Engineering Journal of Qatar University, Vol. 1, 1988.

"COMPARISON OF RECURSIVE PARAMETER IDENTIFICATION TECHNIQUES FOR COMPUTER CONTROL OF POWER SYSTEMS"

By

M.A. Sheirah and **M.A.H. El-Sayed**
Electrical Engineering Department,
Faculty of Engineering,
Qatar University, Doha,
Qatar, Arabian Gulf.

ABSTRACT

This paper outlines the main features of parameter identification in electric power systems. A series of recursive parameter identification techniques is presented, this containing the generalized — and extended least square techniques, the recursive maximum likelihood technique, the stochastic approximation method, and the gradient technique.

These identification techniques are tested using a model of the interconnected power system of two areas to illustrate the applicability of discrete parameter identification for on-line computer control of power systems. The area control errors are considered as the controlled variables (system outputs). The changes in the governor gate position are the manipulated variables, and the variations in load are the disturbances.

To evaluate the performance of the identification technique the integral of the error-squares criteria is used. This error is defined as the difference between the actual system output and the identified model output. A real time package to simulate the system and model of the identification techniques is designed and the performance of the system is recorded. PBRS is used as standard test signal during this study.

1. INTRODUCTION

Identification techniques are used to estimate the parameters of a mathematical model for a dynamical system from measured input-output data. These techniques for parameter identification are now a standard tool in power system engineering. The availability of models in real time is required, as the different power system processes develop. Typical examples of such applications are load frequency control, voltage regulation, boiler control, ... etc. The parameters of the mathematical models can be estimated in real time by recursive identification algorithms. Recursive means that, at any instant t, the algorithm generates a new set of model parameters using the available measured data. This new set is a trial to track the operating conditions of the physical process.

The choice of the best identification technique and its characteristics depends, very strongly, on the system itself. The study of identification techniques and their performance, when applied to solve power system operating and control problems, is the first step in the design of that system. The second step is to use the mathematical models obtained to help the decision makers. The need for such a two-step approach can be seen by comparing the large number of papers with theoretically promising techniques with the small number of actual applications.

In order to choose a suitable identification technique for a given system, it is required to have an exact model system with all its nonlinearities at different operating conditions, together with the implementation of a set of identification techniques. In addition, a performance index of the identifier must be chosen. Comparing the performance indices of the identifiers under same standard conditions allows the judgement of the most convenient technique. The variance of the error between the actual system output and the calculated output based on the identified model is herein used as criterion for comparison.

The literature on recursive identification methods is extensive (1-4). It can even be said that the wealth of different methods makes the intended user confused as to which of them to choose. The purpose of the present paper is not to suggest new methods, even though the class of method to be studied contains algorithms that have not previously been discussed. One aim of the paper is, however, to define a class of algorithms that have the same convergence properties as their off-line counterparts. These off-line methods have been called "prediction error methods" (5, 6). This category contains several commonly used methods such as the least squares, maximum likelihood, stochastic approximation, and gradient techniques.

A general discussion of system identification techniques is first put forward. This is followed by an example of real application of system identification, which application deals with the problem of load frequency control of interconnected power systems. This example has been chosen to display the applicability of system identification concepts to electric power system problems.

2. SYSTEM IDENTIFICATION CONCEPTS

The term "system identification" applies to techniques for determining a mathematical model for a power system's response characteristics by use of observations on its behaviour. This mathematical model for a power system has three aspects:

(i) Hypothesized mathematical structure of system equations,
(ii) Estimation of parameters,
(iii) Verification of identified model.

The basic system identification logic to be discussed is the iterative three-step procedure indicated in Figure (1). Hypothesizing the mathematical structure is the most critical step in system identification. The form of this structure depends mainly on the particular problem being considered. One important criterion of a hypothesized structure is that the vector $\underline{\theta}$ of the unknown parameters can be estimated directly from available observation data. Physical insight is often the best way to insure the identifiability of the model.

Once the mathematical structure has been hypothesized, the next step is to use the observations to obtain an estimate for the value of unknown parameters. In this paper, different identification techniques are implemented, these are listed below (5, 6, 7). For more information, reference may be made to Appendix.

(i) Generalized least square technique (GLS),
(ii) Extended least square technique (ELS),
(iii) Recursive maximum likelihood technique (RML),
(iv) Stochastic approximation technique (SA),
(v) Gradient technique (GT).

Testing the validity of the identified model is almost as important as the actual estimation. Performance evaluation is used to judge the validity of the model. The performance index (PI) is defined as the variance of error between actual output and calculated output using identified parameters.

$$PI = (1/t) \sum_{i=0}^{t} (\hat{y}_i - y_i)^2 \tag{1}$$

in which:

- t : time index
- $\hat{y}_i$: model output at instant i
- y_i : actual system output at instant i

A fundamental limitation of the system identification concept is the fact that sufficient time must pass before enough observations are available to perform the identification. If the system undergoes a major step change at time t_0, the detection logic will be affected by such changes and indicate that the previously identified model is no longer valid. Then a finite time dt must pass before a successful identification of new system is possible. The length of this (dt) can be reduced by adding more measuring devices.

3. PROBLEM FORMULATION

Figure (2) shows a general block diagram representing a system with input u(k) and output y(k). The identifier is to estimate values for model parameters recursively using real input-output data. The system may be represented by a linear discrete model as follows:

$$\begin{aligned} y(k) = & -a_1 y(k-1) - a_2 y(k-2) \;\ldots\ldots\; -a_p y(k-p) \\ & +b_1 u(k-1) + b_2 u(k-2) \;\ldots\ldots\; +b_r u(k-r) \\ & +c_1 e(k-1) + c_2 e(k-2) \;\ldots\ldots\; +c_s e(k-s), \end{aligned} \tag{2}$$

in which the noise e(k) are a sequence of white random variable with zero mean. The parameters a_i, b_i, c_i may or may not vary with k(time). Thus time-varying systems may be modelled by the above equation with time-varying parameters. In this case, for specified values of the parameters an approximate model can represent the system around certain operating conditions. Estimated values of parameters may be varied to track the change in operating conditions.

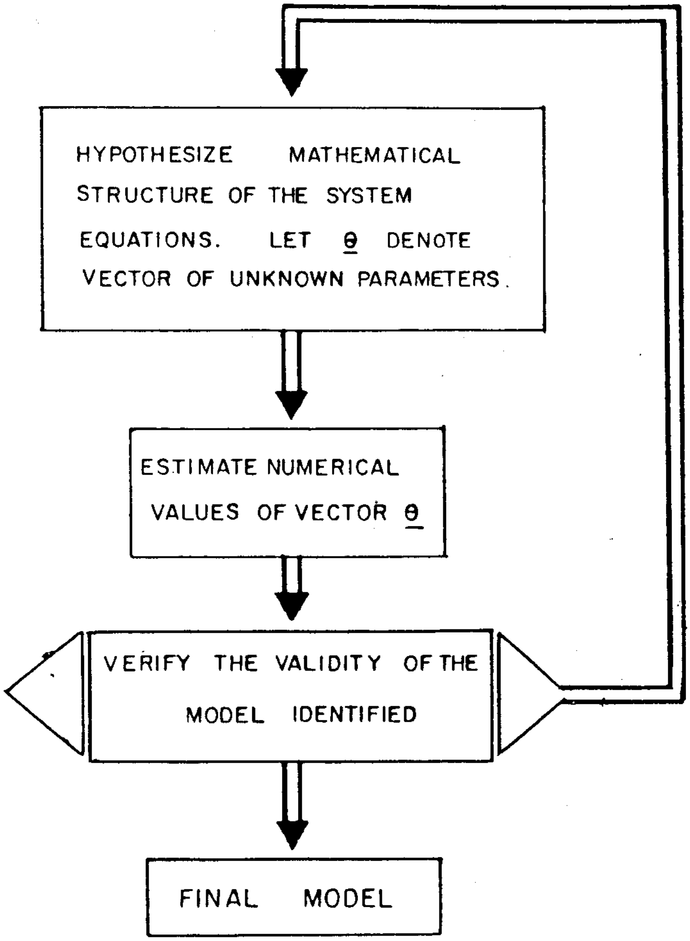

Fig. 1: Basic System Identification Logic.

4. LOAD FREQUENCY CONTROL

In this section, modelling and identification of interconnected power systems are illustrated (8). A model of two areas is simulated and the dynamics of such system are investigated. The study of such a system arises from the fact that the loads on each power area are subjected to random changes (8,9). Adaptive controllers may be so designed as to use different identification techniques. Comparison of such techniques as applied to that system is herein presented.

The objective of load frequency control is to exert control of frequency and simultaneously of power exchange via tie-lines. The frequency error (df), and the increments in the real tie-line power (dp_{tie}), are measured. The weighted sum of df and dp_{tie} is fed back to the controller as an area control error (ACE). The controller manipulates the steam valve opening of the turbine to change the generated power. A block diagram of this two area power system is shown in Figure (3). The average load change in area one was selected to be 0.3 pu; superimposed random load variations may be added. The load in the other area was left unchanged so as to see the effect of one disturbed area on both.

4.1 Response of Interconnected System:

Responses of dp_{tie}, df_1 and df_2 to a step change in dp_{dl} are exhibited in Figure (4). Responses are plotted under open loop condition in which no change in steam valve opening occurs, i.e.

$$P_{cl} = P_{c2} = 0 \tag{3}$$

Results indicate the expected response that the load change dp_1 affects df_1 more than df_2. Changes in df_2 are due to variation in tie-line power dp_{tie}. Should dp_{dl} contain random load variations, the new response would be as that indicated in Figure (5).

On testing the integral control loop, the disturbance was found to be the same as that shown in Figure (5). Figure (6) displays the response of dp_{dl}, dp_{tie}, df_1, df_2, dp_{cl} and dp_{c2} for the closed loop system under integral control. It can be seen that dp_{cl} is almost the filtered signal of dp_{dl}.

4.2 Results of Comparative Study:

The following tests were implemented to compare the identification techniques. The first group of tests includes the development of best model structure and best sampling period. In the second group, each technique is tested to show the effect of identification parameters on system performance. The third group of results comprises the development of a discrete model of the complete system. In order to obtain the best model, a PRBS (pseudo random binary sequence) is connected to

dp_{cl}, Figure (7). The identifier and the performance evaluator were also used. In such case

$$dp_{dl} = dp_{d2} = 0 \tag{4}$$

To test the model order, the sampling period was fixed at 0.1 s (9). The model order was varied from one to seven and the corresponding performance indices (PI) were plotted, Figure (8) (GLS being used). From test results, it can be concluded that a third order model is appropriate since higher order models indicate insignificant reduction in the PI. To choose the best sampling period the GLS technique was used with third order model. Different values for sampling period were selected. It is clear that the total time cannot be used as a base of comparison. Thus, 200 samples in each case were considered, and the total time of simulation had to be changed in correspondence with the change of sampling period. Relevant results are plotted in Figure (9) for sampling periods of 0.05, 0.1, 0.2, 0.3 s. A sampling period of 0.1 s shows good results.

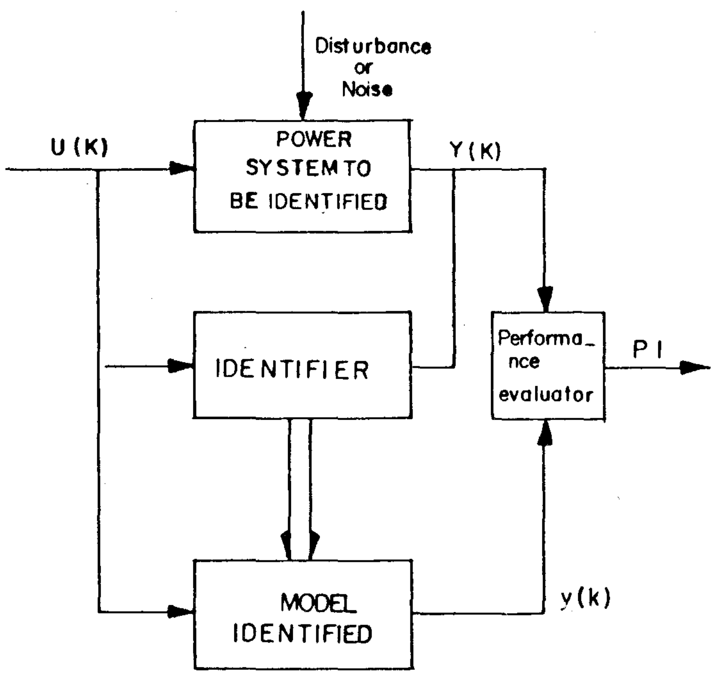

Fig. 2: Identification Scheme.

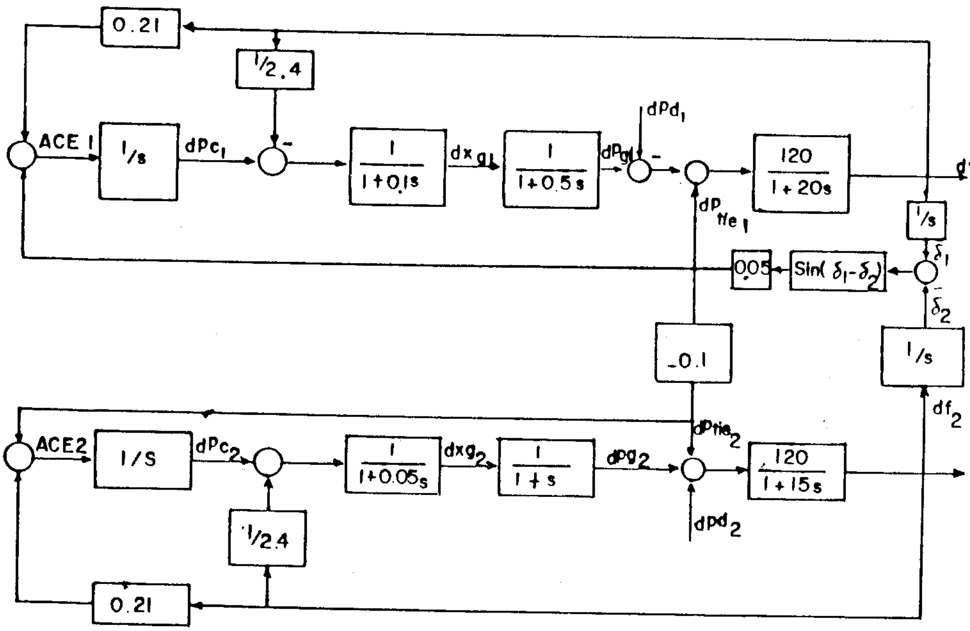

Fig. 3: Block Diagram of Power Frequency Control of a Two Area System.

In the third group of analyses, the effect of the forgetting factor on each technique is studied. The equal weights case is used as basis for comparison. A third order model with 0.1 s sampling period is selected in all cases. Figure (10) displays the PI against time for GLS. The ELS was also tested, relevant results are plotted in Figure (11). The above results indicate that the ELS leads to generally, greater improvement in the PI than the GLS. Repeating the test for RML gave similar results, same conclusions being drawn, Figure (12). Using the SA and GT as base of weighting factor brought in no significant effect, Figures (13) & (14). The GLS technique with equal weights was used to generate a discrete mode for this multi input-multi output system, Figure (15).

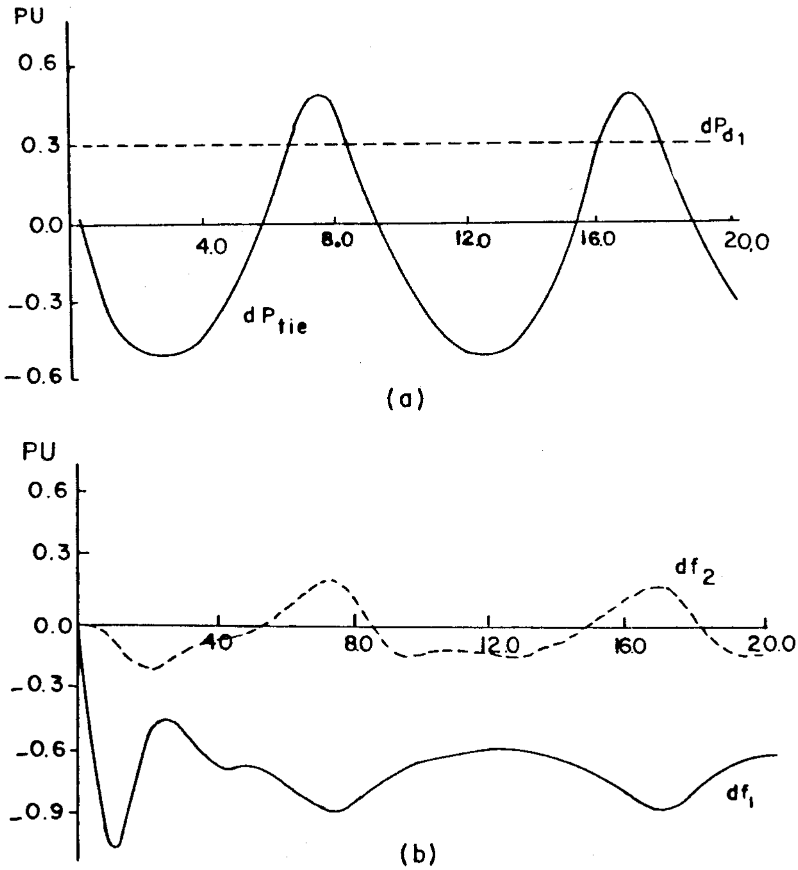

Fig. 4: Response of the Power System to a Step Change in dpd1.

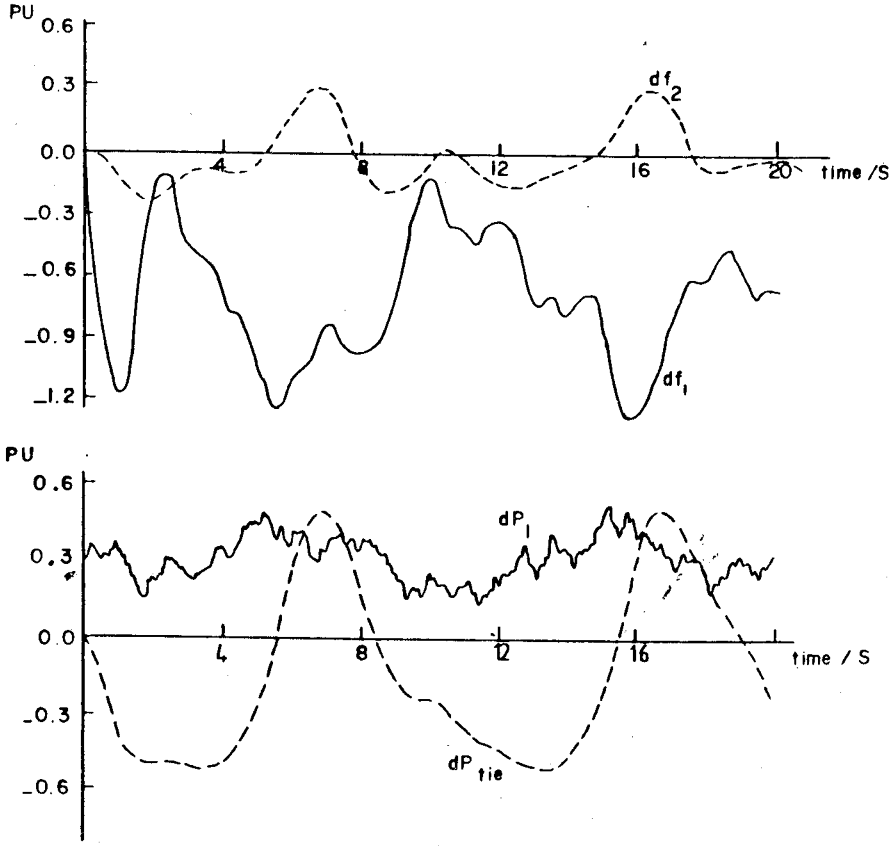

Fig. 5: Response of the Power System to Biased Disturbances.

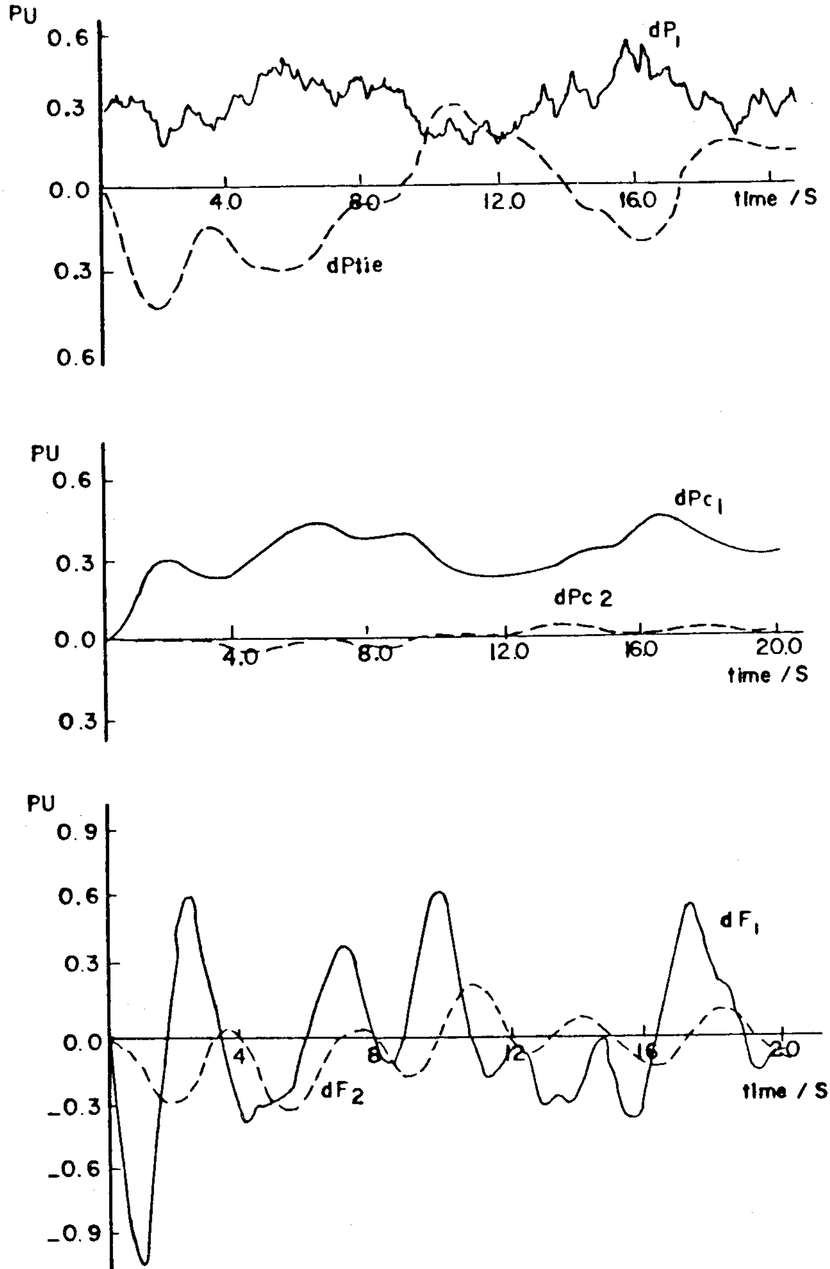

Fig. 6: Response of the Power System Under Integral Control to Biased Disturbance.

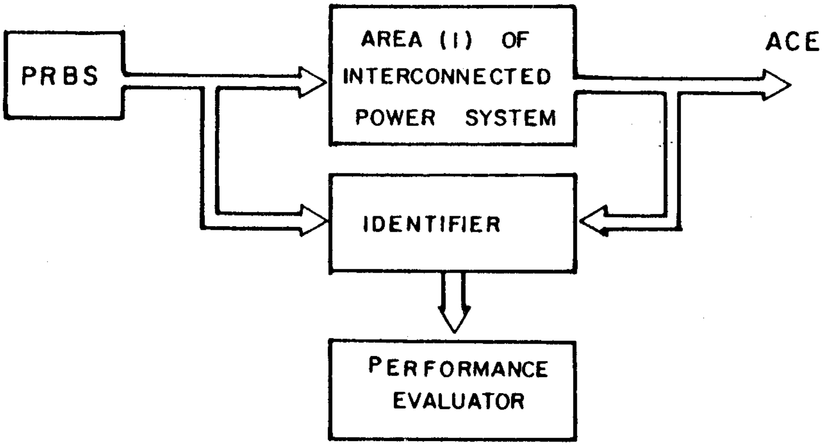

Fig. 7: Schematic Diagram of the Model used for the Comparison Study of the Identification Techniques.

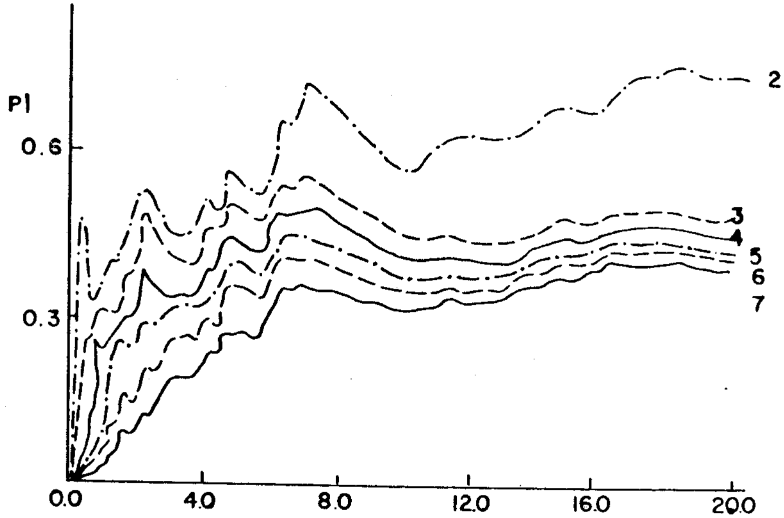

Fig. 8: Effect of the Model Order on the PI of the Identifier for (GLS).

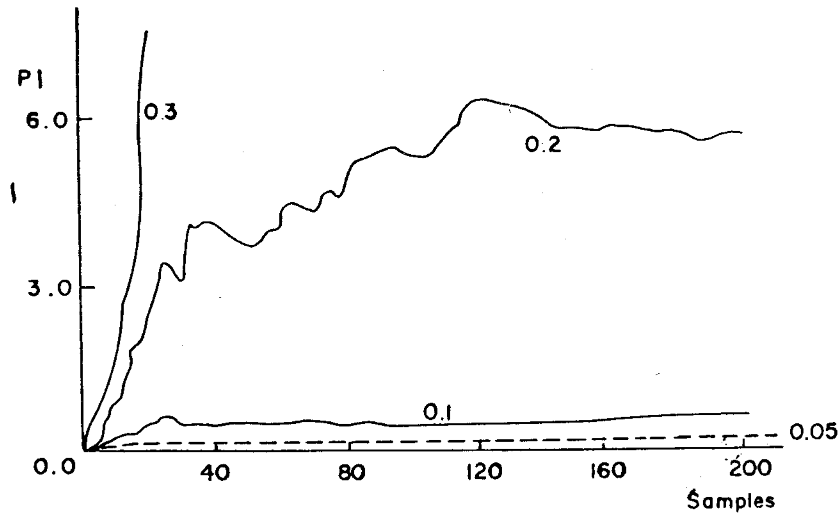

Fig. 9: Performance of the GLS for Different Values of Sampling Periods.

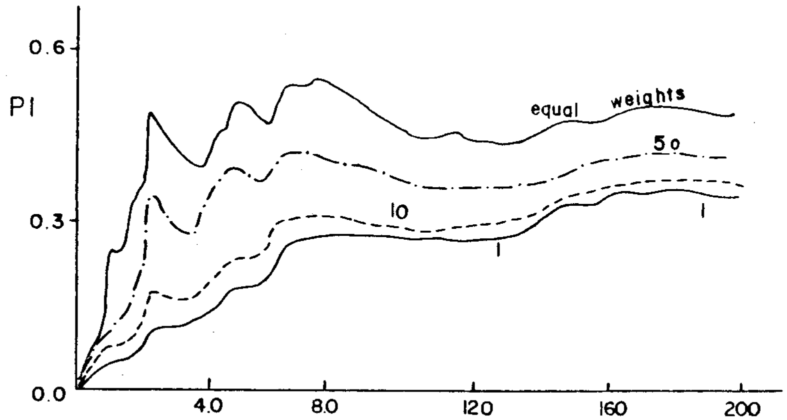

Fig. 10: Effect of the Forgetting Factor of the GLS on the P1 of the Identifier.

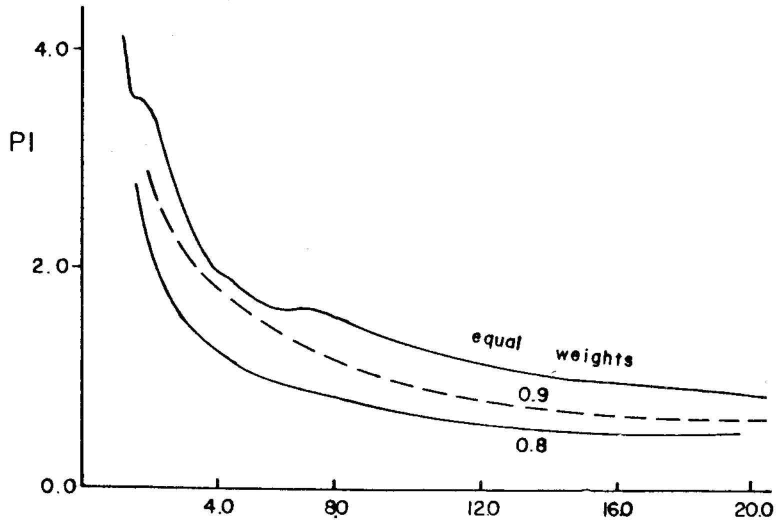

Fig. 11: Effect of the Forgetting Factor on the PI of the Identifier.

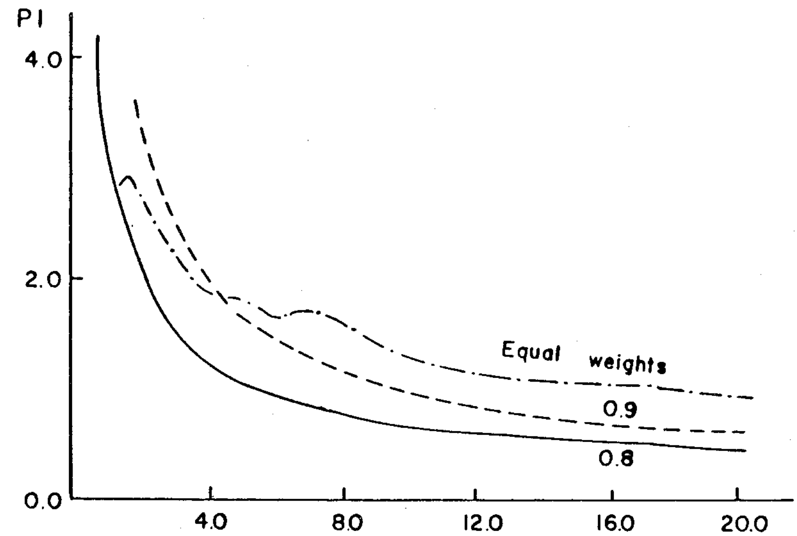

Fig. 12: Effect of the Forgetting Factor of RML on the P1 of the Identifier.

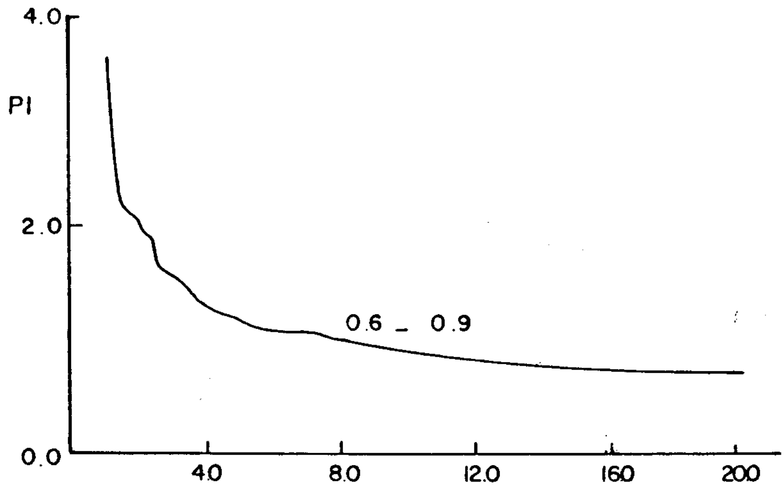

Fig. 13: Effect of the Forgetting Factor of SA on the P1 of the Identifier.

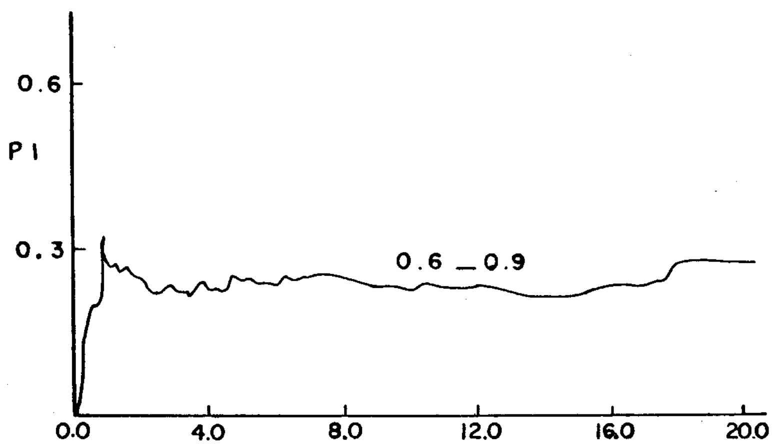

Fig. 14: Effect of the Forgetting Factor of the GT on the PI of the Identifier.

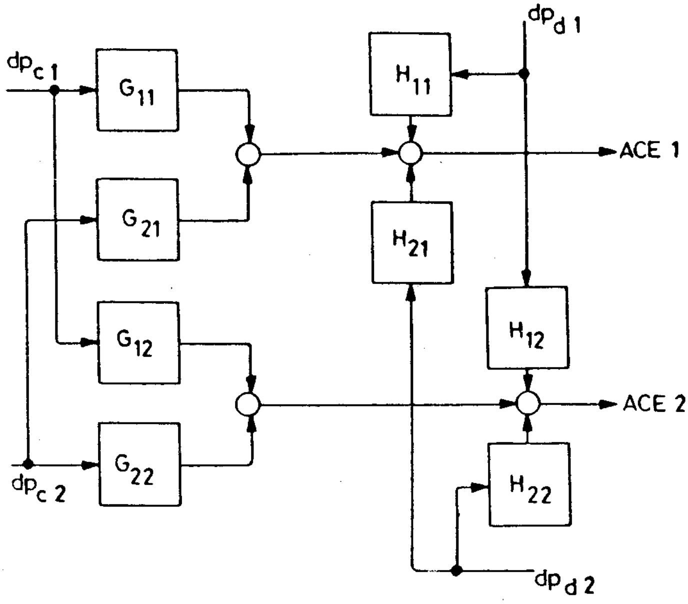

Fig. 15: Discrete Model of the Power System.

where

$$G_{11}=[10^{-3}(2.4z^{-1}+12z^{-2}+7.9z^{-3})]/[1-1.35z^{-1}-0.06z^{-2}]$$

$$G_{21}=[10^{-5}(-0.36z^{-1}-61z^{-2}+66z^{-3})]/[1-1.16z^{-1}-0.26z^{-2}+0.43z^{-3}]$$

$$G_{12}=[10^{-3}(-75z^{-1}-12z^{-2}+68z^{-3})]/[1-0.26z^{-1}-0.28z^{-2}+0.35z^{-3}]$$

$$G_{22}=[10^{-3}(8.8z^{-1}+11z^{-2}+3.9z^{-3})]/[1-1.33z^{-1}-0.15z^{-2}+0.5z^{-3}]$$

$$H_{11}=[10^{-3}(49z^{-1}-40z^{-2}+24z^{-3})]/[1\;\;1.3z^{-1}-0.2z^{-2}+0.5z^{-3}]$$

$$H_{21}=[10^{-3}(86z^{-1}+91z^{-2}-15z^{-3})]/[1\;\;1\,3z^{-1}+0\,2z^{-2}+0\,5z^{-3}]$$

$$H_{12}=[0.15z^{-1}+0.07z^{-2}+0.05z^{-3}]/[1-1.4z^{-1}+0.07z^{-2}+0.11z^{-3}]$$

$$H_{22}=[10^{-3}(49z^{-1}-39z^{-2}+24z^{-3})]/[1-1.32z^{-1}-0.2z^{-2}+0.5z^{-3}]$$

5. CONCLUSION

In this paper a general class of recursive parameter identification techniques is considered and tested. The class of methods considered contains five well-known techniques, the construction of which is fairly straightforward and easily implemented with the use of microprocessors.

Test results are shown to establish the application of identification techniques for load frequency control of interconnected power systems. The control area is represented by a third order discrete model with time varying parameters. Model parameters are identified every sampling period, thus verifying the ability of the model to track the operating conditions dynamically.

A comparative study of different techniques is herein presented and a predefined performance index is evaluated to measure the soundness of used technique.

REFERENCES

1. **Åstrom, K.** and **Eykhoff, P.:** "System Identification — A Survey", Automatica, 7, 123-162, 1971.
2. **Åstrom, K., Borisson, U., Ljung, L.** and **Wittenmark, B.:** "Theory and Application of Self-Tuning Regulators", Automatica, 13, 457-476, 1977.
3. **Blum, J.:** "Multi-Dimensional Stochastic Approximation Methods", Ann. Math. Stat. 25, 737-744, 1954.
4. **More, J.** and **Weiss, H.:** "Recursive Prediction Error Methods for Adaptive Estimation", IEEE Trans., SMC-9, 197-204, 1979.
5. **Soderstrom, T., Jung, L.** and **Custavsson, I.:** "A Theoretical Analysis of Recursive Identification Methods", Automatica, 14, 231-244, 1978.
6. **Gerther, J.** and **Banyaz, C.:** "A Recursive On-line Maximum Likelihood Identification Method", IEEE Trans., AC-19, 816-820, 1974.
7. **Young, P.:** "The Use of Linear Regression and Related Procedures for Identification of Dynamic Processes", Proc. 7th IEEE Symposium on Adaptive Processes, UCLA.
8. **Sheirah, M.** and **Hamza, M.:** "Self Tuning Regulators for Load Frequency Control of Interconnected Power Systems", Paper No. A 78 043-2, PES/IEEE Winter Meeting, N.Y., Jan. 29-Feb. 3, 1978.
9. **Farag, H.:** "Computer Package for System Modelling and Identification", M.Sc. Thesis, Ain Shams University, Egypt, 1982.

APPENDIX

(i) Generalized least square technique (GLS):

The system to be identified is assumed to have the general form:

$$y(t)=-A(q^{-1})y(t-1)+B(q^{-1})u(t-k-1)+C(q^{-1})e(t) \quad (A.1)$$

where

u(t) and y(t) are the input and output of the system

e(t) is the disturbance, which is a sequence of independent random variable

A, B, and C are polynominals in q^{-1}.

k is the pure time delay assumed in the model

$$A(q^{-1})=a_0+a_1q^{-1}+a_2q^{-2} \quad (A.2)$$

$$B(q^{-1})=b_0+b_1q^{-1}+b_2q^{-2} \quad (A.3)$$

$$C(q^{-1})=c_o+c_1q^{-1}+c_2q^{-2} \quad (A.4)$$

where q^{-1} is the shift operator which is defined as

$$q^{-1}y(t) = y(t-1), \text{ t is time index} \quad (A.5)$$

For GLS technique the identified model is given by

$$y(t) = -A(q^{-1})y(t-1) + B(q^{-1})u(t-k-1) \quad (A.6)$$

This model may be written in the form

$$y(t) = \underline{\bar{H}}(t).\underline{\theta} \quad (A.7)$$

where

y(t) is the model output,

$$\underline{\theta}(t) = (a_1, a_2 \ldots.; b_1, b_2 \ldots.,) \quad (A.8)$$

$$\underline{H}(t) = (-y(t-1), y(t-2) \ldots.; u(t-k-1), u(t-k-2) \ldots.) \quad (A.9)$$

Measurements are obtained every sampling period and used to estimate $\underline{\theta}$ at instant t. The GLS technique minimizes the sum of error squares (J) given by

$$J = \Sigma\, w(i) . (\hat{y}(i) - y(i))^2 \quad (A.10)$$

where

y(i) is the actual system output

w(i) is the weighting factor

The sequencial algorithm of the estimator may be defined by the following set of equations:

$$\hat{\underline{\theta}}(t) = \hat{\underline{\theta}}(t-1) + \underline{K}(t)(y(t)-\underline{H}'(t)\hat{\underline{\theta}}(t-1)) \quad (A.11)$$

$$\underline{K}(t) = \underline{P}(t-1)\underline{H}(t)(\underline{H}'(t)\underline{P}(t-1)\underline{H}(t)+1/w(t))^{-1} \quad (A.12)$$

$$\underline{P}(t) = (I - \underline{K}(t)\underline{H}'(t))\underline{P}(t-1) \quad (A.13)$$

w(t) can be adjusted by the user to any of the following options:

$$w(t) = \begin{cases} 1 \\ t \\ t/a & , a > 1 \end{cases} \tag{A.14}$$

$\underline{P}(t)$ is the covariance matrix of the estimation error, and K(t) is the correctio vector. Their initial values are assumed to be

$$\underline{P}(0) = 10^5.(1)\text{, and } \hat{\underline{\theta}}(0) = 10^{-4}.(1, 1, \ldots\ldots) \tag{A.15}$$

The forgetting factor (a) may be chosen under user requirements.

(ii) The extended least squares (ELS)

The estimator assumes an extended prediction model of the form

$$\hat{y}(t) = \underline{H}'(t) . \hat{\underline{\theta}}(t) \tag{A.16}$$

in which:

$$\underline{H}'(t)=(y(t-1)\ldots\ldots; u(t-k-1)\ldots\ldots; e(t-1)\ldots\ldots)' \tag{A.17}$$

In such case the number of estimated parameters is increased. These parameters can be obtained recursively as such:

$$\hat{\underline{\theta}}(t) = \hat{\underline{\theta}}(t-1)+\mu(t)\underline{K}(t)e(t) \tag{A.18}$$

$$\underline{K}(t)=\underline{P}(t)\underline{H}(t)/(1+\mu(t)\{\underline{H}'(t)\underline{P}(t)\underline{H}(t)-1\})' \tag{A.19}$$

$$\underline{P}(t)=(1/\{1-\mu(t)\})\ p(t-1)-\{\underline{P}(t-1)\underline{H}(t)\underline{H}'(t)\underline{P}(t-1)\}/ \{1/\mu(t)-1+\underline{H}'(t)\underline{P}(t-1)\underline{H}(t)\}) \tag{A.20}$$

$$e(t)=\hat{y}(t) - y(t) \tag{A.21}$$

$$\mu(t) = \begin{cases} 1/t & \text{for equal weights} \\ a, 0 < a < 1 & \text{for exponential weights} \end{cases} \tag{A.22}$$

Same initial conditions are used as in GLS.

(iii) Recursive maximum likelihood technique (RML):

In the RML technique the data vector $\underline{H}(t)$ is introduced to a filter before being used by the identifier. The output of the filter is denoted by $\underline{\psi}(t)$. The filter is defined as

$$\underline{\psi}(t) = \left[(1 + q^{-1}C_{t-1}(q^{-1})\right]^{-1}.\underline{H}(t) \tag{A.23}$$

in which $\underline{\psi}$ represents the sensitivity derivative of the prediction error w.r.t. the parameters. The estimator equations are the same as equations (A.12 - A.16) except that $\underline{H}(t)$ is replaced by $\underline{\psi}(t)$.

(iv) The stochastic approximation technique (SA):

SA technique may be considered as recursive estimation method updated by appropriately weighted arbitrary chosen error correction term. The identified model may take the same form as (A.11). The identification algorithm can be defined by:

$$\hat{\underline{\theta}}(t)=\hat{\underline{\theta}}(t-1)+\underline{P}(t)\underline{H}(t)\left[y(t)-\underline{H}'(t)\hat{\underline{\theta}}(t-1)\right] \quad \text{(A.24)}$$

in which:

$$\underline{P}(t) = \begin{cases} (I)\,T(t)\ , \ T(t) = a / t^{\alpha}\ , \ a > 0,\ 0.5 < \alpha < 1 \\ \underline{P}(t-1)-\underline{P}(t-1)\underline{H}(t)\left[1+\underline{H}'(t)\underline{P}(t-1)\underline{H}(t)\right]^{-1}\underline{H}'(t)\underline{P}(t-1) \end{cases} \quad \text{(A.25)}$$

starting values being assumed equal to:

$$\underline{P}(0) = 10^5\,(I)\ ,\ \text{and}\ \hat{\underline{\theta}}(0) = 0 \quad \text{(A.26)}$$

(v) The gradient technique:

The system to be identified is assumed to have the form of equation (A.1). The technique is based on minimizing some measures of error, which is defined by:

$$J(t) = (1/2).e(t)^2 \quad \text{(A.27)}$$

The identification algorithm takes the following form:

$$\underline{\theta}(t)=\underline{\theta}(t-1)+R(t-1)\underline{H}'(t-1)e(t-1) \quad \text{(A.28)}$$

in which

$$R(t)=\text{diag}\left[X_1(t),X_2(t),\ldots\ldots X_p(t)\right]/F(t) \quad \text{(A.29)}$$

$$F(t) = \sum X_i(t)H_i(t) \quad \text{(A.30)}$$

$$X_i(t)= M^{it}\ ,\ M < 1 \text{ or } X_i(t) = 1 \quad \text{(A.31)}$$