ABSTRACT

LAI, JUMING. Parameter Estimation of Excitation Systems. (Under the direction of Mesut E. Baran).

The purpose of the research has been to develop a methodology to simplify the process of parameter estimation of excitation systems. There are two parts in the estimation process, which are the simulation and the optimization.

For the simulation part, the AC1A excitation system model and AC8B excitation system model have been implemented in MALTAB/Simulink, based on the IEEE standard 421.5, which is updated in 2005. On the other hand, for the optimization part, the goal is to look for suitable parameters such that, with the same input, the simulation output will match the field data from the real machine. We formulated the problem as a least square problem and applied Damped Gauss-Newton method (DGN) and Levenberg-Marquardt (LM) method to solve it. We used both the MATLAB Parameter Estimation Toolbox and the MATLAB programs developed by us to implement the algorithms and get the parameters. For both of the AC1A models and AC8B, we did the case studies and validation. And this is also a project sponsored by Progress Energy, who provided two suites of “bump-test” field data of AC1A excitation system and AC8B excitation system as well. Besides the results, we determined that the process of parameter estimation of excitation systems would be try DGN first, and if the simulation response cannot match the measured response well, try LM to get better initial parameters, then try DGN again.

Parameter Estimation of Exitation Systems

by
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BIOGRAPHY

Juming Lai was born and grew up in Guangzhou, Guangdong, China on March 5, 1984. Her father is a civil engineer specialized in air transportation that brought her interests in engineering from her childhood. She showed her interests in math from elementary school, which helps her a lot in the study of engineering. She entered the South China University of Technology (SCUT) in Guangzhou in September, 2002 and got her Bachelor degree majored in Electrical Engineering in June, 2006. And in August of the same year, she entered North Carolina State University as a master student. She is currently a master student in NCSU and graduating in December 2007.

She has wide interests, two of which are music and traveling. At the age of 4 years old, she passed the entrance exam of Xinghai Conservatory of Music in Guangzhou, which only took 15 students out of 1500, and started learning the piano. Now playing piano becomes an important hobby of hers. And from she was 5 years old, she with her parents keeps traveling to either a different province in China or a different country if possible, which makes her an easy-going person who can communicate well and get well along with different people with different cultures.

ACKNOWLEDGMENTS

Firstly, I would like to thank my parents who bring me a family full with love. Thank my father who can always answer my "whys" and keep me curious to the new things. Thank my mother who always tries her best to take care of me in every little detail. And then, I would like to thank my advisor, Dr. Mesut Baran who is professional in academic. He not only advises me on my research, but also listens to my opinions and tells me how to think when meeting a new problem. Also, thanks would be truly sent to every instructor who taught me in the past one and a half year. I did gain a lot from the classes and projects. At last, I would like to thank all my friends, roommates and colleagues in my lab, SPEC, 1250 Partner I, for all the help for my study and life in NC State.

I would like to acknowledge to Progress Energy, Inc. for sponsoring the research. And I also acknowledge the Semiconductor Power Electronic Center (SPEC) for providing the great equipments and wonderful environments for my research.

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Chapter 1

Introduction

1.1 Background

Today, many of the power system planning and design problems are addressed by performing system simulations in time domain. The most common studies are small signal, transient and dynamic stability analyses. Fairly standard models have been developed to represent the system component for these studies – generators, transmission lines and loads. One of the main challenges using these simulation tools is the data needed to represent the system components, as the results are only as accurate as the underlying models and data used in the computer analysis.

The generators are the most important components in these analyses, and unfortunately, determining a proper model and the corresponding parameters is the challenge, as it requires extensive testing of these systems. There are three main components of a generator, which are the synchronous machine, prime mover (turbine/governor) and the excitation system. Among these components, the excitation system plays a critical role of providing field current to the generator, and hence, controlling the terminal voltage of the generator, and also helping to stabilize the system oscillations after a system disturbance.

To accurately represent the excitation system, it is necessary to have adequate model structures and suitable parameter values. Models are usually provided by manufacturers or industry standards, such as IEEE standard [1] [2], which are in frequency-domain representations (Laplace Transform transfer functions). These standards provide suitable models for different “types” of excitation systems. The standards also provide “typical” values for each model. Moreover, the manufacturers of the excitation systems provide data for their excitation systems. Currently it is quite common that in system studies, without any actual data, the engineers have to choose one of these sources to get the model parameter data they need for system studies. Another common problem is that the models available on the commercial software used for the study, such as PSS/E®, may not have the same model provided by the manufacturer. Hence, the engineer has to translate the data from one model to another “similar” model.

The need for more accurate equipment models and model parameter identification has been recognized by organizations responsible for system reliability, such as the North American Electric Reliability Council (NERC) [4]. NERC requires unit-specific dynamics data for the dynamic simulations performed by Transmission Planning organizations.

The resulting models provide a much more accurate representation of generator/excitation system dynamic performance in computer simulations. Some of the benefits of improved models are as follows.

- Better assessment of a generator’s transient stability margin
- Better assessment of a generator’s dynamic stability margin
- More confidence in simulation results
- Compliance with existing and future NERC reliability data requirements

Model parameters, either manufacturer specified or “typical” values, may be grossly inaccurate, for they are often derived from off-line tests by measuring the response of each individual component separately, without considering the effects of loading conditions, and the effects of nonlinear interaction between excitation system and the rest of the system [3]. Moreover, parameters change due to retuning, aging, and equipment changes. Therefore, tools and methods are needed for deriving model parameters from staged tests on the units.

Staged field tests, which provide sufficient information to identifying the parameters, are divided into two groups [4]. One is collecting steady-state measurements, which includes the open circuit saturation curve measurement and online measurements. The former one is the measurement of terminal voltage, field voltage and field current when the generator field excitation is varied. But for brushless excitation system, only terminal voltage can be measured. And the later ones are taken at different load level, the typical points of which are recorded at certain level when the reactive power output changes due to variation of generator field data. The other step is obtaining the dynamic response. The purpose of the dynamic tests is to provide a simple and safe disturbance to excite the system. [4] By comparing the model responses and those obtained from field test, it is obvious to judge the accuracy of parameters, i.e. the less different the response from each other, the more accurate the parameter values.

The traditional way to “tune” the parameter is to have skilled engineers select initial parameters, calculate the difference between measured output and simulation output, and adjust the parameter to reduce the difference. However, the method requires familiarities with the equipment functions and the effects of the change of parameters toward the dynamic response. Unfortunately, such familiarities are quite rare. [4] As a result, the parameter derivation program is needed to simplify the process.

1.2 Problem Description

The focus of this thesis is to develop a process or methodology for determining appropriate parameters of an excitation model selected to represent the specific generator excitation system under consideration.

For this study, two excitation systems and the models to represent them have been provided by Progress Energy. Fig. 1. **1** shows one of the models, AC1A, which represents an Alternating Current (AC) type excitation system. The excitation models are used by the dynamic simulation package PSS/E, and hence PSS/E will be used to compare and validate the models to be replicated on Simulink/Matlab. Progress energy has also provided the staged test results for the two excitation systems. **Fig. 1. 2** shows the excitation response curve obtained from the stage tests. As the figure shows, the stage test involves applying a step change in the set point of the excitation system, which determines the terminal voltage of the generator, and the response obtained is the output, the terminal voltage of the generator. This test is referred in practice as the “bump test”. The problem hence is to estimate the parameters of the selected model such that the response of the model will match the stage test results as closely as possible.

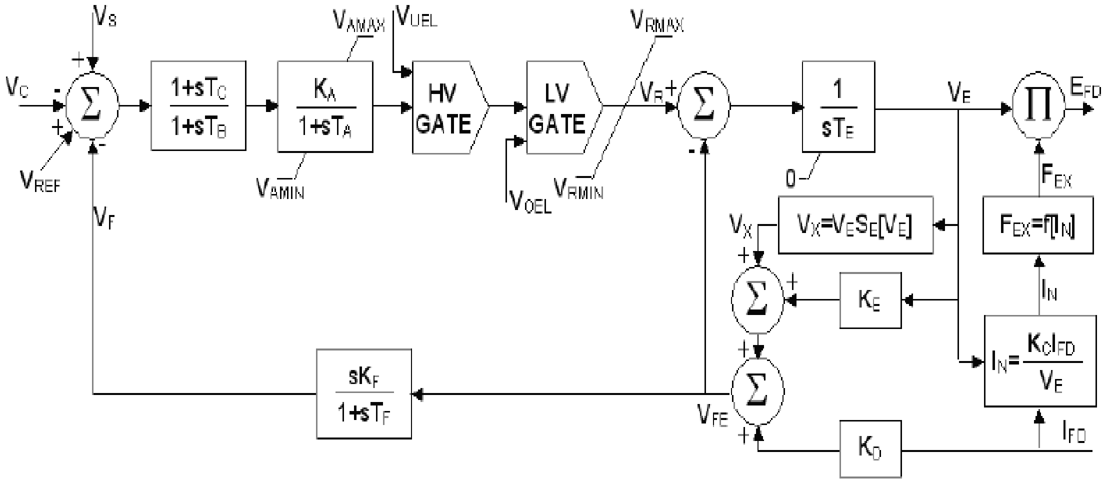


Fig. 1. 1 Type AC1A excitation system (Alternator-rectifier excitation system with non-control rectifiers and feedback from exciter field current)

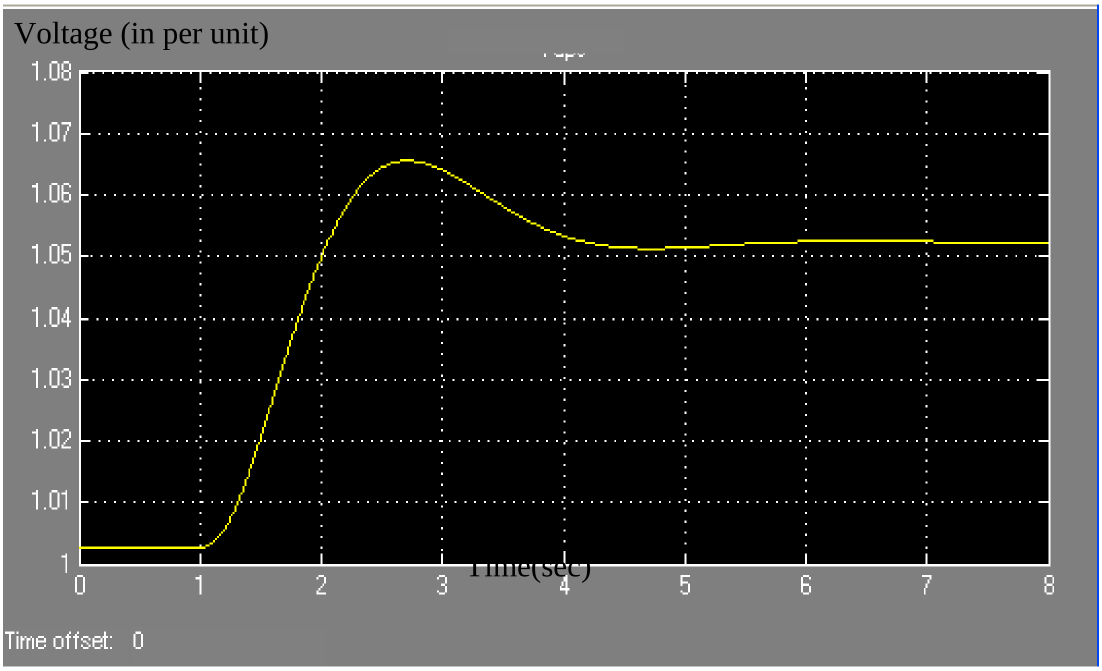


Fig. 1. 2 The excitation response from the stage test

1.3 Related Work

The AC excitation system models represented in IEEE standard 421.5 are nonlinear system models. Most previous work of parameter estimation of the models was either using linear model to approximate the given models, such as the Autoregressive (AR) model, or applying frequency response techniques to identify the parameters of specific exciters [3 5 6 7]. However, most of these approaches require the output of exciter, which cannot be obtained in a brushless excitation system. And errors can come from the process of transferring the parameters in approximated model to the ones of given model. Besides, most of previous work addressed on their own system models rather than the IEEE standard models.

In [3], a time domain approach has been developed to identify the parameters of AC1A in IEEE standard 421.5[1]. They used ARX model, a linear discrete time model, to approximate the transfer function of the system, which is a nonlinear model. ARMAX (Autoregressive moving average with exogenous input model) model is one of the ARX models. The model ARMAX(p,q,d) can be represented as $X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i}$, where $\varphi_i, \theta_i, \eta_i$ are parameters, X_{t-i} is the past value of the signal, ε_{t-i} is the error which is generally assumed to be independent identifically-distributed random variables (i.i.d) sampled from a normal distribution with zero mean, and d_{t-i} is known as the exogenous input. So a model ARMAX(p, q, d) contains the AR(p) and MA(q) models and a known external time series d_t. Besides ARMAX model, basic ARX model also includes BJ (Box-Jenkins) and OE (Output-Error) model, which will be used in different cases.

There are two methods to estimate the coefficients in ARX model structure: Lease square and Instrumental variables. The author used the least-square method to obtain the parameters of approximated model. For the optimization algorithm, a Gauss-Newton method was applied to estimate the parameters of the approximated model. And with the parameters of the ARX model, the parameter values of AC1A model were estimated.

The advantage of the method is that after getting the linear expression of the system, many approaches can be used for estimating the parameters of it. They are to increase the speed of calculation and reduce the cost of it. But the disadvantage is that the approach may bring more errors when both approximating the system model with the linear one and transferring the parameters back from the approximated model to the system model.

In [4], a program was developed by using Simulink and Optimization Toolbox in MATLAB. Simulink allows an easy implementation of the model, in which the system models are represented in Laplace frequency domain. And the Optimization Toolbox is a collection of optimization algorithms with graphic user interface. For the least-square curving fitting problem, the algorithm can be Gauss-Newton and Levenberg Marquardt. Optimization algorithm determines new parameters and passes it to the Simulink, Simlink then gives the corresponding response. “A comparison of the simulation output and the desired one is displayed for each successive pass of the optimization process.” Hence, the users can see how the response changed to fit the given response during the solution process. The author gave an example of implementation of IEEE type 1 excitation system.

Simulink is a convenient graphical tool to implement different excitation models. The user can change a part of the model or the desired curve freely. However, the algorithms are limited to the ones provided in Optimization Toolbox. Besides, MATLAB is interpretive language which takes much more time when running the programs in MATLAB, rather than the compiler languages like C. We tried to use the approach at the beginning of the research, but then we tried to make our codes of the algorithms, such as Gauss-Newton and Levenberg

Marquardt. In the thesis, we programmed in MATLAB for it have a good communication with the system model which we have built in MATLAB/Simulink. But for the following step, we will transplant the program into C or JAVA and have it communicate with the developed model in PSS/E, which is commercial simulation software.

In [5], a time domain method has been developed to identify IEEE- DC1 and IEEE-AC1A model parameters. Similar to the approach in [3], the author used a discrete time model to approximate the system model. Then the least-square method was used to construct the objective function of the problem. But the difference is that in this paper, they use stochastic approximation (SA) to find the point at which the objective function can be minimized to get the parameters. The optimization theory includes two branches known as deterministic optimization and stochastic optimization. And the stochastic approximation (SA) is a cornerstone of stochastic optimization. SA methods are used whenever the noise in the data cannot be ignored. So the SA method creates stochastic equivalents to the classical conjugate gradient methods. An implementation of SA method is shown in the paper to estimate the parameters of AC1 type excitation system. In our case, the noises of signals are in tolerance, so that we did not get into SA methods.

In [6], the discrete-time ARMA (Autoregressive moving average) model was used to approximate each block of the model by matching the frequency response of them. ARMA model is also known as Box-Jenkins models, which is one of the ARX models. The model consists of two parts, autoregressive (AR) part and a moving average (MA) part. [14] The former part is to represent the signal by itself and the later part is to represent the signal by the error terms, which is generally independent identically-distributed random variables (i.i.d.), sampled from a normal distribution with zero mean ($\varepsilon_t \sim N(0,\sigma^2)$). In the paper, the author obtained parameters of approximated ARMA model of each system block and then transferred them back the ones of excitation system model. The approach is similar with the one in reference [3], but the ARMA model would be simpler in this paper, for the author approximated the block of the excitation system separately. We did not choose it because both the approximated model may bring more error and we cannot have so much real data from industry, especially for the brushless machines.

In [7], parameter estimation was performed in frequency-domain. The author utilized FFT and complex curve fitting technique to estimate the parameters of a excitation system model, which is a model developed by Taiwan Power Company. About the curve fitting, the main topics include scatter plot, least square regressions (linear and nonlinear), correlation, normal probability plots and residual plot. Among them, the nonlinear least square regression is widely used, which nicely integrates algebra and statistics. A modified weighted least square (WLS) is described in the paper to obtain the objective function of the curve fitting problem. Then the author performed Fourier Transformation on the time domain responses to an injected wide-bandwidth signal of the system to obtain the frequency response data, in order to estimate the parameters of the model. We did not choose the method for we did not consider the noise of the signal in the problem.

To sum up, the main considerations of choosing algorithms are the speed of convergence, the cost of calculations and the accuracy of the results. And for adopting the algorithm, we have to consider the limitation of tool and data available. Therefore, we plan to develop an parameter estimation tool in C or JAVA that can interface with any simulation tool, with which, when we got data from stage test, we can get the appropriate parameters of the model correspondingly.

1.3.1 Scope of the Thesis:

The study involved first getting a general understanding of each component of the model. Then, models have been implemented in Simulink and verified by using PSS/E. Then a literature review has been conducted. After the review of related work on this problem, we adopted the least square approach to estimate the model parameters. Two optimization methods have been adopted and implemented to solve the least square problem. Two excitation systems have been used to test and assess the performance of the proposed method.

1.4 Abbreviation

IEEE	Institute of Electrical and Electronics Engineering
NERC	North American Electric Reliability Council
AC	Alternating Current
ARMAX	Autoregressive Moving Average with Exogenous input model
BJ	Box-Jenkins
OE	Output-Error
SA	Stochastic Approximation
ARMA	Autoregressive Moving Average
GLS	Generalized Least Square
P.U.	Per Unit

Chapter 2

AC Excitation System Model

2.1 Overview

To capture the behavior of synchronous machine accurately in power system stability studies, it is essential that their excitation systems are modeled in sufficient detail. The models must be suitable for representing the actual excitation equipment performance for large, severe disturbances as well as for small perturbations. [8] Based on excitation power source, excitation systems are categorized into three groups showing as follows, in which the AC excitation systems are what we are concerning in the thesis.

- Type DC Excitation Systems which utilized a direct current generator with a commutator as the source of excitation system power. [9]
- Type AC Excitation Systems which use an alternator (ac machine) and either stationary or rotating rectifiers to produce the direct current needed for the generator field.
- Type ST Excitation Systems in which excitation power is supplied through transformers and rectifier.

A physical layout is shown in figure 2.1 to 2.4.

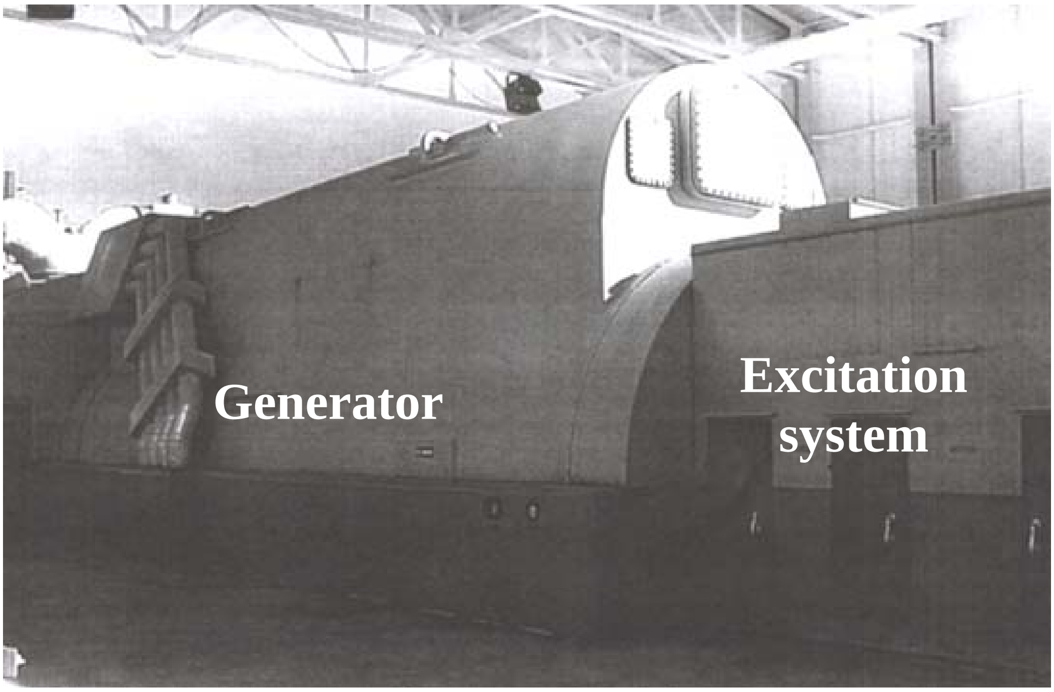


Fig. 2. 1 The real generator and excitation system

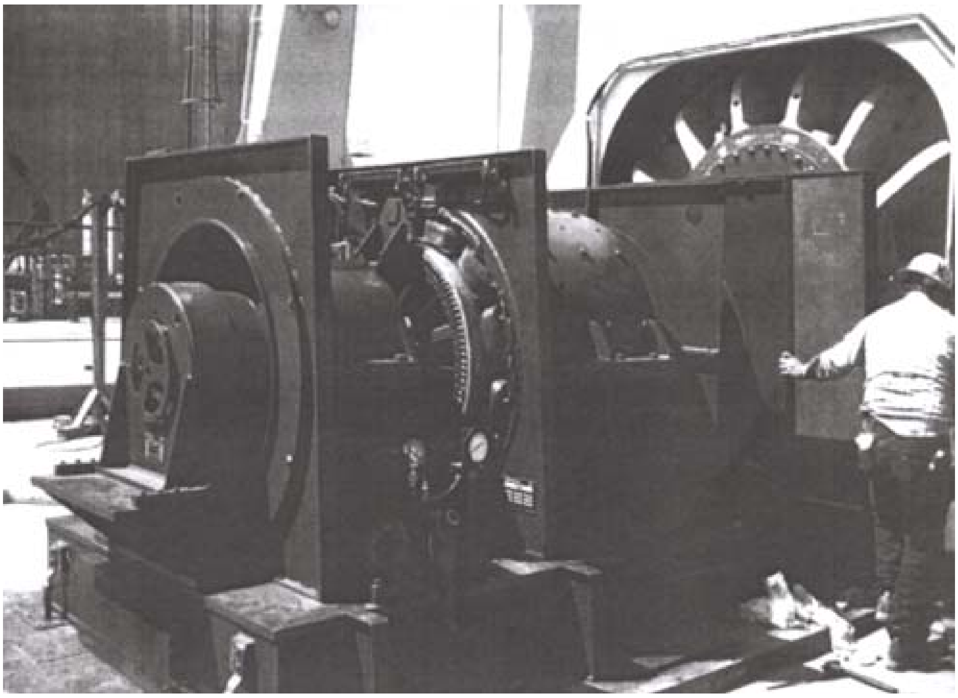


Fig. 2. 2 Inside of the excitation system part

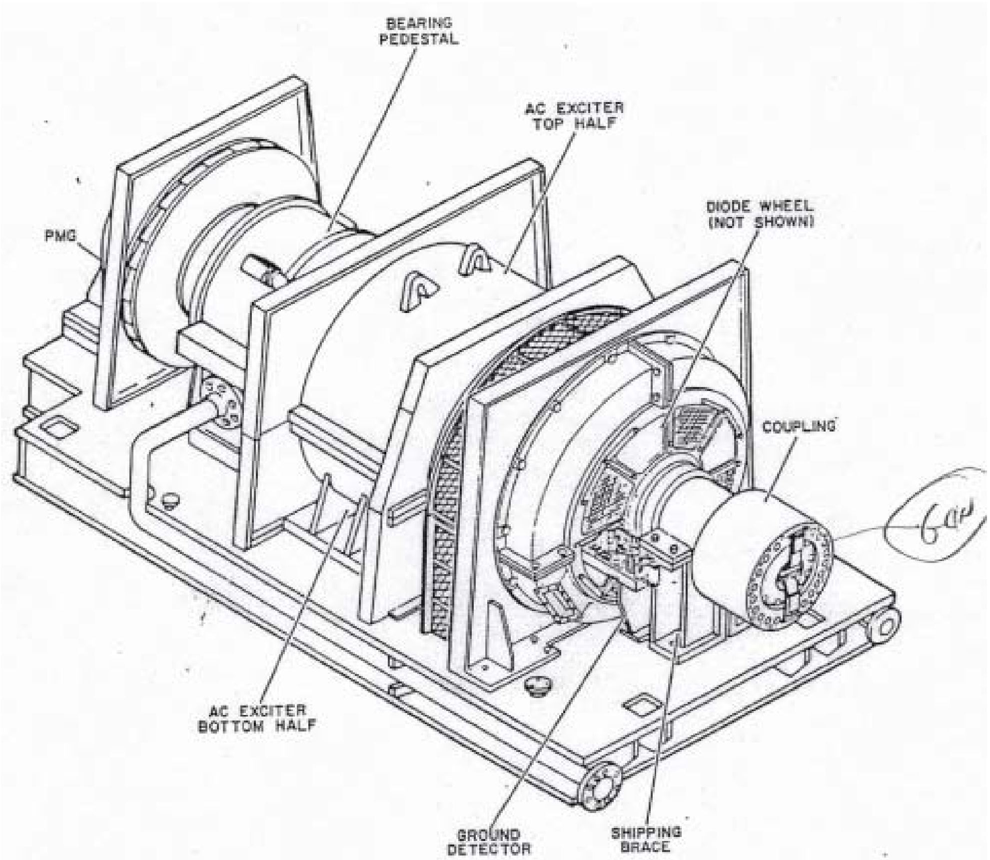


Fig. 2. 3 The structure of Mark III Brushless exciter

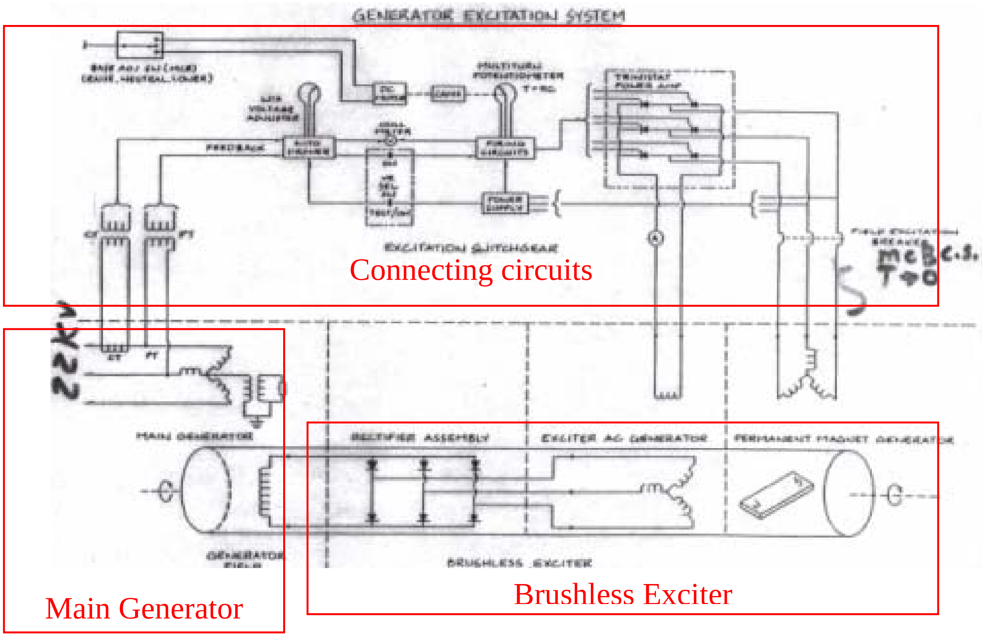


Fig. 2. 4 The circuit of Generator excitation system

In figure 2.5 there is a general functional block diagram, which shows various synchronous machine excitation subsystems with a common nomenclature performed in IEEE std 421.5. Showing in the diagram, the terminal output voltage is sent to the excitation control elements as a feedback signal (V_C and V_S). So when $\overline{V_T}$ is unstable, the control elements provide V_R to control the output of exciter, i.e. adjust the field voltage and field current to have $\overline{V_T}$ back to steady state. V_{REF} is an important input of the control part of excitation systems. Dynamic responses will be recorded, when a step signal is input to the V_{REF} port. And comparing dynamic responses of simulation output and the ones from real machine is the method which is used to ensure the accuracy of models. V_{OEL} and V_{UEL} describe the output signals from overexcitation limiters and underexcitation limiters, respectively, the modeling of which have become a very popular topic recently. [1] V_R, which is the output of voltage regulator, controls the field voltage E_{FD}, in order to control the field current I_{FD} that will be feed into generator.

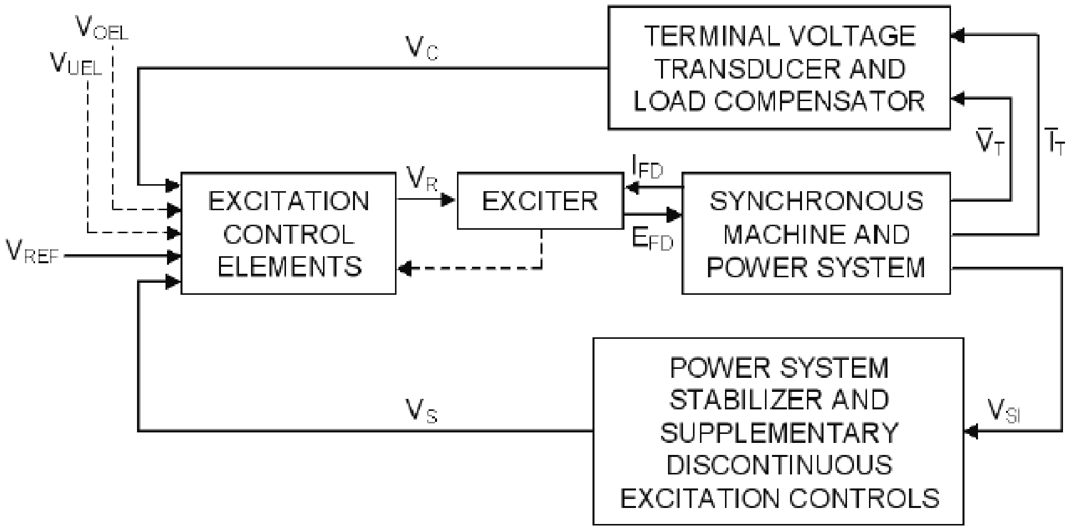


Fig. 2. 5 Functional block diagram of a detailed excitation system model [1]

To simplify the problem, the “terminal voltage transducer and load compensator” and “power system stabilizer and supplementary discontinuous excitation controls” are not considered in the thesis. We can simply represent the block as shown in figure 2.6, in which the excitation system includes both excitation control elements and exciter.

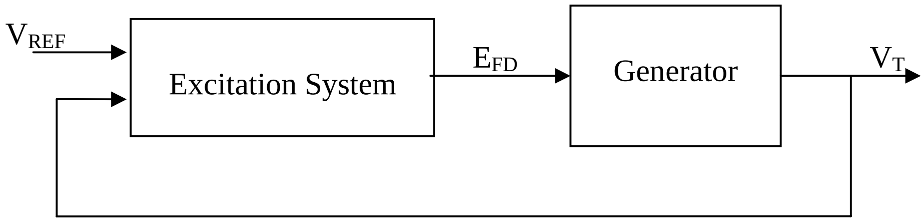


Fig. 2. 6 Simplified functional block

2.2 Per Unit System

The per-unit system is the expression of system quantities as fractions of a defined base unit quantity. [10] i.e. the signals in per-unit systems are normalized to some defined bases.

Firstly, we can define one per unit generator voltage as rated voltage. One per unit exciter output voltage is that voltage required to produce rated generator voltage on the generator air gap line.

Also, excitation system models must interface with the synchronous machine model at both the field terminals and armature terminals. The input control signals to the excitation system are the synchronous machine stator quantities and rotor speed. The per-unit systems used for expressing these input variables are the same as those used for modeling the synchronous machine. Thus, a change of per unit system is required only for those related to the field circuit.

2.3 AC Excitation System Model Examples

The AC1A excitation model and AC8B excitation model are shown in Figure 2.7 and Figure 2.8, respectively.

AC1A Excitation System

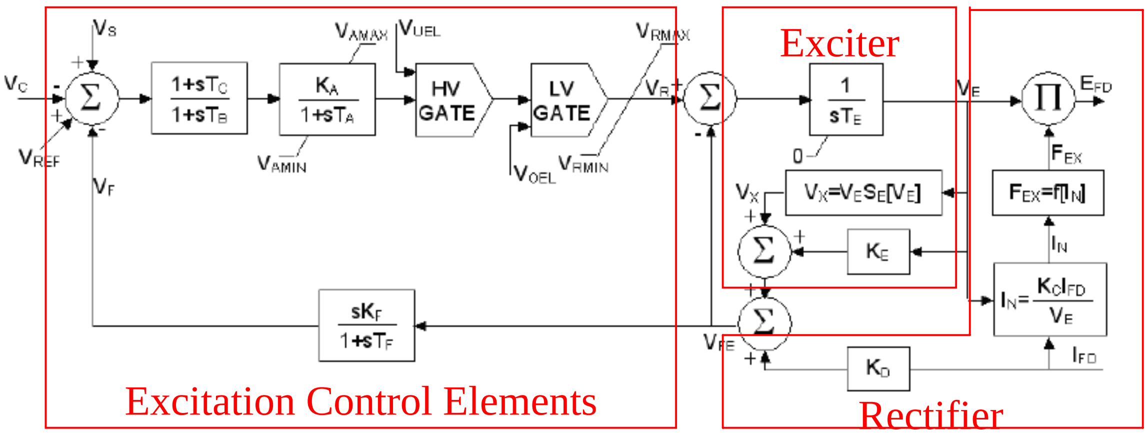


Fig. 2. 7 A partial AC1A Excitation System Block Diagram Showing Major Functional Blocks

AC8B Excitation System

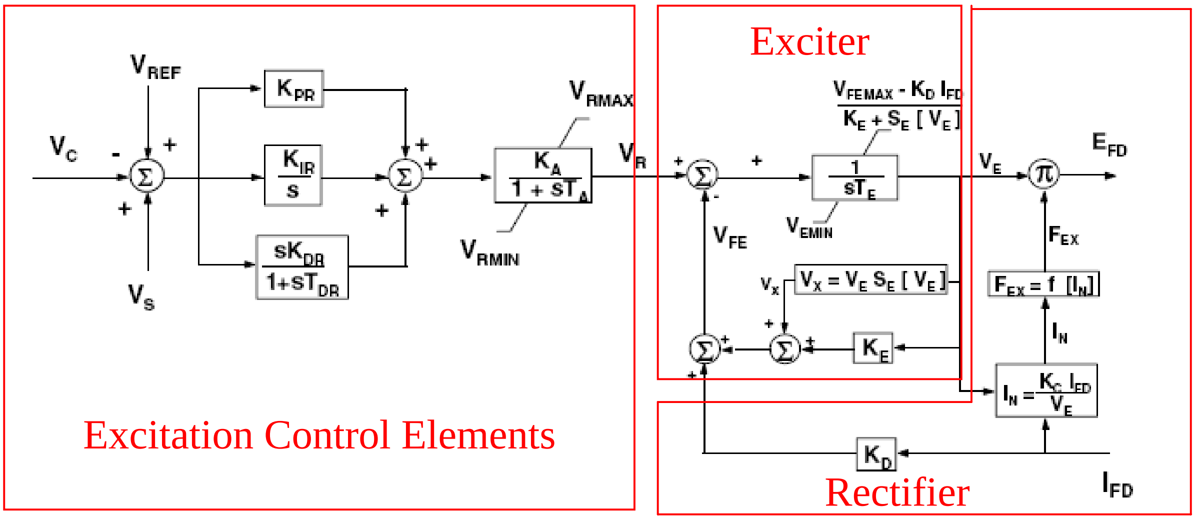


Fig. 2. 8 A partial AC8B Excitation System Block Diagram Showing Major Functional Blocks

2.4 Model Details for the Excitation Systems

2.4.1 Terminal Voltage Transducer and Load Compensator Models

These are the components that transmit the terminal voltage back to the input of the excitation systems.

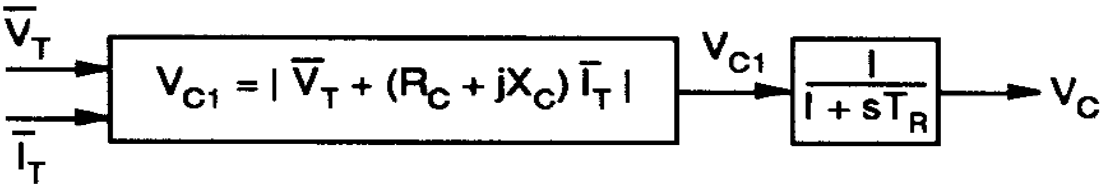


Fig. 2. 9 Terminal Voltage Transducer and Optional Load Compensation Elements

V_T : Terminal voltage

I_T : Terminal current

$R_C + jX_C$: Load compensator impedance

T_R : Regular input filter time constant

2.4.2 Amplifier

Amplifier, represented as the main regulator transfer function, may be the magnetic, electronic or rotating type. The first two types can be represented by the block diagram of figure 2.10.

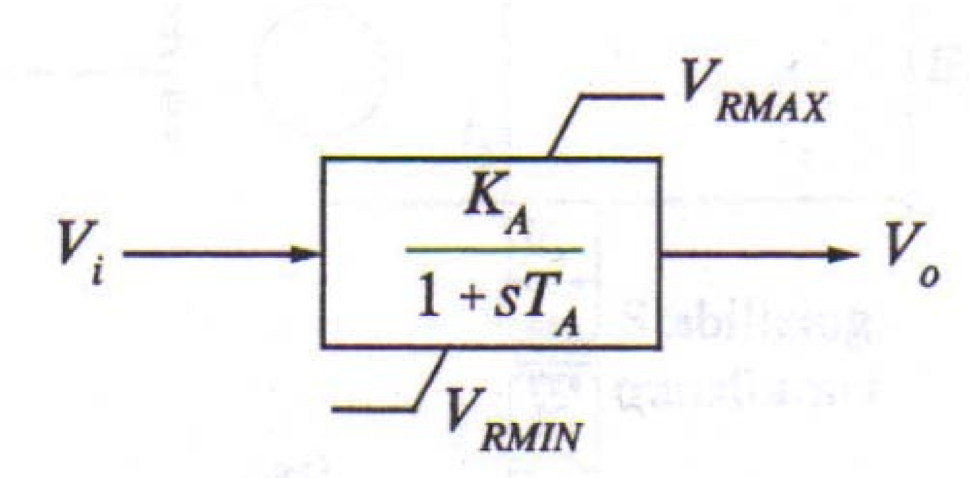


Fig. 2. 10 Amplifier model [10]

K_A: Voltage Regular Gain

T_A: Voltage amplifier time constant

$V_{R\max}$: Maximum value of V_R

$V_{R\min}$: Minimum value of V_R

Non-windup limiter

The block of amplifier is a lag-lead block with non-windup limits; a general representation and implementation of which is shown in Figure 2.11 and Figure 2.12, respectively. Then in principle, we have:

$$f = V_i - V_0 / T_A$$

if $V_0 = V_{Rmax}$, and f > 0, then dy/dt is set to 0

if $V_0 = V_{Rmin}$, and f < 0, then dy/dt is set to 0

otherwise, $V_{Rmin} < V_0 < V_{Rmax}$, then dy/dt = f.

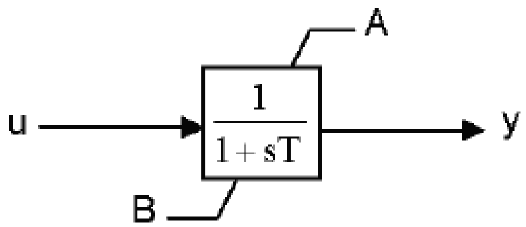


Fig. 2. 11 Non-windup limiter with sample time constant [1]

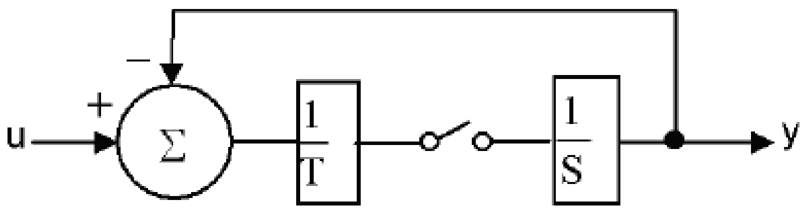


Fig. 2. 12 Implementation of non-windup limiter

2.4.3 Exciter

The exciter is the part in excitation system which connects to generator. It is the component who provides the field current to excite the generator. Among the blocks, the $v_x = V_E S_E(V_E)$ is modeling the exciter saturation characteristics (section 2.4.3.1). For convenience, it is always approximated by $V_X = E_X * S_E(E_X) = A_{EX} e^{B_{EX} E_X}$.

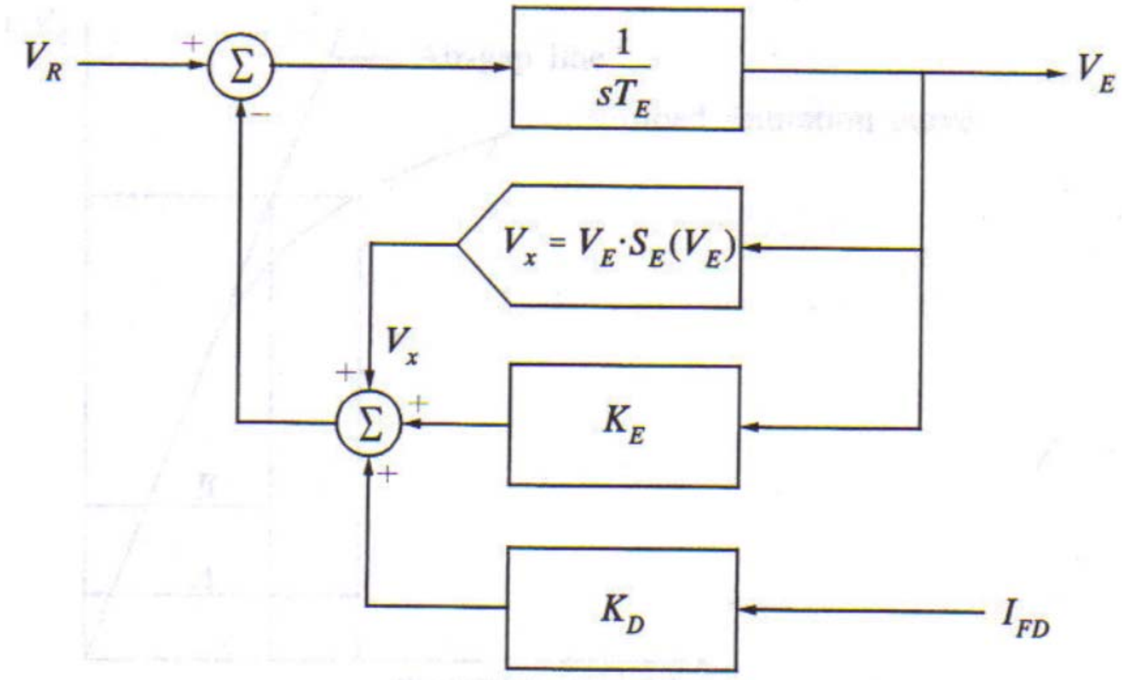


Fig. 2. 13 Block diagram of an AC exciter

T_E : Exciter time constant

V_E : Exciter internal voltage

S_E : Saturation function

K_E : Exciter constant related to self-excited field

$K_D * I_{FD}$: Armature reaction demagnetizing effect.

K_D : Demagnetizing factor.

2.4.3.1 Saturation Function

Saturation function (per unit): $S_E(E_X) = \frac{A - B}{B}$

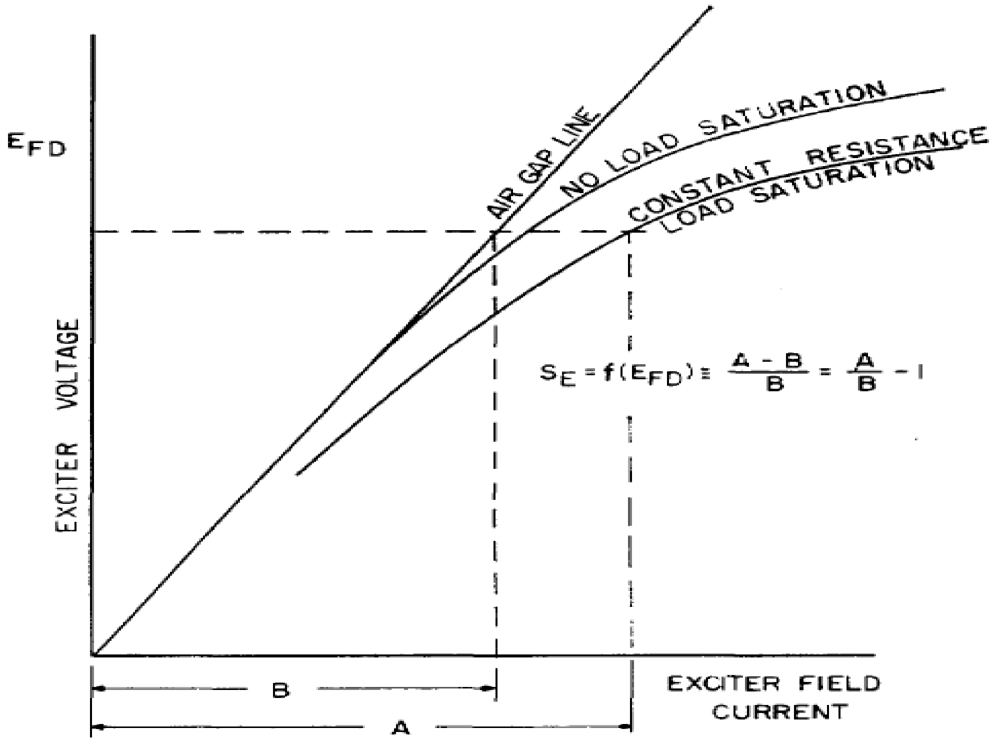


Fig. 2. 14 AC exciter saturation characteristic

2.4.4 Rectifier

Rectifier is to transfer the Alternative current to direct current, which is required for the field current.

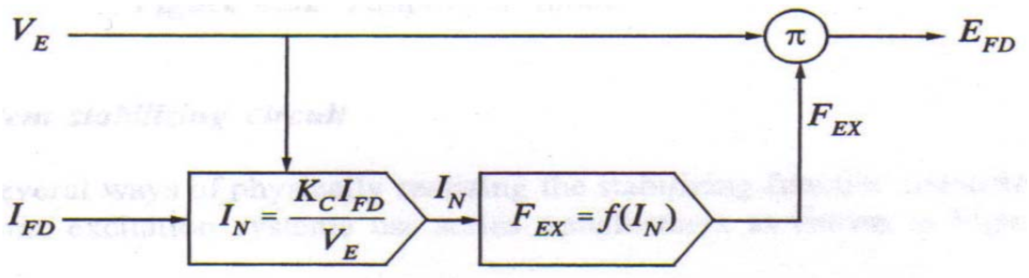


Fig. 2. 15 Rectifier regulation model [10]

E_{FD}: exciter output voltage(applied to generator field)

$E_{FD} = F_{EX} * V_E$: a function of commutation voltage drop

I_{FD}: generator field current

I_N: exciter internal current

$F_{EX} = f(I_N)$: the three modes of rectifier circuit operation

Mode 1: $f(I_N) = 1.0 - 0.577 I_N$, if $I_N \le 0.433$

Mode 2: $f(I_N) = \sqrt{0.75 - I_N^{\ 2}}$, if $0.433 < I_N < 0.75$

Mode 3: $f(I_N) = 1.732(1.0 - I_N)$, if $0.75 \le I_N \le 1.0$

I_N should not be greater than 1.0, but if it is, F_{EX} should be set to zero.

2.5 Summary

There are three basic elements of an excitation system: excitation control components, exciter and rectifier. Besides, terminal voltage transducer and compensator components, and power system stabilizer are additional ones to keep terminal output voltages stable. To know the typical structure of each functional block and understand the function of each suite of blocks in typical models is important in modeling an accurate excitation system and estimating the parameters.

Chapter 3

Parameter Estimation using Least Square Method

Since we want the simulation output of excitation model to follow the measured response at each time point, we can model the problem as a least square problem. To solve this least square problem, we tried the Damped Gauss Newton method and Levenberg Marquardt method, which are two basic method for non-linear optimization problems, to get the local solution of the least square problem.

3.1 Objective function

Let's restate the problem. It is a *nonlinear least squares* problem with an objective function of the form

$$f(x) = \frac{1}{2}\sum_{i=1}^{M} \|r_i(x)\|^2 = \frac{1}{2}R(t)^T R(t) \tag{3.1}$$

in which $r_i(x) = v_i(t:x) - \tilde{v}_i(t), 1 \le i \le M, t = 1,2,\ldots$, the vectors v_i and $\tilde{v}_i$ are the simulation output of an nonlinear model and the measured output of the terminal voltage of the generator, respectively, the vector $R = (r_1, r_2, \ldots, r_M)$ is called the residual,

and $x = (p_1, p_2, \ldots, p_N)^T$ is the vector of unknown parameters. M is the number of observations and N is the number of parameters. For these problems, M>N, so we say the problem is an *overdetermined* problem.

Solving of nonlinear least squares problem is searching for the best approximation to the measure data with model function $v_i(x)$, which has nonlinear dependence on variables x. The best approximation means that the sum of squares of residuals $r_i(x)$ is the lowest possible.

The $M \times N$ Jacobian R' of R is defined by

$$(R'(x))_{ij} = \frac{\partial r_i}{\partial x_j} \qquad 1 \le i \le M, \quad 1 \le j \le N \tag{3.2}$$

With this notation, it is easy to show that

$$\nabla f(x) = R'(x)^T R(x) \in R^N \tag{3.3}$$

The necessary conditions for optimality imply that at the minimizer x^*,

$$R'(x^*)^T R(x^*) = 0 \tag{3.4}$$

There are two main algorithms for solving least square problems, Gauss-Newton method and Levenberg-Marquardt method, which will be introduced as follows.

3.2 Gauss Newton method [12]

<u>Steps of Gauss-Newton method</u>

- set $x_c = x_0$.
- While $\nabla f(x_c) > \tau_r \tau_0 + \tau_a$ & iteration < iteration_max. ($\tau = (\tau_r, \tau_a)$ is the termination criteria)

  (a) Compute the step s

  (b) $x_t = x_c + s$

  (c) Compute $\nabla f(x)$

The Gauss-Newton(GN) algorithm computes the step s as

$$s = -(R'(x_c)^T R'(x_c))^{-1} \nabla f(x_c) = -(R'(x_c)^T R'(x_c))^{-1} R'(x_c)^T R(x_c) \tag{3.5}$$

where R' is the Jacobian of R.

3.3 Calculating the Jacobian numerically

Since the GN method requires computing the gradient $\nabla f(x)$, we need to get Jacobian, since

$$\nabla f(x_c) = R'(x_c) * R(x_c) \tag{3.6}$$

Since we have the model simulated in MATLAB simulink, rather than a formula expression of the system, we used the Finite Difference Method to obtain an approximated Jacobian. There are three forms of the method, which include *forward difference* method (formula 3.7), *backward difference* method (formula 3.8), and *central difference* method (formula 3.9). The central difference method is chosen, for in principle it will bring less errors than either of the other two does.

$$\text{Forward difference method :} \quad f'(x_0) = \frac{f(x_0 + h) - f(x_0)}{h} \tag{3.7}$$

$$\text{Backward difference method :} \quad f'(x_0) = \frac{f(x_0) - f(x_0 - h)}{h} \tag{3.8}$$

$$\text{Central difference method:} \quad f'(x_0) = \frac{f(x_0 + h) - f(x_0 - h)}{2h} \tag{3.9}$$

<u>Verification of getting Jacobian using central difference method</u>

A simple example of a nonlinear least squares problem is constructed. The problem is to identify the two unknown parameters (k and a) of a system $\frac{k}{s+a}$ (Figure 3.1) by minimizing the difference of a numerical prediction and measured data.

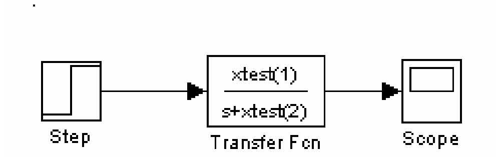


Fig. 3. 1 a simple system for Jacobian approximation test (k=xtest(1), a=xtest(2))

Let $x=(k,a)^T$ be the vector of unknown parameters. When the dependence on the parameters needs to be explicit, we will write $v(t:x)$ instead of $v(t)$. If the outputs are sampled at $\{t_j\}_{j=1}^M$, where $t_j=(j-1)T/(M-1)$, then the observation for output will be $\{v_j\}_{j=1}^M$, then the object function is

$$f(x)=\frac{1}{2}\sum_{j=1}^{M}\left|u(t:x)-u_j\right|^2=\frac{1}{2}R^T(x)R(x) \tag{3.10}$$

on the interval $[0,T]$, where $R(x)=\left[u(1:x)-u_1,\quad u(2:x)-u_2,\quad \cdots \quad u(M:x)-u_M\right]^T$

The Jacobian of f is

$$R'(x)=\begin{bmatrix} \frac{\partial u(1:x)}{\partial k} & \frac{\partial u(1:x)}{\partial a} \\ \frac{\partial u(2:x)}{\partial k} & \frac{\partial u(2:x)}{\partial a} \\ \vdots & \vdots \\ \frac{\partial u(M:x)}{\partial k} & \frac{\partial u(M:x)}{\partial a} \end{bmatrix} \tag{3.11}$$

Where $\frac{\partial u(t:x)}{\partial k}=\frac{u(t:k+h)-u(t:k-h)}{2h}, t=1,2,...,M$

Therefore, the gradient of f is

$$\nabla f(x) = \left(\begin{array}{c} \sum_{j=1}^{M} \frac{\partial u(t:x)}{\partial k}(u(t:x) - u_j) \\ \sum_{j=1}^{M} \frac{\partial u(t:x)}{\partial a}(u(t:x) - u_j) \end{array} \right) = R'(x)R(x) \tag{3.12}$$

By using the time domain solution of the system $\frac{k}{s+a}$, we have the function analytically:

$$f(t) = \frac{k}{a}(1 - e^{-at}) \tag{3.13}$$

As a result, the exact Jacobian can be calculated.

Selecte k=4 a=2 as the optimum parameters and use k=5 a=2.5 as the initial points in simulation. The results are as follows:

Jac_approx=		Jac_true =		Absolute error: Jac_true – Jac_approx =		Relative error: $\frac{Jac\_true - Jac\_approx}{Jac\_true}$ =	
0	0	0	0	0	0	NaN	NaN
0.0907	-0.0173	0.0906	-0.0175	-0.0000	-0.0002	-0.0004	0.0108
0.1649	-0.0613	0.1648	-0.0616	-0.0001	-0.0003	-0.0003	0.0046
0.2257	-0.1216	0.2256	-0.1219	-0.0001	-0.0003	-0.0003	0.0024
0.2754	-0.1910	0.2753	-0.1912	-0.0001	-0.0002	-0.0003	0.0013
0.3161	-0.2641	0.3161	-0.2642	-0.0001	-0.0001	-0.0002	0.0005
0.3495	-0.3374	0.3494	-0.3374	-0.0001	0.0001	-0.0002	-0.0002
0.3768	-0.4085	0.3767	-0.4082	-0.0001	0.0003	-0.0002	-0.0007
0.3991	-0.4757	0.3991	-0.4751	-0.0001	0.0006	-0.0002	-0.0012
0.4174	-0.5381	0.4174	-0.5372	-0.0001	0.0009	-0.0001	-0.0017
0.4324	-0.5953	0.4323	-0.5940	-0.0001	0.0013	-0.0001	-0.0022
0.4446	-0.6471	0.4446	-0.6454	-0.0000	0.0017	-0.0001	-0.0027
0.4547	-0.6937	0.4546	-0.6916	-0.0000	0.0022	-0.0001	-0.0031
0.4629	-0.7352	0.4629	-0.7326	-0.0000	0.0026	-0.0001	-0.0036
0.4696	-0.7720	0.4696	-0.7689	-0.0000	0.0031	-0.0001	-0.0040
0.4751	-0.8044	0.4751	-0.8009	-0.0000	0.0035	-0.0001	-0.0044

As listed above, the errors are very small, so that we can use approximated Jacobian instead of the exact one during the operations.

3.4 Damped Gauss-Newton method

The Gauss-Newton (GN) direction is a descent direction, but the GN method do not have a good global convergence performance. When the initial iteration is near the solution, it dose not suffer from poor scaling of f and converges rapidly. However, when far away from the solution, the Hessian of GN may not be positive definite and the method will fail. To apply the Gauss-Newton method to a global convergence problem, the combination of Gauss-Newton direction with *Armijo rule* is made, which is called *damped Gauss-Newton.*

Armijo rule

The Armijo rule is based on a general convergence theorem showing that modified steepest descent algorithms converge under some conditions.

Principal: If λ is an arbitrarily assigned positive number, $\lambda_m = \lambda / 2^{m-1}, m = 1,2,...,$ and

$x_{k+1} = x_k - \lambda_{m_k} \nabla f(x_k)$, where m_k is the smallest positive integer for which

$$f(x_k - \lambda_{m_k} \nabla f(x_k)) - f(x_k) < \alpha \lambda_{m_k} \left| \nabla f(x_k) \right|^2, k = 0,1,2,... \tag{3.14}$$

Then the sequence $\{x_k\}_{k=0}^{\infty}$ converges to the point x^* which minimizes f.

Steps of Damped Gauss-Newton method

1 $x_c = x_0$.

2 While $\nabla f(x_c) > \tau_r \tau_0 + \tau_a$ & iteration < iteration_max. ($\tau = (\tau_r, \tau_a)$ is the termination criteria)

(a) Compute the direction of a new step d_c.

(b) Set the step size $\lambda = 1$

(c) $x_t = x_c + \lambda d_c$.

(d) Compute $\nabla f(x_t)$

(i) Apply Armijo rule to find an appropriate λ_m

(ii) Update x_t and $\nabla f(x_t)$

3.5 Levenberg-Marquardt Method

The damped Gauss Newton algorithm is effective when used for solving zero residual and small residual problems. But it may fail when the condition number of the matrix $\{R'(x_c)^T R'(x_c)\}$ is too small. Therefore, for the medial residual problems, Levenberg-Marquardt method is chosen.

The Levenberg-Marquardt methods add a regularization parameter $v > 0$ to $\{R'(x_c)^T R'(x_c)\}$ in determining the step s

$$s = -(v_c I + R'(x_c)^T R'(x_c))^{-1} R'(x_c)^T R(x_c) \tag{3.15}$$

where I is the $N \times N$ identity matrix. The matrix $v_c I + R'(x_c)^T R'(x_c)$ is positive definite. And again, if combining the Levenberg-Marquardt with Armijo rule, it become a globally convergent method for the overdetermined least squares problems.

3.6 Approach I: MATLAB/Simulink Parameter Estimation Toolbox

Matlab recently has offered a toolbox for the Parameter Estimation (PE). The toolbox uses

Gauss-Newton (GN) and Levenberg-Marquardt (LM) methods to solve the least square problem. The Gauss-Newton method is given as the “fast” option that provides more precise results, but it may fail when the initial guess for the parameters are far from the solution. It quits when the condition number of matrices in the algorithm is too low or the step length is too small. The condition number is a ratio of the largest singular value to the smallest. The toolbox offers also the “robust” option which uses the Levenberg-Marquardt when Gauss-Newton quits [14]

To facilitate modeling of the system, the toolbox has interface with the simulink. Hence, the model can be developed in simulink. During iterations, the PE toolbox sends the adjusted parameters to the simulink and gets the simulation results from it. The iterations will be terminated generally when either the difference between two curves is smaller than the tolerance that we set before, or the algorithm quits as mentioned before.

3.6.1 Simulink in MATLAB

Simulink is a graphical tool for modeling, simulation and analysis of dynamic systems, in which the systems can be represented by blocks in frequency domain as the ones shown in IEEE std 421.5[1]. Most of the blocks with certain functions can be found in Simulink library, a database in MATLAB, and users can write their own ones by using the “s-function” blocks. With the initial parameters, when the structure of a system is decided, the simulation can be implemented by simply drawing the blocks from the library to Simulink window, connecting them and clicking the “run” button.

3.6.2 Parameter Estimation (PE) toolbox in MATLAB

Optimization Tool box is a collection of routines that extend the capability of MATLAB for problems as nonlinear minimization, equation solving and curve fitting. [3] And the PE toolbox is actually an interface which has the optimization toolbox and the system model in Simulink communicate to each other. (Figure 3.2) Moreover, both of PE toolbox and Simulink have a good communication with workspace in MATLAB. For nonlinear least squares and curve-fitting problems, the desired curve data and initial parameter values can be saved in workspace and input to the toolbox by selecting the names of the vectors correspondingly. The algorithms are mentioned in the previous section. And the output results, which will be shown in the interface of PE toolbox, include the solutions that minimize the difference of between simulation output and desired curve data, and a record of cost function and step size of each iteration.

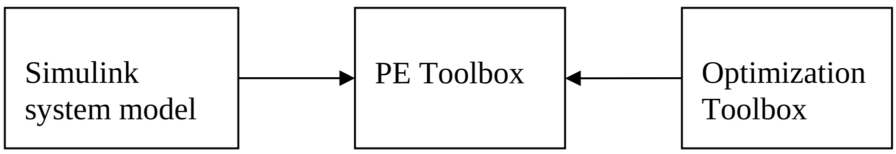


Fig. 3. 2 A sketch map showing how PE toolbox works

3.7 Approach II : Parameter estimation using LM & DGN

Instead of of Simulink and the existed methods in Optimization toolbox in MATLAB, we would like to use other simulation tools. At this rate, we may be able to simulate the system faster using software developed for power system simulation such as PSS/E, and implement more algorithms to efficiently and accurately estimate the parameters.

The interaction between the simulation tool and optimization tool is shown in Figure 3.3.

With initial parameters, simulation output will be obtained from simulation box, which will be entered into some optimization programs, in which the difference of simulation output and desired output will be calculated. If the difference does not satisfy the requirement, the program will adjust the parameter values and get a set of new parameters. With the new parameters, the system simulates again and produces another suite of outputs.

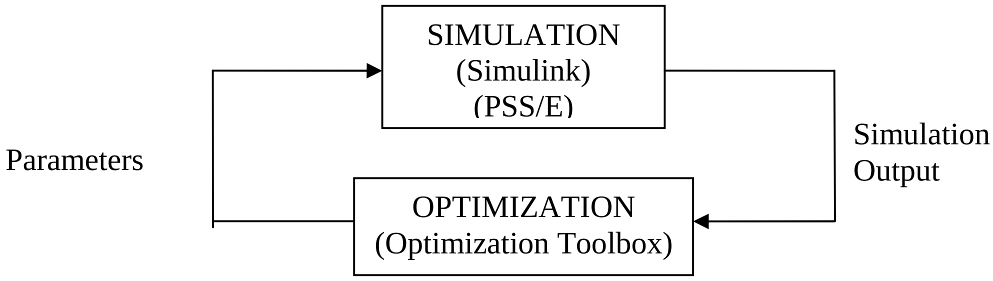


Fig. 3. 3 Optimization environment

As the first step of the implementation, we will use the simulink for simulation, and implement the optimization algorithms in Matlab. Later on, after making sure the program do perform well, we will transplant the program into other computer languages, such as Java or C and use other simulation tool like PSS/E or ETAP to provide the simulation output.

In this thesis, we tried to program the codes of damped Gauss Newton method, which is a typical global optimization method for the nonlinear parameter identification. The results of the implementation of the program on AC1A and AC8B excitation system will be given in the next chapter.

3.8 Summary

We have got two algorithms and two approaches for solving the least squares problem in order to estimate the parameter of excitation system. The algorithms used for least square problems are Gauss-Newton (GN) method and Levenberg-Marquardt (LM) method. GN is effective when there is a good initial guess, but may quit when the initial guess is bad, while LM will always gives a result when the initial guess is far from the solution, but not as effective as GN does. By combining either of the algorithm with Armijo rule, it can be applied to a global convergence problem, for the Armijo rule is for making sure that the step sizes sufficiently decrease.

For solving the parameter estimation problem, we developed two approaches. One is to estimate the parameter of excitation system with MATLAB/Simulink and Parameter Estimation (PE) Toolbox in MATALB, which already has a collection of functions for solving the least square problem. The other one is to do parameter estimation with MATLAB/Simulink and the program developed by ourselves. We are using the same algorithms with the ones used in PE Toolbox, so that we can compare the results of them. And then, in the following work, we can transplant the algorithm to C or Java to increase the speed of operation. Moreover, we may try to implement other algorithms other than the two mentioned before.

Chapter 4

Case Studies and Validations

Progress Energy gave us the data from “bump test”, we are using the data to test the method for parameter estimation. As mentioned in Chapter 1, the system consists of a generator and its excitation system, shown in Figure 4.1. The generator is set to rotate as the speed of 1 p.u. (per unit). The excitation system gets the terminal voltage as the feedback from generator and provides the excitation voltage to the generator.

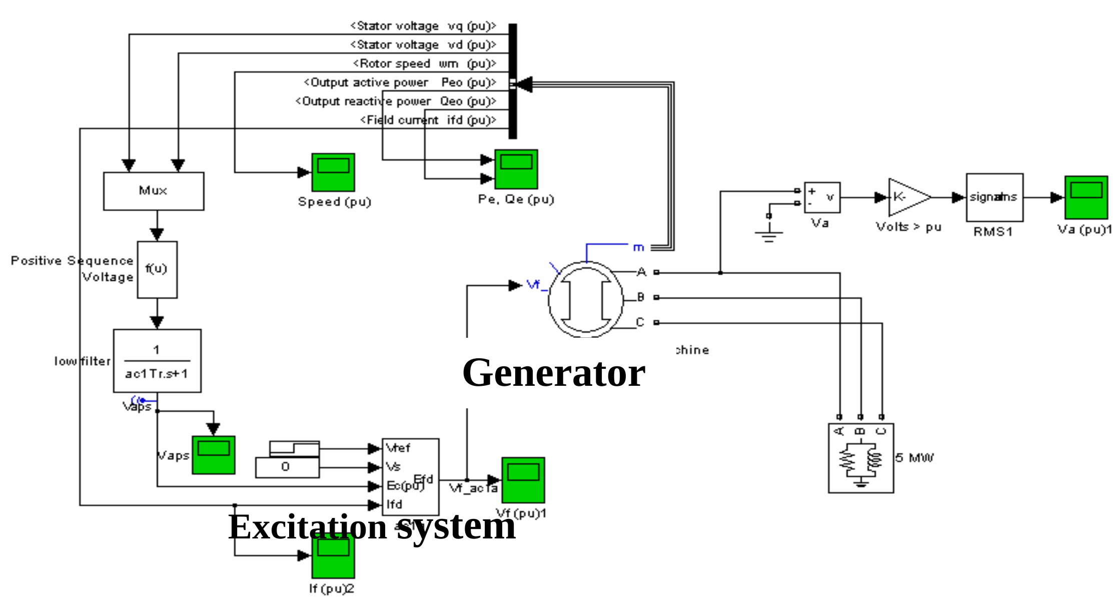


Fig. 4. 1 Test system for estimating parameters of AC1A excitation system

Our project sponsor, Progress Energy, has provided two sets of data for the two excitation systems they had performed the bumped test recently. Both of these excitation systems are of AC type and hence, we choose AC1A and AC8B models to represent them, as suggested by the manufacturer and the Progress Energy.

4.1 Case 1: AC1A with typical parameters

Before doing the parameter estimation, the excitation system has been simulated in MATLAB/Simulink, which is shown in Fig. 4.2.

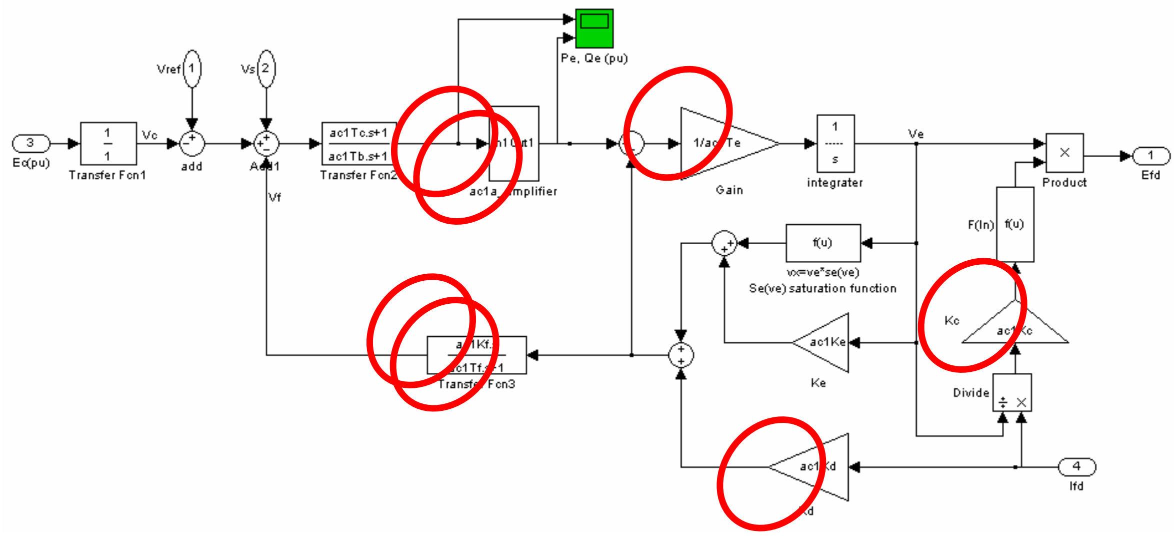


Fig. 4. 2 Implementation of AC1A excitation system in MATLAB/Simulink

There are 6 parameters of this system: ac1Ka, ac1Ta, ac1Te, ac1Kf, ac1Tf, ac1Kc, ac1Kd

Progress Energy has provided the initial values for them, which are basically the typical values given for this type of exciter:

Regulator gain:	ac1Ka = 766
Regulator time constant:	ac1Ta = 0.0200
Exciter time constant:	ac1Te = 1.3000
Damping filter gain:	ac1Kf = 0.0240
Damping filter time constant:	ac1Tf = 1.0000
Rectifier loading factor:	ac1Kc = 0.4860
Demagnetizing factor:	ac1Kd = 0.3556

Fig. 4.3 compares the simulation response with these initial values with the actual measured response obtained from the bump test for this system.

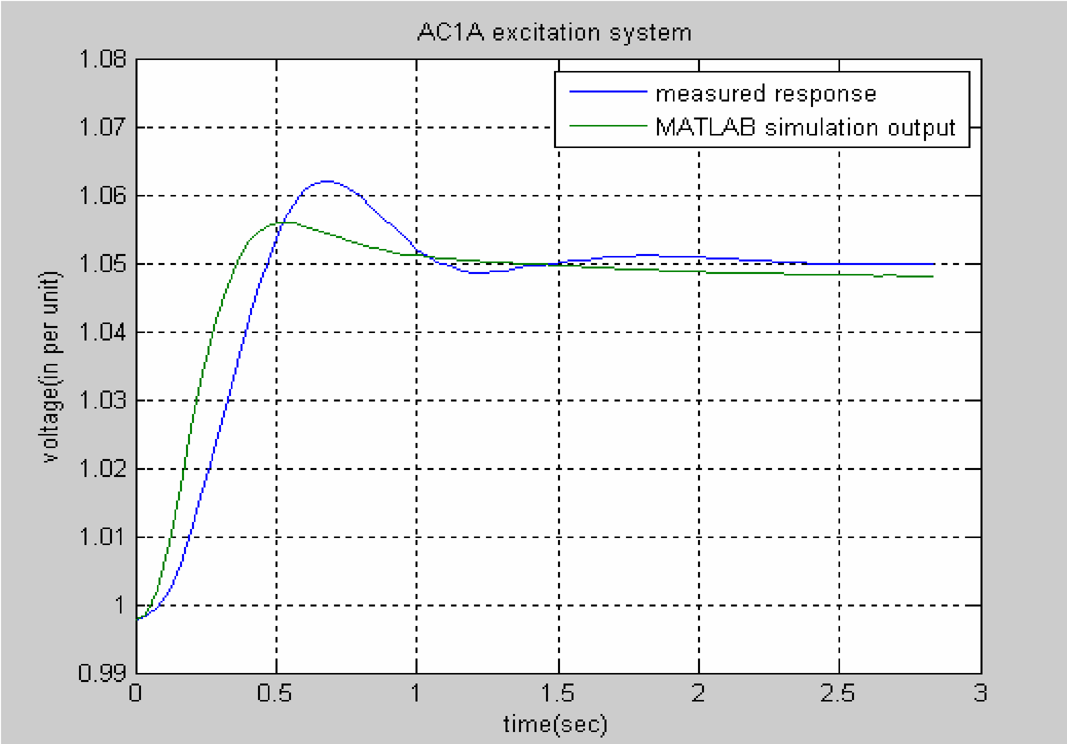


Fig. 4. 3 Model response with typical parameters of AC1A excitation system

4.1.1 Parameter Estimation Using Matlab PE Toolbox

Firstly, the Matlab PE Toolbox has been used to estimate the parameters based on the bump test results given in Fig. 4.3. (Blue line) The robust option has been used for the solution. Figure 4.4, shows the iterations that were taken and, cost function and step size of each iteration. Cost function shows the difference between the simulation output and measured output. And the step size shows convergence speed. As shown in the figure, the optimization terminated for the step size is too small, which means the program cannot find a good enough solution before it converged.

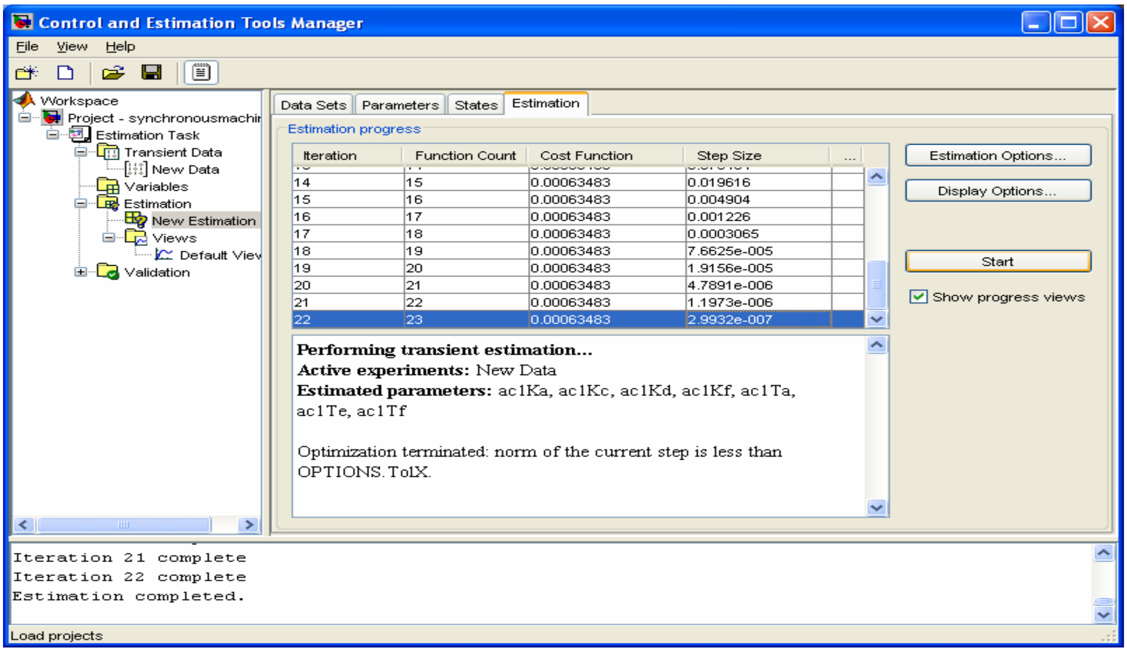


Fig. 4. 4 Cost function and step size of each iteration with typical parameters of AC1A excitation system

The Parameters obtained are as follows:

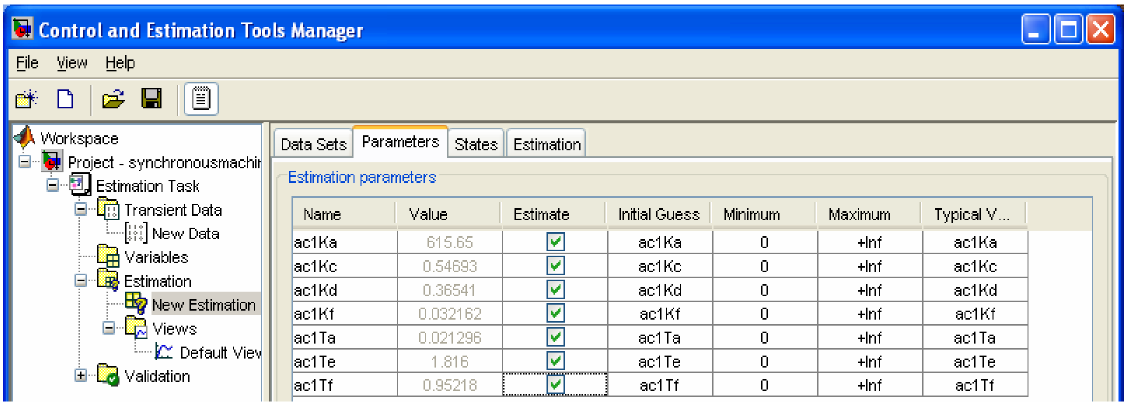


Fig. 4. 5 Estimated parameters of AC1A excitation system starting from typical parameters

	We get:	Initial value:
Regulator gain:	ac1Ka = 615.65	ac1Ka = 766
Regulator time constant:	ac1Ta = 0.021296	ac1Ta = 0.0200
Exciter time constant:	ac1Te = 1.816	ac1Te = 1.3000
Damping filter gain:	ac1Kf = 0.032162	ac1Kf = 0.0240
Damping filter time constant:	ac1Tf = 0.95218	ac1Tf = 1.0000
Rectifier loading factor:	ac1Kc = 0.54693	ac1Kc = 0.4860
Demagnetizing factor:	ac1Kd = 0.36541	ac1Kd = 0.3556

Figure 4.6 compares the simulation response using the estimated parameters with the measured response.

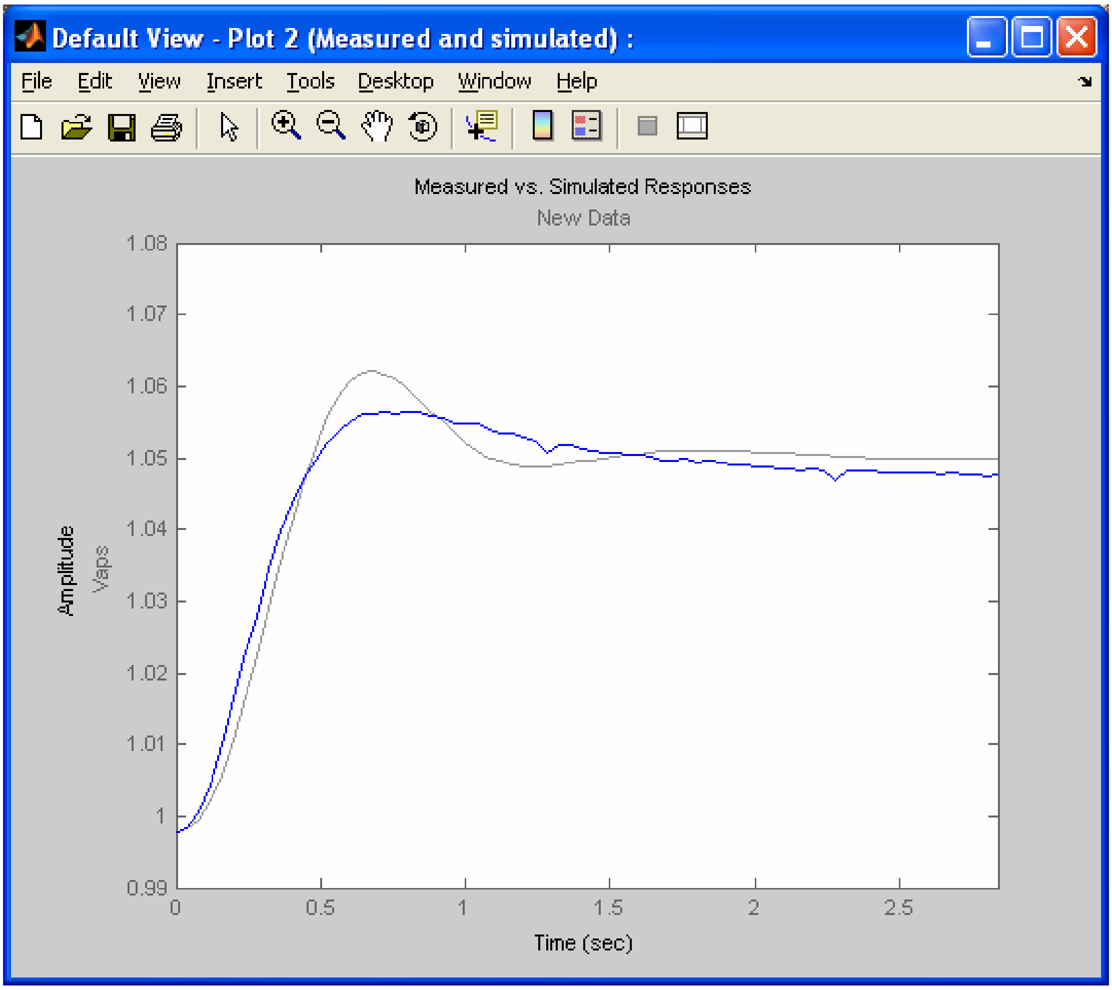


Fig. 4. 6 Final terminal output of generator with typical parameters of AC1A excitation system (Grey - Desired curve, Blue – Simulation output)

Parameter Trajectory

Sensitivity of parameters is another important issue. With knowing the sensitivity of each parameter, when manually adjusting the parameters, the engineer can adjust the one who has the most sensitivity. It will increase the efficiency of the work. From figure 4.5, we can see the regulator gain, regulator time constant and damping filter time constant change a lot.

They can be considered as the main factors for the curve fitting, which means that they have the most sensitivity. There is another plot provided by the PE toolbox, which can also be used to estimate the sensitivity. That is the parameter trajectory plot (figure 4.7), from which we can see the changes of parameters by iteration.

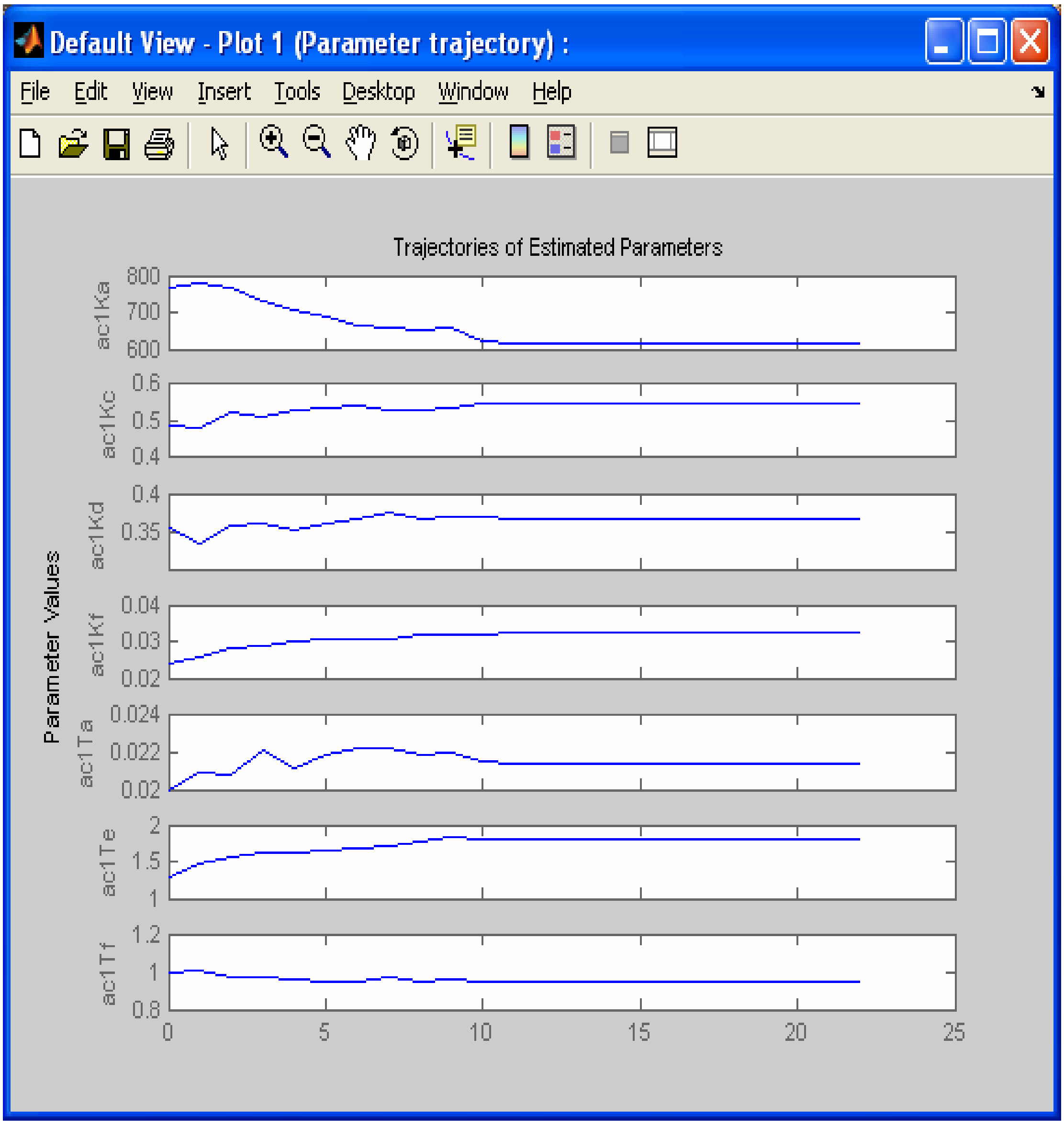


Fig. 4. 7 Parameter trajectory when estimating parameters of AC1A excitation system

4.1.2 Parameter Estimation using Damped Gauss Newton

As the second option, the damped Gauss Newton Method which has been implemented in MATLAB codes has been used to estimate the parameters, using the same initial parameter values. In table 1 listed the iteration history of the operation.

Table 1 Iteration history of parameter estimation of AC1A starting from typical parameters using DGN

Norm(gc)	f(xc)	Armijo iter.	Iteration
0.0034	0.0023	0	0
0.0033	0.0018	9	1
0.0086	0.0018	0	2
0.0036	0.0006	0	3
0.0016	0.0003	0	4
0.0005	0.0002	0	5
0.0002	0.0001	0	6
0.0004	0.0001	0	7
0.0003	0.0001	0	8
0.0004	0.0001	0	9
0.0004	0.0001	0	10

This method yielded the following values:

Xmodel_GN=

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
669.3898	0.0502	3.0419	1.7159	0.0339	0.5123	-0.3254

Fig. 4.8 compares the simulation response with the test data. As it indicates, it is a good fit. The method did converge, but did not converge to the best solution. Since we did not enforce limits, there is a negative parameter which do not match its physical meaning well.

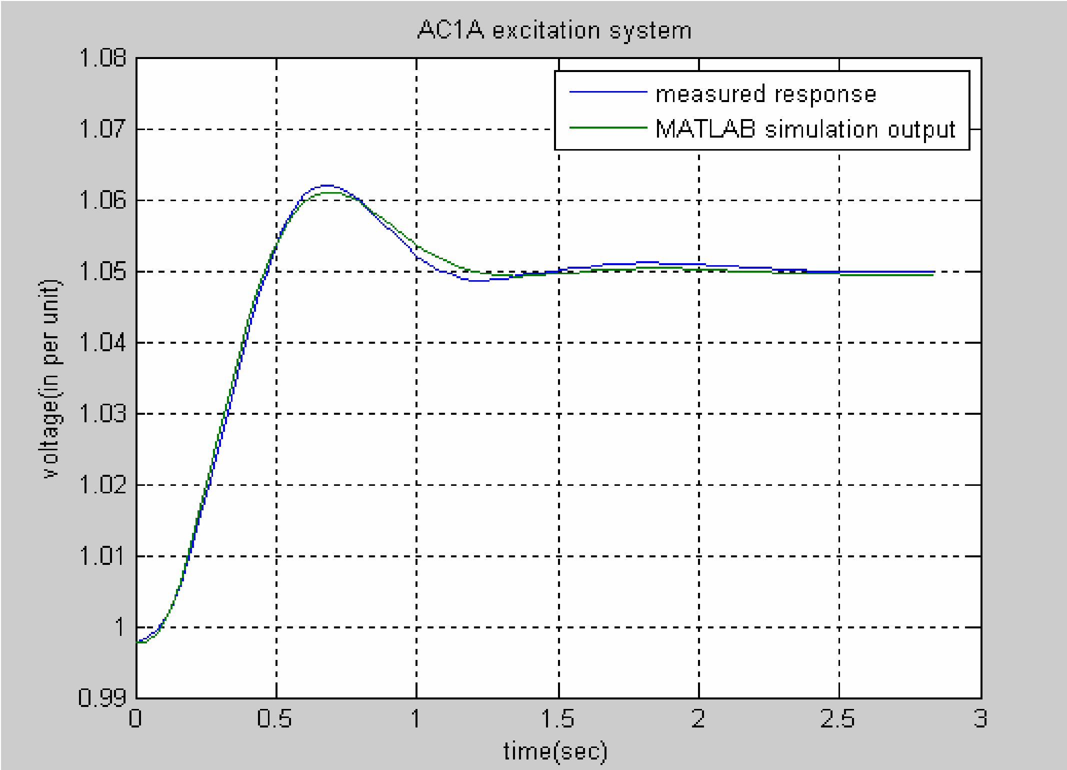


Fig. 4. 8 Final terminal output of generator starting from typical parameters using DGN

4.1.3 Parameter Estimation using LM and DGN

For improving the result, we choose the combination of Levenberg Marquardt method and Damped Gauss Newton method. The LM method has been used to get the better start point P^L first and then DGN method has been used to get the solution. The initial parameters are the same as the previous case, which is

X0 =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
766	0.0200	1.3000	0.0240	1.0000	0.4860	0.3556

4.1.3.1 Levernberg Marquardt

In Table 2 shows the historty of the iteration when using Levenberg Marquardt.

Table 2 Iteration history of parameter estimation of AC1A starting from typical parameters using LM

Norm(gc)	fc	Trust region test itr.	Iterations
0.0034	0.0023	0	0
0.0034	0.0023	1.0000	1
0.0034	0.0023	1.0000	2
0.0061	0.0019	4.0000	3
0.0061	0.0019	1.0000	4
0.0061	0.0019	1.0000	5
0.0061	0.0019	1.0000	6
0.0033	0.0016	2.0000	7
0.0033	0.0016	1.0000	8
0.0096	0.0014	3.0000	9
0.0096	0.0014	1.0000	10
0.0096	0.0014	1.0000	11
0.0096	0.0014	1.0000	12
0.0035	0.0013	5.0000	13
0.0035	0.0013	1.0000	14
0.0035	0.0013	1.0000	15
0.0035	0.0013	1.0000	16
0.0035	0.0013	1.0000	17
0.0071	0.0012	5.0000	18
0.0071	0.0012	1.0000	19
0.0071	0.0012	1.0000	20

This method yielded the following values:

Xmodel_LM =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
500.8150	0.0271	2.0854	1.0073	0.0186	0.4747	0.3537

According to the values of cost functions, the iterations converged. It terminated due to the maximum iteration limit, which means that the program stopped before finding the best solution. As indicated in the Fig. 4.9, the curves did not match to each other well, for the simulation response and the measured response settled down to different points.

Fig. 4.9 compares the result with data.

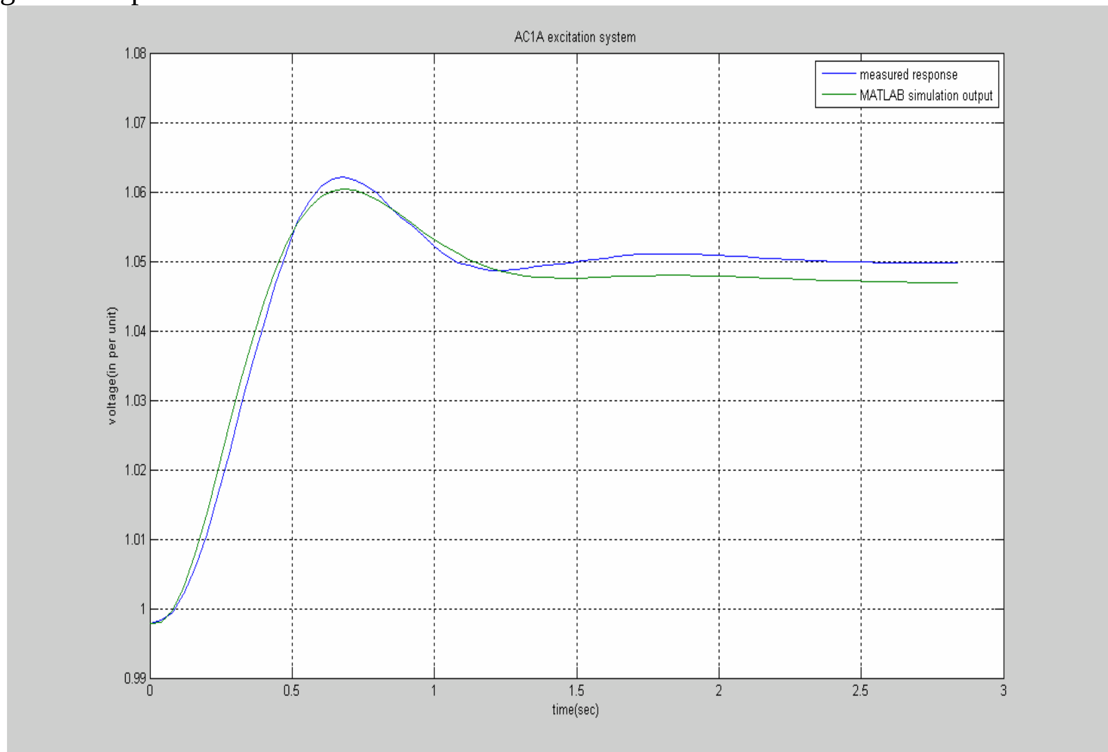


Fig. 4. 9 Final terminal output of generator starting from typical parameters using LM

4.1.3.2 Damped Gauss Newton

In Table 3 shows the history of the iteration when using Gauss Newton starting from the parameters getting from Levenberg Marquardt method P^L, which is

xstart =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
500.8150	0.0271	2.0854	1.0073	0.0186	0.4747	0.3537

Table 3 Iteration history of parameter estimation of AC1A starting from P^L using DGN

Norm(gc)	fc	Armijo Iter.	Iterations
0.0006	0.0004	0	0
0.0008	0.0002	0	1
0.0011	0.0001	0	2
0.0011	0.0001	0	3
0.0010	0.0001	0	4
0.0008	0.0001	0	5
0.0007	0.0000	0	6
0.0006	0.0000	0	7

Table 3 *Continued*

Norm(gc)	fc	Armijo Iter.	Iterations
0.0005	0.0000	0	8
0.0004	0.0000	0	9
0.0003	0.0000	0	10
0.0003	0.0000	0	11
0.0002	0.0000	0	12
0.0001	0.0000	0	13
0.0001	0.0000	6.0000	14
0.0000	0.0000	0	15
0.0000	0.0000	0	16
0.0000	0.0000	0	17
0.0000	0.0000	0	18
0.0000	0.0000	0	19
0.0000	0.0000	0	20

This method yielded the following values:

xcurrent =

ac1Ka ac1Kf ac1Te ac1Tf ac1Ta ac1Kc ac1Kd

1.0e+003 *

1.0427 0.0001 0.0050 0.0018 0.0001 0.0003 -0.0002

The method did converge. Fig. 4.10 shows that the model response matches the measured response quite well.

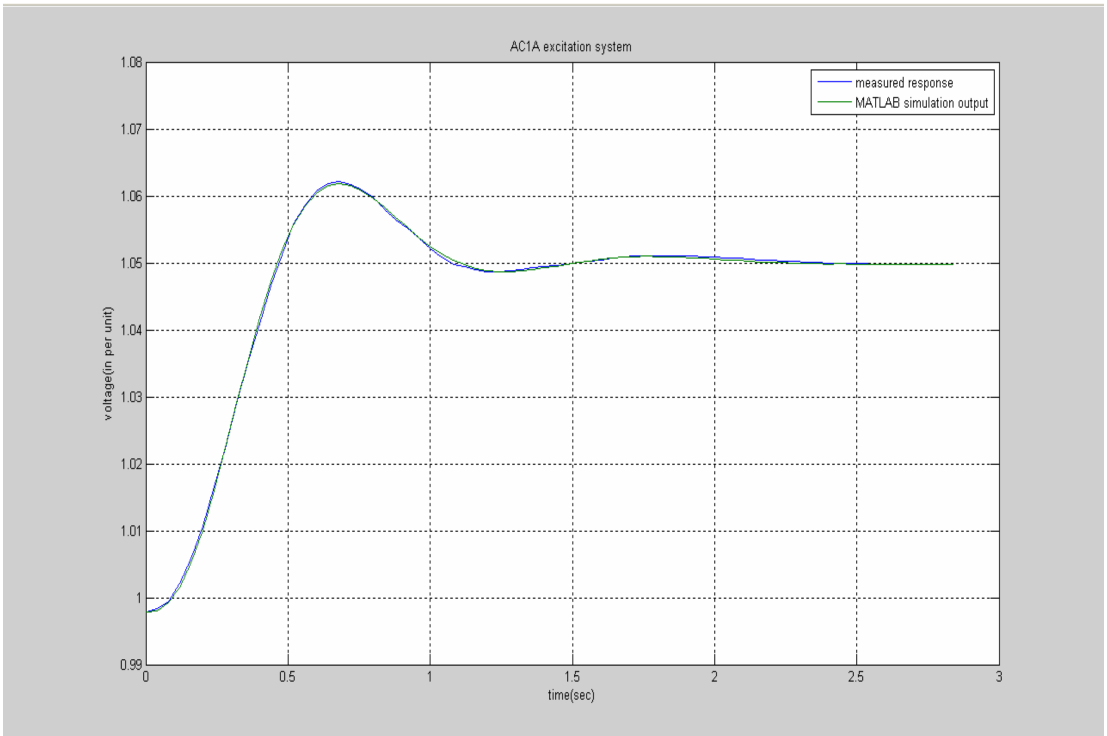


Fig. 4. 10 Final terminal output of generator when estimating AC1A excitation starting from P^L using DGN

4.2 Case 2: AC1A with good initial paramters

When started with typical parameter values, the two methods did not reach the same solution. To find a better solution, John O'connor who is the expert on using these models in Progress Energy, adjusted the parameter values manually to find a better initial point. This new initial parameters have been given as:

Regulator gain:	ac1Ka = 400
Regulator time constant:	ac1Ta = 0.0200
Exciter time constant:	ac1Te = 1.3000
Damping filter gain:	ac1Kf = 0.0240
Damping filter time constant:	ac1Tf = 1.0000
Rectifier loading factor:	ac1Kc = 0.4860
Demagnetizing factor:	ac1Kd = 0.3556

As Fig.4.11 shows these values indeed yield a simulation response that is much closer to the actual response than that of the original parameter values.

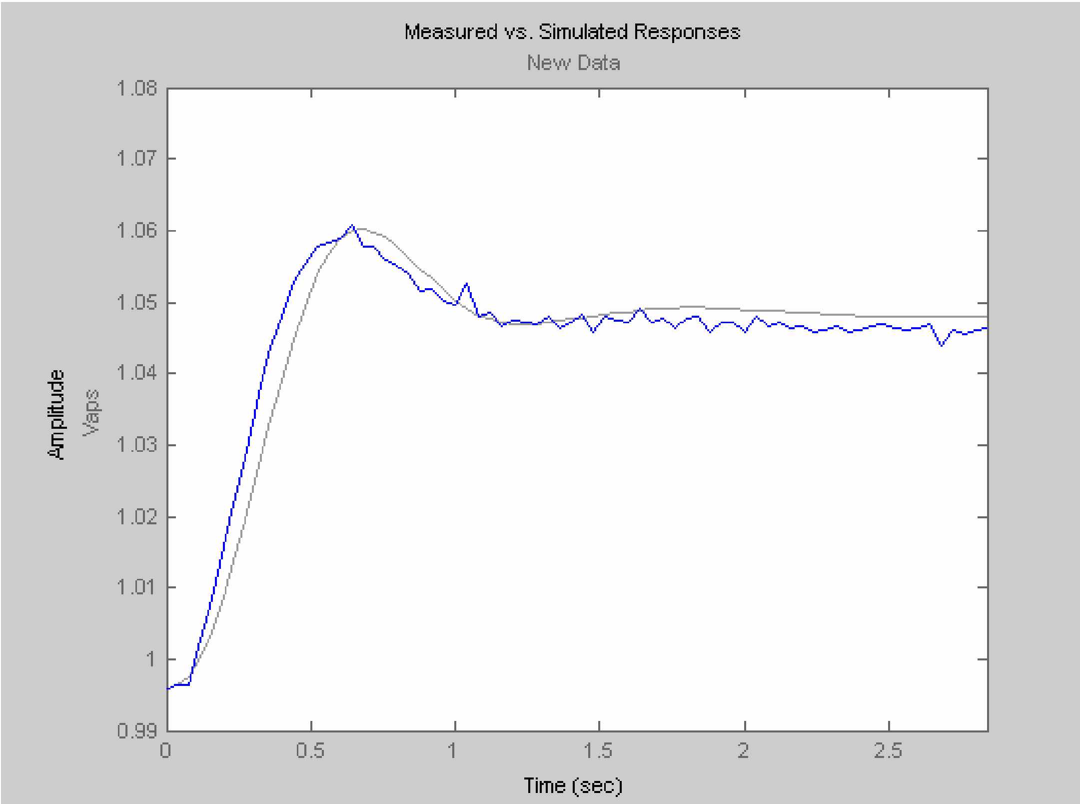


Fig. 4. 11 Model response with good parameters of AC1A excitation system
(Grey - Desired curve, Blue – Simulation output)

4.2.1 Parameter Estimation Using Matlab PE Toolbox

For the case, again we tried Matlab PE Toolbox first to estimate the parameters. The fast option has been used for the solution, for it has good initial points. Figure 4.12 shows the iterations that were taken and, cost function and step size of each iteration. The program may not find a good enough solution before it converge, for the optimization terminated for the step size is too small.

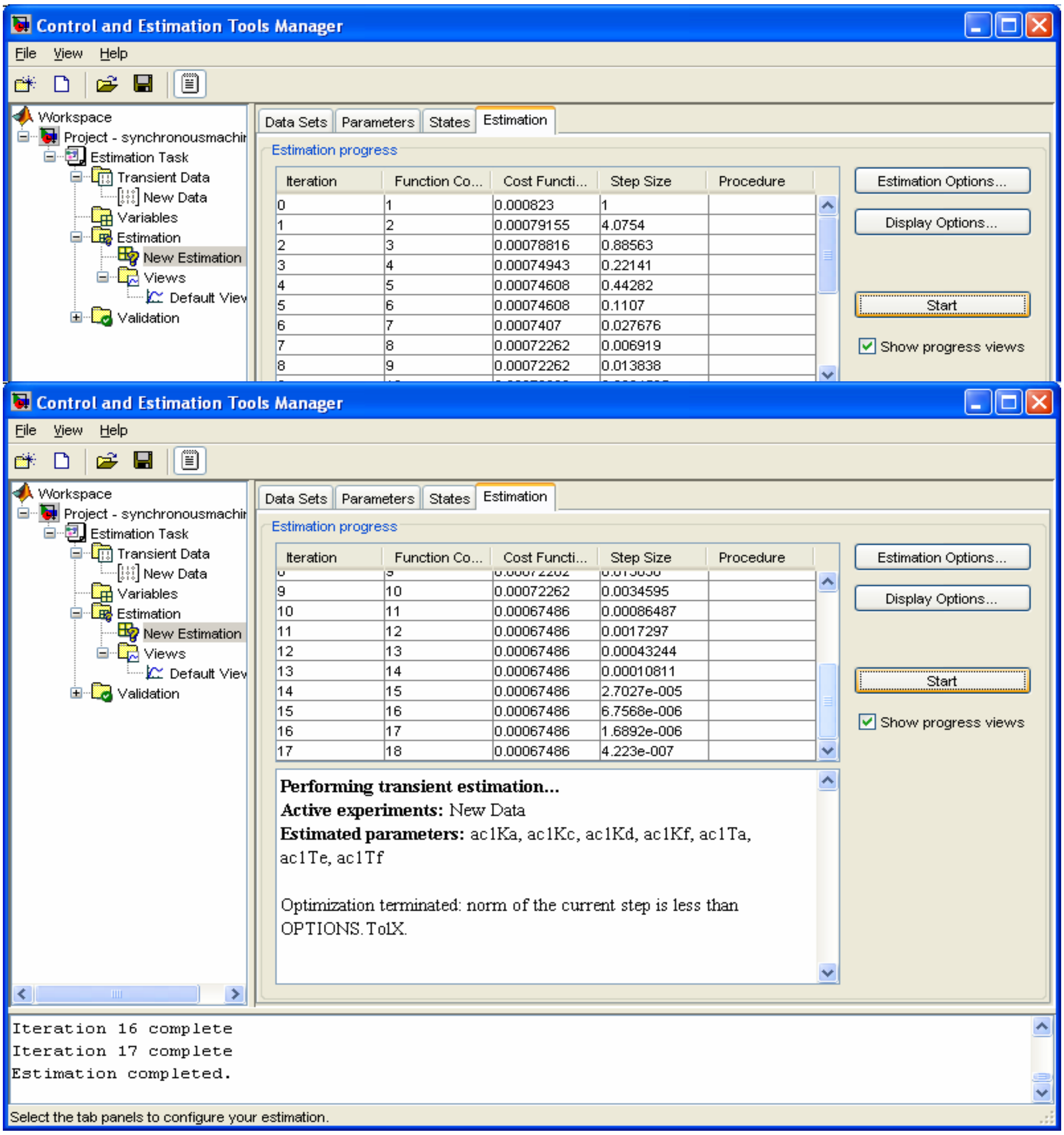


Fig. 4. 12 Cost function and step size of each iteration when estimating AC1A excitation system with good initial paramteres

Parameters obtained are:

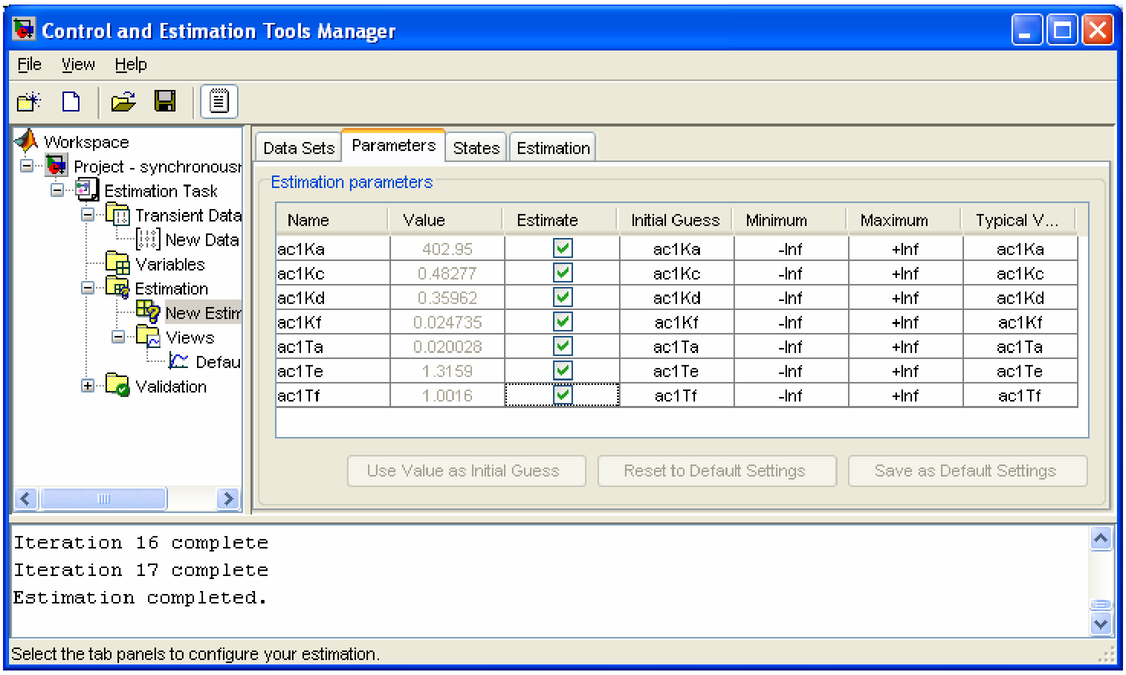


Fig. 4. 13 Estimated parameters of AC1A excitation system starting from good initial parameters

	We get:	Initial value:
Regulator gain:	ac1Ka = 402.95	ac1Ka = 400
Regulator time constant:	ac1Ta = 0.020028	ac1Ta = 0.0200
Exciter time constant:	ac1Te = 1.3159	ac1Te = 1.3000
Damping filter gain:	ac1Kf = 0.024735	ac1Kf = 0.0240
Damping filter time constant:	ac1Tf = 1.0016	ac1Tf = 1.0000
Rectifier loading factor:	ac1Kc = 0.54693	ac1Kc = 0.4860
Demagnetizing factor:	ac1Kd = 0.35962	ac1Kd = 0.3556

Figure 4.14 compares the model response using the estimated parameters with the measured response.

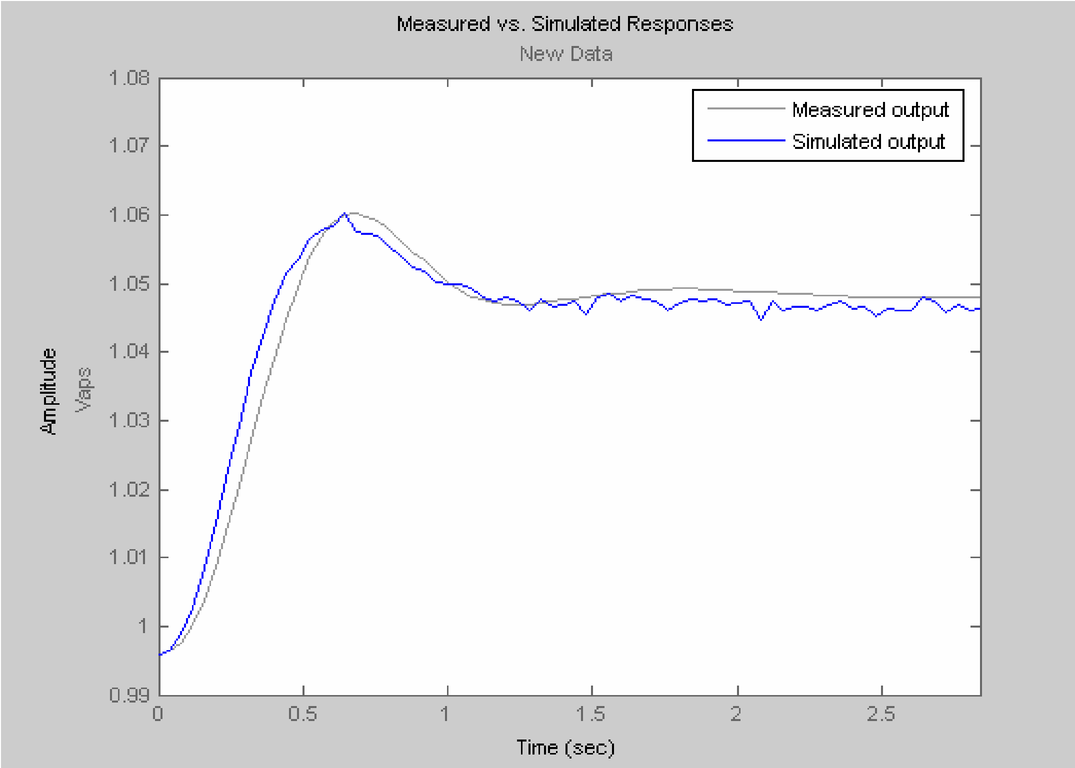


Fig. 4. 14 Final terminal output of generator when estimating AC1A excitation system starting from good parameters (Grey - Desired curve, Blue – Simulation output)

4.2.2 Damped Gauss Newton

The damped Gauss Newton Method implemented in Matlab has also been used to estimate the parameters using the same initial parameter values. Here we also only use DGN method, rather than use the combination of GN method and LM method. In Table 4 listed the iteration history of the operation.

Table 4 Iteration history of parameter estimation of AC1A starting from P^L using DGN

Norm(gc)	f(xc)	Armijo iter.	Iteration
0.0237	0.0066	0	0
0.0035	0.0001	0	1
0.0025	0.0001	0	2
0.0012	0.0000	0	3
0.0005	0.0000	0	4
0.0007	0.0000	0	5
0.0003	0.0000	0	6

This method yielded the following values:

```
Xmodel=
```

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
364.1523	0.0413	1.6724	1.4580	0.0542	0.4860	0.4039

cost: fc = 1.0498e-005

The method converged fast(only 6 iterations) and sufficiently reduced the residuals to 1e-5, which can tell us DGN method works well. When starting from a good initial points, using DGN, the iteration converges well and provides good results The terminal output curve is shown in Fig. 4.15.

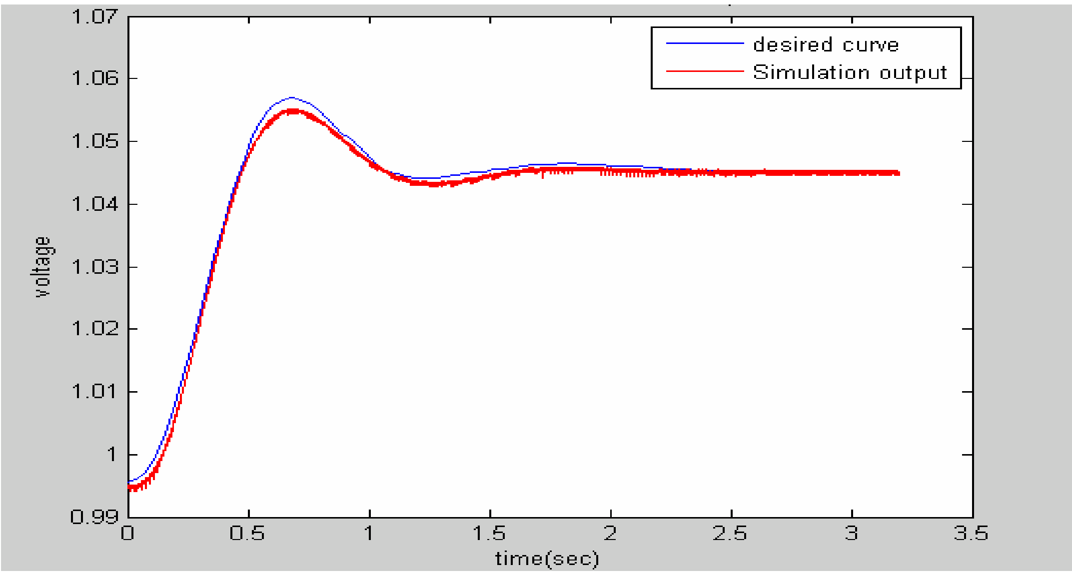


Fig. 4. 15 Final terminal output of generator when estimating AC1A excitation starting from a good initial point

4.3 Case 3: AC1A with Low Parameters

To test the method, we tried two more cases using the combination of LM and DGN. One of them starts from $0.5*P^0$, where P^0 is typical parameters. So the initial parameters are:

X0 =	ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
	383.0000	0.0100	0.6500	0.0120	0.5000	0.2430	0.1778

Fig 4.16 shows the simulation with the initial parameters.

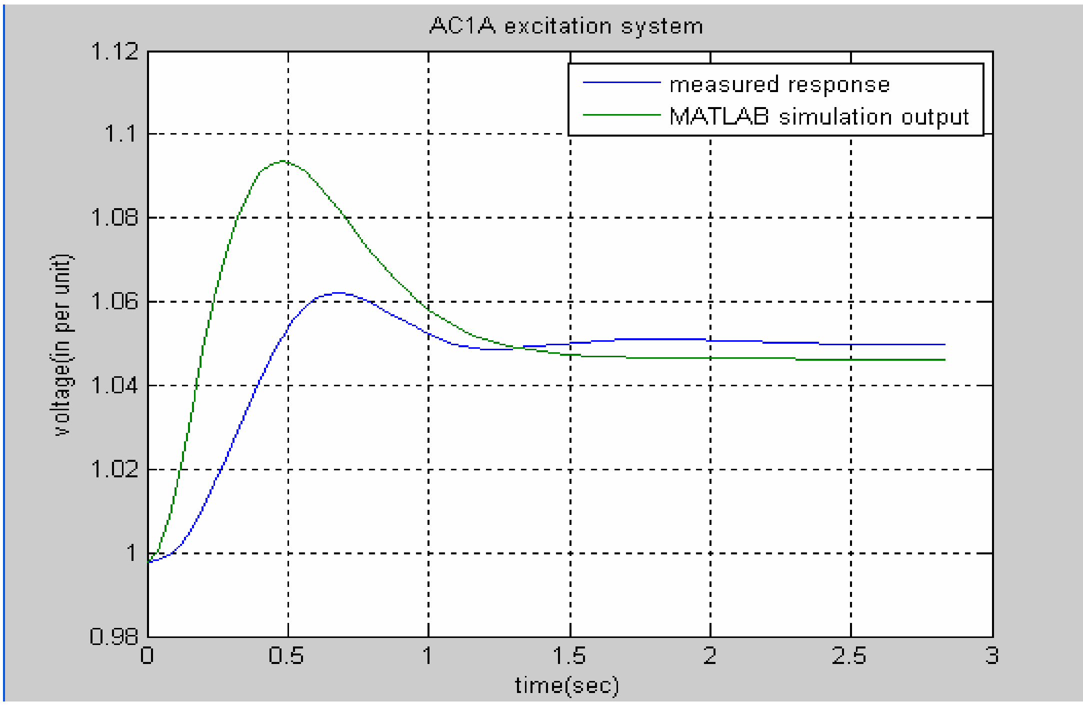


Fig. 4. 16 Model response with low parameters of AC1A excitation system

4.3.1 Levernberg Marquardt

Table 5 shows the history of the iteration when using Levenberg Marquardt.

Table 5 Iteration history of parameter estimation of AC1A starting from low parameters using LM

Norm(gc)	fc	Trust region test itr.	Iterations
0.0378	0.0244	0	0
0.0378	0.0244	1.0000	1
0.0378	0.0244	1.0000	2
0.0378	0.0244	1.0000	3
0.0286	0.0096	2.0000	4
0.0286	0.0096	1.0000	5
0.0286	0.0096	1.0000	6
0.0102	0.0046	2.0000	7
0.0102	0.0046	1.0000	8

Table 5 Continued

Norm(gc)	fc	Trust region test itr.	Iterations
0.0102	0.0046	1.0000	9
0.0102	0.0046	1.0000	10
0.0102	0.0046	1.0000	11
0.0102	0.0046	1.0000	12
0.0019	0.0042	5.0000	13
0.0019	0.0042	1.0000	14
0.0019	0.0042	1.0000	15
0.0019	0.0042	1.0000	16
0.0019	0.0042	1.0000	17
0.0019	0.0042	1.0000	18
0.0019	0.0042	1.0000	19
0.0025	0.0034	2.0000	20

This method yielded the following results:

Xmodel_LM =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
745.5704	0.0248	3.7373	1.2997	0.0048	0.4008	-0.2545

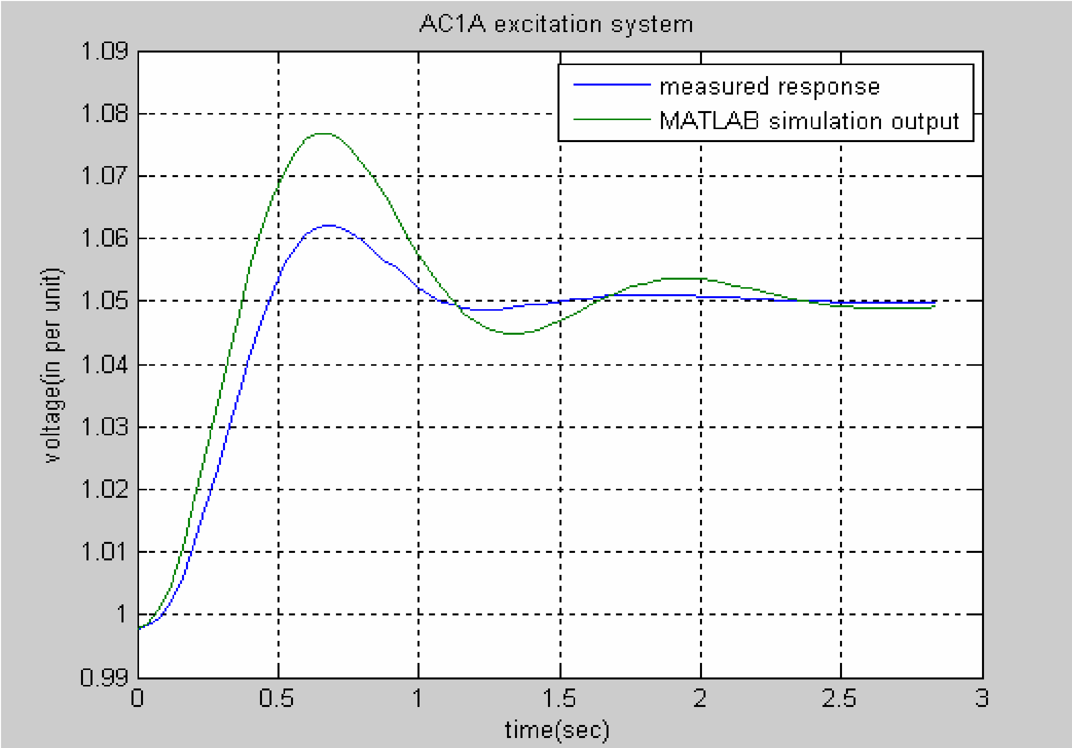


Fig. 4.17 Final terminal output of generator starting from low parameters using LM

From the history, we can see the method did not converge. And from Fig 4.17, we know that the settled point is closed for both of the response, although the dynamic transient part is not matched to each other.

4.3.2 Damped Gauss Newton

In Table 6 shows the history of the iteration when using Damped Gauss Newton starting from P^{LM}, which is

xstart =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
745.5704	0.0248	3.7373	1.2997	0.0048	0.4008	-0.2545

Table 6 Iteration history of parameter estimation of AC1A starting from P^L using DGN

Norm(gc)	fc	Armijo Iter.	Iterations
0.0051	0.0034	0	0
0.0016	0.0004	0	1
0.0011	0.0002	0	2
0.0005	0.0002	0	3

Table 6 Continued

Norm(gc)	fc	Armijo Iter.	Iterations
0.0002	0.0001	0	4
0.0002	0.0001	0	5
0.0002	0.0001	0	6
0.0003	0.0001	0	7
0.0003	0.0001	0	8
0.0002	0.0001	0	9
0.0003	0.0001	0	10
0.0003	0.0001	0	11
0.0003	0.0001	0	12
0.0003	0.0001	0	13
0.0003	0.0001	0	14
0.0003	0.0001	0	15
0.0003	0.0001	0	16
0.0003	0.0001	0	17
0.0003	0.0001	0	18
0.0003	0.0001	0	19
0.0003	0.0001	0	20

This method provided the following results:

xcurrent =

```
     ac1Ka      ac1Kf     ac1Te     ac1Tf     ac1Ta     ac1Kc    ac1Kd

 1.0e+003 *

    1.5465      0.0000    0.0062    0.0014    0.0000    0.0010   -0.0003
```

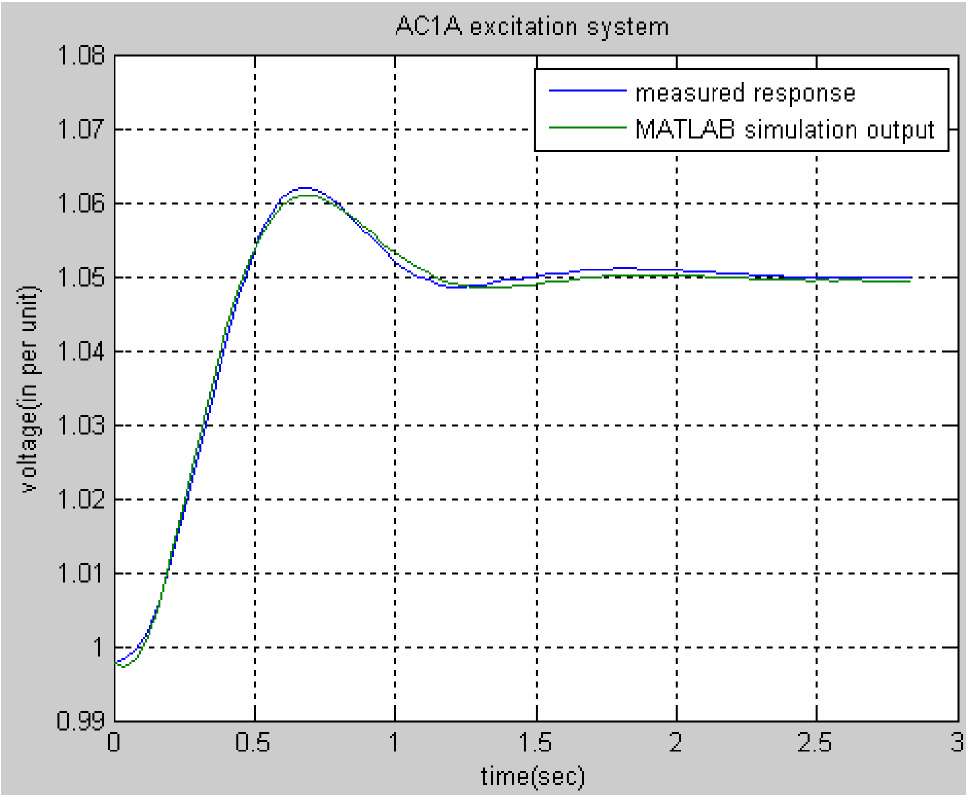


Fig. 4. 18 Final terminal output of generator when estimating AC1A excitation using DGN starting from P^L

The history in Table 6 tells us the method converged very slowly and terminated due to maximum iteration. And from the plot we can tell it converged to a local minimizer such that the responses matched to each other well. In this case, we get a good enough solution from LM so that DGN can provide a good solution. Although it went to another direction, which we can tell from the negative number, it is still a good local solution, for we just considered it as an unconstrained optimization problem.

4.4 Case 4: AC1A with high parameters

Then we tried the initial parameter starting from 1.5*P^0, which means the initial parameters are:

X0 =

ac1Ka ac1Kf ac1Te ac1Tf ac1Ta ac1Kc ac1Kd
1.0e+003*

1.1490 0.0000 0.0020 0.0015 0.0000 0.0007 0.0005

In Fig 4.20 shows the simulation with the initial parameters.

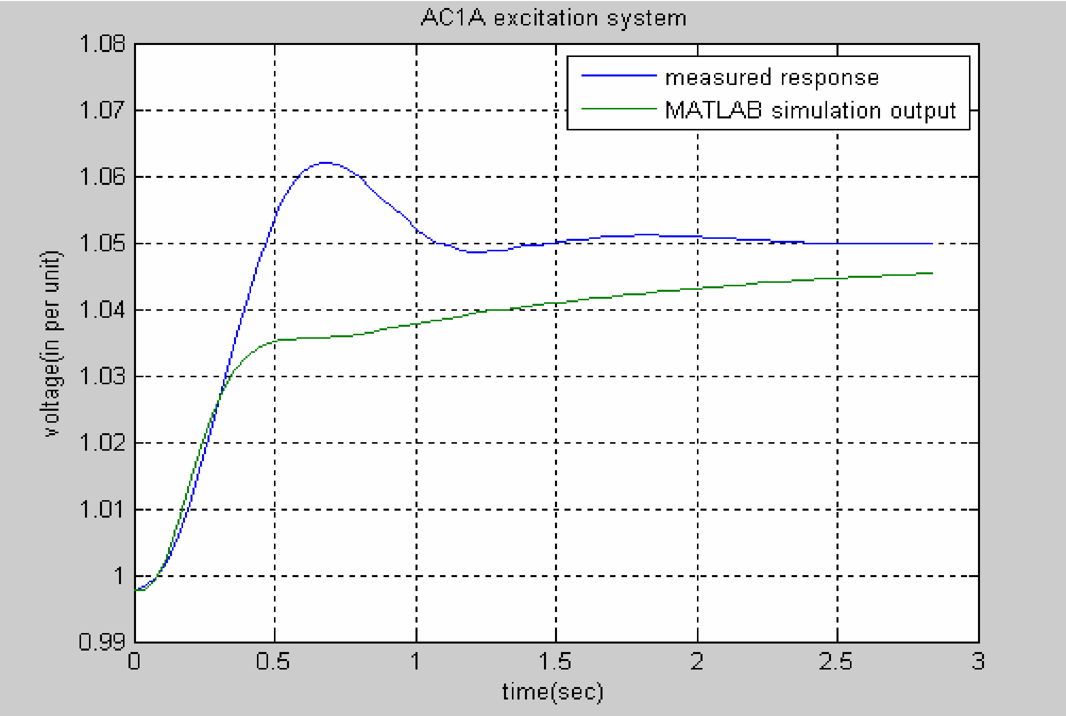


Fig. 4. 19 Model response with high parameters of AC1A excitation system

4.4.1 Levernberg Marquardt

In Table 7 shows the history of the iteration when using Levenberg Marquardt.

Table 7 Iteration history of parameter estimation of AC1A starting from high parameters using LM

Norm(gc)	fc	Trust region test itr.	Iterations
0.0142	0.0244	0	0
0.0142	0.0244	1.0000	1
0.0195	0.0244	1.0000	2
0.0195	0.0244	1.0000	3
0.0195	0.0096	2.0000	4
0.0114	0.0096	1.0000	5

Table 7 Continued

Norm(gc)	fc	Trust region test itr.	Iterations
0.0114	0.0096	1.0000	6
0.0114	0.0046	2.0000	7
0.0114	0.0046	1.0000	8
0.0312	0.0046	1.0000	9
0.0312	0.0046	1.0000	10
0.0312	0.0046	1.0000	11
0.0312	0.0046	1.0000	12
0.0312	0.0042	5.0000	13
0.0312	0.0042	1.0000	14
0.0312	0.0042	1.0000	15
0.0065	0.0042	1.0000	16
0.0065	0.0042	1.0000	17
0.0065	0.0042	1.0000	18
0.0065	0.0042	1.0000	19
0.0065	0.0034	2.0000	20

The results obtained are:

Xmodel_LM =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
751.1027	0.0266	2.7584	1.3613	0.0262	0.6049	0.4179

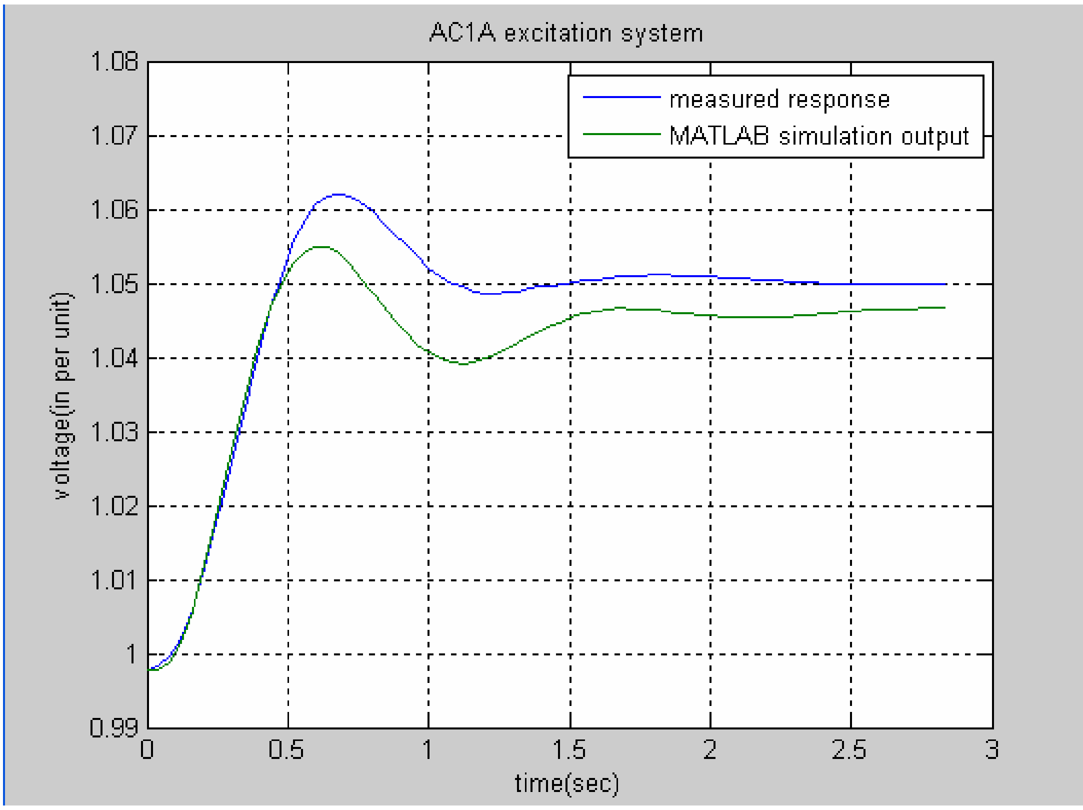


Fig. 4.20 Final terminal output of generator starting from high parameters using LM

From the history, we can see the method did not totally settle down before it converge, so the solution will not be the best point. Fig. 4.21 tells us the settle points are different in both of the curve, which prove that the solution from LM is not good enough. Also, observed from the plot of each iteration, we found that, the simulation output become closer and closer to the measured one as it started, but after getting to some point, it will suddenly change back to a bad shape and try get closer again. We may improve our program by choosing the best solution in the iterations as the solution.

4.4.2 Damped Gauss Newton

In Table 8 shows the historty of the iteration when using Damped Gauss Newton starting from P^L, which is

xstart =

ac1Ka	ac1Kf	ac1Te	ac1Tf	ac1Ta	ac1Kc	ac1Kd
751.1027	0.0266	2.7584	1.3613	0.0262	0.6049	0.4179

Table 8 Iteration history of parameter estimation of AC1A starting from P^L using DGN

Norm(gc)	fc	Armijo Iter.	Iterations
0.0055	0.0026	0	0
0.0018	0.0004	1	1
0.0014	0.0003	2	2
0.0016	0.0003	8	3
0.0011	0.0001	0	4
0.0010	0.0001	0	5
0.0007	0.00008	0	6
0.0006	0.00006	0	7
0.0004	0.00005	0	8
0.0003	0.00005	0	9
0.0004	0.00004	0	10
0.0005	0.00004	0	11
0.0005	0.00004	3	12
0.0006	0.00004	1	13

This method yielded the following values:

xcurrent =

1.0e+003 *

1.5465   0.0000   0.0062   0.0014   0.0000   0.0010   -0.0003

The method did converge and it converged to the same point as with low parameters.

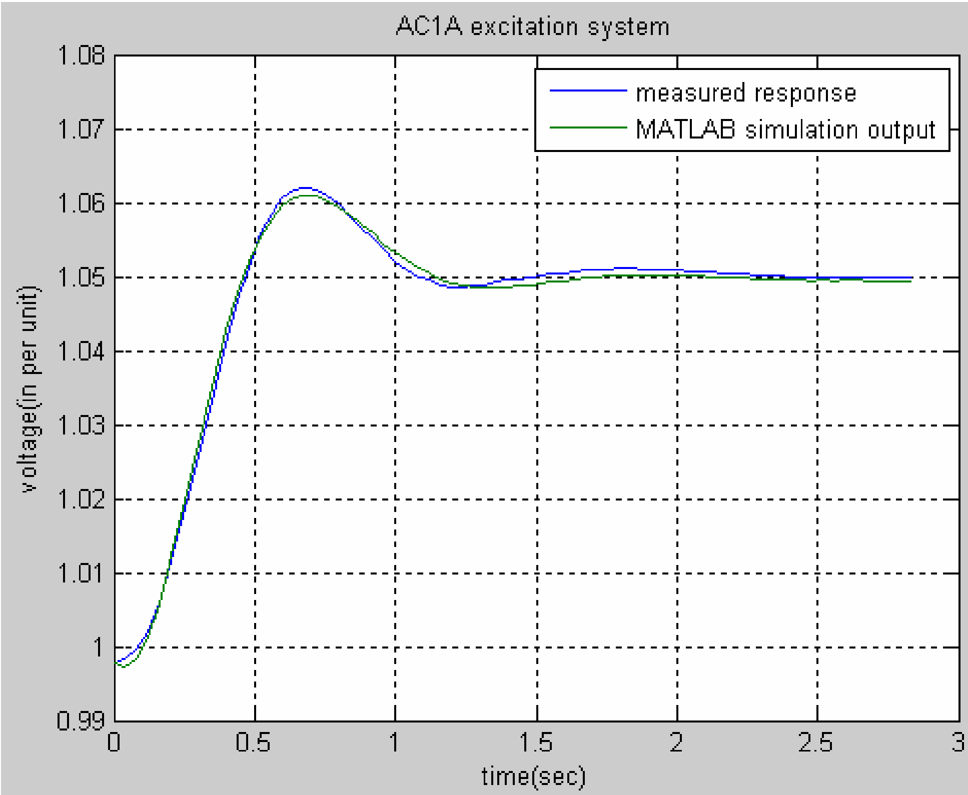


Fig. 4. 21 Final terminal output of generator when estimating AC1A excitation using DGN starting from P^L

4.5 Case 5: AC8B with good initial guess

The excitation system has been simulated in Simulink,which is shown in Fig. 4.23.

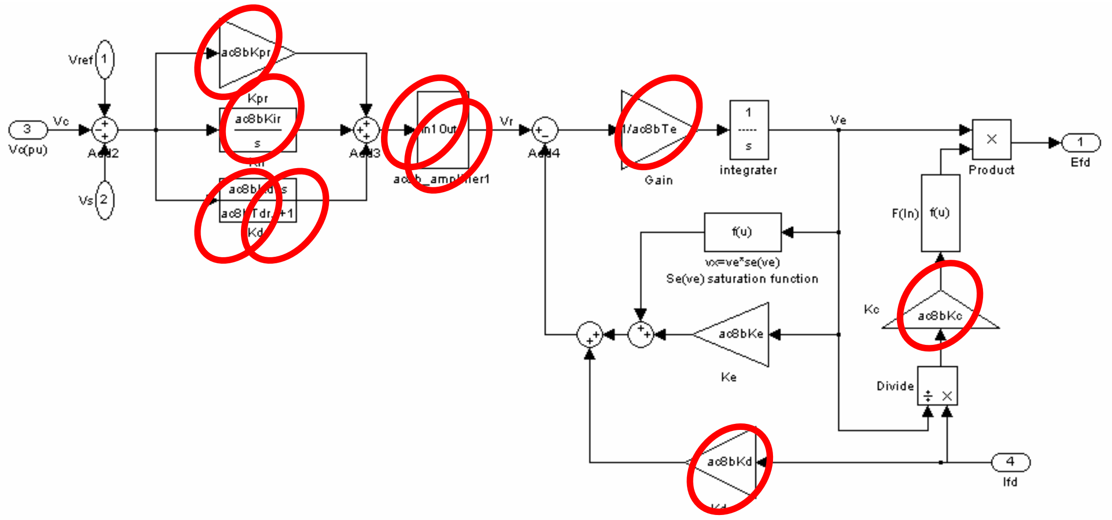


Fig. 4. 22 Implementation of AC8B excitation system in MATLAB/Simulink

There are 9 parameters of this system:

ac8bKpr, ac8bKir, ac8bKdr, ac8bTdr, ac8bTa, ac8bKa, ac8bTe, ac8bKc, ac8bKd

Progress Energy has provided the initial values for them, which are considered as a good initial point:

Voltage regulator proportional gain:	ac8bKpr = 84
Voltage regulator integral gain:	ac8bKir = 5
Voltage regulator derivative gain:	ac8bKdr = 10
Lag time constant:	ac8bTdr = 0.1
Voltage regulator time constant:	ac8bTa = 0
Voltage regulator gain:	ac8bKa = 1
Exciter time constant:	ac8bTe = 1.3
Rectifier loading factor:	ac8bKc = 0.55
Demagnetizing factor:	ac8bKd= 1.1

Besides, Progress Energy provided two suites of bump test data. Figure 4.23 and figure 4.24 are showing us the measured response and the simulation response with these initial values for each suite of data, respectively.

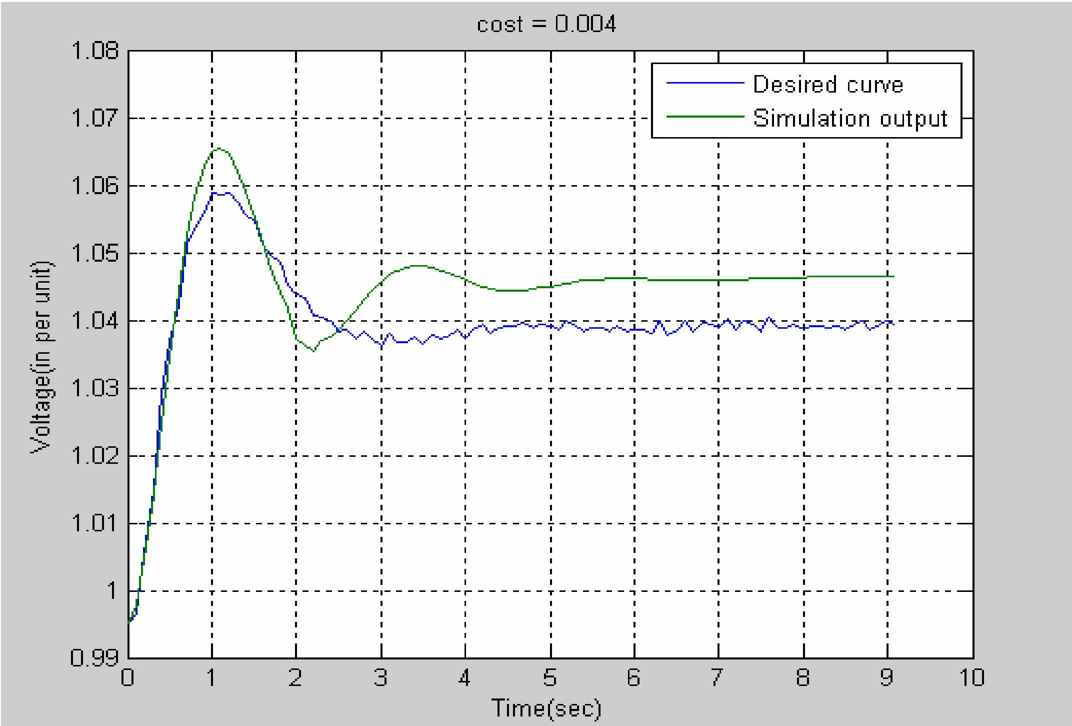


Fig. 4. 23 Model response with good parameters of AC8B excitation system
(Data Unit 1)

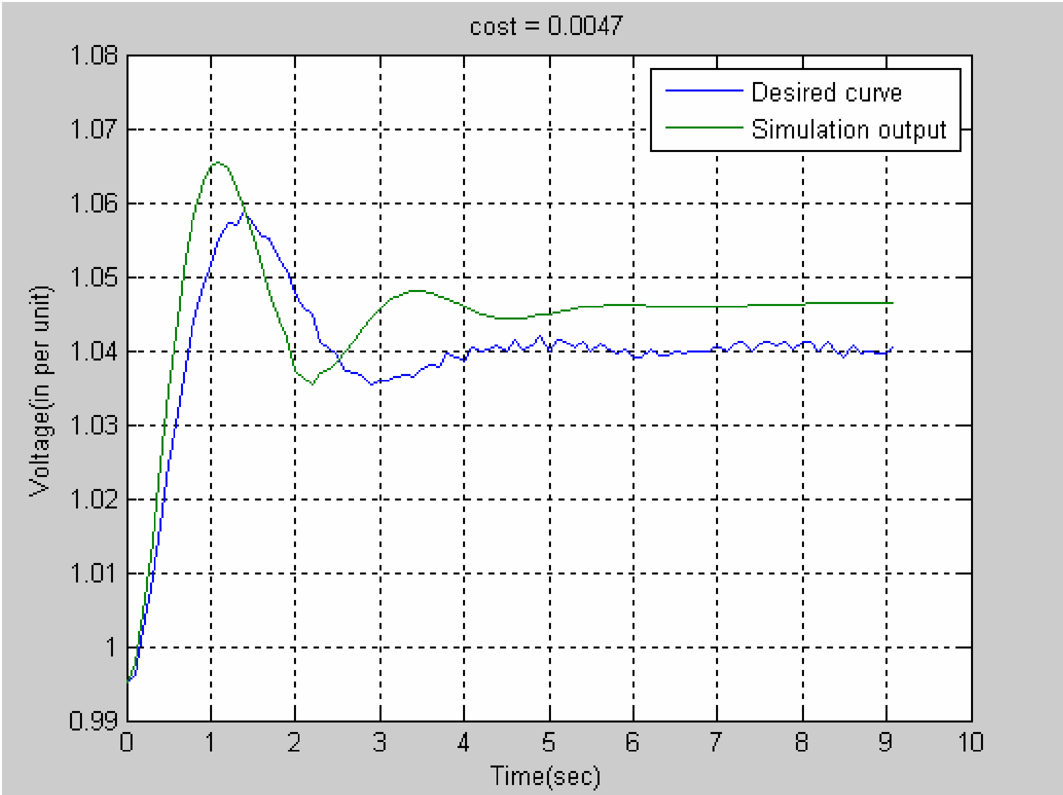
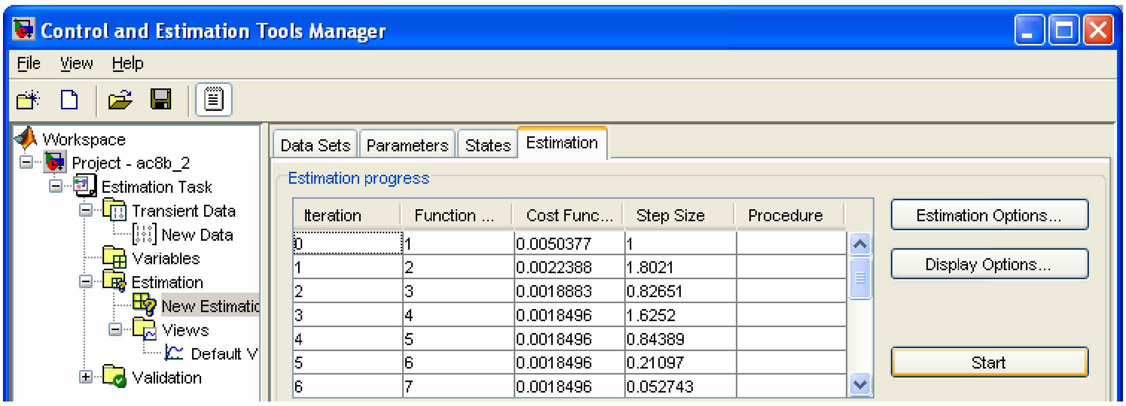


Fig. 4. 24 Model response with good parameters of AC8B excitation system (Data Unit 2)

4.5.1 Parameter Estimation Using Matlab PE Toolbox

4.5.1.1 Data Unit 1

In Fig. 4.25, it shows the iterations, cost function and step size of each iteration.



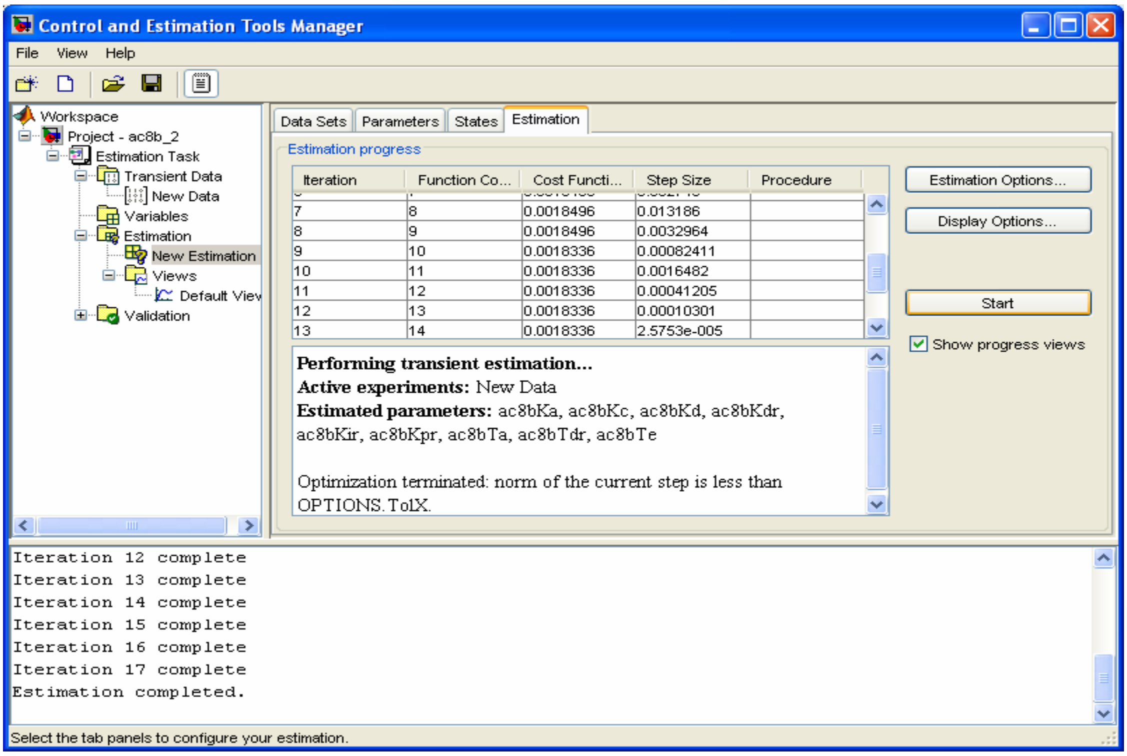


Fig. 4. 25 Cost function and step size when estimating AC8B excitation system with good initial parameters(Unit 1)

Parameters obtained are:

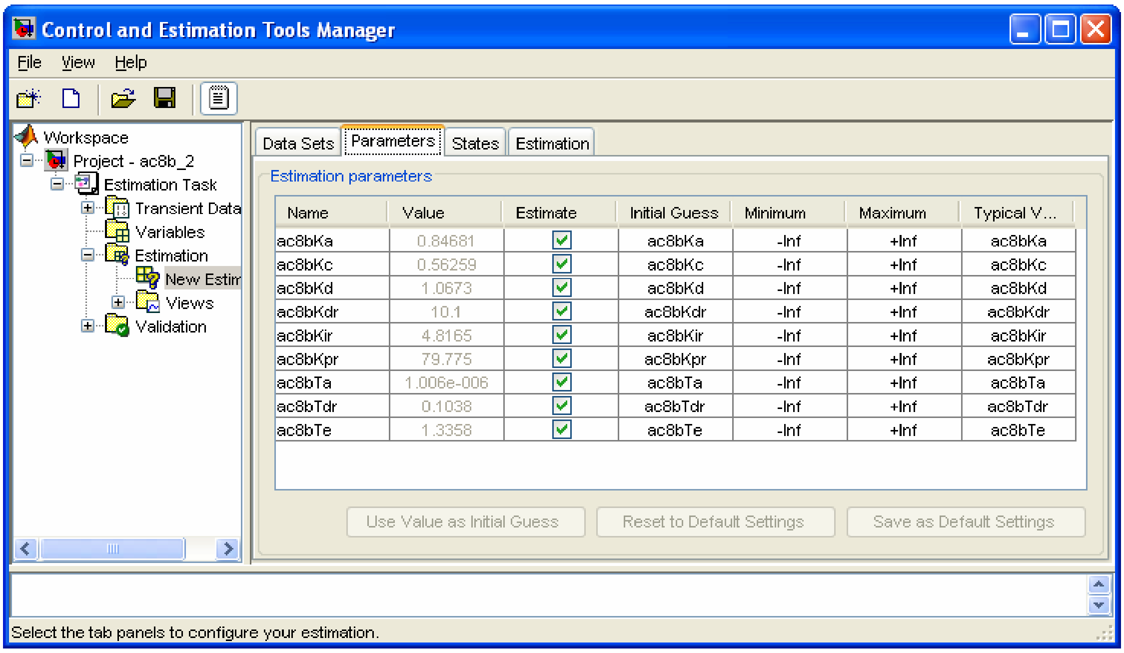


Fig. 4. 26 Estimated parameters of AC8B excitation system(Unit 1)

	We get:	Initial value:
Voltage regulator proportional gain:	ac8bKpr = 79.775	ac8bKpr = 84
Voltage regulator integral gain:	ac8bKir = 4.8165	ac8bKir = 5
Voltage regulator derivative gain:	ac8bKdr = 10.1	ac8bKdr = 10
Lag time constant:	ac8bTdr = 0.1038	ac8bTdr = 0.1
Voltage regulator time constant:	ac8bTa = 0	ac8bTa = 0
Voltage regulator gain:	ac8bKa = 0.84681	ac8bKa = 1
Exciter time constant:	ac8bTe = 1.3358	ac8bTe = 1.3
Rectifier loading factor:	ac8bKc = 0.56259	ac8bKc = 0.55
Demagnetizing factor:	ac8bKd = 1.0673	ac8bKd= 1.1

Figure 4.27 compares the simulation response using the estimated parameters with the measured response.

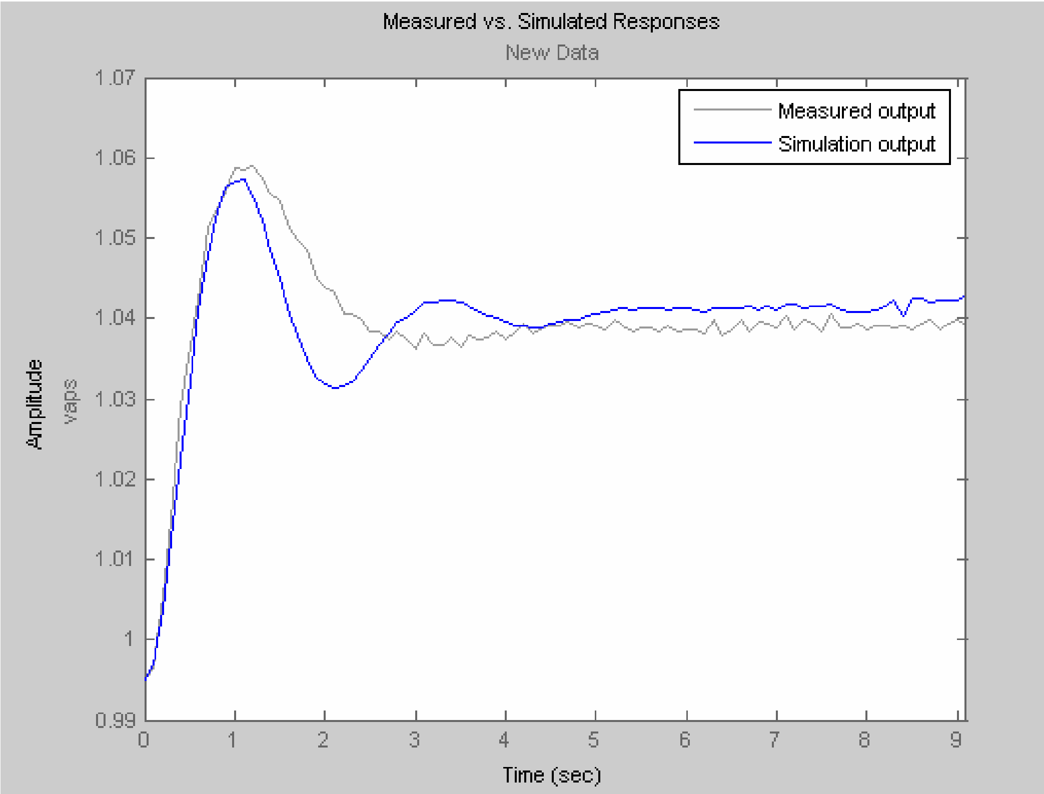


Fig. 4. 27 Final terminal output of generator when estimating AC8B excitation system (Grey - Desired curve, Blue – Simulation output) (Unit 1)

4.5.1.2 Data Unit 2

In Figure 4.28, it shows the iterations that were taken and, cost function and step size of each iteration. As shown in the figure, the optimization terminated for the step size is too small, but the cost function is small enough.

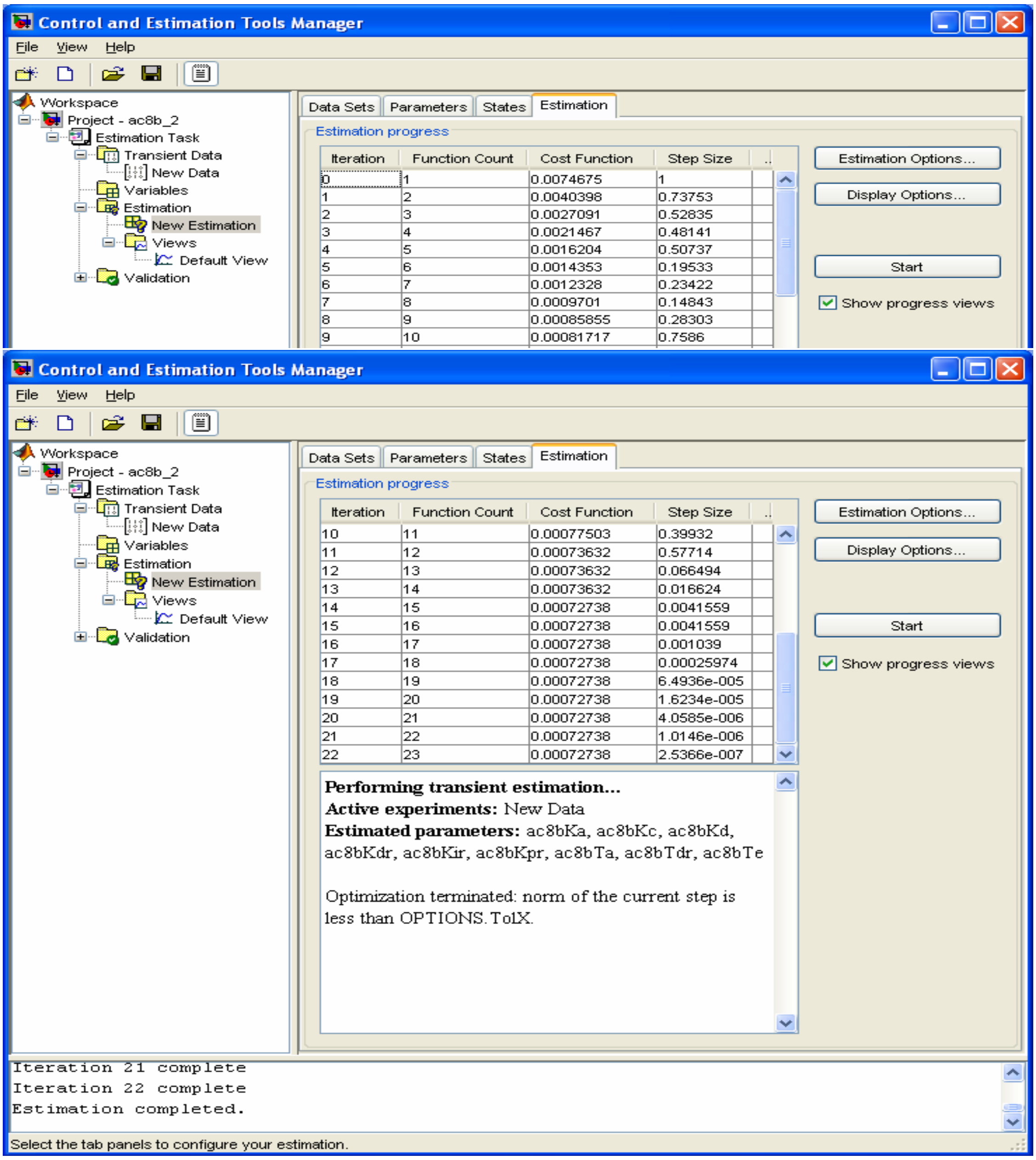


Fig. 4. 28 Cost function and step size of each iteration when estimating AC8B excitation system (Unit 2)

Parameters are

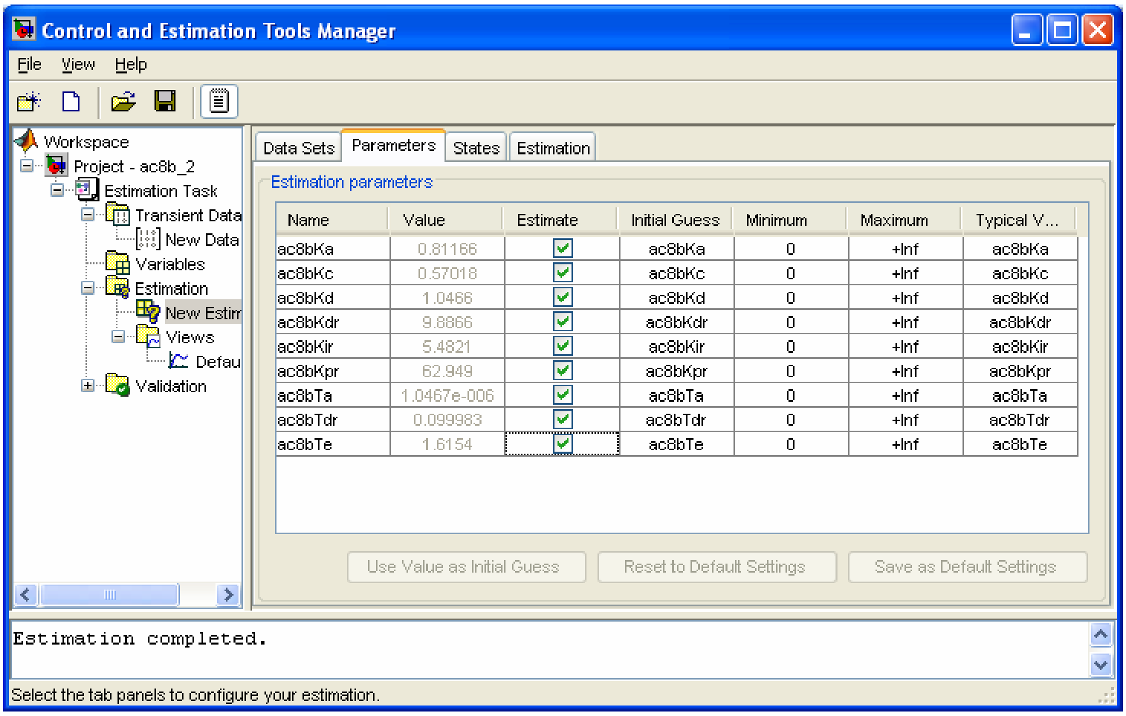


Fig. 4. 29 Estimated parameters of AC8B excitation system(Unit 2)

	We get:	Initial value:
Voltage regulator proportional gain:	ac8bKpr = 62.949	ac8bKpr = 84
Voltage regulator integral gain:	ac8bKir = 5.4821	ac8bKir = 5
Voltage regulator derivative gain:	ac8bKdr = 9.8866	ac8bKdr = 10
Lag time constant:	ac8bTdr = 0.099983	ac8bTdr = 0.1
Voltage regulator time constant:	ac8bTa = 0	ac8bTa = 0
Voltage regulator gain:	ac8bKa = 0.81166	ac8bKa = 1
Exciter time constant:	ac8bTe = 1.6154	ac8bTe = 1.3
Rectifier loading factor:	ac8bKc = 0.57018	ac8bKc = 0.55
Demagnetizing factor:	ac8bKd = 1.0466	ac8bKd= 1.1

Figure 4.30 compares the simulation response using the estimated parameters with the measured response.

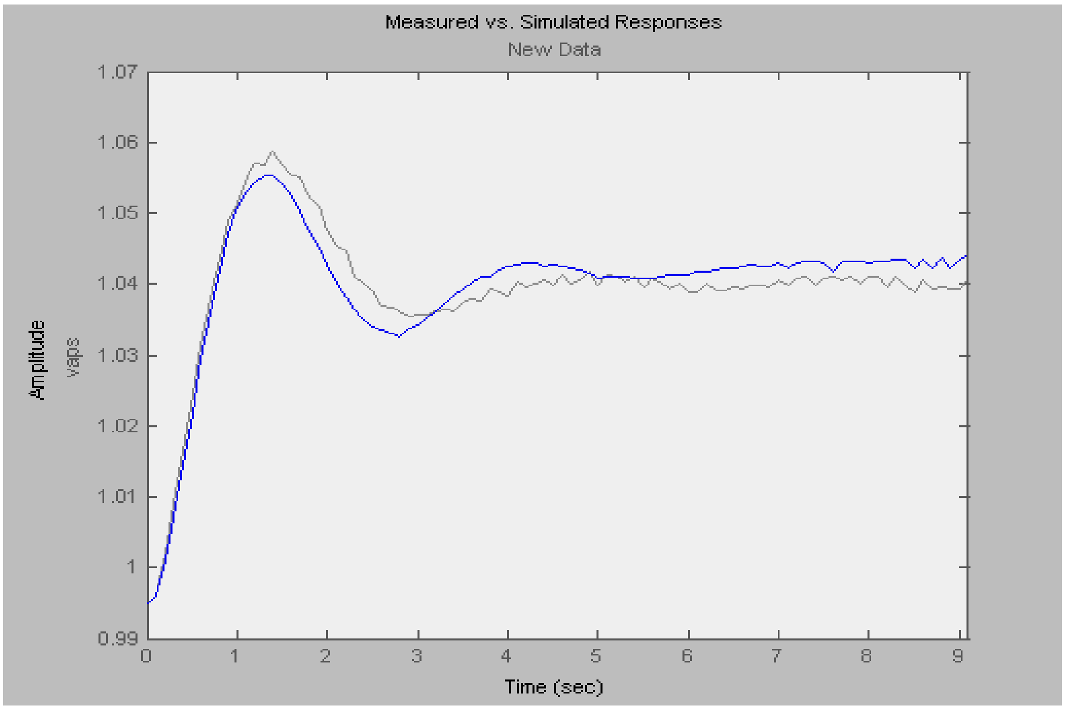


Fig. 4. 30 Final terminal output of generator when estimating AC8B excitation system (Grey - Desired curve, Blue – Simulation output) (Unit 2)

4.5.2 Damped Gauss Newton

4.5.2.1 Data Unit 1

The damped Gauss Newton Method which has been implemented in MATLAB has been used to estimate the parameters, using the same initial parameter values. In Table 9 listed the iteration history of the operation.

Table 9 Iteration history of parameter estimation of AC8B starting from good initial parameters using DGN (Unit 1)

Norm(gc)	fc	Armijo Iter.	Iterations
74.8970	0.0040	0	0
64.3266	0.0022	0	1
58.5847	0.0015	1.0000	2
254.7465	0.0008	0	3
212.7478	0.0008	0	4
4.2138	0.0001	0	5
9.9908	0.0001	0	6
17.6911	0.0001	3.0000	7

This method yielded the following values:

Xmodel_GN=

ac8bKpr	ac8bKir	ac8bKdr	ac8bTdr	ac8bTa	ac8bKa	ac8bTe	ac8bKc	ac8bKd
78.8399	2.4636	37.0485	0.1638	0.0000	0.5564	1.4044	0.0301	0.0511

The method did converge to the solution and it converged rapidly. In Fig. 4.31, it shows the final plot, in which the response of simulation got much closer to the measured output. We can tell when from case2 and this case that, with good initial parameters, DGN works well.

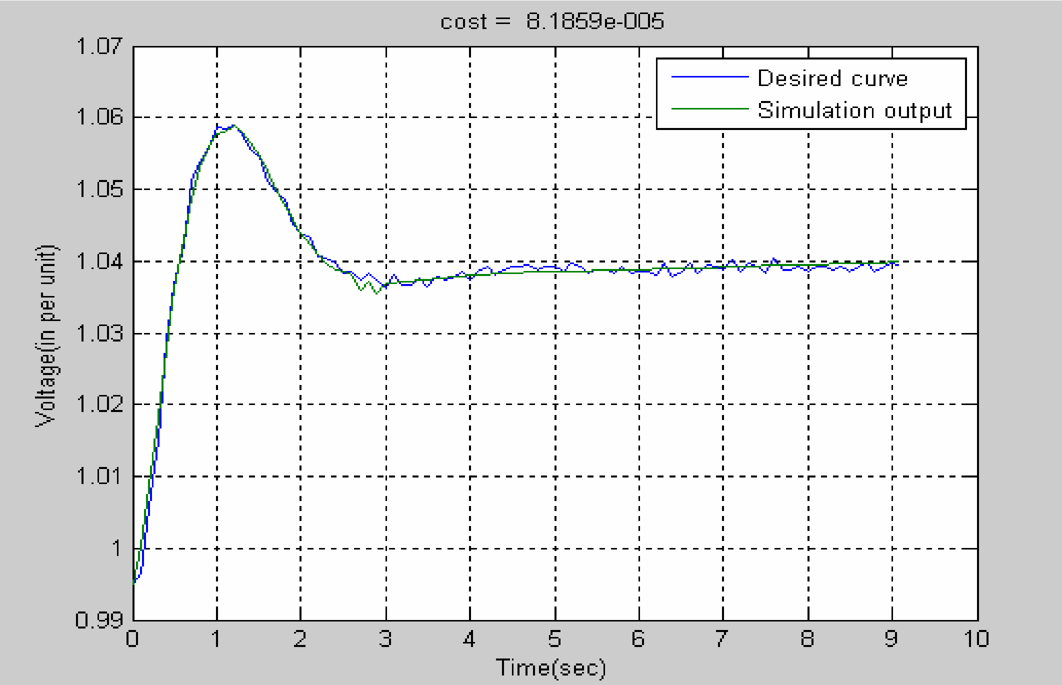


Fig. 4. 31 Final terminal output of generator when estimating AC8B excitation system (Data Unit 1)

4.5.2.2 Data Unit 2

The damped Gauss Newton Method which has been implemented in Matlab has been used to estimate the parameters, using the same initial parameter values. In Table 10 listed the iteration history of the operation.

Table 10 Iteration history of parameter estimation of AC8B starting from good initial parameters using DGN (Unit 2)

Norm(gc)	fc	Armijo Iter.	Iteration
98.6792	0.0047	0	0
41.7514	0.0008	1.0000	1
5.6289	0.0003	1.0000	2
8.2688	0.0002	0	3
11.3389	0.0001	2.0000	4
12.0737	0.0001	0	5
35.5202	0.0001	0	6
5.5072	0.0001	0	7
1.9256	0.0001	5.0000	8
2.1438	0.0000	4.0000	9

This method provided the following values:

Xmodel_GN=

ac8bKpr	ac8bKir	ac8bKdr	ac8bTdr	ac8bTa	ac8bKa	ac8bTe	ac8bKc	ac8bKd
85.6266	2.5912	25.3810	0.2044	0.0000	0.6209	1.8426	0.3233	0.0265

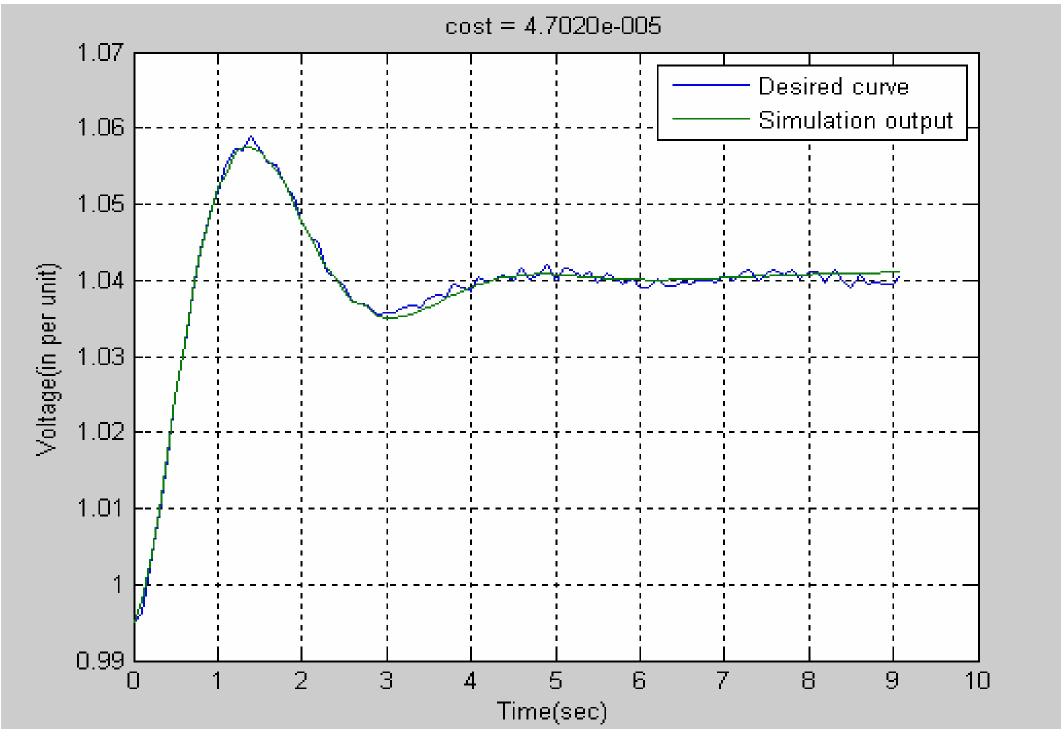


Fig. 4. 32 Final terminal output of generator when estimating AC8B excitation system (Data Unit 2)

4.6 Verification of AC1A excitation system model

4.6.1 About PSS/E

The PTI Power System Simulator (PSS/E) is a package of programs for studies of power system transmission network and generation performance in both steady-state and dynamic conditions. It is a comprehensive power system analysis tool for the modeling, design, planning and analysis for real networks and is the choice of most energy industries globally. [13] Detailed dynamic models of network elements are provided in PSS/E for dynamic analysis.

4.6.2 Comparison of simulation output of AC1A excitation system in both MATLAB and PSSE

For Progress Energy has provided us system network and PSS/E has integrated AC1A excitation system (showing as AC1 exciter in PSS/E), with certain parameter values, it is convenient to obtain the bump test response by simply entering the data. As the following steps, the comparison between the simulation outputs in MATLAB and PSS/E with the same parameters and the desired response is presented case by case.

Case1: Using the parameters provided by MATLAB / Simulink and Optimization Toolbox

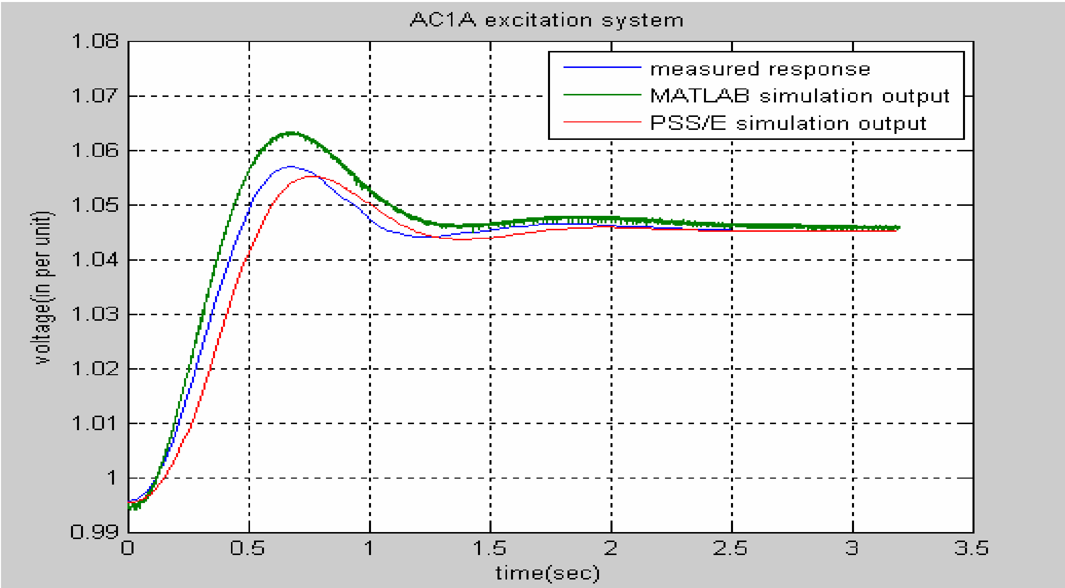


Fig. 4. 33 Simulation outputs of AC1A excitation system in MATLAB and PSS/E with the parameters provided by Optimization Toolbox

Cost function of the simulation output in PSS/E is 6.9144e-004, and the one in MATLAB is 9.6267e-004.

Case2: Using the parameters obtained in Case 1 in section 4.4.

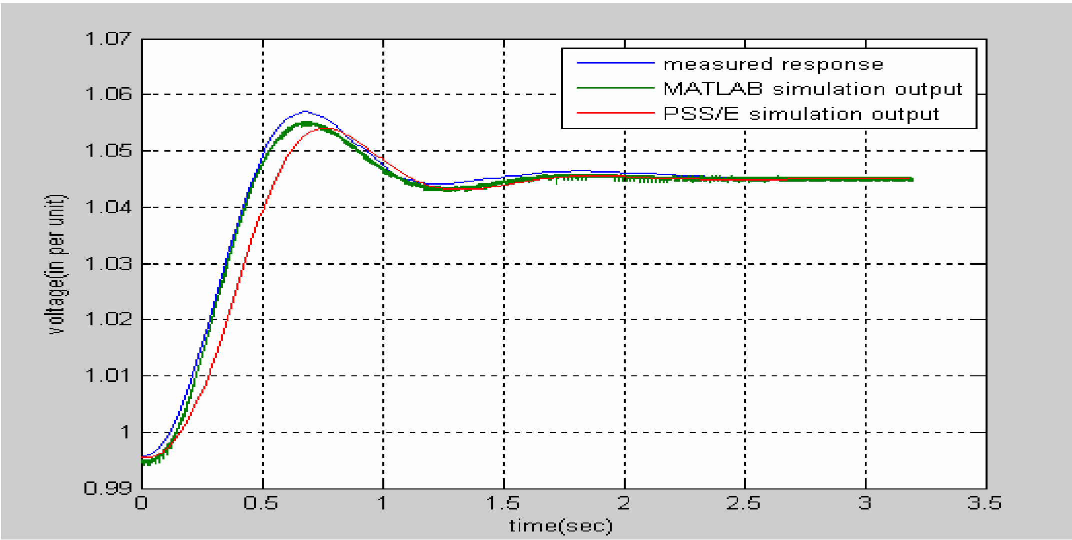


Fig. 4. 34 Simulation outputs of AC1A excitation system in MATLAB and PSS/E with the parameters provided by Case 1 in section 4.4

Cost function of the simulation output in PSS/E is 0.0010, and the one in MATLAB is 7.1094e-005.

Case 3: Using the parameters obtained in Case 2 in section 4.4.

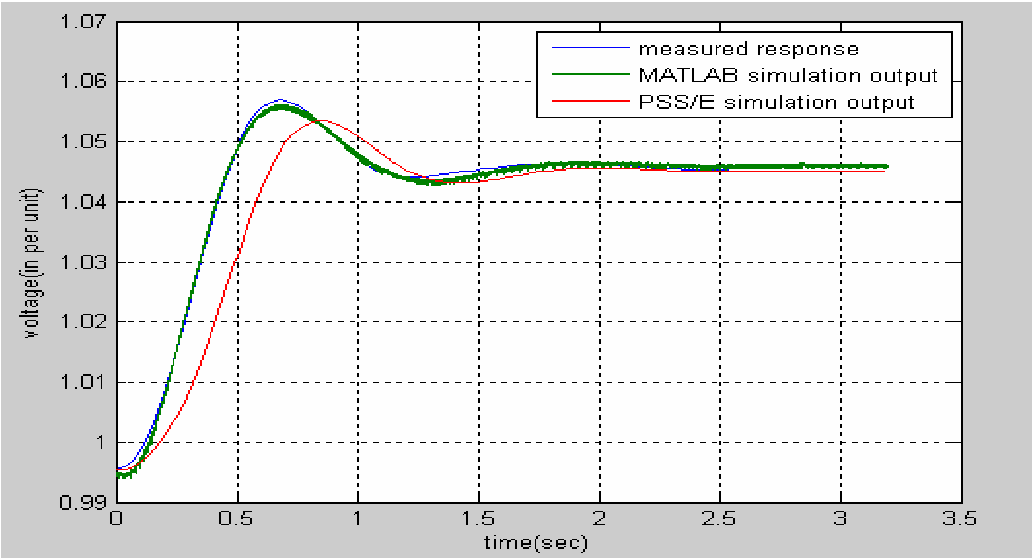


Fig. 4. 35 Simulation outputs of AC1A excitation system in MATLAB and PSS/E with the parameters provided by Case 2 in section 4.4

Cost function of the simulation output in PSS/E is 0.0029, and the one in MATLAB is 3.3027e-005.

Case 4: Using the parameters obtained in Case 2 in section 4.4.

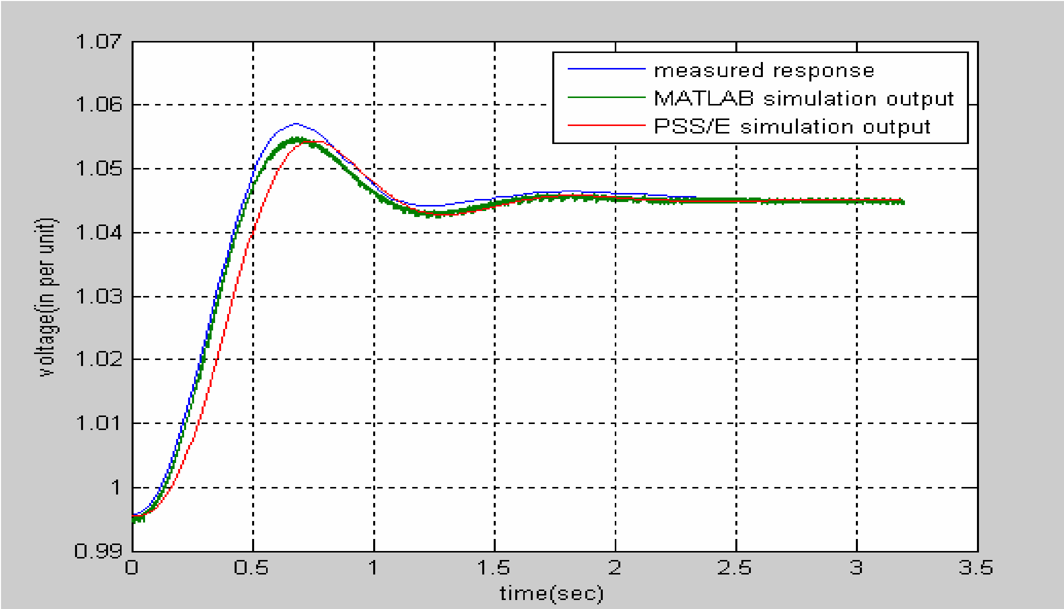


Fig. 4. 36 Simulation outputs of AC1A excitation system in MATLAB and PSS/E with the parameters provided by Case 3 in section 4.4

Cost function of the simulation output in PSS/E is 9.0640e-004, and the one in MATLAB is 9.2019e-005.

4.7 Validation of AC8B excitation system

Showing in Figure 4.40, Progress Energy provided us not only the response of bump test when the reference voltage of excitation system jumped from 1 to 1.05, but also the one of bump test when the reference voltage of excitation system jumped back from 1.05 to 1. Both of the plots and data values are provided. We tried to use the first part which is the response when the reference voltage jumped from 1 to 1.05 to estimate the parameters and use the second part that is the response when the reference voltage jumped back from 1.05 to 1 to validate the models.

Data Unit 1

Figure 4.38 is the final plot when estimating the parameters of AC8B excitation system with the first part of the data unit 1. As we can see, the curves are one on the top of the other. The cost function it is 0.0018. Then with the parameters, a down-edge step signal is input to the AC8B excitation system. The corresponding result is shown in Figure 4.39. We found that the response do to match to each other very well. The cost function of it is 0.0448.

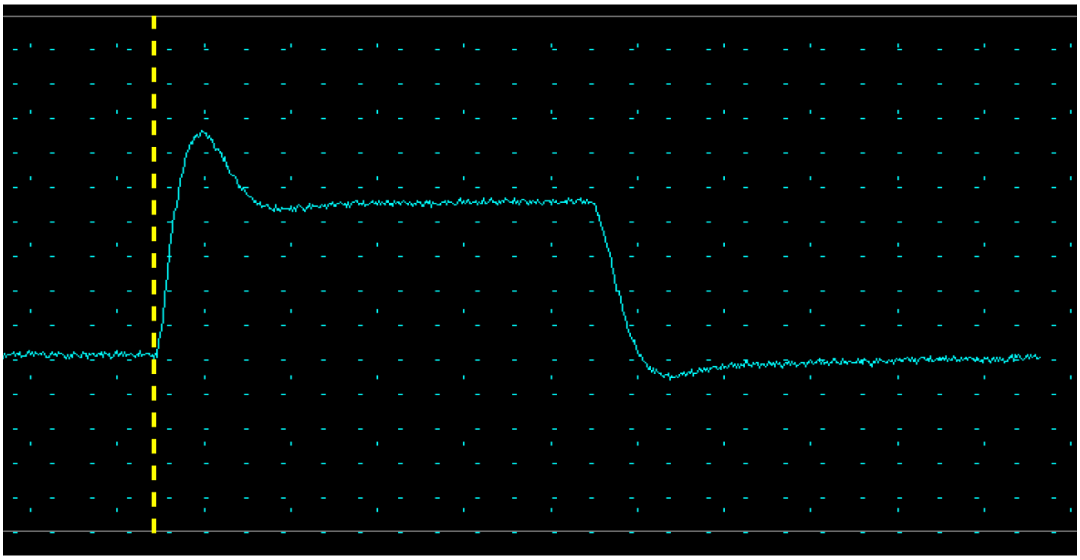


Fig. 4. 37 Data plot of responses of bump test from Progress Energy

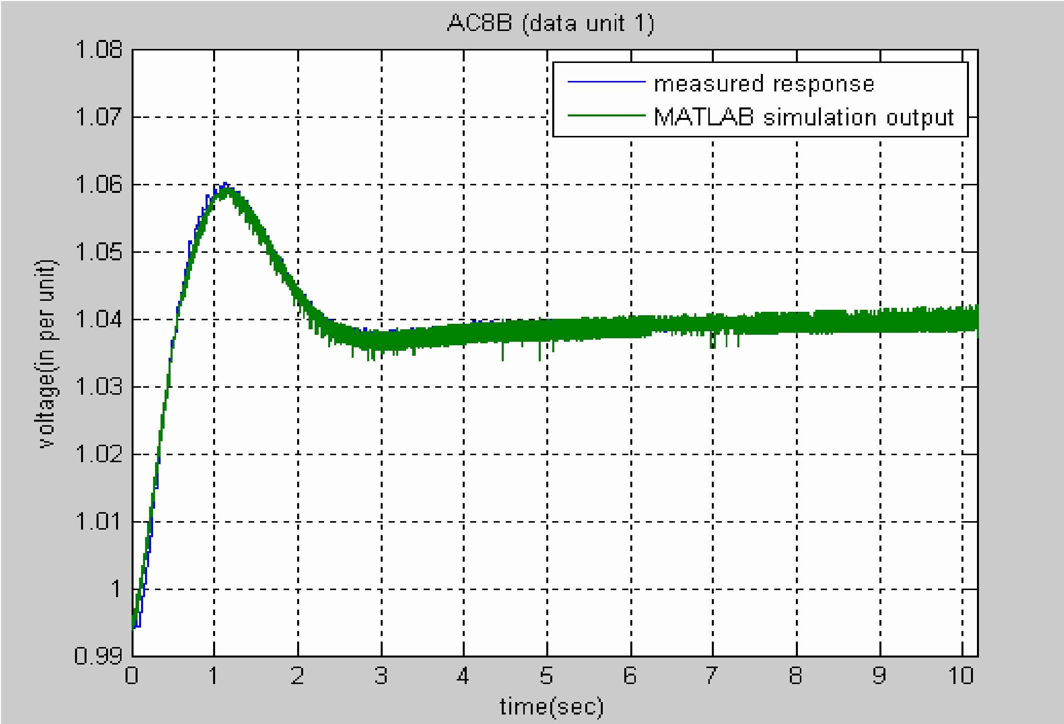


Fig. 4. 38 The final plot when estimating the parameters of AC8B excitation system

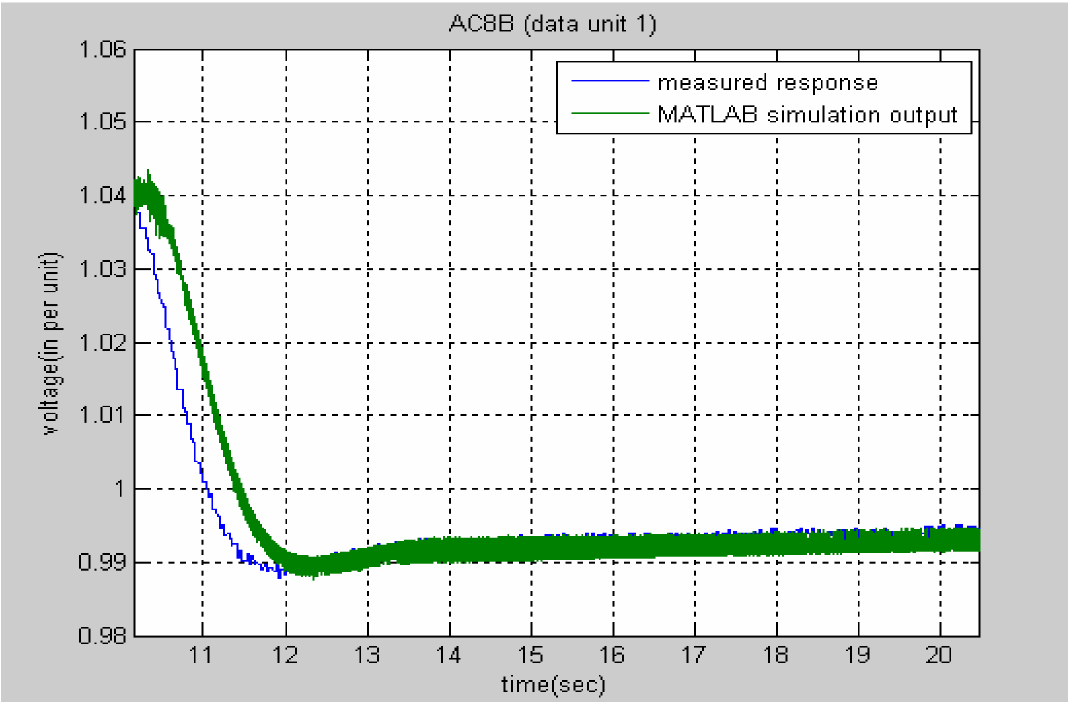


Fig. 4. 39 Validation of AC8B excitation system with the down-edge bump test

4.9 Summary

Two models have been tested, AC1A and AC8B. For the optimization part, we use both the Parameter Estimation Toolbox in MATLAB and the proto type of Damped Gauss-Newton method and Levenberg Marquardt method.

The first three cases are on AC1A excitation system.The first case uses the typical parameters which turned out to be far from the solution. In case 1, we can see the Damped Gauss-Newton method did not converge to the best solution. In case 2, we used Levenberg-Marquardt method to get a closer point to the solution and then used Damped Gauss Newton, but it went to a wrong direction again. Then the expert in Progress Energy played with the parameters and gave us a closer initial guess of the parameters and the Damped Gauss Newton method worked. It converged rapidly and provided a good solution, shown in Case 3. And, in case 4, for the AC8B excitation system, the initial parameters are considered to be a good initial guess, so that we used Damped Gauss-Newton directly and got a good result.

The codes are written in MATLAB language, while the simulation is run in Simulnk, MATLAB. Therefore, one of the following task will be transplanting the program into other software, such as C or JAVA and making sure that they can communicate with the simulation tool well.

In term of the validation of the model, for the AC1A excitation model, we tried to validate it by comparing the bump test response of the simulation output of MATLAB and PSS/E. However, we found that they do not match to each other very well. And by comparing both of the curves with the measured curve, we found that generally the difference between the response in MATLAB and desired curve is smaller. We need to do more work to find the reason. On the other hand, for the AC8B excitation model, there is some delay, but the two curve converge to the same value. Hence, more further work needs to be done for validating the model.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis has laid out a new approach to estimate the parameters of AC excitation systems. The parameter estimations of AC1A and AC8B excitation system are presented as the application of the developed program. MATLAB/Simulink is used for providing the simulation output with certain parameters and the program of Damped Gauss-Newton and Levernberg-Marquardt is used to do the optimization and provide a new guess of parameter values to the simulation tool. The iteration of the program will stop when either the difference between simulation output curve and desired curve is less than the tolerance that has been set before or the number of iteration time has reached the decided maximum iteration time.

There are two methods using in five different cases, MATLAB Parameter Toolbox and MATLAB proto type codes. The previous method is convenient and user-friendly. And by using the later one, we can choose different algorithms and make more advanced developments.

5.2 Future work

The work showing in this thesis is just a piece of the blueprint. Many interesting and meaningful extension issues are waiting for us.

- Transplant the optimization program to other languages such as C or JAVA
- Transplant the simulation to other commercial software like PSS/E or ETAP
- Have the transplanted optimization program communicate with the new simulation software well
- Validate the model with estimated parameters with other methods

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