Design of Power System Stabilizer Using Immune Algorithm

Saeid Kyanzadeh, Malihe M. Farsangi, Hossein Nezamabadi-pour, and Kwang Y. Lee, *Fellow, IEEE*

***Abstract*— This paper investigates the ability of Immune Algorithm (IA) in designing power system stabilizer (PSS) to damp the power system inter-area oscillation. For this the parameters of the PSS are determined by IA using a phase-based objective function. The numerical results are presented on a 2-area 4-machine system to illustrate the feasibility of the proposed method. To show the effectiveness of the designed PSSs, a three phase fault is applied. The simulation study shows that the designed PSSs improve the stability of the system. Also, to validate the results obtained by IA, a simple Genetic Algorithm (GA) is applied for comparison.**

***Index Terms*— Immune algorithm, genetic algorithm, electromechanical oscillations, inter-area oscillation, power system stabilizer, dynamic stability.**

I. 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 the 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]. The reason is that the modern control techniques may give a controller with a high order which is difficult to implement.

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 system, particle swarm optimization and immune algorithm.

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]. In view of this, in this paper an immune algorithm with phase-based objective function is used to design PSS to damp oscillations.

The paper is organized as follows: to make a proper background, the basic concept of the IA is briefly explained in Section II. The optimization problem is formulated in Section III. The results of the IA in a study system are given in Section IV and some conclusions are drawn in Section V.

II. Overview of Immune Algorithm: Clonal Selection Algorithm

The immune algorithm (IA) 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 and continuous parameters and non-linear constraints, without being trapped in local minima. The IA may be used to solve a combinatorial optimization problem.

In the IA, *antigen* represents the problem to be solved. An *antibody* set is generated where each member represents a candidate solution. Also, *affinity* is the fit of an antibody to the antigen. In the IA, the role of antibody lies in eliminating the

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antigen, while the *lymphocyte* helps to produce the antibody [15]-[16].

In the immune system, there are two kind of lymphocyte; T and B; where each of them has its own function. The T lymphocytes develop in bone marrow and travel to *thymus* to mature. The B lymphocytes develop and mature within the bone marrow. The main purpose of the immune system is to recognize all cells within the body and categorize those cells as self or non-self. Self or self antigens are those cells that originally belong to the organism and are harmless to its functioning. The disease-causing elements are known as non-self.

Both B-cells and T-cells have receptors that are responsible for recognizing antigenic patterns by different function. The attraction between an antigen and a receptor cell (or degree of binding) is known as affinity. To handle the infection successfully and effectively, both B-cells and T-cells may be required. After successful recognition, cells capable of binding with non-self antigens are cloned.

In the IA the elements of the population undergo mutations resulting in a subpopulation of cells that are slightly different. Since the mutation rate is high, this mutation is called hypermutation.

By the above description, the principle of IA can be summarized in Fig. 1.

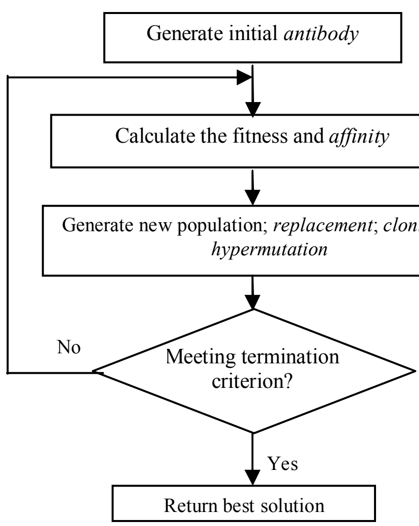

Fig. 1. General principle of the immune algorithm.

As Fig. 1 shows at the first step, n antibody generated randomly and evaluated using a suitable affinity measure. While the affinity of all antibodies is known, new population is generated through three steps; replacement, cloning and hypermutation. These three steps maintain the diversity and help the algorithm to expand the search space. In the replacement step, the low antibodies are replaced. Those with the highest affinity are selected to proliferate by cloning where the cloning rate of each immune cell is proportional to its affinity. If the high affinity antibody has not been cloned, hypermutation is applied where the mutation rate for each immune cell is inversely proportional to its affinity [15]. When the new population is generated, IA continues with repeated evaluation of the antibodies through replacement, cloning and hypermutation until the termination criterion is met. The termination criterion could be the number of iteration or when an antibody of maximal affinity is found.

III. STUDY SYSTEM AND PROBLEM FORMULATION

A 2-area-4-machine system is used. This test system is illustrated in Fig. 2. 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.

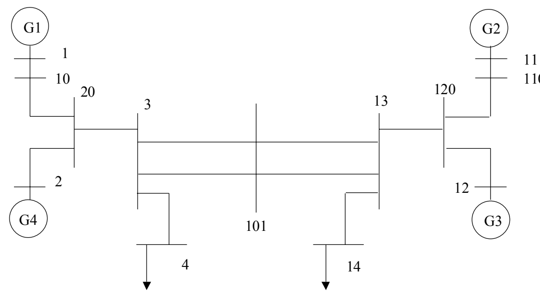

Fig. 2. Single-line diagram of a 2-area study system.

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

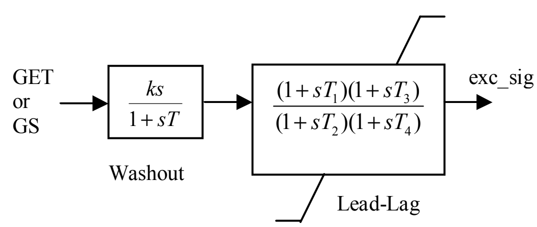

Fig. 3. Power system stabilizer model block diagram.

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

$$\theta = \theta_w + \theta_L \qquad (1)$$

where θ is the phase of PSS, θ_w is the phase of washout and θ_L is the phase of lead-lag compensator.

Fig. 4 shows that the PSS is a supplementary controller to the excitation system.

The ideal stabilizer frequency response in terms of phase (the equation (1)) should be equal to the negative of the phase of the transfer function between the excitation input (V_{ref}) and

GS known as θ_i. Therefore, the parameters of the PSS, T, T_1, T_2, T_3, T_4, are determined by IA by minimizing the following objective or cost function (2-norm of the difference of the two phases):

$$f = \|\theta_i - (-\theta)\|_2 \qquad (2)$$

The PSS parameters can be changed till the algorithm reach to a close fit to the ideal phase angle response characteristics.

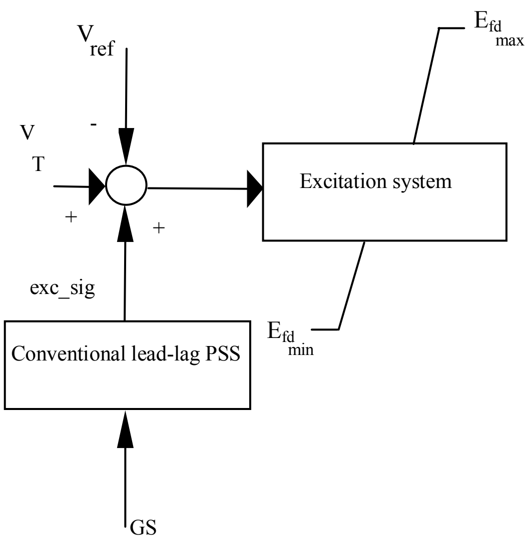

Fig. 4. Excitation system with conventional lead-lag PSS.

IV. DESIGNING OF PSS USING IA

A population of n antibodies are generated randomly, where n is considered to be 50. The goal of the optimization is to find the best value for the PSS parameters, T, T_1, T_2, T_3, T_4 (Fig. 3). Therefore, a configuration is considered for each antibody as a vector $[T, T_1, T_2, T_3, T_4]$.

During each generation, the antibodies are evaluated with some measure of fitness, which is calculated from the objective function defined in (2). Then the best antibody is chosen. In the current problem, the best antibody is the one that has minimum fitness. This antibody is chosen as antigen and the affinity of other antibodies is calculated with the selected antigen. The affinity of each antibody is calculated by the following equation:

$$affinity = \frac{f(antigen)}{f(antibody)} \qquad (3)$$

Moving to a new generation is based on the antibodies with the high and low affinity by using cloning and replacement. Also, the mutation is applied to each generation in order to recognize not only the antigen itself but also antigens that are similar.

The above procedure continues until the last iteration is met. In this paper, the number of iteration is set to be 100.

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. 5. Now the phase of PSS has to be equal to the negative of the ideal phase for Machine 2. Therefore IA starts searching to find the best values for the PSS parameters, T, T_1, T_2, T_3, T_4. In this paper, the value of washout gain k in Fig. 3 is considered to be 50. For each value obtained for the parameters T, T_1, T_2, T_3, T_4, a phase for PSS is obtained. The IA is trying to fit the obtained phase of PSS with the ideal phase of the system shown in Fig. 5. As it can be seen in Fig. 5, 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.

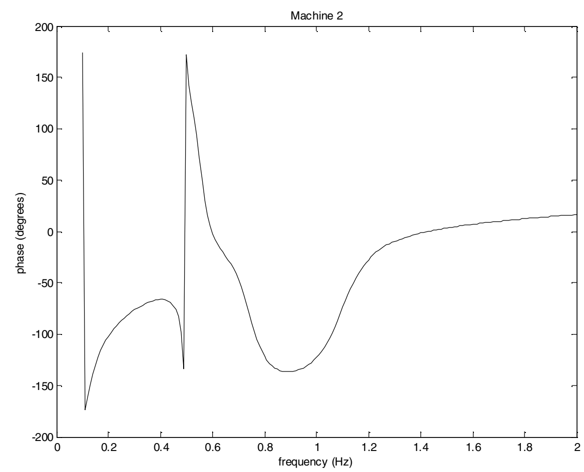

Fig. 5. The negative ideal frequency response characteristic of Machine 2.

The best phase obtained by IA for PSS is shown in Fig. 6 with the following values for T, T_1, T_2, T_3, T_4:

$$T = 4.9275, T_1 = 0.013979, T_2 = 0.043775, T_3 = 0.013914,$$
$$T_4 = 0.048239$$

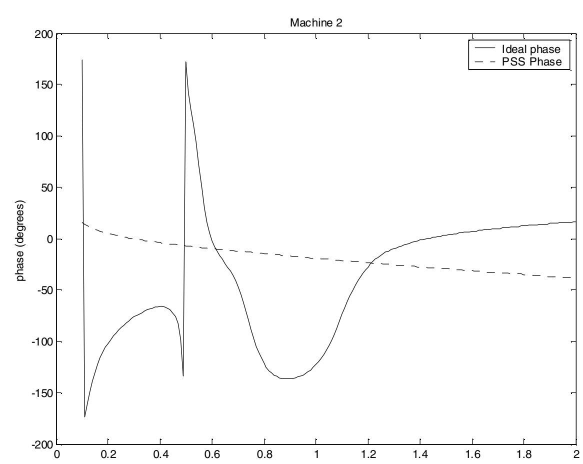

Fig. 6. Comparison of the negative ideal frequency response characteristic and the phase of designed PSS by IA for Machine 2.

With the same procedure, the second PSS is designed for the Machine 3. Fig. 7 shows the phase of Machine 3 and Fig. 8 shows the best fitted phase by IA for the PSS.

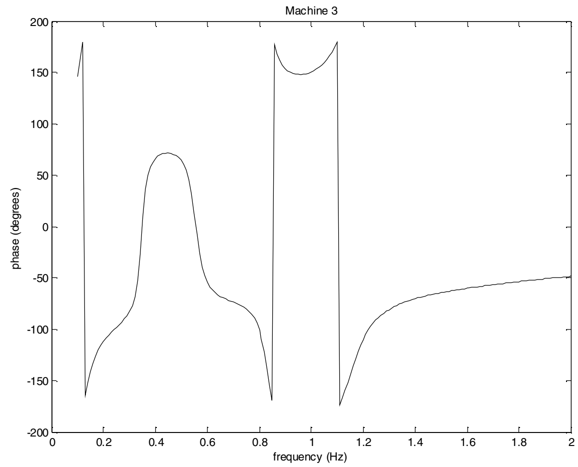

Fig. 7. The negative ideal frequency response characteristic of Machine 3.

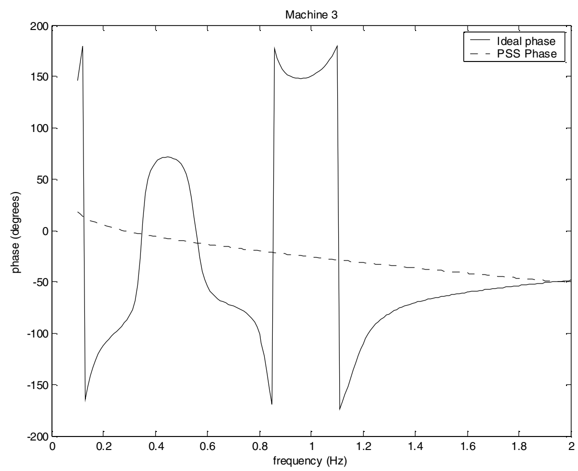

Fig. 8. Comparison of the negative ideal frequency response characteristic and the phase of designed PSS by IA for Machine 3.

The following values are obtained for the second PSS:

$$T = 3.8716, T_1 = 0.008373, T_2 = 0.04337, T_3 = 0.0023861,$$
$$T_4 = 0.04569$$

To validate the obtained result by IA, a simple GA is applied. The number of chromosomes in the population is set to be 50, which is the same as in IA. 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 iterations is considered to be 100, which is the stopping criteria used in IA. The obtained parameters of PSS for Machine 2 by GA are as follows:

$$T = 4.8813, T_1 = 0.0031185, T_2 = 0.0320, T_3 = 0.012587,$$
$$T_4 = 0.04361$$

Also, the following parameters for PSS of Machine 3 are obtained by GA:

$$T = 4.1133, T_1 = 0.0026512, T_2 = 0.042769, T_3 = 0.0051746,$$
$$T_4 = 0.044631$$

For the two designed PSSs by IA and GA, the average best-so- far 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. 9-10. These figures show that IA is performing better in finding the best solution due to hypermutation operator in IA.

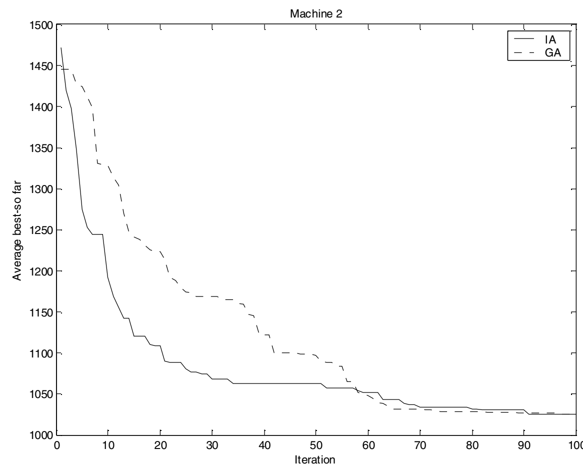

Fig. 9. Convergence characteristics of IA and GA on the average best-so- far in finding the parameters of PSS placed on Machine 2.

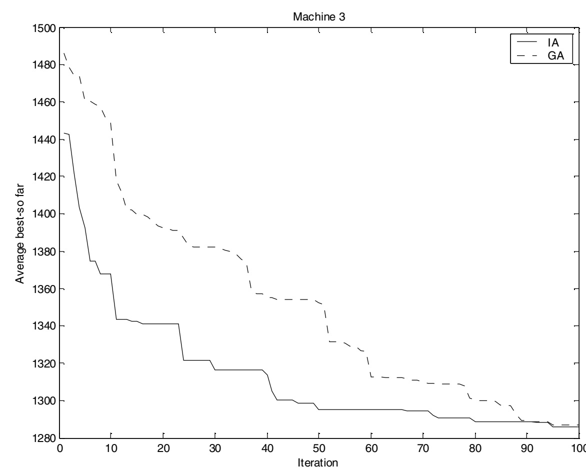

Fig. 10. Convergence characteristics of IA and GA on the average best-so- far in finding the parameters of PSS placed on Machine 3.

Now the designed PSSs by IA and GA are placed in the study system (Fig. 2). To show the effectiveness of the designed PSSs by IA and GA, a time-domain analysis is performed for the study system. A three-phase fault is applied in one of the tie circuits at bus 101. The fault persisted for 70.0 ms; following this, the faulted circuit was disconnected by appropriate circuit breaker. The system operated with one tie circuit connecting buses 3 and 101. The dynamic behavior of the system was evaluated for 15 s. Fig. 11 shows that IA has good ability to design PSSs to damp the oscillations. Also, the machine angles, δ, with respect to a particular machine, were computed over the simulation period and shown in Figs. 12-13. In the study system, Machine 1 is considered as the reference generator.

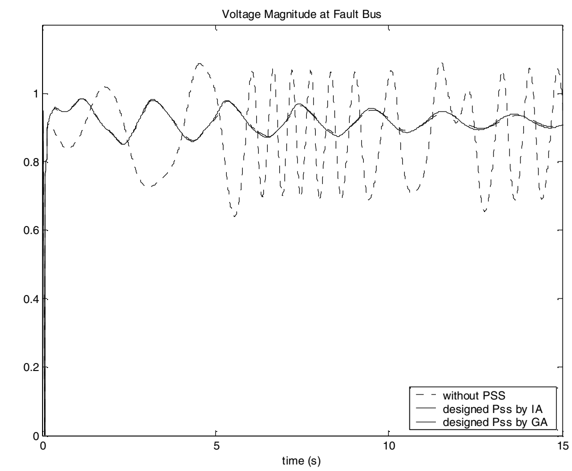

Fig. 11.The response of the system to a three-phase fault at Bus 3.

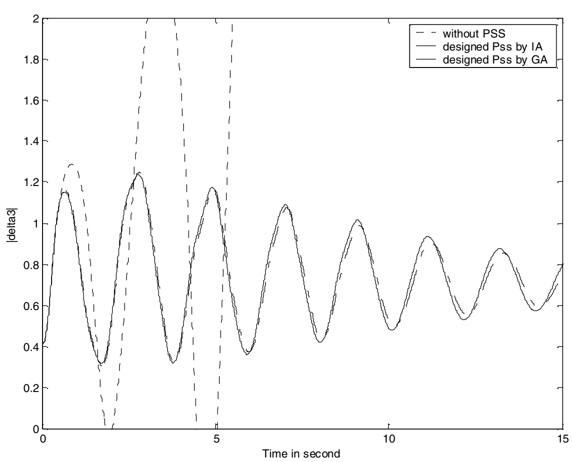

Fig. 12. The response of generator 3 to a three-phase fault.

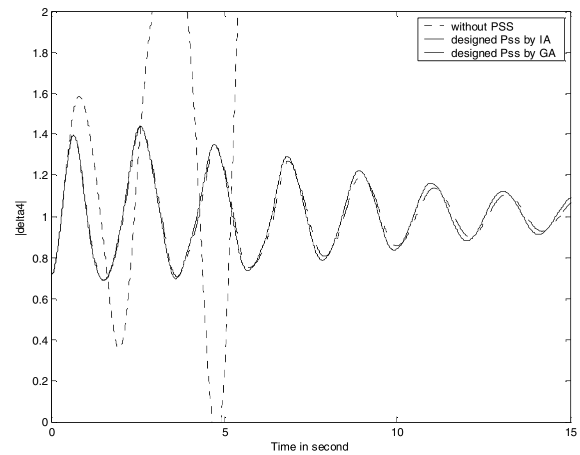

Fig. 13. The response of generator 4 to a three-phase fault.

V. CONCLUSIONS

This paper investigated the ability of Immune Algorithm (IA) in designing power system stabilizer (PSS) to damp the inter-area oscillations. For this the parameters of the PSS are determined by IA using a phase-based objective function. To show the effectiveness of the designed PSSs, a three phase fault is applied at a generator bus. The simulation study shows that the designed PSSs improve the stability of the system. Also, a simple GA is applied to validate the results. The obtained results show that the IA has the ability of solving the complex power system problems. For a future work the PSS can be designed by IA using an eigenvalue-based objective function to compare with the results obtained in this paper. Also, to improve the damping, Static Var Compensators (SVC) can be used and a supplementary controller can be designed by IA for the SVC.

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BIOGRAPHIES

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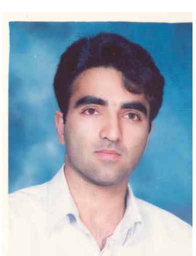

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