial for both parties, since the TSO can use the measurements to improve the estimates and the distribution companies are rewarded with estimates including their networks without the need to have an estimator.

In Svenska Kraftnät, the internal real-time information, measurements collected from its own substations, is transferred through a dedicated communication system named as “Operational Data Network” and the data exchange with external counterparts relies on several Elcom protocol based communication links. Measurement availability is one of the main concern within state estimation, the lost of measurement in critical areas in this case may diverge the estimation solution. Svenska Kraftnät has had some problems with their Elcom connections, mostly for a short time, but sometimes it is also possible for longer periods. This forces the operators to take actions in order to guarantee the acceptable estimator performance.

Due to the fact that power system operating conditions seldom change dramatically, it is possible to use the old estimates to substitute these unavailable measurements. In Swedish estimator, there exist some buses that are allowed to have several so called ADS points replacing measurements which can be either previous estimates or scheduled values. These points are commonly implemented to the areas frequently suffering from measurement unavailability in the aim of keeping network observable when the communication is lost. A minimum number of ADS points are selected under the consideration of computation speed, reliability and storage capability. For instance, about 50 such points can be activated in the E.ON southern distribution network when all the real-time information exchange through the Elcom connection between Svenska Kraftnät and the E.ON control centers is down. This turns out to be effective to obtain observability in a short period.

The study here simulates the utilization of previous estimates to save the network observability when Elcom is out of service. In the Nordic 32 model, the E.ON distribution network in southern Sweden is interpreted as a meshed grid composed by bus 1041, 1042, 1043, 1044 and 1045. When the Elcom is lost, the voltage magnitude measurements at these nodes and power flow data between them become unavailable, consequently, it is not possible to decide an unique solution for states at bus 1041, 1042 and 1043, however the power flow measurements on the transmission lines between 1044 and 4044, 1045 and 4045 still make the bus 1044 and 1045 observable.

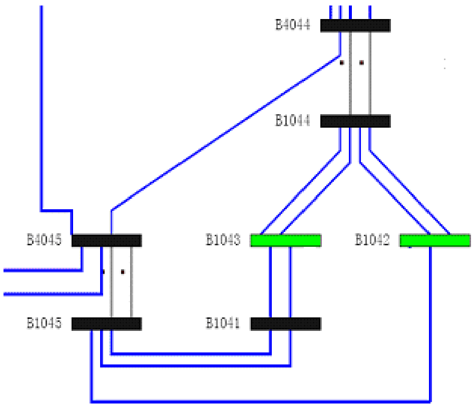

Figure 4.4: Simulated E.ON Distribution Network in Nordic 32 Model

Two scenarios are involved to simulate the slight variation of the power generation and consumption in normal operations. The default Nordic 32 power system operating condition is named as Scenario I, and system operating condition Scenario II is created in which loads in the south is reduced by 10 % whereas generation in the north is decreased by 10 % as well.

In the simulation work here, it is possible to use RMS value of error to assess the deviation of $\hat{x}$ from the "exact" value of x acknowledging the use of this test bed with a know solution created by power flow calculation.

$$RMS^{mag} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^{mag} - \hat{x}_i^{mag})^2} \tag{4.5}$$

$$RMS^{ang} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^{ang} - \hat{x}_i^{ang})^2} \tag{4.6}$$

The RMS value of the estimated voltage angle and magnitudes are calculated respectively under operating scenario I and II. It is repeated 10 times for each in order to suppress the uncertainty acknowledging given random errors on measurements, and then the average value of RMS errors is obtained. It is recognized that the average values of the RMS errors on these two different operating conditions are slightly different.

Experiment Number		Voltage Magnitude Error	Voltage Angle Error
Scenario I	1	0.0058	0.5018
	2	0.0053	0.5637
	3	0.0053	0.6736
	4	0.0055	0.4013
	5	0.0064	0.3544
	6	0.0056	0.4648
	7	0.0049	0.1904
	8	0.0062	0.5622
	9	0.0060	0.6047
	10	0.0052	0.4686
	Average	**0.0056**	**0.4768**
Scenario II	1	0.0056	0.5438
	2	0.0049	0.5326
	3	0.0052	0.4789
	4	0.0060	0.4571
	5	0.0052	0.4355
	6	0.0061	0.6822
	7	0.0053	0.2058
	8	0.0044	0.4440
	9	0.0067	0.6143
	10	0.0041	0.4643
	Average	**0.0053**	**0.4858**

Table 4.5: RMS Voltage Magnitude Error in p.u and Voltage Angle Error in Degree under Operating Scenarios I and II, respectively

The voltage magnitudes and angles on bus 1041, 1042 and 1043 estimated from previous execution are implemented as pseudo measurements to make the whole network observable. In the test, the estimator is fed with these three old estimates pairs cyclically, under the iteration of two different operating scenarios. The solution is still acceptable comparing to the initial one when the iteration was repeated 20 times.

Iteration Number	Voltage Magnitude Error	Voltage Angle Error
1	0.0058	0.5793
2	0.0053	0.4343
3	0.0063	0.6018
4	0.0055	0.3214
5	0.0054	0.8799
6	0.0056	0.5823
7	0.0049	0.4546
8	0.0062	0.6623
9	0.0060	0.6448
10	0.0052	0.8623
11	0.0056	0.7782
12	0.0058	0.7912
13	0.0053	0,8160
14	0.0063	0.9712
15	0.0077	0.7782
16	0.0061	0.6753
17	0.0066	0.7829
18	0.0060	0.8761
19	0.0070	0.8732
20	**0.0074**	**0.8723**

Table 4.6: RMS Voltage Magnitude Error in p.u and Voltage Angle Error in Degree when the selected previous Estimates are implemented with the Iteration of Operating Scenario I and II

Consequently, this mitigation solution is effective in this test system which is able to keep the quality of estimates at an acceptable level when the loss of measurements with short period, the relative error change after 20 estimator executions with the operating iterating conditions relating to the average error for the two scenarios is less than 100%. The test results show this method effective in keeping a convergence solution under absence of certain measurements at a cost of estimation accuracy.

However, the effectiveness of this mitigation strategy is dependent on the system operation statues. The following example shows that, the utilization of the old estimates has limited influence on the estimator convergence when operation condition of the system is under a major change.

In order to find the changes of power consumption which give sufficient impact to the system, sensitivity analysis is carried out, in which the most significant impact to power system states in are defined. According to the result, the increase of real power consumption at bus 46 and reactive power demand at 56, together with the generation reduction at bus 4042 are candidates to introduce the most significant impact to the voltage magnitude in bus 1041, 1042 and 1043. It also reveals that the increase of reactive power at bus 1041 and real power demand at 2011 and decrease of the generation at bus 4012 are the candidates to introduce the most significant impact to the voltage angle in bus 1041, 1042 and 1043. The power generations or consumptions at buses mentioned are decrease to 0. The above changes are introduced to the power system model during the absence of certain measurements while feeding back old estimates to the estimator. The incorporating old estimates are of minor impact to the solution convergence in this case.

Chapter 5

State Estimation with Angle Measurements

5.1 PMU Background

Until recently, the available measurement set from conventional SCADA system does not contain phase angle measurements due to the technical difficulties associated with the synchronization of the measurements at the remote locations. The utilization of the GPS alleviated these difficulties and triggered the development of the PMU.

Synchronized phasor measurement units were developed in the mid-80s. These equipments use GPS transmission to synchronize measurements of positive sequence voltage phasors in the lines connected to those buses. PMU are developed initially from the invention of symmetrical component distance relay. To accomplish synchronization of measurements taken at distant points, several measurements are taken and aligned with time stamps [22]. The following picture is a conceptual example for PMU measurement system.

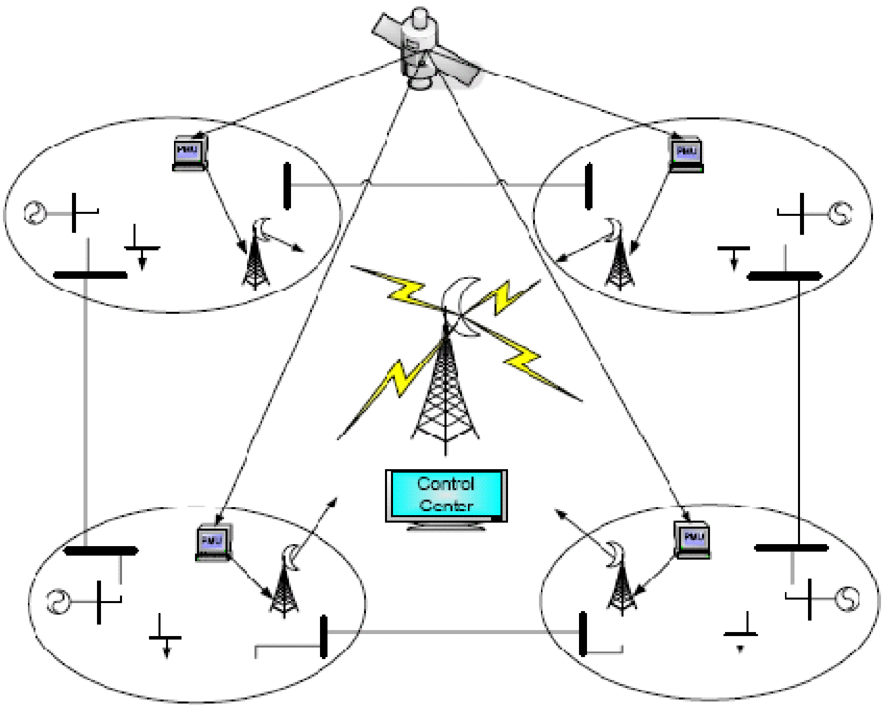

Figure 5.1: Conceptual Diagram from a Synchronized Measuring System [23]

Since the state of the power system is constituted by the positive sequence voltage phasors at all buses, the knowledge of them within the full network can lead to a process of states measuring, instead of state estimation. Some pioneer experiments have already shown that the knowledge of the voltage phasors in the network could contribute to an improved accuracy of the state estimation [22] and [24]. Though the state phasor measurement system is a preferable technique due to its linear mathematical property comparing to the nonlinear state estimation, practically, it is recognized that in most of the power system, the number of PMU are far from sufficient to cover all the buses of the network.

5.2 PMU Placement

Two cases are simulated here and the PMU placement involved in the work here is according to the suggestion from the PMU-project prestudy in Svenska Kraftnät done by Gothia Power. In Case I, voltage angle data are collected from four PMUs located in Harsprånget, Letsi, Kilforsen and Forsmark, which are interpreted as bus 4022, bus 4011, bus 4012 and bus 4042 respectively in the Nordic 32 model. In Case II, together with the existing 4 PMUs in the previous section, two PMUs are placed at the nuclear power plants Ringhals and Oskarshammnsverket, which is interpreted as bus 4063 and bus 4047 respectively in Nordic 32 model. And also there are PMUs located in the stations at the critical transmission corridors “Snitt 2” and “Snitt 4” which means at bus 4031, bus 4032, bus 4041, bus 4042, bus 4061 and bus 4062. In total, twelve PMUs are used in the second case.

5.3 PMU Error Model

The voltage angle measurements are assumed to be in error only due to time synchronization. With GPS synchronization accuracy of the order 1 μ second, the voltage angle measurements are assumed to have normal distributed noise with the standard deviation of 0.018 degree in a 50 Hz power system.

5.4 Incorporating Angle Measurements to State Estimation

There have been a school of thoughts hold the belief that the PMU measurements are superior to the conventional SCADA measured ones, so the PMU utilization should be separated from the SCADA measurements [17]. Others admit the difference between these two measurement sources and it is viable to corporate PMU data into SCADA measurement sets [18].

Some research have proved that PMU measurements could be used to enhance the state estimation results, for example, improving the network observability [25], bad data detection [26], and validating the topology model. These aspects are out of the study scope of these coming two chapters, which focuses on improving the estimation accuracy. This chapter presents two methods using the PMU measured voltage angles in state estimation to improve the estimates.

5.4.1 Incorporating Angle Measurements as Inputs

The coming text presents a straightforward application treating voltage angle measurements as additional measurements that are appended to the conventional ones from the SCADA system. In this case, the hybrid measurements both from SCADA and PMU are fed into the estimator.

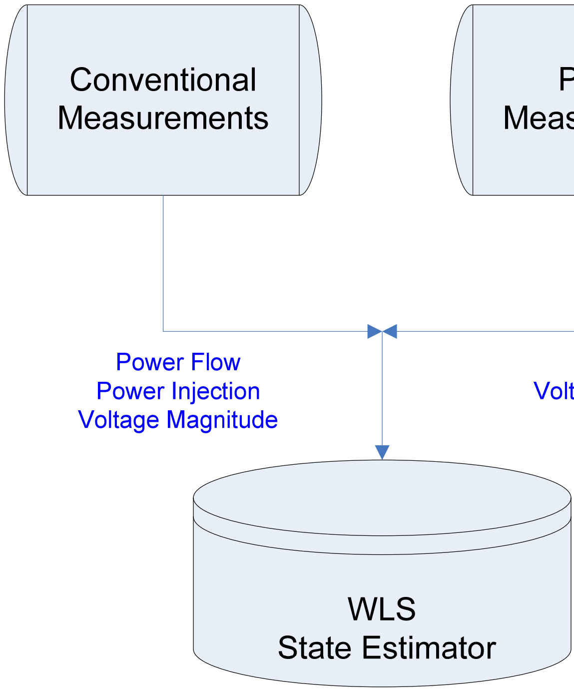

Figure 5.2: Using Phasor Measurements as direct Input to State Estimator

The hybrid measurement set z_2 created by incorporating angle measurements V_{ang}^{syn} to the convention measurement sets. And correspondingly, the main modification to the estimator is the addition of new Jacobian matrix rows for the participating angle measurements. The only non-zero entry in each such row is a partial derivative of an angle measurement with respects to the angle variable of its bus.

$$\frac{\partial V_{ang}^{syn}}{\partial \theta} = 1 \tag{5.1}$$

The RMS errors are used to evaluate the quality of the estimates. The experiments were repeated 10 times under the Operating Scenario I, and in order to suppress the uncertainty acknowledged given random errors on measurements, the average value of RMS errors is calculated.

Experiment Number	Case I (4 PMUs)	Case II (12 PMUs)
1	0.0042	0.0045
2	0.0045	0.0042
3	0.0037	0.0056
4	0.0035	0.0049
5	0.0049	0.0055
6	0.0046	0.0042
7	0.0053	0.0028
8	0.0047	0.0038
9	0.0052	0.0035
10	0.0049	0.0039
Average	**0.0045**	**0.0043**

Table 5.1: RMS Voltage Magnitude Error in p.u

Experiment Number	Case I (4 PMUs)	Case II (12 PMUs)
1	0.1202	0.0601
2	0.1354	0.0797
3	0.1352	0.1655
4	0.1436	0.1196
5	0.2064	0.1059
6	0.1817	0.1288
7	0.1912	0.1419
8	0.1013	0.1046
9	0.1268	0.0847
10	0.1628	0.1443
Average	**0.1505**	**0.1135**

Table 5.2: RMS Voltage Angle Error in degree

The average RMS angle and magnitude error for Scenario I are calculated as 0.4768 and 0.0056 respectively in the previous chapter.

The simulation results prove that adding angle measurements with standard deviations of 0.018 degree is beneficial to estimate accuracy and the larger number of PMU tends to contribute an increasingly positive impact, which are consist to the conclusion drawn in [27]. Also, it can be recognized that the introduction of voltage angle measurements have relatively more significant effect on voltage angle estimates comparing to their magnitudes counterparts.

5.4.2 Incorporating Angle Measurements in Post-processing

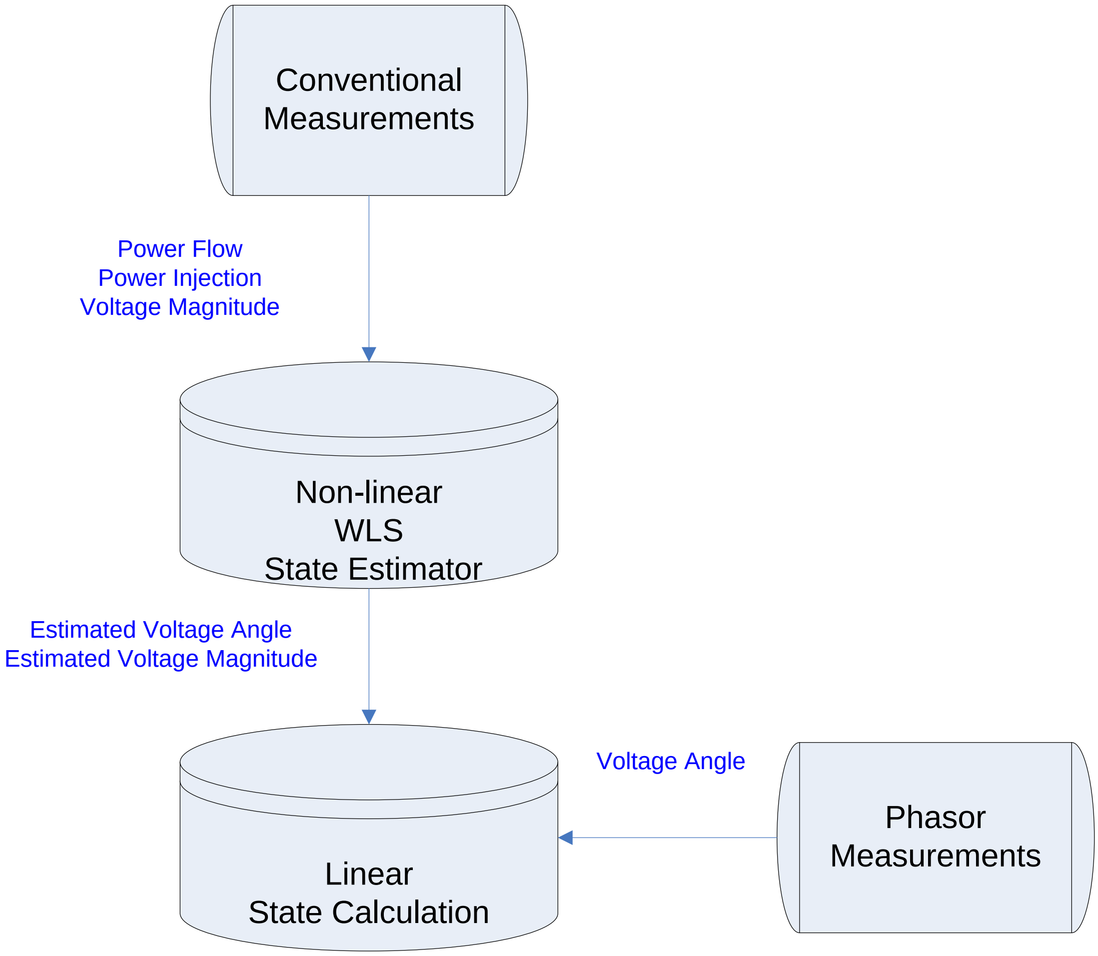

Figure 5.3: Using Phasor Measurements in State Estimation Post-processing

All the input and calculation of the state estimator are preserved the same, only an additional post processing stage is introduced. The estimates are considered as the presudo measurements $V_{mag}^{'}$ and $V_{ang}^{'}$ together with the synchronized PMU measured voltage angle V_{ang}^{syn} are used as the input to a post processing stage. The relationship between the measurement set and the states are linear:

$$\begin{bmatrix} V_{mag}^{'} \\ V_{ang}^{'} \\ V_{ang}^{syn} \end{bmatrix} = \begin{bmatrix} A_{11} & 0 \\ 0 & A_{22} \\ 0 & A_{32} \end{bmatrix} \begin{bmatrix} V_{mag} \\ V_{ang} \end{bmatrix} \tag{5.2}$$

A_{11} and A_{22} are square matrices of whose diagonal elements are 1. A_{32} has the same structure but only the buses where PMU are placed have 1 as the diagonals. All these matrices are of the size $n \times n$, where n is the number of the power system buses.

The linear property of A matrix indicates that calculation in the added post processing stage is linear. In this post-processing stage, the WLS algorithm is used as before despite the linear relationship between the measurements and the states.

To measure the improvement in estimates, the RMS errors are used as an evaluation. The experiments were repeated ten times for Case I and Case II with operating Scenario I.

Experiment Number	Case I (4 PMUs)	Case II (12 PMUs)
1	0.0048	0.0039
2	0.0023	0.0042
3	0.0042	0.0033
4	0.0032	0.0042
5	0.0044	0.0038
6	0.0046	0.0038
7	0.0048	0.0039
8	0.0050	0.0045
9	0.0040	0.0041
10	0.0044	0.0031
Average	**0.0042**	**0.0039**

Table 5.3: RMS Voltage Magnitude Error in p.u

Experiment Number	Case I (4 PMUs)	Case II (12 PMUs)
1	0.2207	0.1227
2	0.1208	0.1072
3	0.1775	0.0718
4	0.1425	0.1061
5	0.1729	0.1081
6	0.1144	0.1361
7	0.1185	0.0920
8	0.1972	0.1699
9	0.1235	0.1374
10	0.1032	0.1041
Average	**0.1491**	**0.1045**

Table 5.4: RMS Voltage Angle Error in degree

The conclusion drawn here are consistent with the one from the test utilizing previous method in section 5.4.1.

5.5 Conclusion

It is recognized that the RMS values of the estimate errors obtained by two methods using voltage angle measurements are comparable, actually, these two techniques are mathematically equivalent, and the detailed proof is presented in [27].

Comparing the former method which suffers from a significant modification of estimator code, the later one benefits the estimator with preserving its conventional structure, in this sense, the risk of deteriorating other EMS applications during the upgrade of estimator can be reduced. However, the later method increases the calculation burden by introducing one extra iteration to the execution.

A conclusion could also be made that the introduction of voltage angle data from PMUs will significantly improve the voltage angle estimation results, meanwhile, has relatively minor impact on the voltage magnitude estimation results. And also the increase of PMU number contributes a beneficial impact on the estimates. It is also observed that the introduction of angle measurements does not have impact on iteration number considering the first algorithm, when flat start is used. All these verify the statements in [28].

Chapter 6

Optimum PMU Placement

6.1 PMU Optimum Placement Review

With the criteria of improving the estimation accuracy, previous researchers have proposed modified simulated annealing method, direct combination, and the tabu search algorithm. All of these three algorithms have been tested on the IEEE standard power system models with the results that these methods are able to lead to optimum solutions [29] and [30]. In [31], a genetic search is suggested with the advantages of being able to mitigate two opposite criteria.

However all these analysis address the design of an entire measurement system, practically, a more attractive suggestion for the state estimation users is indeed incremental enhancement. In general, most utilities and control areas today have few if any PMUs in place, and also have telemetry in place to provide observability for the internal network. Accordingly, when considering the location of new PMUs to increase state estimator performance in a cost effective manner, the problem to be solved is one of incremental measurement placement. That is to find the best places to add 'meters' to a measured system that is already fairly well metered. In other words, power utilities will be more interested in the knowledge of incrementally enhance their existing measurement configuration other than re-design the whole system. So algorithm described in this chapter decides the placement of PMU as additional measurements based on the current measurement configuration.

6.2 Incremental PMU Placement Method

In this study case, the measurement configuration guarantees the whole network to be observable and it is in a state that there are no critical measurements or critical measurement pairs in the system, as proved in chapter 3.2.

Most proposed algorithms for improving accuracy of the state estimator solution via incremental meter placement do so by attempting to reduce uncertainty in the estimated states [32]. A simple approach to use PMU suggested in [2] to improve the estimation accuracy is to implement the PMU measurements to the nodes with less accurate estimates, in other words, PMUs are suggested to be placed at the nodes whose angle state error vector, $x^{ang} - \hat{x}^{ang}$, have large covariance based on the conclusion from previous chapter that introduction of PMU only has major influence to the angle estimates.

The inverse of the gain matrix can be shown to be the covariance matrix of the state error vector when the WLS estimation is used.

$$Cov(x - \hat{x}) = G^{-1} = (H^T R^{-1} H)^{-1} \tag{6.1}$$

The 12 largest covariance of the estimated bus angles are listed in the following table:

Bus Number	Covariance of Angle Estimates
31	4.3486
3	4.1969
11	4.1359
39	4.0445
29	3.9313
23	3.8890
20	3.8231
32	3.8096
4	3.5718
2	3.3916
17	3.1125
28	3.0753

Table 6.1: Covariance of Angle Estimates

Instead of the PMU placement in Case I, chapter 5.2, an OP Case I where 4 PMUs are placed at bus 31, 3, 11 and 39 respectively. And OP Case II is created by further introducing 8 extra PMUs to the bus 29, 23, 20, 32,4 ,2, 17 and 28 despite 4 PMUs used in Optimum Case I, in total, 12 PMUs are involved in the second case. Operating Scenario I is used in the test here.

Experiment Number	OP Case I (4 PMUs)	OP Case (12 PMUs)
1	0.1003	0.0600
2	0.0601	0.0610
3	0.1113	0.0540
4	0.1269	0.0561
5	0.1327	0.0524
6	0.1049	0.0828
7	0.1233	0.1066
8	0.0933	0.0568
9	0.1226	0.0668
10	0.1184	0.0419
Average	**0.1094**	**0.0638**

Table 6.2: RMS Voltage Angle Error in degree

Comparing to the RMS angle error values calculated in the previous chapter, it is quite obvious that the optimum placement of the PMU can significantly improve the estimator accuracy comparing to the previous placement. It is conclude that the beneficial impacts of PMU data on the state estimation depend on the PMU measurement accuracy, calibration, and the number of meters, together with PMU placement.

Chapter 7

PMU Measurement Weight Tuning

The tests in this chapter are performed on the state estimator, GE XA/21, at Svenska Kraftnät

In the WLS state estimation algorithm, the weighting is used for emphasizing the confident measurements while de-emphasizing the ones with less trust. One of the most straightforward and important utilizations of the PMU measurements in the state estimation is to improve the estimates in the whole system scale. The improvement or deteriorate of estimate quality is dependent on the weighting assigned to the introduced measurements given their measurement accuracy comparing to the rests. In other words, low weights on the comparably high accuracy data tend to shade their positive impacts whereas it is possible as well to corrupt the estimates if high weights are given to the less-accurate measurements. In this sense, it is vital to decide suitable weightings for the PMU measurements according to their certain measurement accuracy.

The assessment of the state estimation quality involved here is the WLS objective function *J(x)*, which is defined as the sum of the weighted measurement residues.

$$J(x) = \sum_{i=1}^{m} \frac{(z_i - h_i(x))^2}{R_{ii}} \tag{7.1}$$

Where the weighting R_{ii} is assigned as:

$$R_{\mathrm{ii}} = \sigma_{ii}$$

In this chapter, the PMU placement follows the simulation case 1 in chapter 5.2. The PMU signal is not available in the estimator, consequently, in this test, the voltage angle measurements from PMU are simulated at the bus Harsprånget, Letsi, Kilforsen and Forsmark by feeding the estimates from previous execution cyclically.

As a compromise to the practical or technical difficulties in using a constant measurement set here and limited resources, the test is conducted while the estimator is fed by the real-time SCADA measurements. 3 groups of observations are performed at different time to suppress the impact of random fluctuation of *J(x)* due to the measurements variation. Within each group the changing direction of *J(x)* are sampled 100 times under the iteration of estimator executions with or without PMU. In the estimator, the default standard deviation for voltage magnitude measurements is 1 p.u, for power line measurements it is 3 p.u, and from the GE expert, it is known the one of voltage angle measured by their PMU can reach 0.1 p.u. Since the simulated angle measurements are from old estimates, another candidate standard deviation is proposed as 4 p.u, acknowledging the assumption that the delayed measurements suffer a lower accuracy comparing to the real-time ones. So in this test, the standard deviations 0.1, 1, 3, 4 p.u are selected as candidates. Based on the observation, the probability of the estimation improvement is calculated as:

PMU Measurement Standard Deviations	Observation 1	Observation 2	Observation 3
0.1 p.u	27%	38%	34%
1 p.u	61%	44%	52%
3 p.u	43%	77%	63%
4 p.u	72%	67%	75%

Table 7.1: Improvement Probability of *J(x)* when PMU Measurements are introduced

From the observation, it is concluded that the introduction of measurements with standard deviation of 0.1 p.u actually deteriorates the estimation and standard deviation 1, 3, and 4 p.u are possible candidates to improve the estimation considering the simulated voltage angle measurements. This test could be repeated when the PMU signals are available to the estimator in which a suitable weighting that benefits the estimator most in reducing *J(x)* can be selected.

Chapter 8

Conclusion

In this diploma work, a theoretical foundation in state estimation is laid upon a front of art literature review. Specifically, discussions conducted in this report focused on state estimation algorithms spanning both static and dynamic methods, multi-area state estimation and the PMU utilization in the estimator.

Secondly, a WLS based estimator attached to Nordic power grid model is created in MATLAB acknowledging the literature review. Series of tests are performed in this test bed in which the impacts of uncertainties as input are studied. Besides that, incorporation of PMU measured voltage angles to state estimator is simulated in this model and, as a further investigation, an optimum PMU placement is suggested.

In the end, weight tuning of PMU measurements is studied on the estimator in Svenska Kraftnät. Here, PMU measurements are simulated in the estimator in Svenska Kraftnät by feeding previous estimates cyclically due to the lack of real-time PMU signals. The conclusion suggests that the standard deviations in the range between 4 and 1 p.u could be possible candidates for the simulated PMU measurements considering their accuracy.

Chapter 9

Future Development

9.1 Model Functionality Expansion

The idea of this master thesis is to build up a state estimation test bed which includes an algorithm implementation on a 41 bus power network model coupled with a bad data detection method. A series of experiments about feeding biased inputs into the estimator, substituting the lost measurements with previous estimates and introducing voltage angle measurements from PMU are performed on this platform are discussed in this report. In order to simulate state estimation procedure more fully, the further functionality expansion on the model is appreciated.

9.1.1 Network Observability Analysis

Network observability analysis of power system state estimator is to determine if a unique estimate can be decided for system states acknowledged the given measurement set and their locations in the power grid. In the simulation work here, a perquisite for estimation is that the network is fully observable. However, in real-time operation, taking the measurement availability into consideration, the lost of critical measurements will inevitably create some unobservable islands in the grid model. Besides this, due to the limited number of meters, practical obstacles for setting up data exchange agreements between neighboring system operators or even the unsuitable measurement configurations, it is possible that the given measurements is not able to provide the knowledge of the whole network model. In real time operation, the network observability analysis application identifies all the existing observable islands based on the received measurements at the latest measurement scan before the execution of estimator.

9.1.2 Numerical Topology Error Detection

As stated in chapter 4, topology errors have, in general, a more dramatic influence on the measurement residuals comparing to other biased state estimation input. Therefore, there is a strong need to develop effective mechanisms intended to locate this type of error. Currently, techniques for topology error processing can be categorized based on the moment at which the analysis is performed [4]:

- Priori processing: The assumed statues of circuit breakers are validated in advance before the topology model is feed to estimator by means of local consistency check, rule-based techniques combined with recorded information, etc.

- Posteriori processing: the idea is to combine bad data detection together with the consideration of possibility of topology errors being responsible for biased estimates.

9.2 Multi-area State Estimation

State estimation is a common concern between the TSOs or other system operators who share the joint responsibility of power system operation and control. In Sweden, Svenska Kraftnät is in charge of the transmission power grid, and some other companies, like E.ON, Fortum, and Vattenfall are managing the regional network. Current approach in Sweden is to assign one part as the main responsible and feed requested measurements upwards to the main party and receive estimates in return. In other countries, dependent on their operation concept, other methods to generate states on the neighboring areas exist, such as measurements share or estimates exchange. And also the incorporation of PMU in power system operation coupled with the other new applications in wide area monitor and control will simulate the universal utilization of real-time estimators with high execution speed, consequently, new optimal interaction patterns can be foreseen. Therefore, it is interesting to develop a method for co-operative state estimation for multi-area power systems that acknowledges the shared responsibility and different interaction patterns between transmission system operators. Traditionally, the research in state estimation has been focused on the algorithm improvement. However, in this sense, the main concern may switch to the study of state estimation implementations performance aspects regarding the quality of input.

9.3 Weight Tuning for Real-Time PMU Signals

In this diploma work, the PMU signals are simulated by feeding the angle estimates from the previous execution back to the estimator due to the lack of real-time PMU measurements. It is important to mention, the results here give no suggestions for the real-time PMU measurements due to the fact that simulated measurements involved in the test suffer from the time skew comparing to the real-time PMU measurements. In order to find the suitable weightings for the PMU measurements when their signal is available to the estimator, this test is suggested to be repeated again. Currently, the major obstacle to find a more concrete conclusion here is that it is practically hard to have access to the same measurement set after the execution of estimator. More convincing conclusions could be obtained if it were possible to compare the J(x) of the estimator running with the same SCADA measurements but with or without PMU measurements.

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