Robust Dynamic State Estimation

In Power Systems

A Dissertation Presented

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Abstract

The widespread deployment of Phasor Measurement Units (PMUs) on power systems has facilitated the real-time monitoring of the power systems dynamics. Dynamic State Estimators (DSEs) are used by the investigators to estimate and identify the state variables and parameters of the nonlinear dynamic models within the power systems by using the measurements which are mainly provided by the PMUs. This dissertation addresses fundamental research on dynamic state estimation of the power systems and presents innovative and robust dynamic state estimation approaches for estimation/identification of the state variables/parameters associated with the nonlinear dynamic models within the power systems.

The first part of this dissertation focuses on real-time parameter identification of the nonlinear dynamic load models. For this purpose an Unscented Kalman Filter (UKF) bases DSE is developed to identify the unknown parameters of an exponential dynamic load model in real-time.

As a next step this work presents a two-stage distributed dynamic state estimation approach which remains robust under the occurrence of the bad-data associated with the measurements that are used for the dynamic state estimation. The first stage of the proposed approach utilizes a Least Absolute Value (LAV) linear phasor estimator and the second stage of the proposed approach uses UKF as an efficient DSE.

Observability analysis of the nonlinear dynamic models within the power systems is another topic that is investigated in this dissertation. A Lie-derivative based observability analysis approach is presented in this work which allows us to evaluate the level of the observability for a given measurement associated with a nonlinear dynamic model such as dynamic model of the synchronous generator and load.
This dissertation introduces an UKF based DSE which is named Constrained Iterated Unscented Kalman Filter (CIUKF). One of the main features of the proposed DSE is that it is capable to identify the unknown parameters of the synchronous generators such as inertia constants and transient reactances while estimating the dynamic state variables of the synchronous generator.

This work presents a dynamic state estimation method which remains robust under occurrence of the synchronous generators excitation system failure. Moreover, the proposed approach informs the systems operator about the occurrence of this failure in a timely fashion without any need to locally evaluate the performance of the excitation system by using already existing costly and time-consuming approaches.

Finally in this work a stand-alone robust DSE algorithm will be presented. One of the most important advantages of the proposed approach is that it is capable to evaluate to quality of the measurements provided by the local PMUs in real-time and therefore detect the occurrence of the bad-data associated with measurements.

All of the aforementioned methods in this work will be implemented on the WECC and NPCC test systems and the associated results will be also presented.
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# Contents

1 Introduction .......................................................... 1

1.1 Motivations for the Study .................................................. 2
1.2 Contributions of the Dissertation ............................................ 3
1.3 Dissertation Outline ........................................................... 5

2 Literature Review .............................................................. 7

2.1 Introduction ........................................................................... 7

3 Real-Time Dynamic Parameter Estimation for an Exponential Dynamic Load Model ............................................. 11

3.1 Introduction ........................................................................... 11
3.2 Proposed algorithms and dynamic models .................................. 13
   3.2.1 Exponential dynamic load model ........................................... 13
   3.2.2 Unscented Kalman Filter (UKF) .............................................. 15
3.3 Proposed approach ................................................................ 17
   3.3.1 Implementation of the proposed approach using simulated measurements .............................................. 18
   3.3.2 Implementation of the proposed approach using actual recorded measurements ......................... 21
3.4 Conclusions .......................................................................... 28

4 Linear Phasor Estimator Assisted Dynamic State Estimation .............................................................. 30

4.1 Introduction ........................................................................... 30
4.2 Algorithms and dynamic models .............................................. 32
### 4.2.1 Dynamic model of the generator ................................................................. 33

### 4.3 Proposed approach .......................................................................................... 34

### 4.4 Implementation details ................................................................................... 36

### 4.5 Performance under bad data ........................................................................... 38

### 4.6 Delay mitigation via state prediction .............................................................. 40

### 4.7 Conclusions ..................................................................................................... 46

#### 5 Observability Analysis for Dynamic State Estimation of Synchronous Machines 48

5.1 Introduction ......................................................................................................... 48

5.2 Observability analysis of the machines with complex nonlinear dynamics in the power systems ........................................................................................................ 50

5.2.1 Linear approximation based method for the observability analysis of the nonlinear dynamics ........................................................................................................ 52

5.2.2 Observability analysis of the nonlinear systems using Lie derivatives ................ 54

5.3 Observability analysis of the two-axis model of a synchronous generator with IEEE-Type 1 exciter ........................................................................................................ 55

5.3.1 Implementation of the linear approximation based approach for observability analysis .... 56

5.3.2 Implementation of the Lie-derivatives based approach for observability analysis .......... 60

5.3.3 Validation of the observability analysis results .................................................. 63

5.4 Conclusions ......................................................................................................... 66

#### 6 Constrained Iterated Unscented Kalman Filter for Dynamic State and Parameter Estimation 68

6.1 Introduction ......................................................................................................... 68
6.2 Algorithms of IUKF and constrained UKF based dynamic state estimation ........................................ 70
   6.2.1 Iterated Unscented Kalman Filter (IUKF) ................................................................................... 70
   6.2.2 Constrained UKF based dynamic state estimation ................................................................. 72
6.3 Implementation of the proposed DSEs ............................................................................................. 73
6.4 Conclusions ......................................................................................................................................... 82

7 A Robust Dynamic State Estimator Against Exciter Failures ..................................................... 83
   7.1 Introduction......................................................................................................................................... 83
   7.2 Two alternative implementations of the dynamic state estimators ............................................. 84
   7.3 UKF based dynamic state estimation accounting for the exciter failure ..................................... 88
      7.3.1 Multiple model estimation technique ....................................................................................... 88
      7.3.2 Proposed approach for the dynamic state estimation accounting for exciter failures .......... 89
   7.4 Conclusions ......................................................................................................................................... 92

8 Local Detection of PMU Measurement Errors Using Dynamic State Estimators .................... 93
   8.1 Introduction......................................................................................................................................... 93
   8.2 Proposed approach for the robust dynamic state estimation ...................................................... 95
      8.2.1 An approach for evaluating the performance of DSEs .......................................................... 95
   8.3 Simulation results .............................................................................................................................. 97
      8.3.1 Case study 1 .............................................................................................................................. 98
      8.3.2 Case study 2 .............................................................................................................................. 99
   8.4 Conclusions ......................................................................................................................................... 101
9 Concluding Remarks and Future Work ................................................................. 102

9.1 Concluding remarks ............................................................................................. 102

9.2 Future work ......................................................................................................... 105

Appendix .................................................................................................................... 107

References ................................................................................................................ 112

List of Publications .................................................................................................. 116
List of Figures

3.1 Actual and estimated plot of $P_r$ ................................................................. 19
3.2 Actual and estimated plot of $\alpha_s$ ............................................................. 19
3.3 Actual and estimated plot of $T_p$ ................................................................. 19
3.4 Actual and estimated plot of $\alpha_i$ ............................................................. 19
3.5 Actual and estimated plot of $P_r$ ................................................................. 20
3.6 Actual and estimated plot of $\alpha_s$ ............................................................. 20
3.7 Actual and estimated plot of $T_p$ ................................................................. 20
3.8 Actual and estimated plot of $\alpha_i$ ............................................................. 20
3.9 Voltage of the distribution feeder ($V$) .......................................................... 21
3.10 Estimated values for $P_r$ ............................................................................. 22
3.11 Estimated values for $\alpha_s$ ...................................................................... 22
3.12 Estimated values for $\alpha_i$ ...................................................................... 23
3.13 Estimated values for $T_p$ ............................................................................. 23
3.14 Actual and estimated values for $P_l$ ............................................................ 24
3.15 MSE when tracking total real power ............................................................. 25
3.16 Estimated values for $Q_r$ ............................................................................. 25
3.17 Estimated values for $\beta_s$ ...................................................................... 26
3.18 Estimated values for $\beta_i$ ...................................................................... 26
3.19 Estimated values for $T_q$ ............................................................................. 27
3.20 Actual and estimated values for $Q_l$ ............................................................ 27
3.21 MSE when tracking total reactive power ..................................................... 28
4.1 NPCC test system diagram ......................................................................... 36
5.4 Smallest singular value of the observability matrix using Lie-derivatives-
$\delta$ is the measurement ................................................................. 62
5.5 Smallest singular value of the observability matrix using Lie-derivatives-
$Q_e$ is the measurement .................................................................... 62
5.6 Smallest singular value of the observability matrix using Lie-derivatives-all of the state variables
are used as measurement ....................................................................... 62
5.7 Smallest singular value of the observability matrix using Lie-derivatives - $P_e$ and $Q_e$ are the
measurements .......................................................................................... 63
5.8 Result of dynamic state estimation for the rotor angle- $P_e$ and $Q_e$ are the measurements .......... 64
5.9 Result of dynamic state estimation for the rotor angle- $Q_e$ is the measurement .................... 64
5.10 Result of dynamic state estimation for the rotor angle- $E_{eq}$ is the measurement ................... 65
5.11 Result of dynamic state estimation for the rotor angle- $P_e$ is the measurement .................... 65
5.12 Magnified results of dynamic state estimation for the rotor angle-
$P_e$ and $Q_e$ are the measurements .......................................................... 66
5.13 Magnified results of dynamic state estimation for the rotor angle- $Q_e$ is the measurement ...... 66
6.1 Estimated and true trajectories of the rotor angle-UKF is used as DSE .................. 76
6.2 Estimated and true trajectories of the rotor speed-UKF is used as DSE ...................... 76
6.3 Estimated and true trajectories of the field voltage-UKF is used as DSE ...................... 77
6.4 Estimated and true trajectories of the inertia constant-UKF is used as DSE .................... 77
6.5 Estimated and true trajectories of the d-axis synchronous reactance-UKF is used as DSE ...... 77
6.6 Estimated and true trajectories of the rotor angle-CUKF is used as DSE ......................... 77
6.7 Estimated and true trajectories of the rotor speed-CUKF is used as DSE ......................... 77
6.8 Estimated and true trajectories of the field voltage-CUKF is used as DSE ......................... 77
6.9 Estimated and true trajectories of the inertia constant-CUKF is used as DSE ..................... 78
6.10 Estimated and true trajectories of the d-axis synchronous reactance-CUKF is used as DSE ....... 78
6.11 Estimated and true trajectories of the rotor angle-CIUKF is used as DSE ......................... 79
6.12 Estimated and true trajectories of the rotor speed-CIUKF is used as DSE ......................... 79
6.13 Estimated and true trajectories of the field voltage-CIUKF is used as DSE ......................... 79
6.14 Estimated and true trajectories of the inertia constant-CIUKF is used as DSE ........................................ 79

6.15 Estimated and true trajectories of the d-axis synchronous reactance-CIUKF is used as DSE ...... 79

6.16 Smallest singular value of the observability matrix- Without considering unknown parameters and inputs ........................................................................................................... 80

6.17 Smallest singular value of the observability matrix-Considering unknown parameters and inputs ......................................................................................................................... 80

7.1 Estimated and true trajectories of the rotor angle-UKF is used as DSE ........................................ 86

7.2 Estimated and true trajectories of the rotor angle-IUKF with 5 iterations is used as DSE .......... 86

7.3 Estimated and true trajectories of the rotor angle-IUKF with 10 iterations is used as DSE ........ 87

7.4 Estimated and true trajectories of the rotor angle-UKF is used as DSE .................................. 91

7.5 Estimated and true trajectories of the rotor angle-IUKF is used as DSE .................................. 91

7.6 Result of the multiple estimation technique for UKF and IUKF after the occurrence of the exciter failure ................................................................................................................................. 91

8.1 Estimated and true trajectories of the rotor angle-UKF is used as DSE ...................................... 97

8.2 Calculated performance evaluation metric associated with the main DSE-Case study 1 ........... 98

8.3 Estimated and true trajectories of the rotor angle-using the proposed dynamic state estimation approach ................................................................................................................................................. 99

8.4 Estimated and true trajectories of the rotor angle-Using the conventional approach ............. 99

8.5 Calculated performance evaluation metric associated with the main DSE-Case study 2 .......... 100

8.6 Estimated and true trajectories of the rotor angle-using the proposed dynamic state estimation approach ................................................................................................................................................. 100

8.7 Estimated and true trajectories of the rotor angle-Using the conventional approach .......... 100
List of Tables

4.1 MSE Metrics-Performance under bad data ................................................................. 40
4.2 CPU-Time/Time-Step for the Implementation of LAV based estimator ..................... 43
4.3 MSE Metrics- Assuming delay for the estimated inputs ............................................. 46
5.1 Mean and standard deviation of the smallest singular value of the approximated
observability matrix ........................................................................................................... 58
5.2 Mean and standard deviation of the smallest singular value of the observability matrix-
using Lie-derivatives ........................................................................................................ 60
6.1 CPU-Time/Time-Step for the Implementation UKF, CUKF and CIUKF .................... 80
6.2 Computed MSEs ........................................................................................................... 81
7.1 CPU-time for the estimation of augmented state vector ............................................. 87
Dedicated to my parents
Chapter 1

Introduction

The idea of the power system static state estimation was first proposed by Fred Schweppe in the late 1960s for the purpose of the security assessment of power systems [1]. Numerous algorithms by the investigators are proposed so far for the static state estimation in power systems where the voltage magnitude and phase angles of the buses are estimated by the measurements that are mainly provided by the SCADA systems.

Perhaps the main reason that the majority of the earlier state estimation approaches were focused on the estimation of the static variables of the system was related to the slow rate of the available measurements provided by the instruments that were used by SCADA systems. However since the invention of the Phasor Measurement Units (PMUs) in 1988 the limitation related to the slow rate of available measurements no longer exists. PMUs measure the voltage and current phasors in a synchronized manner with respect to Global Positioning System (GPS). The availability of measured voltage and current phasors by PMUs at rates commensurate with system dynamics made it possible for researchers to investigate implementation of dynamic state estimation for power systems [2-13]. Thus, similar to the use of static state estimation for static security assessment, dynamic state estimation can be used to conduct dynamic security assessment of power systems.

Accurate dynamic models are necessary for dynamic security assessment of power systems. Dynamic State Estimators (DSEs) can be used in real-time to estimate or identify the dynamic state variables and unknown parameters associated with the dynamic models in power systems. Dynamic behavior of power systems is mainly defined by the dynamics of loads and generation units. Therefore this work will propose
robust approaches to dynamic state estimation and identification of the dynamic states and parameters of dynamic models of loads and generators.

1.1 Motivations for the Study

This dissertation is intended to present robust dynamic state estimation approaches in order to facilitate the real-time dynamic security analysis of the large-scale power system which will require the current dynamic states of the system. After investigating the existing approaches in the area of the power system dynamic state estimation some obstacles associated with the proposed approaches were found when they were attempted to be implemented on the actual large scale power systems.

One of the main shortcomings was related to the fact that the effect of the load dynamics and unpredicted topology changes were neglected by the proposed approaches. The second issue was that the existing approaches were not robust under presence of the gross errors associated with measurements that were used for the dynamic state estimation. Another problem related to the proposed approaches was that the measurements were arbitrarily selected for the dynamic state estimation process where it is important to notice that the accuracy of the estimated results provided by the DSEs can be significantly be reduced if improper set of the measurements are used for the dynamic state estimation. Furthermore, in these methods it was assumed that the dynamic models corresponding to the synchronous generators and load are perfectly known, however this assumption may not be valid due to the fact that some of the assumed parameters associated with these dynamic models may not be accurate or may change due the occurrence of the component failures such as failure of the excitation systems of the synchronous machines.

Therefore the main goal of this work was to address these important issues in order to make the implementation of DSEs on the real systems more robust and practical.
1.2 Contributions of the Dissertation

The main contribution of this dissertation is outlined in below:

1. A dynamic state estimation approach to identify unknown parameters associated with a well-investigated exponential dynamic load model is developed. The main advantage of the proposed approach compare to the existing load modeling approaches is that it allows us to identify the unknown parameter associated with the aforementioned dynamic load model in real-time where majority of the existing load modeling approaches try to obtain the parameters corresponding to a load model using the historical load data.

2. A robust distributed dynamic state estimation method is developed. One main advantage of the proposed dynamic state estimation approach compared to the existing approaches is that it remains robust when there are gross errors associated with the measurements that are used for the dynamic state estimation thanks to the usage of a robust linear phasor estimator in the proposed approach. Furthermore, despite some of the existing dynamic state estimation approaches where loads are assumed to remain constant during the dynamic state estimation, the proposed approach takes into the account the effect of the load dynamics and unpredicted topology changes on the dynamic state estimation. The proposed approach also allows us to obtain the dynamic state estimation results for the synchronous generators without a local PMU.

3. A novel approach for observability analysis of the nonlinear dynamic models associated with the synchronous generators and loads is developed. The proposed approach allows us to isolate the complex nonlinear dynamic models of the generators or the loads form the network algebraic equations and separately evaluate the level of the observability for the isolated dynamic equations for a given measurement set.
Furthermore, the proposed approach allows us to identify a proper set of the measurements in order to use for the dynamic state estimation process.

4. In the majority of the earlier proposed dynamic state estimation approaches it is assumed that dynamic models of the synchronous generator are perfectly known. However this assumption may not be valid since some of the parameters or inputs associated with the dynamic model of the synchronous generators may be unknown. In this dissertation a constrained dynamic state estimation approach is introduced which is capable to simultaneously estimate state variables, unknown parameters and inputs associated with the dynamic model of a synchronous generator.

5. A novel dynamic state estimation based approach for real-time failure detection of the excitation systems associated with the synchronous generators is developed. The main advantage of the proposed approach compare to the existing approaches is that it facilitates the detection of such failures remotely and in a timely fashion. Where based on the previously proposed approaches it is necessary to locally investigate the performance of the excitation systems of the synchronous generators which means that the implementation of these approaches can be costly and time consuming.

6. An approach for local bad data detection of the measurements provided by the PMUs is developed. The proposed approach makes it possible to locally evaluate the quality of the measurements provided by the PMUs without any need to implement a system wide robust state estimator.
1.3 Dissertation Outline

This dissertation is composed of nine chapters. The first chapter states the motivation for the presented work and outlines the contributions of the dissertation. The next chapter presents general background information about dynamic state estimation in power systems and reviews the relevant literature to the existing dynamic state estimation approaches.

Chapter 3 focuses on real-time modeling and identification of dynamically changing loads in power systems. An exponential dynamic load model was proposed earlier and was well accepted by several investigators who worked on this topic. This dissertation considers this model and identifies its parameters in real-time by using measurements provided by PMUs. An Unscented Kalman Filter (UKF) is used to track the unknown parameters of the exponential dynamic load model.

Chapter 4, presents a robust distributed dynamic state estimation approach which not only is robust against bad data also makes it possible to obtain the dynamic state estimation results for the generators without a local PMU. The proposed approach also accounts for expected delays in receiving estimated measurements by using a multi-step ahead state predictor to correct for delayed inputs, this procedure can be also useful for the short-term transient stability predictions.

Chapter 5, is concerned about the observability analysis of time-varying nonlinear dynamic model of synchronous generator with its associated control systems. A by-product of observability study is a set of guidelines to choose the appropriate set of measurements or sensors to be used to ensure strong observability for the dynamic states.

The proposed analysis in this dissertation is developed using Lie derivative based observability matrix and its singular values. A two axis synchronous generator and an
associated IEEE-Type1 exciter are used to validate the results of observability analysis with dynamic simulations of disturbance scenarios using different types of measurements.

Chapter 6, presents a robust dynamic state estimator for the synchronous generators with unknown parameters. The estimator uses a Constrained Iterated Unscented Kalman Filter (CIUKF) to estimate the state variables and unknown parameters of a two-axis model of a synchronous generator. The developed estimator’s performance is validated using simulations where the estimator is subjected to arbitrary initialization and large parameter errors. The developed dynamic estimator can potentially be used not only to track the dynamic states but also to detect and identify changes in model parameters with little apriori knowledge about the parameters other than a broad range which can be specified via appropriate constraints.

Chapter 7, presents a robust dynamic state estimation approach against exciter failures. The proposed approach not only remains robust under the failure of the excitation system also detects the occurrence of the exciter failure. UKF and Iterated Unscented Kalman Filter (IUKF) are both used in the proposed approach. Multiple model estimation technique is implemented in order to detect the occurrence of the exciter failure.

Chapter 8, proposes the use of a couple of local PMUs and associated dynamic state estimators in order to detect and remove bad data in PMU measurements. Distinguishing features of the proposed approach is that it facilitates detection of bad-data in local PMU measurements without requiring a system-wide state estimator. The proposed approach relies on a performance evaluation technique which computes the probability density function (pdf) of the residuals provided by a dynamic state estimator. In the proposed approach it is assumed that there are at least two local PMUs that provide measurements to the dynamic state estimators of a synchronous generator.

Finally chapter 9 will conclude the thesis and also mention some of the future work.
Chapter 2

Literature Review

2.1 Introduction

When I started my PhD studies at Northeastern University I was asked by my PhD advisor to perform a transient stability analysis on a simple five bus test system. This system included simplified classical model of the synchronous generators and constant impedance loads. By doing this assignment I noticed that in addition to the topology changes associated with the system (due to the occurrence of the faults or line switching scenarios), the trajectories associated with the dynamic state variables of the synchronous generators namely rotor angles and rotor speeds may also change during the simulations due to the following reasons:

- Generator models: Changes in the trajectories can be different by assuming different generator models.
- Load models: by changing the values corresponding to the constant impedances during the simulation the trajectories of the rotor angles and rotor speeds can be affected.

Now the question was that how we could perform a more accurate transient stability (or any other dynamic) analysis for an actual test system?

According to my observations for the transient stability analysis of the five bus test system, I was aware that in order to accomplish this goal I needed to obtain more realistic
models associated with the loads and generators that could accurately reflect their actual dynamic behaviors.

By investigating the power systems literature I realized that various dynamic models associated with the generators and loads existed.

As an example for the dynamic load models the following models were mostly used by the investigators [14-33]:

- Aggregate load models.
- Exponential dynamic load model.

Here the main goal is to find appropriate values corresponding to the parameters associated with each of these dynamic load models. Furthermore it is important to obtain these parameters in real-time in order find an updated equivalent load model for an actual load due to this fact that the dynamic behavior of the loads may vary during the time.

Numerous approaches are proposed by the investigators for the load modeling which is in fact a system identification problem. As an example for the aggregate load models, genetic algorithms are used by some investigators in order to find the proper values associated with parameters with the load model by using the historical data corresponding to the load [32]. Perhaps the main shortcoming associated with majority of the proposed approaches in the load modeling area is that the it is not possible to implement these approaches in real-time due to the noticeably high computational burden associated with proposed approaches[27].

Due to the time-varying dynamic behavior of the loads, the power delivered by the synchronous generators also have to be adjusted accordingly. When the delivered power by the generators vary due to the load changes, the dynamic state variables associated with the dynamic model of the generators such as rotor angles will also change and be different from their steady state values.
It is important to track the changes associated with the dynamic state variables of the synchronous generators in real-time in order to have a more accurate continuous monitoring of the power systems. As an example for various dynamic studies such as transient stability analysis of the power systems it is necessary to initialize the dynamic equations with the most updated values of the dynamic state variables.

Therefore static state estimation which currently constitutes the foundation of the Energy Management System (EMS) by providing real time pseudo steady state of the system to be used by all other EMS functions should be extended to also estimate the dynamic state variables in addition to the static network variables of the system. This led to the development of the so called “Dynamic State Estimation” solution [33].

One of the first papers that was published in the area of the power systems dynamic state estimation was [34], where Kalman filtering techniques were first applied to estimate the static state variables of the power networks namely voltage phasors of the buses. Since then, there have been various works in this area where the investigators were more interested to track the dynamic state variables of power systems such as rotor angles of the synchronous generators instead of the static state variables. The effect of the load dynamics and unpredicted topology changes were neglected by some of these approaches due to the short duration of interest for performing the dynamic state estimation results [2-13]. As an example in some of these approaches the loads were modeled as constant impedances and then the dynamic state estimation results were obtained for this approximated test system [2]. However, as mentioned earlier this assumption will have a negative impact on the accuracy of the dynamic state estimation due to this fact that the actual loads in the power system have time-varying dynamic behavior and therefore their dynamic behavior should be taken into the account during the dynamic state estimation.

Distributed dynamic state estimation approaches were presented by [6-8] where in all of these approaches it was suggested to directly use the measurements such as terminal voltage and current phasors of the generators within the algorithms of the DSEs.
Therefore the accuracy of the estimated results were dependent on the quality of the measured terminal voltage phasors. In other words these approaches were not robust against the presence of the bad-data associated with measurements that were directly used for the dynamic state estimation.

In [5] the empirical observability Gramian is applied to evaluate the level of observability for the test system by obtaining the reduced $Y_{bus}$ of the system. Here the use of reduced $Y_{bus}$ presents a drawback since it is obtained using approximate constant impedance load models thus reducing the accuracy of the estimated results provided by DSEs.

In the following chapters, more details regarding the aforementioned drawbacks of the existing approaches in the area of the load modeling and dynamic state estimation will be given followed by alternative solutions addressing these shortcomings will be presented.
Chapter 3

Real-Time Dynamic Parameter Estimation for an Exponential Dynamic Load Model

3.1 Introduction

Obtaining more accurate load models, which properly reflect dynamic behavior of loads under various disturbances is one of the challenges in today’s energy management systems. Various on-line applications that rely on dynamic simulation studies require detailed and accurate load models. Use of models that fail to accurately capture the dynamic behavior of loads may lead to inconsistent results for dynamic stability and voltage collapse studies [14-18]. A load model is a mathematical representation related to the measured voltage and/or frequency at a bus, and the real and reactive power consumed by the load [19]. Hence, load modeling is considered as a system identification problem.

As expected, the topic of load modeling occupies a large volume in power systems literature. Proposed load modeling approaches can be broadly classified into two categories: Component-based [22] and measurement-based [23-24] approaches. The drawback of the first category is that it requires full knowledge of the load inventory of typical loads in order to synthesize composite load models. Thus, successful implementation of this approach strongly depends on the true inventory of the loads connected to the feeders, which is regretfully not always available [25]. The second category estimates load parameters using measurements. This gives a more precise picture of real-time loads and their dynamic characteristics [26]. This chapter’s approach...
falls in this second category.

Load models can be broadly classified as either static or dynamic [19]. A static load model does not depend on time [12], and therefore it relates the active and reactive power at a given time to the voltage and/or frequency at the same instant of time. Static load model is suitable to represent static load components such as resistive loads and light bulbs. While they are also used to approximate the dynamic load components, their accuracy is usually not sufficiently high. On the other hand, a dynamic load model describes the load behavior as a function of time and therefore provides a much more accurate tool for dynamic simulations.

This work considers one of the most widely accepted dynamic load models and aims to identify and track its parameters on-line. This is the exponential dynamic load model proposed and described in [23]. Aggregate load model (ZIP augmented with induction motor) is also considered by several researchers [29-32]. Perhaps one of the main shortcomings associated with this model is that, it has considerably more unknown parameters and state variables to be identified and estimated compared to the exponential dynamic load model. Computational burden associated with the estimation of the large number of parameters significantly prohibits the real-time implementation of this model. In order to overcome this limitation, an Extended Kalman Filter (EKF) based technique is used to estimate the dominant parameters of the aggregate load model assuming that the other parameters can be approximated for different types of loads [31]. This approximation however leads to reduced accuracy of the load parameter identification. Other alternatives such as the hybrid learning algorithm which combines the genetic algorithm and nonlinear Levenberg-Marquardt algorithm [32] have also been proposed for parameter identification of the aggregate load model. All of these approaches share the same limitation of high computational burden as a real-time application. In [33] two different approaches for PSS/E CLOD complex load model parameter estimation are investigated. The first approach “Compare and Resimulate” solves for the load model
using a generic nonlinear minimization routine. This approach suffers from long run times and it is vulnerable to measurement error and noise. The second approach is called “Simulate then Calculate” which emulates the time-consuming simulation process using a simple matrix manipulation. This approach reduces the computation time significantly, but also decreases the accuracy of the solution. Furthermore it is sensitive to the distribution which is considered for the parameter set.

The main contribution of the proposed approach in this chapter is that it allows us to obtain the most updated parameters of a well-known dynamic load model, therefore this updated load model can be used in various type of power system studies and simulations in order to have more realistic study of the system.

### 3.2 Proposed algorithms and dynamic models

In this chapter, an Unscented Kalman Filter (UKF) is used as a dynamic state/parameter estimator to track the unknown parameters associated with exponential dynamic load model. Detailed application of the UKF algorithm to the considered exponential dynamic load model is described below.

#### 3.2.1 Exponential dynamic load model

The assumed load model is expressed as a set of non-linear equations, where real (active) and reactive powers consumed by the load are assumed to be related to the voltage in the following non-linear manner [23], [28]:

\[ T_r \frac{dP_r}{dt} + P_r = P_0 \left( \frac{V}{V_0} \right)^{\alpha_r} - P_0 \left( \frac{V}{V_0} \right)^{\alpha_o} \]

\[ P_i = P_r + P_0 \left( \frac{V}{V_0} \right)^{\alpha_i} \]  \hspace{1cm} (3.1)

where:

\( V_0 \) and \( P_0 \) are the voltage and power consumption before a voltage change.
\[ P_r \text{ is the active power recovery,} \]
\[ P_t \text{ is the total active power response,} \]
\[ T_p \text{ is the active load recovery time constant,} \]
\[ \alpha_t \text{ is the transient active load-voltage dependence coefficient, and} \]
\[ \alpha_s \text{ is the steady state active load-voltage dependence coefficient.} \]

Similar equations are also valid for reactive power. The equations related to reactive power part are given below:

\[ T_q \frac{dQ_r}{dt} + Q_r = Q_0 \left( \frac{V}{V_0} \right) - \beta_o \left( \frac{V}{V_0} \right) \]
\[ Q_t = Q_r + Q_0 \left( \frac{V}{V_0} \right)^{\beta_o} \]  \hspace{1cm} (3.2)

Similarly,

\[ v_0 \text{ and } Q_0 \text{ are the voltage and reactive power consumption before a voltage change.} \]
\[ Q_r \text{ is the reactive power recovery,} \]
\[ Q_t \text{ is the total reactive power response,} \]
\[ T_q \text{ is the reactive load recovery time constant,} \]
\[ \beta_t \text{ is the transient reactive load-voltage dependence coefficient, and } \beta_s \text{ is the steady state reactive load-voltage dependence coefficient.} \]

This work focuses mainly on the real-time estimation of the unknown parameters associated with this load model based on measurements. Also it includes the development of a real-time dynamic load model which represents the behavior of the monitored load with an acceptable accuracy. This is accomplished by using an UKF which is implemented as a dynamic parameter estimator for the unknown parameters and state variables of the assumed load model. Here, the unknown parameters are \( \alpha_r, \alpha_s, \text{ and } T_p \)(for
the real power model of (3.1)) and the state variable is \( p_r \). It is needless to say that an equivalent statement is true for the reactive power model of (3.2).

### 3.2.2 Unscented Kalman Filter (UKF)

The UKF uses the unscented transformation [43] for solving nonlinear problems by considering system dynamics and measurement equations as follows:

\[
x_{k+1} = f(x_k, k) + w_k  \\
z_k = h(x_k, k) + v_k
\]

where:

- \( x \in \mathbb{R}^n \) is a discrete state vector.
- \( z \in \mathbb{R}^m \) is a discrete measurement vector.
- \( w_k \sim N(0, Q_k) \) Gaussian process noise at time step \( k \)
- \( v_k \sim N(0, R_k) \) Gaussian measurement noise at time step \( k \)

\( Q_k \) and \( R_k \) are covariance matrices of \( w_k \) and \( v_k \) respectively.

The algorithm of UKF based on 2\( n \) sigma points is expressed by the following steps:

**UKF is initialized as follows:**

\[
\hat{x}_0^+ = E(x_0), \quad P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]
\]

**Time update equations are:**

(a) Calculation of sigma points:

\[
\hat{x}_{k-1}^{\ast (i)} = \hat{x}_{k-1}^+ + x_{v}^{\ast (i)} \quad i = 1, \ldots, 2n
\]

\[
x_v^{\ast (i)} = (\sqrt{nP_{k-1}^+})_i^T \quad i = 1, \ldots, n
\]
\[ x_{i}^{(n+i)} = -\left(\sqrt{nP_{k-1}^*}\right)^T, \quad i = 1, \ldots, n \]  

Please note that \( \sqrt{nP} \) is the \( i \)th row of \( \sqrt{nP} \).

(b) \[ \hat{x}_k^{(i)} = f(\hat{x}_{k-1}^{(i)}, k - 1), \hat{x}_k = \frac{1}{2n} \sum_{i=1}^{2n} \hat{x}_k^{(i)} \]
\[ P_k^- = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{x}_k^{(i)} - \hat{x}_k^-)(\hat{x}_k^{(i)} - \hat{x}_k^-)^T + Q_{k-1} \]  

Measurement update equations are:

(a) Calculation of new sigma points:
\[ \hat{x}_k^{(i)} = \hat{x}_k^- + x_{c}^{(i)} \quad i = 1, \ldots, 2n \]
\[ x_{c}^{(i)} = (\sqrt{nP_k^*})_i^T \quad i = 1, \ldots, n \]
\[ x_{c}^{(n+i)} = -((\sqrt{nP_k^*})_i^T \quad i = 1, \ldots, n \]  

In order to save computational effort step (3.8) can be omitted [43] with a slight degradation in filter performance.

(b) \[ \hat{z}_k^{(i)} = h(\hat{x}_k^{(i)}, k), \quad \hat{z}_k = \frac{1}{2n} \sum_{i=1}^{2n} \hat{z}_k^{(i)} \]
\[ P_e = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{z}_k^{(i)} - \hat{z}_k^-)(\hat{z}_k^{(i)} - \hat{z}_k^-)^T + R_k \]
\[ P_{xz} = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{x}_k^{(i)} - \hat{x}_k^-)(\hat{z}_k^{(i)} - \hat{z}_k^-)^T \]
\[ K_k = P_{xz}P_e^{-1} \]
\[ \hat{x}_k^+ = \hat{x}_k^- + K_k(z_k - \hat{z}_k) \]
\[ P_k^+ = P_k^- - K_kP_kK_k^T \]  

16
3.3 Proposed approach

State dynamics given by (3.3) and the measurement equations given by (3.4) can be developed for the considered exponential dynamic load model given in (3.1) by discretizing the equations using the second order Runge-Kutta method which is a numerically stable discretization method unlike other methods such as Euler method:

\[ P_r(k+1) = P_r(k) + \frac{A + B}{2} \]

\[ A = \frac{\Delta t}{T_r(k)} \times ( -P_r(k) + P_0 \left( \frac{V(k)}{V_0} \right)^{\alpha_r(k)} - P_0 \left( \frac{V(k)}{V_0} \right)^{\alpha_r(k)} ) \]

\[ B = \frac{\Delta t}{T_r(k)} \times ( - (P_r(k) + A) + P_0 \left( \frac{V(k)}{V_0} \right)^{\alpha_r(k)} - P_0 \left( \frac{V(k)}{V_0} \right)^{\alpha_r(k)} ) \]

\[ \alpha_r(k+1) = \alpha_r(k) \]

\[ \alpha_r(k+1) = \alpha_r(k) \]

\[ T_r(k+1) = T_r(k) \]

\[ P_r(k) = P_r(k) + P_0 \left( \frac{V(k)}{V_0} \right)^{\alpha_r(k)} \] \hspace{1cm} (3.10)

Please note that the discretized equations associated with the reactive part (3.2) can be obtained in a similar way.

In order to validate the dynamic estimator performance, a set of measurements is created by dynamic simulations on a system with known load model parameters. UKF is then implemented and used to estimate the augmented state vector which includes the state variable and unknown parameters associated with the exponential dynamic load model:

\[ x_k = [P_r(k), \alpha_r(k), \alpha_r(k), T_r(k)]^T \] \hspace{1cm} (3.11)

where the measurement is assumed to be:

\[ z_k = P_r(k) + v_k \] \hspace{1cm} (3.12)
3.3.1 Implementation of the proposed approach using simulated measurements

Two scenarios are simulated in this section. Both scenarios involve changes in the load model. Measurements are created by using dynamic simulations and subsequently adding Gaussian noise according to the assumed additive noise model of (3.12). These two scenarios are described below.

1) *Scenario 1:*

In this scenario, the true parameters associated with the load model are assumed to be (the values are selected from [28]):

\[ P_0 = 0.867, \alpha_s = -0.32, \alpha_r = 1.65 & T_p = 70[sec]. \]

Here are the detailed steps of the simulated events and assumptions made:

- A voltage drop of \( \Delta V/V_0 = -5.3\% \) occurs at the load bus at \( t = 0 \).
- Load parameter \( \alpha_s \) is increased from -0.32 to -0.28 at \( t = 5 \) min.
- Total simulation time is 10 min and time-step=0.025 sec.
- The UKF is initialized using arbitrary values in (3.5).
- \( R_k = 1e^{-4} \) and \( Q_k = 1e^{-6} \times I_{4x4} \).

The results are shown in Figures 3.1-3.4. Please note that in all plots, dashed and solid lines correspond to the estimated and true trajectories, respectively.
2) Scenario 2:

This scenario is similar to scenario 1 except for the fact that all load parameters are assumed to change linearly during the simulation. Their ranges of change are assumed as follows:

- $\alpha_s$ is reduced from -0.32 to -0.37.
- $\alpha_t$ is increased from 1.65 to 1.7.
- $T_p$ is increased from 70 sec. to 80 sec.

The results are shown in Figures 3.5-3.8.
UKF is observed to successfully track changes in model parameters for both scenarios. It is capable of tracking the unknown and time-varying parameters of the exponential dynamic load model accurately when using simulated measurements and an exponential load model. However, in actual system operation, the load model is simply not known and therefore, UKF’s performance needs to be tested using actual recorded measurements in order to evaluate its performance as an on-line function. This is done in the next section.
3.3.2 Implementation of the proposed approach using actual recorded measurements

In this section, the proposed approach is evaluated based on actual recorded measurement data, where synchronized voltage and power measurements are acquired every 6 seconds for a utility distribution feeder. The total duration of the recordings is 1440 minutes or 24 hours. Figure 3.9 shows that the voltage of the feeder \( V \) increases during this period (from almost 115 kV to 116.5 kV).

![Figure 3.9: Voltage of the distribution feeder (V).](image)

As in section A, UKF is used to estimate the unknown parameters of the assumed exponential dynamic load model. The following assumptions and data are used in implementing the UKF to track parameters of the unknown load based on the recorded measurements:

- A time-step of 6 sec. is used by the filter.
- Total duration of the tracking study is 1440 min.
- UKF is initialized using arbitrary values in (3.5).
- \( R_k = 1e^{-\theta} \) and \( Q_k = 1e^{-\theta} \times I_{4 \times 4} \).
Figures 3.10-3.13 show the estimated values of the assumed exponential load model for the study duration.

![Graph showing Active power recovery](image1)

**Fig.3.10:** Estimated values for $r_P$.

![Graph showing Steady state active load-voltage dependence coefficient](image2)

**Fig.3.11:** Estimated values for $\alpha_s$. 
Note that the true values are not known, so it is not possible to comment on the accuracy of the parameters, however given the long duration of the study time (1440 minutes or 24 hours) one can observe UKF’s tracking of parameters as they gradually change in time.

While the actual parameters of the model are unknown and cannot be directly measured, total active and reactive power are available as measured values. Thus, performance of
the UKF in tracking the total active power can be evaluated by observing the measured
and predicted total active power as shown in Figure 3.14.

In order to quantify the accuracy, the following error metric is used to evaluate the
performance of the UKF in tracking the real-time model of the active power demand:

\[
\sigma_k = \sqrt{\frac{1}{k} \sum_{i=1}^{k} (z_i - \tilde{z})^2}
\]

\[
MSE = \sqrt{\frac{1}{k} \sum_{i=1}^{k} \left(\frac{z_i - \tilde{z}_i}{\sigma_k}\right)^2}
\]  \(3.13\)

where

\(z_i\) and \(\tilde{z}_i\) are the measured and estimated values at time \(i\).

MSE is the mean squared error.

Figure 3.15 illustrates how the MSE value is gradually reduced finally settling below an
acceptable level of 0.25, validating the satisfactory performance of UKF.
A similar study is repeated for the reactive power model of (3.2), where the model parameters are estimated and plotted as shown in Figures 3.16-3.19. Figures 3.17-3.19 illustrate how the exponential dynamic model parameters are tracked by the UKF.

Fig.3.15: MSE when tracking total real power.

Fig.3.16: Estimated values for $Q_r$. 

0 500 1000 1500
0 0.5 1 1.5 2 2.5 3 3.5 4 4.5 5

time [min]

Reactive power recovery [pu]

-2 -1 0 1 2 3 4 5 6

0 500 1000 1500

time [min]
Fig. 3.17: Estimated values for $\beta_s$.

Fig. 3.18: Estimated values for $\beta_t$. 
As in the case of real power model tracking, performance of the UKF is evaluated for tracking the model of the total reactive power. This is accomplished by plotting the total reactive power that is measured and predicted as shown in Figure 3.20.

Fig. 3.19: Estimated values for $T_q$.

Fig. 3.20: Actual and estimated values for $Q_r$. 
Figure 3.21: MSE when tracking total reactive power.

Figure 3.21 shows the plot of MSE for the total reactive power and as evident from the figure MSE gradually reduces to an acceptable level.

It should be mentioned that the computational burden per time step for the proposed dynamic estimator is rather modest due to the small number of state and parameters being tracked. So the approach lends itself readily to real-time implementation.

### 3.4 Conclusions

This chapter is concerned about identification of dynamic load models for power grids. It is recognized that developing and maintaining models that are based on first principles is prohibitively complicated and computationally demanding. Instead, the chapter aims to develop a measurement based model whose parameters can be tracked in real-time. A well-studied and accepted exponential dynamic load model is used as a basis in order to develop an UKF to identify and estimate model parameters in real-time.

The proposed dynamic estimator is first tested using artificially generated measurement data. Subsequently, the estimator performance is evaluated using actual recorded utility
load data captured in 6 second intervals. Both simulation and experimental results indicate that such a dynamic estimator can provide an accurate dynamic load model based on real-time measurements. Given the recent increase in deployment of phasor measurement units in substations, such measurements may be widely available for the proposed application of this chapter in the near future.
Chapter 4

Linear Phasor Estimator Assisted Dynamic State Estimation

4.1 Introduction

Real-time network and machine models are necessary for the dynamic security analysis of the power systems. In order to procure these models, dynamic estimators can be used in the system for tracking the state variables and parameters associated with these models in real-time which provide the most recent estimates for the system and machine dynamic variables. Numerous researchers have so far proposed power system dynamic state estimation algorithms in the literature. The effects of load dynamics and unpredicted topology changes in the system on the dynamic state estimation are neglected by most of these approaches [2-5] due to the short duration of interest for dynamic state estimation results. When the dynamic estimator is considered as a real-time function which remains active continuously during daily operation, then load and network model changes will have to be tracked and accounted for as well.

It can be shown [14-15] that an error in the network model or bus loads will bias the results of such dynamic state estimators. In [5], the level of observability of a power system for dynamic state estimation under a specific PMU configuration is obtained using the empirical observability Gramian, where the reduced admittance matrix of the test system is needed for the implementation of the proposed approach. However, for large scale systems obtaining a valid reduced admittance matrix may not be an easy task due to the lack of proper dynamic load models. It is possible to estimate the dynamic
states of individual generators, namely the power angle and angular speed, in a
distributed manner based only on the measurements taken at the generator terminals [15].

This approach can be implemented based on PMU measurements at each generator
terminal as documented recently in [6-8]. However, viability of the “distributed dynamic
state estimation” is strongly dependent on two assumptions:

- Synchronized voltage and current phasor measurements are always available at every
generator terminal.
- Measurements are free of gross errors.

These assumptions may not be valid for several power systems in operation today. In
fact, PMU measurements are known to experience sudden changes or may become
unavailable (dropped) due to communication system malfunction or noise. Furthermore,
despite the increases in the deployment of PMUs in the recent years, their numbers have
not been at the level yet where it can be assumed that every generating unit has an
installed PMU at its terminals. In this chapter which completes the basic idea and
preliminary results given by the authors in [37], these assumptions are relaxed in order to
design a more robust and reliable dynamic state estimator.

The proposed approach involves a linear phasor estimator which will be used for each
observable zone in the system and a set of distributed dynamic state estimators for each
generator or generator group in order to simultaneously estimate the dynamic state
variables of the machines inside a zone. The main contribution the proposed approach in
this chapter is the way DSE is made “robust” against PMU measurement errors (not only
due to erroneous measurements but also due to various other reasons such as loss of
synchronization, loss of communication channel, etc.) via the use of first stage robust
linear estimator. A second important contribution is the way load modeling is avoided
again due to the use of the first stage linear estimator. Load modeling remains to be a major issue in conventional DSE formulation where network model is reduced down to the generator terminals based on grossly inaccurate assumed static load models. The proposed two-stage dynamic state estimation takes advantage of a fast and robust linear phasor estimator (LAV based estimator) which has the capability to automatically remove bad data associated with the raw measurements at the terminals of the generators. A further advantage provided by the proposed method is the capability to carry out DSE even when the generator terminals are not equipped with a local PMU.

This chapter also develops a short-term predictor for the network states whose estimated values may be available with a finite delay due to the computational time of the linear phasor estimator (which is implemented in a zone with significantly large number of buses). The predictor minimizes any bias due to such delays and improves the performance of the dynamic state estimator for individual generators. The results of simulations for a two-axis synchronous generator with IEEE-Type1 exciter will be shown under different scenarios of interest.

4.2 Algorithms and dynamic models

The linear phasor estimator which provides the required inputs for the distributed dynamic state estimators for the generators uses the Least Absolute Value (LAV) method minimizing the $L_1$ norm of the measurement residuals [1]. The estimator assumes that the power grid is observable by the existing set of installed PMUs. Note that, a modest percentage of system buses need to be populated with PMUs in order to make the entire power system observable [44-45]. Phasor measurements can be obtained during steady state as well as transient conditions [45]. The developed dynamic state estimator (DSE) that is implemented in this study estimates the dynamic state variables associated with two-axis model of a synchronous generator with IEEE-Type1 exciter and it is implemented as an Unscented Kalman Filter (UKF). Given the extensive documentation [1, 37, 47, 48] on the development and implementation of LAV based linear phasor
estimator and UKF (The algorithms of UKF were also given in chapter 3), this section will mainly focus on the description of the dynamic equations associated with the two-axis synchronous generator with IEEE-Type1 exciter.

### 4.2.1 Dynamic model of the generator

Dynamic equations related to a two-axis model of a synchronous generator with IEEE-Type1 exciter \([49-50]\) are given below. In order to simplify the formulation the stator series resistance \((R_a)\) as well as machine saturation are neglected.

**a)** Dynamic equations of a two-axis synchronous generator are given as follows:

\[
\begin{align*}
\dot{\delta} &= \omega - \omega_0 \\
\frac{H}{J_0} \dot{\omega} &= P_m - P_e - D(\omega - \omega_e) / \omega_e \\
T_{dq} \dot{E}_q &= -E_q' - (X_d - X_d')I_d + E_{fd} \\
T_{qd} \dot{E}_d &= -E_d' + (X_q - X_q')I_q \\
\end{align*}
\]

(4.1)

where:

\[
\begin{bmatrix}
V_d \\
V_q
\end{bmatrix}
= \begin{bmatrix}
\sin(\delta) & -\cos(\delta) \\
\cos(\delta) & \sin(\delta)
\end{bmatrix}
\begin{bmatrix}
V \cos(\theta) \\
V \sin(\theta)
\end{bmatrix}
\]

\[
I_d = \frac{E_q' - V_q}{X_d}, \quad I_q = \frac{V_d - E_d'}{X_q}
\]

\[
P_e = V_d I_d + V_q I_q, \quad Q_e = -V_d I_q + V_q I_d
\]

(4.2)

\(\delta\) is the rotor angle, \(\omega\) is the rotor speed, \(P_m\) is the mechanical input power, \(E_q'\) and \(E_d'\) are d-axis and q-axis transient voltages, \(V\) and \(\theta\) are generator terminal bus voltage magnitude and phase angle respectively, \(P_e\) and \(Q_e\) are the active and the reactive power delivered by the generator.

Definitions of the other machine parameters are given in the Appendix.

**b)** Dynamic equations of the IEEE-Type1 exciter:

\[
T_e \dot{E}_{fd} = V_R - K_e E_{fd}
\]
where $E_f$, $V_f$, and $V_R$ are field voltage, scaled output of the stabilizing transformer and scaled output of the amplifier (or pilot exciter) respectively [49-50].

c) Equations (4.1), (4.2) and (4.3) can be compactly expressed as follows:

$$\dot{x} = f(x, u, w)$$

(4.4)

where the state vector $x$ includes the dynamic state variables associated with (1) and (3):

$$x = [\delta, \omega, E'_q, E'_d, E_{pu}, V_f, V_R]^T$$

(4.5)

$u$ is the input vector and includes the generator terminal voltage magnitude and phase angle:

$$u = [V, \theta]^T$$

(4.6)

$w$ is the vector representing the modeling errors.

### 4.3 Proposed approach

In implementing the proposed approach, the first step is to identify the zone(s) for which a linear phasor estimator will be implemented. Zones may be chosen based on geographical areas or voltage levels or any other criteria of interest to the utility operator. More details about zone selection conditions are given by the authors in [15]. It is assumed that a robust linear phasor estimator [47] (which is a LAV based estimator) is implemented for each zone which estimates the voltage phasors of all buses inside the zone ($\hat{v}$ and $\hat{\phi}$) using the measurements provided by the PMUs. Estimated active and reactive power injected by the generators ($\hat{P}$ and $\hat{Q}$) can also be obtained based on the estimated voltage phasors. As shown in [47], the LAV based linear phasor estimator which is used in this work also requires less CPU time compared to its Weighted Least
Squares (WLS) based counterpart estimator when there are bad data in the measurement set. It is well known and documented that WLS estimator is a non-robust estimator and will fail even under single bad measurement [48].

The LAV based estimator which is used in this work not only provides more accurate estimates of bus voltages and power injections but also eliminates the need to have a PMU at each generator terminal, as long as the existing set of PMUs render the entire power system observable. Note that this is an important advantage over the measurement based approach since in most power grids each generation unit may not be monitored by a PMU. Furthermore, even when all units have installed PMUs, measurements to be received from these PMUs may be biased or occasionally be lost due to measurement noise or communication system failures respectively. In these cases, the proposed linear estimator will remain robust and yield unbiased state estimates. It is noted that “robustness” of the linear estimator is bounded by the measurement redundancy, hence presents a limitation which can be overcome by proper measurement design [51].

For each selected zone inside the system, a robust linear phasor estimator is allocated in order to obtain the estimated voltage phasors and also estimated active and reactive power delivered by the generators within that zone. Then these estimated values are used by the dynamic state estimator (DSE) for tracking the dynamic states of each generator ( \( \dot{x} \)). In implementing the DSE, a UKF along with the commonly used two-axis model of a synchronous generator with IEEE-Type1 exciter is used. It should be noted that here the estimated terminal voltage phasor (magnitude and phase) for the generator inside the zone is used as input (u) and estimated active and reactive power injections at the generator terminals are used as measurements (z) for the DSE.
4.4 Implementation details

Proposed estimator is implemented on the well-documented NPCC system [52] with 140 buses and 48 generators including two-axis model of synchronous generators and IEEE-Type1 exciters. The schematic of the test system is given by Figure 4.1. The system is measured by 98 PMUs optimally placed to ensure robustness against loss of any PMU as described in [51]. The following scenario is considered:

- At t= 1 sec. one of the transmission lines is switched out.
- At t=6 sec. another line is switched out.
- At t=15 sec. the second switched out line is reclosed.

ZIP type load models are used to simulate noise free measurements by using a system simulator. These measurements are then modified by adding white noise with zero mean and 0.001 p.u. standard deviation.

Synchronous generator dynamics are simulated based on the following assumptions:

- Mechanical input power is assumed to be unknown, therefore it is considered as an extra state variable, thus (4.5) is modified as follows:
\[ x = [\delta, \omega, E'_q, E'_d, E_{f_0}, V_f, V_R, P_M]^T \]  
\[(4.7)\]

- In order to find the discretized system dynamics and measurement equations, the dynamic equations associated with the two-axis synchronous generator and IEEE-Type1 exciter given by (4.1) and (4.3) are discretized based on the second-order Runge-Kutta method. The discretized equations are given in the Appendix.
- Time-step=0.02 sec.
- UKF is initialized with arbitrary values.
- Duration of the simulation is chosen as 30 seconds.

Figures 4.2-4.9 show results obtained from DSE for the generator (This generator is indicated by red arrow in Figure1). Dashed and solid lines show the estimated and actual trajectories respectively.
Plots shown in Figures 4.2-4.9 illustrate the satisfactory performance of the dynamic state estimator as the system experiences two switching events at t=6 sec. and t=15 sec. Estimated trajectories of various quantities (indicated by dashed lines) follow the true ones very closely.

### 4.5 Performance under bad data

As mentioned earlier, the voltage magnitude and phase angle of the generator’s terminal bus are estimated by a robust linear phasor estimator (LAV based estimator). These are then used as inputs for the DSE. The main advantage of using a linear phasor estimator as a pre-processor for DSE is the availability of unbiased estimates for the terminal voltage phasor magnitude and angle which can be used as inputs by the DSE. When there are bad data in phasor measurements, use of directly measured phasors will yield biased or divergent dynamic state estimates.
In this part the robustness of the proposed approach will be evaluated when there are bad data associated with measured values of the generator terminal voltage magnitude and phase angle. These results will then be compared with those obtained using raw measurements as inputs by the DSE [6-8].

Consider the following scenario which includes bad measurements:

- Starting at t=15 seconds voltage magnitude measurement at the generator terminal is replaced by half of its true value (simulating a scaling error) for a duration of 5 seconds. Generator terminal voltage (magnitude and phase) measurements are added white noise with zero mean and 0.005 p.u. standard deviation for the entire simulation period.
- All other measurements are added white noise with zero mean and 0.001 p.u. standard deviation for the entire simulation period.

The following mean squared error (MSE) metric will be used to evaluate the results of simulations:

$$MSE = \sqrt{\frac{1}{M} \sum_{k=1}^{M} (x_k^i - \hat{x}_k^i)^2}$$  \hspace{1cm} (4.8)

where $x_k^i$ and $\hat{x}_k^i$ are the true and estimated values associated with the $i_{th}$ element of the augmented state vector $x$ given by (4.7) and $M$ is the total number of simulation time steps. Direct use of phasor measurements [6-8] will be referred as the “direct method” and the use of robust linear phasor estimator will be referred as the “proposed method” in the sequel.

Figures 4.10 and 4.11 show plots for estimated rotor angles using both methods.
Fig. 4.10: Actual and estimated $\delta$ by the direct method.  

Fig. 4.11: Actual and estimated $\delta$ by the proposed method.

As evident from the plot in Figure 4.11, the linear phasor estimator effectively removes estimation bias for the subsequent dynamic state estimation.

The MSE metrics associated with each component of the state vector $x$ are computed and shown in Table 4.1 These MSE metrics clearly quantify the improved accuracy when the proposed approach is implemented by using a robust linear phasor estimator for estimating the inputs and measurements for the subsequent DSE.

<table>
<thead>
<tr>
<th>Table 4.1</th>
<th>MSE METRICS—PERFORMANCE UNDER BAD DATA</th>
</tr>
</thead>
<tbody>
<tr>
<td>State variable</td>
<td>$\delta$ (Rad)</td>
</tr>
<tr>
<td>MSE-direct method</td>
<td>0.1402</td>
</tr>
<tr>
<td>MSE-proposed method</td>
<td>0.0051</td>
</tr>
<tr>
<td>State variable</td>
<td>$E_q$ (pu)</td>
</tr>
<tr>
<td>MSE-direct method</td>
<td>3.6385</td>
</tr>
<tr>
<td>MSE-proposed method</td>
<td>0.1012</td>
</tr>
</tbody>
</table>

4.6 Delay mitigation via state prediction

If a selected zone inside the test system include significantly large number of buses, there is an inevitable delay between the time that is stamped on a phasor measurement and the
time its estimate is received from the linear phasor estimator. Hence, the DSE will receive the inputs with a time delay. In order to minimize or completely eliminate the errors due to this delay, a predictor is designed for the state variables. The dynamic estimation algorithm is thus modified. The proposed algorithm has the following three steps:

**Step 1: Estimation of the state vector at \( t-t_d \)**

Based on the dynamic equations given by (4.1) and (4.3), UKF is used to estimate \( x \) at \( t-t_d \) where the filter is also fed by \( z \) and \( u \) at \( t-t_d \). Here \( t_d \) represents the time delay and it can be considered equal or even larger than the processing time associated with the estimation process of linear phasor estimator.

**Step 2: Prediction of the inputs using an autoregressive (AR) model**

An autoregressive time series model of order \( p \), AR\((p)\) is assumed as given by the equation:

\[
X(n) = \sum_{i=1}^{p} a_i X(n-i) + \varepsilon(n) \tag{4.9}
\]

where \( a_1, \ldots, a_p \) are the parameters of the model and \( \varepsilon(n) \) is considered as a white noise. There are different methods to obtain the parameters associated with AR\((p)\) of a specific wide-sense stationary signal such as the least squares method, use of Yule Walker equations, Markov chain Monte Carlo methods, etc. [53]. In this part, considering the last \( N \) samples (before \( t-t_d \)) of the estimated inputs by the linear phasor estimator, the parameters of AR\((p)\) model related to the inputs are obtained. This is accomplished using the least squares method of fitting the model parameters to match recorded data. This
AR(p) model will then be used to predict the inputs for \( t-t_d < \tau \leq t \). Please note that since the inputs are predicted for a few time steps, it can be assumed that during this period the inputs remain stationary, therefore an AR(p) model can be implemented as an estimator for the prediction of the inputs. Here the estimated inputs are denoted by:

\[
\tilde{u}(\tau) = [\tilde{u}(t-t_d+1), ..., \tilde{u}(t)]^T
\]  

(4.10)

**Step3: Prediction of the state vector for** \( t-t_d < \tau \leq t \)

The discretized dynamic equation of the generator is initialized by the estimated state vector at \( t-t_d \). Then, using the predicted inputs obtained in the previous step, these equations are iterated in order to find the predicted state vector for \( t-t_d < \tau \leq t \):

\[
\tilde{x}(\tau) = [\tilde{x}(t-t_d+1), ..., \tilde{x}(t)]^T
\]  

(4.11)

The above procedure can be illustrated by an example. Consider the following case:

- Use the most recent 50 samples to obtain the corresponding AR model for inputs (N=50).
- In order to choose an appropriate order for the AR model, the sample autocorrelation function (ACF) associated with the inputs are obtained as shown in Figure 4.12. In this case the autocorrelation values show a sudden drop for lags greater than 3. Accounting for noise and modeling errors a lag of \( p=5 \) is assumed for the order of the AR model.
- Assume a delay of \( t_d = 20 \) time steps or 0.4 sec. which is significantly larger than the processing time of the linear phasor estimator for estimating the inputs for this test system. It should be noted that for this test system the processing time per time step for estimating the inputs by the linear phasor estimator is almost half of one time step using a standard laptop (specifications given in the Appendix). As an example, Table
4.2 shows the Cpu-Time/time-step for implementing the LAV based estimator for the zones with different number of buses. Also the processing time associated with the UKF for the estimation of the dynamic state variables of the generator is 0.0004 sec. This implies that for the 140-bus NPCC system there will be no delay in the estimation process.

**TABLE 4.2**  
**CPU-TIME/TIME-STEP FOR THE IMPLEMENTATION OF LAV BASED ESTIMATOR**

<table>
<thead>
<tr>
<th>Total number of buses</th>
<th>140</th>
<th>160</th>
<th>267</th>
<th>342</th>
<th>656</th>
<th>1276</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU-Time/Time-step (Sec)</td>
<td>0.013</td>
<td>0.017</td>
<td>0.035</td>
<td>0.05</td>
<td>0.15</td>
<td>0.57</td>
</tr>
</tbody>
</table>

Fig.4.12: Sample autocorrelation function values for the inputs.

Fig.4.13: Block diagram of the proposed method for prediction of the state vector.
Assume that the prediction starts at $t=16.5$ sec.

Figures 4.14-4.17 Show the results of prediction (for all of the following 20 time steps) of $\delta$, $\omega$, $E_{fd}$ and $v_R$.

The assumed time delay is significantly larger than the processing time associated with the estimation of inputs per time step in this example. Therefore this method not only compensates the delay caused by the linear phasor estimator for estimating the inputs, but it also allows prediction of the state variables for a few time steps ahead.

As an example for comparison, the estimated results of $\delta$ and $\omega$ for $15 \text{ sec.} < t < 16 \text{ sec.}$ assuming $t_d = 10 \cdot \Delta t$ are shown by the following figures with and without using the proposed method of this section.
Use of the AR model based predictor appears to effectively remove errors which will otherwise bias the results of DSE as evident from the plots in Figures 4.18-4.21. Also considering both methods, the MSE values associated with the estimated results of $\delta$ and $\omega$ are given in Table 4.3. Computed MSE metrics shown in Table 4.3 quantify the accuracy improvements obtained by using the proposed approach. The main reason for this improvement is due to this fact that the DSE at each time step is receiving the more accurate inputs and measurements which are predicted by the proposed approach and therefore there will not be a delay for the estimated results which can be seen in Figures 4.19 and 4.21.
Please note that for the prediction of the inputs several other predictors were also tested but no improvement observed over the AR model. As an example, for the prediction of V_r, using ARIMA(5,1,1) model (please refer to [53] for more details about this model), a larger MSE value (MSE=0.017) is obtained compared to the case when AR(5) is used and yield a much smaller MSE value (MSE=0.0101). Figure 4.22 shows the results of prediction of V_r by using ARIMA(5,1,1) model which are less accurate than the results obtained by AR(5) showed in Figure 4.17.

**4.7 Conclusions**

This chapter presents a robust two stage dynamic state estimator in order to perform a distributed dynamic state estimation on large scale power networks. Thanks to the usage of a robust linear phasor estimator, highly accurate results for the dynamic state estimation of a two axis synchronous generator within a medium size utility system, in presence of bad data are obtained. The proposed approach also allows us to obtain the
dynamic state estimation results for the generating units without a local PMU. Furthermore, an approach for predicting the state variables of a generator for a few time steps ahead is presented in order to compensate for the delay associated with the robust linear phasor estimator. Simulation results are provided to validate the effectiveness of the proposed approach.
Chapter 5

Observability Analysis for Dynamic State Estimation of Synchronous Machines

5.1 Introduction

Dynamic state estimators (DSEs) are used for tracking the parameters and state variables of the component with nonlinear dynamics such as synchronous generators in the power systems. Obtaining accurately estimated results from DSEs is crucial in order to reliably carry out all applications which rely on results of DSEs. However, accuracy of the estimated results by the DSEs is affected by the measurements that are selected to perform dynamic state estimation. In most of the previously conducted studies in the area of power system dynamic state estimation, measurements are not selected using a systematic procedure, but simply assumed based on commonly metered quantities at the terminals of units [2-13]. This chapter aims to make this selection more systematic by linking this choice to performance metrics of the dynamic state estimation.

Note that in the case of static state estimation, the issue of measurement selection which is directly related to observability analysis is addressed by checking the rank of the measurement jacobian. Similarly for linear dynamic systems, observability analysis can be performed by evaluating the rank of the so called observability matrix associated with the system. However, this approach is valid only for linear time-invariant dynamic systems [40-41]. For nonlinear dynamic systems such as synchronous generators, observability of the dynamic state will depend on the operating point of the system.
Hence, a dynamic system state may become weakly and strongly observable during the daily operation for a given set of measurements.

Observability analysis of nonlinear dynamic systems has drawn the attention of researchers in the past and various approaches have been developed. Among these methods, the use of so-called Lie Derivatives \([41-42]\) and \([54]\) appears to provide the type of information useful in analyzing dynamic state observability of synchronous generators. This approach is used in \([41]\) and \([54]\) to evaluate the level of observability for a test system where classical model of the generators and approximated load models are used for the simulations. Unfortunately most synchronous machines and their associated control systems need to be represented by much more complicated models than the classical generator model.

Furthermore, given the heavy computational burden introduced by the Lie derivatives, it is much more practical to perform observability analysis separately for each machine (without solving the equations for the entire network), since even for a small power system the computational effort can be prohibitively heavy when Lie derivative method is applied to the entire system. In \([5]\) the empirical observability Gramian is applied to evaluate the level of observability for the test system by obtaining the reduced \(Y_{bus}\) of the system. Here the use of reduced \(Y_{bus}\) presents a drawback since it is obtained using approximate constant impedance load models thus reducing the accuracy of the estimated results provided by DSEs.

In this chapter, observability analysis of generator dynamic states will be investigated. First, the commonly used small signal approximation where the nonlinear machine equations are replaced by their first order linear approximations will be implemented. Then the well documented observability theory for linear systems will be used to analyze observability of the system. Next, observability analysis of nonlinear dynamic equations will be carried out using the observability matrix built by computing the Lie derivatives.
Results of these two approaches will be comparatively presented and checked against dynamic simulations of the dynamic equations of a two-axis model of a synchronous generator with IEEE-Type 1 exciter within a medium-size utility test system under various transients and using different sets of measurements. The level of observability associated with the considered system will be compared for different choice of measurements in order to identify the measurements that provide highest level of observability for this type of generator. Moreover, results of observability analysis will be validated by performing dynamic state estimation. Strongly (weakly) observable cases will be shown to converge (diverge) to (from) the true trajectory of the state variables during a transient.

5.2 Observability analysis of the machines with complex nonlinear dynamics in the power systems

Power systems can be modeled by a set of differential algebraic equations (DAE) where the network algebraic equations are coupled with the differential equations of the generators (and dynamic loads) via their terminal voltage phasors \((V_T, \theta_T)\). Therefore, by assuming availability of voltage phasors at machine terminals (either directly measured or estimated), it is possible to isolate individual generator dynamics from the rest of the network equations and perform observability analysis on individual generators separately. The general form of the nonlinear dynamic state and measurement equations of a machine where the terminal voltage phasor is used as input can be expressed in compact form as follows:

\[
\dot{x} = f(x, u', w)
\]
\[ z = h(x, u', v) \]  \hspace{1cm} (5.1) 

where:

- \( x \) is the vector of dynamic states of the generator,
- \( z \) is the measurement vector,
- \( u' \) is the augmented input vector which includes the terminal voltage phasor as well as other inputs \((u)\) associated with the machine \((u'=[u, V_T, \theta_T]^T)\),
- \( w \) is the process noise,
- \( v \) is the measurement noise,
- \( f \) is the nonlinear vector function modeling machine dynamics,
- \( h \) is the vector function of available measurements.

Isolated set of state dynamic and measurement equations given by (5.1) will enable observability analysis to be performed separately for individual machines. As a result, computational effort will be significantly reduced compared to the alternative approaches [41-42] and [54] where the overall DAE of the entire system are used for observability analysis. While the presented approach is general, for the sake of clarity, this chapter [38] will investigate observability analysis associated with the nonlinear dynamics of a two axis model of a synchronous generator with IEEE-Type 1 exciter (The associated dynamic equations are given in chapter 3) and develop guidelines of selecting best set of measurements to achieve most accurate dynamic state estimation results.
5.2.1 Linear approximation based method for the observability analysis of the nonlinear dynamics

Theory of observability for linear time-invariant dynamic systems is well established [40]. Outcome of observability analysis for such systems is binary, i.e. the system is found either observable or unobservable. This decision is based on the rank of the so-called “observability matrix” which can be illustrated by considering the following linear dynamic system:

\[
\dot{x} = Ax(t) + Bu(t) \\
z = Cx(t) + Du(t)
\]  \hspace{1cm} (5.2)

where \( A, B, C \) and \( D \) are constant matrices, \( x \) is the system state vector, \( u \) is the vector of input variables and \( z \) represents the vector of available measurements. Dimension of the state vector is assumed to be \( n \).

Observability matrix for this system can be constructed as:

\[
\tilde{\mathcal{O}} = \begin{bmatrix}
C \\
CA \\
\vdots \\
CA^{n-1}
\end{bmatrix}
\]  \hspace{1cm} (5.3)

The system will be observable if the row rank of the observability matrix is equal to \( n \) [40]. In the case of non-linear systems such as (5.1), a first order approximation for matrices \( A \) and \( C \) can be calculated at a given time-step \( k \), and the corresponding approximate observability matrix (\( \tilde{O}_k \)) can be obtained as follows:
\[
\tilde{\mathbf{O}}_k = \begin{bmatrix} C_k \\ C_kA_k \\ \vdots \\ C_kA_k^{n-1} \end{bmatrix}
\]  

(5.4)

where,

\[ A_k = \frac{\partial f}{\partial x} \bigg|_{x=x_k} \; ; \; C_k = \frac{\partial h}{\partial x} \bigg|_{x=x_k} \]

Given the nonlinear time-varying behavior of the dynamic system, the outcome of observability analysis will also be time dependent. Furthermore, this outcome will no longer be considered binary, but the degree (or strength) of observability for a given measurement set at a given time instant will be of interest. One way to quantify this is by computing the smallest singular value of the approximated observability matrix at each time step. Higher (lower) values of the smallest singular value of the observability matrix indicates stronger (weaker) observability for a given measurement set [41-42] and [54]. Since observability is a local property, the smallest singular value of the observability matrix will change along the trajectory of \(x\).

The main advantage of the linear approximation based approach for evaluating the observability of the nonlinear dynamics is related to its computational simplicity. However, the linear approximation based results may occasionally lead to incorrect observability analysis in particular under highly nonlinear operating conditions involving synchronous machines. Hence, there is a need for a more precise method that can remain valid under such stressed conditions. Such an approach that is based on the Lie-derivatives will be presented for observability analysis in the next section.
5.2.2 Observability analysis of the nonlinear systems using Lie derivatives

Observability analysis of nonlinear dynamic systems have been studied thoroughly in the past and a computationally demanding yet highly accurate method based on the so called Lie derivatives was developed [41-42] and [54]. In this section, Lie derivatives will be used to design an observability analysis approach which will provide a metric for determining the strength of observability for a given measurement set and an operating condition. Consider the below given vector functions of state dynamics and measurements of a system described in (5.1):

\[
\begin{align*}
  f &= [f_1(x,u') \quad \ldots \quad f_n(x,u')]^T \\
  h &= [h_1(x,u') \quad \ldots \quad h_m(x,u')]^T
\end{align*}
\]

(5.5)

where \( n \) and \( m \) are the number of state variables and measurements respectively. The Lie derivative of \( h \) with respect to \( f \) is defined as follows [42]:

\[
L_f h = \frac{\partial h}{\partial x} f = \sum_{i=1}^{n} \frac{\partial h}{\partial x_i} f_i
\]

(5.6)

Note that the zero order Lie derivative of \( h \) with respect to \( f \) is:

\[
L_0^f h = h
\]

(5.7)

Higher order Lie derivatives can then be obtained by the following recursive equation:

\[
L^k_f h = \frac{\partial (L^{k-1}_f h)}{\partial x} f
\]

(5.8)
After obtaining higher order Lie derivatives, the observability matrix $O(x_k)$ of the nonlinear dynamic system at time step $k$ can be constructed by substituting $x_k = x(k)$ in expressions (5.7) and (5.8):

$$O(x_k) = \frac{\partial l(x)}{\partial x}$$

(5.9)

where,

$$l(x_k) = \begin{bmatrix}
L_f^0 h_1(x_k) \\
\vdots \\
L_f^0 h_m(x_k) \\
L_f^1 h_1(x_k) \\
\vdots \\
L_f^{n-1} h_m(x_k)
\end{bmatrix}$$

(5.10)

As in the linear approximation case above, the smallest singular value of the observability matrix calculated at each time step can be used as a metric to track the strength of observability associated with the nonlinear dynamics of the system for the given set of measurements.

### 5.3 Observability analysis of the two-axis model of a synchronous generator with IEEE-Type 1 exciter

This section will illustrate details of observability analysis for a specific example, namely a two-axis model of a synchronous generator with IEEE-Type1 exciter. Initially, the linear approximation based approach will be employed to analyze observability. As mentioned earlier, this is an approximate approach which may lead to invalid results for certain cases. In order to evaluate validity of this approximation, the computationally more complex but more accurate Lie-derivative based approach will also be implemented. Then a set of measurements which will render the generator dynamic states strongly observable will be identified. Finally the results of observability analysis will be
validated using a dynamic state estimator implemented as an UKF. This will be accomplished by illustrating its convergence to the true trajectory for those measurement sets that are identified as strongly observable based on Lie-derivative based approach.

As mentioned earlier a two-axis model of a synchronous generator and its IEEE-Type 1 exciter (Associated dynamic equations were given in chapter 4) will be used in subsequent sections to simulate and test the above described observability analysis methods. Please note that the dynamic equations given by (4.1) and (4.3) are related to the algebraic network equations through the machine terminal voltage phasors. Therefore observability analysis of individual machines can be performed independently by treating the terminal voltage phasor as a known input. Observability analysis will first be carried out using the linear approximation approach as described in section 5.2.1.

### 5.3.1 Implementation of the linear approximation based approach for observability analysis

Here the smallest singular value of the approximate observability matrix (given by (5.4)) associated with a generator-exciter set operating in a medium size power system (NPCC system of [52]) will be obtained. The following assumptions will be made for the simulations:

- A simulation time step of 0.02 seconds will be used.
- Total simulation time will be 25 seconds.
- Simulation scenario involves three line switching events occurring at t=1, 6 and 15 seconds respectively.
- Following categories of measurements will be considered:
  - State variables associated with the generator and exciter.
  - Active and reactive power delivered by the generator.
Note that state variables such as $E_q^*, E_d^*, V_f$ and $V_R$ are not physically measurable. Furthermore, measuring variables $\delta$ and $E_{fd}$ may not be an easy task. Here there are two main reasons for assuming them as available measurements: (1) to be able to compare the level of observability for the generator-exciter set for these measurements versus the other physically available measurements indicated above. Hence, this may provide the necessary incentive to investigate ways of enabling measurement of such quantities either directly or indirectly. (2) To determine the smallest singular value of the observability matrix that is attainable for the ideal case where all state variables are assumed to be available as measurements (strongly observable case). Also try to identify a subset of actually measurable variables which will yield a level of observability commensurate with this ideal case.

Here the terminal voltage phasor of the generator is assumed as a known input along with $P_M$. Therefore the augmented input vector associated with the state and measurement function vectors will be given by:

$$u' = [P_M \quad V_T \quad \theta_T]^T$$

(5.14)

After calculating the smallest singular value of the approximated observability matrix the mean and standard deviations of the smallest singular values are obtained and used as a metric for the evaluation of the level of observability for a given measurement set and disturbance scenario. The mean and standard deviations of the smallest singular value of the approximated observability matrix are given in Table 5.1.
TABLE 5.1: MEAN AND STANDARD DEVIATION OF THE SMALLEST SINGULAR VALUE OF THE APPROXIMATED OBSERVABILITY MATRIX

<table>
<thead>
<tr>
<th>Measurement</th>
<th>$\delta$</th>
<th>$\omega$</th>
<th>$\delta$ and $\omega$</th>
<th>$E'_{q}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.135</td>
<td>0.052</td>
<td>0.205</td>
<td>0.158</td>
</tr>
<tr>
<td>STD</td>
<td>0.006</td>
<td>0.002</td>
<td>0.009</td>
<td>0.001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Measurement</th>
<th>$E'_{d}$</th>
<th>$E'_{fd}$</th>
<th>$V_{f}$</th>
<th>$V_{R}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.062</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>STD</td>
<td>0.001</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Measurement</th>
<th>$P_{e}$</th>
<th>$Q_{e}$</th>
<th>All of the state variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.003</td>
<td>2.077</td>
<td>1.067</td>
</tr>
<tr>
<td>STD</td>
<td>0.0005</td>
<td>0.041</td>
<td>0.009</td>
</tr>
</tbody>
</table>

As evident from the results given in the Table 5.1 the mean of the smallest singular value associated with the approximated observability matrix will have the highest value when the delivered reactive power by the generator ($Q_{e}$) is used as a measurement. In other words, $Q_{e}$ measurement provides a higher level of observability for the nonlinear dynamics of the generator and exciter compared to all the other measurements. It is also peculiar to note that the mean of the smallest singular value for the ideal case of having all state variables measured, yields a lower value than the case of $Q_{e}$ only. This is possibly related to the linear approximation that is used to obtain the observability matrix.

Based on the results given in Table 5.1, $\delta$ and $E_{q}'$ appear to provide higher level of observability compared to the other state variables. Also the smallest singular value of the observability matrix remains zero during the simulations when any of the state variables associated with the dynamics of the exciter ($E_{fd}$, $V_{f}$ and $V_{R}$) are used as measurements. As an example Figures 5.1-5.3 show the trajectory of the smallest singular value of the approximated observability matrix when $\delta$, $Q_{e}$ and all of the state variables are considered.
as measurements respectively.

Fig. 5.1: Smallest singular value of the observability matrix using linear approximation - $\delta$ is the measurement.

Fig. 5.2: Smallest singular value of the observability matrix using linear approximation - $Q_e$ is the measurement.

Fig. 5.3: Smallest singular value of the observability matrix using linear approximation - all of the state variables are used as measurements.

As also mentioned earlier for the ideal case (where all of the state variables are used as measurements) the smallest singular value of the observability matrix remains lower than the case when only the delivered reactive power by the generator is used as
measurements due to the linear approximation that is used for obtaining the observability matrix.

5.3.2 Implementation of the Lie-derivatives based approach for observability analysis

In the previous section the linear based observability analysis approach for evaluating the level of the observability is investigated. Now the more precise Lie-derivatives based approach explained above in section 5.2.2 will be considered and implemented for the observability analysis of this generator. Lie-derivatives based approach is used to obtain the smallest singular value of the observability matrix assuming the same measurements that are considered in the previous section. Table 5.2 shows the results for the calculated mean and standard deviations of the smallest singular value of the observability matrix using the Lie-derivatives.

<table>
<thead>
<tr>
<th>TABLE 5.2: MEAN AND STANDARD DEVIATION OF THE SMALLEST SINGULAR VALUE OF THE OBSERVABILITY MATRIX- USING LIE-DERIVATIVES</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Measurement</strong></td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>STD</td>
</tr>
<tr>
<td><strong>Measurement</strong></td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>STD</td>
</tr>
<tr>
<td><strong>Measurement</strong></td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>STD</td>
</tr>
</tbody>
</table>
In this case, as evident from the results listed in Table 5.2 the reactive power delivered by the generator ($Q_e$) yields a lower value for the calculated smallest singular value of the observability matrix than the ideal case (all of the state variables are used as measurements) and yet still provides the largest value compared to all other measurements. Comparing Tables 5.1 and 5.2, the results that are obtained by using the Lie-derivative based approach validate majority of the results that are obtained by using the linear approximation method with the exception that the inconsistency regarding the ideal (reference) case is no longer present in Table 5.2. Figures 5.4-5.6 show the plots of smallest singular values of the observability matrix using the Lie-derivatives when $\delta$, $Q_e$ and all of the state variables are considered as measurements respectively.

Comparing Figures 5.1 and 5.4 (or 5.2 and 5.5) it is also evident that the trajectories of the smallest singular value of the observability matrix obtained by the Lie-derivative versus the linear approximation based approaches are quite different. Again this illustrates the inaccuracies introduced by the use of linearization based approach for obtaining the observability matrix.

One of the goals of this chapter is to identify a set of measurements which will yield the highest possible level of observability (close to the ideal case) associated with the dynamics of the two-axis model of the synchronous generator and IEEE-Type1 exciter. Figure 5.7 shows that by assuming both delivered active and reactive power as measurements a similar pattern for the smallest singular value of the observability matrix to the ideal case (shown by Figure 5.6) can be obtained. Here the mean and standard deviations of the smallest singular values are 4.12 and 1.835 respectively.
Fig. 5.4: Smallest singular value of the observability matrix using Lie-derivatives-$\delta$ is the measurement.

Fig. 5.5: Smallest singular value of the observability matrix using Lie-derivatives-$Q_e$ is the measurement.

Fig. 5.6: Smallest singular value of the observability matrix using Lie-derivatives-all of the state variables are used as measurement.
5.3.3 Validation of the observability analysis results

Here some of the observability analysis results that are obtained based on the Lie-derivative based approach will be validated by investigating the corresponding dynamic state estimation results. UKF is used in implementing the dynamic state estimator. Based on the results obtained above in the previous sections for various measurements, the level of observability is found to go from a high value when using $P_e$ and $Q_e$ to lower values when these are replaced by $Q_e$, $E_q'$, and $P_e$ in that order. Note that $E_q'$ is not physically measurable yet it is considered to make the evaluation comprehensive disregarding such physical limitations. Now for each of these measurements the result of estimated rotor angle will be shown. It should also be noted that each of these measurements are intentionally modified by an additive white Gaussian noise with standard deviation of 0.001 per unit. The following are assumed in the simulations:

- Arbitrary initial values are considered associated with the state vector of two-axis model of the synchronous generator and IEEE_Type 1 exciter.
- Simulation time-step is 0.02 second.
- Process noise covariance (Q) associated with UKF (details are described in [43]) is
chosen as: \( Q = 1 \times 10^{-4} \times I_{7 \times 7} \).

- Measurement noise covariance (R) associated with the UKF (details are described in [43]) is chosen as: \( R = 1 \times 10^{-3} \times I_{m \times m} \) where \( m \) is the total number of the measurements.

Figures 5.8 and 5.9 show that the estimated results (indicated by dashed lines) converge to the true trajectory faster than the case shown in Figure 5.10. However Figure 5.11 shows that if the active power output of the generator is the only measurement used then the estimated results will diverge from the true trajectory. This is consistent with the low level of observability (weakly observable) provided by the measurement \( P_e \) as shown in Tables 5.1 and 5.2.

![Fig.5.8: Result of dynamic state estimation for the rotor angle- \( P_e \) and \( Q_e \) are the measurements.](image1)

![Fig.5.9: Result of dynamic state estimation for the rotor angle- \( Q_e \) is the measurement.](image2)
Fig. 5.10: Result of dynamic state estimation for the rotor angle - $E_q$ is the measurement.

Fig. 5.11: Result of dynamic state estimation for the rotor angle - $P_e$ is the measurement.

Figures 5.12 and 5.13 show the magnified version of trajectories shown in Figures 5.8 and 5.9. These results showing faster and smoother convergence to the true trajectory are again consistent with the expectations based on the observability analysis results shown in the previous section where $P_e$ and $Q_e$ provide higher level of observability (close to the ideal case) than only $Q_e$. 
Fig. 5.12: Magnified results of dynamic state estimation for the rotor angle. 
$P_e$ and $Q_e$ are the measurements.

Fig. 5.13: Magnified results of dynamic state estimation for the rotor angle. $Q_e$ is the measurement.

5.4 Conclusions

This chapter is concerned about proper observability analysis of dynamic states for synchronous generator and exciter systems. The main goal of the chapter is to establish a systematic observability analysis procedure which can be used to customize the measurement (or sensor) selection for a given type of generator and associated control system. Following the description of two possible approaches to observability analysis (one simple but approximate and one complex but accurate), the chapter presents validation results where strength of observability predicted by different measurement configurations is shown to be consistent with the ability of the dynamic estimator to track the true trajectory of the dynamic states. While the chapter focuses on synchronous
generator and exciter system, presented approaches can be readily applied to observability analysis and sensor selection for tracking dynamic and nonlinear loads.
Chapter 6

Constrained Iterated Unscented Kalman Filter for Dynamic State and Parameter Estimation

6.1 Introduction

In order to perform an accurate dynamic security assessment of the operating state of power systems it is necessary to know the most recent dynamic states associated with the synchronous machines including nonlinear dynamics. DSEs can readily provide such information in real time. Miscellaneous approaches for the dynamic state estimation of the synchronous machines are proposed so far by various investigators. In the majority of the reported studies, it is assumed that the dynamic model of the synchronous machine which is characterized by the values of the associated parameters is perfectly known [2-15]. However, in reality this assumption may not be valid due to the possible existence of unknown parameters in the synchronous generator’s dynamic model. In [8] an Extended Kalman Filter (EKF) based DSE is presented to perform the dynamic state estimation for the synchronous generators with unknown inputs such as excitation field voltage. In this chapter, a robust UKF based dynamic state estimation will be introduced which is capable of providing a highly accurate dynamic state estimation result when it assumes that some of the parameters related to the dynamic model of the synchronous machine are unknown.

Previously it has been shown that UKF has superior performance than the widely used Extended Kalman Filter (EKF). Furthermore, in [56] it has been shown that an improved
version referred as the Iterated UKF (IUKF) could outperform other widely studied DSEs based on IEKF, EKF and UKF with regards to robustness and accuracy of the estimates. The constrained UKF (CUKF) is a technique that is introduced more recently in [57]. It is suitable for cases where DSE is implemented using an UKF and specific constraints are needed to be taken into account during the dynamic state estimation process. In this chapter UKF, CUKF and CIUKF will be comparatively investigated by using them in implementing the DSEs to estimate the augmented state vector of a synchronous generator.

The augmented state will include the unknown parameters and inputs in addition to the state variables related to the dynamic model of the synchronous generator. It is noted that the main motivation behind the use of constrained dynamic state estimation techniques in this work is related to the nonlinear observability analysis of the generator dynamics. It can be shown that by augmenting the state vector with additional unknown parameters and inputs, the dynamic model of the synchronous generator will become weakly observable for a given set of measurements [38]. This will lead to cases where the estimated results provided by a DSE may not converge to the global optima. In particular, for weakly observable dynamic systems, the estimated results may converge to invalid values depending on the way DSE is initialized. On the other hand, typically the unknown parameters associated with a dynamic model are known to vary within a specific range. Hence, this information can be used in form of constraints associated with these parameters during the dynamic state estimation process.

In this chapter, a two-axis model of a synchronous generator within the NPCC test system [52] will be considered for the simulations. It will be assumed that the inertia constant and one of the transient reactances associated with the model are unknown. Moreover, the excitation field voltage will be considered as an unknown input. Then UKF, CUKF and CIUKF will be used to estimate the augmented state vector associated with this generator’s dynamic model.
Dynamic equations associated with two-axis model of a synchronous generator were presented in chapter 4 (given by (4.1)). Moreover the algorithms associated with UKF were given in chapter 3. This chapter will describe the algorithms associated with IUKF and the use of parameter constraints in implementing the UKF based DSEs.

These algorithms will then be tested for a line switching scenario to evaluate their comparative performance and to highlight the benefits of using the constrained UKF based DSEs to track the dynamic states and unknown parameters of synchronous generator models.

6.2 Algorithms of IUKF and constrained UKF based dynamic state estimation

The purpose of this work is to develop an enhanced dynamic state estimator which will remain robust under insufficient or incorrect information about the machine model parameters. To this end, three alternative implementations for the well-known unscented Kalman filter, namely UKF, Constrained UKF (CUKF) and Constrained iterated UKF (CIUKF) will be implemented and comparatively evaluated. It is noted that CIUKF has not been implemented for synchronous generator dynamic state estimation before and this constitutes one of the main contributions of this work.

6.2.1 Iterated Unscented Kalman Filter (IUKF)

IUKF was first proposed in [56] where its superior performance compared to various other filters such as EKF, IEKF and UKF was demonstrated. The algorithm of IUKF has three additional steps compared to the UKF which were described in chapter 3 (by (3.3)-(3-9) ) by steps 1-3 in below:
Step 1: Initialization Iterations:

For each time step obtain $\hat{x}_k^+$ and $P_k^+$ by (3.9) with the following assumptions:

$\hat{x}_{k,0} = \hat{x}_k^0$, $P_{k,0} = P_k^0$, $\hat{x}_{k,1} = \hat{x}_k^1$, $P_{k,1} = P_k^1$ and initialize $j=2$ which indicates the iteration count for IUKF.

Step 2: Calculation of New Sigma Points for Iterations

Obtain new sigma points as described by (3.8):

$$\hat{x}_{k,i}^{(i)} = \hat{x}_{k,i-1} + \chi_{x,i}$$ $i = 1,...,2n$

$$\chi_{x,i} = (\sqrt{nP_{k,i-1}})_i$$ $i = 1,...,n$

$$\chi_{x,\pm}^{(i)} = -n\chi_{x,i}$$ $i = 1,...,n$  (6.1)

Step 3: Iterative Correction of States:

$$\hat{x}_{k,j} = \frac{1}{2n} \sum_{i=1}^{2n} \hat{x}_{k,i}^{(i)}$$

$$\hat{z}_{k,j}^{(i)} = h(\hat{x}_{k,j}^{(i)}, k), \quad \hat{z}_{k,j} = \frac{1}{2n} \sum_{i=1}^{2n} \hat{z}_{k,i}^{(i)}$$

$$P_{z,j} = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{z}_{k,j}^{(i)} - \hat{z}_{k,j})(\hat{z}_{k,j}^{(i)} - \hat{z}_{k,j})^T + R_k$$

$$P_{z,zz,j} = \frac{1}{2n} \sum_{i=1}^{2n} (\hat{x}_{k,j}^{(i)} - \hat{x}_{k,j})(\hat{z}_{k,j}^{(i)} - \hat{z}_{k,j})^T$$

$$K_{k,j} = P_{z,zz,j} P_{z,j}^{-1}$$

$$\hat{x}_{k,j} = \hat{x}_{k,j} - K_{k,j}(z_{k,j} - \hat{z}_{k,j})$$
\[ P_{k,j} = P_{k,j-1} - K_{k,j} P_{k,j} K_{k,j}^T \]  

(6.2)

Note that there is a trade-off between the accuracy of IUKF and the added computational burden as the number of iterations is increased.

6.2.2 Constrained UKF based dynamic state estimation

As mentioned earlier, for some unknown parameters associated with the dynamic model of a synchronous generator it is possible to assume specific constraints when using UKF based DSEs. Previously CUKF was proposed by [57] where the assumed constraints associated with dynamic state estimation can be taken into account during the calculation of the sigma points given by (3.6) and (3.8). The proposed algorithm is described below:

- At time step \( k \):

1) For both UKF and IUKF calculate the \( 2n \) sigma points considering the current posteriori covariance using the equations given by (3.6). Then project the sigma points which are outside the assumed region (this region is determined by the constraints) to the boundary of this region to obtain constrained sigma points:

\[
\hat{x}_{k-1}^{(i)C} = P(\hat{x}_{k-1}^{(i)}) \quad i = 1,\ldots,2n
\]  

(6.3)

where superscript \( C \) stands for “constrained” and \( P \) indicates the “projection”.

2) Transform the constrained sigma points using the state update function:
\[
\hat{x}_k^{(i)} = f(\hat{x}_{k-1}^{(i)}, k-1)
\]  

(6.4)

3) Apply the constraints on the transformed sigma points to obtain the constrained transformed sigma points:

\[
\hat{x}_k^{(i)C} = P(\hat{x}_k^{(i)}) \quad i=1,\ldots,2n
\]  

(6.5)

4) Obtain the priori state estimate and priori covariance matrix as described by (3.7) using the constrained transformed sigma points.

5) Calculate the posteriori state estimate and posteriori covariance based on equations (3.8) and (3.9) using the constrained transformed sigma points.

6) For IUKF obtain the posteriori state estimate and posteriori covariance based on equations (6.1) and (6.2) using constrained transformed sigma points.

### 6.3 Implementation of the proposed DSEs

In this part UKF, CUKF and CIUKF will be implemented to estimate the augmented state vector of a two-axis model of a synchronous generator within the NPCC test system whose details can be found in [52].

The state and input vectors associated with the dynamic equations of a two-axis model of a synchronous generator explained in chapter 4 are given as follows:

\[
x = [\delta, \omega, E'_q, E'_d]^T
\]

\[
u = [P_M, E_{fd}, V, \theta]^T
\]  

(6.6)
Note that here the terminal voltage phasor is used as input in order to perform dynamic state estimation in a distributed manner. The terminal voltage phasor can be directly measured through a local PMU or it can be obtained through a robust linear phasor estimator to make the dynamic state estimation process robust against bad-data or loss of the signal that may happen for a local PMU [36].

The following assumptions will be made for the simulations:

- The value of the inertia time-constant ($H$) and synchronous reactance ($X_{d}$) associated with two-axis model of the synchronous generator are unknown.
- The excitation field voltage is considered as unknown input.

Now the state vector given by (6.6) will be augmented by the unknown parameters and unknown input mentioned above. The augmented state vector will thus be given by:

$$\tilde{x} = [\delta, \omega, E'_q, E'_d, E_{fd}, X_d, H]^T$$

(6.7)

It is noted that tracking the inertia time-constants and having reliable parameter values for generators have been mentioned among the major concerns of transmission operators in a recent PES Magazine article [58]. This constitutes one of the main motivations behind this investigation.

Here the delivered active ($P_e$) and reactive power ($Q_e$) by the generator are used as measurements. Second order Runge-Kutta method is used in order to derive the discretized nonlinear state dynamics and measurement equations given by (4.1) and (4.2) for this generator. For the unknown parameters and input it is assumed that:
\[ E_{fd,k+1} = E_{fd,k} + w_{fd,k} \]

\[ X_{d,k+1} = X_{d,k} + w_{d,k} \]

\[ H_{k+1} = H_k + w_{H,k} \]  \hspace{1cm} (6.8)

where \( w_{fd,k} \), \( w_{d,k} \) and \( w_{H,k} \) are white process noise that also accounts for any modeling errors.

At first, an UKF will be implemented to estimate (6.7) for a two-axis synchronous generator model with the following assumptions:

- A simulation time step of 0.02 seconds will be used.
- Total simulation time will be 25 seconds.
- Simulation scenario involves three line switching events occurring at \( t=1, 6 \) and 15 seconds respectively.
- UKF is initialized with arbitrary values for the augmented state vector:
  \[ \hat{x}_0 = [0,0,0.1,1.0,1.0,1.0,0.0,0.0]^T \]
- \( P_0 = 1e-6 \times I_{7 \times 7} \)
- \( R_k = 1e-3 \times I_{2 \times 2} \) and \( Q_k = 1e-5 \times I_{7 \times 7} \)

The estimated trajectories for the rotor angle, rotor speed, field voltage, inertia constant and d-axis synchronous reactance are plotted in Figures 6.1-6.5 respectively. As evident from these figures although the estimated trajectories for the rotor angle and d-axis synchronous reactance converge to their corresponding true trajectories, estimated trajectories for the rotor speed, field voltage and inertia constant fail to do so. For instance, estimated trajectory for the inertia constant converges to a large and negative value despite the well-known fact that the value of the inertia constant cannot be less than zero. It is noted that augmenting the state vector with more unknown parameters and
inputs lowers the level of observability associated with the dynamics of the system for a given set of measurements (in this case just the active and reactive power measurements delivered by the generator).

Hence, for a weakly observable dynamical system, estimated trajectory of the unknown variables may not converge to the global optima, but instead follow a local optima depending on the initialization of the dynamic estimation process. This is precisely what has happened here.

Next, using identical initialization assumptions as considered for the UKF case above, the CUKF is implemented to estimate the augmented state vector. However, this time a rather obvious fact of the non-negativity of the inertia constant ($H > 0$) is used as a constraint in the estimation formulation. Figures 6.6-6.10 show the estimated trajectories for the rotor angle, rotor speed, field voltage, inertia constant and d-axis synchronous reactance using CUKF. These trajectories follow the true trajectories much more closely compared to the case when UKF is used. However, there are still small but non-negligible differences for certain parameters as evident in Figures 6.9 and 6.10.

![Fig.6.1: Estimated and true trajectories of the rotor angle-UKF is used as DSE.](image1)

![Fig.6.2: Estimated and true trajectories of the rotor speed-UKF is used as DSE.](image2)
Fig. 6.3: Estimated and true trajectories of the field voltage - UKF is used as DSE.

Fig. 6.4: Estimated and true trajectories of the inertia constant - UKF is used as DSE.

Fig. 6.5: Estimated and true trajectories of the d-axis synchronous reactance - UKF is used as DSE.

Fig. 6.6: Estimated and true trajectories of the rotor angle - CUKF is used as DSE.

Fig. 6.7: Estimated and true trajectories of the rotor speed - CUKF is used as DSE.

Fig. 6.8: Estimated and true trajectories of the field voltage - CUKF is used as DSE.
In order to further improve the performance, the CIUKF that uses 5 iterations is implemented to estimate the augmented state vector for the aforementioned synchronous generator assuming the same initialization assumptions that were considered for UKF and CUKF. Figures 6.11-6.15 show the estimated trajectories for the rotor angle, rotor speed, field voltage, inertia constant and d-axis synchronous reactance for this case. The improvements in the accuracy of the estimated trajectories can be observed in the figures. In particular the estimated trajectories for the field voltage, inertia constant and d-axis reactance are significantly more accurate.

As mentioned earlier by augmenting the state vector with unknown inputs and parameters, the level of observability associated with the dynamic model of the generator will be reduced for a given measurement set. This can be validated by plotting the smallest singular value of the observability matrix (indicated by O in Figure 6.16). This matrix is obtained by using the Lie-derivatives [38] for the case where there are no unknown parameters or inputs associated with dynamic model of the synchronous generator. On the other hand, when the state vector is augmented by unknown parameters and inputs, the plot of the smallest singular value of the observability matrix will drop to noticeably smaller levels during the simulations as shown in Figure 6.17. It is noted that the smallest singular value of the observability matrix is used as an indicator for the level
(large values imply strongly observable system) of observability associated with nonlinear dynamic model of the synchronous generator [38].

Fig. 6.11: Estimated and true trajectories of the rotor angle-CIUKF is used as DSE.

Fig. 6.12: Estimated and true trajectories of the rotor speed-CIUKF is used as DSE.

Fig. 6.13: Estimated and true trajectories of the field voltage-CIUKF is used as DSE.

Fig. 6.14: Estimated and true trajectories of the inertia constant-CIUKF is used as DSE.

Fig. 6.15: Estimated and true trajectories of the d-axis synchronous reactance-CIUKF is used as DSE.
Table 6.1 shows the CPU-times associated with UKF, CUKF and CIUKF using 5 iterations. These times are recorded for a laptop computer with core i7-4810mq CPU and 16-Gb DDR3 of memory.

Table 6.1 clearly indicates that CIUKF requires larger CPU-time compared to the CUKF and UKF. However, considering the absolute CPU-time per time step, it is noticeably
smaller than the real-time simulation time-step of 0.02 seconds, thus confirming viability of its real-time implementation.

Considering a time-window including the last 10 seconds of the simulation, the Mean Squared Errors (MSE) associated with each component of the augmented state vector given by (6.7) are calculated for all DSEs discussed in this chapter. They are computed using the following expression and listed in Table 6.2:

$$MSE = \sqrt{\frac{1}{M} \sum_{k=1}^{M} (x_k^i - \hat{x}_k^i)^2}$$  \hspace{1cm} (6.9)

where $x_k^i$ and $\hat{x}_k^i$ are the true and estimated values associated with the $i$th element of the augmented state vector $x$ and $M$ is the total number of simulation time steps within the assumed time-window.

### TABLE 6.2: COMPUTED MSEs

<table>
<thead>
<tr>
<th>Component of the augmented state vector</th>
<th>$\delta$</th>
<th>$\omega$</th>
<th>$E_u'$</th>
<th>$E_d'$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE-using UKF</td>
<td>0.067</td>
<td>0.02</td>
<td>0.001</td>
<td>0.0008</td>
</tr>
<tr>
<td>MSE-using CUKF</td>
<td>0.0174</td>
<td>0.0038</td>
<td>0.0007</td>
<td>0.0002</td>
</tr>
<tr>
<td>MSE-using CIUKF</td>
<td>0.0172</td>
<td>0.0031</td>
<td>0.0006</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Component of the augmented state vector</th>
<th>$E_{pd}$</th>
<th>$X_d$</th>
<th>$H$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE-using UKF</td>
<td>0.121</td>
<td>0.018</td>
<td>211.36</td>
</tr>
<tr>
<td>MSE-using CUKF</td>
<td>0.082</td>
<td>0.0257</td>
<td>2.767</td>
</tr>
<tr>
<td>MSE-using CIUKF</td>
<td>0.033</td>
<td>0.0083</td>
<td>0.831</td>
</tr>
</tbody>
</table>
MSE values given in Table 6.2 confirm that CIUKF provides noticeably more accurate estimation results for the unknown parameters and unknown input associated with the dynamic model of the aforementioned synchronous generator.

### 6.4 Conclusions

In this chapter a constrained and iterated UKF based dynamic state estimation approach is used to perform dynamic state estimation for a synchronous generator with unknown parameters and inputs. The chapter combines the ideas of using constraints on the parameters and iterative state updates per time step for improving accuracy of the dynamic estimation when using UKF as the main computational engine. UKF, Constrained UKF and Constrained IUKF are all implemented to obtain estimated trajectories of the dynamic states of a generator as well as unknown model parameters such as the inertia constant and the d-axis synchronous reactance. It is shown that under identical initialization conditions the constrained iterated UKF provides the best estimates both for the state variables and unknown parameters of the synchronous generator model.
Chapter 7

A Robust Dynamic State Estimator
Against Exciter Failures

7.1 Introduction

Recent studies have shown benefits of implementing dynamic state estimators in order to closely track dynamic states of synchronous generators. These studies were mainly motivated by wide-area control, protection and optimization tasks which required real-time inputs from remotely located synchronous machines. Such inputs may not always be readily available as direct measurements, furthermore even when they are they may be vulnerable to measurement errors or occasional loss of measurements. Hence, having a DSE can greatly facilitate implementation of wide are control systems.

Despite the aforementioned benefits of DSEs, their performances remain strongly dependent on the assumed turbine-generator and associated control system models. Any errors in the assumed parameters of these models will impact the results of the estimation.

One common problem which involves generator and control system models is the failure of exciters as a result of diode failures [59]. When such a failure occurs, the effective exciter model will abruptly change and as a result the dynamic state estimator outputs will become biased. While there are direct methods to detect exciter diode failures, these are typically expensive to implement. A popular indirect method to detect diode failure
is via the exciter field current. It is important to detect such failures in a timely fashion in order to avoid risk of exciter and voltage regulator damage. In this chapter, a practical solution for detection of exciter failures in synchronous generators based on the use of specially DSEs will be described. The approach is motivated by considering the case where at some point during the daily operation of a synchronous generator, the dynamic model related to the exciter may abruptly change. This could be due to an exciter rotator diode failure [59]. Thus, the proposed dynamic state estimation approach in this chapter will not only remain robust against exciter failure but also detect its occurrence in a timely fashion. Hence, the system operator can be promptly informed about the type and location of the exciter failure without requiring costly local investigations on the performance of the specific excitation system.

In this chapter, this is proposed to be accomplished in two steps. In the first step, an alternative dynamic state estimation approach for the synchronous generators with unknown inputs is developed where IUKF is used as a DSE to estimate the augmented state vector (which includes the state variables and unknown inputs) corresponding to the synchronous generator. Then a “multiple model estimation” strategy is implemented in order to identify the correct model corresponding to the test system among different type of the assumed models. This two-step approach with appropriately designed dynamic state estimators will be described in detail in the next sections. The proposed approaches in this chapter will be implemented on a two-axis model of synchronous generator with its IEEE-Type 1 exciter model (associated dynamic model were given in Chapter 4) within the NPCC test system.

7.2 Two alternative implementations of the dynamic state estimators

Dynamic state estimation for the generator and exciter dynamics can be implemented
using two different algorithms. The first algorithm estimates the combined state vector that includes the dynamics of both two-axis model of a synchronous generator and its IEEE-type 1 exciter. In this case the state and input vectors can be expressed as follows:

\[ x_1 = [\delta, \omega, E'_q, E'_d, V_f, V_R]^T \]
\[ u_1 = [P_M, V, \theta]^T \]  \hspace{1cm} (7.1)

The second algorithm estimates the state vector corresponding to the two-axis synchronous generator without considering the dynamics associated with the exciter which means that there will be fewer state variables to estimate however the excitation voltage is needed as an extra known input. Thus the state and input vectors will be:

\[ x_2 = [\delta, \omega, E'_q, E'_d]^T \]
\[ u_2 = [P_M, V, \theta, E_{fd}]^T \]  \hspace{1cm} (7.2)

It is important to consider that measuring the excitation voltage may not be an easy task and it can be considered as an unknown input, therefore the dynamic state estimation approach should be capable of addressing the issue regarding the unknown inputs. In this part an alternative implementation of dynamic state estimation will be presented where IUKF will be used as the estimator. It has been shown that IUKF has better accuracy and performance compared to the other variants of Kalman Filter such as EKF, IEKF, MVEKF and UKF [56]. While IUKF has higher computational burden compared to the UKF and EKF, as will be shown later, the CPU time is still significantly small for the dynamic state estimation of the two-axis synchronous generator and associated exciter. The algorithms related to the UKF and IUKF were given in chapters 4 and 6 respectively.

In this part IUKF will be implemented to estimate the augmented state vector of the synchronous generator which includes the dynamic variables and unknown inputs.
Consider a two-axis synchronous generator with an unknown field voltage and the modified state and input vectors as follows:

\[
\ddot{x}_2 = [\delta, \omega, E'_q, E'_d, E_{fd}]^T
\]

\[
\ddot{u}_2 = [P_M, V, \theta]^T
\]  \hspace{1cm} (7.3)

UKF and IUKF (using two different number of iterations) are used to estimate the augmented state vector of a two-axis synchronous generator within the NPCC test system (details of this system are given in [52]) where:

- Duration of simulation is 30 sec.
- A line is switched at t=1 sec. in the test system.
- Integration time-step is chosen as 0.025 sec.
- Delivered active and reactive powers by the generator are used as measurements.
- Field voltage is considered as an unknown input.

Rotor angle of the generator estimated by UKF, IUKF (using 5 iterations) and IUKF (using 10 iterations) are shown in Figures 7.1, 7.2 and 7.3 respectively. In all Figures dashed lines indicate estimated results and solid lines indicate the true trajectory.
As evident from Figures 7.1-7.3, IUKF has superior performance compared to UKF for the dynamic state estimation of two-axis synchronous generator with unknown inputs. Therefore it is chosen as the implementation method for dynamic state estimation of synchronous generators with unknown inputs in the proposed approach. Table 7.1 shows the CPU-times for UKF and IUKF using 5 and 10 iterations.

TABLE 7.1: CPU-TIME FOR THE ESTIMATION OF AUGMENTED STATE VECTOR

<table>
<thead>
<tr>
<th>Method</th>
<th>UKF</th>
<th>IUKF (N=5)</th>
<th>IUKF (N=10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU-time (Sec.)</td>
<td>0.00013</td>
<td>0.0004</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

As evident from Table 7.1, IUKF requires higher computational effort with respect to the UKF however the CPU time still remains significantly small compared to the simulation time step which is 0.025 sec.
7.3 UKF based dynamic state estimation accounting for the exciter failure

This section will describe the multiple model estimation technique which will be used to identify the true model among several alternative models of a given generator and its associated control systems [43].

7.3.1 Multiple model estimation technique

Let the set $p$ given by \{ $p_1$, $p_2$, ..., $p_N$ \} represent the set of possible values which can be assumed by a given system model [43]. Considering $N$ different models corresponding to the parameters \{ $p_1$, ..., $p_N$ \} and a given measurement $z_k$ at time step $k$, the probability of $p$ being equal to $p_j$ can be computed as:

$$\Pr(p_j \mid z_k) \tag{7.4}$$

This probability is expected to converge to a negligible value during the simulations when an invalid model parameter is used and it will converge to a value close to 1.0 for the valid parameter. The probability given in (7.4) can be computed and updated using the following algorithm:

1. Initialize the probability of each parameter set before any measurements are obtained:
   $$\Pr(p_j \mid z_0) \quad j = 1, ..., N \tag{7.5}$$

2. For each assumed parameter set run a DSE and obtain $\hat{x}_{k,j}$ and $P_{k,j}$ ($j = 1, ..., N$) from each DSE.

3. For each parameter set approximate the pdf of $z_k$ given $p_j$ as follows:
\[ pdf(z_k \mid p_j) \approx \frac{\exp(-r_k^T P_{z,j}^{-1} r_k / 2)}{(2\pi)^{m/2} | P_{z,j}|^{1/2}} \]  

(7.6)

where, \( P_{z,j} \) can be obtained from (3.9) or (6.2), \( r_k = z_k - \hat{z}_{k,j} \) and \( m \) is the total number of the measurements.

4. Estimate the probability that \( p = p_j \) as follows:

\[
Pr(p_j \mid z_k) = \frac{pdf(z_k \mid p_j)Pr(p_j \mid z_{k-1})}{\sum_{i=1}^{N} pdf(z_k \mid p_i)Pr(p_i \mid z_{k-1})}
\]  

(7.7)

### 7.3.2 Proposed approach for the dynamic state estimation accounting for exciter failures

Under the normal operating conditions of a synchronous generator and associated excitation system, it is desired to estimate the state variables of both synchronous generator and the exciter. However when a problem such as the exciter rotator diode failure occurs, then the assumed dynamics of the exciter will not be valid anymore and therefore using the inaccurate dynamic model of the exciter can significantly degrade the accuracy of the estimated results of the state variables provided by the DSE. The following approach is proposed in order to circumvent this problem. Note that this approach not only remains robust against the occurrence of the exciter failure but also properly detects the occurrence of this failure. The steps of the proposed approach are listed below:

- Use an UKF for the dynamic state estimation of the synchronous generator and associated exciter. In this chapter a two-axis model of a synchronous generator and IEEE-Type 1 exciter are considered and thus an UKF is used to estimate the state vector given by (7.1).
• Use an IUKF for the estimation of the augmented state vector associated with synchronous generator assuming that excitation voltage is an unknown input. For a two-axis synchronous generator the augmented state vector is given by (7.2).

• Use multiple model estimation technique for the detection of exciter failure. This will be accomplished by executing both UKF and IUKF in parallel for tracking the states of the synchronous generator and associated exciter. When the exciter failure occurs, the first DSE (UKF) will perform poorly due to the inaccurate dynamic model used for the exciter whereas the performance of the second DSE (IUKF) will not be affected. The probabilities computed by (7.7) corresponding to the models used by the UKF and IUKF will converge to 0 and 1 respectively following the occurrence of the exciter failure.

The proposed dynamic state estimation approach is tested using the two-axis model of synchronous generator with the following assumptions:

• At time =10 sec. the value of the exciter amplifier gain ($K_a$) is changed from 50 (pu) to 30 (pu). This change is intentionally ignored and the old gain value is continued to be used in the dynamic model of the exciter. Dynamic state estimation is carried out using the UKF as described in section 3.2.2.

Figure 7.4 shows the estimated rotor angle by the UKF following the change in the exciter amplifier gain. As evident from this Figure, the estimated rotor angle diverges from the true trajectory due to the exciter model error. On the other hand, IUKF continues to provide accurate estimates for the rotor angle (Figure 7.5) since the performance of the IUKF remains independent of the assumed exciter model.
Note that in a real-life exciter failure scenario the true trajectory will not be known. Therefore, in order to detect the exciter failure it is necessary to evaluate the performance of both estimators. As mentioned before the multiple estimation technique can detect the occurrence of the exciter failure. For example Figure 7.6 shows that the probabilities given by (7.7) for the UKF and IUKF converge to 0 and 1 respectively following the exciter failure.

Fig.7.4: Estimated and true trajectories of the rotor angle-UKF is used as DSE.

Fig.7.5: Estimated and true trajectories of the rotor angle-IUKF is used as DSE.

Fig.7.6: Result of the multiple estimation technique for UKF and IUKF after the occurrence of the exciter failure.
7.4 Conclusions

This chapter considers the problem of detecting and identifying exciter failures for synchronous generators. The main challenge is to not only detect the failure but maintain robust tracking capability of the generator states following the failure. This is accomplished by implementing two alternative dynamic state estimators which are executed in parallel. A probabilistic metric is used to design a failure detection test by which the occurrence of exciter failure can be accurately determined.

The proposed method is implemented and successfully tested on a two-axis model of a synchronous generator with IEEE-Type 1 exciter in the NPCC test system.
Chapter 8

Local Detection of PMU Measurement Errors Using Dynamic State Estimators

8.1 Introduction

Perhaps the main reason that majority of the earlier power system state estimation approaches were focused on the estimation of the static state variables of the system (voltage phasors of the buses) was related to the slow rate of the available measurements provided by the instruments that were used by SCADA systems. Recent availability of voltage and current phasor measurements provided by PMUs at rates commensurate with system dynamics made it possible for researchers to investigate the implementation of dynamic state estimation in power systems. Most of the proposed dynamic state estimation approaches [2-13] assume that PMU measurements are directly used in the state estimation process. Therefore accuracy of the estimated states depends strongly on the quality of the PMU measurements. As an example it has been previously shown [36] that when there are gross-errors associated with PMU measurements, the accuracy of the states estimated by the Dynamic State Estimators (DSEs) can be significantly reduced when these measurements are used without any error processing.

In order to address this issue authors earlier proposed a two-stage dynamic state estimation approach [36], where a Least Absolute Value (LAV) based linear phasor estimator is used in the first stage to eliminate bad data followed by a distributed dynamic
state estimation making the overall estimation robust under various types of bad-data in PMU measurements. Note that robustness of the proposed two-stage dynamic state estimator is directly related to optimal placement of PMUs which not only ensures observability but also sufficient level of redundancy. The down-side is it leads to a significant number of PMUs to be installed in the system. If the PMUs were to be used for a specialized application such as point-to-point monitoring of phase angle differences for a limited set of substation pairs, then placement of two PMUs at the terminal buses may be all that is needed. However, due to the possibility of gross errors occurring in PMU measurements, such an installation will be highly unreliable. In this chapter a simple yet effective solution will be presented in order to ensure robust PMU measurements even under gross errors.

The proposed approach will be implemented to obtain the dynamic state estimation results for a two-axis model of a synchronous generator with IEEE-Type 1 exciter model. In the proposed approach it is assumed that there exist at least two local PMUs for the dynamic state estimation process. One PMU serves as the main PMU for the state estimation process and the other PMU is considered to be a backup PMU. In the proposed approach a DSE will be used associated with each PMU to estimate the dynamic states of the aforementioned synchronous generator. Then a variant of the multiple model estimation technique described in [43] will be implemented in order to quantify the accuracy of the estimated results provided by the DSEs. The final (acceptable) dynamic state estimation results will be selected as those provided by the DSE which will be favored by the performance evaluation method.

In the proposed approach UKF will be used as an efficient DSE. In this chapter first the above mentioned performance evaluation procedure for the two DSEs will be explained. Then the simulation results will be presented where the proposed approach will be tested under bad data associated with PMU measurements.
8.2 Proposed approach for the robust dynamic state estimation

Dynamic state estimator is implemented as an UKF in order to estimate the combined state vector that includes the dynamics of both two-axis model of a synchronous generator and the IEEE-type 1 excite (Associated dynamic equations were given in chapter 4). Hence, the state and input vectors are given as follows:

\[ x = [\delta, \omega, E'_q, E'_d, E_{fd}, V_f, V_R]^T \]
\[ u = [P_M, V, \theta]^T \]  

In the next part an approach for the evaluation of the performance of the DSEs will be presented:

8.2.1 An approach for evaluating the performance of DSEs

Performance evaluation is carried out using similar approach to the multiple model estimation technique described in the chapter 7. It has been shown that at each time step, the calculated pdf of the residuals can be used as an indicator to quantify the performance of a DSE [43]. Same idea is extended to the DSE evaluation in this chapter. At each time step, the pdf of the measurement residuals is updated as follows:

\[
\text{pdf} (r_k) = \frac{\exp(-r_k^TP^{-1}_z r_k / 2)}{(2\pi)^{m/2} |P_z|^{1/2}}
\]  

(8.2)

where, \( P_z \) is obtained from (3.9), \( r_k = z_k - \hat{z}_k \) and \( m \) is the total number of the measurements.
Note that a separate DSE will be implemented for each PMU. Then, the following metric will be calculated at each time step for each DSE:

\[ M_k^j = \frac{pdf(r_k^j)}{\sum_{j=1}^{N} pdf(r_k^j)} \]  

(8.3)

where \( N \) is the total number of the PMUs (DSEs) and \( j \) is the PMU (and corresponding DSE) index. The metric defined by (8.3) will be almost equal to \( 1/N \) under normal operating conditions. The reason is that the performance of the DSEs will be almost identical and so will the calculated pdf of the measurement residuals obtained by the DSEs. Therefore the estimated results provided by any one of the DSEs can be considered as the final (acceptable) dynamic state estimation result. However, in the presence of bad-data associated with one of the PMUs the value of this metric can be significantly reduced for the corresponding DSE.

In this chapter it is assumed that there are only two PMUs and associated dynamic state estimators. One PMU is considered as the primary (main) PMU and the other a backup PMU. Under normal operating conditions, dynamic state estimation results for the main PMU will be used as the final (acceptable) dynamic state estimation results. Under bad-data the corresponding calculated metric of (8.3) will be noticeably reduced. For this reason a detection threshold can be defined and compared against the calculated metric. In the case of reduced metrics the final (acceptable) dynamic state estimation results will be taken as those provided by the DSE with the high metric. Figure 8.1 shows the block-diagram summarizing the proposed approach of selecting the appropriate DSE with unbiased results at each time step.
8.3 Simulation results

The proposed approach will be used to perform the dynamic state estimation of a two-axis model of synchronous generator with associated IEEE-Type 1 exciter within the WECC test system. This test system includes 181 buses and 31 synchronous generators. The following assumptions are made for the simulations:

- Duration of the simulation is 20 sec.
- Simulation time-step is 0.033 sec.
- Starting at t=1.5 sec. several line switching events are simulated.
- Delivered active and reactive power by the generators are considered as measurements for the dynamic state estimation
- White Gaussian noise with std=0.001 are added to the noise free measurements provided by a simulator to obtain the erroneous measurements and inputs for the dynamic state estimation process.

Fig.8.1: Block diagram of the proposed approach for the robust dynamic state estimation.
In order to evaluate the performance of the proposed dynamic state estimation approach under bad-data, two different case studies will be investigated:

**8.3.1 Case study 1**

In this case study, it will be assumed that bad-data will occur in the measured voltage phasor provided by the main PMU. The details of this simulation are given below:

- Starting at t=10 sec. the measured voltage magnitude provided by the main PMU is replaced by 0.8 times of its true value (simulating a scaling error) for a duration of 2 sec.
- The threshold for evaluation the performance of the main DSE is considered to be 0.45

The performance evaluation metric of (8.3) is calculated during the simulation and plotted in Figure 8.2. Estimated trajectory of the rotor angle of the aforementioned synchronous generator is plotted in Figure 8.3. For comparison, the dynamic state estimation results without using the proposed approach (using the conventional approach) for the rotor angle is given by Figures 8.4.

![Fig.8.2: Calculated performance evaluation metric associated with the main DSE - Case study 1.](image-url)
As evident from Figure 8.2, the calculated performance evaluation metric drops to a very small value immediately after occurrence of the bad-data. After 2 seconds, the error is corrected and the value of the calculated metric moves back again to 0.5. This can be also seen from Figure 8.4 where the estimated rotor angle provided by conventional approach converges to the true trajectory almost around the same time that M converges back to 0.5. This is expected since in the absence of bad data the DSE will take a short amount of time to converge back again to the true trajectory.

### 8.3.2 Case study 2

Consider a situation where the delivered active power by the generator carries a large additive white Gaussian noise. In addition the following assumptions are made in simulating this case:

- Starting at t=10 seconds, for a duration of 2 seconds, white Gaussian noise with std=0.1 is added to the values of delivered active power by the generator.
- All other measurements are modified by additive white Gaussian noise with std=0.001.
- The threshold for the metric of performance evaluation of the main DSE is set as 0.45.
The performance evaluation metric $M$ for the generator is plotted in Figure 8.5. The estimated trajectories of the rotor angles based on the proposed and conventional approaches are plotted in Figures 8.6 and 8.7 respectively.

As evident from Figures 8.5, 8.6 and 8.7 the effect of the larger additive white Gaussian noise associated with the delivered active power by the generator on the accuracy of the dynamic state estimation is less than the previous case study. However, still the proposed
approach can successfully identify the PMU with less than acceptable accuracy and ensure delivering robust estimates of the state variable of interest.

8.4 Conclusions

This chapter’s focus is on local detection of gross errors in PMU measurements when more than one PMU is available at a given generation substation. It is assumed that at least two local PMUs are available and a dynamic state estimator associated with each PMU is used to obtain the dynamic state estimation results for a synchronous generator. In the proposed approach at each time-step the performance of each dynamic state estimator is evaluated using a performance metric. This metric is defined and calculated based on the pdf of the residuals obtained from each dynamic state estimator. The proposed approach not only allows detection of gross errors in PMU measurements locally but also provides highly accurate estimates for the dynamic states of the generator.
Chapter 9

Concluding Remarks and Future Work

9.1 Concluding Remarks

The research work presented in this dissertation has focused on real-time parameter identification of the dynamic load models; robust distributed dynamic state estimation of the large-scale power systems; observability analysis of the nonlinear dynamic models in the power systems; real-time failure detection of the components in the power systems; and local bad data detection of the measurements provided by the PMUs. An account of the main contributions of this dissertation is given in below:

1) In chapter 3, UKF is used to identify the unknown parameters of an exponential dynamic load model in real time. The performance of the UKF is first evaluated by considering simulated measurements assuming that the values of the parameters associated with the load model change during the simulation. Then, the proposed dynamic state estimator performance is evaluated using actual recorded utility load data. The simulation results obtained for both cases show that UKF is capable to provided highly accurate estimation results associated with the unknown parameters of the exponential dynamic load model.

2) Chapter 4, presented a robust two-stage dynamic state estimation approach. In the first stage of the proposed estimator a LAV based linear phasor estimator is utilized to estimate the voltage phasors of the buses in the test system. Estimated terminal voltage phasors and the delivered active and reactive powers associated with the
synchronous generators are used as inputs and measurement respectively by the second stage which is the dynamic state estimator in order to estimate the state variables of the synchronous generators. In this chapter it has been shown that the proposed approach remains robust under presence of the bad-data associated with measurement that are used for the dynamic state estimation. The proposed estimator also takes into the account the effects of the load dynamics on the dynamic state estimation. Moreover, by using the proposed approach it is not necessary to have local PMUs at the terminal of the generators. The proposed state estimator is successfully implemented on the NPCC test system and the results are shown in this chapter.

3) Chapter 5, focused on observability analysis of the nonlinear dynamics models associated with the generators or loads in the power systems. In the proposed approach, first by using the terminal voltage phasors of the generators or the loads as available inputs, the associated nonlinear dynamic models are isolated from the network algebraic equations. Then the observability matrix related to the isolated nonlinear dynamic models are obtained by calculating the Lie-derivatives associated with the isolated nonlinear dynamic equations. In the proposed approach the smallest singular value of the observability matrix is used as an indicator for the level of the observability for a given measurement set. The proposed approach also allows us to identify a proper measurement set for the purpose of the dynamic state estimation. In this chapter the proposed approach is successfully implemented to evaluate the level of the observability for a two-axis model of a synchronous generator with its IEEE-Type 1 exciter in the NPCC test system for various measurement sets.

4) In Chapter 6, a UKF based dynamic state estimator is introduced which is capable to perform dynamic state estimation for the synchronous generators with unknown parameters and inputs. Constrained and iterated dynamics state estimation techniques are used in the proposed approach which makes it possible to simultaneously estimate the state variables, unknown parameters and unknown inputs associated with the
dynamic model of a synchronous generator. The proposed dynamic state estimation approach is used in this chapter to perform dynamic state estimation on a synchronous generator in NPCC test system where some parameters and inputs related to the generator model such as inertia constant, d-axis transient reactance and field voltage are assumed to be unknown. The simulation results presented in this chapter illustrate the effectiveness of the proposed approach for the dynamic state estimation of the synchronous generators with unknown parameters and inputs.

5) Chapter 7 presented a dynamic state estimation approach which makes it possible to remotely detect the occurrence of a synchronous generator’s exciter failure without any need to locally investigate the performance of the exciter. The proposed approach takes advantage of UKF, IUKF and multiple model estimation technique. Also an alternative dynamic state estimation approach for the dynamic state estimation of the synchronous generators with unknown inputs is presented in this chapter. The proposed approaches are tested on a two-axis synchronous generator with IEEE-Type 1 exciter in the NPCC test system. Using the proposed approach the occurrence of the exciter failure is successfully detected in a timely fashion.

6) Chapter 8 is concerned about local detection of the bad-data associated with PMU measurements when at least two PMUs are available at a given generation substation. In the proposed approach associated with each PMU a dynamic state estimator is used to obtain the dynamic state estimation results for a synchronous generator. Then the performance of each dynamic state estimator is evaluated using a metric which is calculated based on the pdf of the residuals obtained from each dynamic state estimator. The proposed approach not only is capable to detect the occurrence of the bad-data associated with the measurements provided by the PMUs also it can still provide highly accurate results for the dynamic state estimation process when such failure occurs. The proposed approach is successfully implemented to locally evaluate
the quality of the measurements provided by two PMUs located at a terminal of a synchronous generator in WECC test system.

9.2 Future Work

Based on the results presented in this dissertation, several extensions to this work are identified to be pursued in the future. These are briefly discussed below:

- **Distribution level state estimation:**
  
The robust state estimation approaches that are presented in this dissertation are mainly implemented on the power system transmission level where the system remains balanced for the majority of the time. Therefore the transmission level can be modeled as a single phase positive sequence network. However in the power systems distribution level the systems is typically unbalanced and therefore it is necessary to consider a three phase network for modeling this part of the system. Thus in order to have a successful monitoring and control of the distribution systems it is necessary to implement robust three-phase distribution level state estimator. Therefore robust three-phase distribution level state estimation may be considered for the future research.

- **Inclusion of the AC/DC models and wind units in the dynamic state estimation problem:**
  
In this dissertation the proposed dynamic state estimation approaches are mainly implemented on the test systems with AC components to estimate the dynamic state variables of the synchronous generators. For the future research the extension of the ideas related to the robust dynamic state estimation to the smart test systems with associated
AC/DC models and higher penetration of the distributed generation from wind units is of great interest.

- **Smart PMU:**

  Implementation of the novel techniques for locally evaluating the quality of the measurements provided by the PMUs is considered for the future research. The idea of the local bad-data detection of the measurements presented in this dissertation which requires to have at least two local PMUs at a given substation can be enhanced to be used for the substations with a single PMU.

- **Real-time failure detection of the components such as transformers:**

  In this dissertation a dynamic state estimation approach for the real-time failure detection of the exciter associated with a synchronous generators was presented. For the future work similar idea can be used for the real-time failure detection of other components such as transforms in the power systems.
Appendix

A.1 Discretized equations associated with the two-axis model of a synchronous generator with IEEE-Type1 exciter

Using the second order Runga-Kutta method the discretized equations for two-axis model of a synchronous generator with IEEE-Type1 exciter are given in below:

\[
\omega(k + 1) = \omega(k) + \frac{1}{2} (K'_{\omega} + K''_{\omega})
\]

\[
\delta(k + 1) = \delta(k) + \frac{1}{2} (K'_{\delta} + K''_{\delta})
\]

\[
E'_q(k + 1) = E'_q(k) + \frac{1}{2} (K'_{E'_q} + K''_{E'_q})
\]

\[
E'_d(k + 1) = E'_d(k) + \frac{1}{2} (K'_{E'_d} + K''_{E'_d})
\]

\[
E'_{fd}(k + 1) = E'_{fd}(k) + \frac{1}{2} (K'_{E'_{fd}} + K''_{E'_{fd}})
\]

\[
V_R(k + 1) = V_R(k) + \frac{1}{2} (K'_{V_R} + K''_{V_R})
\]

\[
V_f(k + 1) = V_f(k) + \frac{1}{2} (K'_{V_f} + K''_{V_f})
\]

\[
P_m(k + 1) = P_m(k),
\]

Where \(K'_{\omega}, K''_{\omega}, K'_{\alpha}, K''_{\alpha}, K'_{E'_q}, K''_{E'_q}, K'_{E'_d}, K''_{E'_d}, K'_{V_R}, K''_{V_R}, K'_{V_f}, K''_{V_f}\) are obtained by the following equations:
\[
\begin{bmatrix}
V_d - a \\
V_q - a
\end{bmatrix} = \begin{bmatrix}
\sin(\delta(k)) & -\cos(\delta(k)) \\
\cos(\delta(k)) & \sin(\delta(k))
\end{bmatrix} \begin{bmatrix}
V(k) \cos(\theta(k)) \\
V(k) \sin(\theta(k))
\end{bmatrix} \quad I_d - a = \frac{E'_q(k) - V_q(k)}{X'_d} ,
\]
\[
I_q - a = \frac{V_q(k) - E'_d(k)}{X'_q}
\]
\[
P_e - a = V_d - a \times I_d - a + V_q - a \times I_q - a
\]
\[
K'_\omega = \Delta t \times \frac{\pi f_0}{H} \times (P_{qf} (k) - P_e - a - D(\omega(k) - \omega_b) / \omega_b)
\]
\[
K'_\delta = \Delta t \times (\omega(k) - \omega_b)
\]
\[
K'_{E_d} = \Delta t \times \frac{1}{T_{qo}} (-E'_q(k) + (X_q - X'_q) I_q - a)
\]
\[
K'_{E_q} = \Delta t \times \frac{1}{T_{do}} (-E'_q(k) - (X_q - X'_q) I_d - a + E'_{fd} (k))
\]
\[
K'_{E_p} = \Delta t \times \frac{1}{T_e} (V_R(k) - K_e E_{pd}(k))
\]
\[
K'_{V_x} = \Delta t \times \frac{1}{T_a} (-V_R(k) + K_a (V_{ref} - V(k) - V_f(k))
\]
\[
K'_{V_f} = \Delta t \times \frac{1}{T_f} (-V_f(k) + \frac{K_f}{T_e} V_R(k) - \frac{K_e K_f}{T_e} E_{fd}(k))
\]
\[
\begin{bmatrix}
V_d - b \\
V_q - b
\end{bmatrix} = \begin{bmatrix}
\sin(\delta(k) + K'_\omega) & -\cos(\delta(k) + K'_\omega) \\
\cos(\delta(k) + K'_\omega) & \sin(\delta(k) + K'_\omega)
\end{bmatrix} \begin{bmatrix}
V(k) \cos(\theta(k)) \\
V(k) \sin(\theta(k))
\end{bmatrix} \quad I_d - b = \frac{E'_q(k) + K'_{E_d} - V_q(k)}{X'_d}
\]
\[
I_q - b = \frac{V_q(k) - E'_d(k) - K'_{E_d}}{X'_q}
\]
\[
P_e - b = V_d - b \times I_d - b + V_q - b \times I_q - b
\]
\[
K''_\omega = \Delta t \times \frac{\pi f_0}{H} \times (P_{qf} (k) - P_e - b - D(\omega(k) + K''_\omega - \omega_b) / \omega_b)
\]
\[
K''_\delta = \Delta t \times (\omega(k) + K''_\omega - \omega_b)
\]
\[ K_{E_d}^* = \Delta t \times \frac{1}{T'_{qu}} (-E_d'(k) - K_{E_d}' + (X_q - X_q')I_q - b) \]
\[ K_{E_q}^* = \Delta t \times \frac{1}{T_{do}} (-E_q'(k) - K_{E_q}' - (X_d - X_d')I_d - b + E_{\delta d}(k) + K_{E_d}') \]
\[ K_{E_{\mu}}^* = \Delta t \times \frac{1}{T_e} (V_e(k) + K_{V_e}' - K_e(E_{\mu d}(k) + K_{E_d}'')) \]
\[ K_{V_x}^* = \Delta t \times \frac{1}{T_a} (-V_x(k) - K_{V_x}' + K_a(V_{ref} - V(k) - V_f(k) - K_{V_f}') \]
\[ K_{V_f}^* = \Delta t \times \frac{1}{T_f} (-V_f(k) - K_{V_f}' + K_f(V_e(k) + K_{V_e}') - \frac{K_f K_e}{T_e} (E_{\mu d}(k) + K_{E_d}')) \]

(A.1)

Here \( H \) (Sec) is the inertia constant, \( D \) (pu) is the damping coefficient, \( T_{qu'} \) (sec) & \( T_{qu} \) (sec) are the d-axis and q-axis transient time constants respectively, \( X_d \) (pu) & \( X_q \) (pu) are d-axis and q-axis synchronous reactances respectively, \( X_d' \) (pu) & \( X_q' \) (pu) are d-axis and q-axis transient reactances respectively. \( K_a \) (pu) is the exciter amplifier gain, \( T_a \) (Sec) is the exciter amplifier time constant, \( K_f \) (pu) is the exciter feedback gain, \( T_f \) (Sec) is the exciter feedback time constant. \( T_e \) (Sec) is the self-excited time constant, \( K_e \) (pu) is the self-excited gain. \( V_{ref} \) (pu) is the exciter reference.

A.2 Obtaining Lie-derivatives for a classical model of a synchronous generator

Here a simple example of obtaining Lie-derivatives for a classical generator model will be presented. Detailed description of Lie-derivatives method can be found in [42] and [55].

Consider the differential equations associated with classical model of a synchronous generator given below:
\[
\begin{align*}
\dot{\delta} &= \omega - \omega_0 \\
\frac{H}{\pi f_0} \dot{\omega} &= P_M - P_e - D(\omega - \omega_0)/\omega_0
\end{align*}
\]

\[P_e = \frac{E'V_L}{X'_d} \sin(\delta - \theta_f) \quad (A.2)\]

where \(E\) is the constant internal voltage behind its direct axis transient reactance \(X_d'\) [49]. Assuming the delivered active power as the measurement, Lie-derivatives can be computed using equations (5.6),(5.7), and (5.8):

\[L^0_j h = P_e = \frac{E'V_L}{X'_d} \sin(\delta - \theta_f)\]

\[L^1_j h = \frac{\partial (L^0_j h)}{\partial \delta} \cdot f_1 + \frac{\partial (L^0_j h)}{\partial \omega} \cdot f_2\]

where

\[f_1 = \omega - \omega_0\]

\[f_2 = \left( \frac{H}{\pi f_0} \right)^{-1} \times (P_M - P_e - D(\omega - \omega_0)/\omega_0)\]

\[\frac{\partial (L^0_j h)}{\partial \delta} \cdot f_1 = \frac{E'V_L}{X'_d} \cdot (\omega - \omega_0) \cdot \cos(\delta - \theta_f)\]

\[\frac{\partial (L^0_j h)}{\partial \omega} \cdot f_2 = 0 \quad (A.3)\]

The observability matrix associated with classical model of a synchronous generator can now be calculated using the Lie-derivatives obtained above and equations (5.9) and (5.10):
\[ O(x) = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \]

where,

\[ x = [\delta \quad \omega]^T \]

\[ A = D = \frac{E'V_T}{X'_d} \cos(\delta - \theta_T) \]

\[ B = 0 \]

\[ C = -\frac{E'V_T}{X'_d} (\omega - \omega_b) \sin(\delta - \theta_T) \]  \hspace{1cm} (A.4)

Here again the terminal voltage phasor of the generator \((V_T, \theta_T)\) will be used as a known input in order to isolate the dynamical equations of the synchronous generator from the network equations.
References


List of Publications

• Journal Papers:


• Conference Papers:


