

Damping of power System Oscillation by PSS Using GA

Saeid Kyanzadeh, Malihe M. Farsangi , Hossein Nezamabadi-pour
 Department of Electrical Engineering,
 Shahid Bahonar University of Kerman, Kerman,
 IRAN

Abstract-- Among stability issues, the damping of electromechanical oscillations has been recognized as an important issue in electrical power system operation. This paper investigates the ability of Genetic Algorithm (GA) to design power system stabilizer (PSS) to damp the inter area oscillation. For this the parameter of the PSS are determined by GA using a phased-based objective function. The numerical results are presented on a 2-area 4-machine system to illustrate the feasibility of the proposed method by GA using a phased-based objective function.

Key-Words -- electromechanical oscillations, inter area oscillation, Genetic Algorithm, power system stabilizer, dynamic stability.

1 Introduction

Electromechanical oscillations are inherent phenomena in electric power systems. With the development of extensive power systems, especially with the interconnection of these systems by weak tie-lines, electromechanical oscillations restrict the steady-state power transfer limits and affect operational system economics and security. Therefore, they have become one of the major problems in the power system stability area and have received a great deal of attention. Over the last two decades, there has been extensive research on the stabilization of electromechanical oscillations to enhance system small-signal stability by designing supplemental damping controllers. It is fully accepted that the stabilization of the electromechanical oscillations is only one of many considerations at the power design and planning stage, and therefore must take its place alongside the other considerations such as economics, reliability and operational robustness.

To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems. PSSs augment the power system stability limit and extend the power-transfer

capability by enhancing the system damping of low-frequency oscillations in order of 0.2 to 3.0 Hz.

DeMello and Concordia [1] presented the concepts of synchronous machine stability as affected by excitation control. They established an understanding of the stabilizing requirements for static excitation systems. In recent years, several approaches based on modern control theory have been applied to the PSS design problem. These include optimal control, adaptive control, variable structure control, and intelligent control [2]–[5].

Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag power system stabilizer (CPSS) structure [5]–[8].

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown by many researches that these algorithms are good replacement as tools to solve complex computational problems. Various heuristic approaches have been adopted by researches including genetic algorithm, tabu search, simulated annealing, ant colony and particle swarm optimization.

Also, study on the use of heuristic approaches to seek the optimal design of PSS in a power system is

carried out by the researches around the world [9]-[14]. But in all of them a heuristic approach with eigenvalue-based objective function is used. In this paper a GA with phased-based objective function is used to design PSS to damp oscillations.

2 Overview of GENETIC ALGORITHM

Genetic Algorithm (GA) has desirable characteristics as an optimization tool and offer significant advantages over traditional methods. They are inherently robust and have been shown to efficiently search the large solution space containing discrete or discontinuous parameters and non-linear constraints, without being trapped in local minima [15].

GA may be used to solve a combinatorial optimization problem. The GA searches for a solution inside a subspace of the total search space. Thus they are able to give a good solution of a certain problem in a reasonable computation time. The optimal solution is sought from a population of solutions using random process. Applying to the current population the following three operators create a new generation: reproduction, crossover and mutation. The reproduction is a process dependant on an objective function to maximize or minimize, which depends on the problem.

3 study system and problem formulation

A 2-area-4-machine system is used. This test system is illustrated in Fig. 1. The subtransient model for the generators, and the IEEE-type DC1 and DC2 excitation systems are used for machines 1 and 4, respectively. The IEEE-type ST3 compound source rectifier exciter model is used for machine 2, and the first-order simplified model for the excitation systems is used for machine 3.

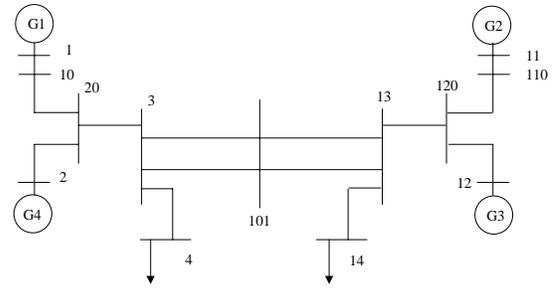


Fig. 1. Single line diagram of a 2-area study system.

Two PSSs are going to design using GA for the above system and placed on machines 2 and 3. The following structure shown by Fig. 2 is used for each PSS where the input to PSS could be generator speed or the generator electrical torque. In this paper, the generator electrical torque (pselect) is considered as input.

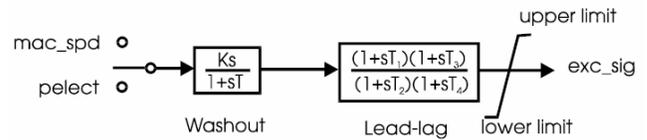


Fig. 2. Power System Stabilizer Model Block Diagram

By considering the above structure for PSS, the following equation can be written for the phase:

$$phase_pss = phase_washout + phase_lead - lag \tag{1}$$

Fig. 3 shows that the PSS is supplementary controller to excitation system.

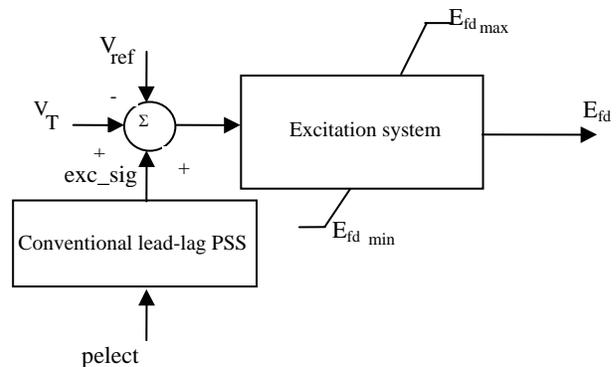


Fig. 3. Excitation system with conventional lead-lag PSS

The ideal stabilizer frequency response in terms of phase (the equation (1)) must equal to negative of the phase of the transfer function between the excitation input (V_{ref}) and pelect known as $phase_s$. Therefore, the parameter of the PSS are determined by GA by minimizing the following objective or cost function (2-norm of the difference of two phases):

$$\min f = \|phase_s - (-phase_pss)\|_2 \tag{2}$$

The PSS parameters can be changed till the algorithm reach to a close fit to the ideal frequency response characteristic.

4 Determining of PSS parameters using GA

The first step in the solution of an optimization problem using GA is the encoding of the variables. The most usual approach is to represent these variables as strings of 0s and 1s. A collection of such strings is called population.

The goal of the optimization is to find the best value for T, T_1, T_2, T_3, T_4 . Therefore, a configuration is considered with five genes. The number of chromosomes is set to be 50.

The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated with some measure of fitness, which is calculated from the objective function.

Moving to a new generation is done from the results obtained for the old generation. A based roulette wheel is created from the obtained values of the objective function of the current population. To create the next generation, new chromosomes, called offsprings, are formed using a crossover operator and a mutation operator. In this paper, one point crossover is applied with the crossover probability $p_c = 0.9$ and the mutation probability is selected to be $p_m = 0.01$. Also, the number of iteration is considered to be 100, which is the stopping criteria.

The best parameters are selected by GA based on 10 independent runs, under different random seeds. First the PSS is designed for machine 2. First of all the negative of the ideal phase for machine 2 is calculated and is shown in Fig. 4. Now the phase of PSS has to equal to the negative of the ideal phase for machine 2. Therefore GA starts searching to find

the best values for T, T_1, T_2, T_3, T_4 . In this paper, the value of k in Fig. 2 is considered to be 200. For each value obtained for T, T_1, T_2, T_3, T_4 , a phase for PSS is obtained. The GA is trying to fit the obtained phase of PSS with the ideal phase of the system shown in Fig. 4. As it can be seen in Fig. 4, the negative phase of machine 2 is highly nonlinear but the objective function in (2) tries to find a phase for PSS with the minimum error.

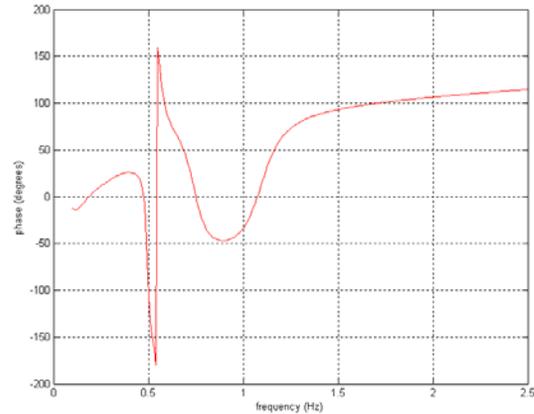


Fig. 4. The ideal frequency response characteristic to design PSS for machine 2.

The best phase obtained by GA for PSS is shown in Fig. 5 with the following values for T, T_1, T_2, T_3, T_4 as follows:

$$T = 50.076, T_1 = 0.2010, T_2 = 0.0133, T_3 = 0.639, T_4 = 1.060$$

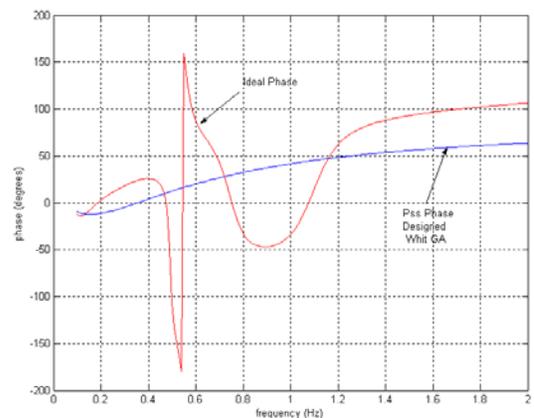


Fig. 5. The ideal frequency response characteristic against the phase of designed PSS by GA for machine 2.

With the same procedure, the second PSS is designed for the machine 3. Fig. 6 shows the phase of machine 3 and Fig. 7 shows the best fitted phase by GA for PSS.

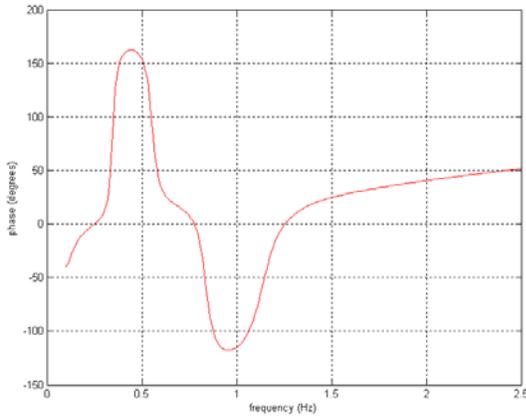


Fig. 6. The ideal frequency response characteristic to design PSS for machine 3.

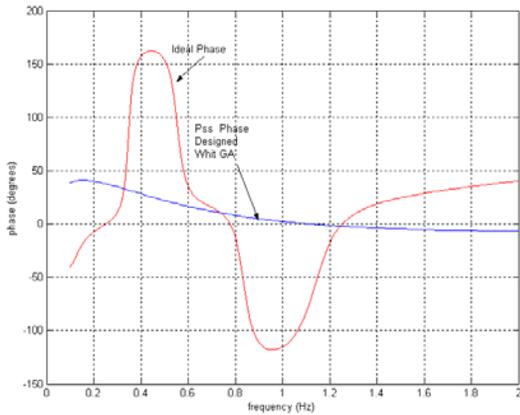


Fig. 7. The ideal frequency response characteristic against the phase of designed PSS by GA for machine 3.

The following values are obtained for the second PSS:

$$T = 23.852, T_1 = 0.1471, T_2 = 0.2777, T_3 = 1.7964, T_4 = 0.3908$$

For the two designed PSSs by GA, the average best-so-far and the mean cost function of each run are recorded and averaged over 10 independent runs. To have a better clarity, the convergence characteristics in finding the best values for PSS parameters are given in Figs. 8-11.

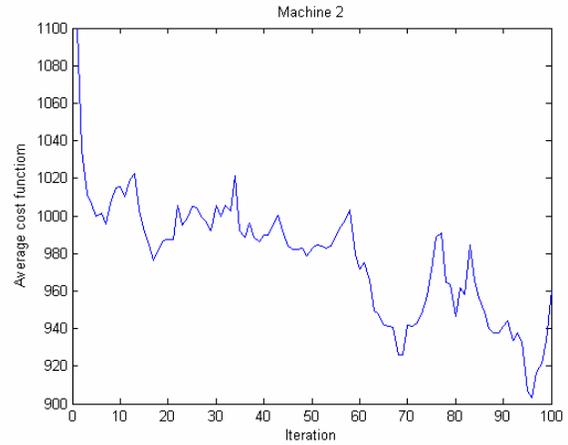


Fig. 8. Convergence characteristics of GA on the average cost function in finding the parameters of PSS placed on machine 2.

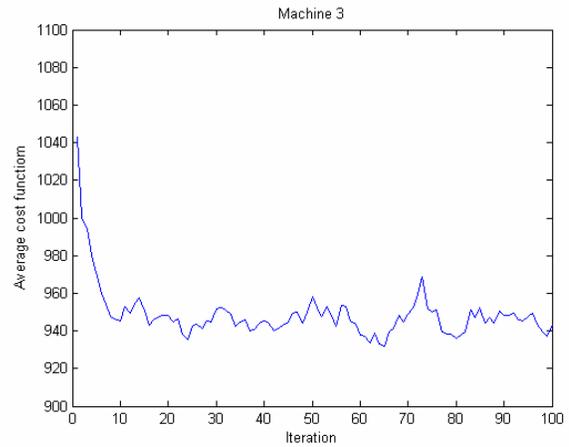


Fig. 9. Convergence characteristics of GA on the average cost function in finding the parameters of PSS placed on machine 3.

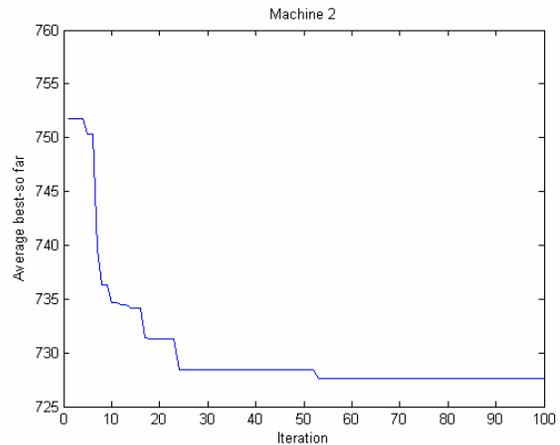


Fig. 10. Convergence characteristics of GA on the average best-so-far in finding the parameters of PSS placed on machine 2

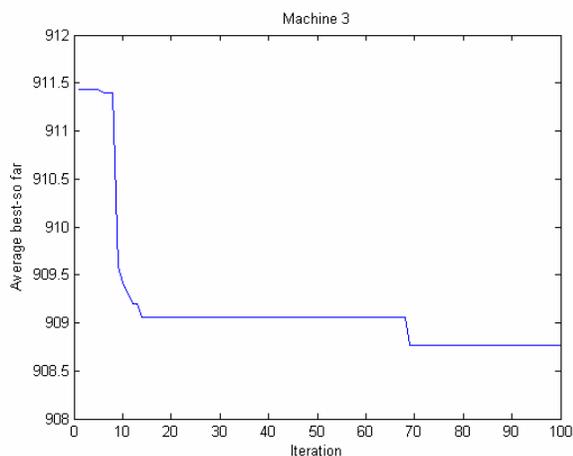


Fig. 11. Convergence characteristics of GA on the average best-so-far in finding the parameters of PSS placed on machine 3

Now the designed PSSs are placed in study system. To show the effectiveness of the designed PSSs a time-domain analysis is performed for the Study System. Fig. 12 shows the dynamic response of the system following a three-phase fault at bus 3 in the Study System. This figure shows the effects of the designed PSSs to damp the oscillations.

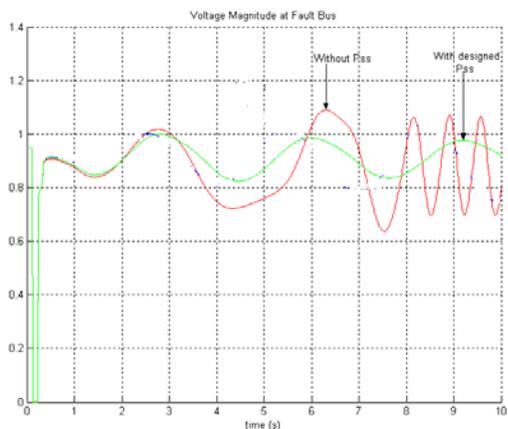


Fig. 12. The response of the system to a three-phase fault at bus 3.

5 Conclusion

This paper investigated the ability of Genetic Algorithm (GA) to design power system stabilizer (PSS) to damp the inter area oscillation. For this the

parameters of the PSS were determined by GA using a phased-based objective function. To show the effectiveness of the designed PSSs, a three phase fault applied at bus 3. The simulation study showed that the design PSS improve the stability of the system. Currently the authors are working on the designing of the PSS by GA using an eigenvalue-based objective function to compare with the results obtained in this paper.

References

[1] F. P. deMello and C. Concordia, "Concepts of synchronous machine stability as affected by excitation control," *IEEE Trans. Power App. Syst.*, vol. PAS-88, pp. 316–329, 1969.

[2] S. M. Osheba and B. W. Hogg, "Performance of state space controllers for turbogenerators in multimachine power systems," *IEEE Trans. Power App. Syst.*, vol. PAS-101, pp. 3276–3283, Sept. 1982.

[3] D. Xia and G. T. Heydt, "Self-tuning controller for generator excitation control," *IEEE Trans. Power App. Syst.*, vol. PAS-102, pp. 1877–1885, 1983.

[5] V. Samarasinghe and N. Pahalawaththa, "Damping of multimodal oscillations in power systems using variable structure control techniques," *Proc. Inst. Elect. Eng. Gen. Transm. Distrib.*, vol. 144, pp. 323–331, Jan. 1997.

[5] Y. L. Abdel-Magid, M. A. Abido, S. Al-Baiyat, and A. H. Mantawy, "Simultaneous stabilization of multimachine power systems via genetic algorithms," *IEEE Trans. Power Syst.*, vol. 14, pp. 1428–1439, Nov. 1999.

[6] E. Larsen and D. Swann, "Applying power system stabilizers," *IEEE Trans. Power App. Syst.*, vol. PAS-100, pp. 3017–3046, 1981.

[7] G. T. Tse and S. K. Tso, "Refinement of conventional PSS design in multimachine system by modal analysis," *IEEE Trans. Power Syst.*, vol. 8, pp. 598–605, May 1993.

[8] P. Kundur, M. Klein, G. J. Rogers, and M. S. Zywno, "Application of power system stabilizers for enhancement of overall system stability," *IEEE Trans. Power Syst.*, pp. 614–626, May 1989.

[9] Y. L. Abdel-Magid and M.A. Abido, "Optimal multiobjective design of robust power system stabilizers using genetic algorithms," *IEEE Trans. Power Syst.*, vol. 18, pp. 1125–11325, Aug. 2003.

[10] Y. L. Abdel-Magid and M.A. Abido, "Optimal design of power system stabilizers using evolutionary

programming, *IEEE Trans Energy Conversion*, vol. 17, pp. 429–436, Dec. 2002.

[11] M.A. Abido, Optimal design of power-system stabilizers using particle swarm optimization, *IEEE Trans Energy Conversion*, vol. 17, pp. 406–413, Sept. 2002.

[12] Y. L. Abdel-Magid, M.A. Abido and A.H Mantaway, Robust tuning of power system stabilizers in multimachine power systems Power Systems, *IEEE Trans. Power Syst.*, vol. 15, pp. 735–7405, May. 2000.

[13] M.A. Abido, Robust design of multimachine power system stabilizers using simulated annealing, *IEEE Trans Energy Conversion*, vol. 15, pp. 297–304, Sept. 2000.

[14] M.A. Abido and Y. L. Abdel-Magid, A hybrid neuro-fuzzy power system stabilizer for multimachine power systems; *IEEE Trans. Power Syst.*, vol. 13, pp. 1323–1330, Nov. 1998.

[15]] D. E. Goldberg, *Genetic algorithms in search, optimization, and machine learning*. New York : Addison-Wesley, 1989.