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NEURAL NETWORK BASED MODELING OF SYNCHRONOUS MACHINES FROM ON-LINE OPERATING DATA

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

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* * * * *

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A comprehensive system identification procedure is developed to estimate and track the stability parameters of a synchronous generator from time-domain on-line response data. In order to accurately estimate the parameters of the machine model at various test and operating conditions, a multistage identification procedure is proposed. This procedure is verified experimentally by performing both small- and large-disturbance tests on a 7.5 kVA, 220 V, 1800 rpm synchronous generator.

Small disturbance tests are conducted by perturbing the excitation reference voltage in the range 2% to 5% with the generator on-line and delivering power to the infinite bus. Test responses obtained through small disturbance tests are used to estimate stator circuit parameters, field-to-stator turns-ratio, and the field resistance over various operating conditions. Also, by estimating the mutual inductances over several different operating conditions, it is possible to model machine saturation. In this study, artificial neural networks are used to establish generalized saturation models which can take into account several machine variables that are known to influence saturation.

Large disturbance tests are conducted by perturbing the excitation reference voltage in the range 17% to 25% with the generator on-line and delivering power to the infinite bus. Such tests are used to identify rotor body parameters. Large disturbance tests when conducted over a wide range of operating conditions can be used to investigate variations in rotor body parameters as the operating point shifts. Indeed, tests conducted on the 7.5 kVA generator reveal that certain
rotor body parameters are non-linear functions of generator operating condition. A novel artificial neural network based technique is proposed to map variables representative of generator operating condition to each non-linear rotor body parameter.

Artificial neural networks provide a viable means for estimating unmeasurable components of a synchronous generator's state vector by processing sequences of available measurements. These unmeasurable components are typically composed of currents in the rotor body circuits. The proposed observers should account for model parameter non-linearities and provide accurate estimates of rotor body currents irrespective of generator operating condition. By reconstructing the state vector, recursive estimation techniques may be used to estimate machine model parameters.
to my family
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CHAPTER 1

INTRODUCTION

1.1 Overview and Motivation

A problem of emerging importance in power systems operation is the on-line tracking of generator model parameter values. This is evidenced by growing research interest in the estimation of model parameters from on-line response data [10-16]. From an operational perspective, the purposes of repetitive estimation of machine parameters are to provide:

- an accurate set of model parameters for precise stability analysis.
- implementation of auxiliary control strategies, such as excitation control.
- mechanism by which the relative health of the generator can be monitored (model based fault detection).

Generator model parameters are typically provided by the manufacturer upon delivery of the machine. These parameters are calculated from machine design data or through off-line test procedures such as load rejection tests or open- and short-circuit tests. Standstill test procedures such as frequency-response (SSFR) and time-response (SSTR) tests have also been employed for parameter estimation. It should be noted that the parameters of the machine model tend to deviate substantially from corresponding values obtained via off-line testing. Such deviations may be attributed to magnetic saturation, effect of centrifugal forces on winding contacts, internal temperature etc. According to [17], off-line parameter estimates are generally not verified by
field tests. Furthermore, excitation and governor control systems are tuned in the field and the resulting settings are generally not modified for use in on-line stability analysis. The preceding statement indicates the most pressing need currently identified by utilities: better assessment of machine models in normal operation today. Notwithstanding this economically driven need, a broader, technical perspective has to be kept in mind, since many issues still await a satisfactory solution and should, in the long run, be adequately treated if improved understanding of synchronous machine phenomenological behavior is the ultimate goal.

In commercial stability programs where generator equations are formulated in terms of equivalent circuit parameters, customarily only orthogonal axis stator-to-rotor mutual inductances namely, \( L_{ad} \) and \( L_{aq} \) are adjusted according to generator operating condition. These adjustments are made to account for machine saturation. Correct characterization of saturation is essential for field excitation calculations, for excitation system design purposes, and in properly representing generator loading angles. All other model parameters are assumed to be held constant at values obtained from off-line testing. Simulation results from transient stability analysis studies, using such models, generally agree reasonably well with on-site measurements recorded during actual disturbances.

In the field of synchronous machine identification, it has been the practice to accept a model if it leads to a fitting that "looks good." Although practical, this is a very loose definition of the precision that a model should offer. More effort should be invested in a statistical diagnosis of the model, to establish a proper system order and confidence bounds on the estimated parameters, with respect to the actual data used in building the model. Obviously, poorly informative data sets will also lead to certain parameter values which may be accepted on the basis of their goodness-of-fit, until a close examination of their standard deviation (or coherency) reveals that they deserve only limited credit. Thus, it would be desirable to obtain an accurate set of model parameter values from on-line disturbance response data.
Recent advances in on-line parameter estimation techniques have made it possible to estimate the parameters of the machine model from on-line operating data. These advances have made it possible to conclude that machine model parameters are non-linear functions of operating condition dependent machine variables. These variables which include measurable voltages and currents, rotor power angle, and machine speed, are then brought together into one or more mathematical relationships portraying the variation of each machine parameter as non-linear functions of machine variables. Due to the high dimensionality of the variables involved, only some but not all of the variables that are thought to influence parameter variation are considered.

It is to be recognized that a round-rotor synchronous machine is a highly non-linear system. In the past, simplified synchronous machine models have been used to model generator dynamics. Experience suggests that although the assumed models can be used to study the overall power system characteristics, none of the assumed model structures is an exact mathematical representation of the actual physical system. Thus, synchronous machine modeling has often been a compromise between exact machine physical representation and gross simplification of system dynamic behavior.

In recent years, various artificial neural network (ANN) structures have been proposed and applied to solve problems in system identification and control [19-24]. Of particular interest is their ability to utilize non-linearities in their structure to perform complex mappings and generalize from examples presented. Recognizing that the synchronous machine is a highly non-linear system, artificial neural networks provide a viable means for modeling machine non-linear characteristics.

1.2 Problem Statement

Based on the above discussions, it is desirable to list the objectives of this research study. These are summarized below:
1. *Development of multivariate parameter estimation procedure*: The primary task of this research is to develop a comprehensive estimation procedure to estimate and track the stability parameters of a synchronous generator from time-domain on-line response data. The proposed technique should be general enough to be applied to large utility generators where data for parameter estimation purposes can be captured either through unattended transients initiated by the network (such as transmission-line faults, line switching, outages etc.) or through staged on-line tests.

2. *Tracking of field-to-stator turns-ratio and field-winding degradation*: Shorted turns in a field winding of large turbo-generators are a common problem whose detection and localization have remained elusive. Since the problem eventually leads to an imbalance condition, it would be desirable to develop a procedure to track the field resistance and field-to-stator turns ratio from on-line operating data. This would facilitate detection of a degrading condition that would warrant repairs before a full short-circuit develops between turns.

3. *Saturation modeling*: Machine saturation is a complex phenomenon involving machine internal flux pattern which in turn depends on external loading conditions, excitation level, and the relative position of the rotor with respect to the magnetic axis of the stator winding. There exists no generalized synchronous generator saturation model which can accommodate all the physical factors that are known to affect saturation. There is a need to identify physical variables which might influence machine saturation and consequently develop a multidimensional ANN based strategy to map these variables into the saturation manifold.

4. *Modeling of rotor body parameters*: The round-rotor synchronous machine has a highly complex rotor structure. It is generally accepted that in order to account for the flow of eddy currents in the solid rotor-iron of such a machine, two or more fictitious rotor-
circuits are to be used in each orthogonal axis of the equivalent circuit representations of the machine model. Each fictitious rotor body circuit comprises of resistances and leakage-inductances which are thought to be non-linear functions of machine operating condition. Using on-line parameter estimation techniques, it is desirable to investigate the variation of rotor body parameters over the normal operating range of the generator. ANNs can then be used to model these parameters as functions of operating condition dependent machine variables.

5. Development of observers for estimation of unmeasurable rotor body currents:
Measurements acquired during synchronous generator testing are often a small subset of the machine’s state vector. The remaining unmeasurable components of the state vector are typically composed of currents in the rotor body circuits which encapsulate high frequency sensitivity due to the flow of eddy currents in the solid rotor-iron. It is desirable to develop an observer based strategy wherein unmeasurable rotor body currents can be estimated by processing sequences of measurements obtained during large disturbance transient events. Such a strategy would require the development of observers which can account for model parameter non-linearities and provide accurate estimates of rotor body currents irrespective of generator operating condition. By reconstructing the state vector, recursive estimation techniques may be used to estimate machine model parameters.

6. Field testing: The proposed methodology should be investigated in a laboratory environment. For this objective, data obtained through extensive on-line testing of a 7.5 kVA laboratory generator will be utilized.
CHAPTER 2

LITERATURE REVIEW

Synchronous generators are the principal source of electric energy in power systems. An understanding of their characteristics, and accurate modeling of their dynamic performance are of fundamental importance to the study of power system stability. The modeling and analysis of the synchronous machine has always been a challenge. Since the introduction of Park's two-axis theory [25] in the late 20s, various researchers have attempted to develop synchronous machine models which can accurately characterize machine dynamic behavior. The purpose of this chapter is to survey some of the advances in synchronous machine modeling and parameter estimation techniques.

2.1 Synchronous Machine Models

For the purposes of analyzing the transient performance of the synchronous machine, the dynamics are, in general, described either by the circuit models utilizing basic elements such as resistances and inductances or by time-constants and reactances reflecting the eigen-values of the system. Figure 2.1 summarizes typical synchronous machine models using the equivalent circuits given in reference [29]. A more comprehensive summary of synchronous generator models is provided in IEEE Standard 1110 (reference [64]). Based on these models, it has been shown that the dynamic responses of synchronous generator operation can be predicted with good accuracy.
Figure 2.1: Synchronous machine models
2.2 Overview of Modeling Procedures

Many papers have been published on synchronous machine modeling using standstill frequency response (SSFR) [1-4,30,31,38] and standstill time response (SSTR) [5,7,8,32-34,39] tests. Around the late seventies, a large EPRI project jointly performed in Canada, the USA, and the UK successfully applied SSFR methods to actual utility grade machines and investigated analytical procedures for deriving stability models from such tests [28]. Since then, SSFR testing has developed to such an extent that an IEEE committee [29] drafted a standard thereon (IEEE Std. 115). Recently, significant progress has been reported in the numerical analysis of SSFR test data for deriving higher order models [30-31]. However, despite the continuing advances in SSFR understanding and implementation, by the end of the eighties, several investigators had turned to SSTR methods. With regards to signal strength, instrumentation required for testing purposes, and observability, SSTR testing is now favored over SSFR testing.

In this context of synchronous machine modeling using time-domain techniques, various parameter estimation schemes were proposed, including weighted non-linear least-squares [37], multiple exponential fitting [41,42], recursive time-domain identification [43], and maximum likelihood estimation [5,7,8]. Sanchez-Gasca [32], Le [33], Namba [34], Kamwa [35-37], Canay [39], and Jaleeli [40] have studied estimation of machine parameters using time-domain data. In reference [40], a quasi-linearization based least squares algorithm is used to estimate machine parameters from noise-corrupted data. However, the algorithm is very sensitive to noise. Indeed, research work by Goodwin [44], Le & Wilson [33] confirm that the least squares algorithm is very sensitive to noise corrupted data. To overcome the effects of noise, Keyhani and his co-investigators developed a new approach wherein the effects of noise can be effectively dealt with by using the maximum likelihood (ML) estimation technique [4]. References [5,7,8] describe the estimation of synchronous machine parameters from SSTR data using the maximum likelihood algorithm.
Although standstill testing in the time and frequency domains gained rapid popularity, owing to the simplicity of their implementation even on very large machines, they are sometimes criticized for their excessively low levels of test currents, not to mention that certain rotational effects cannot be observed during standstill [29, 31]. These limitations have motivated a sustained effort to modernize the procedures (IEEE Std-115) through rotating time-domain response (RTDR) testing based on small [13] or large [45] signal perturbations around an operating point. Parameter estimation methods based on RTDR test data are more complicated and many now assume a constant speed for analytical tractability [11-13, 45].

Early studies attempted to validate SSTR or SSFR based models against on-line response data [8, 46]. However, much work remains to be done, especially for large machines for which the test current levels are usually so low that the working point shifts into the low current non-linearity of the saturation curve. The need to adjust a weak standstill model to rated current is avoided by on-line tests (load rejection test, decrement test, field or line excitation switching, etc.). Instead of such tests serving for validation only, they are used to enhance and even estimate model parameters. The following section looks at some of the investigative efforts towards on-line modeling and parameter estimation techniques.

2.3 Review of On-line Modeling Techniques

On-line methods are particularly attractive since the machine's service need not be interrupted and parameter estimation is performed by processing measurements obtained during the normal operation of the machine. On-line time response techniques involve initiating a disturbance while the machine is under normal operating conditions. The disturbance can be small - such as a step change (normally less than 5%) in the excitation reference voltage, or it can be a large disturbance - such as load rejection, line outages, and line switching tests.
Recent attempts to estimate synchronous machine parameters from on-line measurements are now described. Reference [10] describes an online technique to estimate machine parameters using the Extended Kalman Filter (EKF). The authors show that while the technique can successfully determine armature circuit parameters and field resistance, the estimation of rotor circuit parameters is not possible since the EKF is particularly sensitive to noise in the measurements, and due to insufficient excitation of the rotor circuits. References [11, 12] describe a conjugate gradient search algorithm to search for optimal machine parameters over a feasible solution space. The width of the solution space is dictated by scaling nominal parameters by small real numbers. Reference [14] describes a de-coupled online method for identifying a generator’s transient and sub-transient parameters from online measurements collected by initiating disturbances through the application of pseudo-random binary signals to the excitation system. Investigations into modeling synchronous generator parameters as a function of operating condition have been reported in reference [16].

2.4 Saturation Modeling

The various implications of synchronous generator saturation have been discussed extensively in the literature for many years. Most techniques of representing saturation make use of the open-circuit saturation characteristics provided by the manufacturer. This is usually done by using the open-circuit saturation curve in the $d$-axis to determine the saturation factor for any operating condition. The factor is then applied equally to both the $d$-axis and $q$-axis mutual inductances $L_{ad}$ and $L_{aq}$ respectively. As pointed out by Dandeno, El-Serafi, Shackshaft and other researchers, the extent of saturation in the $d$- and $q$-axis is not identical; saturation in the $q$-axis is much greater than that in the $d$-axis due to the presence of rotor teeth along the magnetic path in the $q$-axis [48, 49].
Due to the inaccurate nature of manufacturer provided saturation data and variable saturation levels for the $d$- and $q$-axis mutual inductances, the saturation effect of the $dq$ axes is often modeled using steady-state measurements of the generator terminals under various loading conditions. By doing so, the total mmf of the air gap, or the air gap voltage, which is considered to be the principal factor affecting saturation, can be calculated based on machine terminal quantities. Consequently, the saturation factors on the $dq$ axes are often presented as non-linear functions of the air gap voltage (flux). Such a practice has been employed by many experts in the area of saturation modeling.

In the early seventies, Lemay and Barton [47] showed how to incorporate a basic two-factor saturation model into the linearized state-space matrix of a synchronous machine for dynamic stability studies. In recent years, saturation factor methods have been introduced to accurately model machine saturation [47-50, 52-56]. These methods involve suitably modifying the $d$- and $q$-axis mutual inductances, which are essentially functions of magnetizing currents in the core, air-gap mmf, or the air-gap voltage (flux). In reference [51], de Mello and Hannett proposed a saturation model based on the air-gap voltage. In order to take into account that saturation changes with different rotor positions along the air-gap, El-Serafi [52] introduced saturation factors which are varied according to the resultant mmf in the $d$- and $q$-axis. The effects of loading on the saturation trajectory were studied by Shackshaft [48] who proposed a model in which the conventional air-gap voltage magnitude dependent saturation functions are modified according to the air-gap voltage angle as well. In reference [53], Minnich et al proposed a finite-element-method (FEM) to model machine saturation wherein the $d$- and $q$-axis saturation behavior is described as a product of two functions. The first represents the total flux saturation as a function of the voltage behind an internal reactance. The second saturation function is controlled by the $q$-axis component of the internal flux as a lesser correction to the saturation
implied by the total flux saturation under load. Reference [65] compares three different non-linear saturation modeling schemes for representing generator saturation under loaded conditions.

While various saturation models have long been used in stability programs with astonishing practical success, some were shown by Sauer [62] to be physically inconsistent. This highlights the need for good prediction models [63, 64], as well as for models that convey a physical significance [52, 57] that can be used to explain and interpret saturation phenomena. In this context, relevant issues include cross-saturation in salient pole machines, leakage-path saturation, and tests for determining the parameters of advanced saturation models [54].

Summarizing the above discussion, the independent variables used in representing the non-linear variations of the saturation factors are either the terminal voltage, current, or a combination of these quantities including the phase angle. In addition, the leakage reactances, sub-transient reactances, and Potier reactances are often incorporated into these independent variables in order to reflect the dependency of saturation factors on machine power angles under loaded conditions.

2.5 Overview of Multilayer Feedforward Neural Networks

The multilayer feedforward perceptron has often been used in neural network based system identification studies. The fundamental computational unit of such a network is called a processing element. Figure 2.2 shows the schematic of a typical processing element which forms a weighted sum of its inputs and passes the result through a non-linear transformation (also called transfer function) to the output. The transfer function may also be linear in which case the weighted sum is propagated directly to the output path. Feedforward networks, in general, consists of a number of processing elements connected together to form multiple layers. The network is essentially feedforward because information flows along one direction (from the input
layer to the output layer via one or more hidden layers). Figure 2.3 shows a typical two layer feedforward network.

Data presented at the network’s input layer, is processed and propagated through a hidden layer, to the output layer. Training a network is the process of iteratively modifying the strengths (weights) of the connecting links between processing elements as patterns of inputs and corresponding desired outputs are presented to the network. A common form of training viz., supervised training involves modifying the weights of the input connections and also of the connections between layers as sequences of inputs and corresponding desired outputs are presented to the network. Using an adaptation algorithm, the weights of the network are adjusted so as to minimize a pre-defined objective function. A widely used objective function is the sum squared error between actual network outputs and corresponding desired outputs. In multilayer feedforward networks, the error between the actual output and the desired output at any instant depends on the network’s weights at that instant. The backpropagation algorithm [26] is typically used to adjust the weights of multilayer feedforward networks.

\[
\begin{align*}
\text{Summation: } I &= \sum_{i} w_{i} \cdot x_{i} \\
\text{Transfer: } Y &= f(I)
\end{align*}
\]

Figure 2.2 : Schematic diagram of basic processing element
Figure 2.3: Typical two layer feedforward neural network

2.6 Feedforward Neural Networks for System Identification

The typical system identification problem can be stated as follows. Given an input vector $x$, and a corresponding system output vector $y$, we would like to be able to construct a model of the system which when subjected to the same input $x$ produces an output $\hat{y}$ which approximates $y$ to within a reasonable degree of accuracy. The conventional mathematical approach involves constructing a function $G$ based on a set of input/output patterns and using this function for pairing vector $\hat{y}$ to vector $x$. In general, $G$ is a mapping from the set where vector $x$ takes its values to the set where $y$ takes its values. Various techniques for obtaining $G$ are available from ones that are tailor made to the application to general orthogonal functions expansion and neural network structures.
According to reference [18], "One disadvantage of conventional modeling techniques is that a lot of work has been devoted to the identification of linear systems...Non-linear system identification is an area that has received little attention", partly because of the difficulties in expressing system non-linearities in precise mathematical terms. In contrast, neural networks require no knowledge of the mathematical basis of the system and can replace conventional models when the system is not known in precise mathematical terms.

In neural network based system identification, the task of the neural network is to learn the functional mapping between system input $x$ and corresponding output $y$ (Figure 2.4). Neural network based identification of a system comprises of two distinct steps: 1) choosing an optimal network architecture, and 2) adjusting the parameters of the chosen architecture, by means of an adaptation algorithm, to minimize a certain fit criterion.
The following discussion draws comparisons between conventional and neural network based approaches to system modeling. Viewing the system as a *black-box*, the first step is to choose a model structure that best fits the system. According to reference [70], "conventional structures include Auto-Regressive (AR) models, Box-Jenkins models for linear systems, and Volterra models for non-linear systems." Often these structures are not easily modifiable. In the case of neural networks, after determining model inputs and outputs, one decides on a particular network topology. The structure of the neural network may easily be modified by adding additional processing elements, or multiple layers, or even altering network configuration. Once a suitable structure is established, numerical techniques such as parameter estimation are used to establish model parameters. Parameterization in neural networks involves modifying the connection weights and transfer functions.
CHAPTER 3

FORMULATION OF MACHINE MODEL EQUATIONS FOR ON-LINE MODELING AND PARAMETER ESTIMATION

3.1 Introduction

In the previous chapter, a brief introduction to some of the more commonly used $d$- and $q$-axis equivalent circuits was given. In addition to these models, recent investigations into standstill modeling involving field excitation have suggested the development of the model structure shown in Figure 3.1. The branch containing $R_{f\text{ield}}$, $L_{f\text{ield}}$ represents the effect of eddy currents. The model structure shown in Figure 3.1 accurately describes the dynamics of the 7.5 kVA synchronous machine studied in this research. According to reference [8], the model is referred to as Model 3'.3.

In order to describe the on-line dynamics of the machine model, it is desirable to formulate the differential equations of Model 3'.3 in a state-space form. In addition to this formulation, a linear on-line small disturbance model is formulated to facilitate recursive estimation of stator circuit parameters namely stator resistance, $R_a$, mutual inductances $L_{ad}$ and $L_{aq}$, and field-to-stator turns ratio $a$ from small excitation disturbance data. It must be noted that the $d$- and $q$-axis equivalent circuits are coupled through the speed-voltage terms $\omega_r$, $\lambda_d$ and $\omega_r$, $\lambda_q$. A procedure is proposed to estimate the speed-voltage terms from on-line operating data to allow de-coupled formulation of $d$- and $q$-axis state-space models.
Figure 3.1: Model 3':3: On-line model structure

Model 3':3 is based on the reciprocal per-unit system in which all model parameters are referred to the stator [8]. To use the above models with actual units of resistance and inductance in the estimation procedure, the following turns-ratio transformation between the field and the stator should be used:

\[ i_{fd} = \frac{2}{3} \alpha i_{fd}^*; v_{fd} = \frac{v_{fd}^*}{\alpha}; R_{fd} = \frac{3}{2} \alpha^2 R_{fd}^* \]

where \( i_{fd}^* \) is the field winding current in amperes, \( v_{fd}^* \) is the field voltage in volts, both quantities measured on the field side of the generator. \( R_{fd}^* \) is the field winding resistance in ohms as measured on the field side. \( i_{fd}, v_{fd}, \) and \( R_{fd} \) denote corresponding transformed quantities on the stator side of the generator through the field-to-stator turns ratio \( \alpha \).
3.2 Formulation of Coupled On-line Machine Model Equations

For discrete-time systems, the coupled state-space representation of the equivalent circuit models in Figure 3.1 can be written as:

\[
X(k+1) = A(\Theta) \cdot X(k) + B(\Theta) \cdot U(k) + w(k) \\
Y(k+1) = C \cdot X(k+1) + v(k+1)
\]  \hspace{1cm} (3.1)

\(w(k)\) and \(v(k)\) denote the process and measurement noise, respectively. Also,

\[
X = [i_q, i_d, i_{2q}, i_{3q}, i_{id}, i_{f1d}, i_{fd}]^T; \quad Y = [i_q, i_d, i_{fd}]^T; \\
U = [v_q, v_d, 0, 0, 0, 0, 0, v_{fd}]^T;
\]

The parameter vector is given by:

\[
\Theta = \left[ R_q, R_{fd}, R_{id}, R_{f1d}, L_1, L_{ad}, L_{fd}, L_{f1d}, \alpha, R_{2q}, R_{3q}, L_{eq}, L_{eq}, L_{2q}, L_{3q} \right]^T; 
\]  \hspace{1cm} (3.2)

The system matrices \(A(\Theta), B(\Theta),\) and \(C\) are given in reference [8].

3.3 Model Formulation for Small Disturbance Conditions

The model structure shown in Figure 3.1 may be simplified for small disturbance modeling. Note that since the disturbance is small, the rotor speed, \(\omega_r\), is assumed to be essentially constant at synchronous speed \(\omega_s\). Furthermore, since the machine is connected through a transformer to the power system, the rate-of-change of flux-linkages can be ignored.
under small disturbance conditions [13]. Hence, at time instant \( k \), the output equations for the machine models are written as:

\[
\begin{align*}
\v_d (k) &= -R_d i_d (k) - \omega \lambda_q (k) \\
\v_q (k) &= -R_d i_q (k) + \omega \lambda_d (k)
\end{align*}
\]  

(3.3)

where \( \lambda_d \) and \( \lambda_q \) represent the stator \( d \)- and \( q \)-axis flux-linkages. At steady-state and small excitation disturbance conditions, rotor body currents are practically negligible. Thus, equation (3.3) can be represented by a linear model as:

\[
Y(k) = H(k) \cdot \Theta(k) + \nu(k)
\]  

(3.4)

In equation (3.4), \( Y = [v_d \ v_q]^T \); \( \Theta = [R_a \ a L_{ad} \ L_q \ L_d]^T \), and \( \nu \) represents the measurement noise.

Without rotor body dynamics under small disturbance conditions, the matrix \( H \) is a function of two-axis terminal currents and field current given by

\[
H = \begin{bmatrix}
-i_d & 0 & \omega i_q & 0 \\
-i_q & 2 \omega i_{fd} & 0 & -\omega i_d
\end{bmatrix}
\]  

(3.5)

3.4 Model Formulation for Large Disturbance Conditions

In Section 3.3, two assumptions were made to facilitate simplification of the machine model for small disturbance modeling. While the variations in rotor speed, rate-of-change of flux-linkages and the rotor body currents can be ignored for small disturbance modeling, it is not possible to ignore these effects under large disturbance conditions. It must be emphasized that while the system of equations given by equation (3.1) can be utilized for large disturbance modeling, the system matrices need to be updated at every time instant to account for variations.
in rotor speed during large disturbance transient events. Furthermore, if the machine model is represented by equation (3.1), it is not possible to perform de-coupled estimation of machine model parameters.

The $d$- and $q$-axis circuits of Figure 3.1 are coupled through the speed-voltage terms. It will first be shown that using a record of experimentally measured input/output data ($v_d, v_q, i_d, i_q, i_{id}$) obtained during a large disturbance transient event, it is possible to estimate stator $d$- and $q$-axis flux-linkages, provided an estimate of stator resistance, $R_a$, is known beforehand. An estimate of $R_a$ can be obtained from small disturbance modeling studies.

Under large disturbance conditions, the rate-of-change of stator flux-linkages cannot be ignored. In such cases, machine stator voltage equations are arranged in a state-space form to solve for the flux-linkages $\lambda_d$ and $\lambda_q$ using numerical integration.

$$X(k + 1) = A \cdot X(k) + B \cdot U(k)$$

(3.6)

where $X = [\lambda_d \lambda_q]^T$. Matrices $A$, $B$, $U$ are defined as

$$A = \begin{bmatrix} 0 & \omega_r \\ -\omega_r & 0 \end{bmatrix}; \quad B \cdot U = \begin{bmatrix} v_d + R_a i_d \\ v_q + R_a i_q \end{bmatrix}$$

(3.7)

In matrix $A$, machine speed $\omega_r$ in rad/sec can be computed from the following relationship:

$$\omega_r = \omega + p\delta$$

(3.8)

where $\omega$ is the synchronous speed in rad/sec, and $\delta$ is the measured power angle in radians. The operator $p$ denotes differentiation with respect to time. It must be noted that in the laboratory, a Power Angle Instrument (PAI) [66] is used to measure generator power angle. The PAI produces
a relatively noise-free signal. Simulations show that the effect of differentiating the power angle does not introduce significant levels of noise.

If $I_d, I_q, V_d, V_q$ correspond to the steady-state stator $d$- and $q$-axis currents and voltages respectively, the following equations may be used to compute initial flux-linkages at steady state (prior to a transient disturbance) for use in solving equation (3.6):

$$\begin{align*}
\lambda_d &= \frac{R_a I_q + V_q}{\omega_r} \\
\lambda_q &= -\frac{R_a I_d + V_d}{\omega_r}
\end{align*}$$

(3.9)

With estimates of stator $d$- and $q$-axis flux-linkages, the speed-voltage terms appearing in the $d$- and $q$-axis equivalent circuits of Figure 3.1 can be computed. This would facilitate in decoupling equation (3.1) into two subsystems, one for each orthogonal axis:

For the $d$-axis model,

$$\begin{align*}
X_d(k+1) &= A_d(\theta_d) \cdot X_d(k) + B_d(\theta_d) \cdot U_d(k) \\
Y_d(k) &= C_d \cdot X_d(k)
\end{align*}$$

(3.10)

where,

$$\begin{align*}
X_d &= [i_d \ i_d \ i_{feid} \ i_{fd}]^T \\
U_d &= [v^* \ 0 \ 0 \ v^*]^T \\
Y_d &= [i_d \ i_{fd}]^T; \\
\theta_d &= [R_a \ R_{fd} \ R_{feid} \ L_l \ L_{ad} \ L_{fd} \ L_{feid} \ L_f] \theta \ a]^T
\end{align*}$$

For the $q$-axis model,
\[
\begin{aligned}
X_q(k+1) &= A_q(\theta_q) \cdot X_q(k) + B_q(\theta_q) \cdot U_q(k) \\
Y_q(k) &= C_q \cdot X_q(k)
\end{aligned}
\]

(3.11)

where,

\[
X_q = [i_q, i_{1q}, i_{2q}, i_{3q}]^T; \\
U_q = [v_{q}^*, 0, 0]^T; \\
Y_q = [i_q] \\
\theta_q = [R_d, R_{1q}, R_{2q}, R_{3q}, L_1, L_{oa}, L_{1q}, L_{2q}, L_{3q}]^T;
\]

Equations (3.10) and (3.11) constitute the de-coupled forms of equation (3.1). Decoupling the \(d\)- and \(q\)-axis equations facilitates de-coupled estimation of machine parameters. In the above formulation, the voltages \(v_d^*\) and \(v_q^*\) are defined as:

\[
\begin{aligned}
v_d^* &= v_d + \lambda_q \omega_r \\
v_q^* &= v_q - \lambda_d \omega_r
\end{aligned}
\]

(3.12)

In equations (3.10) and (3.11), continuous time matrices \(A^*, B^*\) for each orthogonal axis are presented below.

\[A^* = -L^{-1}R; \quad B^* = L^{-1}\]

where the \(L\) and \(R\) matrices for the \(d\)- and \(q\)-axis circuits are shown below.

For the \(d\)-axis model,
For the $d$-axis model, $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$;

For the $q$-axis model, $C = [1 \ 0 \ 0 \ 0]$.

The discrete-time matrices parameter matrices $A$ and $B$ for each orthogonal axis can then be computed from $A^*$ and $B^*$ as shown in reference [67]. Also matrix $C$, for each axis is given below:

For the $d$-axis model, $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$;
CHAPTER 4

MATHEMATICAL TECHNIQUES FOR MODEL PARAMETER ESTIMATION

4.1 Introduction

In order to identify synchronous machine model parameters from time-domain response data, various parameter estimation algorithms are utilized. The type of estimation algorithm to be used depends on whether model equations are expressed in a linear form (as in small disturbance modeling) or state-space form (for large disturbance modeling), and the availability of model states in the form of measurements. If all states of the machine model are available for measurement, the parameters of the machine model may be estimated recursively. However, in the absence of full state measurement, non-linear minimization techniques have to be used to estimate model parameters through iterative minimization of a pre-defined cost-function. It should be recognized that the problem of establishing network weights and biases is also a parameter estimation problem. This chapter also outlines two algorithms to identify the parameters (weights and biases) of multilayer feedforward artificial neural networks.

4.2 Recursive Maximum Likelihood Algorithm

The recursive maximum likelihood (RML) algorithm may be used when model equations are expressed in a linear form, as in small excitation disturbance modeling studies (Section 3.3). It should be noted that all states of such a linear model are available for measurement at each time instant \( k \). For instance, in equation (3.4), \( Y(k) \) and \( H(k) \) are known at each sampling instant \( k \). The recursive maximum likelihood algorithm processes the data one sampling instant at a time and
estimates vector $\Theta$ at each sampling instant. Denoting $Y(k)$ by $Y_k$ and $H(k)$ by $H_k$, the following steps may be used to recursively update the vector $\Theta$ [13]:

1. Measurement noise variance and mean update, $\sigma^2_{k+1}$ and $m_{k+1}$

\[
\begin{align*}
\sigma^2_{k+1} &= \sigma^2_k + \frac{1}{k+1} [Y_{k+1} - m_k]^2 - \sigma^2_k \\
m_{k+1} &= m_k + \frac{1}{k+1} (Y_{k+1} - m_k)
\end{align*}
\] (4.1)

2. Error covariance update, $R_{k+1}$

\[
R_{k+1} = R_k - R_k H_{k+1} (H_{k+1}^T R(k) H_{k+1} + \sigma^2_{k+1})^{-1} H_{k+1}^T R_k
\] (4.2)

3. Estimation update, $\hat{\Theta}_{k+1}$

\[
\hat{\Theta}_{k+1} = \hat{\Theta}_k + R_{k+1} H_{k+1} (\sigma^2_{k+1})^{-1} (Y_{k+1} - H_{k+1}^T \hat{\Theta}_k)
\] (4.3)

In equations (4.1)-(4.3), $\hat{\Theta}_k$ denotes the estimate of vector $\Theta$ based on measurement until the $k^{th}$ sampling instant. Also, the recursions are started by assuming $m_0 = m_k$, and $\hat{\Theta}_0 = 0$. In addition, large values are used for $\sigma_k^2$ and diagonal matrix $R_0$. An assumption of very large values of $R_0$ signifies the absence of confidence in the initial parameter vector $\hat{\Theta}_0$ [68].

4.3 Generalized Least Squares Algorithm

This algorithm recursively arrives at the parameter estimates by minimizing the sum of the squares of the errors between system outputs and corresponding model outputs for the same inputs applied to both the system and the model [67]. The model equations are represented in a
state-space form, and provided that all states of the model are available for measurement, the
algorithm recursively estimates the state-space parameter matrices. Let the discrete-time state-
space representation of the model be given by:

$$X(k+1) = A(\theta) \cdot X(k) + B(\theta) \cdot U(k)$$  \hspace{1cm} (4.4)

Since all states are assumed to be available for measurement, it is not necessary to write
the associated output equation, i.e, output vector $Y(k) = X(k)$. The following steps may be used to
recursively update the system matrices $A(\theta)$ and $B(\theta)$ starting from time instant $k = 0$. Let $m$ and
$n$ denote the dimensions of vectors $U(k)$ and $X(k)$ respectively.

1. Using the available measurements, form the state vector $X(k)$ at time instant $k$.
2. Form a vector $F(k)$ containing system states and inputs for each time instant $k$

$$F^T(k) = [X^T(k) \ \ U^T(k)]$$  \hspace{1cm} (4.5)

3. Form initial parameter matrix $\hat{C}$ at time instant $k = 0$.

$$\hat{C} = [\hat{A}(\theta) \ \ \hat{B}(\theta)]$$  \hspace{1cm} (4.6)

In equation (4.6), $\hat{A}(\theta)$ and $\hat{B}(\theta)$ denote estimates of system matrices $A(\theta)$ and $B(\theta)$. At
time instant $k = 0$, all elements of matrices $\hat{A}(\theta)$ and $\hat{B}(\theta)$ are initialized to zero.

4. Form initial $S(k)$ at time instant $k = 0$. $S(0)$ is a diagonal matrix of size $(m+n) \times (m+n)$ with
large valued numbers along the main diagonal.
5. Compute state vector estimate at time instant $k+1$.
\[ \hat{X}(k+1) = \hat{C}(k) \cdot F(k) \]  

(4.7)

6. At time instant \( k+1 \), calculate error between actual state and estimated state.

\[ e(k+1) = X(k+1) - \hat{X}(k+1) \]  

(4.8)

7. Update matrix \( S \) using the equation

\[ S(k+1) = S(k) - \frac{S(k)F(k)F^T(k)S^T(k)}{1 + F^T(k)S(k)F(k)} \]  

(4.9)

8. Update parameter matrix \( \hat{C} \)

\[ \hat{C}(k+1) = \hat{C}(k) + e(k+1)F^T(k)S(k+1) \]  

(4.10)

9. Revert to step (5) and repeat steps (5) through (8) for all \( k \).

The continuous-time matrices may then be computed from the discrete-time matrices using the procedure outlined in reference [67].

4.4 Output Error Method

This parameter estimation algorithm is used when the system can be represented in a state-space form, but not all system states are available for measurement. The actual system is assumed to be represented by the following discrete time state-space equations.
where \( w(k) \) and \( v(k) \) denote zero-mean process noise and the output measurement noise respectively. \( \theta \) is the actual parameter vector.

The estimation system model with the estimated parameter vector \( \hat{\theta} \) is assumed to be represented by the following state space equations.

\[
\begin{align*}
X(k+1) &= A(\theta) \cdot X(k) + B(\theta) \cdot U(k) + w(k) \\
Y(k) &= C \cdot X(k) + v(k)
\end{align*}
\] (4.11)

\[
\begin{align*}
\hat{X}(k+1) &= A(\hat{\theta}) \cdot \hat{X}(k) + B(\hat{\theta}) \cdot U(k) \\
\hat{Y}(k) &= C \cdot \hat{X}(k)
\end{align*}
\] (4.12)

Let \( e(k) \) represent the error between actual system output and estimated model output at time instant \( k \). Thus,

\[
e(k) = Y(k) - \hat{Y}(k)
\] (4.13)

In order to make the estimated parameter vector, \( \hat{\theta} \), approach the actual parameter vector, \( \theta \), it is desired to minimize a cost function defined as:

\[
V(\theta) = \frac{1}{N} \sum_{k=0}^{N} \{ e^T(k) e(k) \}
\] (4.14)

Equation (4.14) denotes the sum squared error between the actual system output and estimated model output averaged over all time instants \( k = 0 \ldots N \).

The cost function defined above can be minimized using an iterative technique called Newton's method. To obtain a minimum value of \( V(\theta) \), say at the \( n^{th} \) iteration, \( V(\theta) \) can be expanded as:
\( V(\theta_n + \Delta \theta) = V(\theta_n) + \text{Grad}^T \cdot \Delta \theta + \frac{1}{2} \Delta \theta^T \cdot \text{Hess} \cdot \Delta \theta + \cdots \)  
(4.15)

where \( \text{Grad} \) and \( \text{Hess} \) denote the gradient vector and Hessian matrix of \( V(\theta) \) respectively, i.e.,

\[
\text{Grad} = \frac{\partial V(\theta_n)}{\partial \theta_n} ; \quad \text{and} \quad \text{Hess} = \frac{\partial^2 V(\theta_n)}{\partial^2 \theta_n}
(4.16)
\]

To minimize equation (4.15), higher order terms may be neglected and the partial derivative of \( V(\theta) \) is made equal to zero, i.e.,

\[
\frac{\partial V(\theta_n + \Delta \theta)}{\partial \theta_n} = 0
(4.17)
\]

Using Newton's approach, \( \theta_n \) can be computed iteratively as:

\[
\begin{cases}
\Delta \theta = -\text{Hess}^{-1} \cdot \text{Grad} \\
\hat{\theta}_{n+1} = \hat{\theta}_n + \Delta \theta
\end{cases}
(4.18)
\]

The gradient vector and the Hessian matrix are computed numerically using the method of finite differences.

4.5 Backpropagation Algorithm for Neural Network Weight Adjustment

The backpropagation algorithm has widely been used to estimate the weights and biases of multilayer feedforward ANNs. The algorithm uses a gradient search technique to minimize a cost function equal to the sum squared difference between the desired outputs presented to the output layer of the network and actual network outputs. The network is trained by initially
select small random weights and then presenting all training data repeatedly. The following is a discussion of the backpropagation algorithm.

Consider a feedforward multi-layer perceptron with \( R \) processing elements in the input layer, \( S_1 \) processing elements in the first hidden layer, \( S_2 \) processing elements in the second hidden layer, and so on until the output layer (\( M^{th} \) layer) which contains \( S_M \) processing elements.

The net input to the zeroth layer is given by

\[
a^0 = p
\]

(4.19)

where \( p \) = input vector of size \( R \times 1 \).

Also, the net input to layer \( k+1 \) is given by

\[
a^{k+1} = f^{k+1}(W^{k+1}a^k + b^{k+1})
\]

(4.20)

In equation (4.20), \( k = 0, 1, 2, \ldots, M-1 \). In addition, \( a^{k+1} \) is the net output of the elements of layer \( k+1 \). \( W^{k+1} \) is the weight matrix connecting the elements of layer \( k+1 \) to the elements of the preceding layer \( k \), and \( b^{k+1} \) is the vector of weights connecting elements of layer \( k+1 \) to the bias. \( f^{k+1} \) is the non-linear transformation associated with each element of layer \( k+1 \). \( W^{k+1} \) is of size \( S_{k+1} \times S_k \). Vectors \( a^k, a^{k+1}, \) and \( b^{k+1} \) are of sizes \( S_k \times 1, S_{k+1} \times 1, \) and \( S_{k+1} \times 1 \) respectively.

The task of the network is to learn the mapping between a set of input patterns and corresponding output patterns. This set is given by \( \{(p_1, t_1), (p_2, t_2), \ldots, (p_Q, t_Q)\} \) where \( Q \) = total number of input/output patterns.
The performance index of the network is given by:

\[ V = \frac{1}{2} e_q^T e_q \]  \hspace{1cm} (4.21)

where \( e_q = t_q - a_q^M \) is the error for the \( q^{th} \) input pattern. \( t_q \) is the target vector for the \( q^{th} \) input pattern. \( a_q^M \) is the output of the network when the \( q^{th} \) input pattern \( p_q \) is presented. \( a_q^M \) and \( t_q \) are each of size \( S_M \times 1 \).

The backpropagation algorithm proceeds as follows:

**Step 1:** Calculate the sensitivities at the output layer:

\[ \delta^M = -\tilde{F}^M (n^M)(t_q - a_q^M) \]  \hspace{1cm} (4.22)

where,

\[ \tilde{F}^M (n^M) = diag([\dot{f}^M (n^M (1)) \dot{f}^M (n^M (2)) \ldots \dot{f}^M (n^M (S_M))]) \]  \hspace{1cm} (4.23)

\( n^M (i) \) is the net input to unit \( i \) in the \( M^{th} \) layer.

\[ \dot{f}^M (i) = \frac{df^M (i)}{di} \]

In equation (4.22), \( \tilde{F}^M (n^M) \) is of size \( M \times M \). Vector \( (t_q - a_q^M) \) is of size \( S_M \times 1 \), and vector \( \delta^M \) is of size \( S_M \times 1 \).
Step 2: Propagate the sensitivities back using:

\[ \delta^k = -\hat{f}^k (W^k)^T \delta^{k+1} \]  

(4.24)

Step 3: Update network weights and biases using:

\[ \Delta w^k (i, j) = -\alpha \frac{\partial \hat{V}}{\partial w^k (i, j)} ; \quad w^k (i, j) = w^k (i, j) + \Delta w^k (i, j) \]  

(4.25)

\[ \Delta b^k (i) = -\alpha \frac{\partial \hat{V}}{\partial b^k (i)} ; \quad b^k (i) = b^k (i) + \Delta b^k \]  

(4.26)

\[ \delta^k (i) = \frac{\partial \hat{V}}{\partial n^k (i)} \]  

(4.27)

In equations (4.25) and (4.26), \( \alpha \) is the learning rate [26, 69]. It can also be shown that

\[ \frac{\partial \hat{V}}{\partial w^k (i, j)} = \delta^k (i) a^{k-1} (j) \]  

(4.28)

\[ \frac{\partial \hat{V}}{\partial b^k (i)} = \delta^k (i) \]  

(4.29)

The above steps are repeated until the performance index given by equation (4.21) is minimized or falls below a certain pre-set threshold.

4.5 Levenberg-Marquardt Backpropagation Algorithm

In reference [69], the authors proposed a modification to the backpropagation algorithm using the Levenberg-Marquardt method for minimizing the cost function. The resulting prescription for training the neural network is called the Levenberg-Marquardt Backpropagation (LMBP).
Consider a function $V(x)$ to be minimized with respect to a parameter vector $x$.

Newton's method for minimizing $V(x)$ is:

$$\Delta x = -[\nabla^2 V(x)]^{-1} \nabla V(x) \quad (4.30)$$

where $\nabla^2 V(x)$ is called the Hessian matrix, and $\nabla V(x)$ is the gradient.

Let

$$V(x) = \sum_{i=1}^{N} e_i^2(x) \quad (4.31)$$

where $N =$ total number of data points over which $V(x)$ is to be minimized.

It can be shown that

$$\nabla V(x) = J^T(x) e(x) \quad (4.32)$$

$$\nabla^2 V(x) = -J^T(x) J(x) \quad (4.33)$$

where $J(x)$ is called the Jacobian matrix, and is given by:

$$J(x) = \begin{bmatrix}
\frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\
\frac{\partial e_2(x)}{\partial x_1} & \frac{\partial e_2(x)}{\partial x_2} & \cdots & \frac{\partial e_2(x)}{\partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial e_N(x)}{\partial x_1} & \frac{\partial e_N(x)}{\partial x_2} & \cdots & \frac{\partial e_N(x)}{\partial x_n}
\end{bmatrix} \quad (4.34)$$

In equation (4.34), $x_n$ denotes the $n^{th}$ element of vector $x$.

Substituting equations (4.32) and (4.33) in equation (4.30), the update becomes
\[ \Delta x = [J^T(x)J(x)]^{-1}J^T(x)e(x) \]  

(4.35)

The Levenberg-Marquardt modification is:

\[ \Delta x = [J^T(x)J(x) + \mu I]^{-1}J^T(x)e(x) \]  

(4.36)

where \( I \) is an identity matrix. Also, the parameter \( \mu \) is multiplied by another parameter \( \beta \) if a step would result in an increased \( V(x) \). (Note that we would like to minimize \( V(x) \)). If a step reduces \( V(x) \), \( \mu \) is divided by \( \beta \). For small \( \mu \) (and hence small \( \mu I \)), we have Newton minimization. For large \( \mu \) (and hence large \( \mu I \)), we have Levenberg-Marquardt minimization.

The following is a discussion on the computation of the Jacobian matrix. The expression

\[ \hat{V} = \frac{1}{2} e_q^T e_q = \frac{1}{2} \sum_{q=1}^{Q} e_q^2 \]  

is equal in form to equation (4.31) where:

\[ x = [w^1(1,1) \ w^1(1,2) \ \cdots \ w^1(S_1,R) \ b^1(1) \ b^1(2) \ \cdots \ b^1(S_1) \ w^2(1,1) \ w^2(1,2) \ \cdots \ b^M(S_M)]^T \]

Also, in equation (4.31), \( N = Q \times S_M = \) total number of data points.

Standard backpropagation calculates terms like

\[ \frac{\partial \hat{V}}{\partial w^k(i,j)} = \frac{\partial \sum_{q=1}^{S_M} e_q^2(m)}{\partial w^k(i,j)} \]

For the elements of the Jacobian matrix that are needed for the LM algorithm, we need to calculate terms like

\[ \frac{\partial e_q(m)}{\partial w^k(i,j)} \]. These terms can be computed using standard backpropagation with one modification at the output layer:
\[ \Delta^M = -\hat{F}^M (n^M) \]  

Each column of the above matrix is a sensitivity vector that must be propagated through the network to compute one row of the Jacobian.

The following is a summary of the LMBP algorithm:

1. Present all inputs and compute corresponding outputs using equations (4.19) and (4.20).
   Compute the errors at the output layer using \( e_q = t_q - \hat{a}_q^M \). Compute the sum squared error (SSE) over all inputs \( V(x) \).

2. Compute the Jacobian matrix using equations (4.37), (4.24), (4.28), (4.29), and (4.34).

3. Solve equation (4.36) to obtain \( \Delta x \).

4. Re-compute the SSE using \( x = x + \Delta x \). If this new sum squared error is smaller than that computed in step 1, divide \( \mu \) by \( \beta \). Let \( x = x + \Delta x \) and go back to step 1. If the SSE is not reduced, multiply \( \mu \) by \( \beta \) and go back to step 3.

5. Declare convergence when the norm of the gradient is less than a pre-specified tolerance \( \varepsilon \).
   i.e., \( \| \nabla V(x) \| < \varepsilon \), or when sum of squares has been reduced to some error goal.
CHAPTER 5

TEST PROCEDURES FOR TIME-DOMAIN ON-LINE MACHINE MODELING

5.1 Introduction

The purpose of this chapter is to outline the test procedures for identifying the parameters of a 7.5 kVA, 220 V, 60 Hz, 1800 rpm round rotor synchronous generator from on-line response data. In Section 5.2, a brief outline of the experiment is presented along with a description of measurements required for on-line machine modeling. Section 5.3 outlines a procedure to transform abc reference frame stator responses to corresponding quantities in the dq reference frame. Data acquired from small excitation disturbance testing must be validated prior to use in estimation. Data validation procedures are described in Section 5.4. Measurements acquired from testing the synchronous machine on-line are usually noise corrupted. For the purposes of machine modeling and parameter estimation, noise in the measured signals needs to be filtered. Measurement noise filtering is the topic of discussion in Section 5.5.

5.2 Outline of Experiment and Description of Measurements

The experimental arrangement of a one-machine-infinite-bus system is shown in Figure 5.1. In order to obtain the necessary responses for on-line machine modeling and identification, three-phase generator voltages \( (v_a, v_b, v_c) \) and currents \( (i_a, i_b, i_c) \), and generator field winding voltage \( (v_{fd}) \) and current \( (i_{fd}) \) must be measured. Figure 5.2 shows a schematic representation of the measurement configuration installed on the 7.5 kVA laboratory machine. To facilitate
conversion of machine $abc$ terminal quantities to the $dq$ reference frame, rotor power angle must also be measured. The power angle is obtained using the Power Angle Instrument (PAI) developed by EPRI and the Arizona Public Service Company [66]. In addition, generator three-phase output power is also measured using a watt-transducer. Using this test setup, both small excitation reference voltage disturbances and large disturbances can be performed. An external input, $\Delta V_{\text{ref}}$, in Figure 5.1 is used to initiate the disturbances. For small excitation disturbance testing, the magnitude of $\Delta V_{\text{ref}}$ should be between 2% and 5% of $V_{\text{ref}}$. However, for large excitation disturbance testing, the magnitude of $\Delta V_{\text{ref}}$ should approximately be between 17% and 25% of $V_{\text{ref}}$.

![Single-line connection diagram for the 7.5 kVA synchronous generator under test](image)

Figure 5.1: Single-line connection diagram for the 7.5 kVA synchronous generator under test
5.3 Data Transformation

It should be noted that by using the rotor power angle $\delta$, it is possible to transform stator voltages and currents from the $abc$ frame of reference to the $dq$ axes. The following equations may be derived to facilitate this transformation [8,13]. All quantities are instantaneous and in actual units. Before transforming stator voltages and currents to the $dq$ reference frame, it is important to recognize that the following transformations are only valid if the stator voltages and currents are in the positive $abc$ sequence and not in the negative ($acb$) sequence. Also, it is not necessary to transform the field-voltage and field-current.

\begin{align*}
V_t &= \sqrt{\frac{v_a^2 + v_b^2 + v_c^2}{4.5}} \quad \text{volt} \\
i_t &= \sqrt{\frac{i_a^2 + i_b^2 + i_c^2}{1.5}} \quad \text{amp} \\
P &= i_a v_{ab} - i_c v_{hc} \quad \text{watt}
\end{align*}

(5.1)  
(5.2)  
(5.3)
\[ Q = \frac{v_{ab}i_c + v_{bc}i_a + v_{ca}i_b}{\sqrt{3}} \quad \text{VAR} \quad (5.4) \]

\[ v_d = v_t \sin \delta \quad \text{volt} \quad (5.5) \]

\[ v_q = v_t \cos \delta \quad \text{volt} \quad (5.6) \]

\[ i_d = \frac{P \sin \delta + Q \cos \delta}{1.5v_t} \quad \text{amp} \quad (5.7) \]

\[ i_q = \frac{P \cos \delta - Q \sin \delta}{1.5v_t} \quad \text{amp} \quad (5.8) \]

Also, total power in the \( dq \) reference frame can be calculated using the equations:

\[ P = \frac{3}{2}(v_di_d + v_qi_q) \quad \text{watt} \quad (5.9) \]

\[ Q = \frac{3}{2}(v_qi_d - v_di_q) \quad \text{VAR} \quad (5.10) \]

5.4 Data Validation

5.4.1 Validation of Instantaneous \( dq \) Reference Frame Voltages and Currents

Equations (5.1) through (5.8) may be used to transform the \( abc \) reference frame voltages and currents to corresponding quantities in the \( dq \) reference frame. Next, equations (5.9) and (5.10) may be used to calculate real and reactive powers in the \( dq \) reference frame which can then be compared against measured real and reactive powers.

5.4.2 Approximate Validation of Power Angle Using Steady-State Generator Model

Using the voltage behind transient reactance model, the following equation may be used to compute the voltage behind the transient reactance, \( E \), and the power angle, \( \delta \), at steady state conditions.
\[ E \angle \delta = V_\phi \angle 0 + I_\phi \angle \theta (R_a + jX_s) \text{ volt} \quad (5.11) \]

In equation (5.11), \( V_\phi \) represents the measured rms value of generator line-to-neutral voltage, and \( I_\phi \) represents the measured rms value of generator line-current. Also, the power factor angle \( \theta \) can be computed (not measured) as the phase difference between \( V_\phi \) and \( I_\phi \). The calculated value of \( \delta \) is compared against the measured value.

It should be noted that the above is only an approximate validation because equation (5.11) includes the armature resistance \( R_a \), and the synchronous reactance \( X_s \). Both values are approximated from estimates obtained during SSTR testing of the 7.5 kVA generator as described in reference [8]. The synchronous reactance \( X_s \) is computed using linear mutual inductances \( L_{ad} \) or \( L_{aq} \) as follows:

\[ X_s = X_d = X_q = 2 \pi \times 60 \left( L_{ad} + L_l \right) \text{ ohm} \quad (5.12) \]

The assumption \( L_{ad} \approx L_{aq} \) is purely an approximation. In reality, owing to machine saturation \( L_{ad} \) and \( L_{aq} \) will depend on machine operating condition and may not necessarily be equal.

5.4.3 Validation of Field Current at Steady-State

At steady state, the stator voltage equations of the synchronous generator may be compactly expressed as:

\[ Y = H \cdot \Theta \quad (5.13) \]

where vectors \( Y, \Theta \) and matrix \( H \) are defined below:
\[ Y = [v_d, v_q]^T; \]
\[ H = \begin{bmatrix}
-i_d & 0 & \omega \cdot i_q & 0 \\
-i_q & \frac{2}{3} \omega \cdot i_{fd} & 0 & \omega \cdot i_d \\
\end{bmatrix}; \]
\[ \Theta = [R_a, a \cdot L_{ad}, L_q, L_d]^T; \]

In the above formulation all quantities in \( Y \) and \( H \) are instantaneous quantities and in actual units. The components of parameter vector \( \Theta \) are also given in actual units, and are obtained from standstill testing of the 7.5 kVA generator as described in [8]. By incorporating measured currents \( i_d, i_q, \) and \( i_{fd} \) into matrix \( H, \) stator voltages \( v_d, v_q \) are computed using equation (5.13) which are then compared against corresponding experimental voltages obtained by using equations (5.5) and (5.6). It must be emphasized that this validation procedure is again an approximation because standstill parameter estimates are used in vector \( \Theta. \) Under on-line conditions, the parameter values in vector \( \Theta \) might deviate from corresponding standstill parameter estimates.

5.5 Measurement Noise and Filtering

Data acquired from testing the synchronous generator on-line is usually noise corrupted. Contributing factors include excitation system AC to DC rectification process, quantization errors in sensors, surrounding electromagnetic interference etc. Figure 5.3 shows sample plots of measured stator voltages and currents with the generator delivering 1000 W of power to the bus at rated field current. Also, Figures 5.4 and 5.5 show plots of other measurements obtained by initiating a small excitation disturbance test at the same operating condition with the magnitude of the perturbation \( \Delta V_{ref} \) equal to 5\% of \( V_{ref}. \) After converting machine terminal measurements to the \( dq \) reference frame, it is clear that there is a significant amount of measurement noise as shown in Figure 5.6. For the purposes of machine modeling and parameter estimation, noise in
the measured signals is filtered using the moving average method. Figure 5.7 shows plots of the filtered measurements. Although the data are still noisy, the noise level is significantly reduced.

Figure 5.3: Measured positive sequence stator voltages and currents
Figure 5.4: Measured synchronous generator field voltage $v_{fd}$ and field current $i_{fd}$

Figure 5.5: Measured power angle $\delta$ and total three-phase-power $P$
Figure 5.6: Transformed stator voltages and currents
Figure 5.7: Filtered machine responses
 CHAPTER 6

MODELING PROCEDURE METHODOLOGY DEVELOPMENT

6.1 Introduction

In Chapter 3, various synchronous machine model representations were presented. The objective of parameter estimation is to accurately estimate the components of the model parameter vector $\theta$. It must be emphasized that injecting white noise into the system to estimate model parameters is not desirable because white noise excites unnecessary system modes. It must be remembered that most power system oscillations are in the frequency range 0.01 Hz. to 100 Hz. Furthermore, the structure of the machine model depends on the operating condition of the machine. For instance, at steady-state and small disturbance conditions, the rotor body circuits are not excited and the machine model is essentially linear. While data measured by performing small disturbance tests contain enough information to estimate armature- and field-winding parameters, the estimation of rotor body parameters is not possible as the rotor body is not excited to yield sufficient estimation information. However, as will be seen, large disturbance data may be used to estimate rotor body parameters.

6.2 Methodology Development

In order to investigate the methodology of using small- and large-disturbance data to recover generator model parameters, a series of simulation studies are conducted. Synthetic data required for parameter estimation purposes are generated by simulating a one-machine-infinite-bus system. The Appendix lists system parameters used to generate synthetic data.
Initially, parameter estimation procedures will be investigated using noise free synthetic data. The objective of these studies is to study the effect of parameter initialization on the estimated parameters. In order to simulate the effects of measurement noise, random gaussian noise with zero mean and unit variance will be added to the noise-free signals. Simulated noise-corrupted measurements will then be used to estimate model parameters. The objective here is to investigate the robustness of the estimation algorithm to measurement noise.

It must be emphasized that the machine model used in the one-machine-infinite-bus simulation is selected depending on the test condition to be simulated. This is because the machine model used in the simulation studies must accurately portray machine behavior during actual test conditions. For instance, to realistically simulate small excitation disturbance test conditions, the assumptions made in Section 3.3 must be implemented in the one-machine-infinite-bus simulation program. i.e., rotor body currents and the rate-of-change of flux linkages must be ignored. Thus, to accurately simulate small excitation disturbance test conditions, a linear machine model must be used. Ideally speaking, there should be no discrepancy between the machine model used in generating synthetic data, and the corresponding machine model used for estimating model parameters. If a linear model is used in generating synthetic data, a linear model must be used for parameter estimation. However, it would be desirable to study the effects of using a comprehensive machine model (including rotor body windings and the rate-of-change of stator flux-linkages) for simulation purposes and a linear machine model for parameter estimation purposes on the estimation results. Therefore, according to the machine models used for synthetic data generation and parameter estimation, several simulation studies are conducted. Section 6.3 describes these studies in greater detail.

It may be recalled from Section 3.2 and 3.4 that for large excitation disturbance tests, no simplifying assumptions were made with regard to the machine model. For simulation purposes, the machine model given in Section 3.2 may be utilized in the one-machine-infinite-bus program
to generate synthetic data. However, owing to analytical tractability, the de-coupled machine
model given in Section 3.4 may be utilized for parameter estimation purposes.

6.3 Estimation of Linear Model Parameters Small Disturbance Operating Data

6.3.1 Linear Model for Synthetic Data Generation

From a practical standpoint, applying the assumptions given in Section 3.3, the machine
can be represented by a linear model (see equation (3.4)) for small excitation disturbance
simulations. As explained in Section 4.2, the parameter vector $\Theta$ of such a linear machine model
can then be estimated recursively using the recursive maximum likelihood algorithm. In order to
illustrate the estimation procedure, consider the simulated measurements shown in Figure 6.1.
These measurements were obtained directly from the one-machine-infinite-bus simulation by
perturbing $\Delta V_{ref}$ by 5% with the generator delivering 2200 W of power to the bus. Figure 6.2
shows a plot of the estimates against the instant of time at which the sampled data is collected.
All parameters have converged to constant values even though the initial parameters are assumed
to be zero. Table 6.1 lists the estimated parameters.

6.3.1.1 Effect of Parameter Initialization on Linear Model Parameters

The effects of model parameter initialization on the estimation results are investigated in
this section. The simulated measurements of Figure 6.1 are processed using the RML algorithm.
However, instead of initializing model parameters to zero, the initial parameters are chosen
randomly from a uniform distribution in the interval $(0,1)$. Figure 6.3 shows a plot of the
parameter estimates and Table 6.2 lists the estimated parameters. Additional studies were
conducted with the initial parameters chosen to be 10 times larger than the corresponding true
values. In all cases, all parameters converged to their true values. It should be emphasized that in
a practical setting, the initial parameters should be chosen judiciously from any information
available apriori. For instance, if model parameters are available from SSTR tests, these may be used as initial values prior to start of the estimation procedure.

6.3.1.2 Effect of Measurement Noise on Linear Model Parameters

In order to study the effects of measurement noise on the RML estimation procedure, noise corrupted measurements are generated by adding zero mean independent white gaussian noise to the noise-free signals. The variance of the noise depends on the signal-to-noise ratio (SNR) being considered. The noise corruption equation is given by

\[ s_n(k) = s(k) + \alpha(k) w(k) \]  \hspace{1cm} (6.1)

where \( s_n \) and \( s \) represent the noise-corrupted and noise-free signals respectively. \( w \) is a random error vector with a gaussian distribution \( N(0,1) \). The terms \( \alpha \) and the signal-to-noise ratio are defined as:

\[ \alpha(k) = \frac{s(k)}{SNR}, \quad SNR = \left[ \frac{\sum_{k=1}^{N} s^2(k)}{\sum_{k=1}^{N} (\alpha(k)w(k))^2} \right]^{1/2} \]

Using the above equations, simulated noise corrupted measurements are generated. These measurements are then processed by the recursive maximum likelihood algorithm to yield estimates of linear model parameters. Figure 6.4 shows simulated measurements obtained with \( SNR = 5000 \). Figure 6.5 shows the recursively estimated parameters plotted against time. Notice that although the measurements are noisy, the parameter trajectories are relatively noise-free. Table 6.3 lists the estimated parameters obtained with measurements obtained at several different SNR levels. Notice that with small amounts of noise (\( SNR \geq 5000 \)), the percentage errors between the actual parameters and corresponding estimated parameters are less than 2%.
However, with large amounts of noise (SNR < 5000), the parameter estimates deviate considerably from corresponding actual values. The results of the study also suggest that the parameter worst affected by measurement noise is the armature resistance, $R_a$. However, if $R_a$ is fixed at its actual value during the estimation procedure, the percentage errors in parameters $aL_{ad}$, $L_q$, and $L_d$ are seen to be considerably smaller. Table 6.4 lists the results with $R_a$ fixed at 0.4205 $\Omega$ during the estimation procedure.

![Graphs showing simulated small disturbance responses](image)

**Figure 6.1**: Simulated small disturbance responses
Figure 6.2: Recursively estimated linear model parameters with all parameters initialized to zero prior to start of estimation procedure

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.4205</td>
<td>0.4205</td>
</tr>
<tr>
<td>$aL_{ul}$</td>
<td>0.0244</td>
<td>0.0244</td>
</tr>
<tr>
<td>$L_u$</td>
<td>0.0490</td>
<td>0.0490</td>
</tr>
<tr>
<td>$L_d$</td>
<td>0.0485</td>
<td>0.0485</td>
</tr>
</tbody>
</table>

Resistance ($\Omega$), Inductance ($H$)

Table 6.1: Linear model parameter estimates with all parameters initialized to zero prior to start of estimation procedure
Figure 6.3: Recursively estimated linear model parameters with random parameter initialization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual</th>
<th>Initial</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.4205</td>
<td>0.7578</td>
<td>0.4205</td>
</tr>
<tr>
<td>$\alpha L_{ad}$</td>
<td>0.0244</td>
<td>0.1270</td>
<td>0.0244</td>
</tr>
<tr>
<td>$L_q$</td>
<td>0.0490</td>
<td>0.0510</td>
<td>0.0490</td>
</tr>
<tr>
<td>$L_d$</td>
<td>0.0485</td>
<td>0.4612</td>
<td>0.0485</td>
</tr>
</tbody>
</table>

Resistance ($\Omega$), Inductance (H)

Table 6.2: Linear model parameter estimates with random parameter initialization
Figure 6.4: Simulated small disturbance responses with additive gaussian noise. SNR = 5000
Figure 6.5: Recursively estimated linear model parameters obtained by processing the simulated measurements of Figure 6.4

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>SNR = 50000:1</th>
<th>SNR = 10000:1</th>
<th>SNR = 5000:1</th>
<th>SNR = 1000:1</th>
<th>SNR = 500:1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
</tr>
<tr>
<td>( R_a )</td>
<td>0.4205</td>
<td>0.4204</td>
<td>0.0238</td>
<td>0.4202</td>
<td>0.0713</td>
<td>0.4143</td>
</tr>
<tr>
<td>( a L_{ad} )</td>
<td>0.0244</td>
<td>0.0244</td>
<td>0.0000</td>
<td>0.0244</td>
<td>0.0000</td>
<td>0.0244</td>
</tr>
<tr>
<td>( L_q )</td>
<td>0.0490</td>
<td>0.0490</td>
<td>0.0000</td>
<td>0.0490</td>
<td>0.0000</td>
<td>0.0490</td>
</tr>
<tr>
<td>( L_d )</td>
<td>0.0485</td>
<td>0.0485</td>
<td>0.0000</td>
<td>0.0485</td>
<td>0.0000</td>
<td>0.0482</td>
</tr>
</tbody>
</table>

Resistance (\( \Omega \)); Inductance (\( H \))

Table 6.3: Linear model parameter estimates with noise corrupted measurements
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>SNR = 50000:1</th>
<th>SNR = 10000:1</th>
<th>SNR = 5000:1</th>
<th>SNR = 1000:1</th>
<th>SNR = 500:1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$aL_{ref}$</td>
<td>0.0244</td>
<td>0.0244 0.0000</td>
<td>0.0244 0.0000</td>
<td>0.0244 0.0000</td>
<td>0.0236 3.2786</td>
<td>0.0224 8.1967</td>
</tr>
<tr>
<td>$L_q$</td>
<td>0.0490</td>
<td>0.0490 0.0000</td>
<td>0.0490 0.0000</td>
<td>0.0490 0.0000</td>
<td>0.0490 0.0000</td>
<td>0.0490 0.0000</td>
</tr>
<tr>
<td>$L_d$</td>
<td>0.0485</td>
<td>0.0485 0.0000</td>
<td>0.0485 0.0000</td>
<td>0.0483 0.4123</td>
<td>0.0451 7.0103</td>
<td>0.0402 17.113</td>
</tr>
</tbody>
</table>

Resistance (Ω); Inductance (H)

Table 6.4: Linear model parameter estimates with noise corrupted measurements. $R_q$ fixed during estimation

6.3.2 Comprehensive Model for Synthetic Data Generation

In this study, rotor body windings are included in the machine model used to generate synthetic data. Also included are the rate-of-change of stator flux-linkages, i.e., the machine model presented in Section 3.2 is used in the one-machine-infinite-bus program to generate synthetic data for parameter estimation purposes. As before, a linear model is used for parameter estimation purposes.

Simulated measurements are generated by perturbing the excitation reference voltage, $\Delta V_{ref}$, by 5% with the generator delivering 2200W of power at rated terminal voltage. These measurements are subsequently processed by the RML algorithm to yield estimates of linear model parameters. Table 6.5 summarizes results obtained for different three levels of $\Delta V_{ref}$ with the generator delivering 2200 W of power at rated terminal voltage. Results indicate that the percentage errors between the actual parameters and the estimated linear model parameters are quite significant. These errors should be attributed to discrepancies between the simulation model (model used to generate synthetic data in the one-machine-infinite-bus simulation) and the estimation model (linear model). Also, the percentage errors gradually reduce with reduction in the magnitude of $\Delta V_{ref}$. With $\Delta V_{ref} = 1\%$ of $V_{ref}$ the rotor body currents are so small that a linear model is sufficient to approximate generator dynamics. No further improvement in estimation
performance could be achieved by further reducing the magnitude of $\Delta V_{ref}$. Also, the parameter with the largest percentage error is the armature resistance, $R_a$. RML estimation studies were repeated with $R_a$ fixed at its actual value of 0.4205 $\Omega$. Table 6.6 presents a summary of the results obtained. Comparing the results presented in Tables 6.5 and 6.6, it is seen that the percentage errors between the actual and estimated parameters can be significantly reduced by holding $R_a$ at its actual value during the estimation procedure.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>$\Delta V_{ref} = 5 %$</th>
<th>$\Delta V_{ref} = 3 %$</th>
<th>$\Delta V_{ref} = 1 %$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
</tr>
<tr>
<td>$R_a$</td>
<td>0.4205</td>
<td>1.2670</td>
<td>-201.30</td>
<td>1.1787</td>
</tr>
<tr>
<td>$aL_{rad}$</td>
<td>0.0244</td>
<td>0.0295</td>
<td>-20.901</td>
<td>0.0285</td>
</tr>
<tr>
<td>$L_q$</td>
<td>0.0490</td>
<td>0.0510</td>
<td>-4.0816</td>
<td>0.0508</td>
</tr>
<tr>
<td>$L_d$</td>
<td>0.0485</td>
<td>0.0662</td>
<td>-36.949</td>
<td>0.0626</td>
</tr>
</tbody>
</table>

Table 6.5: Linear model parameter estimates for different $\Delta V_{ref}$ levels. Comprehensive machine model used to generate synthetic data.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>$\Delta V_{ref} = 5 %$</th>
<th>$\Delta V_{ref} = 3 %$</th>
<th>$\Delta V_{ref} = 1 %$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
</tr>
<tr>
<td>$aL_{rad}$</td>
<td>0.0244</td>
<td>0.0250</td>
<td>-2.4590</td>
<td>0.0238</td>
</tr>
<tr>
<td>$L_q$</td>
<td>0.0490</td>
<td>0.0490</td>
<td>0.0000</td>
<td>0.0490</td>
</tr>
<tr>
<td>$L_d$</td>
<td>0.0485</td>
<td>0.0509</td>
<td>-4.9484</td>
<td>0.0458</td>
</tr>
</tbody>
</table>

Table 6.6: Linear model parameter estimates for different $\Delta V_{ref}$ levels. Comprehensive machine model used to generate synthetic data. $R_a$ fixed during estimation.
6.4 Estimation of Rotor Body Parameters

In order to estimate rotor body parameters, it is necessary to excite machine rotor body circuits so as to yield sufficient information for parameter estimation purposes. In a laboratory environment, large excitation disturbance tests may be conducted to excite the rotor body circuits. To investigate the feasibility of estimating rotor body parameters, simulation studies are conducted with the generator operating in a one-machine-infinite-bus environment. It should be noted that variations in machine speed, rate-of-change of stator flux-linkages cannot be neglected during large disturbances. For simulation purposes, the machine model given in Section 3.2 is utilized in the one-machine-infinite-bus program to generate synthetic data. However, the decoupled machine model given in Section 3.4 is utilized for parameter estimation purposes.

Figure 6.6 shows a plot of simulated measurements obtained by perturbing generator excitation reference voltage $\Delta V_{ref}$ by 15% with the generator delivering 2200 W of power to the bus. In order to de-couple the $d$- and $q$-axis equivalent circuits, the procedure described in Section 3.4 is utilized to compute voltages $v_d^*$ and $v_q^*$ (see Figure 6.7). The de-coupled machine model is formulated according to equations (3.10) and (3.11). Parameter vectors $\theta_d$ and $\theta_q$ can then be estimated independently using a record of voltages $v_d^*$, $v_q^*$, $v_{fd}$, and currents, $i_d$, $i_q$, $i_{fd}$. Note that although the $d$- and $q$-axis rotor body currents are available directly from the one-machine-infinite-bus simulation, they cannot be measured in a practical setting. Therefore, $\theta_d$ and $\theta_q$ have to be estimated in the absence of information pertaining to the rotor body currents. To estimate $\theta_d$ and $\theta_q$, a batch Output Error Method (OEM) is used to process a block of input/output data over a given time period. Figure 6.8 shows a block diagram of the estimation process. Vectors $U_d$, $Y_d$, $U_q$, and $Y_q$ comprise simulated voltages and currents obtained during large disturbances and are defined in equations (3.10) and (3.11) respectively. The OEM
algorithm iteratively minimizes the error between vectors \( Y_i \) and \( \hat{Y}_i \) (\( i = d- \) or \( q \)-axis) and requires a set of initial model parameters. Since estimates of \( R_a, L_l, L_{ad}, L_{aq}, R_{fd}^*, \) and \( a \) are available from small excitation disturbance studies, they can be kept at fixed values during the OEM estimation. However, good initial values are required for the remaining rotor body parameters. In this study, the \( d \)-axis rotor body parameters are initialized randomly with values chosen from a uniform distribution over the interval \((0,1)\). However, initializing the \( q \)-axis rotor body parameters in a similar manner did not result in convergence. In order to overcome the convergence problem, all \( q \)-axis rotor body parameters were initialized to 1.2 times their actual values. It must be realized that in a practical setting, rotor body parameters may be initialized at values estimated from conventional standstill tests, or from design data provided by the machine manufacturer. Using the block of input/output data given in Figures 6.6 and 6.7, the OEM algorithm is used to estimate the \( d \)- and \( q \)-axis rotor body parameters. Tables 6.7 and 6.8 summarize the estimation results.

6.4.1 Effect of Measurement Noise on Rotor Body Parameters

To study the influence of measurement noise on the rotor body parameter estimates, noise corrupted measurements are generated by adding zero mean independent white gaussian noise to simulated large disturbance responses. The noise corruption equation is given by equation (6.1). Simulated large disturbance responses are obtained by adding noise of varying SNR levels to the noise-free signals of Figure 6.6. After applying the procedure to de-couple the \( d \)- and \( q \)-axis equivalent circuits, the OEM algorithm is used to estimate the rotor body parameters. Tables 6.9 and 6.10 summarize the estimated rotor body parameters for simulated noise corrupted large disturbance responses obtained at various SNR levels. Parameters \( R_a, L_l, L_{ad}, L_{aq}, R_{fd}^* \) and \( a \) are kept fixed at values listed in Tables 6.7 and 6.8 during the estimation procedure. In addition, all 59
rotor body parameters are initialized to values shown in Tables 6.7 and 6.8. Results indicate that it is possible to estimate the $d$-axis rotor body parameters with a significant degree of accuracy even with SNRs as low as 50:1. However, the influence of measurement noise is more pronounced on the $q$-axis rotor body parameters where the percentage errors are significantly larger than corresponding errors in the $d$-axis rotor body parameter estimates.

Figure 6.6: Simulated large disturbance responses
Figure 6.7: Simulated voltages $v_d$ and $v_q$

$\theta_d = [R_d, R_m, R_{sh}, L_d, L_q, L_{ld}, L_{lq}, L_{f}, L_{fq}]^T$; $\theta_q = [R_q, R_{sq}, R_{qf}, L_q, L_{dq}, L_{d}, L_{dq}, L_{dq}]^T$:

$d$-axis parameter estimation

$q$-axis parameter estimation

Figure 6.8: Illustrating decoupled estimation of $d$- and $q$-axis model parameters
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual</th>
<th>Initial</th>
<th>Estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.4205</td>
<td>0.4205</td>
<td>[0.4205]</td>
</tr>
<tr>
<td>$R_{id}$</td>
<td>0.8792</td>
<td>0.7361</td>
<td>0.8792</td>
</tr>
<tr>
<td>$R_{f/id}$</td>
<td>184.70</td>
<td>0.3282</td>
<td>184.70</td>
</tr>
<tr>
<td>$R_{pl}$</td>
<td>1.3336</td>
<td>1.3336</td>
<td>[1.3336]</td>
</tr>
<tr>
<td>$L_l$</td>
<td>0.0011</td>
<td>0.0011</td>
<td>[0.0011]</td>
</tr>
<tr>
<td>$L_{ad}$</td>
<td>0.0474</td>
<td>0.0474</td>
<td>[0.0474]</td>
</tr>
<tr>
<td>$L_{ld}$</td>
<td>0.0504</td>
<td>0.7564</td>
<td>0.0504</td>
</tr>
<tr>
<td>$L_{f/ad}$</td>
<td>2.0568</td>
<td>0.9910</td>
<td>2.0568</td>
</tr>
<tr>
<td>$L_{f/d}$</td>
<td>0.3412</td>
<td>0.6326</td>
<td>0.3412</td>
</tr>
<tr>
<td>$L_{f/ld}$</td>
<td>0.0000</td>
<td>0.3653</td>
<td>0.0000</td>
</tr>
<tr>
<td>$a$</td>
<td>0.5154</td>
<td>0.5154</td>
<td>[0.5154]</td>
</tr>
</tbody>
</table>

Resistance ($\Omega$), Inductance (H)
[] indicates parameter was kept constant during estimation

Table 6.7: Estimated $d$-axis model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual</th>
<th>Initial</th>
<th>Estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_u$</td>
<td>0.4205</td>
<td>0.4205</td>
<td>[0.4205]</td>
</tr>
<tr>
<td>$R_{iq}$</td>
<td>0.6434</td>
<td>0.7721</td>
<td>0.6434</td>
</tr>
<tr>
<td>$R_{2iq}$</td>
<td>2.3579</td>
<td>2.8294</td>
<td>2.3579</td>
</tr>
<tr>
<td>$R_{3iq}$</td>
<td>2.6992</td>
<td>3.2390</td>
<td>2.6992</td>
</tr>
<tr>
<td>$L_l$</td>
<td>0.0011</td>
<td>0.0011</td>
<td>[0.0011]</td>
</tr>
<tr>
<td>$L_{uiq}$</td>
<td>0.0479</td>
<td>0.0479</td>
<td>[0.0479]</td>
</tr>
<tr>
<td>$L_{iq}$</td>
<td>0.0042</td>
<td>0.0050</td>
<td>0.0042</td>
</tr>
<tr>
<td>$L_{2iq}$</td>
<td>0.0007</td>
<td>0.0008</td>
<td>0.0007</td>
</tr>
<tr>
<td>$L_{3iq}$</td>
<td>0.0231</td>
<td>0.0277</td>
<td>0.0231</td>
</tr>
</tbody>
</table>

Resistance ($\Omega$), Inductance (H)
[] indicates parameter was kept constant during estimation

Table 6.8: Estimated $q$-axis model parameters
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>SNR = 500:1</th>
<th>SNR = 100:1</th>
<th>SNR = 50:1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
</tbody>
</table>

- **R_{ld}**: 0.8792, 0.8792, 0.0000, 0.8792, 0.0000, 0.8789, 0.0341
- **R_{feid}**: 184.70, 184.70, 0.0000, 184.69, 0.0054, 184.69, 0.0054
- **L_{ld}**: 0.0504, 0.0504, 0.0000, 0.0504, 0.0000, 0.0501, 0.5952
- **L_{feid}**: 2.0568, 2.0568, 0.0000, 2.0568, 0.0000, 2.0571, -0.0145
- **L_{d}**: 0.3412, 0.3412, 0.0000, 0.3412, 0.0000, 0.3412, 0.0000
- **L_{fid}**: 0.0000, 0.0000, -0.0000, -0.0000, -0.0000, 0.0000, 0.0000

**Resistance (Ω); Inductance (H)**

Table 6.9: $d$-axis rotor body parameter estimates with simulated noise corrupted data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual value</th>
<th>SNR = 500:1</th>
<th>SNR = 100:1</th>
<th>SNR = 50:1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
<tr>
<td></td>
<td>Est. value</td>
<td>Perc. error</td>
<td>Est. value</td>
<td>Perc. error</td>
</tr>
</tbody>
</table>

- **R_{lq}**: 0.6434, 0.6434, 0.0000, 0.6191, 3.7768, 0.6102, 5.1600
- **R_{2q}**: 2.3579, 2.3579, 0.0000, 2.3572, 0.0297, 2.3501, 0.3308
- **R_{3q}**: 2.6992, 2.6993, -0.0037, 3.2328, -19.768, 3.2330, -19.776
- **L_{lq}**: 0.0042, 0.0042, 0.0000, 0.0041, 2.3809, 0.0032, 21.951
- **L_{2q}**: 0.0007, 0.0007, 0.0000, 0.0007, 0.0000, 0.0004, 42.857
- **L_{3q}**: 0.0231, 0.0231, 0.0000, 0.0283, -22.511, 0.0273, -18.818

**Resistance (Ω); Inductance (H)**

Table 6.10: $q$-axis rotor body parameter estimates with simulated noise corrupted data

### 6.5 Multistage Modeling Procedure

In this section, a three stage parameter estimation procedure is proposed to estimate the components of the model parameter vector $\theta$. 63
**Stage 1: Estimation of Linear Model Parameters:**

The first stage of the estimation process involves the estimation of armature- and field-circuit parameters from small disturbance data. In addition to estimating the armature resistance $R_a$, the mutual inductances $L_{ad}$ and $L_{aq}$ will be estimated along with the field-to-stator turns ratio, $a$, and the field resistance, $R_{fd}$. By conducting small disturbance tests over a wide range of operating conditions, the estimated mutual inductances can be used in the development of generalized saturation models as explained below.

**Stage 2: Development of ANN Saturation Model**

Saturated mutual inductances estimated in the previous stage will be used in the development of a neural network based saturation model. By developing a suitable training pattern, variables representative of machine operating condition will be mapped to experimentally obtained mutual inductances $L_{ad}$ and $L_{aq}$ from Stage 1.

**Stage 3: Estimation and Modeling of Rotor Body Parameters**

Using information from Stages 1 and 2 of the multistage modeling procedure, and data acquired from large disturbance conditions, a procedure to estimate rotor body parameters will be developed. By conducting large disturbance tests over a wide range of operating conditions, possible non-linearities in rotor body parameters with shifts in machine operating point will be investigated. Artificial neural networks will be used to map variables representative of machine operating condition to each non-linear rotor body parameter.

The models developed in each of the above stages must be validated in order to establish confidence in the parameter estimates.
6.6 Estimation of Linear Model Parameters from Experimental Data

As explained in Section 6.3, small disturbance data may be used to estimate armature- and field-circuit parameters. Small disturbance responses are obtained by introducing small perturbations, $\Delta V_{ref}$, in the generator's excitation reference voltage $V_{ref}$. These perturbations should be of the magnitude 2% to 5% of $V_{ref}$. It must be emphasized that small excitation disturbance tests do not significantly alter the operating status of the system, and are fairly easy to conduct even on large utility generators [71].

The machine model utilized for identifying machine linear parameters is given in Section 3.3. The parameter vector given by $\Theta = [R_a \ a \ L_{ad} \ L_q \ L_d]^T$ is estimated recursively by processing stator voltages, $v_d$, $v_q$, and currents, $i_d$, $i_q$, and $i_{fd}$ using the recursive maximum likelihood algorithm outlined in Section 4.2. Utilizing filtered generator responses given in Figure 5.7, the components of vector $\Theta$ are estimated recursively. As shown in Figure 6.9, these estimates are plotted against the instant of time at which the sampled data is collected. All parameters have converged to constant values even though the initial parameters are assumed to be zero. In order to extract the turns-ratio, $a$, from the product $a \cdot L_{ad}$, the following procedure is adopted. Assume $L_I = 3\%$ of $L_d$. Calculate mutual inductances using $L_{ad} = L_d - L_I$ and $L_{aq} = L_q - L_I$. Finally, the turns-ratio $a$ can be computed by dividing the estimated product $(a \cdot L_{ad})$ by the estimated value of $L_{ad}$. The field resistance $R_{fd}^*$ may be computed by dividing the measured steady-state field voltage, $V_{fd}^*$, with the steady-state field current, $I_{fd}^*$. Table 6.11 lists the estimated parameters.
Figure 6.9: Trajectories of recursively estimated model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
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<tr>
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<tr>
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<tr>
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</tr>
<tr>
<td>$\alpha$</td>
<td>1.1971</td>
</tr>
</tbody>
</table>

Resistances (Ω), Inductances (H)

Table 6.11: Linear model parameters estimated from experimental data
CHAPTER 7

ARTIFICIAL NEURAL NETWORK BASED SATURATION MODELING

7.1 Introduction

This chapter presents the results of an artificial neural network based technique to model generator saturation. The effects of excitation level, power angle, and real power generation on generator saturation are included in the modeling process. To illustrate the technique, small excitation disturbance tests are conducted on the 7.5 kVA round-rotor synchronous generator at various levels of excitation and loading. Small excitation disturbance responses are processed by the recursive maximum likelihood algorithm developed in Stage 1 of the estimation process to yield estimates of mutual inductances $L_{ad}$ and $L_{aq}$ at each operating condition. By developing a suitable training pattern, variables representative of generator operating condition are mapped to mutual inductances $L_{ad}$ and $L_{aq}$. The developed models are validated with measurements not used in the training process and with large disturbance responses.

7.2 Estimation of Saturated Mutual Inductances

Using the steps outlined in Stage 1 of the multistage modeling procedure, small excitation disturbance tests are conducted on the 7.5 kVA generator to estimated the saturated mutual inductances $L_{ad}$ and $L_{aq}$ at various levels of excitation and power generation. It is desirable to graphically visualize the variation of $L_{ad}$ and $L_{aq}$ as a function of all machine variables ($v_d$, $v_q$, $i_d$, $i_q$, $v_{fd}^*$, and $i_{fd}^*$) representative of generator operating condition. However, such a visualization is
not possible because we can only represent this variation in three-dimensions at the most. But if we consider some of the machine variables to be constant, the variation of $L_{ad}$ and $L_{aq}$ can be portrayed in terms of the remaining variables. For instance, Figure 7.1 depicts the variation of $L_{ad}$ and $L_{aq}$ as a function of generator power angle and average field current at the machine's rated terminal voltage. It must be understood that at rated terminal voltage, the field current and the power angle are representative of the operating condition of the generator. At under-excited conditions, when the generator is delivering small amounts of real power, machine saturation is small. However, at large values of field current and power angle when the machine is delivering a substantial amount of real power, the extent of saturation is quite considerable.

Figure 7.1: Variation of saturated mutual inductances as a function of power angle, $\delta$, and field current, $I_{fd}$.
7.3 Neural Network Saturation Model

In this work, artificial neural networks will be used to represent the saturated mutual inductances as functions of operating condition dependent machine variables. In order to develop the ANN saturation models, the input pattern must comprise of variables representative of generator operating condition. In this study, the measurable variables are selected as \( v_d, v_q, i_d, i_q \), and \( i_{fd} \). The field voltage is not included as part of the input pattern because it is simply a scaled version of the field current obtained during small excitation disturbance testing. In this study, the mathematical relationship between the input and output patterns can be described as:

\[
\begin{align*}
L_{adv} &= N_d(v_d \ v_q \ i_d \ i_q \ i_{fd}) \\
L_{aqd} &= N_q(v_d \ v_q \ i_d \ i_q \ i_{fd})
\end{align*}
\] (7.1)

where \( N_d \) and \( N_q \) are non-linear neural network mappings to be established. The subscript \( s \) denotes saturated values of corresponding mutual inductances.

The multi-layer feedforward perceptron used in this study is shown in Figure 7.2 and consists of 5 processing elements in the input layer, corresponding to each generator variable given in equation (7.1). A single processing element in the output layer corresponds to the saturated mutual inductance \( (L_{adv} \text{ or } L_{aqd}) \) being modeled. The number of elements in the hidden layer is arbitrarily chosen depending on the complexity of the mapping to be learnt. A hyperbolic tangent (tanh) transfer function is used in all hidden layer elements, while all elements in the input layer and output layer have linear (1:1) transformations. The backpropagation algorithm is used to train the neural network such that the sum squared error, \( E \), between actual network outputs, \( O \), and corresponding desired outputs, \( \zeta \), is minimized over all training patterns \( \mu \).
After estimating the non-linear mapping \( N_d \) (or \( N_q \)) of equation (7.1) in terms of the neural network, the network output \( L_{uis,est} \) (or \( L_{asq,est} \)) is computed from the 5x1 input vector \( P \) according to the following equation:

\[
L_{uis,est} = W_2 \cdot \text{tanh}(W_1 \cdot P + B_1) + B_2
\]  

(7.3)

where the term \( L_{uis,est} \) denotes the estimated saturated mutual inductance \( (i = d\text{-} or q\text{-axis}) \). \( W_2 \) denotes the matrix of connecting weights from the hidden layer to the output layer. \( W_1 \) is the weight matrix from the input layer to the hidden layer. If there are \( m \) processing elements in the hidden layer, \( W_2 \) is of size \( 1 \times m \), and \( W_1 \) is of size \( m \times 5 \). Bias terms \( B_2 \) and \( B_1 \) are used as connection weights from an input with a constant value of one. \( B_2 \) and \( B_1 \) denote the \( 1 \times 1 \) and \( m \times 1 \) bias vectors from the bias to the output layer, and from the bias to the hidden layer respectively.

The task of training is to determine the matrices \( W_1, W_2 \), and bias vectors \( B_1, B_2 \).

7.4 ANN Saturation Model Development

In this section, a multidimensional non-linear neural network mapping is established to map small excitation disturbance responses to a set of experimentally obtained saturated mutual inductances. Using the identified mutual inductances obtained over various operating conditions as the output pattern, and measured machine responses as the input pattern, the machine saturation model can be established by using two multilayer feedforward ANNs (one for each orthogonal axis) trained by the backpropagation algorithm. Let the input pattern \( P \) be given by:

\[
P = [V_d \ V_q \ I_d \ I_q \ I_{sd}^*]^T;
\]

70
where $V_d, V_q, I_d, I_q, I_{fd}$ represent the per-unitized average values of the orthogonal axis voltages and currents. Also, let the output pattern for each mutual inductance ANN model be the per-unitized $L_{ads}$ and $L_{aqs}$. It should be noted that per-unitized values are used instead of actual values to avoid plasticity problems that can occur during training. For instance, it was recognized that even with small weights in the network, the summations can be very large. The derivatives of the tanh function can be close to zero at large summation values. Since the derivative is a multiplier in the backpropagation weight update equations, learning stops for processing elements with large summation values. This phenomenon wherein the network loses its ability to react to any new data is referred to as plasticity [26].

Figure 7.2: Multilayer feedforward ANN based generator saturation model
In this study, the training set consisted of 42 five-dimensional input patterns for each ANN model. The sum squared error criterion for training was set at 0.01. The number of elements in the hidden layer of the ANN models were established through a trial-and-error procedure. Initially one processing element was used in the hidden layer of each ANN. Using such a 5-1-1 structure, we attempted to train each ANN model but failed to achieve convergence. By gradually increasing the number of elements in the hidden layer, we were able to train the networks such that the sum squared error criterion is met. Convergence could be achieved by using a large number of processing elements in the hidden layer. However there is a danger of over-fitting i.e., the network memorizes the patterns used in training but cannot generalize and respond accurately to previously unseen patterns. Thus, after training, it is necessary to use an independent cross-validation data set comprising of patterns that are not part of the training set. See Figures 7.3 and 7.4. Using a cross-validation set, it is possible to judge whether the networks are able to generalize properly. It must be remembered that the weights of the ANN models are adjusted only during training. Using the above procedure, we found the optimal number of elements in the hidden layer for the $d$- and $q$-axis saturation models to be equal to 5 and 10 respectively.

The performance of the ANN saturation models established above are compared against a cross-validation data set comprising of per-unitized average values of orthogonal axis voltages and currents obtained from small excitation disturbance testing, not previously included in the training set. 20 such patterns are presented to the trained ANN models. The values of mutual inductances estimated by the saturation models are compared with actual values obtained by using the steps outlined in Stage 1 of the multistage modeling procedure outlined in Chapter 6. As shown in Figures 7.5 and 7.6, the ANN saturation models can correctly interpolate between patterns not used in the training process.
ANN SATURATION MODEL

\[ P = [V_d \ V_q \ I_d \ I_q \ I_{qd}]^T ; \]

Back-Propagation Algorithm

Sum squared error
\[ E = \sum_{\mu} (\zeta_\mu - O_\mu)^2 \]

Note:
\[ \zeta = \text{Desired output} \] (i.e., \( L_{ad} \) or \( L_{aq} \))
\[ O = \text{ANN output} \] (i.e., \( \hat{L}_{ad} \) or \( \hat{L}_{aq} \))

Figure 7.3: ANN saturation model training

TRAINED ANN SATURATION MODEL

\[ P = [V_d \ V_q \ I_d \ I_q \ I_{qd}]^T ; \]

Modify ANN structure and retrain

Is \( SSE < \) Tolerance \( \varepsilon \) ?

No

Yes

Implement ANN Saturation Model

Figure 7.4: ANN saturation model cross-validation
Figure 7.5: Actual and ANN estimated mutual inductances for the $L_{a dx}$ saturation model.

Figure 7.6: Actual and ANN estimated mutual inductances for the $L_{aqx}$ saturation model.
7.5 Model Validation

In order to verify the accuracy of the ANN saturation models under large disturbance conditions, two large excitation disturbance tests were conducted. Using measured voltages $v_d$, $v_q$ and $v_{fd}$, the currents $i_d$, $i_q$, and $i_{fd}$ are simulated (see equation (3.1)) and compared against corresponding measured currents. For simulation purposes, it is necessary to consider the rate-of-change of stator flux linkages. Also, the rotor speed variation is to be included in the computation. However, if equation (3.1) is used for simulation purposes, it would involve updating model parameter matrices at every time instant to account for rotor speed variation during large disturbance conditions. In order to avoid this, voltages $v_d^*$ and $v_q^*$ are first computed using equations (3.6) through (3.9), and equation (3.12). Note that in order to compute $v_d^*$ and $v_q^*$, measured responses of stator voltages and currents are to be used along with the stator resistance, $R_a$, estimated from Stage 1 of the modeling process (see equation (3.7)). Next, voltages $v_d^*$, $v_{fd}^*$, are applied as inputs to the $d$-axis machine model as given by equation (3.10) to simulate for the currents $i_d^*$ and $i_{fd}^*$. Similarly, $v_q^*$ is used as input to the $q$-axis machine model (equation (3.11)) to simulate for the current $i_q^*$.

For simulation purposes, the values of mutual inductances used in the machine models are obtained from neural network saturation models developed in the previous section. The values of $R_a$, $R_{fd}$, and $a$ used in the machine model are from Table 6.11. The remaining rotor body parameters are assumed to be equal to values obtained from standstill time-domain testing of the test generator as described in reference [8]. In Figures 7.7 and 7.8, currents recorded during large excitation disturbances are compared with simulated currents. Figure 7.7 corresponds to the case when the generator is delivering 1000W of power with the field under-excited. Figure 7.8 corresponds to the case when the generator is delivering 1750W of power with the field over-excited. Both tests are conducted at rated voltage.
An inspection of Figures 7.7 and 7.8 reveals that the mutual inductances used in the machine models adequately portray generator steady-state behavior. However, there are discrepancies between measured and simulated currents during the transient. These discrepancies are most likely due to deviations in actual rotor body parameters from corresponding SSTR estimates used in the machine model.

Summarizing the results presented in this chapter, it can be concluded that the estimated ANN saturation models can readily be incorporated into existing transient stability programs to accurately account for generator saturation.

Figure 7.7: Simulated and measured machine responses with generator delivering 1000W of power and field under-excited.
Figure 7.8: Simulated and measured responses with generator delivering 1750W of power and field over-excited
CHAPTER 8

ESTIMATION AND ARTIFICIAL NEURAL NETWORK BASED MODELING OF ROTOR BODY PARAMETERS

8.1 Introduction

Stage 3 of the estimation process involves the estimation of rotor body parameters from measurements collected on-line at several operating conditions. To illustrate the technique, large excitation disturbance tests are conducted on the 7.5 kVA round-rotor synchronous generator at various levels of excitation and loading. The results presented in this chapter indicate that certain rotor body parameters vary in a non-linear manner with shifts in generator operating condition. A novel ANN based technique is presented to map variables representative of generator operating condition to each non-linear rotor body parameter. Finally, the developed models are validated with measurements not used in the training process and with large disturbance responses.

8.2 Estimation of Rotor Body Parameters from Large Disturbance Data

In order to estimate the rotor body parameters, large disturbance tests are to be conducted so as to sufficiently excite the rotor body circuits to yield enough information for parameter estimation. It must be noted that although it may not be possible to conduct large excitation disturbance tests on utility generators owing to system stability considerations, such tests are feasible in a laboratory environment. For utility generators, large disturbance data may be acquired as and when transient events such as transmission line faults, line switching, outages etc.
occur. Large excitation disturbance responses are obtained by introducing large perturbations, \( \Delta V_{\text{ref}} \), in the generator's excitation reference voltage \( V_{\text{ref}} \). These perturbations should be in the range 17\% to 25\% of \( V_{\text{ref}} \).

It must be noted that for estimation purposes, the machine model can be represented by the de-coupled system of equations given by equations (3.10) and (3.11). Notice that although the rotor body circuits are excited during large disturbance conditions, it is not possible to physically measure the rotor body currents. Therefore, not all states of state-vectors \( X_d \) and \( X_q \) are available for measurement. Thus, in the absence of full state measurement, non-linear minimization techniques have to be used in order to estimate model parameters.

For estimation purposes, a batch Output Error Method (OEM) is used to estimate the parameter vector using a block of input/output data over a fixed time period. It must be noted that the form of equations (3.10) and (3.11) allows de-coupled estimation of \( d \)- and \( q \)-axis model parameters. Vectors \( U_d, Y_d, U_q, \) and \( Y_q \) comprise measured voltages and currents obtained during large disturbance conditions and are defined in equations (3.10) and (3.11) respectively.

The OEM estimation algorithm requires a set of pre-determined initial parameters. The SSTR parameters shown in reference [8] are used to initialize the rotor body parameters. It is not necessary to re-estimate the armature-circuit parameters \( \{R_a, L_i, L_{ad}, \text{and } L_{aq}\} \), field resistance \( (R_{fd}^*) \), and the field-to-stator turns-ratio \( (\alpha) \), since accurate estimates were obtained from Stages 1 and 2 of the estimation process. Thus, \( R_a, L_i, L_{ad}, L_{aq}, R_{fd}^* \), and \( \alpha \) are fixed during the OEM estimation. Such a technique helps in preventing unwanted biases in the estimation process which may make it impossible to accurately describe the non-linear effects of the machine.

Table 8.1 illustrates the estimation results obtained by perturbing the excitation reference voltage by 20\% with the generator delivering 2000W of power with the field over-excited. The test was conducted at rated terminal voltage.
As shown in Table 8.1, parameter $L_{fjd}$ is a negative valued number. In recent literature, there have been extensive discussions about the physical significance of this parameter. According to references [64, 78, 79], this inductance represents the flux that links the field and damper winding circuits, but that does not link the field and the stator. In reference [31], Canay attempts to explain how the sign of $L_{fjd}$ depends on the magnetic coupling between the field, damper winding, and stator circuits. In reference [77], Kamwa and Viarouge argue that while the existence of $L_{fjd}$ significantly enhances the modeling of machine dynamic responses, the parameter has no physical significance as such.

To estimate the rotor body parameters, large excitation disturbance tests were conducted over a wide range of excitation levels and loading conditions. The purpose of these studies is to investigate possible variations of rotor body parameters as a function of generator operating condition. Estimation results reveal that rotor body parameters $R_{ld}$, $L_{ld}$, $L_{fjd}$, $R_{iq}$, and $L_{iq}$ are operating condition dependent. No appreciable differences were noticed between the SSTR and on-line parameter estimates of $R_{feld}$, $L_{feld}$, $R_{3q}$, $L_{3q}$, $R_{3q}$, and $L_{3q}$.

8.3 Development of ANN Rotor Body Models

Each non-linear operating-condition dependent rotor body parameter is modeled by an individual ANN. Thus, a total of 6 ANNs are used to model the rotor body parameters. Each ANN model has 2 inputs, 1 output and a single hidden layer comprising of an arbitrary number of processing elements approximated during training. The input pattern to each ANN rotor body model comprises of the real power (in watt) and the power angle (in radian) of the generator. Stator and field voltage/current variables are not included as part of the input pattern because rotor body parameter values are estimated at rated voltage. Hence, the operating condition of the generator at rated voltage is determined uniquely by the real power and the corresponding power angle. The real power is scaled by a factor of 3000 so as to keep each variable of the input pattern
in the same numeric range. The output pattern comprising of 1 processing element is the rotor body parameter to be modeled by the ANN. Thus,

\[
P = [\text{Power} / 3000 \ \delta]^T ;
\]

\[
\theta_{r,\text{est}} = W_2 \cdot \tanh(W_1 \cdot P + B_1) + B_2
\]

The output of the neural network, \(\theta_{r,\text{est}}\) refers to the rotor body parameter estimated by the particular ANN model. \(\theta_{r,\text{est}}\) is in actual units (in ohm or henry) referred to the stator of the synchronous generator.

The non-linear mappings between the ANN input variables and operating condition dependent rotor body parameters are portrayed in Figures 8.1 to 8.3. During the weight-adjustment procedure, the estimated input and output patterns shown in Figures 8.1 to 8.3 are used as training data. The weights and biases of the ANN models are adjusted to minimize the sum squared error between the actual output of the ANN and the desired output. The sum squared error threshold was fixed at 0.001. All ANN models are trained using the backpropagation algorithm.

8.4 Model Validation

In order to verify the accuracy of the established neural network models, two large excitation disturbance tests were conducted. Using measured voltages \(v_d^*, v_q^*\) and \(v_{d^*}\), the currents \(i_d, i_q\) and \(i_{d^*}\) are simulated (see equations (3.10) and (3.11)) and compared against corresponding measured currents. For simulation purposes, the parameter values used in the machine models are obtained from neural network models developed in the previous sections. In Figures 8.4 and 8.5, currents recorded during large excitation disturbances are compared with simulated currents. Figure 8.4 corresponds to the case when the generator is delivering 1007W of power at rated field current. Figure 8.5 corresponds to the case when the generator is delivering
760W of power with the field over-excited. Both tests are conducted at rated voltage. While these figures indicate a good match between corresponding simulated and measured currents, it is important to understand the reason for minor discrepancies between the two currents. The machine model used in this study is only an approximation of the actual round-rotor machine which theoretically has an infinite number of rotor body circuits [31]. The parameters estimated in this study represent the best fit of the machine's operating responses for the particular machine model under consideration. While higher-order model structures could have been used in this research, it is our belief that the amount of effort and expense involved should be justifiable in relation to the dynamics being investigated.

Table 8.2 compares the operating-condition dependent rotor body parameters estimated by the output-error algorithm and the established ANN rotor body models for the two data sets described above. These results indicate that the ANN models can correctly interpolate between patterns not used in the training process.

8.5 Discussion

The machine described in this study is a laboratory generator. Although only excitation disturbance data is utilized in this research study, it is believed that additional data sets obtained from load rejection tests, sudden short-circuit tests etc. may also be utilized in order to yield more accurate rotor body ANN models. For large utility generators, data acquired from disturbances caused by transient events such as line-switching, transmission line-faults, outages etc. may be included in the training set.

The modeling technique proposed in this study when applied to large utility generators would facilitate direct implementation of the developed ANN models into synchronous machine dynamic simulation programs for use in transient stability studies with minimal program alteration effort. Furthermore, the proposed technique can be used to estimate a trajectory for
each parameter of the machine model, as the machine moves from one operating condition to another. By comparing the latest estimate of a parameter with an earlier trajectory of the same parameter, it may be possible to detect particular types of incipient faults [67]. This is because any deviations in machine model parameters from normal trajectories will have embedded causes in them such as aging, field-winding inter-turn shorts etc.

<table>
<thead>
<tr>
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<th>q-axis</th>
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<td>Parameter</td>
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<td>$a$</td>
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Resistance (Ω), Inductance (H)
[] indicates parameter was kept constant during estimation

Table 8.1 Estimated model parameters with generator delivering 2000 W of power at rated voltage with field over-excited
<table>
<thead>
<tr>
<th>Parameter</th>
<th>OEM Estimate</th>
<th>ANN Estimate</th>
<th>% Error</th>
<th>OEM Estimate</th>
<th>ANN Estimate</th>
<th>% Error</th>
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<td>-1.6807</td>
<td>0.0056</td>
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<td>5.3571</td>
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</table>

Resistance (Ω), Inductance (H)

Table 8.2: Comparison of rotor body parameters estimated by the OEM algorithm and ANN rotor body models
Figure 8.1: Transfer functions of $R_{ud}$ and $L_{ud}$ ANN models
Figure 8.2: Transfer functions of $L_{fl}$ and $L_{f1d}$ ANN models
Figure 8.3: Transfer functions of $R_{1q}$ and $L_{1q}$ ANN models
Figure 8.4: Simulated and measured generator currents with the generator delivering 1007W of power at rated field current

Figure 8.5: Simulated and measured generator currents with the generator delivering 760W of power with over-excited field
CHAPTER 9

NEURAL NETWORK OBSERVERS FOR ESTIMATION OF UNMEASURABLE ROTOR BODY CURRENTS FROM ON-LINE RESPONSE DATA

9.1 Introduction

Measurements acquired during synchronous generator testing are often a small subset of the synchronous generator state vector. In the absence of information pertaining to the generator's unmeasurable states (such as currents in the rotor body circuits), estimation algorithms based on non-linear minimization techniques have to be used to estimate machine model parameters. However, if complete state information is available, recursive algorithms may be used to estimate model parameters.

Observers have often been used to estimate state information by processing available measurements. Investigators have developed various observers for estimating the state vector of a synchronous generator [72-75]. Neural networks, with their parallel processing abilities provide a viable means for re-constructing, in real time, the synchronous generator's state vector from a set of measurements. In this chapter, two neural network based techniques will be developed to map synchronous generator measurements to unmeasurable generator rotor body currents. The first technique will be based on a linear model of the generator. While the application of the linear model represents a simplified mapping of the terminal measurements to the rotor body currents, the results will provide necessary insight on neural network structure, choice of network inputs, observer robustness to noise etc. The second technique will be based on a non-linear model of the
generator wherein machine model parameters are non-linear functions of generator operating condition. The task of the observer in this case is to account for model parameter non-linearities and provide accurate estimates of rotor body parameters irrespective of generator operating condition. Observer robustness towards noise and parameter variation will be investigated and enhanced through simulation studies. Finally, the observers will be tested with experimentally obtained data to provide estimates of unmeasurable rotor body currents. These estimates will then be used with experimental measurements to recursively estimate synchronous generator parameters.

9.2 Problem Formulation

In Section 3.4, a de-coupled system of equations was formulated to model the generator for large disturbance conditions. Assuming that each de-coupled system is observable, the unmeasurable states at any instant of time can be estimated by processing sequences of available measurements. i.e., there is a strong correlation between measurable and unmeasurable states. Neural networks provide a suitable means of extracting this underlying correlation by learning from synthetic data generated through perturbation of an assumed machine model with known parameters. During training, all state variables of the machine model are assumed measurable. This would correspond to a stage when simulations are carried out to obtain a sufficiently accurate observer model. The trained observers may then be implemented on-line to estimate rotor body currents by processing measurements acquired in an actual operating environment.

In order to apply ANNs for the observation task, the following issues are to be examined:

- Define a suitable set of observer input patterns for the observation task. What should the training pattern be?
- Is the observer robust to small deviations in synchronous generator parameters?
- Is the observer robust to noisy measurements?
9.3 Artificial Neural Network Based Estimation of Rotor Body Currents

Looking at equations (3.10) and (3.11), a set of observers is proposed (one for each orthogonal axis) which can map sequences of measurable voltages, currents, and flux-linkages to unmeasurable rotor body currents. Let the vector of rotor body currents at any instant of time $k$ be denoted by $\zeta(k)$. Also, let $\xi(k)$ be the vector comprising of sequences of measurable voltages, currents, and stator flux-linkages. For the $d$-axis state-space representation of Model 3.3 whose dynamics are represented by equation (3.10):

$$
\begin{align*}
\xi(k) &= [v_d^*(k), v_{fd}(k), i_d(k), i_{fd}(k), \lambda_d(k)]^T; \\
\zeta(k) &= [i_d(k), i_{fd}(k)]^T.
\end{align*}
$$

A similar set of vectors may be formulated for the $q$-axis ANN observer. The $l_j$'s denote arbitrary lags from time instant $k$ and are approximated during through cross-correlation studies between measurable and unmeasurable machine variables, or during neural network development. If the values of $l_j$ are too small, there might be incomplete observation of system states, while choosing large values of $l_j$ ensures that all the information needed to estimate rotor body currents is available, possibly in a redundant (but consistent) form. We wish to train our neural network observers such that

$$
\zeta(k) = N(\xi(k))
$$

where $N(\cdot)$ is the neural network mapping that gives the best estimate of $\zeta$ for all $k$. All quantities in equation (9.2) are given in actual units. As shown in Figure 9.1 (a), the mapping $N(\cdot)$ can be established by presenting sequences of $\xi(k)$ to the input layer of the network and corresponding desired output to its output layer such that a cost function proportional to the error
between the vector of actual rotor body currents, $\zeta(k)$, and the vector estimated rotor body currents (network outputs), $\hat{\zeta}(k)$, is minimized for all $k$. For the $d$-axis observer, $\hat{\zeta}(k)$ is given by:

$$\hat{\zeta}(k) = [\hat{i}_{id}(k) \quad \hat{i}_{f1d}(k)]^T$$  \hspace{1cm} (9.3)

After training, the observer is implemented on-line to produce estimates of rotor body currents by processing measurements obtained during large disturbance transient events. As shown in Figure 9.1 (b), estimates of rotor body currents can then be used with measured input/output vectors, $U$ and $Y$, to estimate model parameters.

![Diagram](image)

**Figure 9.1:** ANN observer training and observer based parameter estimation
9.4 Linear Artificial Neural Network Observers

The methodology for utilizing neural networks for estimating synchronous generator rotor body currents is illustrated by considering the generator model given in equation (3.10) wherein model parameters are fixed at nominal values obtained by SSTR testing of the 7.5 kVA machine as described in reference [8]. The model is observable, linear, and time-invariant. Under such cases, the mapping given by equation (9.2) can be realized using a single-layer linear neural network [76]. Network output \( \hat{\zeta} \) computed from the input vector \( \xi \) using the equation:

\[
\hat{\zeta} = W \cdot \xi \tag{9.4}
\]

The objective of training is to minimize a cost function defined as:

\[
J(W) = \langle \| \zeta - W \cdot \xi \|^2 \rangle \tag{9.5}
\]

The operator \( \| \cdot \| \) represents the euclidean norm of a vector, and \( \langle \cdot \rangle \) represents an averaging operation over the set of patterns. As explained in [76], the matrix \( W \) can be established through linear regression.

9.4.1 Simulation Studies

Extensive simulation studies have been performed to investigate the performance of the proposed ANN observer based parameter estimation technique. In order to generate necessary data required for observer training, testing, and parameter estimation, dynamic simulations are performed on a 7.5 kVA, 60 Hz, 220V, 1800 rpm synchronous generator model connected to an infinite bus through a transmission line. Reference [8] lists machine model parameters used in the simulation.
9.4.1.1 Observer Training

In order to choose a suitable number of lags for use in the input vector of the observer, cross-correlations were calculated between simulated measurable variables \( \dot{v}_d, \dot{v}_{fd}, \dot{i}_d, \dot{i}_{fd}, \) and simulated un-measurable rotor body currents \( i_{ld} \) and \( i_{eld} \). Based on these cross-correlations, the number of lags were set to 1 each. Thus, there are 10 processing elements in the ANN observer's input layer and 2 elements in its output layer (corresponding to \( i_{ld} \) and \( i_{eld} \)). There is no hidden layer. All processing elements have linear activation functions.

Data for training the neural network observer is obtained by initiating a step change of 3% in the prime-mover torque, \( T_{pm} \), when the synchronous generator is delivering approximately 2 kW of power to the infinite bus. The vectors \( \xi(k) \) and \( \zeta(k) \) are formed at each time instant \( k \). The \( d \)-axis ANN observer model is identified by presenting patterns of \( \xi(k) \) and corresponding \( \zeta(k) \) to the input and output layer of the neural network respectively. In this study, 30 ten-dimensional patterns presented at random were used to identify the weight matrix \( W \).

9.4.1.2 Observer Testing

To test the effectiveness of the trained ANN observer in estimating rotor body currents under online conditions, simulated measurements were generated with the machine operating in a one-machine-infinite-bus environment. It should be noted that under practical operating conditions, measurements acquired experimentally will be input to the ANN observer instead of simulated measurements. The test data set is obtained by initiating a step change of 7% in the prime-mover torque when the generator delivering approximately 3.4 kW of power. 5000 test patterns of ten-dimensional input vectors were presented to the network. Figure 9.2 portrays the actual and estimated rotor body currents \( i_{ld} \) and \( i_{eld} \). Percentage errors between the actual and estimated currents are shown in Figure 9.3.

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As a measure of performance, the mean-squared-error between the true rotor body currents (obtained from the one-machine-infinite-bus simulation) and the estimated rotor body currents (ANN observer outputs) is computed:

\[ E = \frac{1}{N} \sum_{k=1}^{N} (i(k) - \hat{i}(k))^2 \text{ amp}^2 \]  

(9.6)

where \( i \) and \( \hat{i} \) correspond to the true and estimated rotor body currents in ampere. Table 9.1 shows the estimation errors in \( i_{ld} \) and \( i_{feld} \) for the test case considered.

<table>
<thead>
<tr>
<th>Rotor body current</th>
<th>( E ) (amp(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( i_{ld} )</td>
<td>3.0816e-10</td>
</tr>
<tr>
<td>( i_{feld} )</td>
<td>3.9184e-11</td>
</tr>
</tbody>
</table>

Table 9.1: Estimation errors for \( d \)-axis ANN observer

9.4.1.3 Observer Based Parameter Tracking

We now investigate the robustness of the observer to synchronous generator parameter deviations, and illustrate its feasibility in tracking machine parameters. As an example, we present the use of the proposed observer in tracking shorted turns in the generator field winding. This is accomplished by tracking the field resistance, \( R_{fd}^* \), and field-to-stator turns ratio, \( a \), from on-line operating data.
Figure 9.2: Actual and estimated rotor body currents

Figure 9.3: Percentage errors between actual and estimated rotor body currents
The performance of the ANN observer in tracking simulated changes in field resistance is investigated by changing $R_{fd}^*$ by about 0.34% from 1.3336 Ω to 1.3291 Ω. With this value of $R_{fd}^*$ and the field-to-stator turns ratio equal to 0.5145 (all other generator parameters equal to values listed in [8]), simulated measurements of $v^*_d, v^*_fd, i^*_d, i^*_fd$, and $\lambda_d$ were generated with a 3% step change in $T_{pm}$ when the generator is delivering 2 kW of power. The vector $\xi$ is then created at each instant $k$ and fed to the input of the ANN observer to produce estimates of rotor body currents $\hat{i}_d(k)$ and $\hat{i}_{fd}(k)$. The estimates of rotor body currents are incorporated into the state vector $X_d$:

$$X_d = [i_d, \hat{i}_d, \hat{i}_{fd}, i_{fd}]^T;$$

This is used along with vector $U_d$ (see equation (3.10)) to estimate all machine parameters by means of the generalized least squares algorithm. Estimation errors are shown in Table 9.2.

Results of the estimation procedure are shown in Table 9.3.

<table>
<thead>
<tr>
<th>Rotor body current</th>
<th>$E$ (amp$^4$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i_{ld}$</td>
<td>2.1481e-05</td>
</tr>
<tr>
<td>$i_{fd}$</td>
<td>4.2415e-08</td>
</tr>
</tbody>
</table>

Table 9.2: Estimation errors with simulated change in $R_{fd}^*$
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Actual</th>
<th>Estimated</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.42050</td>
<td>0.41980</td>
<td>1.6646e-01</td>
</tr>
<tr>
<td>$R_{fd}$</td>
<td>1.32910</td>
<td>1.32880</td>
<td>2.2257e-02</td>
</tr>
<tr>
<td>$R_{ld}$</td>
<td>0.87920</td>
<td>0.87900</td>
<td>2.2747e-02</td>
</tr>
<tr>
<td>$R_{fld}$</td>
<td>184.700</td>
<td>185.39</td>
<td>-3.7358e-01</td>
</tr>
<tr>
<td>$L_{l}$</td>
<td>0.00110</td>
<td>0.00110</td>
<td>0.0000e+00</td>
</tr>
<tr>
<td>$L_{ad}$</td>
<td>0.04740</td>
<td>0.04741</td>
<td>-2.1097e-02</td>
</tr>
<tr>
<td>$L_{fd}$</td>
<td>0.34120</td>
<td>0.34320</td>
<td>-5.8616e-01</td>
</tr>
<tr>
<td>$L_{ld}$</td>
<td>0.05040</td>
<td>0.05041</td>
<td>-1.9841e-02</td>
</tr>
<tr>
<td>$L_{fld}$</td>
<td>2.05680</td>
<td>2.06610</td>
<td>-0.4521e-01</td>
</tr>
<tr>
<td>$a$</td>
<td>0.51450</td>
<td>0.51465</td>
<td>-2.9154e-02</td>
</tr>
</tbody>
</table>

Resistance ($\Omega$), Inductance (H)

Table 9.3: Actual and estimated $d$-axis model parameters with simulated change in $R^*_{fd}$

9.4.1.4 Experiments with Noise

To investigate the effect of noise on ANN observer performance, noise corrupted measurements generated by adding zero mean independent white gaussian noise to noise-free signals, are applied to the ANN observer. Using equation (6.1), simulated noise corrupted measurements are generated and applied to the input of the trained ANN observer. As shown in Table 9.4, with low levels of SNR the performance of the ANN observer (designated Observer #1) deteriorates significantly.

One method of improving observer robustness is to increase the number of measurement delays used in the ANN observer input vector, $\xi$. Increasing the number of delays creates redundant information in the vector $\xi$ which helps in increasing its resistance to noise. Two additional observer models are considered. Observer #2 has 20 elements in its input layer (i.e., number of delays in $v^*_d, v^*_{fd}, i_d, i^*_d$ and $\lambda_d$ were set to 3 each). Observer #3 has 85 elements in its input layer (i.e., number of delays in $v^*_d, v^*_{fd}, i_d, i^*_d$ and $\lambda_d$ were set to 16 each). Following the
procedure explained earlier, both observer models are trained and tested with noise corrupted measurements. Results of the study are shown in Table 9.4.

<table>
<thead>
<tr>
<th>SNR</th>
<th>Observer #1</th>
<th>Observer #2</th>
<th>Observer #3</th>
</tr>
</thead>
<tbody>
<tr>
<td>No noise</td>
<td>7.5874e-10</td>
<td>2.6411e-10</td>
<td>2.9574e-10</td>
</tr>
<tr>
<td>50000:1</td>
<td>8.5688e-04</td>
<td>2.7819e-04</td>
<td>2.8294e-06</td>
</tr>
<tr>
<td>25000:1</td>
<td>3.4600e-03</td>
<td>3.2547e-03</td>
<td>6.5332e-05</td>
</tr>
<tr>
<td>12500:1</td>
<td>1.3353e-02</td>
<td>1.6297e-03</td>
<td>9.8043e-05</td>
</tr>
<tr>
<td>5000:1</td>
<td>8.7576e-02</td>
<td>1.0064e-02</td>
<td>6.8115e-05</td>
</tr>
<tr>
<td>1000:1</td>
<td>2.1975e+00</td>
<td>2.5409e-01</td>
<td>7.4195e-03</td>
</tr>
<tr>
<td>500:1</td>
<td>8.6047e+00</td>
<td>9.6054e-01</td>
<td>3.0081e-02</td>
</tr>
</tbody>
</table>

Table 9.4: ANN observer performance with noise corrupted measurements

9.5 Non-Linear Artificial Neural Network Observers

In Section 9.4, we showed how linear neural networks can be trained to estimate unmeasurable rotor body currents by processing sequences of measurements acquired during transient disturbances. The work presented in Section 9.4 assumed that nominal machine model parameters are used to generate simulated measurements for observer development. However, the implementation of a linear neural network in an actual operating environment will result in incorrect estimates of rotor body currents. This is because machine model parameters estimated on-line can deviate substantially from corresponding nominal estimates obtained off-line. Indeed, Chapter 8 shows that on-line machine model parameter estimates are non-linear in nature and influenced by generator operating condition.

In view of the above factors, it is imperative to develop ANN observers which can account for model parameter non-linearities and provide accurate estimates of rotor body currents irrespective of generator operating condition over the normal operating range of the generator.
Instead of using nominal machine parameters, data for training the observers are generated through off-line simulations of a machine model whose parameters are varied according to on-line parameter estimates obtained in Chapter 8. The mapping described by equation (9.2) should therefore be non-linear in nature. Instead of using a single neural network observer to estimate the currents $i_{ld}$ and $i_{qld}$, a pair of observers is proposed.

Let $N_{ld}$ represent the mapping from $\xi(k)$ to $i_{ld}(k)$, and let $N_{qld}$ represent the mapping from $\xi(k)$ to $i_{qld}(k)$. i.e.,

$$\begin{align*}
    i_{ld}(k) &= N_{ld}(\xi(k)) \\
    i_{qld}(k) &= N_{qld}(\xi(k))
\end{align*}$$

(9.7)

All quantities in equation (9.7) are given in actual units. $N_{ld}$ and $N_{qld}$ are non-linear in nature. It is desired to establish these mappings by using a pair of multi-layer feedforward perceptrons (one for each rotor body current).

Each multi-layer feedforward perceptron used in this study consists of $n$ processing elements in the input layer, each processing element corresponding to each element of vector $\xi(k)$. A single processing element is used in the output layer of each network corresponding to the rotor body current ($i_{ld}(k)$ or $i_{qld}(k)$) whose mapping is to be established. The number of hidden layers, and the number of processing elements in the hidden layer of each network are established during observer development. The weights and biases of each network are established by presenting patterns of $\xi(k)$ to the input layer and corresponding desired rotor body currents to the output layer of each network so as to minimize the following cost functions:

$$\begin{align*}
    E_{ld} &= \sum_k [i_{ld}(k) - \hat{i}_{ld}(k)]^2 \\
    E_{qld} &= \sum_k [i_{qld}(k) - \hat{i}_{qld}(k)]^2 \\
    \text{amp}^2
\end{align*}$$

(9.8)
In equation (9.8), $E_{ld}$ and $E_{feld}$ represent the sum squared errors (SSE) between actual currents $i_{ld}$, $i_{feld}$ and estimated currents, $\hat{i}_{ld}$, $\hat{i}_{feld}$ produced by each ANN observer respectively. Training is the process of iteratively adjusting the weights of the networks such that the errors $E_{ld}$ and $E_{feld}$ are minimized. Throughout this investigation, the Levenberg-Marquardt backpropagation algorithm is used to train the neural network such that the sum squared errors defined in equation (9.8) are minimized over all training patterns.

After training, the observers are tested with experimentally obtained on-line measurements to provide estimates of unmeasurable rotor body currents. i.e., the elements of vector $\xi(k)$ are obtained experimentally and input to each ANN observer to estimate $\hat{i}_{ld}$, and $\hat{i}_{feld}$. These estimated rotor body currents are then incorporated into the $d$-axis state-vector $X_d$ along with measured currents $i_d$, and $i_{fd}^*$ as:

$$X_d = [i_d \quad \hat{i}_{ld} \quad \hat{i}_{feld} \quad i_{fd}^*]^T$$

The vector $X_d$ along with vector $U_d$ (also obtained from measurement) are processed by the generalized least squares algorithm to estimate the $d$-axis parameter vector.

9.5.1 Observer Development

9.5.1.1 Generation of Training Data

In order to generate necessary data for $d$-axis observer development, equation (3.10) can be simulated to obtain the state vector $X_d$ in response to a pre-specified input vector $U_d$. In order to ensure richness of the training set, inputs $v_d^*$ and $v_{fd}^*$ are chosen to be random gaussian signals with zero mean and unit variance. To ensure that the magnitudes of all measured state variables
are realistic and within the normal operating range of the generator, the field-voltage $v_{fd}^*$ is scaled by a factor of 10. Table 9.5 lists the $d$-axis machine model parameters used to generate training data for the $d$-axis ANN observer. The parameters listed in Table 9.5 were estimated experimentally by conducting large excitation disturbance tests on the 7.5 kVA synchronous generator as explained in Chapter 8.

9.5.1.2 Cross-correlation Analysis

Using the simulated states, cross-correlations were calculated between measurable variables ($v_{d}^*$, $v_{jd}^*$, $i_d$, $i_{jd}$, $\lambda_d$) and un-measurable rotor body currents ($i_{fd}$, $i_{fjd}$). Figure 9.4 shows the cross-correlation between $i_{fd}$ and $i_d$, $i_{fjd}$ for data generated by simulating the machine model with parameters listed under Case 1 in Table 9.5.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
<th>Case 6</th>
<th>Case 7</th>
<th>Case 8</th>
<th>Case 9</th>
<th>Case 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
<td>0.4205</td>
</tr>
<tr>
<td>$R_d$</td>
<td>0.5664</td>
<td>0.4921</td>
<td>0.1044</td>
<td>1.0940</td>
<td>2.1049</td>
<td>2.8168</td>
<td>2.6869</td>
<td>1.6736</td>
<td>1.1041</td>
<td>0.6279</td>
</tr>
<tr>
<td>$R_{kid}$</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
<td>184.70</td>
</tr>
<tr>
<td>$R_{fjd}$</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
<td>0.5589</td>
</tr>
<tr>
<td>$L_i$</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
</tr>
<tr>
<td>$L_{ld}$</td>
<td>0.0200</td>
<td>0.0329</td>
<td>0.0437</td>
<td>0.0345</td>
<td>0.0367</td>
<td>0.0451</td>
<td>0.0341</td>
<td>0.0314</td>
<td>0.0255</td>
<td>0.0294</td>
</tr>
<tr>
<td>$L_{jd}$</td>
<td>0.0257</td>
<td>0.0151</td>
<td>0.1279</td>
<td>0.0555</td>
<td>0.0662</td>
<td>0.1180</td>
<td>0.0077</td>
<td>0.0436</td>
<td>0.0364</td>
<td>0.0145</td>
</tr>
<tr>
<td>$L_{fjd}$</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
<td>2.0568</td>
</tr>
<tr>
<td>$L_{fd}$</td>
<td>0.0200</td>
<td>0.0247</td>
<td>0.0574</td>
<td>0.0533</td>
<td>0.0341</td>
<td>0.0750</td>
<td>0.0352</td>
<td>0.0647</td>
<td>0.0647</td>
<td>0.0605</td>
</tr>
<tr>
<td>$L_{fjd}$</td>
<td>-0.0087</td>
<td>-0.0032</td>
<td>-0.0133</td>
<td>-0.0083</td>
<td>-0.0063</td>
<td>-0.0465</td>
<td>-0.0074</td>
<td>-0.0251</td>
<td>-0.0243</td>
<td>-0.0127</td>
</tr>
</tbody>
</table>

Table 9.5: $d$-axis machine model parameters estimated at ten different operating conditions
Studies reveal the presence of peaks in the cross-correlation functions indicating a high degree of correlation between data separated by the corresponding discrete time-instant. For instance, Figure 9.4 indicates a high degree of correlation between $i_{id}(k)$ and $i_4(k)$, and also between $i_{id}(k)$ and $i_{id}(k)$. Also, the contributions of $i_{id}(k-l)$ and $i_{id}(k-l)$ on $i_{id}(k)$ decrease gradually with an increase in the value of lag $l$ ($l = 1, 2, 3...$). Based on these studies, it is seen that the input vector of the neural network observer can be made sufficiently large to incorporate a large window of delayed measurements. However, if $l$ is made very large, the size of the neural network's input layer will increase proportionally. For instance, if $l = 11$, the number of processing elements in the observer's input layer will be equal to $(11+1) \times 5 = 60$. The issue of sizing the input vector optimally is then based on the concept of parsimony. If the performance of the neural network observer does not show significant improvement with an increase in the size of the input vector, then it is favorable to use a fewer number of delays in the measurable inputs.

9.5.1.3 Observer Training

Using the simulated currents obtained by perturbing the $d$-axis machine model with $v_d$ and $v_{qd}$ as described in Section 9.5.1.1, 10 sets of data were generated corresponding to each case listed in Table 9.5. Each data set is comprised of data corresponding to 100 different time instants. Thus, a total of 1000 input/output patterns are used for presentation to each of the observers for training.

Using the above data sets, vector $\xi(k)$ is formed at each time instant $k$. Initially, $l_1$ through $l_5$ were set equal to 1. Therefore, each observer has 10 elements in the input layer and 1 element in the output layer. Only one hidden layer is used in each network, with the number of hidden layer elements specified arbitrarily during training. The convergence criterion for each ANN observer is set to $1e^{-12}$ amp. Also, the number of elements in the hidden layer of each neural
network is made equal to 2. The parameters of each observer were initialized randomly to small real numbers. For each observer, 1000 input/output patterns were presented during training. However, it was seen that even by progressively increasing the number of hidden layer elements from 2 to 5, it was not possible to train the networks to satisfy the convergence criterion.

Applying a trial-and-error procedure, it was seen that by gradually increasing the number of lags in the input layer to 5 (i.e., \( l_1, l_2, l_3, l_4, \) and \( l_5 = 5 \)), each ANN observer could be trained to satisfy the convergence criterion. The number of processing elements in the hidden layer is chosen arbitrarily during observer development. It was seen that the number of processing elements in the hidden layer of each observer for optimal training is equal to 3. All processing elements in the input and output layers have linear activation functions, whereas all elements in the hidden layer have hyperbolic tangent (tanh) activation functions.

![Figure 9.4: Cross-correlation function between \( i_{td} \) and \( i_d, i_{td}^* \)](image_url)
9.5.2 Robustness Considerations

9.5.2.1 Robustness to Deviations in $L_{ad}$

In order to test the influence of $d$-axis machine saturation on observer performance, simulated test-data sets were generated with $L_{ad}$ varying in increments from 0.01 H to 0.05 H in steps of 0.01 H. All other parameters of the $d$-axis machine model are made equivalent to values listed in Table 9.5, Case 1. Table 9.6 lists the sum-squared-errors between the actual and estimated values of $i_{id}$ and $i_{feda}$ for the data sets under consideration.

<table>
<thead>
<tr>
<th>$L_{ad}$ (H)</th>
<th>SSE in $i_{id}$ (amp$^2$)</th>
<th>SSE in $i_{feda}$ (amp$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0100</td>
<td>7.3588e-09</td>
<td>2.3470e-12</td>
</tr>
<tr>
<td>0.0200</td>
<td>2.1785e-09</td>
<td>8.525e-09</td>
</tr>
<tr>
<td>0.0300</td>
<td>9.7682e-10</td>
<td>3.6611e-15</td>
</tr>
<tr>
<td>0.0400</td>
<td>1.7288e-09</td>
<td>6.3722e-16</td>
</tr>
<tr>
<td>0.0500</td>
<td>1.5852e-09</td>
<td>5.9507e-15</td>
</tr>
</tbody>
</table>

Table 9.6: SSEs in $i_{id}$ and $i_{feda}$ with simulated variations in $L_{ad}$

Next, the ANN estimated rotor body currents are used in a recursive parameter estimation procedure to yield estimates of $d$-axis machine model parameters. The percentage errors between actual and estimated parameter values are computed for each of the eleven $d$-axis parameters for each test case under consideration. Next, the average percentage errors for each parameter are calculated by computing the mean of the percentage error for each parameter obtained over the 5 different test cases listed above. Figure 9.5 shows a bar chart of the average percentage error for each of the eleven $d$-axis model parameters.
9.5.2.2 Robustness to Noise

In order to investigate the effect of measurement noise on the performance of the trained ANN observers, noise corrupted measurements are generated by adding zero mean independent white gaussian noise to the noise free signals. These noise corrupted signals are then applied to the ANN observers. The equation used to generate the noise corrupted signals is given by equation (6.1). The variance of the noise depends on the signal-to-noise ratio (SNR) under consideration.

Simulated noise corrupted measurements of \( v_d^* \), \( v_{fd}^* \), \( i_d \), \( i_{fd} \), and \( \lambda_d \) are then applied (with appropriate lags) to the input layer of the trained ANN observers. The sum squared errors between the actual rotor body currents \( (i_{id}, i_{feid}) \) and the estimated rotor body currents \( (\hat{i}_{id}, \hat{i}_{feid}) \) are used to quantify observer performance. In the following studies, the parameters of the machine model used to generate the simulated data are listed in Table 9.5, Case1. As shown in Table 9.7, with low SNR levels (i.e., large amount of noise), the performance of the ANN observers deteriorate significantly. For the sake of comparison, the SSE for the noise free case is also given.
Figure 9.5: Average percentage errors for each d-axis model parameter

\[ \Theta = [R_a \quad R_{fd}^* \quad R_{ld} \quad R_{feld} \quad L_1 \quad L_{ad} \quad L_{ld} \quad L_{feld} \quad L_{fd} \quad L_{fd} \quad a]^T \]

Table 9.7: SSEs in \(i_{ld}\) and \(i_{feld}\) with different SNR levels in the noise corrupted measurements.  
No. of elements in ANN input layer = 30
As explained in Section 9.4.1.4, observer robustness towards noise can be improved by enhancing the size of the ANN input vector by increasing the number of delays used in the input measurements. Table 9.8 shows the sum squared errors between the actual rotor body currents \((i_{id}, i_{fid})\) and estimated rotor body currents \((\hat{i}_{id}, \hat{i}_{fid})\) by presenting noise corrupted measurements to observers each of which contain 40 elements in their respective input layers (i.e., \(I_1...I_5 = 7\)).

It must be remembered that while the number of measurement delays used in the ANN input vector can be made very large, the complexity of training increases because the number of parameters (weights and biases) to be estimated also increases. Therefore, a trade-off has to be made between the size of the neural network and the accuracy of the results desired. Studies indicate that the SSEs in \(i_{id}\) and \(i_{fid}\) should be no more than \(1e-5 \text{ amp}^2\) and \(1e-6 \text{ amp}^2\) respectively for reasonably accurate parameter estimation purposes (i.e., for the errors in the parameter estimates to be \(\leq 3\%\)).

<table>
<thead>
<tr>
<th>SNR</th>
<th>SSE in (i_{id})(amp(^2))</th>
<th>SSE in (i_{fid})(amp(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>No noise</td>
<td>9.1901e-08</td>
<td>7.1156e-15</td>
</tr>
<tr>
<td>100,000:1</td>
<td>1.0222e-08</td>
<td>2.0431e-09</td>
</tr>
<tr>
<td>50,000:1</td>
<td>1.3562e-07</td>
<td>8.6402e-09</td>
</tr>
<tr>
<td>10,000:1</td>
<td>1.2074e-06</td>
<td>2.2016e-07</td>
</tr>
<tr>
<td>5,000:1</td>
<td>4.2082e-06</td>
<td>8.1252e-07</td>
</tr>
<tr>
<td>1,000:1</td>
<td>1.0417e-04</td>
<td>2.0559e-05</td>
</tr>
<tr>
<td>500:1</td>
<td>4.0772e-04</td>
<td>8.0198e-04</td>
</tr>
<tr>
<td>100:1</td>
<td>1.0728e-02</td>
<td>2.1192e-03</td>
</tr>
</tbody>
</table>

Table 9.8: SSEs in \(i_{id}\) and \(i_{fid}\) with different SNR levels in the noise corrupted measurements. No. of elements in ANN input layer = 40
9.5.2.3 Robustness to Deviations in Field Resistance $R_{\text{fd}}$

In the preceding discussion, the observer was developed to account for variations in $L_{\text{adh}}$, $R_{\text{ldh}}$, $L_{\text{fdh}}$, and $L_{\text{fd}}$. These parameter variations were attributed to changes in machine operating condition. However, the field resistance, $R_{\text{fd}}^*$, and field-to-stator turns-ratio, $\alpha$, were kept unchanged during the course of observer development. It must be mentioned that in an actual machine, one might anticipate $R_{\text{fd}}^*$ to deviate slightly about its average value because of heating in the field-winding. Experimental results indicate that $R_{\text{fd}}^*$ varied in the range 0.5573 $\Omega$ to 0.5594 $\Omega$, with an average value of 0.5589. Thus the percentage variation in $R_{\text{fd}}^*$ is in the range -0.089% to 0.3% about the average value of 0.5589 $\Omega$.

In order to study the effects of variations in $R_{\text{fd}}^*$ on observer performance, simulation studies were conducted by incorporating field resistance variations in the range $\pm$ 0.3% in the test set. It was seen that even with a $\pm$ 0.1% change in the field resistance, the SSEs in $i_{\text{ld}}$ and $i_{\text{field}}$ are approximately 0.5 amp$^2$ and 0.25 amp$^2$ respectively. Judging from the fact that the SSEs for both observers are extremely large, it can be seen that both observers are very sensitive to changes in $R_{\text{fd}}^*$.

In order to make the observers more robust to deviations in field resistance, simulated variations in $R_{\text{fd}}^*$ are introduced into the training sets. For each of the 10 cases listed in Table 9.5, simulated variations of $\pm$ 0.3% in $R_{\text{fd}}^*$ are introduced in the machine model to generate the training set. Therefore, a total of 30 cases were generated, each case comprising of 100 input/output patterns. Hence, the total number of patterns in the training set are equal to 3000. The number of processing elements in the input layer of each ANN observer were set equal to 40. It was seen that to accurately perform the desired mapping, each observer required 8 processing elements in the input layer. After training both observers to account for deviations in field
resistance, simulation studies were conducted to investigate observer performance due to deviations in \( R_{fd}^* \). 11 test cases were considered with \( R_{fd}^* \) varying in the range -0.5% to +0.5% about the average value of 0.5589 \( \Omega \). In addition, two more test cases were considered with \( R_{fd}^* \) deviating by ±1%. The results of the study are presented in Figure 9.6. These results indicate that both observers are accurately able to estimate rotor body currents even with small deviations in field resistance.

Figure 9.6: SSEs in \( i_{fd} \) and \( i_{fd}^{*} \) with simulated variations in \( R_{fd}^* \). Both observers trained by incorporating simulated variations of ±0.3% in \( R_{fd}^* \) in the training set.
9.5.3 Experimental Studies

In order to verify the effectiveness of implementing the developed ANN observers in an experimental setting, large excitation disturbance tests are conducted on the actual 7.5 kVA laboratory generator. Figure 9.7 shows the filtered orthogonal axis responses obtained by perturbing the generator's excitation reference voltage by 20% with the generator operating over-excited and delivering 500 W of power to the bus. The sampling time for data-acquisition purposes is 500 μsec. All responses are filtered to remove measurement noise.

The experimental measurements are input to the trained observers by constructing the vector $\xi$ for each ANN observer according to equation (9.1) where $I_1...I_5 = 7$. Figure 9.8 shows the observed rotor body currents obtained by presenting 7900 sequential patterns of input vectors to each observer. The estimated rotor body currents are then incorporated into the state vector $X_d$ and used along with input vector $U_d$ (see equation (3.10)) to recursively estimate model parameters. Table 9.9 lists the parameter estimates. In order to verify the validity of these estimates, the parameter values listed in Table 9.9 are incorporated into the machine model. Experimental voltages $v_d$ and $v_{\phi d}$ are then applied to the model to obtain simulated currents. These simulated currents are compared with corresponding measured currents and observed rotor body currents as shown in Figure 9.9.
Figure 9.7: Experimentally measured $d$-axis responses
Figure 9.8: Rotor body current estimates produced by $d$-axis ANN observers

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_a$</td>
<td>0.4207</td>
</tr>
<tr>
<td>$R_{td}$</td>
<td>0.5679</td>
</tr>
<tr>
<td>$R_{fstd}$</td>
<td>182.21</td>
</tr>
<tr>
<td>$R^*_{fa}$</td>
<td>0.5588</td>
</tr>
<tr>
<td>$L_I$</td>
<td>0.0010</td>
</tr>
<tr>
<td>$L_{rad}$</td>
<td>0.0203</td>
</tr>
<tr>
<td>$L_{rd}$</td>
<td>0.0261</td>
</tr>
<tr>
<td>$L_{fstd}$</td>
<td>2.0572</td>
</tr>
<tr>
<td>$L_{fa}$</td>
<td>0.0199</td>
</tr>
<tr>
<td>$L_{f1d}$</td>
<td>-0.0073</td>
</tr>
<tr>
<td>$a$</td>
<td>1.1971</td>
</tr>
</tbody>
</table>

Table 9.9: Recursively estimated model parameters
9.6 Conclusions

The results presented in this chapter demonstrate the feasibility of implementing neural network observers to estimate unmeasurable synchronous rotor body currents from sequences of measurements obtained on-line. Experimental studies performed on the 7.5 kVA generator reveal that the estimated rotor body currents are acceptably accurate for use along with on-line responses in recursively estimating model parameters.
10.1 Conclusions

The primary contribution of this research study is the development and implementation of on-line system identification techniques for synchronous generator parameter estimation. These techniques have been verified in a laboratory environment through extensive testing of a 7.5 kVA, 220V, 1800 rpm round-rotor synchronous generator. Based on these studies, the following conclusions are drawn:

1. Small excitation disturbance tests can be conducted to estimate armature circuit parameters, field resistance, and field-to-stator turns ratio. These tests can be conducted even on large utility generators without compromising system stability.

2. The recursive maximum likelihood algorithm which processes small excitation disturbance responses to estimate linear model parameters requires no apriori information about the initial parameter vector. The algorithm is robust and can be implemented on-line to automatically yield estimates of linear model parameters whenever there is a small disturbance.

3. By conducting small excitation disturbances over a wide range of operating conditions, trajectories of mutual inductances $L_{qf}$ and $L_{aq}$ are established over the entire working range of the generator. These trajectories reveal non-linearities in the estimated mutual inductances suggesting that machine saturation is indeed a complex phenomenon involving several machine variables.
4. Artificial neural networks are developed by mapping generator terminal- and field-variables to mutual inductances at various conditions of loading and excitation. Validation and large disturbance studies indicate that these models can correctly estimate mutual inductances over the operating range of the generator. These saturation models can readily be implemented in existing transient stability programs to accurately account for generator saturation.

5. Large disturbance responses yield information pertaining to rotor body parameters. In the laboratory, large disturbance tests were staged by perturbing the excitation reference voltage in the range 17% to 25% of $V_{ref}$. It is realized that due to system stability considerations, it may not be possible to stage such tests on large utility generators. For utility grade machines, digital fault recorders may be used to record machine responses as and when large disturbances such as transmission line faults, outages etc. occur.

6. A novel procedure to de-couple $d$- and $q$-axis equivalent circuit models has been developed. This procedure utilizes measurable $d$- and $q$-axis stator voltages and currents, along with the armature resistance estimated from Stage 1 of the modeling process to estimate the speed-voltage terms. Such a procedure enables de-coupled estimation of machine model parameters from large disturbance data.

7. In order to accurately estimate rotor body parameters, it is necessary to keep certain model parameters at fixed values during the batch OEM estimation procedure. The parameters obtained from Stages 1 and 2 of the estimation process are kept at fixed values and not re-estimated. Only the rotor body parameters are estimated using large disturbance responses.

8. An important conclusion of this research is that certain rotor body parameter values depend on machine operating condition. By conducting large disturbance tests over the entire operating range of the generator, it is possible to establish trajectories for each estimated rotor
body parameter. These trajectories show that rotor body parameters, $R_{td}$, $L_{td}$, $L_{fd}$, $L_{fd}$, $R_{lq}$, and $L_{lq}$ are non-linear functions of operating condition dependent machine variables.

9. Artificial neural networks are used to model the non-linear variation of each rotor body parameter as a function of generator real power, $P$, and power angle, $\delta$. It is seen that these rotor body ANN models can accurately produce estimates of rotor body parameters over the operating range of the generator. The modeling technique proposed in this study when applied to large utility generators would facilitate direct implementation of the developed ANN models into synchronous machine dynamic simulation programs for use in transient stability studies with minimal program alteration effort.

10. Artificial neural networks also provide a practicable means of estimating unmeasurable rotor body currents by processing measurable large disturbance generator responses. The developed ANN observers are shown to be robust to machine parameter variations and to measurement noise. It is shown that the estimated rotor body currents can be used in conjunction with measurable machine responses to recursively estimate model parameters. Such a procedure may be applied to track parameters from one operating condition to the next.

10.2 Future Work

The results presented in this study show that machine model parameters can indeed be estimated using time-domain on-line response data. It is seen that the parameter estimates are non-linear and are influenced by generator operating condition. Based on the results obtained, the following list of suggestions is proposed for future research.

1. Large utility generators are highly non-linear. The proposed multistage estimation procedure should be investigated for modeling such generators.
2. While only excitation disturbance tests were conducted in this research study to estimate model parameters, it would be interesting to consider machine response obtained from transmission line faults, power outages etc. in estimating the model parameter vector.

3. On-line parameter estimation facilitates the development of a trajectory for each model parameter as the generator moves from one operating condition to the next. After identifying the non-linear parameters, artificial neural networks may be used to map measurable machine variables to non-linear model parameters.

4. The feasibility of using on-line parameter estimates to identify the presence of shorted turns in the field windings of large utility generators should be investigated. It must be remembered that the conventional synchronous machine parameter models incorporate *lumped* representations of physical components and processes. In large generators with several hundred turns, a minor inter-turn short-circuit in the field winding may not necessarily manifest itself through changes in (lumped) values of $R_{jl}$ and $a$. The inter-turn short may have to be substantially large before the on-line system identification algorithms are able to detect the presence of a fault. These issues should be studied carefully.

5. It is generally recognized that incipient faults generally manifest themselves by a number of symptoms which produce characteristic signatures in machine responses. The feasibility of using neural networks for incipient failure detection by extracting underlying signatures in machine responses should be investigated. It is believed that neural networks can be utilized both in software and hardware implementation for real-time failure detection and in providing accurate and coherent information to plant operators.

6. A comprehensive system identification procedure should be developed to model associated excitation systems and power system stabilizers from on-line response data.
BIBLIOGRAPHY


This Appendix lists the simulation parameters and dynamic equations for simulating the one-machine-infinite-bus system described in Chapter 6 of this dissertation.

A.1 Simulation Parameters

A.1.1 Synchronous Generator and Transmission Line Parameters

Unless indicated otherwise, all parameters are specified in per-unit.

- $R_s$: stator resistance = 0.0324
- $X_{ad}$: direct-axis magnetizing reactance = 1.3771
- $X_{aq}$: quadrature-axis magnetizing reactance = 1.3719
- $X_d$: direct-axis stator reactance = 1.4091
- $X_q$: quadrature-axis stator reactance = 1.4236
- $R_{fd}$: field-winding resistance = 0.5804
- $R_{ld}$: resistance associated with direct-axis rotor-body winding $ld$ = 0.0678
- $R_{fdld}$: resistance associated with direct-axis rotor-body winding $fe1d$ = 14.2341
- $X_{fd}$: field-winding leakage reactance = 9.9130
- $X_{ld}$: leakage reactance associated with rotor-body winding $ld$ = 1.4643
- $X_{fdld}$: differential leakage inductance = 0.0000
- $X_{fe1ld}$: leakage reactance associated with rotor-body winding $fe1d$ = 59.7567
- $R_{lq}$: resistance associated with quadrature-axis rotor-body winding $lq$ = 0.0496
- $R_{2q}$: resistance associated with quadrature-axis rotor-body winding $2q$ = 0.1817
- $R_{3q}$: resistance associated with quadrature-axis rotor-body winding $3q$ = 0.2080
\( X_{1q} \)  
leakage reactance associated with rotor-body winding \( 1q \)  
0.1220

\( X_{3q} \)  
leakage reactance associated with rotor-body winding \( 2q \)  
0.0203

\( X_{4q} \)  
leakage reactance associated with rotor-body winding \( 3q \)  
0.6711

\( H \)  
inertia constant  
3.0 sec

\( R_t \)  
transmission line resistance  
0.0600

\( X_t \)  
transmission line reactance  
0.6014

A.1.2 Excitation System Parameters

\( K_A \)  
exciter gain  
50

\( T_A \)  
exciter time-constant  
0.02 sec

A.1.3 Power System Stabilizer Parameters

\( K_P \)  
proportional gain  
3.2070

\( K_I \)  
integral gain  
0.0980

\( T_w \)  
washout time-constant  
0.5 sec

A.2 Dynamic Equations

A.2.1 Synchronous Generator and Transmission Line Equations

The per-unit dynamic equations of the synchronous generator and the transmission line

\[
U(t) = R \cdot X(t) + L \cdot pX(t)
\]  
(A.1)

In the above,

\[
X = [i_q \ i_d \ i_{1q} \ i_{2q} \ i_{3q} \ i_{1d} \ i_{f\phi d} \ i_{f\phi d}]^T;
\]

\[
U = [v_{qb} \ v_{db} \ 0 \ 0 \ 0 \ 0 \ E_x]^T;
\]
Matrices $L$ and $R$ are represented as:

$$R = \begin{bmatrix}
-(R_a + R_t) & -\frac{\omega_r}{\omega_e} (X_d + X_t) & 0 & 0 & 0 & \frac{\omega_r}{\omega_e} X_{ad} & \frac{\omega_r}{\omega_e} X_{ad} & \frac{\omega_r}{\omega_e} X_{ad} \\
\frac{\omega_e}{\omega_r} (X_q + X_t) & -(R_a + R_t) & -\frac{\omega_r}{\omega_e} X_{aq} & \frac{\omega_r}{\omega_e} X_{aq} & \frac{\omega_r}{\omega_e} X_{aq} & 0 & 0 & 0 \\
0 & 0 & R_{1q} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & R_{2q} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & R_{ld} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & R_{fd} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & X_{ad}
\end{bmatrix}$$

$$L = \begin{bmatrix}
-(X_q + X_t) & 0 & X_{aq} & X_{aq} & X_{aq} & 0 \\
0 & -(X_r + X_d) & 0 & 0 & 0 & X_{ad} \\
-X_{aq} & 0 & X_{1q} + X_{aq} & X_{aq} & X_{aq} & 0 \\
-X_{aq} & 0 & X_{2q} + X_{aq} & X_{aq} & X_{aq} & 0 \\
-X_{aq} & 0 & X_{3q} + X_{aq} & X_{aq} & X_{aq} & 0 \\
0 & -X_{ad} & 0 & 0 & 0 & X_{1d} + X_{f1d} + X_{ad} \\
0 & -X_{ad} & 0 & 0 & 0 & X_{f1d} + X_{ad} \\
0 & -X_{ad} & 0 & 0 & 0 & X_{ad} (X_{ad} + X_{f1d}) \\
0 & \frac{X_{ad}}{R_{fd}} & 0 & 0 & 0 & \frac{X_{ad}}{R_{fd}} (X_{ad} + X_{f1d})
\end{bmatrix}$$
In addition, the mechanical equations describing the turbine connected to the generator are represented by the following sets of equations:

\[ T_e = \psi_d i_q - \psi_q i_d \]  \hspace{1cm} (A.2)

\[ \delta = \omega_r - \omega_e \]  \hspace{1cm} (A.3)

\[ \dot{\omega}_r = \frac{1}{2H} (T_{pm} - T_e) \]  \hspace{1cm} (A.4)

In the above equations, \( T_{pm} \) is the prime-mover torque, \( T_e \) is the generator electromagnetic torque, and \( H \) is the generator inertia constant. All quantities are in per-unit. In addition, \( \omega_r \) and \( \omega_e \) represent the rotor speed and the generator synchronous speed respectively. \( \omega_r \) and \( \omega_e \) are expressed in radian/sec. The generator power angle, \( \delta \), is expressed in radians.

Also, the stator flux-linkage equations are given by:

\[ \psi_d = -X_d i_d + X_{ad} (i_{1d} + i_{f1d} + i_{fd}) \]  \hspace{1cm} (A.5)

\[ \psi_q = -X_q i_q + X_{aq} (i_{1q} + i_{2q} + i_{dq}) \]  \hspace{1cm} (A.6)

In equation A.1, \( v_{qb} \) and \( v_{db} \) represent bus voltages in the \( dq \) reference frame which can be computed from orthogonal axis stator voltages using the generator power angle \( \delta \).

\[ v_{qb} = v_s \cos(\delta) \]  \hspace{1cm} (A.7)

\[ v_{db} = v_s \sin(\delta) \]  \hspace{1cm} (A.8)
A.2.2 Excitation System Equation

The excitation system used in this study is represented by the following equation:

\[ E_x = \frac{K_A}{1 + sT_A} (V_{ref} - V_r + V_{pss}) \]  \hspace{1cm} (A.9)

In the above equation, \( V_{ref} \) is the excitation reference voltage, \( V_r \) is the generator terminal voltage, and \( V_{pss} \) is the stabilizing signal generated by the power system stabilizer, all quantities in per-unit.

A.2.3 Power System Stabilizer Equation

The power system stabilizer considered in this study is represented by the following equation:

\[ V_{pss} = \frac{sT_w}{1 + sT_w} \left( K_p + \frac{K_I}{s} \right) (\omega_r - \omega_x) \]  \hspace{1cm} (A.10)

A.3 Selection of Base Values

To facilitate conversion of per-unit voltages and currents obtained from the one-machine-infinite-bus simulation to corresponding quantities in actual units, the following procedure is used to determine base values.

**Step 1:** Define system wide base 3-phase apparent power, \( S_{base} = 3730 \) VA.

**Step 2:** Specify rated generator line-to-line voltage, \( V_{ll} = 220 \) V.

**Step 3:** Select base frequency, \( f_{base} = 60 \) Hz.

**Step 4:** Determine the peak phase-to-neutral base stator voltage, \( V_{s, base} \) in volts.
Step 5: Determine the peak stator current per-phase, $I_{s,\text{base}}$ in amperes

$$I_{s,\text{base}} = \frac{S_{\text{base}}}{\frac{1}{2} V_{s,\text{base}}} \quad \text{(A.12)}$$

Step 6: Calculate stator base impedance in ohms

$$Z_{s,\text{base}} = \frac{V_{s,\text{base}}}{I_{s,\text{base}}} \quad \text{(A.13)}$$

Step 7: Calculate the stator base inductance in henries

$$Z_{s,\text{base}} = \frac{Z_{s,\text{base}}}{2 \cdot \pi \cdot f_{\text{base}}} \quad \text{(A.14)}$$

Step 8: Assuming a suitable turns-ratio, $a$, calculate the base field current in amperes

$$I_{f,\text{d, base}} = \frac{3 I_{s,\text{base}}}{2a} \quad \text{(A.15)}$$

In this study, $a = 0.5154$. This value was obtained from SSTR tests conducted on the machine under study.

Step 9: Calculate the base field voltage in volts

$$V_{f,\text{d, base}} = \frac{S_{\text{base}}}{I_{f,\text{d, base}}} \quad \text{(A.16)}$$
Step 10: Calculate the base field impedance in ohms

\[
Z_{fd, base} = \frac{V_{fd, base}}{I_{fd, base}} \quad (A.17)
\]