01 Nov 2000

Nonlinear Parameter Estimation of Excitation Systems

Rajeev Bhaskar

Mariesa Crow
Missouri University of Science and Technology, crow@mst.edu

Eric Ludwig

Kelvin T. Erickson
Missouri University of Science and Technology, kte@mst.edu

et. al. For a complete list of authors, see https://scholarsmine.mst.edu/ele_comeng_facwork/1178

Recommended Citation

R. Bhaskar et al., "Nonlinear Parameter Estimation of Excitation Systems," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1225-1231, Institute of Electrical and Electronics Engineers (IEEE), Nov 2000.
The definitive version is available at https://doi.org/10.1109/59.898094

Nonlinear Parameter Estimation of Excitation Systems

Rajeev Bhaskar, *Student Member, IEEE*, M. L. Crow, *Senior Member, IEEE*, E. Ludwig, *Member, IEEE*, Kelvin T. Erickson, *Member, IEEE*, and Kirit S. Shah, *Member, IEEE*

***Abstract*—This paper details the nonlinear parameter estimation process of an IEEE AC1A type exciter using time-domain system identification techniques. This paper discusses nonlinear parameter estimation techniques, systematic and random noise mitigation strategies, and system validation. This study establishes a strong basis for excitation system parameter estimation.**

***Index Terms*—Excitation systems, parameter estimation, system identification.**

I. INTRODUCTION

POWER system small signal, transient, and dynamic stability studies are only as accurate as the underlying models used in the computer analysis. The validity of the results of these studies depends heavily on the accuracy of the model parameters of the system components. In practice, the parameters commonly used in stability studies are manufacturer specified values, or "typical" values. These typical values 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. While parameter estimation of synchronous machines has been well documented, parameter estimation of excitation systems has only begun to receive thorough attention. This paper reports the results of an on-going project to develop parameter estimation techniques for Ameren Corporation's (formerly Union Electric Co.) Rush Island Plant.

The objective of this study is to establish a procedure to perform parameter estimation of an AC1A type excitation system using on-line data measurements. This requires that any perturbation signal used to excite the dynamics of the excitation system must have an insignificant effect on the overall operation and output of the system. Most previous work on excitation system parameter estimation is not applicable for on-line time-domain system identification. In [1], the parameters of the excitation system were estimated using a conjugate gradient averaging stochastic approximation method. This method utilizes data signals in the time domain and is used to estimate the parameters of IEEE DC1 and AC1A type excitation systems. The data used for the estimation process was collected during a lightning strike, which provided a very significant, and unwanted, perturbation to the system. The difficulty from using such large perturbation signals on which to base parameter estimation is that i) the estimation procedure cannot typically be validated by a second trial, and ii) large perturbations frequently cause limiters within the system to be hit which may mask some of the dynamics essential to estimate all of the system parameters.

The majority of the previous work in this area have typically employed frequency response techniques to estimate the parameters of specific exciters that were not representative of standard excitation systems. In [2], the authors use frequency response techniques to estimate the parameters of a pumped storage excitation system. The system is perturbed by white noise fed into the system from two different points. In [3], parameter estimation is performed utilizing the FFT and complex curve fitting techniques in the frequency domain. The excitation system under test is that same as that in [2], and the same input perturbations were used. In [4], parameter estimation was performed by using an FFT to convert sampled data to the frequency domain. In the frequency domain, the Wiener–Hopf formula and dynamic curve fitting techniques were used for system identification. The system was excited through the use of a pseudo random binary signal (PRBS) input into the mixing amplifier of the automatic voltage regulator.

In [5], the authors applied a pseudo random binary signal into the reference voltage setting of the pilot exciter. In [5], only the linear parameters of the pilot and main exciter of the AC1A excitation system were estimated. This paper extends the work in [5] to include the nonlinear saturation function and the nonlinear regulating rectifier function of the main exciter.

II. THE EXCITATION SYSTEM MODEL

The excitation system under consideration is a Westinghouse brushless excitation system (also known as the IEEE AC1A type excitation system). This is a field controlled alternator rectifier exciter. This system consists of an alternator main exciter with noncontrolled 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 the modules, 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

Manuscript received May 26, 1999. This works was supported by Ameren Corporation (formerly Union Electric) and the National Science Foundation under Grant ECS-9257208.

R. Bhaskar, M. L. Crow, E. Ludwig, and K. T. Erickson are with the Department of Electrical and Computer Engineering, University of Missouri-Rolla, Rolla, MO 65409-0040.

K. S. Shah is with the Ameren Corporation, 1901 Chouteau Avenue, St. Louis, MO 63166.

Publisher Item Identifier S 0885-8950(00)10352-9.

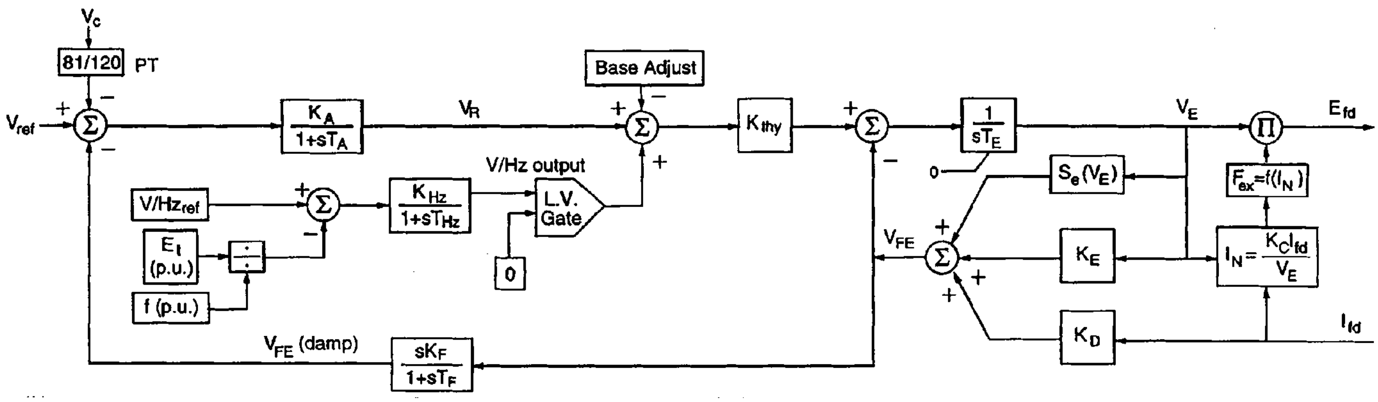

Fig. 1. IEEE-ACIA excitation system.

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 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.

A model suitable for simulating the performance of this exciter, using available system stability software such as ETMSP and SSSP, is the IEEE standard AC1A exciter [6]. A model of this exciter is shown in Fig. 1. This model is linear with the exception of the rectifier operation function $(F_{ex} = f(I_N))$ and the saturation function $(S_e(V_E))$ of the main exciter.

This paper is based upon the system model of the Ameren/UE Rush Island Plant developed jointly by Ameren Corp. and Ontario Hydro. This model was extensively analyzed by Ameren and Ontario Hydro and is found to accurately capture the dynamic response of the actual excitation system. This paper reports the results of a study to develop suitable parameter estimation techniques to reproduce the derived system model.

III. Parameter Estimation by System Identification

System identification is the process whereby the model or structure of a system is determined using a limited number of input and output data measurements, which may or may not be disturbed by noise. The system identification procedure can be characterized by the following steps [7]:

1) Specify and parameterize a class of mathematical models that represent the system to be identified.
2) Apply an appropriately chosen test signal to the system and record the input–output data.
3) Select the model in the specified class that best fits the statistical data.
4) Estimate the parameters using the given selected model(s).
5) Perform a validation test to see if the model(s) chosen adequately represent the system with respect to final identification objectives.
6) If the validation test passed, the procedure terminates. Otherwise another class of models must be selected and steps 2) through 5) repeated.

A. Data Collection

As stated previously, the system identification process uses a set of input/output data measurements. In order to extract useful information correlating the input and output signals, the input signal must be large enough to perturb the system significantly such that all dynamics are excited, yet small enough not to adversely affect the output. In this study, a pseudo random binary signal (PRBS) was used as the perturbation signal, injected into the pilot exciter through the reference voltage setting V_{ref}. The characteristics of the PRBS are such that it has random switching time between two values, a maximum and minimum, which are held constant. The PRBS has a high energy content and the spectrum has a wide frequency content, which is capable of exciting all of the dynamics within the system. Since the minimum and maximum values of the signal may be specified, the magnitude of the PRBS can be set such that the output of exciter is minimally affected. In the Rush Island study system, a PRBS signal of magnitude 0.1 V or greater superimposed onto the reference voltage causes limits within the excitation system to be hit. Many of the violated limits are implicit to the actual excitation system and are not explicitly modeled in the IEEE-AC1A Excitation System. Since it was the intent of this study to be able to estimate all of the excitation system dynamics, it is desirable to use a small enough perturbation such that no limits are exceeded. Due to the high energy content of the PRBS, it was determined that a PRBS of magnitude 0.05 V is sufficient to excite the dynamics of the system sufficiently well to extract meaningful output. Table I shows the effect of the various magnitudes of the PRBS on the terminal voltage output. For small perturbations, each limit is only enforced for a fraction of a second during the switching period and the output response is no longer a one-to-one mapping with the input. However, even though the output signal is corrupted, the brief period of limit enforcement still enables the majority of the PRBS-induced dynamics to propagate through the system. Although the limiters

TABLE I
EFFECT OF PRBS MAGNITUDE ON TERMINAL VOLTAGE

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

may cap one or more signals, a range of dynamics is still observable. Thus, different minimum and maximum voltage swings in Table I occur for PRBS magnitudes greater than 0.05 V. For large perturbations where the limiters acted for longer periods of time, the voltage magnitude maximums should converge to a consistent value.

B. Data Conditioning

Once the data is obtained, it must be conditioned before it can be used in the system identification. The three primary conditioning steps are: removing the signal bias and initial transients, data set averaging, and low-pass filtering. If the system data contains an offset value, the estimation procedures are forced to apply extra parameters to compensate for the offset level, making the computation more complex and prone to error, thus it is preferable to use zero mean data. The best method of producing a zero mean data sample is to subtract the physical equilibrium value from each sampled data point in the data set [8]. In most cases, however, the system equilibrium point is not available or known with sufficient accuracy, therefore a zero mean signal can be obtained by subtracting the mean of the sampled data from each of the sample data points.

Data set averaging is used to reduce the effect of random noise in the data measurements which typically arise from the data acquisition system. In practice, this implies that several data sets of the same signal, in response to an identical perturbation, have been taken. Data set averaging may be obtained as

$$\hat{x}(t_i) = \frac{1}{k}\sum_{j=1}^{k} x_j(t_i) \qquad i = 1, \cdots, N \tag{1}$$

where k is the number of data sets and N is the number of data points per set. The effects of the random noise tend to cancel as several sets of data are averaged. However, the noise can only be reduced to a certain degree and not totally eliminated. The authors found that only minimal improvements were achieved by averaging together more than ten sets of data. In cases where large perturbation signals, such as lightning strikes, are used, it is not possible to obtain several sets of output data from the same input string, thus data set averaging is not an option.

Data set averaging is only effective in reducing random noise; averaging has minimal effect on systematic noise such as the high-frequency noise produced by the power amplifier. In addition to averaging, the output data sets can be low pass filtered to remove the residual random noise and the systematic noise. Since the systematic noise is of a known frequency (2520 Hz) from the power amplifier, the high-frequency content of the signal can be easily filtered using a low-pass Butterworth filter or even a notch, or bandstop, filter. In this system, the systematic noise is injected into the system through the signal V_{FE}. The high-frequency noise is propagated throughout the main exciter and pilot exciter, but is filtered by the long time constants of the generator, yielding a relatively noise-free terminal voltage signal. Filtering is not as effective on mitigating random noise however. The filtering process tends to overly "smooth" the output, which can result in a loss of information, especially at breakpoints in the waveform. Such loss of information is shown in Fig. 2 which shows a filtered waveform versus the noisy data and the same data without noise. Note that at the breakpoints, due to the switching of the PRBS, the filtered waveform does not effectively capture the abrupt change in dynamics.

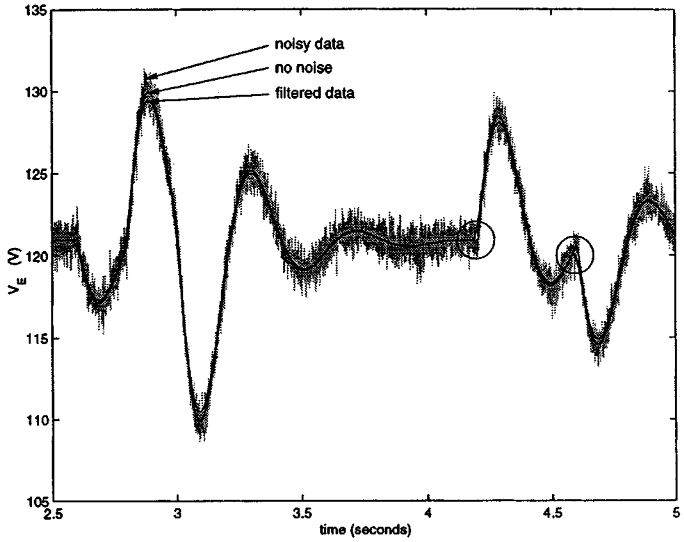

Fig. 2. Effect of filtering.

IV. MODEL STRUCTURE SELECTION

The general polynomial representation of the parametric model is:

$$A(q)y(t) = \frac{B(q)}{F(q)}\,u(t-nk) + \frac{C(q)}{D(q)}\,e(t) \tag{2}$$

where q is the shift operator and $A(q)$ through $F(q)$ are polynomials in q of varying orders. The order of the polynomials correspond to the number of either the poles or zeros in the transfer function that relates the output to the input or the error. The data is then "best fit" to the system being identified using one of the various model structures. The number of poles and zeros required in each polynomial is dictated by the actual structure of the excitation system. Since the parameters of the standard IEEE AC1A model is to be estimated, the structure, along with the number of poles and zeros of the model to be identified, is already well defined. Given the location of physically available input and output signals, the full excitation system could be modeled as a combination of zero-, first-, and second-order transfer functions.

Each of the algorithms used to correlate the input and output data using one of the parametric model structures minimizes the square of prediction error between the data, where the prediction error is defined as the difference between the actual measured output of the system and the predicted output. A least squares estimation method is employed to identify an ARX model whereas

TABLE II
COMMON PARAMETRIC MODEL STRUCTURES WITH ASSOCIATED POLYNOMIALS

Model	Polynomials Used
AR	A
ARX	A, B
ARMAX	A, B, C
ARARX	A, B, D
BJ	B, C, D, F
OE	B, F
PEM	A, B, C, D, F

a PEM algorithm using a Gauss–Newton method is utilized to estimate the parameters of ARMAX, BJ, and OE models. See [8, (pp. 81–89)] for more details. Table II lists some of the commonly used parametric model structures and the polynomials from (2) which are used.

The noise contained in the data measurement may cause the system identification using a particular model structure to be inaccurate. This does not mean that the system from which the data was taken cannot be identified. In this case, another model structure or fitting algorithm should be chosen and the identification recalculated. One standard means of assessing parameter accuracy is to substitute the estimated parameters into the derived model and compare the simulated response against the original output data. If the simulated and original responses are within some tolerance of each other (as determined by the user), then the parameters are accepted, otherwise a different model structure should be utilized.

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. A discrete to continuous conversion was accomplished using a pole-zero matching technique which matches the poles and zeros of the transfer function. The result of this conversion is a numerator and denominator of the estimated continuous time transfer function given in descending powers of the continuous time operator s. In the event where the parameter being identified was a constant, as in the transducer shunt, transformer turns ratio, and a few of the main exciter parameters, a direct pole-zero match could not be obtained. In these instances, the conversion was made using the zero order hold method.

V. NONLINEAR PARAMETER ESTIMATION

The primary objectives of this paper are to extend the work of [5] to include the estimation of the nonlinear functions. The nonlinear functions in the main exciter are the saturation function and the rectifier regulation function.

A. Saturation Function

The saturation function is modeled as an exponential function of the input signal V_E:

$$S_e(V_E) = ae^{bV_E} \tag{3}$$

where

$$V_{FE} = K_E V_E + S_e(V_E) + K_D I_{fd} \tag{4}$$

In the linear analysis presented in [5], the saturation function was linearized around the equilibrium point V_{E0} to yield:

$$S_e(V_E) \approx S_e(V_{E0}) + abe^{bV_{E0}}(V_E - V_{E0}) \tag{5}$$

$$= \hat{S}_e V_E + S_{e0} \tag{6}$$

where $\hat{S}_e = abe^{bV_{E0}}$. From Fig. 1, the saturation function is combined with the constant block K_E to form the single input/single output transfer function between the output V_{FE} and input V_E:

$$V_{FE} = (K_E + \hat{S}_e)V_E \tag{7}$$

Note that several problems arise when using a linearized model for the estimation process. Not only can the constants a and b of the original saturation function S_e not be extracted from the transfer function since they now appear as a product, but the saturation constant $\hat{S}_e$ cannot be extracted independently from the gain K_E. Thus during the linear parameter estimation, the parameters a, b, and K_E are not observable.

In order to independently obtain each parameter, a nonlinear approach to the estimation must be taken. Using a similar approach as before, the saturation function is expanded using a Taylor series expansion about the operating point V_{E0} yielding:

$$\begin{aligned} V_{FE} = {} & K_E V_E + ae^{bV_{E0}} + abe^{bV_{E0}}(V_E - V_{E0}) \\ & + \frac{1}{2!}ab^2 e^{bV_{E0}}(V_E - V_{E0})^2 \\ & + \frac{1}{3!}ab^3 e^{bV_{E0}}(V_E - V_{E0})^3 \\ & + \text{higher order terms} \end{aligned} \tag{8}$$

If the higher order terms are neglected, this can be posed as a fourth-order linear regression with powers of $(V_E - V_{E0})$ as the inputs and V_{FE} as the output. Using one of the minimization algorithms to solve the fourth-order linear regression yields the following parameter vector:

$$\theta = \begin{bmatrix} ae^{bV_{E0}} + K_E V_{E0} \\ abe^{bV_{E0}} + K_E \\ \frac{1}{2!}ab^2 e^{bV_{E0}} \\ \frac{1}{3!}ab^3 e^{bV_{E0}} \end{bmatrix} \tag{9}$$

The unknown model parameters may be extracted directly from the parameter vector as:

$$b = 3\frac{\theta(4)}{\theta(3)} \tag{10}$$

$$K_E = \frac{b\theta(1) - \theta(2)}{bV_{E0} - 1} \tag{11}$$

$$a = \frac{\theta(2) - K_E}{be^{bV_{E0}}} \tag{12}$$

This approach has an advantage over the linearized approach in that each individual parameter can be estimated.

This procedure works well when the signal-to-noise ratio is large. From (8), the difference $(V_E - V_{E0})$ is intended to capture the dynamic excursions of V_E from nominal. However, for systems with considerable noise, this term essentially becomes

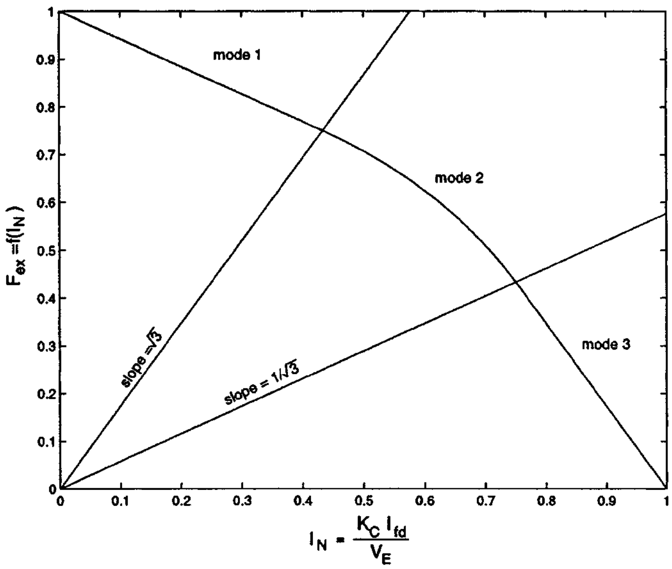

Fig. 3. Rectifier regulation function.

the noise content, that is then squared and cubed to form the regression series. One approach that is effective in minimizing the noise effects on the nonlinear parameter estimation is to consider only the first three terms in the regression. The parameters may then be obtained from the three nonlinear equations using an iterative approach such as the Newton–Raphson method.

B. Rectifier Regulation Function

All ac sources that supply rectifier circuits have an internal inductance. This inductance alters the process of commutation and causes a nonlinear decrease in output voltage as a function of rectifier current [6]. The three-phase, full-wave bridge circuits commonly employed have three distinct modes that are determined by the rectifier load current. The three modes of operation represented by the following piecewise nonlinear equations [6]:

$$F_{ex} = 1 - 0.577 I_N \quad I_N < 0.433 \tag{13}$$

$$F_{ex} = \sqrt{0.75 - I_N^2} \quad 0.433 < I_N < 0.75 \tag{14}$$

$$F_{ex} = 1.732(1 - I_N) \quad I_N > 0.75 \tag{15}$$

where

$$I_N = \frac{K_C I_{fd}}{V_E}. \tag{16}$$

The rectifier regulation function, shown in Fig. 3, is a nonlinear function in I_N, the normalized exciter load current. The load current I_N is a function of I_{fd}, the synchronous machine field current, V_E the exciter voltage, and K_C, the rectifier loading factor proportional to the commutating reactance.

In the linear analysis in [5], the rectifier regulation function was modeled as a constant single input/single output block relating V_E to E_{fd}, where

$$E_{fd} = K_{I_N F_{ex}} V_E. \tag{17}$$

In this case, not only was the mode of operating nondeterminable, but the parameter K_C was not observable. In the nonlinear function, the parameter to be estimated is the rectifier loading factor K_C. To properly estimate this parameter, however, the operating mode of the rectifier must first be determined. The mode was determined in an iterative approach. At each sample point, V_E and I_{fd} are used to calculate F_{EX} which in turns yields three possible values for K_C:

$$K_C = \frac{1 - F_{EX}}{0.577 \frac{I_{fd}}{V_E}} \quad \text{mode 1} \tag{18}$$

$$= \frac{V_E}{I_{fd}} \sqrt{0.75 - F_{EX}^2} \quad \text{mode 2} \tag{19}$$

$$= \frac{V_E}{I_{fd}} \left(1 - \frac{F_{EX}}{1.732}\right) \quad \text{mode 3} \tag{20}$$

These values are then used to calculate I_N from (16) to determine the mode. The values of K_C which are determined are then averaged over the sample space to yield the parameter estimate. In most instances, the rectifier predominantly operates in mode 1.

TABLE III
MAIN EXCITER ESTIMATION RESULTS USING ARMAX AND PEM

Parameter	Original 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	174.461	173.124	174.173
T_E	0.755e-1	0.755e-1	0.750e-1	0.754e-1
K_D	0.077e-1	0.073e-1	0.071e-1	0.069e-1
K_E	9.685e-2	9.692e-2	9.692e-2	9.690e-2
a	3.668e-2	3.643e-2	3.649e-2	3.713e-2
b	6.836e-3	6.018e-3	5.945e-3	6.068e-3
K_C	1.000e-2	1.001e-2	0.099e-2	1.007e-2

VI. PARAMETER ESTIMATION RESULTS

The excitation model developed by Ontario Hydro was used as the basis for the parameter estimation. This model was used to study the effects of various system identification algorithms, noise levels, and perturbation signals on the accuracy of the estimated parameters. The excitation system was simulated using a ± 0.05 volt pseudo random binary signal perturbation injected into the reference voltage setting of the pilot exciter at 2.6 seconds after initialization. The systematic noise was modeled as a 1 Volt, 2520 Hz signal injected into the rectifier with a firing angle of 90°, which is a "worst case" scenario because the 90° signal contains the highest harmonic content. The input and output signals were sampled every 50 microseconds.

Various combinations of the factors which influence the estimation of the parameters were considered: estimation algorithm (ARX, ARMAX, PEM), random noise magnitude, low-pass filter cutoff frequency, number of averaged data sets, rectifier firing angle, and systematic noise magnitude. The pilot exciter contains only linear blocks and the parameter estimation results for this portion of the exciter are reported in [5]. Using a combination of factors gives the linear and nonlinear parameter estimation results shown in Table III for the main exciter. The "original" parameter values are those values which were estimated in the initial study by Ontario Hydro and were used in the simulation as accurate values.

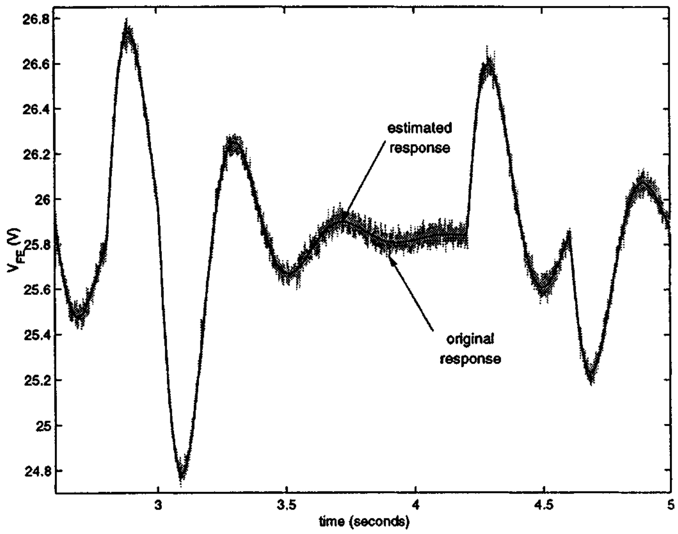

Fig. 4. Estimated versus original response of V_{FE}.

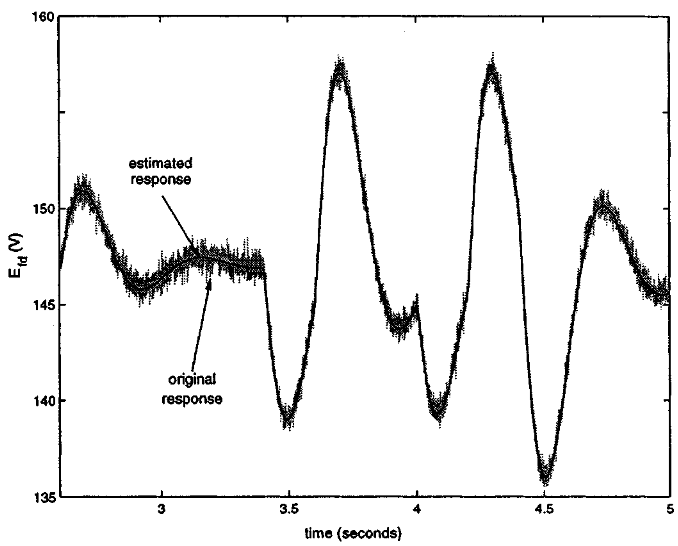

Fig. 5. Estimated versus original response of E_{fd}.

The saturation function parameters a and b are very susceptible to noise, in part because they are very small and the overall saturation is only a small part of the response of V_{FE}. The dynamic response of V_{FE} is dominated by the linear gain K_E, thus K_E is able to be accurately estimated, even in the presence of considerable noise.

The parameters were validated in two ways. First, the parameters were compared against the original values. This gives a quantitative comparison. However, in most cases, the "actual" values of parameters are not known. In this situation, the validation must be more qualitative than quantitative. One means of ascertaining the accuracy of the estimated parameters is to compare the calculated response of the system using the estimated parameters against the actual response of the system. If the two responses are similar to the desired degree of accuracy, then the estimated parameters are accepted. Several signal comparisons are shown in Figs. 4 and 5.

VII. Discussion and Conclusions

The main goal of this paper is to present the results of the nonlinear parameter estimation of an excitation system using time domain signals. The feasibility of estimating the parameters of Ameren/UE's Rush Island excitation system, a representation of an IEEE AC1A type exciter, was determined. The pilot exciter of the excitation system contains primarily linear blocks, which can be estimated using linear techniques which were previously discussed in [5]. The main exciter, however, contains several nonlinear blocks, which cannot be accurately estimated with linear techniques. Several nonlinear estimation algorithms were presented which were shown to accurately estimate the parameters of these nonlinear blocks.

Several features of the systems were shown to have varying degrees of impact on the accuracy of the estimated parameters. The two steps in the identification process which have the most impact on the accuracy of the parameters are the signal conditioning and the choice of algorithm.

Signal conditioning primarily consisted of noise handling and bias term removal. The bias term removal was typically straightforward in that each data sample was averaged to obtain the average bias term, which was then subtracted from the entire sample to yield zero mean bias. Noise conditioning proved to be more problematic however. The magnitude of the systematic rectifier noise had 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 saturation parameters significantly. Because the magnitude of the saturation parameters, a and b is very small, the nonlinear saturation function is highly susceptible to random noise. This effect can be mitigated to some degree by averaging sets of data together. The number and choice of sets can greatly affect the accuracy as well. In general, the more sets of data which are averaged, the more accurate the results. However, it is not practical to obtain and average large numbers of sets of data. Also, it was found in practice, that for large noise levels, a third order linear regression approach (requiring a nonlinear iterative numerical solution) yielded superior results to the fourth-order linear regression given in (9).

The output E_{fd} of the main exciter is a nonlinear function of the inputs V_E and I_{fd} which are related through the constant parameter K_C and the nonlinear rectifier regulation functional block. Under normal operation, the rectifier will operate primarily in mode 1. Using the proposed method, it is possible to iteratively ascertain the operating mode of the rectifier at each data sample point and then extract the desired parameter K_C. The estimation of the parameter K_C was relatively impervious to noise levels and accurate results were obtained.

The choice of estimation algorithm, such as the least squares estimator (ARX) or the Gauss–Newton minimization (ARMAX and PEM), used in the identification of the parameters did not have much impact on the results. Each algorithm produced similar results when performing the estimations under the same conditions. This was not unexpected, however, since the ARMAX and PEM algorithms utilize two polynomials to model noise. These algorithms are thus better able to handle the noise in the system than the ARX algorithm which only uses one polynomial. However, since data conditioning was used to mitigate the noise effects prior to applying the algorithms, the difference in the parameter estimations was not large. If one model structure is found to produce inaccurate results, another model can be selected.

REFERENCES

[1] J.-C. Wang *et al.*, "Identification of excitation system models based on on-line digital measurements," *IEEE Transactions on Power Systems*, vol. 10, no. 3, Aug. 1995.

[2] C. M. Liaw *et al.*, "Parameter estimation of excitation systems from sampled data," *IEEE Transactions on Automatic Control*, vol. 37, no. 5, May 1992.

[3] C.-S. Liu *et al.*, "Indentification of exciter constants using a coherence function based weighted least squares approach," *IEEE Trans. Energy Conversion*, vol. 8, no. 3, Sept. 1993.

[4] S. Shande *et al.*, "Identification of parameters of synchronous machine and excitation system by on-line test," in *Proceedings of IEE Int'l. Conference on Advances in Power System Control, Operation, and Management*, 1991.

[5] E. Ludwig *et al.*, "A feasbility study of on-line excitation system parameter estimation," *IEEE Trans. on Power Systems*, vol. 13, no. 3, Aug. 1997.

[6] *IEEE recommended practice for excitation system models for power system stablity studies*, IEEE Std. 421.5, 1992.

[7] J. Schoukens and R. Pintelon, *Identification of Linear Systems*. Elmsford, NY: Pergamon Press, 1991.

[8] L. Ljung, *System Identification: Theory for the User*. Englewood Cliffs, NJ: Prentice Hall, 1987.

Rajeev Bhaskar received his B.E.E.E. in electrical engineering from the University of Rorkee, India. He has been a graduate student in electrical and computer engineering at the University of Missouri–Rolla since September 1997. His research interests are computer applications in power engineering.

M. L. Crow received her B.S.E. degree from the University of Michigan in 1985, and her M.S. (1986) and Ph.D. (1989) degrees from the Univ. of Illinois, Urbana/Champaign. She is presently an Associate Professor of Electrical and Computer Engineering at the University of Missouri–Rolla. Dr. Crow's area of research interests has concentrated on developing computational methods for dynamic security assessment.

E. Ludwig received his B.S.E.E. degree from the University of Missouri–Rolla in May 1995 and his M.S.E.E. from UM–Rolla in 1996. Mr. Ludwig is currently the Electrical Engineering Manager for Speedline Technologies. Mr. Ludwig is a member of IEEE and PES.

Kelvin T. Erickson (SM'77–M'84) received the B.S. and M.S. degrees in electrical engineering from the University of Missouri–Rolla, in 1978 and 1979, respectively, and the Ph.D. degree in electrical engineering from Iowa State University, Ames, in 1983. From 1979 to 1986, he was employed by Fisher Controls International, Inc., Marshalltown, IA. In 1986, he joined the faculty of the University of Missouri–Rolla, Rolla, MO, where he currently is an Associate Professor. His present research interests are in the areas of nonlinear system identification, plantwide process control, and manufacturing automation.

Kirit S. Shah received his Ph.D. in electrical engineering from the University of Missouri–Rolla in 1976. He is currently Supervising Engineer–Transmission and Interconnections of the Transmission Planning Department for Ameren Corporation. He is active in various Mid-America Interconnected Network (MAIN) committees and is chairman of the North American Electric Reliability Council (NERC) System Dynamic Database Working Group (SDDWG). He has been involved in several EPRI projects and is a member of the Grid Operations and Planning Business Area Council (GOP-BAC).