Proceedings of the Sixth IASTED International Conference
EUROPEAN POWER AND ENERGY SYSTEMS
June 26–28, 2006, Rhodes, Greece

PATTERN SEARCH OPTIMIZATION FOR ESTIMATING SYNCHRONIZING AND DAMPING TORQUE COEFFICIENTS

J.S. Al-Sumait
College of Technological Studies
Electrical Engineering Department
jalsumait@yahoo.com

A.K. Al-Othman
College of Technological Studies
Electrical Engineering Department
alothman@paaet.edu.kw

W.S. Borisly
Telecommunication Institute
Electrical and Electronic Department
whutr@hotmail.com

Public Authority for Applied Education and Training (PAAET), KUWAIT

ABSTRACT
This paper presents an efficient digital methodology for estimating synchronizing and damping torque coefficients of a synchronous machine. These coefficients are used as a measurement of power system stability. The proposed algorithm is based on Pattern search (PS). technique that uses digital samples of the machine time responses to perform the estimation process. The problem is formulated as a dynamic estimation problem. The goal is to minimize the error square of the estimated coefficients. The method is tested using simulated case study. Results are reported and compared with those obtained using genetic algorithms (GA) and particle swarm optimization estimation technique. The comparison shows that the proposed method can successfully estimate the required coefficients even in very critical stable cases where other methods may fail. It is also shown that the presence of bad data has no effect on the estimated results. The method can be considered as a very reliable and accurate tool for estimating the damping and synchronizing torque coefficient for power system stability assessment.

KEY WORDS
Pattern search (PS), Estimation, particle swarm optimization (PSO), Stability, Damping & Synchronizing Coefficient.

1. Introduction

This dynamic stability study is concerned with the performance of power system under small perturbations. It is very essential in power system planning, operation and control to study the behavior of power system when subjected to these disturbances. The main objective of these kinds of studies is to analyze the Electro-mechanical oscillations resulting from poorly damped rotor oscillations to evaluate the dynamic system stability. Due to the dynamic nature of power system, the operating conditions of the system change with time. Therefore, it is necessary to track the system stability on-line. This is done by estimating certain stability indices on basis of the given data and updates these indices as new data are received. Synchronizing and damping torque coefficients (K_s and K_d) are used as stability measurement indices. In terms of these coefficients, both of them must be positive for stable operation of the machine[1, 2].

Several methods have been proposed to estimate the synchronizing and damping torque coefficients. Some of these methods are based on linearizing the system equations and solving them in the frequency domain [3, 4]. Reference [3] decomposes the change in electromagnetic torque into two orthogonal components in the frequency domain. The two equations are expressed in terms of the load angle deviation then solved directly. Static and dynamic time domain estimation methods were also proposed. Least square error technique is one of the most popular static estimation techniques used for optimal parameter estimation [5]. Some limitations and disadvantages are associated with application of static estimation techniques. For example, when dealing with non-stationary waveforms, as in our case, estimates should be up-dated always. Kalman filtering algorithm is an example of dynamic state estimation techniques used to overcome some of static method disadvantages. The filter can be used to perform the estimation process on-line [6]. Reference [7] introduced a fast and efficient stochastic dynamic algorithm for on-line estimation of synchronizing and damping torque coefficients. The algorithm is based on using a discrete time-dynamic filter. Reference [8] presented a comparison between least square, Kalman filter and genetic algorithms techniques as used for performance evaluation of power system dynamic stability.

Recently, a global unconstrained optimization method, developed by the researches in the optimization community, had received a tremendous attention. The method is called Pattern search. In reference [9], the author introduced an abstract definition of pattern search methods for solving nonlinear unconstrained optimization problem. The author exploits her characterization of pattern search methods to establish a global convergence theory that does not enforce a notion of sufficient decrease. Moreover, the authors of [10] presented a convergence theory for pattern search methods for solving bound constrained nonlinear program. The authors proved global convergence despite the fact that pattern search methods do not have explicit information concerning the gradient and its projection onto the feasible region. Finally, a historic discussion of direct search methods for unconstrained optimization is presented in reference [11]. The authors gave a modern prospective on the classical family of derivative-free algorithms, focusing on the development of direct search methods during their golden age from 1960 to 1971.

This paper proposes a robust and efficient digital technique for estimation of synchronizing and damping torque coefficients. The method is used to estimate synchronizing and damping torque coefficients (K_s and K_d) from the machine time responses of the change in rotor angle $\Delta\delta(t)$, the change in rotor speed $\Delta\omega(t)$ and the change in electromagnetic torque $\Delta T_e(t)$. The problem is formulated as a dynamic estimation problem. The goal is to minimize the error square in the estimated coefficients. The proposed PS technique is used to find the optimum solution of the formulated problem. To investigate the potentials of the proposed method, many simulated test cases of the adopted system are considered. Eigenvalues analysis has been carried out to assess the effectiveness of the proposed method. In addition, the performance of POS is compared with other estimation methods such as (GA) and particle swarm optimization.

2. Proposed Problem Formulation

In this study a single machine connected to infinite bus system is considered [12]. The system comprises a steam-generator connected via a tie line to a large system represented as infinite bus. System data is given in the appendix. The synchronous generator is represented by Park's equations with the third order linear model. The dynamic stability study is performed by linearizing the power system under consideration around an operating point to represent the system in state space model. The machine differential equations, the exciter equation and the block diagram can be found in reference [12].

The Electro-magnetic torque variations may be broken down into two components: the synchronizing torque component is in phase and proportional with $\Delta\delta(t)$, and the damping torque is in phase and proportional with $\Delta\omega(t)$. Then we can write mathematical form:

$$Te(t) = \Delta\delta(t)\, K_s + \Delta\omega(t) K_d \tag{1}$$

Using A/D converter and choosing an adequate sampling frequency, $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$ are sampled and a set of n equations in the form of equation 1 is obtained. In matrix form equation (1) will be

$$\begin{bmatrix} \Delta T_e(t_1) \\ \Delta T_e(t_2) \\ \\ \Delta T_e(t_n) \end{bmatrix} = \begin{bmatrix} \Delta\delta(t_1) & \Delta\omega(t_1) \\ \Delta\delta(t_2) & \Delta\omega(t_2) \\ \\ \Delta\delta(t_n) & \Delta\omega(t_n) \end{bmatrix} \begin{bmatrix} \mathrm{K_s} \\ K_d \end{bmatrix} \tag{2}$$

In a compact matrix form, equation (2) can be rewritten in discrete state space form at any time step k as:

$$Z(k) = H(k) X(k) + e(k) \tag{3}$$

where

$Z(k)$ is nx1 measurement vector ΔTe

$H(k)$ is nx2 connection matrix

$X(k)$ is 2x1 state vector to be estimated (K_s , K_d)

$e(k)$ is nx1 measurement error vector to be minimized.

It is clear that the described system of equations (3) is a highly over-determine system. The main objective now is to find the best estimate of the vector $X(k)$. The problem is an unconstrained optimization one. The PS approach presented in this work is employed to find the optimum values of the state vector $X(k)$ that minimize the error square vector $e(k)$, using the following objective function:

$$O.F = \sum_{i=1}^{n} e_i^2 \tag{4}$$

Where e_i is the particles individual error for every generation.

3. Pattern Search Optimization

The Pattern Search (PS) optimization routine is an evolutionary technique that is suitable to solve a variety of optimization problems that lie outside the scope of the standard optimization methods. Generally, PS has the advantage of being very simple in concept, and easy to implement and computationally efficient algorithm. Unlike other heuristic algorithms, such as GA [13, 14], PS possesses a flexible and well-balanced operator to enhance and adapt the global and fine tune local search. A historic discussion of direct search methods for unconstrained optimization is presented in reference [11]. The authors gave a modern prospective on the classical family of derivative-free algorithms, focusing on the development of direct search methods.

The Pattern Search (PS), algorithm proceeds by computing a sequence of points that may or may not approaches to the optimal point. The algorithm starts by establishing a set of points called mesh, around the given point. This current point could be the initial starting point supplied by the user or it could be computed from the previous step of the algorithm. The mesh is formed by adding the current point to a scalar multiple of a set of vectors called a pattern. If a point in the mesh is found to improve the objective function at the current point, the new point becomes the current point at the next iteration. This maybe better explained by the following:

First: The Pattern search begins at the initial point X_0 that is given as a starting point by the user. At the first iteration, with a scalar =1 called mesh size, the pattern vectors are constructed as $[0\ \ 1]$, $[1\ \ 0]$, $[-1\ \ 0]$ and $[0\ \ -1]$, they may be called direction vectors. Then the Pattern search algorithm adds the direction vectors to the initial point X_0 to compute the following mesh points:

$$X_0+[1\ \ 0]$$
$$X_0+[0\ \ 1]$$
$$X_0+[-1\ \ 0]$$
$$X_0+[0\ \ -1]$$

Figure 1 illustrates the formation of the mesh and pattern vectors. The algorithm computes the objective function at the mesh points in the order shown.

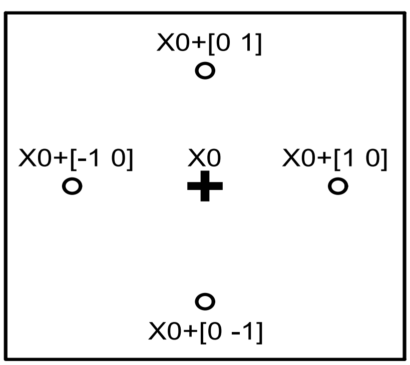

Fig. 1: PS Mesh points and the Pattern.

The algorithm polls the mesh points by computing their objective function values until it finds one whose value is smaller than the objective function value of X_0. If there is such point, then the poll is successful and the algorithm sets this point equal to X_1.

After a successful poll, the algorithm steps to iteration 2 and multiplies the current mesh size by 2, (this is called the expansion factor and has a default value of 2). The mesh at iteration 2 contains the following points: 2*[1 0] $+X_1$, 2*[0 1] $+X_1$, 2*[-1 0] + X_1 and 2*[0 -1] $+X_1$. The algorithm polls the mesh points until it finds one whose value is smaller the objective function value of x1. The first such point it finds is called X_2, and the poll is successful. Because the poll is successful, the algorithm multiplies the current mesh size by 2 to get a mesh size of 4 at the third iteration because the expansion factor =2.

Second: Now if iteration 3, (mesh size= 4), ends up being unsuccessful poll, i.e. none of the mesh points has a smaller objective function value than the value at X_2, so the poll is called an unsuccessful poll. In this case, the algorithm does not change the current point at the next iteration. That is, $X_3 = X_2$. At the next iteration, the algorithm multiplies the current mesh size by 0.5, a contraction factor, so that the mesh size at the next iteration is smaller. The algorithm then polls with a smaller mesh size.

The Pattern search algorithm will repeat the illustrated steps until it finds the optimal solution for the minimization of the objective function. The algorithm stops when any of the following conditions occurs:

- The mesh size is less than mesh tolerance.
- The number of iterations performed by the algorithm reaches the value of max iteration.
- The total number of objective function evaluations performed by the algorithm reaches the value of Max function evaluations.
- The distance between the point found at one successful poll and the point found at the next successful poll is less than X tolerance.
- The change in the objective function from one successful poll to the next successful poll is less than function tolerance.

All the stopping criteria of the Pattern search algorithm can be pre-defined subject to the problem at hand.

4. Results and Analysis

MATLAB® package is used to simulate the study system. The block diagram in [12], shown in the appendix, is built and the required $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$ samples are generate in Simulink. Different study cases, stable and unstable, are simulated under different kind of disturbances. Data window size is varied between 5 to 30 seconds. Number of samples also varied between 150 to 400 samples within the considered window. $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$ for case 1 are shown in fig. 2.

A set of MATLAB® files implementing PS algorithm are built in order to solve the estimation problem. The search is started after coding the objective functions for all 4 cases. Then we Loaded the generated samples, $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$, from Simulink into MATLAB® function. The "psearchtool" function in the Direct Search Toolbox in MATLAB® was implemented to solve the minimization of the objective function problem in hand. Fig. 3 shows the processing of the function "psearchtool" to generate the best value of the objective function and the mesh size in each iteration. It can be shown that after only five iterations the algorithm is directed to the optimal solution. Moreover, (PS) algorithm needed only 12 iterations to lock on the mesh size towards reaching the optimal minimum of the objective function. And the mesh size did not exceed 2, which means that the PS algorithm senses the direction of the optimal solution after only 2 iterations.

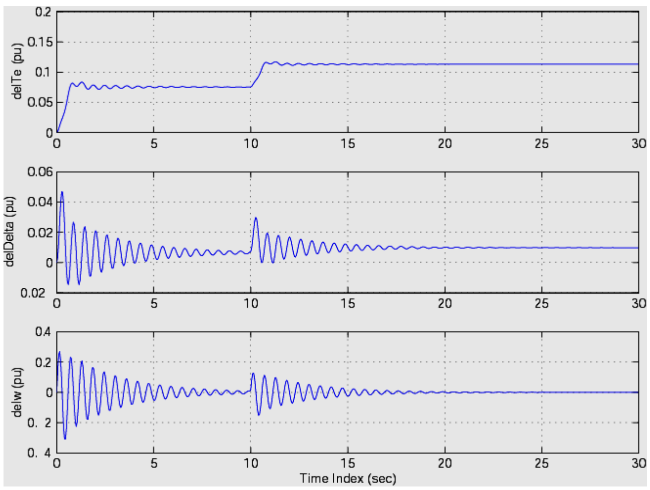

Fig. 2: $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$ with disturbance at 10 seconds.

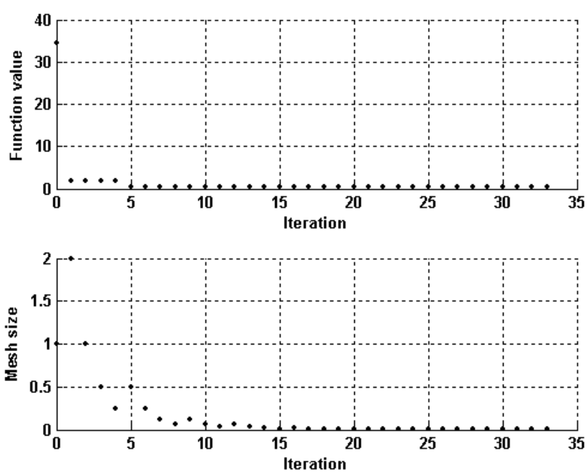

Fig. 3: Iterations of PS vs. Best objective function value and Mesh Size.

Table 1 shows results obtained for four different study cases. Different gains are used to simulate these cases [12]. In this table the estimated coefficients obtained using the proposed method, GA and the particle swarm optimization method (PSO), from references [15, 16], are shown below for comparison with PS. It is found that 400 samples, (within a data window size of 20 seconds after the disturbance), are sufficient to represent the behavior and to obtain the solution. Results obtained indicate that systems 1 and 3 are stable systems since both K_s and K_d are positive. As noted earlier that both K_s and K_d have to be positive as a condition for stability. The negative values of K_s and K_d obtained for systems 2, 4 and 5 indicate that these systems are unstable.

Table 1
Comparison of Estimated Parameters

Case#	Genetic algorithm		Particle Swarm		Pattern Search	
	K_s	K_d	K_s	K_d	K_s	K_d
1	10.2663	0.0016	10.3121	0.0050	10.2842	0.0039
2	-0.0561	-0.0235	-0.0462	-0.0298	-0.0508	-0.0234
3	0.3254	0.0022	0.3044	0.0024	0.3291	0.0010
4	-0.0455	-0.0221	-0.0428	-0.0219	-0.0430	-0.0215

To assess all the findings with regards to the issue of stability, the block diagram representing the dynamics of the system at hand (fourth degree) is linearized. Then the state space model, i.e. matrices A, B, C and D, of the model are obtained. The electromechanical-mode eigenvalues of the system for all cases are worked out in the table 2. In all cases, the three methods give accurate and close results. So PS introduces accuracy in all cases, and it is proved to be reliable in stable or unstable cases.

Table 2
Simulated Cases and its Corresponding Eigenvalues

Case #	Stability	Eigenvalues
1	Stable	$-0.3527 \pm j10.9458$ $-2.6099 \pm j3.21810$
2	Unstable	$0.3606 \pm j5.3995$ $-3.1194 \pm j4.6198$
3	Stable	$-0.0871 \pm j7.1144$ $-2.5884 \pm j8.5020$
4	Unstable	0.5011 ± 5.4120 -3.1028 ± 4.6017

Figure 4 illustrates the nature of PS in the number of computation of the value of the objective function to obtain the optimal solution of case 1. The upper figure shows the number of calculations for the mesh point in every iteration. And since we set the complete poll option to "off" in the Poll option pane, the algorithm will stop computing the values of the objective functions for the rest of the mesh points at the first objective function value of the mesh points, which is less than the objective function value of the current point. This will lead PS to compute less number of function count (123 counts), approximately 10% less of the total function count. In the lower graph, we set the algorithm to conduct a complete poll, which means computing the objective function value for all of the mesh points. This will assure the algorithm to find the global minimum, and the total count became 137. However, PS produced the same optimal solution in both cases.

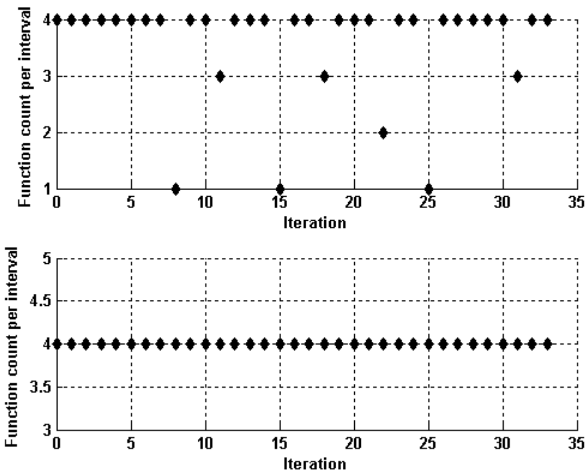

Fig. 4: PS function counts per interval in non complete poll and complete poll.

In addition to the accuracy the proposed algorithm offers another advantage when dealing with data contaminated with bad measurements (bad data). It is important to mention that all the estimated coefficients in table 1 are acquired from accurate error-free data sets. To simulate bad measurement at different time, zeros were introduced deliberately in the data obtained for $\Delta T_e(t)$, $\Delta\delta(t)$ and $\Delta\omega(t)$. The amount of bad data introduced is about 10 %. Cases 1 and 3 are used for comparison. The estimates for K_s and K_d using PS were never affected. The out come is almost identical for the results obtained in table 1 for both case 1 & 3. Mean while, it is obvious PS converged to almost identical coefficient for both case 1 and 3 to the ones in table and ultimately leads to proper decision concerning the stability of each case.

Figure 5 shows the values of the estimated variables K_s and K_d for each objective function count. It clear that the algorithm calculates a wide range of the unknown variables to assure that the solution that it returns is the optimal solution.

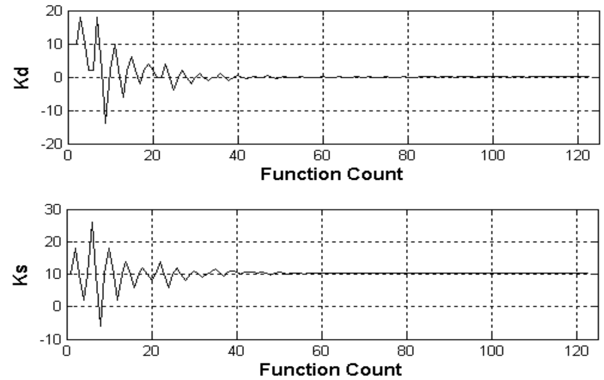

Fig. 5: PS assumptions for the unknown variables for every objective function calculation count.

5. Conclusion

This paper presents the application of Pattern search techniques for optimal estimation of the synchronizing and damping torque coefficients of a synchronous machine. The problem is formulated as an estimation problem. PS technique is used to find the optimum parameters based on minimization of the sum of the errors square in the process. The method is tested using different simulated cases. The performance of PS is compared with that of the GA and Particle Swarm Optimization. The method can be considered as a very reliable and efficient tool in the area of power system stability analysis.

Acknowledgements

The effort of Dr. H.K. Ebraheem is most appreciated in this paper, particularly, in proposing the usage of *Pattern Search* optimization and developing the constraint handling mechanism.

References

[1] M. Kelein, G.J. Rogers, and P. Kundur, "A Fundamental study of inter-area oscillations in power systems," *IEEE Transaction On Power Systems PWRS*, vol. 6, pp. 914 -921, 1991.

[2] L. Rouco and J. Perez-Arriaga, "Multi-area analysis of small signal stability in large electric power systems by SMA," *IEEE Transaction On Power Systems PWRS*, vol. 8, pp. 1257-1265, 1993.

[3] S.E.M. DeOliveria, "Synchronizing and damping torque coefficients and power system steady-state stability as affected by VAR compensation," *IEEE Transaction On Power Systems, PWRS*, vol. 9, pp. 109-119, 1994.

[4] F. P. DeMello and C. Concordia, "Concepts of Synchronous machine as affected by excitation control," *IEEE Transaction on Power System Apparatus*, vol. PAS-87, pp. 835-844, 1968.

[5] R. T. H. Alden and A.A. Shaltout, "Analysis of damping and synchronizing torque's; Part1:general calculation method," *IEEE Transaction on Power System Apparatus*, vol. PAS-98(5), pp. 1696-1700, 1979.

[6] E.A. Abu-AlFeilat, N. Younan, and S. Grzybowski, "Estimating the synchronizing and damping torque coefficients using Kalman filtering," *Electric Power System Research Journal*, vol. 52, pp. 145-149, 1999.

[7] K.M. EL-Naggar and A. AL-Othman, "A Discrete Stochastic Method for Estimating Synchronizing and Damping Torque Coefficients," presented at Second IASTED International Conference on Power and Energy Systems (EuroPES 2002), Crete, Greece, 2002.

[8] E. A. Feilat, "Performance estimation techniques for power system dynamic stability using least squares, Kalman filtering and genetic algorithms," presented at Southeastcon 2000. Proceedings of the IEEE, 2000.

[9] V. Torczon, "On the convergence of pattern search algorithms," *SIAM Journal on Optimization*, vol. 7, pp. 1-25, 1997.

[10] R.M. Lewis and V. Torczon, "Pattern search algorithms for linearly constrained minimization," *SIAM Journal on Optimization*, vol. 10, pp. 917-941, 1999.

[11] R.M. Lewis, V. Torczon, and M.W. Trosset, "Direct search methods: then and now," *Journal of Computational and Applied Mathematics*, vol. 124, pp. 191-207, 2000.

[12] P.W. Sauer and M.A. Pai, *Power System Dynamics and Stability*: Prentice Hall Inc., 1998.

[13] D.E. Goldberg, *Genetic algorithms in search, optimization, and machine learning*. Reading, Mass.: Harlow: Addison-Wesley, 1989.

[14] Z. Michalewicz, *Genetic algorithms + data structures = evolution programs*, 3rd rev. and extended ed. Berlin; New York: Springer-Verlag, 1996.

[15] K.M. EL-Naggar and A. AL-Othman, "A Genetic based Technique for Identification of Symmetrical Components for Power System Protection," presented at Fourth IASTED International Conference on Power and Energy Systems (EuroPES 2004), Rhodes, Greece, 2004.

[16] A.K. AL-Othman and K.M. EL-Naggar, "Estimating Synchronizing and Damping Torque Coefficients Using Particle Swarm Optimization," presented at IASTED conference on "Energy and Power Systems"(EPS 2005), Benalmadena, Spain, 2005.

Appendix

X_d=2.5, $X_d^{'}$ = 0.39, X_q=2.1, X_e=0.5 (all in p.u.)
$T_{d\,o}^{'}$= 5 sec., H=6 sec., ω_s=377 r/s
Initial conditions are: V_t =1 p.u., $V_{I.B.}$=1.05 p.u.
Constants are all given in reference.