This is to certify that the

thesis entitled

Modularized Global Dynamic State
Estimation for Power Systems

presented by

Mohamad Hasan Modir-Shanechi

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in Systems Science

Robert Schlueter
Major professor

Date July 6, 1979

MODULARIZED GLOBAL DYNAMIC STATE ESTIMATION FOR POWER SYSTEMS

By

Mohamad Hasan Modir Shanechi

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHLIOSOPHY

Department of Electrical Engineering
and
Systems Science

1979

ABSTRACT

MODULARIZED GLOBAL DYNAMIC STATE
ESTIMATION FOR POWER SYSTEMS

By

M. Hasan Modir Shanechi

The subject of this thesis is "Modularized global dynamic state estimation for power systems". Based on a linearized model of the electromechanical dynamics of each generator, this dynamic state estimation problem is formulated to estimate the voltage angle and frequency at any set of load and generator buses which constitute a subarea of the power system where such a dynamic state estimate is desired.

This dynamic state estimation problem is formulated such that measurement and model information from the system external to the subarea are not required. The elimination of the need for external model data and measurement is achieved by measuring the power flows on the tie lines connecting the external and internal system.

Three different dynamic load models are developed which assume that the load at each load bus can be decomposed into different load types and that each load

type can be modeled by a Markov process. Identification of the parameters of these load models and incorporating them in the dynamic state estimator eliminates the need for measurement at all load buses.

The study system for the dynamic state estimator is divided into modules and the dynamics of each module is decoupled from any other module, thus eliminating the need for synchronized measurements at all points of the study area and the process of modularization permits the model to be updated on-line and with minimum on-line computation for changes in unit commitment, network configuration and load flow. Since these changes are local in character and thus every module will not have to be updated for each system change, and since the network reduction of all modules simultaneously requires less computation and is more accurate than a single network reduction of the network for the entire study area, the on-line computation for model updating can be kept at a reasonable level.

To get all angle and frequency estimates from all modules referenced to a common reference, a global referencing procedure is developed. This procedure uses the already measured tie line power flows between the modules in a least squares algorithm and not only provides referencing, but also provides for bad data detection, identification and rejection of these tie line power flow measurements.

M. Hasan Modir Shanechi

A computer program for estimation of the angle and frequency at a module is developed and used against the dynamic simulation of MECS to provide;

a) verification of the assumption that a classical stability model can be used for each generator,

b) determination of maximum measurement error and minimum sampling rate that will result in accurate estimates of angle, frequency fluctuations and a rms coherency measure,

c) determination of the sampling rate and the number and location of measurements necessary in order to provide accurate and fast reconvergence of state estimates after a major disturbance,

d) determination of the level of accuracy of the parameters of the linear model needed to obtain accurate estimates. In doing so it was also verified that neglecting voltage regulator dynamics would not affect the accuracy of the estimates unduly.

ACKNOWLEDGEMENT

I would like to express my gratitude to the members of my guidance committee for their invaluable contribution to my doctoral program. Specifically I would like to thank Dr. Rosenberg for his stimulating questions; Dr. Barr for the enjoyable experience of taking his classes; Dr. Park for what I learned from his guidance and leadership qualities in research and all the meaningful conversations I had with him; not all of them restricted to academic per se; and Dr. Schlueter not so much for the help that he gave me in academic matters, although they were great and many, but most of all for his friendship and help during my stay in this country. He was much more than a research advisor to me and he will always be remembered as such.

During these years I learned a lot about life and people of the United States and many other countries which I value very much and I established many friendships which I cherish dearly. I am grateful to be part of the community and most grateful to have met all those who became my friends.

I must also acknowledge the financial support I received from the Division of Engineering Research, Michigan State University.

TABLE OF CONTENTS

Chapter		Page

CHAPTER I

INTRODUCTION

Dynamic state estimation is a prerequisite for several significant improvements in the security and stability of a power system which will result by enhancing the following power system operating functions:

(1) - security assessment

(2) - security enhancement; and

(3) - control in the normal, alert, emergency and restorative operating state.

A global dynamic state estimator would assist security assessment [1,2]

(1) in its security monitoring task by providing an accurate estimate of electrical frequency at every bus in the system and/or a measure of coherency between any two buses as a function of time.

(2) in its security analysis role by providing data for possible transient security measures [3,4] and a better data base for developing dynamic equivalents for transient security analysis [5,6,7].

The global dynamic state estimator could assist in security enhancement [1,2] by providing data for new preventive and corrective controls, which would operate in the alert and emergency operating states respectively, and would

(1) adjust levels of generation, using an optimal power dispatch that minimizes both the total cost of generation and a weighted sum of on-line estimates of the coherency measure [4] between pairs of buses. This power dispatch would adjust generation to relieve line overloads and thus increase the dynamic structural integrity and security of the system;

(2) perform line switching operations to improve the coherency between coherent groups based on an on-line estimate of the coherency measure between pairs of buses;

(3) adjust relaying logic [4] in order to maintain the relative level of coherency between coherent groups when loss of a line would cause a serious loss of coherency between these groups and affect system security;

(4) adjust relaying logic [2] so that lines connecting coherent groups could be opened on command to form islands when total system collapse appears imminent.

Dynamic state estimation could improve control in the normal, emergency, and restorative state in several ways. A global dynamic state estimator would be required for the optimal automatic generation control [8] proposed to improve the response of the power system to changes in load and compensate present power system dynamics. A local dynamic state estimator could be used to provide local state information on a particular generator and the buses it is directly connected to for discrete control strategies [9], which are used in the emergency operating state to maintain synchronization after a severe contingency. Global dynamic state information could also be used in the emergency operating state for optimal load shedding algorithms [4] which could be used to reduce local mismatch in generation and load based on the dynamic estimate of frequency or a dynamic coherency measure determined from the dynamic state estimator. Finally, a global dynamic state estimator would be used in restorative operating state to reconnect sections of the system after a breakup. The reconnection would require an accurate estimate of frequency at buses which are being synchronized and then reconnected by switching in a transmission line.

Global dynamic state estimation of an entire power pool or some subarea or local dynamic state estimation of a generator and the buses it is directly connected to has been very difficult for the following two reasons:

(1) an accurate model of power system dynamics is difficult to determine because the dynamics are nonlinear and depend on the operating condition which is constantly changing;

(2) the huge size of a power system and the inability to decouple the dynamics of some portions of this system from other portions where a dynamic state estimator is not desired has made dynamic state estimation impractical. Particular difficulties that are associated with this problem are; (a) the computational burden of computing the dynamic state of the entire power system in real time; (b) the data burden of obtaining and constantly updating model information for this entire system; (c) the communication and instrumentation burden of making measurements at a fast sampling rate (greater than 5/sec.) throughout this power system and then transmitting this data to a central computing facility.

From the discussion of the applications for dynamic state estimation, there are two basic types of dynamic state estimators required, global and local dynamic state estimators which are discussed in more detail in the following two subsections.

1.1 Local Dynamic State Estimators

Local dynamic state estimator, would provide information on the state of the generator to be controlled in relation to buses that are directly connected to it. This estimator would provide dynamic state information for use with discrete controls used to maintain synchronization in the emergency operating state. A very desirable feature for this estimator would be to require only measurements on the generator bus where the discrete control is to be applied and require model information only for the generator being controlled and the transmission lines that are directly connected to it.

Zaborszky et al. [10,11,12] have obtained a local equilibrium state estimator based on the following assumptions:

(1) separate state estimators would be implemented to provide estimates of real and reactive power injections from the generator, real and reactive load power fluctuations, and the voltage behind transient reactance, but the local equilibrium state estimator would not be based on a single dynamic model of the generator voltage regulator, the governor turbine energy system, and the electrical network connected to the generator high side transformer bus;

(2) all measurements on the high side transformer bus are perfect;

(3) the complex voltage at buses directly connected to this controlled generator are constant.

The advantages of this local dynamic estimator is that

(1) it provides a dynamic estimate of the accelerating power that will attempt to move the generator away from its local equilibrium reference and which must be compensated for by emergency state control procedures;

(2) it does not require any measurements of voltage or power except at the high side transformer bus at which the generator to be controlled is located;

(3) it does not require model information on transmission lines or generators except those that are connected to the high side transformer bus where these measurements are made.

The major limitations of this local equilibrium state estimator are

(1) it could only be used for the discrete control strategies in the emergency operating state and could not be used for security assessment, security enhancement and control

in the normal, alert and restorative operating state applications because it does not provide estimates of voltage angles and frequencies at every load and generation bus required for such applications. Each local equilibrium state estimate is referenced to equilibrium reference angle that are in no way referenced to a common bus and which are dynamic and not constant as assumed.

(2) The local equilibrium state estimator is susceptible to gross errors due to bad data because this estimator does not use a composite model of the generator, turbine energy system, and electrical network, bad data detection and identification for measurement and model data is not possible.

(3) A linear simple state model based on the local equilibrium state, which is required for computing on-line control, is only valid for a very short interval after the contingency occurs and thus the model and any resultant control based on it would be limited to a short duration after the contingency.

A second local dynamic state estimator is that of Miller and Lewis [13,14]. The generator to be controlled is represented by a fifth order linear model (not a linearized one) with flux linkages as states. This is an accurate model of the individual generator, but the state of this model is not the local equilibrium state and thus is not useful for control strategies that attempt to modify the accelerating power experienced by the unit. However the state of this model permits accurate estimates of real and reactive power and currents I_q and I_d out of the machine which would be useful in discrete controls that affect the network or the voltage regulator. Major disadvantages of this estimator are;

(1) it could not be used for global dynamic state applications not only because it could not provide direct estimates of angle and frequency but also because the sampling rate and integration step sizes required would pose too large a computation and communication burden with present technology,

(2) bad data detection and identification for this estimator would be difficult because the estimator does not use a composite model of the generator, governor energy system, and electrical network and thus could not effectively check a set of redundant measurements and model data.

1.2 Global State Estimators:

Several global dynamic state estimators reported to date have been tracking static state estimators [15, 16,17].

Measurements are routinely taken on different locations of power system and on different elements or functions of elements of the state vector. Writing the network equations using Kirchhoff's law and using these measurements to solve the resulting equations analytically, a load flow solution is obtained. Measurements are not always reliable and they usually are in error by some maximum deviation or percentage error. Therefore many more measurements are taken than are needed for the load flow solution. Assuming the system to be in steady state condition and using these redundant measurements in a least squares algorithm, an optimal static estimate of the states of the system is obtained.

Therefore [15] "a static state estimator is a data processing algorithm (set of equations) for use on a digital computer to transform (process, convert) meter readings and other information available up to the present time into an estimate of the value of the static state vector at the present time".

The static estimator algorithm has to be repeated in its entirety every ΔT seconds where ΔT is the sampling period of the measurements and information system. This implies that the estimator has to be reinitialized every ΔT seconds or at best every few sampling periods. This difficulty is compounded because dynamics of the system are neglected.

To overcome the problem of initialization some authors [15,16,17] have proposed using the previous estimated state as the initial value with the reasoning that [16] "if no appropriate state transition model is available one supposes a model with the state remaining the same except for an increase in uncertainty or noise". A model for the system is assumed in which state at time $T + \Delta T$ is regarded unchanged from its values at time T except for addition of some disturbance, where this disturbance is modelled by a stochastic process.

Although [17] "these proposed techniques do provide for dynamic up-dating of the system state variable estimates, they do not provide for the estimate of dynamic changes which are likely to occur. This is true due to the associated stochastic nature of load demands," and lack of a representative dynamic model of system and load. Thus, these techniques may be classified as a dynamic tracking state estimator since they track the system's present response and do not estimate the future response.

A second approach to global dynamic state estimation is to linearize the dynamics of the entire U.S.

power system for some system configuration and operating condition. The research [18] has centered on the development of separate dynamic state estimators for individual subsections of this system which either:

1. do not have complete system model information outside its own area, or
2. do not have complete set of measurements on the system outside its own area.

The performance of the global state estimator, made up of these separate estimator modules, is obviously seriously degraded as the quantity of information on the model or measurement outside the area which it is to perform state estimation is decreased. The problem of updating the model parameters based on system configuration or operating condition changes has not been dealt with as part of the research.

1.3 Research Objectives

The objectives of the research in this thesis is to develop a global dynamic state estimator for angle and frequency signals at all load and generator buses in a pool or area in order to provide information for the security assessment, security enhancement and control functions described earlier in this chapter. The only application discussed for which global dynamic state estimation would be inappropriate is supplementary discrete controls, which are used in the emergency operating state and require an estimator that can provide estimates of large dynamic fluctuations in both P-f and Q-V dynamics.

The global dynamic state estimator estimates angle and frequency deviations using a linearized classical stability model based on a classical generator model and a static state estimator that indicates network configuration, unit commitment, and load flow information. The dynamic state estimate of angle and frequency, composed of the sum of the static state estimate and the dynamic Kalman state estimate, of dynamic deviations from these static estimates, is thus more accurate and reliable than the tracking static estimate [15,16] that uses no dynamic model information.

The global dynamic state estimator will not need either model information or measurements of the system external to the study area, where the dynamic state estimate is desired, because the effects of the external system dynamics are represented by measurements of the power flows on lines that connect the internal and external system model which are used as inputs into the internal system model. This estimator thus overcomes the tradeoff between performance of the estimator and the amount of data (model information and measurements of the external system) which occurred in the work of Tacker [18].

Four extremely important aspects of global dynamic state estimation that have not been adequately addressed in the previous literature, and which will be investigated in this thesis, are:

(1) the need to update the dynamic system model used in the estimator for changes in unit commitment, network configuration, and load flow conditions that are known from the static state estimator

(2) the need to provide capability for bad-data detection and identification as in static state estimation so that the data base provided by the dynamic state estimator is reliable and can be used for the security assessment, security enhancement and control functions mentioned earlier

(3) the need to provide a dynamic load model as a means of eliminating the necessity to measure the dynamic load fluctuations at every bus

(4) the need to keep the on-line computation and communication requirements to a minimum.

The need to quickly update the system model on-line based on unit commitment, network configuration, and load flow information from the static state estimator is accomplished by modularizing the state estimation of the study area by decoupling the dynamics of subareas or modules within the study area by measuring the power flows on lines connecting each module with every other module. A local dynamic state estimator for each module is then developed based on a linearized dynamic model unit commitment, network configuration and load flow conditions with the power flow measurements on lines connecting this module to other modules and the external system used as inputs. The dynamic model for each module can be easily updated because the number of load and generation buses in any module is kept small so that updating the network model and subsequent network reduction to obtain a state model of angles and frequency deviations at internal generator buses is feasible. The modularization overcomes the large computational burden of repeatedly updating the entire dynamic model of the study area because

(1) the effects of changes in unit commitment, network configuration and load flow are local in character and thus every module will not have to be updated for each system change

(2) the network reduction of all modules simultaneously requires less computation and is more accurate than a single network reduction of the network for the entire study area.

The modularized dynamic state estimators are all locally referenced to a particular bus within that module and thus the global dynamic estimator could not be used for utility- or pool-wide tasks such as security assessment, security enhancement, or control unless the references for each modularized dynamic state estimator are referenced to a common bus in the study area. Global referencing procedures are developed that reference these modularized dynamic state estimators using the power flow measurements on the lines that connect modules.

The need to detect and identify bad-data for each modularized dynamic state estimator is accompolished by using a dynamic model for each module and providing redundancy in measurements of frequency and power. Bad data detection and identification is accomplished on the global reference procedure by using a least squares algorithm based on redundant measurements of power flows on all lines connecting all modules.

Three different dynamic load models are proposed, discussed, and investigated in this research. The dynamic load models do not depend on voltage or frequency at a bus but are based on the same logic used for developing models for load prediction [19].

The need to limit computation and communication requirements for the dynamic state estimator is accomplished by

(1) modularizing the dynamic state estimation of a study area so that on-line update of the dynamic model is computationally feasible;

(2) modularizing the state estimation of the study area and thus eliminating the need for synchronizing measurements taken in each module and eliminate the need of model and measurement from other modules in the state estimation of each module

(3) development of load models that eliminate the need to communicate load measurements from every bus in the study area.

CHAPTER 2

DYNAMIC STATE ESTIMATION IN POWER SYSTEM

The purpose of this chapter is to discuss the objectives of, and the differences between the global and local dynamic state estimation. Specifically, the following topics are discussed:

(1) The general constraints on the size of the study area for both the local and global dynamic state estimators;

(2) The general constraints placed on the data available from the external area for both local and global dynamic state estimators;

(3) a discussion of two local dynamic state estimator formulations that satisfy (1) and (2) and their advantages and disadvantages;

(4) research objectives and a general discussion of a global dynamic state estimator that meets the constraints (1) and (2) above.

2.1 General Constraints on the Study Area for a Dynamic State Estimator

The formulation of any dynamic state estimator must satisfy certain constraints on the study area, where a dynamic state estimate is desired, and the external area, where no dynamic state estimate is needed. The local equilibrium dynamic state estimator [10,11] has been the only dynamic state estimator that has effectively dealt with these constraints. Once these constraints are clearly stated local and global dynamic state estimators can be formulated that meet these constraints.

The size of a study area for either a local or global dynamic state estimator must be chosen based on the following criteria

(1) The instrumentation and data acquisition system requirements to measure and collect the data sampled synchronously at a rate sufficient for the particular dynamic state estimator should be minimized; and

(2) The computational requirements for performing dynamic state estimations must be minimized.

The instrumentation, data acquisition, and computation requirements are quite different for the local and global dynamic state estimator.

For a local dynamic state estimator the study area should be the external generator bus, its high side transformer bus, and all buses that are connected to this generator bus by transmission lines. The size of this study area is chosen based on the following facts

(1) The purpose of the local dynamic state estimator is to provide dynamic information on the state of the generator and the state of the buses directly connected to it for the discrete controls in the emergency operating state,

(2) The ease in determining the state of the internal generator bus and all buses connected to the high side transformer bus by measurement of the voltage on this bus and complex powers flowing into this bus (high side transformer) from the generator and transmission lines.

For the global dynamic state estimator the study area is generally the pool or subarea under control of some pool or coordination center. The size of the area in some cases may be constrainted by;

(1) the instrumentation and data acquisition requirements to make synchronized measurements at several locations at a 5/sec. sampling rate. This sampling rate is slower than for local dynamic state estimator because the purpose of the global estimator is to estimate dynamic fluctuations in the angle and frequency at all buses in the study area and need not estimate voltage magnitude or reactive power dynamics for the applications discussed in Chapter 1.

(2) The computational requirements to update the dynamic model used for dynamic state estimation so that the model remains valid for changes in unit commitment, network configuration, or load flow conditions which occur over a time period of minutes, hours, etc. The modularization of the dynamic estimator for a study area will affect the computation requirement for updating the model for the estimator.

2.2 General Constraints on Data from the External Area

The feasibility of dynamic state estimation is not only determined by the instrumentation, data acquisition and computation requirement for the internal area but also by these same requirements for the external area. It is clear that for a dynamic state estimator to be feasible no model information and no measurements must be assumed to be available from the external area. The study and external area dynamics are generally tightly coupled through the power flows on the transmission lines that connect them. Since the purpose of this research is to estimate the state of the study system on-line, the need to explicitly model the external system can be eliminated if the power flows on these transmission lines are measured and used as inputs for the study system model required for the dynamic state estimation.

For the local dynamic state estimation, the measurement of voltage on the high side transformer bus and the complex power from the generator and all transmission lines permit the determination of the voltage magnitude and angle of the internal generator bus and all buses connected to the high side transformer bus by transmission lines. This determination of the state of the electrical network from measurements at one bus can be referenced to the local equilibrium state [10,11], to the voltage angle of an imaginary machine running unloaded and at the same speed as the generator, that is the internal bus angle of the machine [13,14], or the angle of the high side transformer bus. Thus there are at least three possible forms for the local dynamic state estimator. In each case the local dynamic state estimator based on the dynamic model of the generator would provide a dynamic state estimate of the generator and the state of the network directly connected to it without measurement or model information from the external system, which is all lines, buses, and generators not directly connected to the high side transformer bus for the single generator where dynamic state estimation is desired.

For the global dynamic state estimation the measurements of real power injections at terminal buses of a study area connected to the external area will serve as inputs to the linear dynamic model for the study area used in the global dynamic state estimator, thus eliminating the need to make measurements or model the external area. However, in this case these measurements are not sufficient to determine the global dynamic state estimate because the study area for the global dynamic state estimator is large. This difficulty can be partially alleviated, as is shown later, by modularizing the study area.

2.3 Local Dynamic State Estimation Problem

The purpose of a local dynamic state estimator is to provide an accurate state estimate of the state of generator dynamics and the state of the electrical network directly connected to it for local control in the emergency operating state. Therefore the estimator should estimate both P-f and Q-V dynamic fluctuation for the study area and should use a model that is valid for large excursions due to contingencies. Thus both generator-exciter-voltage regulator as well as governor-turbine energy system dynamics should be included in the model used for the local dynamic state estimator.

There are three possible reference frames upon which local dynamic state estimators which meet the study area and external area constraints, could be based. A local dynamic state estimator based on the local equilibrium state [10,11] is not a single dynamic state estimator based on a single dynamic model for deviations from the equilibrium state but rather is a composite of (1) a dynamic estimator for the voltage behind transient reactance based on generator; exciter, voltage regulator dynamics [20]; (2) a dynamic state estimate of injected electrical power at the internal generator bus based on a model of turbine energy system dynamics [21]; (3) estimates of load power based on a dynamic load model; and (4) measurements of complex voltage on the high side transformer bus and complex powers from the generator and on each transmission line. This local dynamic state estimator has the advantage of using the local equilibrium state so that the null state is the global equilibrium and thus the state is the essential information for any discrete controls used on the generator during the emergency operating state. The principal disadvantage is that bad data detection and identification, which would be desirable for the assurance that the state estimate is reliable and can be used for control, would be difficult because there is no composite model of the generator, turbine energy system, and electrical network referenced to the equilibrium reference for the study area, and thus a check of the measurements and model data would be difficult due to lack of measurement redundancy in each separate estimator.

A second local dynamic state estimator could be formulated based on a composite network model, generator-exciter model, and turbine energy system model referenced to the angle of the high side transformer bus. Bad data detection and identification could be performed more easily to check measurement and model data because the composite model would check every measurement and model parameter against each other. However, since the state of the model is not the local equilibrium state it would not be as useful for the discrete control strategies used in emergency control. However this local dynamic state estimator could provide the data base for computing the local equilibrium state and thus would

(1) provide the information needed for control (local equilibrium state)

(2) perform bad data detection, identification and rejection to make the estimate reliable.

This approach to obtaining a local equilibrium dynamic state estimator appears superior to the one proposed by Zaborszky [10,11]. This topic is not persued because the major research topic of this thesis is global dynamic state estimation which has many applications and which is far less developed both theoretically and conceptually.

2.4 Global Dynamic State Estimation

The purpose of the global dynamic state estimator is to provide dynamic estimates of angle and frequency at all load and generation buses in a pool or area for the security assessment, security enhancement, and control functions mentioned in Chapter 1 with the exception of discrete supplementary control which requires local dynamic state estimator. The model used for the estimator only requires P-f dynamics because these applications based on global dynamic estimation do not require knowledge of Q-V dynamics and because inclusion of these dynamics would require such small integration step sizes and sampling periods that hardware requirements for global dynamic estimation would make implementation impractical. Governor turbine energy system dynamics are eliminated to reduce the order of the model and is justified because it will be shown that frequency measurements and adjustment of damping in the model can compensate for elimination of these dynamics. A linearized classical stability model will be used to develop a Kalman state estimator for the dynamic deviations in angle and frequency signals because these deviations are assumed small and because a static state estimate provides slowly time varying estimates of the nominal values of these angle and frequency signals. The dynamic estimate of the angle and frequency signals at all load and generator buses is thus the sum of the static and dynamic state estimates of the variables.

The global dynamic state estimator to be developed will be based on having a classical generator model and accurate data on the unit commitment, network configuration, and the static estimate of the state from a static state estimator. The dynamic deviations from this static state estimate will be determined using a Kalman estimator and thus should be much more accurate and reliable than a tracking static estimator due to the use of system model information.

The global dynamic estimator is prcduced by:

(1) modularizing the global dynamic estimator in order to reduce the computation and thus permit quick on-line update of the linearized dynamic system model based on changes in unit commitment, network configuration, and load flow. Each of these modularized dynamic state estimators is locally referenced to a bus in the module,

(2) a global referencing procedure that references each of the modularized dynamic state estimators to a common reference bus in the study area so that the global dynamic state estimator can be used for pool or area security assessment, security enhancement, and control applications discussed in Chapter 1.

Bad data detection and identification would be performed on each modularized dynamic state estimator and on the global referencing procedure to permit bad data rejection necessary to provide the reliable data base needed for the applications discussed in chapter 1.

CHAPTER 3

MODULARIZED GLOBAL DYNAMIC STATE ESTIMATION

The modularized dynamic state estimation problem is now formulated. A model of generator, electrical network, load and measurement process will be developed and justified for this application. To make dynamic state estimation feasible, the system model is modularized and the Kalman filter equations for each module are developed. In the next chapter a referencing procedure is developed to aggregate these modularized dynamic state estimates into a global dynamic state estimate.

3.1. Modularization of the Study Area

The study area, which could be a power pool or a company's operation, is split into sections which are here called modules. These modules could be overlapping or nonoverlapping. The composite of all these modules comprise the study area. For each module the rest of the study area together with the external area constitutes that module's external area. It is assumed that there are M modules and N generators in the study area, and N_j generators in the jth module with $N \leq \sum_{j=1}^{M} N_j$, as there could be some generators common to two or more modules. Also it is assumed that there are K load buses in the study area and K_j load buses in module j, with $K \leq \sum_{j=1}^{N} K_j$. It should be noted here that the high side transformer bus of each generator is represented by a load bus.

The modularization of the global dynamic state estimator requires that

(1) the dynamic system model for each module be decoupled from the dynamics of other modules so that model information and measurements in one particular module is the only data required to produce the state estimate for that module

(2) that a common, reliable reference be established for all modules so that the estimators for each module can be combined to form a global estimator for security assessment, security enhancement and control applications for large utilities or pools.

The purpose of decoupling the dynamic model and state estimator for each module is

(1) to eliminate the need to transmit model data and measurements to one central processor;

(2) to eliminate the need to synchronize measurements taken in each module; which can be a very costly requirement;

(3) to permit rapid on-line update of model parameters which change due to changes in unit commitment, network conditions and load flow provided by the static state estimator. The decoupling of the model for each module reduces the computational requirements by (1) reducing the number of lines in the network for which synchronizing torque coefficients must be updated and (2) by reducing the order of the matrix to be inverted in order to update a closed form dynamic model.

3.2. Electrical Model of Generator

A classical voltage behind synchronous reactance generator model will be used for the global dynamic state estimator because

(1) this estimator is only intended to provide an accurate estimate of the dynamic fluctuations in the deviations of voltage angle and frequency at any bus in the study area. This estimator is not intended to estimate the large transient angle and frequency deviations immediately after a contingency because; (i) the linearized power system model, which makes state estimation for a large system feasible, would be invalid for representing the effects of large excursions after a

contingency, (ii) a higher order nonclassical generator model would be required, which includes generator and voltage regulator dynamics, if estimates of the state were required immediately after a contingency, (iii) the sampling period for measurements, and the itegration step size for an estimator which models generator and voltage dynamics would be so small that the data acquisition and computational hardware requirements would make global state estimation for transient conditions impractical

(2) the applications for which this global dynamic state estimator is proposed, which were discussed in chapter one, do not require; (i) estimates of voltage magnitude or reactive power deviations; (ii) accurate estimate of angle and frequency deviations immediately after a contingency, but would require accurate estimates seconds after such a contingency.

3.3 Governor-Boiler-Energy Systems Model

Assuming the frequency fluctuations to be so small that torque and power are proportional, the electromechanical model for the ith generator in the jth module has the form;

$$\frac{d}{dt}\,\Delta\delta^{s}_{ij}(t) = \Delta\omega_{ij}(t)$$

$$\frac{d}{dt}\,\Delta\omega_{ij}(t) = \frac{1}{M_{ij}}(\Delta PM_{ij}(t) - \Delta PG_{ij}(t)) - \frac{(D_{ij} + K_{ij})}{M_{ij}}\,\Delta\omega_{ij}(t)$$

$$i = 1,2,\ldots,N_j \;,\quad j = 1,2,\ldots,M$$

where

$\delta^{s}_{ij}(t)$	the angle at the internal generator bus of the ith machine in the jth module in the synchronous frame of reference (SF) - radians
$\omega_{ij}(t)$	the frequency at the ith machine in the jth module - radians/seconds
M_{ij}	the inertia of the generator
D_{ij}	the damping coefficient of the generator
K_{ij}	the added term for the damping of the governor-turbine-energy system and voltage regulator
$PM_{ij}(t)$	the mechanical input power to the generator - P.U.
$PG_{ij}(t)$	the electrical output power of the generator - P.U.
$i = 1,2,\ldots,N_j$	index numbering the generators
$j = 1,2,\ldots,M$	index numbering the modules.

In this model, the governor-boiler turbine energy system dynamics are neglected and their effect is modeled as an added damping term. This is reasonable because the objective is to develop a model that will accurately represent the synchronizing oscillations in a power system and let the measurements of real power and frequency account or correct for the slower dynamics associated with the governor-turbine-energy system. Also $\Delta PM_{ij}(t)$ is set equal to zero since for the above reasons it has slow dynamics. The random fluctuations of $\Delta PM_{ij}(t)$ can be represented in a compensenting noise term added to other input noise terms if needed.

3.4. Linearized Model of the Network

The network equations of the jth module in polar form are linearized with the real power equations decoupled from the reactive power equations to obtain;

$$\begin{bmatrix} \underline{\Delta PTG}_j(t) \\ \\ \underline{\Delta PTL}_j(t) \end{bmatrix} = \begin{bmatrix} \dfrac{\partial \underline{PTG}_j(t)}{\partial \underline{\delta}_j^s(t)} & \dfrac{\partial \underline{PTG}_j(t)}{\partial \underline{\theta}_j^s(t)} \\ \\ \dfrac{\partial \underline{PTL}_j(t)}{\partial \underline{\delta}_j^s(t)} & \dfrac{\partial \underline{PTL}_j(t)}{\partial \underline{\theta}_j^s(t)} \end{bmatrix} \left| \begin{array}{l} \begin{bmatrix} \Delta \underline{\delta}_j^s(t) \\ \\ \Delta \underline{\theta}_j^s(t) \end{bmatrix} \\ \underline{\delta}_j^s(t) = \underline{\delta}_j^{so}(t) \\ \underline{\theta}_j^s(t) = \underline{\theta}_j^{so}(t) \\ \underline{E}_j(t) = \underline{E}_j^o(t) \\ \underline{V}_j(t) = \underline{V}_j^o(t) \end{array} \right.$$

$$\underline{PTG}_j^T(t) = [PTG_{1j}(t),\ PTG_{2j}(t),\ldots,PTG_{N_j j}(t)]$$

$$\underline{PTL}_j^T(t) = [PTL_{1j}(t),\ PTL_{2j}(t),\ldots,PTL_{K_j j}(t)]$$

$$\underline{\delta}_j^{s^T}(t) = [\delta_{1j}^s(t),\ \delta_{2j}^s(t),\ldots,\delta_{N_j j}^s(t)]$$

$$\underline{\theta}_j^{s^T}(t) = [\theta_{1j}^s(t),\ \theta_{2j}^s(t),\ldots,\theta_{K_j j}^s(t)]$$

$$\underline{E}_j^T(t) = [E_{1j}(t),\ E_{2j}(t),\ldots,E_{N_j j}(t)]$$

$$\underline{V}_j^T(t) = [V_{1j}(t),\ V_{2j}(t),\ldots,V_{K_j j}(t)]$$

where

$PTG_{ij}(t)$ real power injection at internal generator bus i into module j in P.U.

$PTL_{ij}(t)$ real power injection at load bus i into module j in P.U.

$\delta_{ij}^s(t)$ as defined before with the operating point value of $\delta_{ij}^{so}(t)$

$\theta_{ij}^s(t)$ the voltage phase angle at load bus i in module j in the synchronous frame of reference (SF), with the operating point value of $\theta_{ij}^{so}(t)$;

$E_{ij}(t)$ the magnitude of voltage behind synchronous reactance of the ith machine in module j;

$V_{ij}(t)$ the voltage magnitude at load bus i in module j.

It should be noted that $PTL_{ij}(t)$ is equal to $-PL_{ij}(t)$, the power withdrawn by load at bus i if bus i is only a load bus and does not have any connection with the external area for module j, that is $PTL_{ij}(t) = -PL_{ij}(t)$. If bus i is a terminal bus for module j, which implies, a transmission line connects it with the external area for that module, then $PTL_{ij}(t)$ is the sum of the power injected to the module from external area at this bus $PE_{ij}(t)$, and the power withdrawn for load at this bus $-PL_{ij}(t)$, i.e.

$$PTL_{ij}(t) = PE_{ij}(t) - PL_{ij}(t).$$

These equations depend on the present operating point $(\underline{\theta}_j^{so} \underline{V}_j^o)$ and $(\underline{E}_j^o \ \underline{\delta}_j^{so})$ and the present electrical network configuration. This data would be obtained from the static state estimator and would be updated at a rate sufficient to maintain model validity for changes in unit commitment, network configuration or load flow conditions. For large changes in the network, the model may not be valid for a certain period until an update occurs based on an updated static state estimate. In this case the accuracy of the updated model, the redundancy of measurements, and the short time interval where the model is invalid, should all contribute to a very quick reconvergence of the dynamic state estimator. The update rate for this network model and the level of measurement redundancy needed to assure reconvergence and a sufficient speed of convergence will be partially investigated in this research.

It has been noted that the network model includes injections at terminal buses. Measuring these injections over time and using these measurements as inputs into the linearized state model eliminates the need to model the external area because the coupling of the state of the module under study and external area are accounted for in $\Delta PE_{ij}(t)$. It should be noted that $\Delta PTL_{ij}(t)$ is not just the injection on the tie line that connects to terminal bus i in study area j but also the load injection at that bus. To determine $\Delta PTL_{ij}(t)$ requires measurement of both the real power on the tie line and the load at terminal bus i.

3.5. Dynamic Model for a Module in the Study Area

A reference bus for each modularized dynamic state estimator is necessary so that the state is not referenced to some completely independent synchronous reference, which may not be operating in synchronism with the power system. The angle and frequency fluctuations in the system can only be placed in proper perspective in terms of stability and security if these fluctuations are somehow referenced to the system module in which they occur.

For module j the reference angle is chosen to be the angle of internal bus voltage of generator number one, $\delta_{1j}(t)$. When referenced to this angle the system equations are going to be in a reference frame called machine one angle frame of reference [12].

The state vector for the jth module is then defined to be;

$$\underline{X}_j(t) = \begin{bmatrix} \Delta\underline{\delta}_j(t) \\ \\ \Delta\underline{\omega}_j(t) \end{bmatrix}$$

$$\underline{\delta}_j^T(t) = [\delta_{2j}(t),\ldots,\delta_{N_j j}(t)]$$

$$\underline{\omega}_j^T(t) = [\omega_{1j}(t),\ldots,\omega_{N_j j}(t)] \ .$$

Also define;

$$\underline{\theta}_j^T(t) = [\theta_{1j}(t),\ldots,\theta_{K_j j}(t)]$$

where

$$\delta_{ij}(t) = \delta_{ij}^s(t) - \delta_{1j}^s(t)$$

$$\theta_{ij}(t) = \theta_{ij}^s(t) - \delta_{1j}^s(t).$$

Since only the difference between angles is desired, the s superscript angles can be in any frame of reference SF or otherwise [12].

Given this notation the generator model would be

$$\frac{d}{dt}\,\Delta\delta_{ij}(t) = \Delta\omega_{ij}(t) - \Delta\omega_{1j}(t) \qquad i = 2,\ldots,N_j$$

$$\frac{d}{dt}\,\Delta\omega_{ij}(t) = -\frac{1}{M_{ij}}\,\Delta PG_{ij}(t) - \frac{(D_{ij} + K_{ij})}{M_{ij}}\,\Delta\omega_{ij}(t)$$

$$i = 1,\ldots,N_j, \quad j = 1,2,\ldots,M$$

or in the vector matrix form;

$$\dot{\underline{X}}_j(t) = \begin{bmatrix} \underline{0} & \hat{\underline{I}}_j \\ \underline{0} & -\underline{M}_j^{-1}\underline{D}_j \end{bmatrix} \underline{X}_j(t) + \begin{bmatrix} \underline{0} \\ -\underline{M}_j^{-1} \end{bmatrix} \Delta\underline{PG}_j(t) \qquad (1)$$

where

$$\hat{\underline{I}}_j = \begin{bmatrix} -1 & \\ -1 & \\ \vdots & \underline{I} \\ -1 & \end{bmatrix}$$

$\underline{I} = \text{diag}\{1, 1, \ldots, 1\}$

$\underline{M}_j = \text{diag}\{M_{1j}, M_{2j}, \ldots, M_{N_j j}\}$

$\underline{D}_j = \text{diag}\{(D_{1j} + K_{1j}), \ldots, (D_{N_j j} + K_{N_j j})\}.$

The linearized network model for the jth module would then be

$$\begin{bmatrix} \Delta\underline{PTG}_j(t) \\ \Delta\underline{PTL}_j(t) \end{bmatrix} = \begin{bmatrix} \dfrac{\partial\underline{PTG}_j(t)}{\partial\underline{\delta}_j(t)} & \dfrac{\partial\underline{PTG}_j(t)}{\partial\underline{\theta}_j(t)} \\ \dfrac{\partial\underline{PTL}_j(t)}{\partial\underline{\delta}_j(t)} & \dfrac{\partial\underline{PTL}_j(t)}{\partial\underline{\theta}_j(t)} \end{bmatrix} \Bigg|_{\substack{\underline{\delta}_j(t) = \underline{\delta}_j^o(t) \\ \underline{\theta}_j(t) = \theta_j^o(t) \\ \underline{E}_j(t) = \underline{E}_j^o(t) \\ \underline{V}_j(t) = \underline{V}_j^o(t)}} \begin{bmatrix} \Delta\underline{\delta}_j(t) \\ \Delta\underline{\theta}_j(t) \end{bmatrix} \qquad (2)$$

Define

$$\underline{\Gamma}_j = \frac{\partial\underline{PTL}_j(t)}{\partial\underline{\theta}_j(t)} \qquad \text{and}$$

$$\underline{\pi}_j = \frac{\partial \underline{PTL}_j(t)}{\partial \underline{\delta}_j(t)}$$

then from the last of these equations

$$\Delta\underline{\theta}_j(t) = \underline{\tau}_j^{-1} \quad \Delta\underline{PTL}_j(t) - \underline{\tau}_j^{-1} \quad \underline{\pi}_j \quad \Delta\underline{\delta}_j(t) \ . \qquad (3)$$

Substituting in the upper half of these equations results in the following expression;

$$\Delta\underline{PG}_j(t) = \Delta\underline{PTG}_j(t) = \underline{T}_j \quad \Delta\underline{\delta}_j(t) + \underline{S}_j \quad \Delta\underline{PTL}_j(t) \qquad (4)$$

where

$$\underline{T}_j = [\frac{\partial \underline{PTG}_j(t)}{\partial \underline{\delta}_j(t)} - \frac{\partial \underline{PTG}_j(t)}{\partial \underline{\theta}_j(t)} \quad \underline{\tau}_j^{-1} \quad \underline{\pi}_j]$$

and

$$\underline{S}_j = \frac{\partial \underline{PTG}_j(t)}{\partial \underline{\theta}_j(t)} \underline{\tau}_j^{-1} .$$

Further substitution of (4) into (1) results in a closed form state model for module j;

$$\underline{\dot{X}}_j(t) = \underline{A}_j\underline{X}_j(t) + \underline{B}_j \quad \Delta\underline{PTL}_j(t) \qquad (5)$$

$$\underline{A}_j = \begin{bmatrix} \underline{0} & \underline{\hat{I}}_j \\ -\underline{M}_j^{-1} \ \underline{T}_j & -\underline{M}_j^{-1}\underline{D}_j \end{bmatrix} \text{ and } \quad \underline{B}_j = \begin{bmatrix} \underline{0} \\ -\underline{M}_j^{-1}\underline{S}_j \end{bmatrix} .$$

The invertibility of matrix $\underline{\tau}_j$ is proved in reference [10].

The ability to perform a rapid update of $\underline{T}_j$ and $\underline{S}_j$ each time the static state estimate is computed depends on the number of generators N_j and load buses K_j in a module since the elements of matrix

$$\begin{bmatrix} \dfrac{\partial \underline{PTL}_j(t)}{\partial \underline{\delta}_j(t)} & \dfrac{\partial \underline{PTL}_j(t)}{\partial \underline{\theta}_j(t)} \\ \dfrac{\partial \underline{PG}_j(t)}{\partial \underline{\delta}_j(t)} & \dfrac{\partial \underline{PTL}_j(t)}{\partial \underline{\theta}_j(t)} \end{bmatrix}$$

must all be updated, matrix

$$\underline{\tau}_j = \frac{\partial \underline{PTL}_j(t)}{\partial \underline{\theta}_j(t)}$$

must be inverted, and $\underline{T}_j$ and $\underline{S}_j$ must be calculated. Increasing the number of modules M both (1) decreases the total number of synchronizing torque coefficients to be updated since these coefficients will not be calculated for lines that connect modules and (2) decreases the computation to form $\{\underline{T}_j\}_{j=1}^{M}$ and $\{\underline{S}_j\}_{j=1}^{M}$ since M matrix inversions each of small dimension requires less computation than one matrix inversion of large dimension due in part to the extraordinary efforts needed to invert large matrices accurately. Moreover, since the effects of unit commitment, network configuration or load flow changes are often localized, the model for each module need only be updated when the effects on model parameters is sufficient to warrant an update. If there were only one module for an entire power pool, the entire model could need to be updated every time a subsection of it required updating, vastly increasing the computational requirements for model updating.

Reducing the size of the modules and thus increasing the number of modules will however increase the total number of measurements required to perform dynamic state estimation in a study area because;

(1) measurements are required in each module for all the real power flows on all lines that connect this module to other modules. This condition not only imposes a requirement to measure line flows in the study area which would not necessarily be measured if one module were used but also requires measurement on each end of these lines to get the correct PE_{ij} value for each module.

(2) a certain level of measurement redundancy is required in each module in order to assure bad data detectability and identifiability in each module. These measurements must be in addition to line measurements because the line measurements are inputs and do not provide information on the state of the module.

Reduction of module size will thus reduce the computation for updating the state estimate and thus reduce computer hardware requirements for dynamic state estimation but will increase the instrumentation and data acquisition costs for retaining a reasonable level of measurement redundancy in each module. The subject of bad data detection and identification for dynamic state estimation on a power system is beyond the scope of this thesis and is a subject for further research. The level of measurement redundancy for good estimation and fast reconvergence after a disturbance however will be considered in this research.

3.6. Dynamic Load Model

A dynamic model for load power deviation $\Delta \underline{PL}_j(t)$ in module j has not been required since it was assumed that the load power was measured and known perfectly at every bus k in the module. This assumption requires many measurements all synchronized and taken at a fast sampling rate which may not be practical.

A dynamic model of the load power deviations $\Delta \underline{PL}_j(t)$ is proposed in this section in order to eliminate the need to make synchronized measurements of load power at all load buses at this high (> 5/sec) sampling rate. Three different load models will be developed which assume that the load at each bus can be decomposed into different load types and that each load type can be modeled as a Markov process. These models differ from those presently being developed under EPRI and DOE support in that

(1) the dependence of each load type on voltage magnitude and frequency is ignored

(2) the Markov models ignore all structure information available from particular knowledge of the load type and assumes a structure that lacks any dependence on voltage and frequency at the load bus

(3) the parameters and order of these Markov process models need to be identified based on measurements of load of each type and cannot be derived based on knowledge of the kind of load being modeled.

Although the work done under the EPRI and DOE projects [22] may provide load models that could be used for dynamic state estimation, the Markov process models proposed here are simple and reflect the general forms of the models that are possible.

A general model of the load power deviation will be proposed and the three specific load models will then be discussed and developed based on the general model form. The load power deviations in module j are assumed to satisfy

$$\Delta \underline{PL}_j(t) = \underline{H}_j \, \Delta \underline{q}_j(t)$$

$$\Delta \dot{\underline{q}}_j(t) = \underline{F}_j \Delta \underline{q}_j(t) + \underline{G}_j \underline{W}_j(t)$$

where $\underline{W}_j(t)$ is a white process

$$E\{\underline{W}_j(t)\} = \underline{0}$$

$$E\{\underline{W}_j(t_1)\underline{W}_j^T(t_2)\} = \underline{Q}_j\delta(t_1 - t_2)$$

with initial conditions

$$E\{\underline{\Delta q}_j(0)\} = \underline{0} \qquad E\{\underline{\Delta q}_j(0)\underline{\Delta q}_j^T(0)\} = \underline{\Psi}_j$$

$$E\{\underline{\Delta q}_j(0)\ \underline{W}_j^T(t)\} = \underline{0}.$$

3.6.1. Low Pass White Noise Model

The simplest dynamic model for load power deviations $\underline{\Delta PL}_j(t)$ is to assume that the loads at every load bus k are independent, low-passed, white noise processes with bandwidth f_{kj} such that

$$\Delta PL_{kj}(t) = \Delta q_{kj}(t)$$

$$\Delta \dot{q}_{kj}(t) = -f_{kj}\Delta q_{kj}(t) + f_{kj}W_{kj}(t)$$

$$E\{W_{kj}(t)\} = 0,\ E\{W_{kj}(t_1)W_{kj}(t_2)\} = \delta(t_1 - t_2)Q_{kj}$$

such that

$$\underline{H}_j = \underline{I}$$

$$\underline{F}_j = \text{diag}\{-f_{1j},-f_{2j},\ldots,-f_{K_j j}\}$$

$$\underline{G}_j = -\underline{F}_j = \text{diag}\{f_{1j},f_{2j},\ldots,f_{K_j j}\}$$

$$\underline{Q}_j = \text{diag}\{Q_{1j}\ Q_{2j}\ \ldots\ Q_{K_j j}\}$$

$$\underline{W}_j^T(t) = (W_{1j}(t),W_{2j}(t),\ldots,W_{K_j j}(t))$$

$$\underline{PL}_j^T(t) = \underline{q}_j^T(t) = (q_{1j}(t)\ q_{2j}(t)\ \ldots\ q_{K_j j}(t)).$$

A more general and realistic model might occur if the white processes $\underline{W}_j(t)$ were correlated so that $\underline{Q}_j$ was not diagonal.

3.6.2. Load Component Model

A second load model assumes that the load at each bus in module j can be decomposed into ℓ_j different load types $\Delta q_{ij}(t)$, $i = 1,2,\ldots,\ell_j$ such as commercial, residential, agricultural, etc. and

$$\Delta PL_{kj}(t) = \sum_{i=1}^{\ell_j} h_{ki}^{j} \Delta q_{ij}(t), \; k = 1,2,\ldots,K_j$$

here h_{ki}^{j} is the percentage of load type i $(\Delta q_{ij}(t))$ present at load bus k in module j $(\Delta PL_{kj}(t))$ with $\sum_{i=1}^{\ell_j} h_{ki}^{j} = 1$. Each of these load components $\Delta q_{ij}(t)$ is assumed to be independent Markov process with a differential equation of order n_{ij}, that is

$$\Delta q_{ij}^{(n_{ij})}(t) = \sum_{n=1}^{n_{ij}} f_{in}^{j} \Delta q_{ij}^{(n_{ij}-n)}(t) + g_{ij} W_{ij}(t)$$

where $W_{ij}(t)$ are scalar white noise processes with statistics

$$E\{W_{ij}(t)\} = 0$$

$$E\{W_{ij}(t_1) W_{ij}(t_2)\} = \delta(t_2 - t_2) Q_{ij}$$

and

$$E\{W_{i_1 j}(t_1)\; W_{i_2 j}(t_2)\} = 0 \quad , i_1 \neq i_2 \;\forall\; i_1, i_2 \in [1, \ell_j].$$

Now define the auxiliary variables

$$\Delta q_{ij1}(t),\ldots,\Delta q_{ijn_{ij}-1}(t)$$

by the relations

$$\Delta q_{ij1}(t) = \Delta \dot{q}_{ij}(t)$$

$$\Delta q_{ij2}(t) = \Delta \ddot{q}_{ij}(t)$$

$$\vdots$$

$$\Delta q_{ijn_{ij}-1}(t) = \Delta q_{ij}^{(n_{ij}-1)}(t)$$

$$\Delta \underline{q}_{ij}^T(t) = [\Delta q_{ij}(t),\Delta q_{ij1}(t),\ldots,\Delta q_{ijn_{ij}-1}(t)]$$

Then

$$\Delta \dot{\underline{q}}_{ij}(t) = \underline{F}_{ij}\Delta \underline{q}_{ij}(t) + \underline{G}_{ij}\underline{W}_{ij}(t),\ i = 1,\ldots,\ell_j$$

where

$$\underline{F}_{ij} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & & 0 \\ & & & \ddots & \\ 0 & & & & 1 \\ f^j_{in_{ij}} & \cdot & \cdot & \cdot & f^j_{i1} \end{bmatrix}$$

$$\underline{G}_{ij}^T = [0,0,\ldots,g_{ij}].$$

Aggregating these models for each load component, define

$$\Delta \underline{q}_j^T(t) = [\Delta \underline{q}_{1j}^T(t),\ldots,\Delta \underline{q}_{\ell_j j}^T(t)]$$

then

$$\Delta \underline{PL}_{kj}(t) = \underline{H}_{kj}^{T}\, \Delta \underline{q}_j(t), \quad k = 1,2,\ldots,K_j$$

where

$$\underline{H}_{kj}^{T} = [\overbrace{h_{k1}^{j},0,0,\quad 0}^{n_{1j}\text{ term}},\ \overbrace{h_{k2}^{j},0,\ldots,0}^{n_{2j}\text{ terms}},\ldots,\ \overbrace{h_{k\ell_j}^{j},0,0,\ldots,0}^{n_{\ell_j j}\text{ term}})$$

and $$\Delta \underline{PL}_j(t) = \underline{H}_j \Delta \underline{q}_j(t)$$

$$\underline{H}_j = \begin{bmatrix} \underline{H}_{1j}^{T} \\ \vdots \\ \underline{H}_{K_j j}^{T} \end{bmatrix}$$

and $\Delta \underline{q}_j(t)$ satisfies the differential equation

$$\Delta \dot{\underline{q}}_j(t) = \underline{F}_j\, \Delta \underline{q}_j(t) + \underline{G}_j\, \underline{W}_j(t)$$

$$\underline{W}_j^{T}(t) = [\underline{W}_{1j}(t),\ldots,W_{\ell_j j}(t)]$$

$$\underline{F}_j = \begin{bmatrix} F_{1j} & 0 & 0 & \cdots & 0 \\ 0 & \underline{F}_{2j} & \cdot & & \\ & & & \cdot & \\ & & & & \cdot \\ 0 & 0 & & & \underline{F}_{\ell j} \end{bmatrix}$$

$$\underline{G}_j = \begin{bmatrix} \underline{G}_{1j} & 0 & 0 & \cdots & 0 \\ 0 & \underline{G}_{2j} & \cdot & & \\ & & & \cdot & \\ & & & & \cdot \\ 0 & 0 & & & \underline{G}_{\ell j} \end{bmatrix}$$

$$\underline{Q}_j = \text{diag}\{Q_{1j},\ldots,Q_{\ell j}\}\ .$$

In the above discussion it was assumed that $W_{ij}(t)$ are uncorrelated, dropping the assumption results in a more general case and a nondiagonal $\underline{Q}_j$ matrix.

3.6.3. Geographical Load Model

The fact that each geographical area has a particular load characteristic, provides the basis for the third load model. Assuming there are ℓ_j different geographical areas, each with a load dynamic given by a Markov process $\Delta q_{ij}(t)$, and that the load at each load bus is composed of a percentage (h^j_{ki}) of the load $\Delta q_{ij}(t)$ of each of the ℓ_j geographical areas in module j so that

$$\Delta \underline{PL}_{kj}(t) = \sum_{i=1}^{\ell_j} h^j_{ki} \Delta q_{ij}(t) \ .$$

Assuming a differential equation of order n_{ij} for load type $\Delta q_{ij}(t)$, the structure of the geographical load model will be identical to the structure of the component load model and thus

$$\Delta \underline{PL}_j(t) = \underline{H}_j \; \Delta \underline{q}_j(t)$$

$$\Delta \dot{\underline{q}}_j(t) = \underline{F}_j \; \Delta \underline{q}_j(t) + \underline{G}_j \; \underline{W}_j(t)$$

$$E\{\underline{W}_j(t)\} = \underline{0}$$

$$E\{\underline{W}_j(t_1)\underline{W}_j^T(t_2)\} = \delta(t_1 - t_2)\underline{Q}_j$$

where matrices $\underline{H}_j$, $\underline{F}_j$ and $\underline{G}_j$ will have identical structure to those for the component load model. Here again $\underline{Q}_j$ may or may not be diagonal.

3.7. Complete State Space Model of a Module

In this section a complete state space model for the system is developed and the measurement vector is defined. It is shown that the model of a module has the following general form

$$\dot{\underline{X}}(t) = \underline{A}\ \underline{X}(t) + \underline{B}\ \underline{u}(t) + \underline{G}\ \underline{W}(t)$$
$$\underline{Y}(t) = \underline{C}\ \underline{X}(t) + \underline{v}(t) \qquad (6)$$

where $\underline{u}(t)$ represents the known measured signals; $\underline{W}(t)$ is a white disturbance process that is used to produce the stochastic load model or the measurement noise associated with the measurement of injected power. The process $\underline{v}(t)$ is the measurement noise on those measured signals used to produce the dynamic state estimate. The white processes $\underline{W}(t)$ and $\underline{v}(t)$ are uncorrelated with statistics:

$$E\{\underline{W}(t)\} = \underline{0}$$
$$E\{\underline{W}(t_1)\ \underline{W}^T(t_2)\} = \underline{Q}\ \delta(t_1 - t_2) \qquad (7)$$

$$E\{\underline{v}(t)\} = \underline{0}$$
$$E\{\underline{v}(t_1)\ \underline{v}^T(t_2)\} = \underline{R}\ \delta(t_1 - t_2)\ . \qquad (8)$$

The initial conditions are assumed to be uncorrelated with $\underline{v}(t)$ and $\underline{W}(t)$ with statistics

$$E\{\underline{X}(0)\} = \underline{0}$$
$$E\{\underline{X}(0)\ \underline{X}^T(0)\} = \underline{\Sigma}(0). \tag{9}$$

In this section the j subscript which refers to the module under consideration is dropped for the ease of notation but it is understood that the following equations are derived for an individual module.

In section (3.5) the linearized model for module j was derived. It is repeated here for the ease of reference. (The j subscript is dropped.)

$$\begin{bmatrix} \Delta\dot{\underline{\delta}}(t) \\ \Delta\dot{\underline{\omega}}(t) \end{bmatrix} = \begin{bmatrix} \underline{0} & \hat{\underline{I}} \\ -\underline{M}^{-1}\underline{T} & -\underline{M}^{-1}\underline{D} \end{bmatrix} \begin{bmatrix} \Delta\underline{\delta}(t) \\ \Delta\underline{\omega}(t) \end{bmatrix} + \begin{bmatrix} \underline{0} \\ -\underline{M}^{-1}\underline{S} \end{bmatrix} \Delta\underline{PTL}(t). \tag{5}$$

To completely specify the model $\Delta\underline{PTL}(t)$ dynamics has to be specified. As was mentioned in section (3.6) the dynamic fluctuation of $\Delta\underline{PTL}(t)$ can be followed by (1) measurements at each load bus or by (2) modeling the load dynamics and measuring the power injections into the module. The first option is generally not feasible for a large utility or a pool due to the cost of measuring and communicating these load measurements at every load bus in the study area to a central processor. Thus in general a load model has to be developed so that (dropping subscript j)

$$\Delta\underline{PTL}(t) = \Delta\underline{PE}^o(t) - \Delta\underline{PL}(t) \tag{10}$$

where $\Delta \underline{PE}^{o}(t)$ are the measured line power injection into module j from other modules and the external area and the load power model is (dropping subscript j)

$$\begin{aligned} &\Delta \underline{PL}(t) = \underline{H}\ \Delta \underline{q}(t) \\ &\Delta \dot{\underline{q}}(t) = \underline{F}\ \Delta \underline{q}(t) + \underline{G}_q \underline{W}_q(t) \qquad (11) \\ &E\{\underline{W}_q(t)\} = \underline{0} \quad E\{\underline{W}_q(t_1)\underline{W}_q^T(t_2)\} = \underline{Q}_q \underline{\delta}(t_1 - t_2) \\ &E\{\underline{X}(0)\ \ \underline{W}_q^T(t)\} = \underline{0} \end{aligned}$$

where the subscript q is added for notational convenience. The measurements of power injected into the module has white measurement noise

$$\begin{aligned} &\underline{PE}^{o}(t) = \underline{PE}(t) + \underline{W}_E(t) \\ &E\{\underline{W}_E(t)\} = \underline{0} \quad E\{\underline{W}_E(t_1)\underline{W}_E^T(t_2)\} = \underline{Q}_E\, \delta(t_1 - t_2) \qquad (12) \end{aligned}$$

where $\underline{W}_E(t)$ is uncorrelated with $\underline{W}_q(t)$ and $\underline{X}(0)$.

Substitution of the above equations (11, 12) in equation (5), the following augmented state model results

$$\begin{bmatrix} \Delta \dot{\underline{\delta}}(t) \\ \Delta \dot{\underline{w}}(t) \\ \Delta \dot{\underline{q}}(t) \end{bmatrix} = \begin{bmatrix} \underline{0} & \hat{\underline{I}} & \underline{0} \\ -\underline{M}^{-1}\underline{T} & -\underline{M}^{-1}\underline{D} & \underline{M}^{-1}\underline{SH} \\ \underline{0} & \underline{0} & \underline{F} \end{bmatrix} \begin{bmatrix} \Delta \underline{\delta}(t) \\ \Delta \underline{w}(t) \\ \Delta \underline{q}(t) \end{bmatrix} + \begin{bmatrix} \underline{0} \\ -\underline{M}^{-1}\underline{S} \\ \underline{0} \end{bmatrix} \Delta \underline{PE}(t) + \begin{bmatrix} \underline{0} & \underline{0} \\ \underline{M}^{-1}\underline{S} & \underline{0} \\ \underline{0} & \underline{G}_q \end{bmatrix} \begin{bmatrix} \underline{W}_E(t) \\ \underline{W}_q(t) \end{bmatrix} \qquad (13)$$

To put this equation in the form of equations (6), (7) define;

$$\underline{X}(t) = \begin{bmatrix} \Delta\underline{\delta}(t) \\ \Delta\underline{\omega}(t) \\ \Delta\underline{q}(t) \end{bmatrix} \quad \underline{u}(t) = \Delta\underline{PE}^{o}(t) \quad \underline{W}(t) = \begin{bmatrix} \underline{W}_E(t) \\ \underline{W}_q(t) \end{bmatrix}$$

$$\underline{A} = \begin{bmatrix} \underline{0} & \hat{\underline{I}} & \underline{0} \\ -\underline{M}^{-1}\underline{T} & -\underline{M}^{-1}\underline{D} & \underline{M}^{-1}\underline{SH} \\ 0 & 0 & F \end{bmatrix} \quad \underline{B} = \begin{bmatrix} \underline{0} \\ -\underline{M}^{-1}\underline{S} \\ \underline{0} \end{bmatrix}$$

$$\underline{G} = \begin{bmatrix} \underline{0} & \underline{0} \\ \underline{M}^{-1}\underline{S} & \underline{0} \\ \underline{0} & \underline{G}_q \end{bmatrix} \quad \underline{Q} = \begin{bmatrix} \underline{Q}_E & \underline{0} \\ \underline{0} & \underline{Q}_q \end{bmatrix} \quad E\{\underline{X}(0)\ \underline{X}^T(0)\} = \underline{\Sigma}(0)$$

Having developed the state model (13), input vector $\underline{u}(t)$, and disturbance $\underline{W}(t)$, the measurement or output vector is now discussed.

An initially attractive set of measurements are the frequency and real power at every generator in the module

$$\begin{aligned} \Delta\underline{PG}^{o}(t) &= \Delta\underline{PG}(t) + \underline{W}_G(t) \\ \Delta\underline{\omega}^{o}(t) &= \Delta\underline{\omega}(t) + \underline{W}_W(t) \end{aligned} \qquad (14)$$

where the measurement noise $\underline{W}_G(t)$ and $\underline{W}_W(t)$ are uncorrelated with each other and with the system input disturbance $\underline{W}(t)$ and initial condition $\underline{X}(0)$ and have statistics;

$$E\{\underline{W}_G(t)\} = \underline{0}$$
$$E\{\underline{W}_G(t_1) \quad \underline{W}_G^T(t_2)\} = \underline{Q}_G \, \delta(t_1 - t_2) \tag{15}$$

$$E\{\underline{W}_\omega(t)\} = 0$$
$$E\{\underline{W}_\omega(t_1) \quad \underline{W}_\omega^T(t_2)\} = \underline{Q} \, \delta(t_1 - t_2) \ . \tag{16}$$

These observation equations can be expressed in the form of the model state using equation (4) in Section 3.5

$$\Delta\underline{PG}(t) = \underline{T} \quad \Delta\underline{\delta}(t) + \underline{S} \quad \underline{PTL}(t)$$

and equation (10) and (12) of this section so that

$$\underline{Y}(t) = \underline{\hat{C}} \ \underline{x}(t) + \underline{v}(t)$$

$$\underline{Y}(t) = \begin{bmatrix} \Delta\underline{PG}^o(t) - \underline{S} \ \Delta\underline{PE}^o(t) \\ \Delta\underline{\omega}^o(t) \end{bmatrix} =$$

$$\begin{bmatrix} \underline{T} & \underline{0} & -\underline{SH} \\ \underline{0} & \underline{I} & \underline{0} \end{bmatrix} \begin{bmatrix} \Delta\underline{\delta}(t) \\ \Delta\underline{\omega}(t) \\ \Delta\underline{q}(t) \end{bmatrix} + \begin{bmatrix} \underline{W}_G(t) + \underline{SW}_E(t) \\ \underline{W}_\omega(t) \end{bmatrix}$$

$$\underline{\hat{C}} = \begin{bmatrix} \underline{T} & \underline{0} & -\underline{SH} \\ \underline{0} & \underline{I} & \underline{0} \end{bmatrix} \qquad \underline{v}(t) = \begin{bmatrix} \underline{W}_G(t) + \underline{S} \ \underline{W}_E(t) \\ \underline{W}_\omega(t) \end{bmatrix}$$

The measurement process statistics (8) for this set of observations are

$$E\{\underline{v}(t)\} = 0 \qquad \underline{E}\{\underline{v}(t_1) \quad \underline{v}^T(t_2)\} = \underline{\hat{R}} \, \delta(t_1 - t_2)$$

where

$$\underline{R} = \begin{bmatrix} \underline{Q}_G + \underline{S}\ \underline{Q}_E \underline{S}^T & \underline{0} \\ \underline{0} & \underline{Q}_\omega \end{bmatrix}$$

Since the $\Delta\underline{PE}^o(t)$ measurement has been used both as input vector and also as part of the observation vector, the resulting measurement process disturbance $\underline{v}(t)$ would be correlated with the system input disturbance

$$E\{\underline{W}(t_1)\ \underline{V}^T(t_2)\} = \begin{bmatrix} \underline{S}\ \underline{Q}_E \underline{S}^T & \underline{0} \\ \underline{0} & \underline{0} \end{bmatrix} \delta(t_1 - t_2)\ .$$

Therefore the conventional Kalman filter equations can not be used since these equations require that $\underline{W}(t)$ and $\underline{v}(t)$ should be uncorrelated.

The observation vector for the modularized dynamic state estimator is thus limited to measurements of frequency to avoid correlation of the measurement and input disturbance processes. The observation equation then becomes

$$\begin{aligned} \underline{Y}(t) &= \underline{C}\ \underline{x}(t) + \underline{v}(t) \\ &= \Delta\underline{\omega}(t) + \underline{W}_\omega(t) \end{aligned}$$

where

$$\underline{C} = [\underline{0}\quad \underline{I}\quad \underline{0}] \qquad \underline{v}(t) = \underline{W}_\omega(t).$$

The statistics of the measurement process are therefore

$$E\{\underline{v}(t)\} = \underline{0} \qquad E\{\underline{v}(t_1)\ \underline{v}^T(t_2)\} = \underline{R}\ \delta(t_1 - t_2)$$

where $\underline{R} = \underline{Q}_\omega$.

It should be noted that an initially attractive method of reducing the computation necessary to compute the dynamic state estimator is to use dynamic model

$$\begin{bmatrix} \Delta\dot{\underline{\delta}} \\ \Delta\dot{\underline{\omega}} \end{bmatrix} = \begin{bmatrix} 0 & \hat{\underline{I}} \\ \underline{0} & -\underline{M}^{-1}\underline{D} \end{bmatrix} \begin{bmatrix} \Delta\underline{\delta} \\ \Delta\underline{\omega} \end{bmatrix} + \begin{bmatrix} \underline{0} \\ -\underline{M}^{-1} \end{bmatrix} \Delta\underline{PG}(t)$$

and measure $\Delta\underline{PG}(t)$. Although the network model does not have to be determined or updated, the resultant dynamic state estimator would be very susceptible to gross errors due to bad data because the model has so little structural information that it would not effectively detect or identify bad data. This estimator would also be very susceptible to measurement errors in $\Delta\underline{PG}(t)$ and $\Delta\underline{\omega}(t)$ and to roundoff errors in computation because of the lack of network structural information in the model.

3.8. The Kalman Filter Equations for a Module

In the last section the general form of the system equation and its observation vector, in the continuous time form, were derived. In this section the system equation in (1) the sampled data form and in (2) the discrete time form are derived and for each case the Kalman filter equations for the optimum, unbiased estimate of the states of the system are presented.

3.8.1. The Sampled Data Form of Equations of the System

In the previous discussion the input vector $\underline{u}(t)$ and the observation vector $\underline{y}(t)$ were treated as continuous time signals. Actually they are not measured continuously but in a sampled data fashion, such that $\underline{u}(t)$ and $\underline{y}(t)$ are known only at time instants $n\Delta T$, where ΔT is the sampling period. Keeping $\underline{u}(t)$ constant and equal to $\underline{u}(n\Delta T)$ for the time interval $[n\Delta T, (n+1)\Delta T)$ would result in the following form for the system;

$$\dot{\underline{X}}(t) = \underline{A}\ \underline{X}(t) + \underline{B}\ \underline{u}(n\Delta T) + \underline{G}\ \underline{w}(t),\ n\Delta T \leq t < (n+1)\Delta T$$

$$\underline{Y}(n\Delta T) = \underline{C}\ \underline{X}(n\Delta T) + \underline{v}(n\Delta T) \qquad (18)$$

$$E\{\underline{v}(n\Delta T)\} = \underline{0}$$

$$E\{\underline{v}(n\Delta T)\underline{v}^T(m\Delta T)\} = \underline{R}\ \delta_{nm}$$

$$E\{\underline{W}(t)\} = \underline{0}$$

$$E\{\underline{W}(t_1)\underline{W}^T(t_2)\} = \underline{Q}\ \delta(t_1 - t_2)$$

$$E\{\underline{W}(t)\underline{v}^T(n\Delta T)\} = \underline{0}$$

$$E\{\underline{X}(0)\ \underline{X}^T(0)\} = \underline{\Sigma}(0)$$

$$E\{\underline{X}(0)\} = \underline{0}$$

$$E\{\underline{X}(0)\underline{W}^T(t)\} = E\{\underline{X}(0)\underline{v}^T(n\Delta T)\} = \underline{0}\ .$$

The Kalman filter equation for this sampled data form of the system equations are now presented [24, 23].

Suppose the best (in the mean squares sense) estimate of the state at time $t_n = n\Delta T$ immediately after the observation $\underline{Y}(n\Delta T)$ is taken is $\tilde{X}(t_n/n)$ i.e.

$$\underline{\tilde{X}}(t_n/n) = E\{\underline{X}(t)/\underline{Y}(i\Delta T),\ i = 1,2,\ldots,n\}$$

with error variance matrix

$$\underline{\Sigma}(t_n/n) = E\{[\underline{X}(t_r) - \underline{\tilde{X}}(t_n/n)][\underline{X}(t_n) - \underline{\tilde{X}}(t_n/n)]^T\} .$$

In the time interval $(n\Delta T, (n+1)\Delta T)$, no new observation is available. Therefore the best state estimate $\underline{\tilde{X}}(t/n)$ is governed by the system differential equations;

$$\dot{\underline{\tilde{X}}}(t/n) = \underline{A}\ \underline{\tilde{X}}(t/n) + \underline{B}\ \underline{u}(t_n), \quad t \in (n\Delta T, (n+1)\Delta T]$$
$$\underline{u}(t_n) = \underline{u}(n\Delta T) \tag{19}$$

with initial condition $\underline{\tilde{X}}(t/n)|_{t=n\Delta T} = \underline{\tilde{X}}(t_n/n)$ and the error variance matrix for this estimate $\underline{\Sigma}(t/n)$ satisfies the differential equation;

$$\dot{\underline{\Sigma}}(t/n) = \underline{A}\ \underline{\Sigma}(t/n) + \underline{\Sigma}(t/n)\underline{A}^T + \underline{G}\ \underline{Q}\ \underline{G}^T \tag{20}$$

with initial condition $\underline{\Sigma}(t/n)|_{t=n\Delta T} = \underline{\Sigma}(t_n/n)$. The solution to these differential equations in terms of the system transition matrix $\underline{\Phi}(t,\tau) = \exp[\underline{A}(t-\tau)]$ is given by;

$$\underline{\tilde{X}}(t/n) = \underline{\Phi}(t, t_n)\underline{\tilde{X}}(t_n/n) + \int_{t_n}^{t} \underline{\Phi}(t,\tau)d\tau\ \underline{B}\ \underline{u}(t_n) \tag{21}$$

$$\underline{\Sigma}(t/n) = \underline{\Phi}(t,t_n)\underline{\Sigma}(t_n/n)\underline{\Phi}^T(t,t_n) + \int_{t_n}^{t} \underline{\Phi}(t,\tau)\underline{G}\ \underline{Q}\ \underline{G}^T\underline{\Phi}^T(t,\tau)d\tau \tag{22}$$

$$t \in (n\Delta T, (n+1)\Delta T].$$

At time $t_{n+1} = (n+1)\Delta T$ the state estimate vector given by (21) is $\underline{\tilde{X}}(t_{n+1}/n)$ with the associated error variance $\underline{\Sigma}(t_{n+1}/n)$, but at this time a new observation $\underline{Y}[(n+1)\Delta T]$ becomes available so that the state estimate vector and the error variance matrix have to be corrected by the following relations;

$$\underline{\tilde{X}}(t_{n+1}/n+1) = \underline{\tilde{X}}(t_{n+1}/n) + \underline{K}(n+1)\{\underline{Y}[(n+1)\Delta T] - \underline{C}\ \underline{\tilde{X}}(t_{n+1}/n)\} \tag{23}$$

$$\underline{\Sigma}(t_{n+1}/n+1) = \underline{\Sigma}(t_{n+1}/n) - \underline{K}(n+1)\underline{C}\ \underline{\Sigma}(t_{n+1}/n) \tag{24}$$

where

$$\underline{K}(n+1) = \underline{\Sigma}(t_{n+1}/n)\underline{C}^T[\underline{C}\ \underline{\Sigma}(t_{n+1}/n)\underline{C}^T + \underline{R}]^{-1}\ . \tag{25}$$

Having these updated values for the state estimate and error variance, they can be used in equations (21) and (22), with n replaced by n+1 and so on. The whole algorithm starts with the initial conditions

$$\begin{aligned} \underline{\tilde{X}}(t_o/o) &= \underline{0} \\ \underline{\Sigma}(t_o/o) &= \underline{\Sigma}(0)\ . \end{aligned} \tag{26}$$

3.8.2. The Discrete Version of the Model and its Optimal Kalman Filter Equations

By discretizing the sampled data equations of the system (18) we obtain for the system equations [24],

$$\underline{X}(n+1) = \underline{\Phi}\ \underline{X}(n) + \underline{B}_D\underline{u}(n) + \underline{W}(n)$$

$$\underline{Y}(n+1) = \underline{C}\ \underline{X}(n) + \underline{v}(n)$$

$$E\{\underline{X}(0)\} = E\{\underline{v}(n)\} = E\{\underline{W}(n)\} = \underline{0} \tag{27}$$

$$E\{\underline{W}(n)\ \underline{W}^T(m)\} = \underline{Q}_D\ \delta_{n,m}$$

$$E\{\underline{v}(n)\ \underline{v}^T(m)\} = \underline{R}\ \delta_{n,m}$$

$$E\{\underline{X}(0)\ \underline{X}^T(0)\} = \underline{\Sigma}(0)$$

$$E\{\underline{X}(0)\ \underline{v}^T(n)\} = E\{X(0)\ \underline{W}^T(n)\} = E\{\underline{v}(n)\ \underline{W}^T(m)\} = \underline{0}$$

where;

$$\underline{\Phi} = \exp(\underline{A}\Delta T)$$

$$\underline{B}_D = \int^{\Delta T} \exp[\underline{A}(\Delta T - 2)]B\ d\tau$$

$$\underline{Q}_D = \int^{\Delta T} \exp[\underline{A}(\Delta T - 2)\underline{G}\ Q\ G^T \exp[A^T(\Delta T - 2)]d\tau$$

For this discrete model the Kalman filter equations are [22, 23];

$$\underline{\tilde{X}}(n+1/n+1) = \underline{\Phi}\ \underline{\tilde{X}}(n/n) + \underline{B}_D u(n) + \underline{K}(n+1)\{\underline{Y}(n+1) - \underline{C}[\underline{\Phi}\ \underline{\tilde{X}}(n/n) + \underline{B}_D\underline{u}(n)]\} \tag{28}$$

$$\underline{\Sigma}(n+1/n+1) = \underline{\Sigma}(n+1/n) - \underline{K}(n+1)\underline{C}\ \underline{\Sigma}(n+1/n) \tag{29}$$

where

$$\underline{K}(n+1) = \underline{\Sigma}(n+1/n)\underline{C}^T[\underline{C}\ \underline{\Sigma}(n+1/n)\underline{C}^T + \underline{R}]^{-1}$$

$$\underline{\Sigma}(n+1/n) = \underline{\Phi}\ \underline{\Sigma}(n/n)\underline{\Phi}^T + \underline{G}\ \underline{Q}\ \underline{G}^T \tag{30}$$

The algorithm starts with initial conditions;

$$\underline{\Sigma}(o/o) = \underline{\Sigma}(o) \quad \text{and} \quad \underline{\tilde{X}}(o/o) = \underline{0} \qquad (31)$$

CHAPTER FOUR

GLOBAL REFERENCING FOR MODULARIZED DYNAMIC STATE ESTIMATORS

The decoupling of the dynamic model of each module from the dynamic models of the other modules by measuring the real power flows on all transmission lines that connect the modules is essential if a global dynamic state estimation is to be feasible. However, the modularized dynamic state estimators cannot provide a global dynamic state estimate for the whole area because each of the modularized state estimators has a separate reference generator and these reference generators have not been referenced to a global reference for the entire area. Thus, the modularized state estimators could only be used to assess security and stability margins within the subarea where it provides a dynamic state estimate and could not be used together for global security assessment, security enhancement, or control tasks in the area unless a global reference was provided. Also the dynamic state estimator for a module is vulnerable to bad data in the measurement of the injected power flows from other modules, because these power flows are used as input to the system and there is no consistency check on these measurements to detect and identify bad data.

To overcome these two disadvantages, two general methods of referencing the modularized dynamic state estimators are presented. It is shown that by globally referencing these modularized estimators, a global dynamic estimate of the entire study area and a procedure for bad data detection and identification on power flow measurements between modules are obtained.

Some preliminary remarks are necessary before the referencing procedure can be discussed. In the referencing procedure the following assumptions and notations have been used;

1 - Without loss of generality it is assumed that the reference angle for module one $\delta_{11}(t)$ is the reference angle for the static state estimator and also it is going to be used as the reference angle for the global dynamic state estimator referencing. In case the static state estimator's reference is not the same as the angle chosen to reference the global dynamic state estimator, it is sufficient to subtract the value of this angle, as given by static state estimator, from all incoming static state angle estimates, to get them all referenced to $\delta_{11}(t)$. The value of this angle, $\delta_{11}(t)$, is then arbitrary and can conveniently be set equal to zero at all times, i.e. $\delta_{11}(t) = 0 \ \forall t$;

2 - with the above convention the static state estimates of internal generator bus angles $\delta^\circ_{ij}(t)$ and the load bus angles $\theta^\circ_{kj}(t)$ for module j are referenced to the generator bus angle $\delta^\circ_{11}(t) = 0$.

3 - The dynamic angles of these same buses are $\delta_{ij}(t)$ and $\theta_{kj}(t)$ where

$$\begin{aligned} \delta_{ij}(t) &= \delta^\circ_{ij}(t) + \Delta\delta_{ij}(t) & i &= 1,2,\ldots,N_j \\ & & j &= 1,2,\ldots,M \\ \theta_{kj}(t) &= \theta^\circ_{kj}(t) + \Delta\theta_{kj}(t) & k &= 1,2,\ldots,K_j \ . \end{aligned}$$

Here $\delta_{ij}(t)$ and $\theta_{kj}(t)$ are globally referenced angles and $\Delta\delta_{ij}(t)$ and $\Delta\theta_{kj}(t)$ are the dynamic angle deviations which are globally referenced to $\Delta\delta_{11}(t) = 0$ where $\delta_{11}(t) = \delta^\circ_{11}(t) + \Delta\delta_{11}(t) = 0$;

4 - For module j, the angle estimates given by the modularized dynamic state estimator, $\Delta\tilde{\delta}_{ij}(t)$ and $\Delta\tilde{\theta}_{kj}(t)$, are referenced to the deviation of the internal generator bus angle, $\Delta\delta_{1j}(t)$, so that

$$\begin{aligned} \Delta\tilde{\delta}_{ij}(t) &= \Delta\delta_{ij}(t) - \Delta\delta_{1j}(t) & i &= 2,3,\ldots,N_j \\ & & j &= 2,3,\ldots,M \\ \Delta\tilde{\theta}_{kj}(t) &= \Delta\theta_{kj}(t) - \Delta\delta_{1j}(t) & k &= 1,2,\ldots,K_j \end{aligned}$$

and for angles in module one

$$\begin{aligned} \Delta\tilde{\delta}_{i1}(t) &= \Delta\delta_{i1}(t) - \Delta\delta_{11}(t) = \Delta\delta_{i1}(t) \\ & \qquad\qquad i = 2,3,\ldots,N_1 \\ \Delta\tilde{\theta}_{k1}(t) &= \Delta\theta_{k1}(t) - \Delta\delta_{11}(t) = \Delta\theta_{k1}(t) \\ & \qquad\qquad k = 1,2,\ldots,K_1 \end{aligned}$$

Therefore the globally referenced angles are

$$\delta_{ij}(t) = \delta^{\circ}_{ij}(t) + \Delta\tilde{\delta}_{ij}(t) + \Delta\delta_{1j}(t)$$

$$\theta_{kj}(t) = \theta^{\circ}_{kj}(t) + \Delta\tilde{\theta}_{kj}(t) + \Delta\delta_{1j}(t) \ .$$

Since the first two terms in the right of the equality sign are available from the static state estimator (the first term) and dynamic state estimator (the second term) all that is needed to reference module j to the global reference is to somehow estimate the value of $\Delta\delta_{1j}(t)$ (the deviation of the local reference angle with respect to the global reference) and add it to the already available static state estimate and locally referenced modularized dynamic state estimate.

A very simple method for providing a global reference frame for these modularized dynamic state estimators is to make one generator be common to all modules and thus all modules would be referenced to the internal generator bus of this generator. Note that this procedure implies

$$\delta_{1j}(t) = \delta_{11}(t) = 0, \quad j = 2,3,\ldots,M \ .$$

If the use of a common generator for reference is impossible, which may often be the case for large systems, two other approaches are possible and given in the following subsections.

4.1. Reference by Association

In this scheme

(1) one generator should be common to and its internal bus angle, $\delta_{11}^{s}(t)$ used as reference to as many modules as possible;

(2) each of the remaining modules, which do not contain this reference generator, should share a generator with a module that has the reference generator. The angle of the internal bus of this common generator in the module without the reference generator will be used as reference for this module and constrained to be the same as its value in the module with reference generator.

For the first group of modules, those with the reference generator, the angles $\delta_{1j_1}(t)$ are of course constrained to be identical, that is,

$$\delta_{1j_1}(t) = \delta_{11}(t) = 0 \quad , \; j_1 \in [1,2,\ldots,M_1]$$

which implies $\Delta\delta_{1j_1}(t) = \Delta\delta_{11}(t) = 0$ since

$$\delta_{ij_1}(t) = \delta_{11}^{\circ}(t) + \Delta\delta_{1j_1}(t), \; j_1 \in [1,2,\ldots,M_1]$$

where $\delta_{11}^{\circ}(t)$ is the estimate of the internal generator bus angle for the reference generator, obtained from the static state estimator and assumed zero.

The global state estimates $\{\theta_{kj_1}\}_{k=1}^{K_{j_1}}$ and $\{\delta_{ij_1}\}_{i=1}^{N_{j_1}}$ for modules $j_1 = 1,2,\ldots,M_1$ are simply the sum of the static state estimate and the local modularized dynamic state estimate

$$\theta_{kj_1}(t) = \theta^{\circ}_{kj_1}(t) + \Delta\tilde{\theta}_{kj_1}(t) \qquad k = 1,2,\ldots,K_{j_1}$$

$$\delta_{ij_1}(t) = \delta^{\circ}_{ij_1}(t) + \Delta\tilde{\delta}_{ij_1}(t) \qquad i = 1,2,\ldots,N_{j_1}$$

For the second group of modules, those sharing a common generator other than reference one for the first group $\delta_{11}(t)$, generator $(1j_2)$ in module j_2 is generator (ℓj_1) in module j_1. A reference by association would require that the reference angle $\delta_{1j_2}(t)$ for module j_2 be equal to the angle $\delta_{\ell j_1}(t) = \delta^{\circ}_{\ell j_1}(t) + \Delta\delta_{\ell j_1}(t)$ where

$$\ell \in \{1,2,\ldots,N_{j_1}\},\ j_1 \in \{1,2,\ldots,M_1\},\ j_2 \in \{M_1+1,\ldots,M\}.$$

To produce global state estimates for modules $j_2 \in \{M_1+1,\ldots,M\}, \Delta\delta_{1j_2}(t) = \Delta\delta_{\ell j_1}(t)$ must be added to $\{\theta_{kj_2}(t)\}_{k=1}^{K_{j_2}}$ and $\{\delta_{ij_2}(t)\}_{i=1}^{N_{j_2}}$

$$\theta_{kj_2}(t) = \theta^{\circ}_{kj_2}(t) + \Delta\tilde{\theta}_{kj_2}(t) + \Delta\delta_{\ell j_1}(t),\ k = 1,2,\ldots,K_{j_2}$$

$$\delta_{ij_2}(t) = \delta^{\circ}_{ij_2}(t) + \Delta\tilde{\delta}_{ij_2}(t) + \Delta\delta_{\ell j_1}(t),\ i = 1,2,\ldots,N_{j_2}$$

The reference by association procedure suffers from two major difficulties which would prevent it from ever being implemented as a practical referencing procedure;

(1) The referencing procedure is vulnerable to bad data, because if $\Delta\delta_{\ell j_1}(t)$ were in error all the global estimates in module j_2 would be in error and hence not useful.

(2) $(M-1)$ extra generator models would be needed since the reference generator models for all modules $j_2 \in \{M_1+1,\ldots,M\}$ would be common with generator models (ℓj_1) in module $j_1 \in \{1,\ldots,M_1\}$ and because the reference generator models in modules $j_1 \in \{1,\ldots,M_1\}$ represent a single generator.

4.2. Reference by Line Measurement

It may be more desirable to split the study area into completely nonoverlapping modules and for each module to treat the rest of the study area as part of external area.

A procedure for global referencing is developed that utilizes the measurements of dynamic power fluctuations on lines that connect the modules. These measurements are required to decouple the dynamic models for each module and since they are already available, their use to provide a reliable accurate global reference for the modularized dynamic state estimator is desirable. The development of this global referencing procedure will be carried out in three stages.

(1) - It will be shown that module j can be referenced to module one using the following data:

(I) The dynamic measurement of the real power on a single transmission line connecting them;

(II) The static and the dynamic state estimates of the voltage angle at both ends of this line;

(III) The static estimate of voltage magnitude at both ends of this line. Here measurement of voltage magnitude and reactive power at only one end of the line would provide this information if the static estimate of voltage magnitude at both ends of the line is not available or its use is not desirable;

(IV) The line parameters.

This data is used to calculate the reference angle $\Delta\delta_{1j}(t)$ that references module j to the reference angle of module 1 assuming that this angle is always zero.

(2) - It will be shown that module j can be much more accurately and reliably referenced to module 1 if a least squares procedure is used to estimate the reference angle $\Delta\delta_{1j}(t)$ from the data on all lines connecting module one and j. The least squares

estimates can be more accurate and reliable using the data on all lines rather than on just one single line because the errors in the dynamic measurement of real power, the static estimate of voltage magnitudes at two ends of the line, and the static and dynamic state estimates of voltage angles at both ends of the line can be averaged out and because bad data on a particular line can be detected, identified and eliminated from use in the referencing procedure. This least squares procedure for referencing any two modules could be used to reference

(a) dynamic state estimators for different areas or pools where 1 and j would represent areas rather than modules within an area;

(b) a global referencing procedure for an area where all modules $j = 2,3,\ldots,M$ could be referenced to module $j = 1$.

(3) - It is shown that the least squares procedures for referencing module j to module 1 by estimating $\Delta\delta_{1j}(t)$ from the data on all lines connecting these two modules can be extended to estimating $\{\Delta\delta_{1j}(t)\}_{j=2}^{M}$ in one step so that these estimates could be based on the data (as listed in (1) above) on all lines connecting all modules within the area rather than

just on data for lines connecting module 1 to a particular module j for each j.

Three stages of development for the global referencing procedure are presented in the next three subsections.

4.2.1. <u>Referencing Two Modules from Line Measurements</u>

As was mentioned earlier, all that is needed to reference module j to module 1 is to add the deviation of local reference angle, $\Delta\delta_{1j}(t)$ (with reference to module 1), to the sum of locally referenced dynamic estimate of angle deviation $\Delta\tilde{\delta}_{ij}(t)$ and $\tilde{\theta}_{kj}(t)$, and the globally referenced static estimate of the angles $\delta^{\circ}_{ij}(t)$ and $\theta^{\circ}_{kj}(t)$ and thus obtain global dynamic estimates

$$\delta_{ij}(t) = \delta^{\circ}_{ij}(t) + \Delta\tilde{\delta}_{ij}(t) + \Delta\delta_{1j}(t) \qquad i = 1,2,\ldots,N_j$$

$$\theta_{kj}(t) = \theta^{\circ}_{kj}(t) + \Delta\tilde{\theta}_{kj}(t) + \Delta\delta_{1j}(t) \qquad k = 1,2,\ldots,K_j$$

where $\Delta\delta_{11} = 0$ and $\Delta\tilde{\delta}_{1j} = 0 \quad j = 1,2,\ldots,M$

$\Delta\delta_{1j}(t)$ can be obtained and module j can be referenced to module 1 if a line exists connecting load bus k_1 in module 1 to load bus k_j in module j. Using the measurement of real power flow in this line $P_{k_j k_1}(t)$ and the static estimates of the voltage magnitudes at both ends of the line $|V^{\circ}_{k_j}(t)|$ and $|V^{\circ}_{k_1}(t)|$ and also the line parameters $R_{k_j k_1}$ and $X_{k_j k_1}$. The angle difference $\theta_{kj}(t) - \theta_{k1}(t)$ is obtained from the formula [19, 25];

$$P_{k_j k_i}(t)$$

$$= \frac{1}{R^2_{k_j k_1} + X^2_{k_j k_1}}[R_{k_j k_1}|V^\circ_{k_j}(t)|^2$$

$$- R_{k_j k_1}|V^\circ_{k_j}(t)||V^\circ_{k_1}(t)|\cos(\theta_{kj}(t) - \theta_{k1}(t))$$

$$+ X_{k_j k_1}|V^\circ_{k_j}(t)||V^\circ_{k_1}(t)|\sin(\theta_{kj}(t) - \theta_{k1}(t))]$$

or the approximate equation [24]

$$P_{k_j k_1}(t) = \frac{1}{X_{k_j k_1}}[|V^\circ_{k_j}(t)||V^\circ_{k_1}(t)|\sin(\theta_{kj}(t) - \theta_{k1}(t))].$$

Since

$$\theta_{kj}(t) = \theta^\circ_{kj}(t) + \Delta\tilde{\theta}_{kj}(t) + \Delta\delta_{1j}(t)$$

$$\theta_{k1}(t) = \theta^\circ_{k1}(t) + \Delta\tilde{\theta}_{k1}(t) + \Delta\delta_{11}(t)$$

$$\Delta\delta_{11}(t) = 0$$

the reference angle satisfies

$$\Delta\delta_{1j}(t) = \underbrace{(\theta_{kj}(t) - \theta_{k1}(t))}_{1} - \underbrace{(\theta^\circ_{kj}(t) + \tilde{\theta}^\circ_{kj}(t))}_{2}$$

$$+ \underbrace{(\theta^\circ_{k1}(t) + \Delta\tilde{\theta}_{k1}(t))}_{3} \quad . \qquad (32)$$

In the right side of the above equation, the first term is obtainable from the power flow measurement; the second term is the sum of static and dynamic estimates of angle and angle deviation as given by the global static and local dynamic state estimators which is assumed known at module j; the third term is similar to the second term except that it is known in module 1 and must be transmitted to module j to determine $\Delta\delta_{1j}(t)$ that is used to obtain the global dynamic state estimates in module j. No reference angle need be determined for module 1 since the global reference is in this module and its value is arbitrary and set equal to zero.

Although the above scheme is capable of providing the $\Delta\delta_{1j}$ information it is not very reliable since there is no redundancy in measurement and if the measurement device gives bad data all the angles in this module would be in error with no way of detecting, identifying and rejecting this bad data. It should be noted that the bad data detection and identification algorithm of the dynamic state estimator of module j cannot detect any erroneous measurement of the inter module tie line flow measurements as these tie line flows are inputs to this estimator and thus there is no consistency check for them. In this agrument it is supposed that estimation for each module is done in different geographical locations because the modules are assumed to be different utilities or pools. If all the estimators for different modules were to be done in one location as in the case when all modules are in a single utility or pool, there could be consistency checks, but as will be discussed later in this section a more general algorithm for finding $\Delta\delta_{1j}$ would be used in this case.

4.2.2. <u>Least Squares Method of Referencing Two Modules</u>

Suppose there are L°_{j1} tie lines connecting buses $k_1 1, \ldots, k_h 1, \ldots, k_{L^{\circ}_{j1}} 1$ in module one to buses $k_1 j, \ldots, k_h j, \ldots, k_{L^{\circ}_{j1}} j$ in module j respectively, then for bus $k_h j$, $h \in [1, \ldots, L^{\circ}_{1j}]$

$$\theta_{k_h j}(t) = \theta^{\circ}_{k_h j}(t) + \Delta\tilde{\theta}_{k_h j}(t) + \Delta\delta_{1j}(t)$$

subtracting $\theta_{k_h 1}(t)$ from both sides gives;

$$\theta_{k_h j}(t) - \theta_{k_h 1}(t) = \theta^{\circ}_{k_h j}(t) + \Delta\tilde{\theta}_{k_h j}(t) + \Delta\delta_{1j}(t) - \theta_{k_h 1}(t) .$$

But since $\theta_{k_h 1}(t) = \theta^{\circ}_{k_h 1}(t) + \Delta\tilde{\theta}_{k_h 1}(t) + \Delta\delta_{11}(t)$ and $\Delta\delta_{11}(t) = 0$, the above expression becomes;

$$\theta_{k_h j}(t) - \theta_{k_h 1}(t) = \theta^{\circ}_{k_h j}(t) - \theta^{\circ}_{k_h 1}(t) + \Delta\tilde{\theta}_{k_h j}(t) - \Delta\tilde{\theta}_{k_h 1}(t) + \Delta\delta_{1j}(t)$$

from which

$$\Delta\delta_{1j}(t) = (\theta_{k_h j}(t) - \theta_{k_h 1}(t)) - (\theta^{\circ}_{k_h j}(t) + \Delta\tilde{\theta}_{k_h j}(t))$$
$$+(\theta^{\circ}_{k_h 1}(t) + \Delta\tilde{\theta}_{k_h 1}(t))$$

which is identical to (32) in the previous section, so that the discussion of how to obtain each term applies here exactly.

To provide measurement redundancy and also a means for detecting and identifying bad measurements L_{j1} of the power flow measurements $(L_{j1} \leq L^{\circ}_{j1})$ would be used in a static state estimation algorithm to obtain the optimum, unbiased, least squares estimate of $\delta_{1j}(t)$.

Defining the measurement vector

$$\underline{Z}^T_{j1}(t) = [Z_{k_1 j}(t), \ldots, Z_{k_h j}(t), \ldots, Z_{k_{L_{j1}} j}(t)]$$

where $Z_{k_h j}(t)$ is the value of $\Delta\delta_{1j}(t)$ obtained from measurements on line h, and the static and local dynamic state estimates, given by

$$Z_{k_h j}(t) = (\theta_{k_h j}(t) - \theta_{k_h 1}(t)) - (\theta^{\circ}_{k_h j}(t) - \Delta\tilde{\theta}_{k_h j}(t))$$
$$+(\theta^{\circ}_{k_h 1}(t) + \Delta\tilde{\theta}_{k_h 1}(t)). \quad (33)$$

Then $\underline{Z}_{j1}(t) = \underline{h}_{L_{j1}} \Delta\delta_{1j}(t) + \underline{W}_{j1}(t)$ where $\underline{h}^T_{L_{j1}} = [1, 1, \ldots, 1]$ is a $L_{j1} \times 1$ vector of 1's and $\underline{W}^T_{j1}(t) = [W_{k_1 j}(t), \ldots, W_{k_h j}(t), \ldots, W_{k_{L_{j1}} j}(t)]$. $\underline{W}_{j1}(t)$ is the noise associated with this model and it is composed of the following components

$$\underline{W}_{jl}(t) = \underline{V}_{jl}(t) + \xi_{jl}(t) + \xi^{\circ}_{jl}(t) + \xi_{lj}(t) + \xi^{\circ}_{lj}(t) + \varepsilon_{lj}(t)$$

where

$$\underline{V}^{T}_{jl}(t) = [V_{k_1 j}(t),\ldots,V_{k_{L_{jl}} j}(t)]$$

$$\underline{\xi}^{T}_{jl}(t) = [\xi_{k_1 j}(t),\ldots,\xi_{k_{L_{jl}} j}(t)]$$

$$\underline{\xi}^{\circ T}_{jl}(t) = [\xi^{\circ}_{k_1 j}(t),\ldots,\xi^{\circ}_{k_{L_{jl}} j}(t)]$$

$$\underline{\xi}_{lj}(t) = [\xi_{k_1 l}(t),\ldots,\xi_{k_{L_{jl}} l}(t)]$$

$$\underline{\xi}^{\circ}_{lj}(t) = [\xi^{\circ}_{k_1 l}(t),\ldots,\xi^{\circ}_{k_{L_{jl}} l}(t)]$$

$$\underline{\varepsilon}^{T}_{lj}(t) = [\varepsilon_{k_1 lj}(t),\ldots,\varepsilon_{k_{L_{jl}} lj}(t)]$$

$V_{k_h j}(t)$ noise in obtaining $(\theta_{k_h j}(t) - \theta_{k_h l}(t))$ from the power flow measurements at module j;

$\xi_{k_h j}(t)$ a posteriori noise associated with $\Delta\tilde{\theta}_{k_h j}(t)$, the output of the local dynamic state estimator for module j;

$\xi^{\circ}_{k_h j}(t)$ noise associated with $\theta^{\circ}_{k_h j}(t)$, the output of static state estimator, this term also contains the communication noise if static state estimation is done globally and the states are transmitted to module j;

$\xi_{k_h 1}(t)$ a posteriori noise associated with $\Delta\tilde{\theta}_{k_h 1}(t)$, the output of dynamic state estimator for module one;

$\xi^{\circ}_{k_h 1}(t)$ a posteriori noise associated with $\theta^{\circ}_{k_h 1}(t)$, the output of static state estimator. It also includes the communication noise of transmitting this information to module one;

$\varepsilon_{k_h 1j}(t)$ communication noise in transmitting $\theta^{\circ}_{k_h 1}(t) + \Delta\tilde{\theta}_{k_h 1}(t)$ from module one to module j.

The statistics for these noise vectors follows

$$E[\underline{W}_{j1}(t)] = E[\underline{V}_{j1}(t)] = E[\underline{\xi}_{j1}(t)] = E[\underline{\xi}^{\circ}_{j1}(t)] = E[\underline{\xi}_{1j}(t)]$$

$$= E[\underline{\xi}^{\circ}_{1j}(t)] = E[\underline{\varepsilon}_{1j}(t)] = \underline{0}$$

$$E[\underline{\xi}_{1j}(t)\ \underline{\xi}^{T}_{1j}(t)] = \underline{\Sigma}_{L_{j1}1}(t)$$

$$E[\underline{\xi}_{j1}(t)\ \underline{\xi}^{T}_{j1}(t)] = \underline{\Sigma}_{L_{j1}j}(t)$$

$$E[\underline{\xi}^{\circ}_{1j}(t)\ \underline{\xi}^{\circ T}_{1j}(t)] = \underline{\Sigma}^{\circ}{}_{L_{j1}1}(t)$$

$$E[\underline{\xi}^{\circ}_{j1}(t)\ \underline{\xi}^{\circ T}_{j1}(t)] = \underline{\Sigma}^{\circ}_{L_{j1}j}(t)$$

$$E[\underline{\varepsilon}_{1j}(t)\ \underline{\varepsilon}^{T}_{1j}(t)] = \underline{C}_{1j}(t)$$

$$E[\underline{V}_{j1}(t)\ \underline{V}^{T}_{j1}(t)] = \underline{\tilde{R}}_{j1}(t)$$

$$E[\underline{\xi}^{\circ}_{j1}(t)\ \underline{\xi}^{T}_{j1}(t)] = \underline{\Sigma}_{j1^{\circ},j1}(t)$$

$$E[\underline{\xi}^\circ_{jl}(t)\ \underline{\xi}^{\circ T}_{lj}(t)] = \underline{\Sigma}_{jl^\circ,lj^\circ}(t)$$

$$E[\underline{\xi}^\circ_{jl}(t)\ \underline{\xi}^{T}_{lj}(t)] = \underline{\Sigma}_{jl^\circ,lj}(t)$$

$$E[\underline{\xi}_{jl}(t)\ \underline{\xi}^{\circ T}_{lj}(t)] = \underline{\Sigma}_{jl,lj^\circ}(t)$$

$$E[\underline{\xi}_{jl}(t)\ \underline{\xi}^{T}_{lj}(t)] = \underline{\Sigma}_{jl,lj}(t)$$

$$E[\underline{\xi}^\circ_{lj}(t)\ \underline{\xi}^{T}_{lj}(t)] = \underline{\Sigma}_{lj^\circ,lj}(t)\ .$$

The nine remaining covariance matrices are zero because $\underline{\varepsilon}_{lj}$ and $\underline{V}_{jl}$ can be assumed uncorrelated with each other and the other errors. From this we get

$$E[\underline{W}_{jl}(t)\ \underline{W}^T_{jl}(t)] = \underline{R}_{jl}(t) = \tilde{\underline{R}}_{jl}(t) + \underline{\Sigma}_{L_{jl}l}(t) + \underline{\Sigma}_{L_{jl}j}(t)$$

$$+ \underline{\Sigma}^\circ_{L_{jl}l}(t) + \underline{\Sigma}^\circ_{L_{jl}j}(t) + C_{lj}(t) + 2[\underline{\Sigma}_{jl^\circ,jl}(t)$$

$$+ \underline{\Sigma}_{jl^\circ,lj^\circ}(t) + \underline{\Sigma}_{jl^\circ,lj}(t) + \underline{\Sigma}_{jl,lj^\circ}(t) + \underline{\Sigma}_{jl,lj}(t)$$

$$+ \underline{\Sigma}_{lj^\circ,lj}(t)]$$

The optimal, unbiased, least squares estimate of $\Delta\delta_{lj}(t)$ would be

$$\Delta\hat{\delta}_{lj}(t) = S_{jl}(t)\underline{h}^T_{L_{jl}}\ \underline{R}^{-1}_{jl}(t)\ \underline{Z}_{jl}(t)$$

where $S_{jl}(t)$ is the a posteriori variance of the estimate,

$$S_{jl}(t) = (\underline{h}^T_{L_{jl}}\ \underline{R}^{-1}_{jl}(t)\ \underline{h}_{L_{jl}})^{-1}\ .$$

If $\underline{R}_{jl}(t)$ is considered to be diagonal $\underline{R}_{jl}(t) = \mathrm{diag}(r^2_{k_1}(t),\dots,r^2_{k_{L_{jl}}}(t))$. Then $S_{jl}(t) = (\sum_{h=1}^{L_{jl}} \frac{1}{r^2_{k_h}(t)})^{-1}$ and

$$\Delta\hat{\delta}_{1j}(t) = S_{j1}(t)\left(\sum_{h=1}^{L_{j1}} \frac{Z_{k_h j}(t)}{r^2_{k_h}(t)}\right)$$

when all diagonal elements of $\underline{R}_{j1}(t)$ are identical $r^2_{k_h}(t) = r^2(t)\ \forall\ h \in \{1,\ldots,L_{j1}\}$ then

$$S_{j1}(t) = \frac{r^2(t)}{L_{j1}}$$

and

$$\Delta\hat{\delta}_{1j}(t) = \frac{\sum_{h=1}^{L_{j1}} Z_{k_h j}(t)}{L_{j1}} .$$

This static state estimator gives $\Delta\tilde{\delta}_{1j}(t)$ for modules having direct connection to module one. If there is any other module j_2 which does not have direct connection to module one then the same procedure could be followed using the tie line flows between this module and any module j_1 which does have connection with module one to get the difference $\Delta\hat{\delta}_{j_2 j_1}(t)$, then the actual difference would be $\Delta\hat{\delta}_{1j_2}(t) = \Delta\hat{\delta}_{j_2 j_1}(t) + \Delta\hat{\delta}_{1j_1}(t)$. In this way all the modules can be referenced to the global reference.

Although this scheme gives a good estimate of $\Delta\delta_{1j}(t)\ \forall\ j \in [1,2,\ldots,M]$ it is not using all the available information, since for each inter module tie line there are two measurements, one at each end, available and this procedure uses less than half of these measurements. Therefore it should be used only when dynamic state estimation is done in separate locations, and the state in the global reference frame is needed at individual module locations, perhaps to be used in an optimal or suboptimal local control strategy.

4.2.3. The Global Least Squares Referencing Procedure

If a central computer is doing the dynamic state estimation for all the modules, all the available information can be used in a single static state estimator to obtain the maximum consistency and minimum uncertainty.

For any two modules j_1 and j_2 that have $L_{j_2 j_1}$ direct tie line connections define

$$\underline{Z}_{j_2 j_1}(t) = \underline{h}_{L_{j_2 j_1}} \Delta\delta_{j_1 j_2}(t) + \underline{W}_{j_2 j_1}(t)$$

$$j_1, j_2 \quad [1,\ldots,M]$$

$$\underline{Z}_{j_1 j_2}(t) = \underline{h}_{L_{j_2 j_1}} \Delta\delta_{j_1 j_2}(t) + \underline{W}_{j_1 j_2}(t)$$

where $\underline{Z}_{j_2 j_1}$ and $\underline{Z}_{j_1 j_2}$ are $L_{j_2 j_1} \times 1$ vectors with elements similar to (33), $\underline{h}^T_{j_2 j_1} = [1,\ldots,1]$ is a $L_{j_2 j_1} \times 1$ vector of 1's, $\underline{W}_{j_2 j_1}(t)$ and $\underline{W}_{j_1 j_2}(t)$ are $L_{j_2 j_1} \times 1$ relevant noise vectors and

$$\Delta\delta_{j_2 j_1}(t) = \Delta\delta_{1 j_1}(t) - \Delta\delta_{1 j_2}(t)$$

$$\Delta\delta_{j_1 j_2}(t) = \Delta\delta_{1 j_2}(t) - \Delta\delta_{1 j_1}(t)$$

Define the state vector for the static state estimation to be

Define the state vector for the static state estimation to be

$$\Delta\underline{\delta}(t) = \begin{bmatrix} \Delta\,\delta_{12}(t) \\ \Delta\,\delta_{13}(t) \\ \vdots \\ \Delta\,\delta_{1M}(t) \end{bmatrix}$$

and the observation vector

$$\underline{Z}^T(t) = [\underline{Z}_{21}^T(t), \underline{Z}_{12}^T(t), \ldots, \underline{Z}_{M1}^T(t), \underline{Z}_{1M}^T(t), \underline{Z}_{32}^T(t), \underline{Z}_{23}^T(t), \ldots$$

$$, \underline{Z}_{j_2 j_1}^T(t), \underline{Z}_{j_1 j_2}^T(t), \ldots, \underline{Z}_{MM-1}^T(t), \underline{Z}_{M-1M}^T(t)]$$

where $j_1 < j_2$ and $j_1, j_2 \in [1,2,\ldots,M]$ such that there is at least one tie line directly connecting modules j_1 and j_2.

The model for static state estimation thus would be

$$\underline{Z}(t) = \underline{H}\Delta\underline{\delta}(t) + \underline{W}(t)$$

where

$$\underline{W}^T(t) = [\underline{W}_{21}^T(t), \underline{W}_{12}^T(t), \ldots, \underline{W}_{M1}^T(t), \underline{W}_{1M}^T(t), \underline{W}_{32}^T, \underline{W}_{23}^T(t), \ldots$$

$$, \underline{W}_{j_2 j_1}^T(t), \underline{W}_{j_1 j_2}^T(t), \ldots]$$

with $E[\underline{W}(t)\underline{W}^T(t)] = \underline{R}$ and $E[\underline{W}(t)] = \underline{0}$ and $\underline{H}$, represented on the next page, is a matrix with elements 1, -1, 0. This matrix has M-1 columns and L rows where L is twice the total number of tie lines between all modules.

$$
H = \begin{array}{c}
\\
\end{array}
\overset{\begin{array}{cccccc} 2 & 3 & J_1 & J_2 & M-1 & M \end{array}}{
\left[\begin{array}{cc:c:c:cc}
\underline{h}_{L_{21}} & \underline{0} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\
-\underline{h}_{L_{21}} & \underline{0} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\
\underline{0} & \underline{h}_{L_{31}} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\
\underline{0} & -\underline{h}_{L_{31}} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\
\hdashline
\underline{0} & \underline{0} & \underline{0} & \underline{0} & \underline{0} & h_{L_{M1}} \\
\underline{0} & \underline{0} & \underline{0} & \underline{0} & \underline{0} & -h_{L_{M1}} \\
-\underline{h}_{L_{32}} & \underline{h}_{L_{32}} & \underline{0} & \underline{0} & \underline{0} & 0 \\
\underline{h}_{L_{32}} & -\underline{h}_{L_{32}} & \underline{0} & \underline{0} & \underline{0} & \underline{0} \\
\hdashline
\underline{0} & \underline{0} & -\underline{h}_{L_{j_2 j_1}} & \underline{h}_{L_{j_2 j_1}} & \underline{0} & \underline{0} \\
\underline{0} & \underline{0} & \underline{h}_{L_{j_2 j_1}} & -\underline{h}_{L_{j_2 j_1}} & \underline{0} & \underline{0} \\
\hdashline
\underline{0} & \underline{0} & \underline{0} & \underline{0} & -\underline{h}_{L_{MM-1}} & -\underline{h}_{L_{MM-1}} \\
\underline{0} & \underline{0} & \underline{0} & \underline{0} & h_{L_{MM-1}} & -\underline{h}_{L_{MM-1}}
\end{array}\right]}
$$

Here the covariance matrix R(t) is very complicated, but nevertheless obtainable from the available information. Since the dominant noise terms in each component of $\underline{W}(t)$, say, $\underline{W}_{j_2j_1}(t)$ are the measurement noise $\underline{V}_{j_2j_1}(t)$ and communication term $\underline{\varepsilon}_{j_2j_1}(t)$, and these terms are mutually independent and uncorrelated one simplifying assumption would be to consider

$$\underline{R}(t) = \text{Block diag}[\underline{R}_{21}(t),\underline{R}_{12}(t),\ldots,\underline{R}_{M1}(t),\underline{R}_{1M}(t),\underline{R}_{32}(t),$$

$$\underline{R}_{23}(t),\ldots,\underline{R}_{j_2j_1}(t),\underline{R}_{j_1j_2}(t),\ldots] .$$

At any rate from this model the optimal unbiased, least squares estimate of $\Delta\underline{\delta}(t)$ is

$$\Delta\hat{\underline{\delta}}(t) = \underline{S}(t)\ \underline{H}^T\ \underline{R}^{-1}(t)\ \underline{Z}(t)$$

where $\underline{S}(t)$ is the a posteriori variance matrix of the estimate;

$$\underline{S}(t) = (\underline{H}^T\ \underline{R}^{-1}(t)\underline{H})^{-1}.$$

Once the estimation problem is put in the above form, there are a host of efficient optimal or suboptimal algorithms together with associated bad data detection and identification schemes, available for this static state estimation. This subject is not pursued further in this research but could be the subject of some further study to find out the most appropriate scheme.

It was noted before that the dynamic estimation algorithm for each module cannot detect or identify bad measurements in the tie line flows, it should be pointed out here that this static estimation algorithm, besides being used to obtain the global reference information, provides a means for detecting and identifying bad data in the tie line flow measurements.

4.3. Implementation

The global dynamic state estimator for a large area could be implemented either,

(1) using a single large central computer to compute all modularized dynamic state estimates and reference angles for each module, or;

(2) using a distributed computer network where each modularized dynamic state estimate is computed by a separate minicomputer and then this local state estimate along with power flow measurements on the tie lines between modules is sent to a central pool or area control center computer where these modularized dynamic state estimates are referenced globally.

The centralized computer implementation would require that frequency measurements at generator buses in the module and power measurements on all lines connecting this module with other modules and the external system be communicated to the central computer for each module. It is assumed here that global static state estimation is done at the location of this central computer such that this information does not require communication.

The distributed computer implementation would require that frequency measurements at generator buses in the module and the power measurements on all lines connecting this module with other modules and the external system be communicated to the local computer. This requires the same amount of communication as the previous case. In addition to these information;

a) local static state information from the central computer has to be communicated to the local computer for each module,

b) local modularized dynamic state estimates has to be communicated from the local computer back to the central computer, and;

c) the power measurements on all lines between modules has to be communicated to the central computer for computation of the reference angles, since it is assumed that reference angles for each modularized dynamic state estimator are estimated in the central computer.

It should be noted that even if reference angles were to be computed at the local computer as in 4.2.2, it would not result in less communication since in this case for each line between modules the angle at the other end of this line had to be communicated to the local computer for referencing.

Since centralized computer implementation requires far less data communication than the distributed computer implementation, it seems more reasonable to do the global dynamic state estimation in a central computer and in module form. The benefits of performing global dynamic state estimation in modules for a study are:

(1) - to minimize the number of parameters in the matrix given in (5) to be updated, because the total number of elements in matrices for the M modules will be less than the number of elements in a one matrix for an entire study area. Moreover parameters to be updated due to a change in operating condition or network structure can be kept to the local module or modules where it has occurred and thus eliminate the need to change all parameters, which would be necessary if one module covered the entire study area;

(2) - make possible the on-line network reduction necessary to determine the matrix $\underline{T}_j$. This network reduction can either be

accomplished using standard network reduction algorithms or by inverting the matrix

$$\underline{\tau}_j = [\frac{\partial \underline{PTL}_j}{\partial \underline{\theta}_j}].$$

(3) - to eliminate the need to synchronize all power and frequency measurements made in an area. Since the computation of the estimates for each module do not depend on measurements for other modules, the measurements for one module need not be made synchronously with measurements made in other modules. The elimination of the requirement of synchronization of all measurements can drastically reduce the cost of the data acquisition system required.

In selecting the module size and its components there are some constraints that have to be met and some considerations that have to be observed;

(a) - The first constraint is the module size, it cannot be too big, as then the network reduction for each module would become too time costly or equivalently the dimension of the matrix $\underline{\tau}_j = [\frac{\partial \underline{PTL}_j}{\partial \underline{\theta}_j}]$ would be such that the computer cannot invert it. This matrix has dimension $k_i \times k_i$ where k_i is the number of load buses at each module.

Since every generator's high side transformer bus is represented by a load bus, k_j would be the actual number of high side transformer buses in a module. The number of high side transformer buses in a module is constrained and cannot be increased more than a certain level decided by the particular computer's capability.

(b) - The topology of the network has to be considered during the modularization. Components for each module should be selected such that the number of connections between modules be minimum, because each tie line between two modules necessitates two measurements, one at each end of it. So an effort has to be made to include those generators and load buses that are strongly connected to each other, as part of one module. This implies that each strongly coherent group should comprise one module. No effort has been made in this research to investigate possible benefits of modularizing around the boundaries of coherent groups against possible inclusion in one module of generators from different coherent group.

(c) - Overmodulization should be avoided, because the more the study area is split the less consistency is present in the model and the higher is the overall number of measurements. It seems a good strategy to try to maximize the size of the modules up to the limits set by the restrictions in (a) and (b) above.

In the final analysis the choice of different ways of modularization depends on the specific pool, its available computer and communication facilities and the policy of its member companies.

CHAPTER FIVE

PERFORMANCE OF THE DYNAMIC STATE ESTIMATOR

The objective of this chapter is twofold:

1 - To validate the assumption that the linear approximation to the nonlinear dynamic system is a good one, and

2 - To investigate the performance of the dynamic state estimator as a function of; a) the size of the error in measurement of frequency, b) the sampling rate of measurement under both normal and transient condition, c) the location and the number of frequency measurements taken and, d) error in obtaining the model parameters.

5-1 The Test System

A seven station dynamic equivalent model of The Michigan Electric Coordinated Systems (MECS) was used to provide the data for investigation of the above mentioned objectives. This equivalent model is described in detail in reference [26]. In this model all the load buses have been eliminated through a Ward-Hale network reduction, so that only internal generator buses are retained. The Kyger station was treated as the external system and the ties between the Kyger station and three stations namely, Ludington, Karn and St. Clair were cut to provide the systems with some internal buses. Stations Palisades, Monroe 1, 2 and Monroe 3, 4, then were the only boundary buses with ties to the external systems (Kyger station). The power flows over the tie lines between these boundary buses and the Kyger station were used as input to the system.

For the linear model it was assumed that the ratio of the damping over inertia for all the machines in the study area were the same, so that the linear state space representation of the study system in Uniform Machine One Frame of Reference [12] was;

$$\dot{\underline{X}} = \underline{A}\,\underline{X} + \underline{B}\,\underline{U} + \underline{G}\,\underline{W}$$

where

$$\underline{X} = \begin{bmatrix} \underline{X}_1 \\ \\ \underline{X}_2 \end{bmatrix} \qquad \underline{X}_1 = \begin{bmatrix} \Delta\delta_2 \\ \vdots \\ \Delta\delta_6 \end{bmatrix} \qquad \underline{X}_1 = \begin{bmatrix} \Delta\omega_2 \\ \vdots \\ \Delta\omega_6 \end{bmatrix}$$

$$\Delta\delta_i = \Delta\delta_i^s - \Delta\delta_1^s \quad \text{and} \quad \Delta\omega_i = \Delta\omega_i^s - \Delta\omega_1^s$$

$$\underline{U} = \begin{bmatrix} 0 \\ \\ \underline{U}_1 \end{bmatrix} \qquad \underline{U}_1 = \begin{bmatrix} \Delta PE_1 \\ \Delta PE_2 \\ \Delta PE_3 \end{bmatrix}$$

$$\underline{W} = \begin{bmatrix} 0 \\ \\ \underline{W}_1 \end{bmatrix} \qquad \underline{W}_1 = \begin{bmatrix} W_2 \\ \vdots \\ W_6 \end{bmatrix}$$

$$A = \begin{bmatrix} \underline{0} & \underline{I} \\ \underline{MT} & -\sigma\underline{I} \end{bmatrix}$$

$$\underline{MT} = \begin{bmatrix} -122.82 & 20.57 & 3.38 & 19.94 & 22.29 \\ 9.75 & -66.91 & -2.03 & 11.68 & 12.85 \\ 1.65 & 1.88 & -60.83 & 4.31 & 4.48 \\ 10.37 & 13.11 & 0.55 & -103.82 & 41.10 \\ 12.46 & 14.68 & 0.93 & 41.50 & -109.36 \end{bmatrix}$$

and $\sigma = 0.31811$.

The value of $\underline{MT}$ was obtained based on a base case load flow solution and the value of σ was obtained by the procedure described in the next section.

5-2 Determination of the Added Term to the Damping

The damping used in the linearized model consists of two parts, one part is the actual damping D_i associated with the machine and the load, and the second part is the contribution of the governor loop to the damping.

The governor loop has a low frequency gain $K_i = P_i/R$ where P_i is the machine capacity and R is the regulation constant. The gain $K_i G_i(\omega)$ of this loop decreases with frequency and the justification for representing this loop by a constant is not immediately apparent. The assumption that the governor loop can be represented by a gain $f_i K_i$ is based on the fact that the dominant modes of the synchronizing oscillations lie in a range between 0.5 and 2.0 Hz. and the frequency response of the governor loop $K_iG_i(\omega)$ is relatively constant over this range. Thus it is possible to approximate the gain of the governor loop as

$$K_iG_i(j\omega)=K_if_i, \quad \pi \le \omega \le 4\pi \qquad \text{rad./sec.}$$

An additional assumption is made that one can use an average damping ratio on all machines that is defined as $\sigma = \frac{1}{6} \sum_{i=1}^{6} D_i+fK_i/M_i$ and thus σ can be varied by varying f.

To verify these assumptions the nonlinear dynamic system was simulated under a set of steady state initial condition and deterministic loading. After two seconds of steady state simulation the angle at Karn station was increased by five degrees to simulate a fault. The power flows between external system and internal system determined from this simulation were used as input for different simulation runs of the linearized model under the same set of initial conditions. The damping ratio σ was adjusted until the linearized dynamic model with constant gain governors approximated the response from the nonlinear dynamic model with dynamic governors. That is, a damping ratio of $\sigma = \frac{1}{6} \sum_{i=1}^{6} D_i+fK_i/M_i$ was used in the linear model with different values of f and the resulting trajectories were compared with the original nonlinear dynamic simulation. Comparison of these results demonstrated that $f = 0.05$ is the most appropriate value.

Figure 5-1 is a comparison of the angle trajectory of Karn station as obtained from nonlinear dynamic simulation with governor dynamics versus the linear dynamic simulation with $\sigma = \frac{1}{6} \sum_{i=1}^{6} D_i + 0.05K_i/M_i = 0.31811$ used as the uniform damping ratio.

5-3 Validation of the Linear Model

To validate the assumption that a second order linear model with appropriate damping ratio represents the nonlinear seventh order model with dynamic governor models under both normal and transient condition the following additional simulation was performed.

The nonlinear model was simulated under the presence of random load and after two seconds of steady state simulation the angle at Karn station was increased by five degrees. The linear second order state space representation of the study area was simulated with the tie line flows between the study area and external area (Kyger station) obtained from the nonlinear simulation and used as input to this linear model. A value of $\sigma = 0.31811$ was used for the damping ratio.

In Figure 5-2 plots of the angle trajectory at Karn station is shown for these two simulations, which clearly confirms the validity of the above assumption, since the linearized model with constant gain governor tracks the machine responses from the nonlinear model with dynamic governors for both steady state operation where

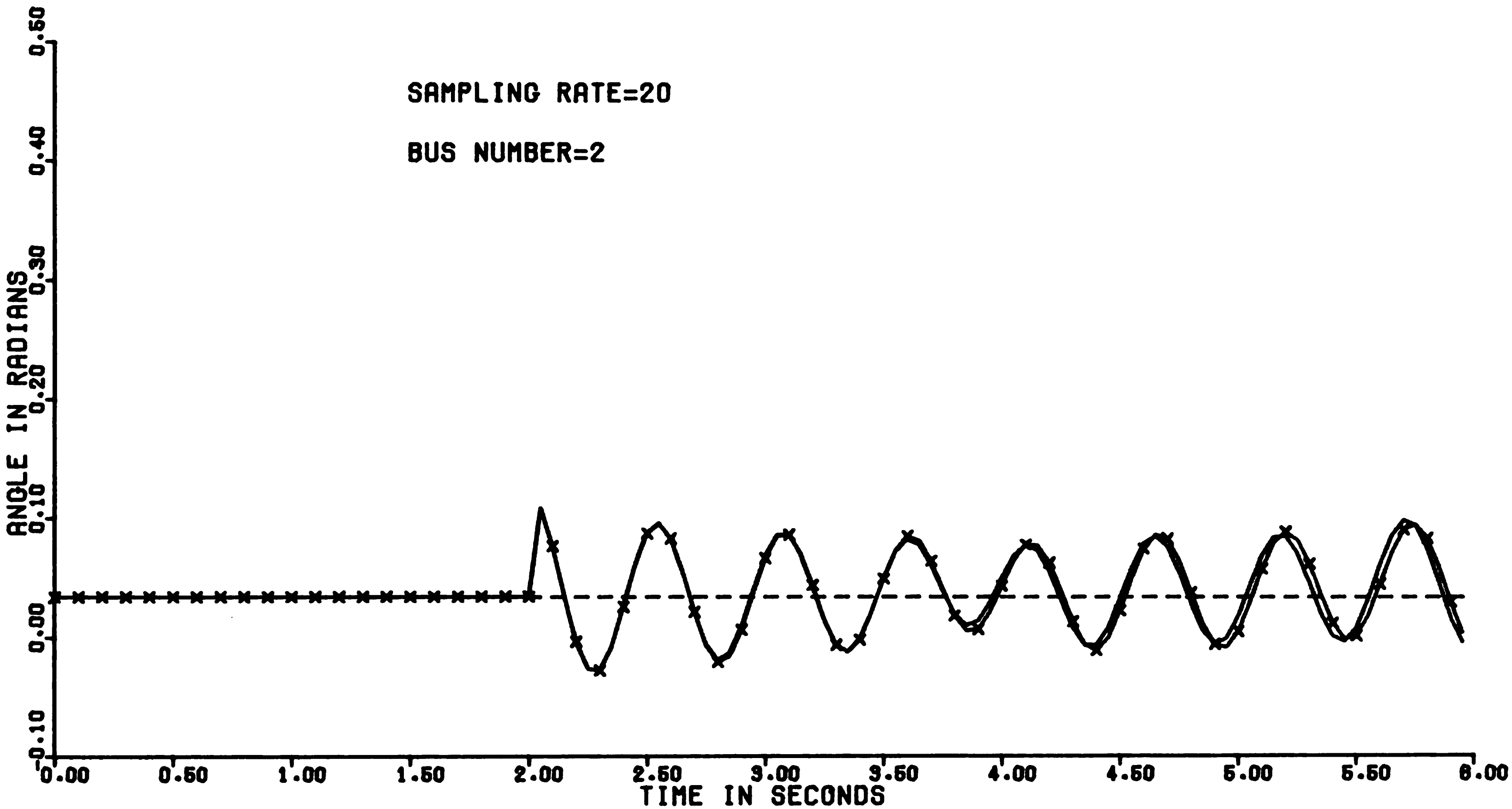

FIGURE 5-1. COMPARISON OF ANGLE AT KARN STATION.

DETERMINISTIC LOAD

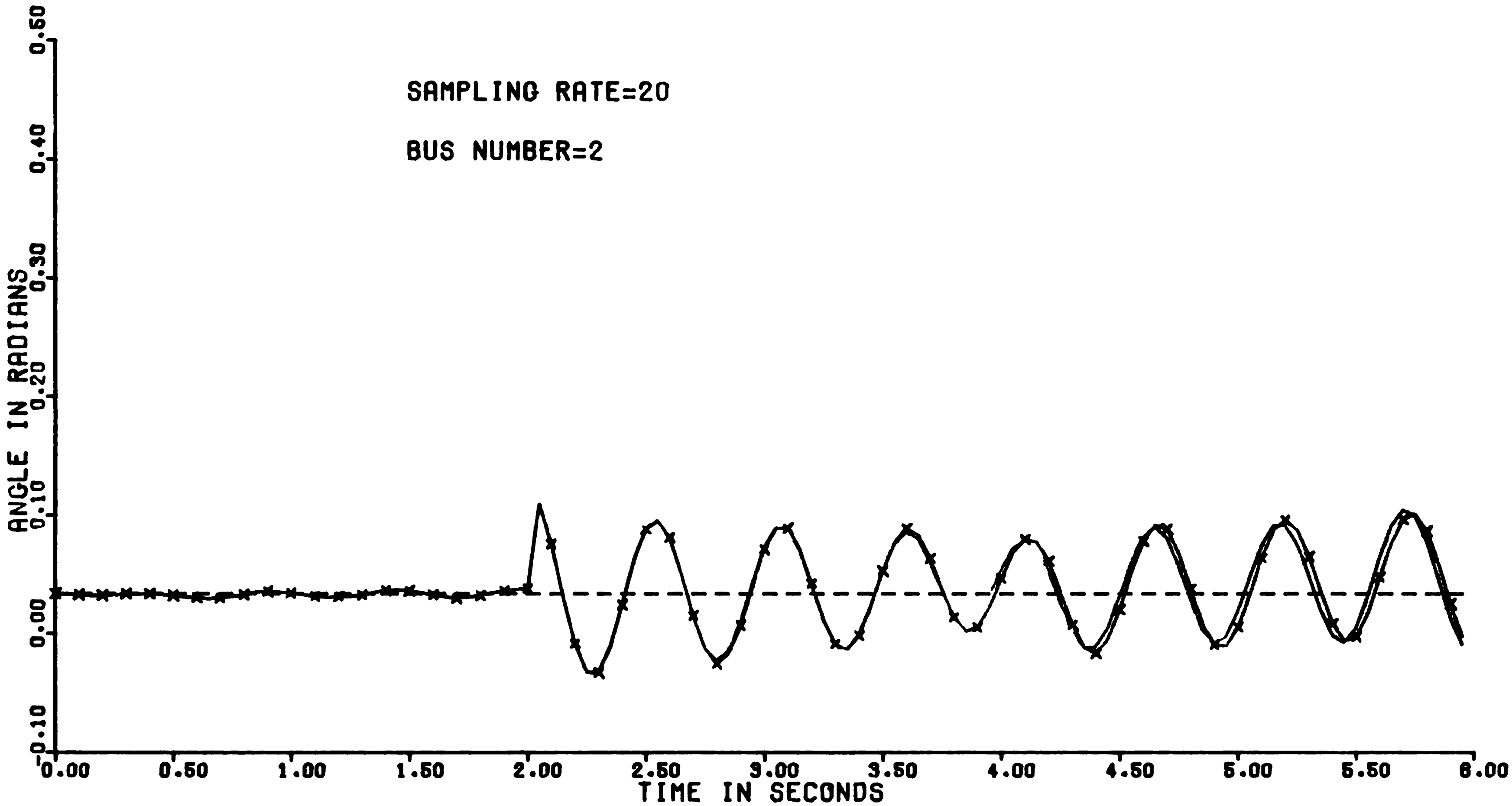

FIGURE 5-2. COMPARISON OF ANGLE AT KARN STATION.

RANDOM LOAD

random load fluctuations are present and the transient condition where an instantaneous change in angle occurs on the Karn machine.

5-4 Performance of the Dynamic State Estimator

To investigate the performance of the dynamic state estimator under different conditions, the nonlinear dynamic system was simulated under random loading condition and after two seconds of steady state simulation an accelerating power of 3.3 per unit was applied at Karn station for 3 cycles to simulate a fault condition.

The standard deviation for the random loads were chosen so that the standard deviation of the simulated power and frequency fluctuations in the steady state would be identical to those found on actual measurements of tie line powers [27].

The power flows between internal and external system and the frequency at different buses of the system were stored to be used partly as measurement vector for the dynamic state estimator and partly for comparison with the output of the dynamic state estimator. The measurements of frequency and power used as inputs to the dynamic state estimator are formed by sampling the stored data from this simulation and adding a discrete white noise with variances σ_p and σ_f to power and frequency respectively.

5-4-1 Effect of Different Measurement Noise Levels

To investigate the performance of the dynamic state estimator under different measurement noise levels, the sampled frequency values stored from the nonlinear dynamic simulation were corrupted by independent white noise with $3\sigma_f$ maximum errors of 0.01 Hz., 0.001 Hz. and 0.0001 Hz. respectively at a sampling rate of 20 samples per second. Using these different values of measurement noise, the steady state covariance matrix of the estimated dynamic angle and frequencies were calculated.

The range of values of the steady state 3σ maximum error in estimated frequency and angle for different buses and for these different measurement noise levels are tabulated in Table 5-1.

This table shows that frequency measurements with maximum frequency measurement error of 0.01 Hz. is just barely adequate for dynamic state estimation, since the maximum error in estimated frequency at any bus is at most 0.005 Hz. which is approximately one quarter of the maximum frequency deviations due to the presence of random load under normal operating conditions.

The frequency estimates are significantly more accurate than the frequency measurements at a maximum frequency measurement error of 0.01 Hz. The maximum error of frequency estimates is approximately equal to the maximum error in measurements when this maximum measurement error

Table 5-1. Performance of Estimator under Different Measurement Noise Levels

$3\sigma_f$ frequency measurement error	0.01 Hz.	0.001 Hz.	0.0001 Hz.
$3\sigma_f$ steady state frequency error	0.003 - 0.005 Hz.	0.00081 - 0.00097 Hz.	0.0001 Hz.
$3\sigma_a$ steady state angle error	0.153° - 0.240°	0.057° - 0.095°	0.03° - 0.084°

is 0.001 Hz. and 0.0001 Hz. since the dynamic model for the estimator does not effectively filter the noise from the measurements at these low measurement noise levels. The maximum error of angle estimates changes significantly as the maximum measurement error decreases from 0.01 Hz. to 0.001 Hz., but does not change significantly as the maximum measurement error decreases from 0.001 Hz. to 0.0001 Hz. because apparently the accuracy of the angle estimates depend more on the accuracy of the dynamic model than on frequency measurement error when this measurement error is small.

A power frequency recorder [27] can presently measure frequency at a rate of five samples per second with a maximum error of 0.001 Hz. and a new Real Time Digital Data Acquisition System (RTDDAS) can measure frequency at twenty samples per second with a maximum error of something less than 0.001 Hz. It is thus clear that the RTDDAS samples sufficiently fast to provide frequency estimates with maximum errors of less than 5% of the maximum frequency deviations due to random load fluctuation and much less than 5% of maximum frequency deviations due to contingencies. The accuracy of the angle estimates using the RTDDAS are excellent and could not be appreciably improved if a more accurate frequency measurement were possible.

Based on the above results and discussions, for the rest of this chapter, it is assumed that the dynamic state estimator has measurements with maximum error of $3\sigma_f = 0.001$ Hz. available.

5-4-2 Effect of Measurement Sampling Rate

As discussed in Chapter Three there are two sets of measurements required for dynamic state estimation, a) the power flows between external and internal system to be used as input to the linear model and b) the frequencies at different generator buses in the internal area to be used as the measurement vector.

To investigate the effect of the rate at which these measurements are taken on the performance of the estimator the 3σ steady state maximum error for frequency and angle at different buses of the system are calculated for different sampling rates. Table 5-2 is a comparison of these results which show that as the rate of sampling increases the error in the estimated value of frequency and angle decreases. The increase in accuracy for frequency estimates is negligible, as the frequency measurement is very accurate ($3\sigma_f = 0.001$ Hz.). The accuracy in angle estimates improves more noticeably, since it is about twice as accurate in case of 20 per second than in case of a 5 per second sampling rate. But overall because of the excellent accuracy of 5 per second sampling rate on one hand and the higher cost of implementation for 10 and 20 per second sampling rate on the other it is concluded that a rate of five measurement per second is adequate for dynamic state estimation.

Table 5-2. Performance of the Estimator under Different Sampling Rates

Sampling Rate	5 per sec.	10 per sec.	20 per sec.
$3\sigma_f$ steady state frequency error	0.00091-0.00099 Hz.	0.00087-0.00098 Hz.	0.00081-0.00097 Hz.
$3\sigma_a$ steady state angle error	0.082° - 0.215°	0.064° - 0.132°	0.052° - 0.099°

It should be noted that as the natural modes of tie line power fluctuations are between 0.5 and 2 Hz., it is not desirable to use sampling rates less than 5 per second.

5-4-3 Effect of Location and Number of Measurements Taken

To determine the effects of the number and location of measurements taken, the steady state error covariance matrix was calculated and compared for the different cases considered. The following results were obtained:

a) Table 5-3 shows the maximum $3\sigma_f$ and $3\sigma_a$ error in the estimated values of frequency and angle at bus number three, namely the St. Clair station. The frequency of this bus was measured in every run while frequency measurements at other buses were dropped one by one. It can be seen that as the number of measurements decrease, the accuracy of the estimates decreases too, but this decrease in the accuracy of the estimates is very very small. Also it is seen that the change in the accuracy of the estimates due to the location of measurements is negligible (compare lines 2 and 3 or 4 and 5).

Based on these results it is concluded that as long as the frequency measurement at a bus is available to the dynamic state estimator, the accuracy of the estimated angle and frequency at that bus is almost constant regardless of the number and location of other frequency measurements.

Table 5-3. Effect of Number and Location of Frequency Measurements in the Steady State Estimated Frequency and Angle Error at Bus #3.

line #	Buses that have frequency measurement	$3\sigma_f$ steady state frequency error at Bus 3 Hz.	$3\sigma_a$ steady state angle error at Bus 3 degree
1	1, 2, 3, 4, 5, 6	0.000925	0.080
2	1, 2, 3, 4, 5	0.000927	0.080
3	1, 3, 4, 5, 6	0.000928	0.081
4	1, 3, 4, 5	0.000930	0.082
5	1, 2, 3, 4	0.000930	0.083
6	1, 3	0.000939	0.087

b) Table 5-4 shows the maximum $3\sigma_f$ and $3\sigma_a$ error in the estimated values of angle and frequency for normal random load fluctuations for bus #6 (Monroe 3-4) when measurements at that bus are not available and measurements at other buses are eliminated one by one. The first line of this table gives the maximum $3\sigma_f$ and $3\sigma_a$ error for frequency and angle at bus #6 when all the frequency measurements are available and has been included as a benchmark against which the results for subsequent runs can be compared.

In the second run frequencies at all buses except bus #6 are measured and it can be seen that the maximum errors in estimated angle and frequency increase almost three and eight times respectively. This maximum error in estimated frequency is about as big as half the maximum error in frequency due to the oscillation of frequency under random loading. Lines three and four in this table show the results for runs when an additional frequency measurement is eliminated. In both of these cases it is seen that the maximum error has increased from the previous case but it is seen that the maximum error is much larger when the measurement at bus 5 is eliminated because bus 5 is much more coherent with bus 6 than bus 2 and thus helps supply more information about the frequency and angle at bus 6. The additional two runs confirm that the error in angle and frequency estimates at a bus where no

Table 5-4. Effect of Number and Location of Frequency Measurements in the Steady State Estimated Frequency and Angle Error at Bus #6.

Case #	Buses that have frequency measurement	$3\sigma_f$ steady state frequency error at Bus #6		$3\sigma_a$ steady state angle error at bus #6	
		Hz.	ratio	degree	ratio
1	1, 2, 3, 4, 5, 6	0.00097	1	0.09874	1
2	1, 2, 3, 4, 5	0.0079	8.14	0.2618	2.65
3	1, 3, 4, 5	0.0093	9.65	0.3030	3.07
4	1, 2, 3, 4	0.01496	15.36	0.4745	4.80
5	1, 2	0.01633	16.83	0.5392	5.46
6	1, 3	0.01591	16.40	0.5278	5.34

measurements is available continue to increase if additional measurements at other buses are eliminated.

From these runs it can be concluded that when the frequency at a bus is not measured the maximum error in the estimated frequency becomes comparable with the frequency deviations due to random load; that is, it shows that the model and the frequency measurements at other buses are unable to estimate frequency at this bus accurately enough so that the effect of random fluctuation of load on frequency would be detectable. Therefore in the normal operating state and in the absence of any disturbances the coherency measure, which is important in order to determine (1) weaknesses in the network and thus the dynamic structure and (2) the dynamic stability of any portion of the power system, cannot be obtained. Thus it would be imperative to measure frequency at every significant generator bus if this coherency measure were to be determined in the normal state. When a disturbance, fault or switching operation, occur then the angle fluctuations would be of a much higher magnitude than the fluctuation due to random load and thus in this case, as will be seen later, the coherency measure can be obtained even if some buses do not have frequency measurements.

This run also shows that the location of the frequency measurements has a significant effect on the accuracy of the estimated states. If the frequency at a bus is not measured but the frequency at a bus coherent with it is measured (line 3) the error in estimated value is far less than if a bus which is not as coherent had frequency measurement instead (line 4).

This result suggests that if in implementation there is a constraint in the number of measurement devices such that not all the buses could have frequency measurement available, an effort has to be made to include at least one frequency measurement from every coherent group.

c) By comparing the plotted error in estimated angle for different number of measurements it is concluded that when frequency measurement at any bus is available the error in estimated angle at that bus is negligible and the convergence of the estimate at that bus is immediate regardless of how many additional measurements are available. Figure 5-3 shows the error in estimated angle at Karn station when the only measurement available to the estimator is the frequency measurement at this bus. It can be seen that after the insertion of the fault, the error increases momentarily but after 6 cycles the measurement corrects this error and the estimator converges. It should be noted that this is the worst case since Karn in the bus with the fault, so that the error in estimated angle and the time to converge is far less for other buses if they have frequency measurements available and observe the effects of the same contingency.

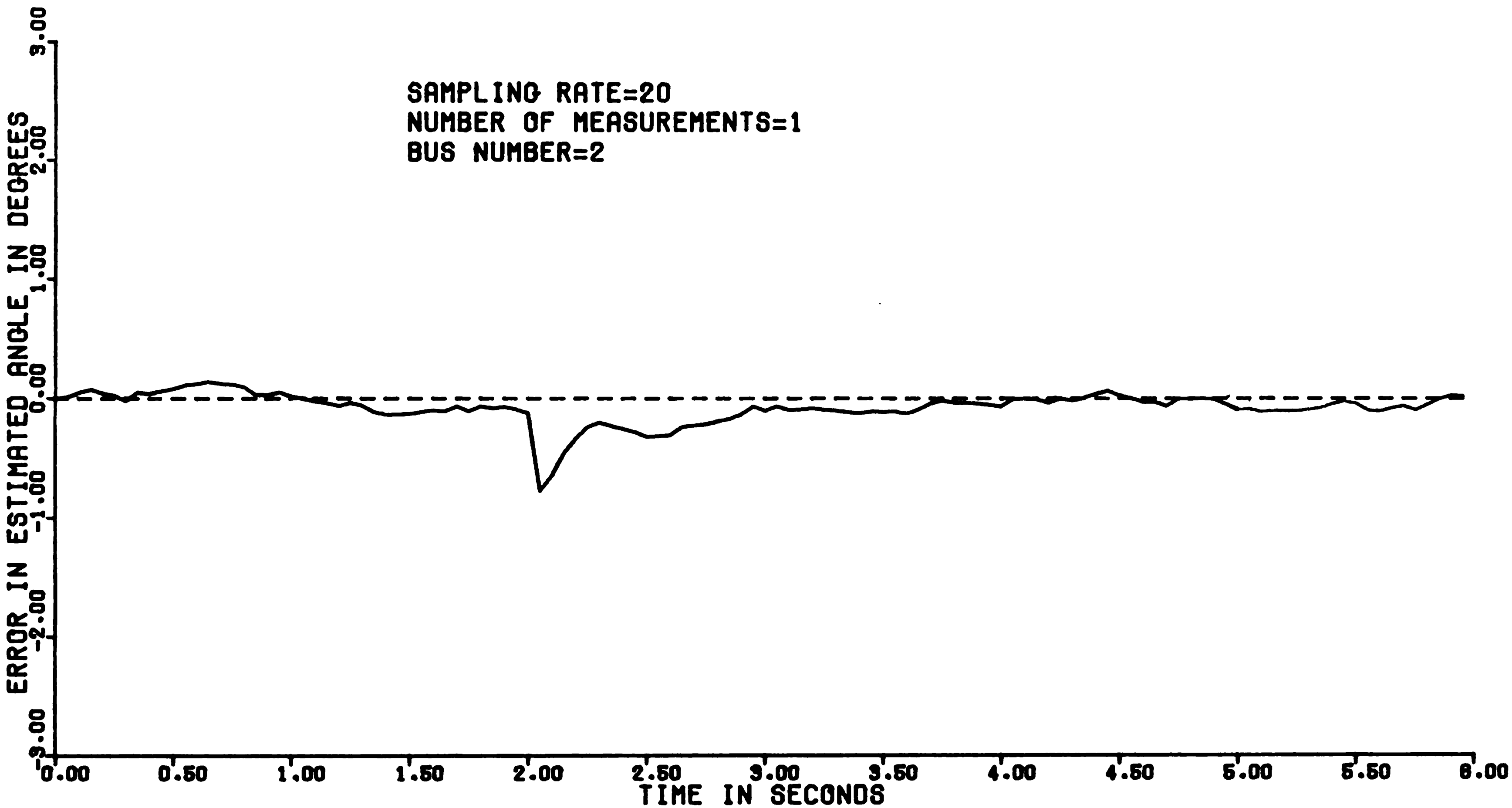

FIGURE 5-3. COMPARISON OF ERROR AT KARN STATION.

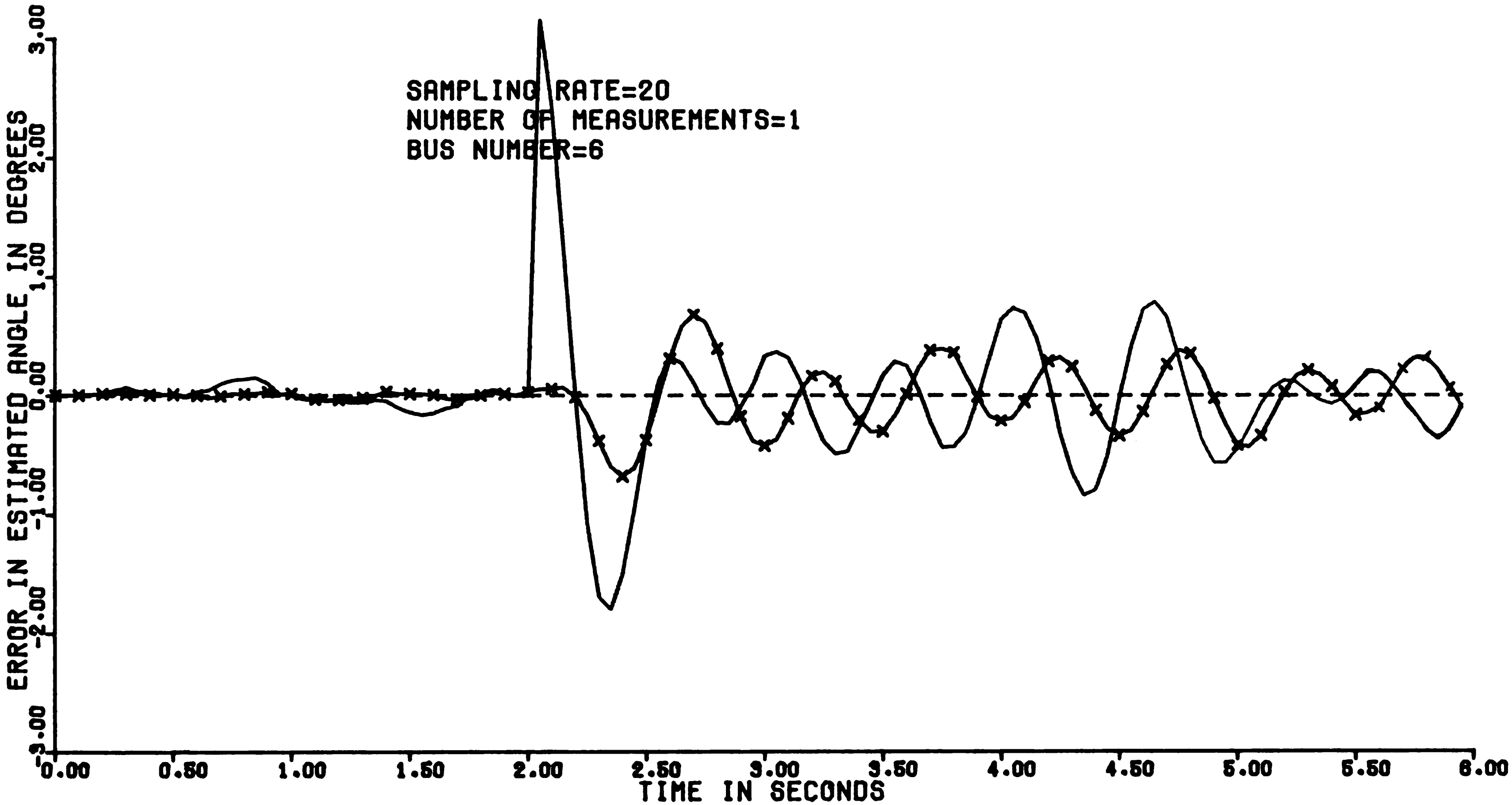

FIGURE 5-4. COMPARISON OF ERROR AT MONROE 3-4.

When a bus does not have frequency measurement available, the overall number of measurements are important. In general the more measurements that are available the lower will be the error in estimated angle and the faster will be the convergence at a bus without frequency measurements. In this case the location of measurements are very crucial, since, with the same number of measurements, the error in estimated angle at a bus without frequency measurement is far less and its convergence is much faster if a bus coherent with this bus has frequency measurement available. Figure 5-4 is a comparison of error in estimated angle at Monroe 3-4 station (bus number 6) when only one frequency measurement (beside the frequency measurement at bus number one which is the reference bus and always has the frequency measurement) is available. The plot with the symbols is the error when bus number three which is very coherent with bus number six has frequency measurement and the solid plot is error when bus number two, which is not as coherent with bus number six, has measurement. It is seen that, although bus number two is the bus with the fault, since it is not very coherent with bus number six its measurement is not as effective as the measurement at bus number three.

5-4-4 Effect of Error in Model Parameters

Dynamic state estimator uses a linearized model based on the operating point information given by the static state estimator. When this information is erroneous due to either operating point changes as the normal slow change to follow the load or a contingency, the parameters in the linearized model are no longer exact. To find out how much the model parameters can be in error and how far the operating point can change before it becomes necessary to update the linearized model, the matrix MT was multiplied by a constant K in the range .4 to 1.6; that is, the parameters were changed from 40% to 160% of their true value and the $3\sigma_a$ and $3\sigma_f$ maximum error in estimated angle and frequency at bus number six and the coherency measure between this bus and the other buses of the system were calculated. The result showed that when all buses do have frequency measurements, although the errors in estimated values increase by changing the parameters, this error is so small that it would not pose any problem.

Table 5-5 shows the values of $3\sigma_a$ and $3\sigma_f$ maximum error in estimated angle and frequency at bus number 6 as calculated statistically, when frequency at this bus is not measured. It also shows the coherency measure between this bus and buses number three and four. Bus number three is strongly coherent with bus number six whereas bus number four is not.

From this table it can be seen that as the model parameters are increased from their true value to 160%

Table 5-5

K	$3\sigma_a$ in degree	$3\sigma_f$ in Hz.	C_{64}	C_{63}
1.6	1.0483	.0406	.243930	.031544
1.5	.9586	.0362	.243957	0.031464
1.4	.8580	.0314	.243988	0.031385
1.3	.7535	.0266	0.244029	0.031289
1.2	.6685	.0223	0.244074	0.031225
1.1	.6489	.0200	0.244123	0.031209
1.0	.7390	.0200	0.244170	0.031225
.9	.9342	.0258	0.244215	0.031432
.8	1.2075	.0333	0.244266	0.031749
.7	1.5666	.0430	0.244350	0.032311
.6	2.0959	.0556	0.244520	0.033377
.5	2.9761	.0794	0.244859	0.035637
.4	4.3670	.0904	0.245353	0.040087

of it the errors increase by 100% whereas when they are decreased to 40% of their true value these errors increase by more than 500%. Also from the coherency measures it is seen that when parameters increase both coherency measures decrease but this decrease is very small. In the other direction when the parameters decrease coherency measures increase and this increase is more pronounced and less proportional. It should be pointed out that in this particular test system, because of the large difference between coherency measures, even with parameters at 40% of their true value, the coherency evaluation can be carried out without much problem. However, if in a system the coherency of the machines is not as clearly determined then having too large an error in parameters could pose problems in coherency measure evaluation.

It can be concluded that the performance of the estimator does not depreciate significantly when the parameters are up to 40% overvalued or 20% undervalued. This result further validates the assumption of constant voltage behind syncromous reactance and the ignoring of the voltage regulator dynamics made in Chapter Three, since changes in voltage are not going to change the parameters more than the range considered here under normal conditions.

CHAPTER SIX

CONCLUSION AND FUTURE INVESTIGATION

A local dynamic state estimator would provide state information on a single generator and the buses directly connected to the high side transformer at this generator. This local dynamic state estimator can provide the information for improved supplementary discrete control strategies that would either reduce accelerating power or stiffen the network connected to this generator. This dynamic state estimator is practical because measurements are only required at the generator bus and because the dynamic model used is decoupled from the dynamics of other generators or loads. This local dynamic state estimator cannot provide information for global power system applications because it does not indicate angle and frequency estimates referenced to a single slack bus, which are required for the application of a global dynamic state estimator.

The global dynamic state estimate of frequency and angle at every bus in a particular utility or pool can provide the following information

(1) - transient power imbalances and their propagations through a system, by the observation of changes in frequency and angle at all buses, due to contingencies such as line switching, generator dropping, load shedding, or electrical faults. This information could be used in global control strategies when relaying or supplementary discrete control strategies have not adequately compensated for the contingency and the effects of the contingency are large and spread throughout the system.

(2) - global power imbalance through observation of large frequency deviations on all buses in a region, utility, or pool for improved steady state secure dispatch.

(3) - weakness in dynamic structure due to

a) - weakness of a particular equivalent line connecting two internal generator buses

b) - weakness in all equivalent lines connected to a particular generator bus indicating that this bus may be susceptible to loss of stability for a contingency at that bus

c) - weakness in the equivalent lines in an entire region, utility or pool indicating a possible dynamic stability problem by on-line computation of an rms coherency measure as a transient security measure. Other transient security measures such as transient energy could also be estimated.

These weaknesses in dynamic structure can be compensated for by

. optimal generation dispatch to unload overloaded lines

. load shedding to unload overloaded lines

. line switching to improve coherency

. series capacitor switching to improve coherency

. phase shifting transformer adjustment to unload overloaded lines

. relay logic adjustment to prevent further loss of coherency between buses in different groups that are very incoherent

(4) - The coherent groups in a power system determined from on-line computation of the rms coherency measure. The identification of coherent groups can be used to

(a) - coordinate control on coherent groups that swing as a single generator

(b) - adjust relaying logic so that if controlled islanding is necessary the islands will be the structurally coherent groups that can best survive the islanding process.

(5) - The rms coherency measure required in the optimal secure dispatch for emergency, extremesis, or restorative operating state. Incorporation of the properly weighted rms coherency measure in the objective function of the optimal secure dispatch algorithm has been shown to cause generation shifting and/or load shedding that would

a) stiffen weak lines by unloading the lines
b) improve the transient security of the system for a contingency at a particular bus by stiffening all equivalent lines connected to this particular bus by unloading these lines
c) improve dynamic stability by stiffening the entire network by unloading all lines. This process will tend to stiffen weak lines most and will thus unload lines connecting coherent groups. This has the beneficial effect of preparing the system for controlled islanding by reducing the mismatch in any group if the relaying logic caused the islands to be the coherent groups

d) maintain very secure operation in the restorative operating state as the system is reconnected.

(6) - Transient operating constraint violations for optimal secure dispatch. These transient constraints could be imposed on the secure dispatch problem only with dynamic state information to determine violations.

(7) - The external fluctuations necessary for determination of dynamic equivalents required by on line transient stability programs.

The principal contribution of this research is to develop a global dynamic state estimator that can be used in the above applications. Specifically the contribution of this research are:

(1) - establishing the <u>feasibility</u> of global dynamic state estimation by developing a computational procedure that, a) does not require measurement or model information on the external system. The need for external system model and measurement data is eliminated by measuring the power flows on the tie lines connecting the external and the internal systems and using these tie line power flows as input into the linear dynamic model of the internal system, b) does not require measurements at

all load buses in the study system. The elimination of the need for power measurement at all load buses is accomplished by using a dynamic model for the loads. Three different and distinct dynamic load models are developed which assume that the load at each load bus can be decomposed into different load types and that each load type can be modeled by a Markov process. c) uses a simple classical transient stability model for each generator thus reducing the order of the model and keeping the measurement sampling rate at below 20 per second. d) does not require immense number of synchronized measurements and immense on line computation for obtaining the state estimates. The study system has been divided into modules and the dynamics of each module has been decoupled from every other module thus eliminating the need for synchronized measurements at all points of the study area and keeping the computation for computing the estimates at each module at a manageable level. e) does not require immense off-line computation to update the model for changes in network configuration, unit commitment or load flow. The model can be updated on-line and with minimum on-line computation since the effects of changes in unit commitment, network configuration and load flow are local in character and thus every module will not have to be updated for each system change and since the network reduction of all modules simultaneously requires less computation and is more accurate than a single network reduction of the network for the entire study area. f) permits bad data detection, identification and rejection schemes to be used to not only determine bad model and measurement information in each module but also bad power flow measurements between the modules. Because of modularization of the study system a global referencing procedure is required to get all angles and frequencies referenced to a single common reference. A global referencing procedure is developed that uses the already measured tie line power flows between the modules in a least squares algorithm which not only provide referencing but also bad tie line power flow measurement detection and identification.

(2) - determining the maximum measurement error and minimum sampling rate that will produce accurate estimate of angle, frequency fluctuations and

rms coherency measure.

(3) - determining the sampling rate and the number and location of measurements necessary in order to provide accurate and fast reconvergence of state estimates after a major disturbance.

(4) - determining the level of accuracy of the parameters of the model needed to obtain accurate frequency, angle and rms coherency measure estimates. In doing so it was also verified that the neglection of voltage regulator dynamics would not affect the accuracy of the estimate unduly.

(5) - verifying the validity of the assumption that a classical transient stability model can be used for each generator.

This research has established the feasibility of global dynamic state estimation. To be able to incorporate and make full use of the on-line global dynamic state estimator more research has to be done in the following two areas:

1 - further investigation of the dynamic state estimation algorithm itself.

2 - development of security indices and controls to fully use the global dynamic state estimator in improving the security of the power system.

The first category would include:

a) further investigation of the validity of the assumption of the adequacy of using a classical transient stability model for the dynamic state estimator. This assumption was partially verified by showing that the performance of the dynamic state estimator derived based on a specific load flow condition was insensitive to small changes in load flow conditions in the system simulation (which were not included in the dynamic state estimator model). The validity of using the classical transient stability model for the dynamic state estimator should be further verified on a nonclassical transient stability simulation model where dynamic rather than static changes in system voltages occur.

b) investigation of the modularization procedure. In this research the importance of the modularization in making the dynamic state estimation feasible was pointed out but no simulation or analysis was done to find out which of the two methods proposed would be the best considering both accuracy of referencing procedure and the computational cost. As was mentioned in chapter four the size of each module is limited by the capability of the particular computer to be used and by the capability of the measurement and communication devices which are to provide synchronized measurements for each module. Once the upper limit on the size of the module is determined, no precise procedure for choosing the appropriate buses belonging to each module has been determined and is thus a second topic for investigation with respect to modularization. It was shown in this research that when two coherent generators are present in the same module measuring frequency at one of them would result in state estimates of the other which is quite accurate for the desired application. This fact suggests that modularization around boundaries of coherent groups would result in saving on the amount of measurements and communications required. More research is needed in this area to determine exactly how the modularization has to be carried out when a module is either too large or too small to include a complete coherent group.

c) investigation of the form of computer implementation. Since the dynamic state estimator is modularized it is possible to carry out the estimation process either using one large computer (array processing), or using mini computers to process different modules (distributed processing). Further investigation is necessary to establish the advantages of one of these methods.

d) choice of the appropriate bad data detection schemes. The referencing procedure described earlier provides for bad data detection schemes of the static state estimator to be used for the power flow measurements. Research is needed in choosing the most appropriate bad data detection, identification and rejection schemes or developing new algorithms for both the referencing as well as the modularized dynamic state estimator components of this global dynamic state estimator.

e) identification of the parameters of the load model. A general dynamic model for the load was developed to be used by the dynamic state estimator. The parameters of this load model have to be identified. Since this load model parameters are system dependent, cooperation of industry in their identification is crucial. Also, this load model does not depend on the frequency but the dynamic state estimation procedure, as developed in this research, can handle the first order dependence of load on frequency. Therefore more research has to be done in the identification of the load model parameters and investigation of the appropriateness of making the load model frequency dependent.

In the second category areas needing further research are:

a) development of global control strategies that use transient power imbalance and their propagation through the system and serve as a back up for discrete control strategies when they are unable to control the effects of a contingency locally.

b) development of algorithms to compute an on-line rms coherency measure as a transient security measure and manual and automatic controls that would compensate for the dynamic structural weakness in the system observed through this coherency measure. These controls would strengthen the weak lines according to the methods enumerated at the beginning of this chapter.

c) defining suitable transient operating constraints and incorporating them in the control strategies and dispatch schemes to result in a more secure transient alert and transient emergency operation state.

d) development of algorithms to use global power imbalance in steady state secure dispatch.

e) development of altorithms to identify coherent groups in the system and possibly coordinate system voltage and AGC control strategies based on these coherent groups.

f) development of algorithms to identify on-line or frequently updated dynamic equivalents from the dynamic state estimator for the external system to be used by the on-line transient stability programs.

g) improving the local dynamic state estimator based on the understanding of and information given by the global dynamic state estimator.

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