# MODEL IDENTIFICATION OF AUTOMATIC VOLTAGE REGULATORS

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Abstract. Adequate modeling of power plants and systems is required when planning their operation. Often there is lack of such data and typical parameters have to be used, difficulting the assessment of emergency strategies and stability control. The paper reports on an application of identification methods to the modeling of Automatic Voltage Regulators (AVR) of electrical generators. IEEE standard linear models are to be fitted with the adequate parameters to reproduce system responses. Two time domain identification methods are used: the one-shot least square method and the recursive least square method. The application of the methods to two chilean power plants are reported. Parameters for both plant AVRs are obtained, reproducing the system behaviour. Further developments are discussed.

Keywords. Power system control; Identification; Voltage control; Modeling; Least-squares estimation.

## INTRODUCTION

The analysis and control of electric power systems requires adequate modelling of system components. This is particularly important when new stabilizing measures are being assessed for critically stable power systems. Presently, manufacturers often provide dynamic models of the equipment being installed. However, parameters are usually modified when commissioning the plants, particularly controller parameters. Besides, models are not always available for older plant.

The need to identify models and estimate parameters in electrical power systems has lead many researchers to explore alternative methods of measurement, identification and validation, following closely the research boom on identification in the control engineering field [Young, 1981; Norton, 1986; Unbehauen, 1987]. Models for synchronous generators and loads have been identified using different methods. Identification of equivalent reduced order models for parts of a power system has also been tested [Rudnick and others, 1980].

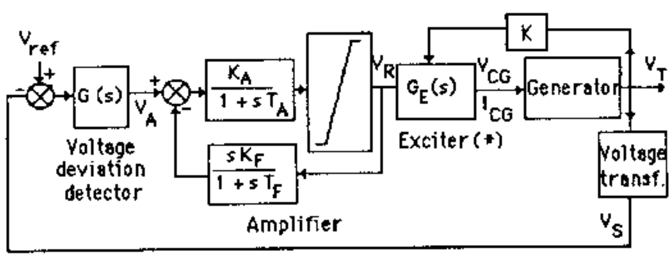
The subject of automatic voltage regulator (AVR) identification has also been a subject of interest. Frequency domain methods have been explored by Gibbard and other [1975], which performed a comprehensive set of tests to determine the parameters of a real excitation system, using small signal measurements. Hope and others [1977] and Bollinger and other [1982] used frequency response methods with seudo random binary signals for identification.

This work reports on the application of time domain methods to AVR identification. Non linear optimization algorithms such as Gauss-Newton, conjugate direction and Marquardt were studied by Morales [1980], with simulated time responses. Actual plant AVR measurements with linear least square one-shot and recursive estimation methods are reported here.

## PROBLEM FORMULATION

The problem is one of developing an identification algorithm to be used by engineers to determine standard IEEE AVR models [IEEE Committee, 1968] of power system plants. AVR models whose parameters are to be estimated are single-input-single-output continuous-time linear models, in the form of standard transfer functions that can be used by common step-by-step integration power system transient stability and steady-state stability computer programs. AVRs to be measured vary widely in their characteristics, some being totally electronic while others are electro-mechanic. Constraints are that the plants where measurements are to be made are operating connected to the electric power grid, and they can be taken out of service for reduced periods of time to install measurement equipment.

The objective is to develop an automatic tool that estimates all parameters, without the traditional approximate gain and time constant calculations of some frequency domain methods. The tool is to be developed, simulated and tested on real power plant in the Chilean interconnected electric power system. Two power plants of different control technology are to be used for the testing of the tool: El Toro power plant (commissioned in 1973, with Brown Boveri electro-mechanic AVRs) and Antuco power plant (commissioned in 1981, with Hitachi electronic AVRs). Figures 1 and 2 present block diagram models for the Antuco and the El Toro AVRs, obtained through inspection of the physical elements of the equipment. IEEE standard models were chosen, finding those closest to the physical structures presented. Model type 1S, shown in Fig. 3, was used for the Antuco AVR, and model type 1, shown in Fig. 4, for the El Toro AVR.




(*)includes automatic phase shifter, pulse amplifier and thyristors

Fig. 1. Model for the Antuco AVR

## EXPERIMENT DESIGN

The experiments for data acquisition considered the generator operating connected to the electric network and the introduction of an impulse-type perturbation in the AVR system through the inclusion of a resistance in one of the phases of the three-phase voltage feedback of the AVR, as shown on Fig. 5.

The measurements were made using an IBM personal computer (640kB, two 360 kB floppy disks) with a 12 bit data acquisition A/D converter, model DT 2801-A, with 8 differential channels and a conversion rate of 27.5 kHz (Lucero and other, 1987). Isolation transformers, current transformers and a shunt resistance were used to adequate signal values. The sampling rate per channel used was 3 kHz. A signal preprocessing was performed to obtain average values for the field voltage measurements and effective values for the generator busbar voltage measurements every half cicle of the 50 Hz grid frequency.

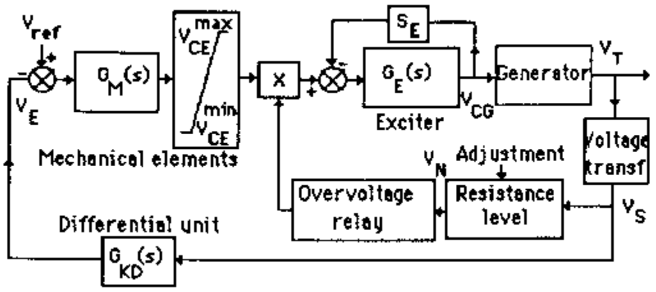



Fig. 2. Model for the El Toro AVR

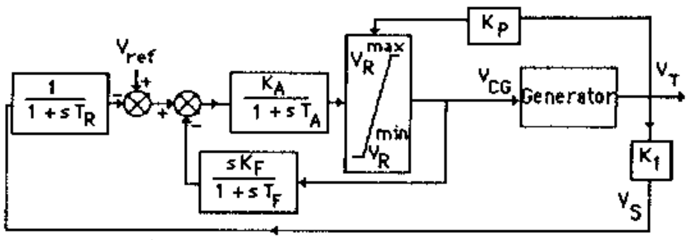



Fig. 3. Standard IEEE 1S model for the Antuco AVR

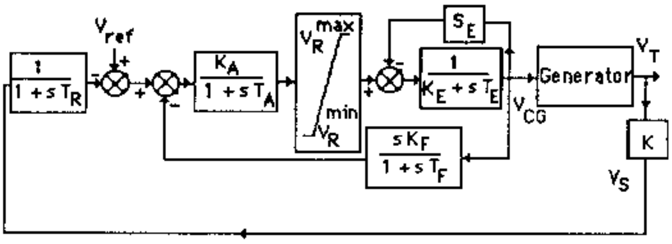



Fig. 4 . Standard IEEE 1 model for the El Toro AVR

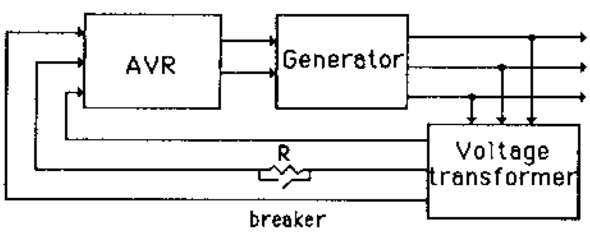



Fig. 5. Impulse perturbation through a resistance and a switch

ESTIMATION METHODS

Linear least square one-shot and recursive estimation methods are used for the identification of the AVR models. An important number of processes can be characterized by the ARMA type linear model [Isermann, 1981; Unbehauen, 1987], defined in the z domain by

$$Y(z) = \frac{B(z^{-1})}{A(z^{-1})} z^{-d} U(z) + \frac{D(z^{-1})}{C(z^{-1})} W(z) \qquad (1)$$

Doing some simplifications it is possible to derive particular model structures from the general model of Eq. (1), reducing the number of parameters of the model and therefore, the computational requirements [Young,1969a; Young, 1969b]. For example, considering

$$C(z^{-1}) = A(z^{-1}) \text{ and } D(z^{-1}) = 1 \qquad (2)$$

the Least Square (LS) model is obtained

$$A(z^{-1})\, Y(z) = B(z^{-1})\, z^{-d}\, U(z) + W(z) \qquad (3)$$

The LS model may also be described by a difference equation

$$Y(k) = c - a_1 Y(k-1) - \ldots - a_m Y(k-m) + b_1 U(k-d-1) + \ldots + b_n U(k-d-n) + W(k) \qquad (4)$$

Coefficients c, $a_1$, ..., $a_m$, $b_1$, ..., $b_n$ contain all the information on the process dynamics and the problem is one of interpreting and obtaining that information correctly. Coefficient c was introduced to consider signal values independent of the operating point.

Standard IEEE AVR models may be discretized using numerical rectangular integration and a difference equation such as Eq. (4) is obtained [Rudnick and coworkers,1988]. Coefficients of Eq. (4) may be estimated in an optimal manner from operating data, using the least square estimation algorithm, either in its direct one-shot version or the recursive one [Isermann, 1981; Unbehauen, 1987]. Gains and time constants of the AVR blocks are then obtained directly from those optimal coefficients [Rudnick and coworkers,1988].

RESULTS FOR THE ANTUCO AVR

One-shot algorithm

Eight tests at the Antuco plant gave the coefficients, shown in Table 1, of the difference equation (Eq. (4)) corresponding to the IEEE 1S linearised model. All tests were made with the generator connected to the network, but they vary from no-load to full load. Gains and time constants of the corresponding AVR blocks obtained from those optimal coefficients are shown in Table 2. Table 3 gives information on error between system and model responses.

Therefore, parameter values are within the range

$$0.0477 \le T_a \le 0.0773$$
$$0.0103 \le T_f \le 0.0174$$
$$117.8843 \le K_a \le 133.8089$$
$$0.0002 \le K_f \le 0.0004$$

TABLE 1 Coefficients of the difference equation

| Test | c | $a_1$ | $a_2$ | $b_1$ | $b_2$ |
|---|---|---|---|---|---|
| 1 | 15.472 | -0.522 | -0.357 | 24.836 | -9.174 |
| 2 | 15.006 | -0.568 | -0.307 | 22.870 | -7.685 |
| 3 | 14.005 | -0.706 | -0.180 | 18.986 | -4.817 |
| 4 | 16.350 | -0.535 | -0.324 | 24.687 | -8.144 |
| 5 | 14.542 | -0.641 | -0.236 | 20.809 | -6.105 |
| 6 | 15.266 | -0.581 | -0.301 | 18.744 | -3.336 |
| 7 | 12.261 | -0.742 | -0.165 | 21.481 | -9.106 |
| 8 | 15.342 | -0.657 | -0.216 | 15.909 | -0.432 |

TABLE 2 AVR parameters (one-shot method)

| Test | $T_a$ | $T_f$ | $K_a$ | $K_f$ |
|---|---|---|---|---|
| 1 | 0.0526 | 0.0159 | 130.6718 | 0.0004 |
| 2 | 0.0539 | 0.0151 | 123.3691 | 0.0004 |
| 3 | 0.0657 | 0.0134 | 124.6775 | 0.0003 |
| 4 | 0.0477 | 0.0149 | 117.8843 | 0.0003 |
| 5 | 0.0578 | 0.0141 | 120.2995 | 0.0003 |
| 6 | 0.0703 | 0.0122 | 131.7448 | 0.0003 |
| 7 | 0.0623 | 0.0174 | 133.8089 | 0.0004 |
| 8 | 0.0773 | 0.0103 | 123.0701 | 0.0002 |

TABLE 3 Response error- model versus system

| Test | Error | | Standard deviation | |
|---|---|---|---|---|
| | Average | % | Magnitude | % |
| 1 | 0.0179 | 1.809 | 0.2481 | 25.120 |
| 2 | 0.0149 | 1.529 | 0.2650 | 27.218 |
| 3 | 0.0172 | 1.698 | 0.3306 | 32.532 |
| 4 | 0.0094 | 1.060 | 0.2279 | 25.568 |
| 5 | 0.0164 | 1.532 | 0.2276 | 21.265 |
| 6 | 0.0200 | 1.506 | 0.2155 | 16.199 |
| 7 | 0.0248 | 1.807 | 0.3256 | 23.758 |
| 8 | 0.0181 | 1.429 | 0.1958 | 15.444 |

System responses against model responses for two different tests are given in Figs. 6 and 7.

Recursive algorithm

The same eight tests gave the coefficients shown in Table 4 of the difference equation when using the recursive algorithm. The coefficients correspond to the last iteration of the least square recursive algorithm. Gains and time constants obtained from those coefficients are shown in Table 5. There are no significant differences with the parameters obtained with the one-shot algorithm, but the error average values reduce as shown in Table 6.

TABLE 4 Coefficients of the difference equation

| Test | c | $a_1$ | $a_2$ | $b_1$ | $b_2$ |
|---|---|---|---|---|---|
| 1 | 15.318 | -0.542 | -0.338 | 24.573 | -9.069 |
| 2 | 14.972 | -0.570 | -0.307 | 23.343 | -8.194 |
| 3 | 14.083 | -0.693 | -0.192 | 19.203 | -4.957 |
| 4 | 16.024 | -0.547 | -0.315 | 24.977 | -8.764 |
| 5 | 14.647 | -0.638 | -0.238 | 20.730 | -5.921 |
| 6 | 15.790 | -0.539 | -0.339 | 18.769 | -2.836 |
| 7 | 12.328 | -0.740 | -0.166 | 21.440 | -9.001 |
| 8 | 15.101 | -0.674 | -0.200 | 15.344 | -0.010 |

TABLE 5 AVR parameters (recursive method)

| Test | $T_a$ | $T_f$ | $K_a$ | $K_f$ |
|---|---|---|---|---|
| 1 | 0.0569 | 0.0158 | 129.9721 | 0.0004 |
| 2 | 0.0531 | 0.0154 | 124.0131 | 0.0004 |
| 3 | 0.0655 | 0.0135 | 125.7339 | 0.0003 |
| 4 | 0.0473 | 0.0154 | 118.1515 | 0.0004 |
| 5 | 0.0583 | 0.0140 | 120.9368 | 0.0003 |
| 6 | 0.0701 | 0.0118 | 131.5811 | 0.0003 |
| 7 | 0.0621 | 0.0172 | 133.1271 | 0.0004 |
| 8 | 0.0799 | 0.0100 | 122.6198 | 0.0001 |

TABLE 6 Response error- model versus system

| Test | Error | | Standard deviation | |
|---|---|---|---|---|
| | Average | % | Magnitude | % |
| 1 | +0.0049 | +0.492 | 0.2486 | 25.170 |
| 2 | -0.0013 | -0.134 | 0.2644 | 27.153 |
| 3 | -0.0025 | -0.848 | 0.3300 | 32.473 |
| 4 | -0.0020 | -0.225 | 0.2260 | 25.355 |
| 5 | -0.0013 | -0.118 | 0.2284 | 21.338 |
| 6 | -0.0006 | -0.052 | 0.2165 | 16.273 |
| 7 | +0.0010 | +0.070 | 0.3257 | 23.770 |
| 8 | -0.0006 | -0.046 | 0.1970 | 15.545 |
| 5 | +0.0164 | +1.532 | 0.2276 | 21.265 |

Parameter values are within the following ranges

$$0.0473 \le T_a \le 0.0799$$
$$0.0100 \le T_f \le 0.0172$$
$$118.1515 \le K_a \le 133.1271$$
$$0.0001 \le K_f \le 0.0004$$

Figures 8 and 9 show the evolution of four coefficients of the difference equation when using the recursive algorithm. Initial oscillations are due to the chosen starting values for the coefficients. Figure 10 gives system response against model response for one test.

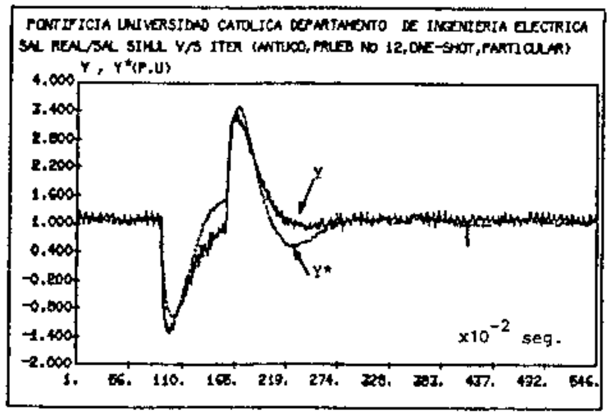



Fig. 6. Real (Y) versus model (Y*) response for 0.5 sec. perturbation. Generator on no-load.

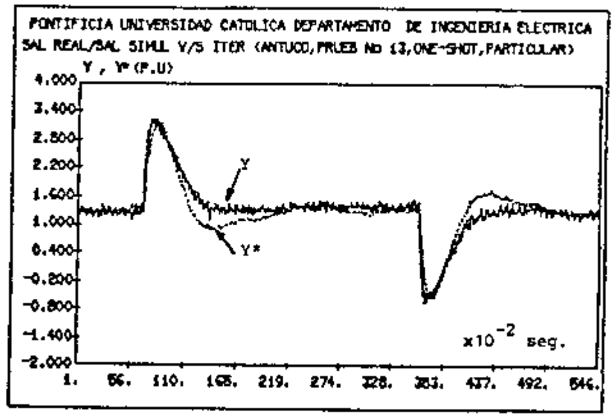



Fig. 7. Real (Y) versus model (Y*) response for 2.82 sec. perturbation. Generator on full load.

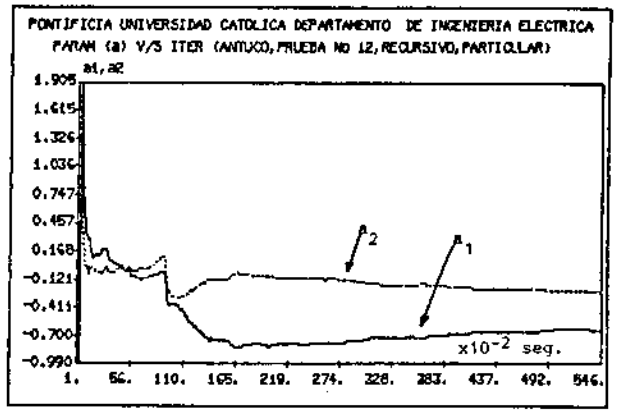



Fig. 8. Evolution of coefficients $a_1$ and $a_2$ for test with 0.5 sec. perturbation. Generator on no-load.

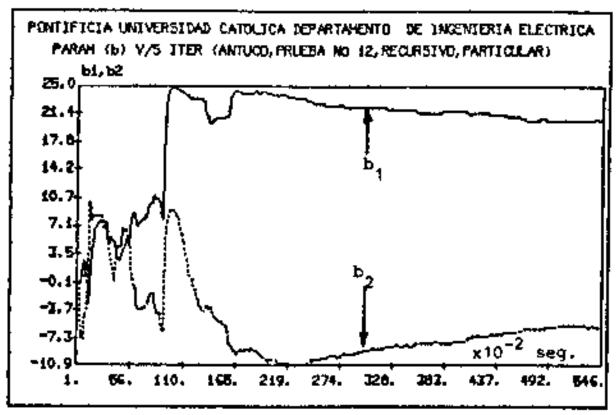



Fig. 9. Evolution of coefficients $b_1$ and $b_2$ for test with 0.5 sec. perturbation. Generator on no-load.

RESULTS FOR THE EL TORO AVR

One-shot algorithm

Ten tests at the El Toro plant provided the coefficients of the difference equation, corresponding to the IEEE 1 linearised model. Gains and time constants of the corresponding AVR blocks obtained from those coefficients are given in Table 7. Parameter $K_e$ was chosen to be 1.

The one-shot algorithm does not work adequately for this AVR. The error grows to values between 17% and 78%. Besides, it estimates parameter values with no physical sense, like negative time constants. The best results are obtained for test 5 when the smallest and shortest perturbation was applied.

TABLE 7 AVR parameters (one-shot method)

| Test | $T_a$ | $T_e$ | $T_f$ | $K_a$ | $K_f$ |
|---|---|---|---|---|---|
| 1 | 0.0034 | -3.778 | -0.012 | 11.822 | 0.3685 |
| 2 | 0.0045 | -0.415 | -0.111 | 2.2174 | 0.4333 |
| 3 | 0.9461 | 0.0065 | 0.0590 | 14.360 | -0.021 |
| 4 | 0.1646 | 0.0060 | 0.3459 | 3.2563 | 0.0399 |
| 5 | 1.3614 | 0.0092 | 0.0129 | 14.945 | -0.051 |
| 6 | 0.6561 | 0.0054 | 0.1613 | 2.6174 | -0.048 |
| 7 | 1.2031 | 0.0068 | 0.0293 | 17.399 | -0.035 |
| 8 | 0.0050 | -2.475 | 0.0644 | 30.935 | 0.1074 |
| 9 | 1.7822 | 0.0081 | 0.0145 | 14.411 | -0.097 |
| 10 | 1.0190 | 0.0054 | 0.1180 | 4.7136 | -0.086 |

Recursive algorithm

The same ten tests were used to obtain the coefficients of the difference equation, when using the recursive algorithm. Gains and time constants of the corresponding AVR blocks obtained from those coefficients are given in Table 8.

The recursive algorithm reduces the error values for El Toro to ±0.8%, but some parameter values obtained still have no physical sense. Again, the best results are obtained for the test with the smallest and shortest perturbation. Figure 11 shows system against model responses for that particular test. Figure 12 shows the evolution of three coefficients of the difference equation when using the recursive algorithm in that particular test. Parameters had not stabilized completely at the end of the test.

TABLE 8 AVR parameters (recursive method)

| Test | $T_a$ | $T_e$ | $T_f$ | $K_a$ | $K_f$ |
|---|---|---|---|---|---|
| 1 | -0.010 | -4.173 | 0.0036 | 8.4982 | 0.5352 |
| 2 | 0.9980 | 0.0206 | 0.0077 | 7.7186 | -0.080 |
| 3 | -0.004 | -17.81 | 0.0025 | 8.9535 | 2.0310 |
| 4 | 0.9693 | 0.0275 | 0.0070 | 7.8510 | -0.082 |
| 5 | 0.8873 | 0.0269 | 0.0071 | 9.8444 | -0.052 |
| 6 | 0.0006 | -372.7 | -0.001 | 8.6755 | 43.008 |
| 7 | 1.4027 | 0.0235 | 0.0078 | 12.659 | -0.083 |
| 8 | 1.3451 | 0.0074 | 0.0259 | 10.772 | -0.087 |
| 9 | -0.018 | -2.722 | 0.0044 | 12.834 | 0.2422 |
| 10 | 1.0210 | 0.0217 | 0.0075 | 9.8277 | -0.066 |

MODEL VALIDATION

The best AVR models obtained for both plants are checked with other tests to assess their behavior.

Antuco model (test 6 and one-shot algorithm)
IEEE type 1S AVR
$T_a$=0.0703 $T_f$=0.0122 $K_a$=131.7448 $K_f$=0.0003

Figure 13 shows the response of the indicated model for test 8 as compared to the actual system response. Similar matchings are obtained for all tests, independent of generator loading and size and duration of test perturbation. The small values of the obtained $T_f$ and $K_f$ suggest the convenience of further testing.

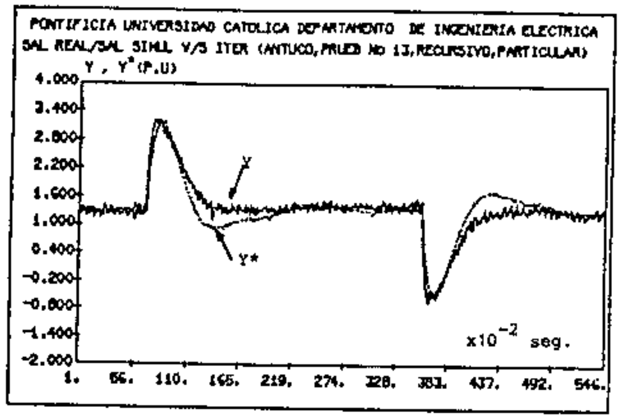



Fig. 10. Real (Y) versus model (Y*) response for 2.82 sec perturbation. Generator on full load.

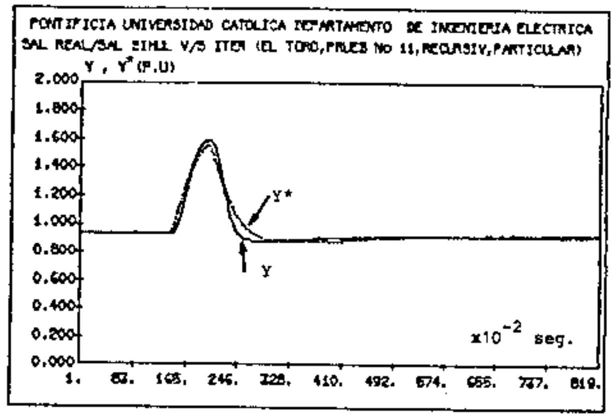



Fig. 11. Real (Y) versus model (Y*) response for 0.5 sec. perturbation. Generator on no-load.

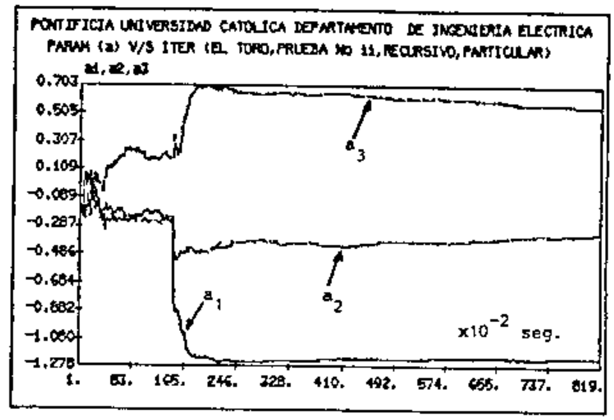



Fig. 12. Evolution of coefficients $a_1$, $a_2$ and $a_3$ for test with 0.5 sec. perturbation. Generator on no-load.

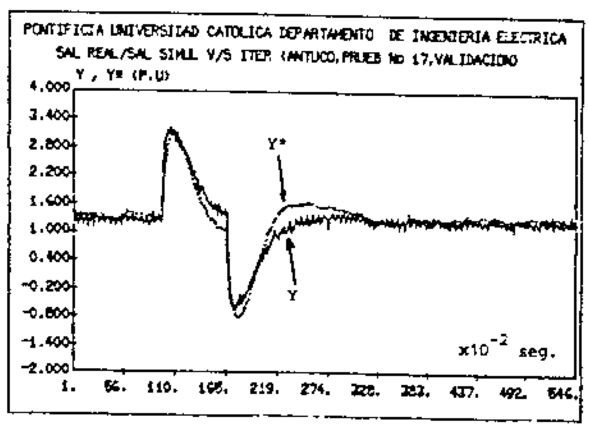



Fig. 13. Real response (Y, test 8) versus response of specified model (Y*) for Antuco

El Toro model (test 5 and recursive algorithm)
IEEE type 1 AVR
$T_a$=0.8873 $T_e$=0.0269 $T_f$=0.0071 $K_a$=9.8444 $K_e$=1.0000 $K_f$=-0.0521

The El Toro identification was considered unsuccessful, particularly using the one-shot algorithm. The different tests lead to different sets of parameters being estimated. Even for a particular test, parameters vary if obtained with the one-shot or the recursive algorithm. The indicated model is the best one obtained with the recursive algorithm. Figures 14 shows a limited matching between the response of that model for test 1 as compared to the actual system response. Matchings are worse for other tests.

## DISCUSSION AND CONCLUSIONS

An application of time domain linear identification methods to the modeling of AVRs of electrical generators is reported, using IEEE standard linear models to reproduce system responses. The time domain one-shot least square method and the recursive least square method allowed to identify models of an electronic AVR of a Chilean power plant. Models provided by the manufacturer, that did not represent system behavior, have been questioned based on the reported work.

Nevertheless, the methods experienced problems when used for an electromechanic AVR of another older power plant. The authors originally blamed the problems to the size and duration of perturbations leading to a non linear behavior of the regulator and to the discontinuous response of the mechanical link in that particular AVR. However, preliminary studies indicate that the identification algorithms may be improved. The authors are therefore making further studies to extend the reported work and also test alternative methods. Subjects being considered are:
-preprocessing of measurements to filter steady state values and avoid using coefficient c in Eq. (4)
-identification using non linear optimization algorithms
-recursive identification over long measurement periods without artificial perturbations

The application of the final methods to other plants in the Chilean power system is also being considered.

## ACKNOWLEDGMENTS

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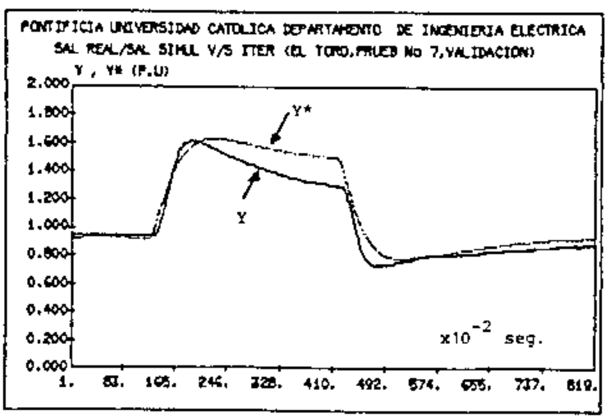


Fig. 14. Real response (Y, test 1) versus response of specified model (Y*) for El Toro

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