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A Feasibility Study of On-Line Excitation System Parameter Estimation

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Abstract

This paper details a feasibility study of estimating excitation system parameters during on-line operation using time-domain system identification. This study concentrates on identifying the appropriate exciter model, developing an input signal that would provide a proper level of perturbation such that the dynamics of the system can be captured, analyzing the effects of both systematic and random noise, developing algorithms to perform the parameter estimation, testing, and validating the obtained system parameters. This study established a strong basis for estimating the system parameters during on-line operation.

Key Words: Parameter estimation, excitation systems, system identification

1 Introduction

The analysis of power system phenomena such as voltage collapse and low frequency oscillations often requires the use of small signal stability software and/or time domain simulation. The validity of the results of these packages depends greatly on the accuracy of the model parameters of the system components. Many parameters which are used in studies are either "manufacturer specified" or "typical" values which may be grossly inaccurate, as various parameters may drift over time or with operating condition. Thus, it is desirable to develop methods for estimating component parameters, preferably during on-line operation. While parameter estimation of synchronous machines has been well documented, parameter estimation of excitation systems has only begun to receive thorough attention.

This paper details a feasibility study of estimating excitation system parameters during on-line operation, using time-domain system identification. This study concentrates on identifying the appropriate exciter model, developing an input signal that will provide a proper level of perturbation such that the dynamics of the system can be captured, analyzing the effects of both systematic and random noise, developing algorithms to perform the estimation, testing, and validating the obtained parameters.

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Frequently, it is necessary to invest considerable resources to obtain excitation system parameters. Union Electric Company contracted Ontario Hydro to obtain the parameters of their Rush Island Plant and many of their other plants as well. This procedure required many engineering hours and required each system to remain off-line through-out most of the testing. The primary reason for the off-line test is that the required perturbations to the system are large enough to impact the terminal voltage levels of the generator, and secondly, many of the component signals could only be isolated by dismantling several of the control boards. For this reason, Union Electric commissioned a study to determine the feasibility of determining the parameters without the heavy investment of engineering hours, without deleteriously impacting the system during on-line operation, and using signals which are easily accessible. The highpoints and main conclusions of this feasibility study are presented in this paper. This study was implemented based on a model of the actual Rush Island excitation system built by Ontario Hydro as a result of their system testing. This paper presents the methodology of the system identification approach, the application of both systematic and random noise to the system signals, and the numerical results of the estimated parameters. The study established a strong basis for estimating the system parameters during on-line operation.

Previously, very little work has focused on obtaining excitation system parameters. In [1], a time-domain approach was proposed for obtaining the system parameters. The data used for the estimation was obtained during a lightening strike, which provided a very significant perturbation to the system. The authors fit the data to several excitation system models including the IEEE AC1 (which is a representation of the Rush Island excitation system) and the DC1 models. In on-line applications, a perturbation of this size is not acceptable. Several other authors have taken the approach of employing a frequency domain-based estimation. Most of these works, however, were for specific exciters and were not representative of an IEEE standard model for use in standard stability simulations [2]-[4].

2 The Excitation System Model

The Rush Island excitation system is a brushless excitation system. This is a field controlled alternator rectifier exciter. This system consists of an alternator main exciter with non-controlled rectifiers to convert the AC current into the DC current needed by the generator. Several control devices are also included in the excitation system. These include a damping module, a V/Hz limiter, a voltage error detector, minimum and maximum excitation limiters, a load compensator, a signal mixer, a trinistat three-phase firing circuit, and a trinistat three-phase power amplifier (thyristors). Each of these mod-

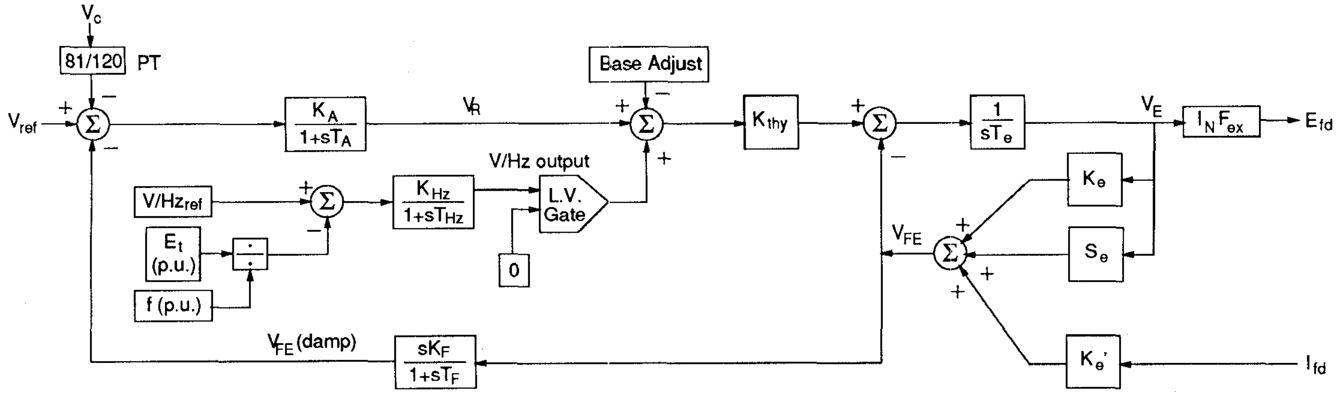

Figure 1: AC1 type exciter used in the study

ules, separately, have a specific function within the exciter. The main exciter's output is determined by the trinistat three-phase power amplifier, whose firing angle is determined by the trinistat firing circuit. The signal mixer generates an error signal which is fed into this firing circuit, which, in turn, determines the firing angle used. Under normal operating conditions, the output of the voltage error detector, which compares the actual terminal voltage to a specified reference voltage, establishes the signal mixer output. The main exciter field current is fed back through the damping module to produce a closed loop configuration. This helps stabilize the system and maintain a constant voltage output. The minimum excitation limiter, maximum excitation limiter, and V/Hz limiter are included to prevent the generator from operating in a greatly underexcited, greatly overexcited, or saturated region, respectively. The load compensator provides compensation for the transformer impedance or line drop at the output of the generator. All of these devices, together, are considered to be the pilot exciter, which supplies the field current to the main exciter. The main exciter is not, therefore, self-excited, and the voltage regulator power is taken from a source not affected by external transients. This model may be represented by the IEEE standard AC1 type exciter shown in Figure 1.

Union Electric and Ontario Hydro developed a computer-based model of the excitation system, using the visual simulation software package **VisSim** (manufactured by Visual Solutions). The model was extensively analyzed by UE and Ontario Hydro and is found to accurately simulate the response of the actual excitation system during open circuit operation of the generator. Thus in this study, the parameter estimation process is based on estimating the parameters of the VisSim model, under the assumption that if the VisSim model parameters can be estimated, then so can the actual system parameters. Open circuit operation was chosen to simplify the generator model, which in this study is taken to be known. There is a multitude of literature on the estimation of generator parameters; therefore, this was not included as part of this study.

3 Parameter Estimation by System Identification

System identification (SI) is defined as the study of determining the model or structure of a system using a limited number of input and output data measurements, which may or may not be disturbed by noise [5]. The process by which system identification is performed contains five general steps. The first is to collect input-output data from the experimental design (or process) to be identified. Next, the data is examined and conditioned so as to remove any bias terms and reduce the effect of any large disturbances that are not a result of the process being identified (i.e., noise). Thirdly, a model structure for the process must be defined and selected. After the model structure has been selected, the best fit model in the selected structure (or the parameters of the model) is computed using the obtained input-output measurements. Finally, the resulting model is examined for accuracy and validity. The validity of the calculated model can be checked using various techniques, one of which includes simulation of the resulting model using the obtained input data from the actual system as input and comparing the output data of the actual system to that of the system containing the estimated parameters.

In order to accurately estimate the parameters of the excitation system, the VisSim model (also known as the function model) had to modified in two ways. The first modification came in the form of a perturbation signal that would disturb the system such that the dynamics of the system would be captured in the input/output data measurements. The greater the dynamics within the signal, the more accurate the parameter estimation. However, it was desired to design the perturbation signal, such that the parameter estimation could be performed on-line. Because of this, a perturbation signal had to be designed such that it would dynamically excite the system, yet have a minimal impact on the output of the system (V_C). The second modification came in the form of noise. The model did not initially include any noise input. However, it is known that systematic noise due to the inverter type power amplifier occurs in the actual excitation system. Due to the feedback configuration of the excitation system, this noise is propagated throughout the entire system. Also, in on-line measurements, random noise in the data acquisition system is prevalent, and therefore must be modeled.

3.1 Input Signal Perturbation

The pseudo random binary signal (PRBS) was chosen as the perturbation signal. The characteristics of the signal are such that it has a random switching time between two values, a maximum and minimum, which are held constant. The spectrum of this signal has a wide band of frequency content, which excites the dynamics within the system. Since the minimum and maximum values of the signal may be specified, the magnitude of

Table 1: Effect of PRBS Magnitude on V_C

PRBS (V)	$V_{C_{max}}$ (p.u.)	$V_{C_{min}}$ (p.u.)	p.u. swing
± 1.0	123.0 (1.025)	117.5 (0.979)	0.0458
± 0.5	121.5 (1.013)	118.7 (0.989)	0.0233
± 0.1	120.3 (1.003)	119.7 (0.998)	0.0049
± 0.05	120.2 (1.002)	119.9 (0.999)	0.0024

Table 2: Physically Measurable Signals

Signal	Signal
V/Hz Output	$V_R(V_{reg})$
I_{FE}	V_{ED} Output
V_{FE}	V_C
V_{FE}(damp)	

the PRBS can be set such that the output of the overall system is not significantly disturbed. Due to the accessibility of the reference voltage (V_{ref}), this signal was chosen as the injection point for the perturbation signal. With the constantly changing setpoint, the system was continually making adjustments to match the setpoint value, thus dynamically exciting the system. In the Rush Island system, a PRBS signal of magnitude 0.1 V or greater superimposed onto to the reference voltage causes limits within the excitation system to be violated. It was determined that a PRBS of magnitude 0.05 V is sufficient to excite the dynamics of the system without affecting the overall system significantly. Table 1 shows the effect of the various magnitudes of the PRBS on the output V_C.

3.2 Noise

There are two types of noise in the excitation system: systematic noise due to the inverter type power amplifier and random noise due to the data acquisition equipment. The inverter type power amplifier rectifies a 420 Hz, three-phase, AC signal to a DC signal using gated thyristors. The gates are provided to control the firing angle, or gate delay, on the thyristors. This firing angle will determine whether the output of the rectifier will have a positive, negative, or zero average dc voltage output. Representative waveforms of the signals produced by the rectifier for three different gate delay angles (30, 90, and 150 degrees) are shown in Figure 2. The inverter type power amplifier's (rectifier) output is V_{FE}; therefore, the systematic noise was added into the model at the summing junction that produces V_{FE} in the main exciter. Due to the configuration of the main exciter, the systematic noise is propagated throughout the main exciter. It is also propagated through the pilot exciter by the feedback of I_{FE}. The relatively long time constant associated with the generator, however, naturally filters out this noise; therefore, the effects of the rectifier noise are not seen at the output of the generator (V_C).

Random noise enters the data through the data acquisition equipment. This random noise is approximated by zero mean, white Gaussian noise. In this study, the magnitude of the noise was varied to determine the highest magnitude of random noise that could be tolerated and still produce a reasonable estimate of the parameters.

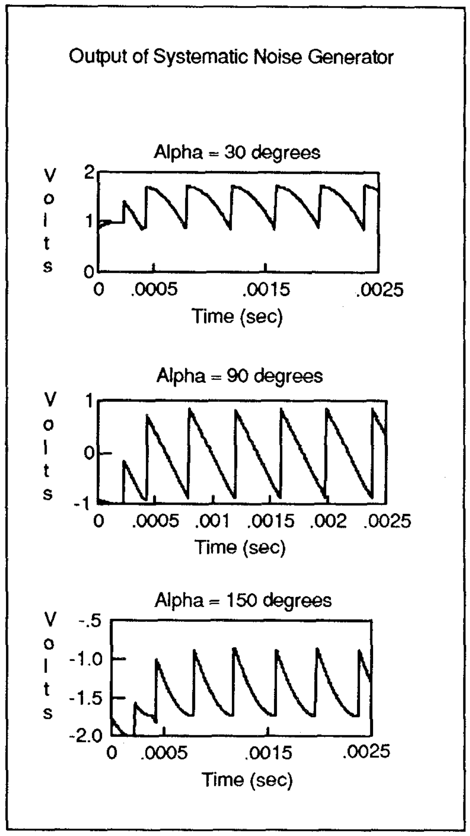

Figure 2: Typical rectifier waveforms

3.3 Data Collection

The first step in performing the data collection of the input and output data is to determine which of the signals in the desired model are physically measurable. The usable signals are given in Table 2, where V_{ED} is the output of the voltage error detector and is not shown in Figure 1 due to the simplification of the model. The following manually adjusted quantities are also assumed to be known: reference voltage (V_{ref}), volts/hertz reference (V/Hz_{ref}), per unit frequency (f (pu)), and base adjust into the firing circuit. In addition to the physically measurable signals, the transfer function of the (assumed known) generator yielded the "derived" signals E_{FD} and I_{FD}. Lastly, it was assumed that $E_t(pu)$ and V_E were also obtainable.

3.4 Transfer Functions

The obtainable input/output signals, both measured and derived, break the model up into several parts. Each of these parts can be described by a transfer function relating an output signal to an input signal and the parameters contained between them. The SI process used actually estimates transfer functions, not individual parameters. By isolating and determining a variety of transfer functions from the developed SI process, the individual parameters may be derived from these transfer functions. Once the transfer functions were developed, they could be used to validate the estimates of the parameter estimation algorithms. The excitation system includes two nonlinear blocks: the saturation block and the rectifier mode block. Under nominal operation (as in this study), the rectifier mode block can be assumed to remain in a fixed mode, and is therefore modeled as a constant gain value ($I_N F_{EX}$). The saturation function (S_E), however, is linearized in order to obtain a linear transfer function.

3.5 Signal Conditioning

Each of the input/output data sets must be conditioned to remove the high frequency content, any initial transients due to initial conditions, and the bias within the signals. One method to reduce the effect of noise in the data measurements during estimation is to average several noisy data sets together. In actual practice, this implies that several data sets of the same signal, in response to an identical perturbation, had been taken. The more sets averaged together, the better the estimation will be. After the averaging process, the averaged noisy data signals were then passed through a lowpass filter to remove the high frequency content (noise) associated with the systematic and random noise. The filtered data was then conditioned to remove any initial transients. The estimation algorithms assume that the system is in steady state at the onset of the PRBS perturbation. Due to the initial conditions set on the integrators in the VisSim functional model, the system experienced initial transients for the first few seconds of simulation. The initial transients died out at approximately 2 seconds, after which time the PRBS was injected into the system. Lastly, the bias in each data signal was removed by computing the average of each data set (which should be close to the steady-state value) and subtracting this average from each data point. This made each of the data signals zero mean.

3.6 Estimation

In the estimation process, there are two types of models: parametric and non-parametric. A parametric model concentrates the information of the model structure into a set of parameters using a parameter vector. Since the structure of the excitation system model was already known, a parametric model was used in this study. The general polynomial representation of the transfer function of a parametric model structure is:

$$A(q)y(t) = \frac{B(q)}{F(q)}u(t-nk) + \frac{C(q)}{D(q)}e(t) \qquad (1)$$

where q is the shift operator and $A(q)$ through $F(q)$ are polynomials in q of varying orders. The vector $y(t)$ is the output, $u(t-nk)$ is the input with delay (if required), and $e(t)$ is the error signal (or noise). The various parametric models are variations of the general equation where specific polynomials are of order zero. For example, the ARX (auto regressive with extra input) has polynomials $C(q), D(q)$ and $F(q)$ of order zero. The ARMAX (auto regressive with moving average and extra input) has polynomials $D(q)$ and $F(q)$ of order zero. The PEM model structure is a general model structure which encompasses all of the polynomials given in equation 1. During the validation stage, the accuracy of the system response is analyzed to determine whether the chosen model is acceptable, and if not, a different model may be chosen. The selection of the model structure must include not only the type of model to be used, but also the order of the polynomials within the model. The order of the polynomials correspond to the number of both the poles and zeros in the transfer function that relates the output to the input or the error. Then, a best fit approximation is used to calculate the parameters of the chosen model to best approximate the desired transfer function. A least squares minimization is used to perform the approximation of the ARX model parameters, while a Gauss-Newton minimization is performed in the estimation of the ARMAX and PEM model parameters.

3.7 Output

The last step in the parameter estimation process is to convert the estimated discrete time transfer function parameters (in q) to continuous time transfer function parameters (in s), since the continuous time parameters of the excitation system are desired and the data is, by nature, discrete. This dictated that a discrete to continuous conversion be performed. The conversion was accomplished using a pole-zero matching technique which matches the poles and zeros of the transfer functions.

4 Test Results

In order to estimate the parameters, the VisSim simulation of the Rush Island excitation system was run, the data collected, and the estimation algorithms executed. The simulation was conducted using a simulation step size of 5×10^{-5} seconds. This step size was selected such that is was much smaller than the frequency of the systematic noise (2520 Hz), which was the highest frequency in the system with the exception of the PRBS. The PRBS perturbation of $\pm 0.05V$ was injected into the system after the initial transients had died out (approximately 2.6 seconds into the simulation). The first tests conducted contained a no noise base case and cases where only systematic noise was considered. The results of these tests are shown in Table 3. The systematic noise in these tests was modeled using a magnitude of one volt as the three-phase input into the rectifier and a firing angle of 90 degrees. This represented a "worst case" scenario because the 90 degree signal contains the highest harmonic content.

Table 3: Estimation results with zero random noise

Estimation Results of Pilot Exciter

Parameter	Actual Value	Est. Value No Noise	Est. Value Unfiltered Sys. Noise	Est. Value Filtered Sys. Noise
K_{Hz}	11.9177	11.92869	11.9287	11.9287
T_{Hz}	0.1700	0.17011	0.17012	0.17012
K_A	0.00483	0.005037	0.01233	0.00497
T_A	0.006	0.006248	0.0153	0.0062
K_F	0.08402	0.08434	0.0939	0.08422
T_F	1.18999	1.19005	1.2516	1.19076

Estimation Results of the Main Exciter

Parameter	Actual Value	Est. Value No Noise	Est. Value Unfiltered Sys. Noise	Est. Value Filtered Sys. Noise
K_{Thy}	174.472	174.472	213.9605	174.211
T_e	0.07554	0.07554	0.0927	0.0754
$S_E + K_E$	0.0974	0.0974	0.0874	0.0975
PT	0.675	0.6746	0.6757	0.6748
K_d	0.00766	0.00758	0.0077	0.0073
$I_N F_{EX}$	1.215	1.216	1.2136	1.2146

After the base case was conducted, various tests were performed utilizing various combinations of the variables in the system which would influence the estimation of parameters: estimation technique (arx, armax, or pem), random noise magnitude, lowpass filter cutoff frequency, number of averaged data sets, firing angle on the rectifier, and three-phase magnitude into the rectifier. A sample of these tests are shown in Tables 4-5. All the results shown in a particular figure utilize the estimation technique, rectifier firing angle, and three- phase magnitude into the rectifier shown at the top of the figure. The title of each column indicates the amount of random noise (in percentage of the steady state operating point of that signal) and the number of times each signal was averaged.

Note that without noise in the system, the estimated parameters contain only the slightest error. Also, the systematic noise was found to have a negligible impact on the estimation of most of the excitation system parameters, with the exception of the time constant associated with the voltage error detector. The very fast time constant associated with T_A is the most probable cause of the inaccuracy of the estimation. It is noted, however, that the estimate for this parameter can be greatly improved by filtering the data before performing the estimation.

Table 4: Estimation Results using ARX, $\alpha = 90°$, and a 1 V Input into Rectifier

Estimation Results of Pilot Exciter

Parameter	Actual Value	Est. Value 0.5% noise avg=5	Est. Value 0.5% noise avg=10	Est. Value 1% noise avg=10
K_{Hz}	11.9177	12.2857	11.7084	12.4406
T_{Hz}	0.1745	0.1754	0.1688	0.1779
K_A	0.00483	0.00904	0.00710	0.02802
T_A	0.00600	0.01104	0.00870	0.03177
K_F	0.08402	0.0483	0.08695	0.12040
T_F	1.18999	1.1811	1.19218	1.19360

Estimation Results of Main Exciter

Parameter	Actual Value	Est. Value 0.5% noise averg=5	Est. Value 0.5% noise averg=10	Est. Value 1% noise averg=10
K_{thy}	174.472	169.018	170.6974	167.406
T_e	0.07554	0.0732	0.0739	0.0725
$S_E + K_E$	0.0974	0.0975	0.0975	0.0978
PT	0.675	0.6720	0.6672	0.6419
K_d	0.00766	0.0069	0.0065	0.0045
$I_N F_{EX}$	1.215	1.198	1.2032	1.2148

The random noise, however, did have a significant effect on the outcome of the parameter estimates. Although most of the parameters could be estimated fairly accurately with small amounts of random noise injected, it was found that several of the parameter estimates were relatively intolerant to the random noise. The type of estimation algorithm used in the identification of the parameters did not seem to have an impact on the accuracy of the results. Each algorithm produced similar results when performing the estimations under the same conditions.

In order to validate the estimated parameters, they were inserted into the functional model and internal signals were compared with signals produced by the original functional model. Several of the signal comparisons are displayed in Figures 3-5 (note: the first second of the simulation during which the start-up transients are decaying has been omitted). These "estimated" signals were derived using the estimated parameters from the following test scenario: estimation algorithm=arx, three-phase rectifier input = 1 V, firing angle = 90°, cutoff frequency in main exciter signals = 10 Hz, cutoff frequency in pilot exciter signals = 50 Hz, random noise level = 0.5% of signal level, and 5 sets of data were averaged. Although the steady state value of the signals have a slight error (due to the error in the parameters), the response of the signals to a disturbance is shown to be quite similar. This validates that the estimated parameters can be used to correctly model the dynamic response of the system.

Table 5: Estimation Results using ARMAX and PEM, $\alpha = 90°$, and a 1 V Input into Rectifier

Estimation Results of Pilot Exciter

Parameter	Actual Value	Est. Value 0.5% noise averg=5	Est. Value 0.5% noise averg=10	Est. Value 1% noise averg=10
K_{Hz}	11.9177	12.333	12.2274	12.4712
T_{Hz}	0.1700	0.1745	0.1730	0.1766
K_A	0.00483	0.00983	0.007028	0.02227
T_A	0.0060	0.01204	0.00857	0.02989
K_F	0.08402	0.04987	0.04718	0.06459
T_F	1.18999	1.1912	1.1913	1.16523

Estimation Results of Main Exciter

Parameter	Actual Value	Est. Value 0.5% noise averg=5	Est. Value 0.5% noise averg=10	Est. Value 1% noise averg=10
K_{Thy}	174.472	174.4614	173.1237	174.1729
T_e	0.07554	0.07550	0.0750	0.0754
$S_E + K_E$	0.0974	0.0975	0.0975	0.0974
PT	0.675	0.6610	0.6715	0.6513
K_d	0.00766	0.0073	0.0071	0.0069
$I_N F_{EX}$	1.215	1.2254	1.2128	1.2053

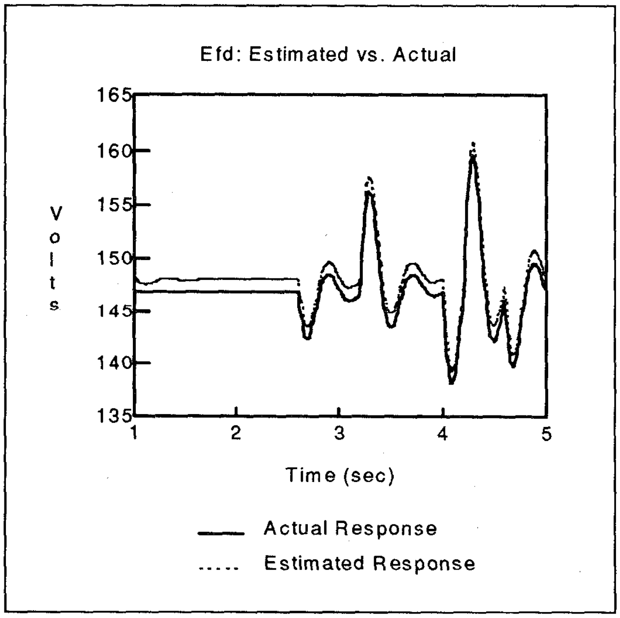

Figure 3: Estimated vs. Actual Response of E_{fd}

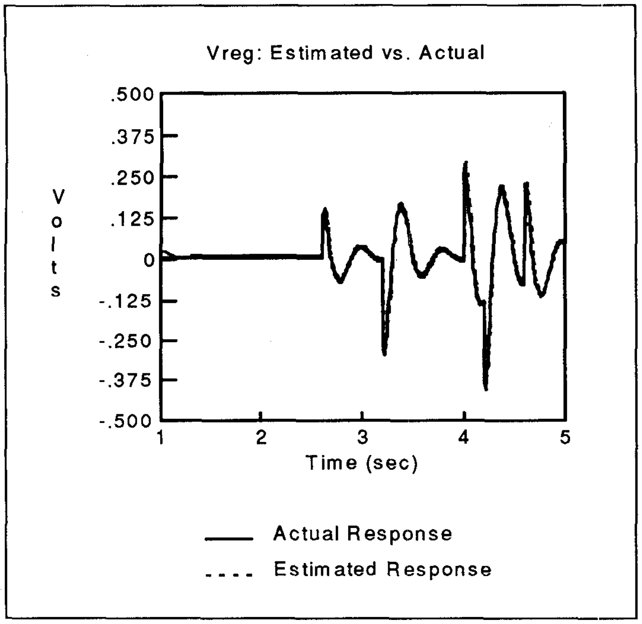

Figure 4: Estimated vs. Actual Response of V_{reg}

5 Identifiability, Observability, and Confidence Intervals

Identifiability and observability were not covered in depth in this study. The data that was collected came from a simulation that, with the exception of random noise, produced reproducible data. It must be noted that this study was a feasibility study to determine whether the proposed method could be used to identify the parameters. This goal was accomplished. Regarding the observability and identifiability of the parameters of the actual system it must also be noted that the model parameters are estimated using actual data. If a particular parameter does change, but does not effect the output data (i.e. becomes non-identifiable), then the estimator will not capture the change in the parameter. It could be argued, however, that if the parameter did not change enough to effect the output signal, then the change has no effect on the response of the system. The change does not become significant (in the overall scheme) until the response of the system is effected. If this occurs, the data acquisition equipment should pick up this change in the output data and the estimation algorithms will compensate for this and produce an estimate with the changed parameter taken into consideration. Confidence intervals were not introduced due to the availability of the accurate model. By comparing the estimated parameters to those in the functional (accurate) model, one can determine the accuracy of the estimated parameters. Furthermore, the dependence of the interval on such variables as the magnitude of random noise makes this analysis difficult and beyond the scope of this study.

6 Discussion and Conclusions

Several observations can be made from the results of this study. The first is that the magnitude of the rectifier noise had a negligible effect on the accuracy of the estimations (due to the low pass filtering of the signals). The magnitude of the random noise, however, did effect the accuracy of the results significantly. The results of the full study show that as the magnitude of the random noise increased, the accuracy decreased. Due to the difficulty in testing every combination of variables, the results provided in this paper give the reader a sense of the accuracy as the magnitude of the noise increases. Since the noise magnitude can be effected by such things as the quality of the data acquisition equipment, the determination of how much noise can be tolerated in order to obtain a specific accuracy is left for each user to decide. In the full study, the effect of averaging the data was also investigated. Many sets (or pairs) of the simulated input/output data were taken and averaged in order to derive the parameters. It was found that as more data sets were averaged together, the estimation became more accurate. For further discussion on these topics and results of various combinations of the variables (firing angle, rectifier amplitude, etc.) see [6].

The proposed method was established to estimate the linear parameters of the IEEE-AC1 type exciter; however, it can also be adapted to work with almost any model. The method contains an estimator that can be changed to accommodate almost any linear model structure. If one model is found to produce inaccurate results, another model may be selected and investigated. The basic parameter estimation procedure stays the same. First, a model must be chosen, The signals that can be readily measured or derived must then be assessed, the estimation performed, and the results verified. If a model structure is not available, the MatLab SI toolbox is capable of calculating a best fit model. In most cases, however, a small signal stability program accepts only variations of a standard model. The focus of this study, therefore, was to identify the linear parameters of a standard excitation model.

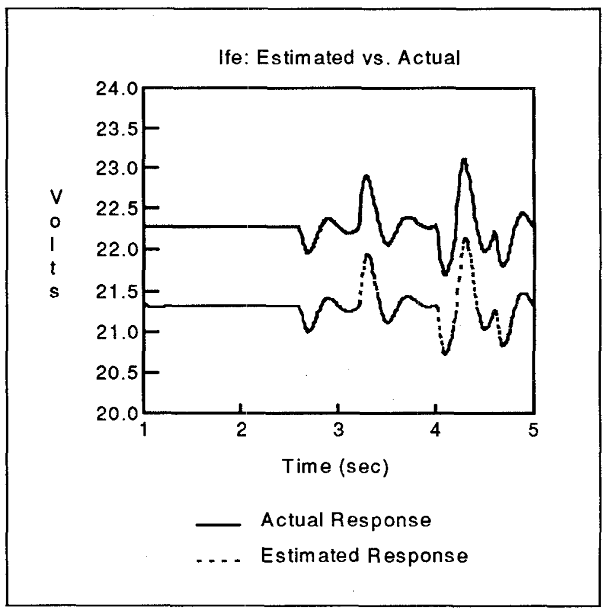

Figure 5: Estimated vs. Actual Response of I_{fe}

It is important to note that this study focused on deriving the linear parameters of the system. The simulation that was used to derive the parameters still contained the nonlinearities; however, the perturbation was chosen such that the non-linear windup limits of the system would not be exceeded. This allowed for accurate estimation of the linear time constants.

Since most of the parameters in the standard stability programs are linear, the results of this study prove to be very useful. The examination of excitation system parameters, however, is not complete. This feasibility study concentrated on estimating the linear parameters of the excitation system, and was the first part of a two phase study. The second phase is currently underway and concentrates on deriving an estimation algorithm to determine the non-linear parameters (saturation constants, windup limits, etc.) of the excitation system. It is believed that once the non-linear parameters have been incorporated into the model, the accuracy of the results will improve. The results of both phases will provide the essential information needed to determine the most accurate data on the operating limits of a particular system.

It is proposed that upon completion of the two phase study, the estimation method developed will produce accurate estimates of the parameters under various operating conditions (i.e. heavy/light load, over/under excitation, etc.) Further investigation and analysis is needed utilizing actual data in order to verify this assumption.

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