Honey Bee Mating Optimization Technique Based Multi-machine Power System Stabilizer Design

Ali Nazari[1] and Amin Safari[2]
[1]*Department of Electrical Engineering, Shahid Rajaee University, Tehran, Iran*
[2]*Department of Electrical Engineering, Ahar Branch,*
Islamic Azad University, Ahar, Iran
a-safari@iau-ahar.ac.ir

Abstract

In this paper, a new approach based on the Honey bee mating optimization (HBMO) technique is proposed to tune the parameters of the multi-machine power system stabilizers (PSSs). The honey-bee mating process has been considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of real honey-bee mating. The PSSs parameters tuning problem is converted to an optimization problem with time domain-based objective function which is solved by a HBMO algorithm. To ensure the robustness of the proposed stabilizers, the design process takes a wide range of operating conditions into account. The performance of the newly designed PSSs is evaluated in a three-machine power system subjected to the different types of operating conditions in comparison with the genetic algorithm based PSSs. The effectiveness of the proposed technique is demonstrated through nonlinear time-domain simulation studies over a wide range of loading condition.

Keywords: *Power system stabilizer, Honey bee mating optimization, Dynamic stability, Low frequency oscillation, Multi-machine power system*

1. Introduction

Stability of power systems is one of the most important aspects in electric system operation. This arises from the fact that the power system must maintain frequency and voltage levels, under any disturbance, like a sudden increase in the load, loss of one generator or switching out of a transmission line, during a fault [1]. Since the development of interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2 to 3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. Moreover, low-frequency oscillations present limitations on the power-transfer capability. To enhance system damping, the generators are equipped with PSSs that provide supplementary feedback stabilizing signals in the excitation systems [2]. Novel intelligent control design methods such as fuzzy logic controllers [1] and artificial neural network controllers [3] have been used as PSSs. Unlike other classical control methods fuzzy logic and neural network controllers are model-free controllers; *i.e.*, they do not require an exact mathematical model of the controlled system. Moreover, speed and robustness are the most significant properties in comparison to other classical schemes. H_∞ optimization techniques [4] have been also applied to robust PSS design problem. However, the importance and difficulties in the selection of weighting functions of H_∞ optimization have been reported. In addition, the additive and/or multiplicative uncertainty representation cannot treat situations where a nominal stable system becomes unstable after being perturbed.

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, 6]. The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. On the other hand, Kundur, *et al.*, [7] have presented a comprehensive analysis of the effects of the different CPSS parameters on the overall dynamic performance of the power system. It is shown that the appropriate selection of CPSS parameters results in satisfactory performance during system upsets. In addition, Gibbard [8] demonstrated that the CPSS provide satisfactory damping performance over a wide range of system loading conditions. The robustness nature of the CPSS is due to the fact that the torque-reference voltage transfer function remains approximately invariant over a wide range of operating conditions. A gradient procedure for optimization of PSS parameters at different operating conditions is presented in [9]. Unfortunately, the optimization process requires computations of sensitivity factors and eigenvectors at each iteration. This gives rise to heavy computational burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima and the solution obtained will not be optimal [10]. Unfortunately, the problem of the PSS design is a multimodal optimization problem (*i.e.*, there exists more than one local optimum). Thus, conventional optimization methods that make use of derivatives and gradients are, in general, not able to locate or identify the global optimum, but for real-world applications, one is often content with a good solution, even if it is not the best. Consequently, heuristic methods are widely used for global optimization problems [11].

Recently, global optimization techniques like genetic algorithms (GA), evolutionary programming, simulated annealing, and rule based bacteria foraging, particle swarm optimization and chaotic optimization algorithm [12-17] have been applied for PSS parameters optimization. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. However, the performance of evolutionary strategy greatly depends on its parameters, and it often suffers the problem of being trapped in local optima so as to be premature convergence. Over the last decade, modeling the behavior of social insects, such as ants and bees, for the purpose of search and problem solving has been the context of the emerging area of swarm intelligence. Honey bee is among the most closely studied social insects and honey bee mating may also be considered as a typical swarm based approach to problem optimization, in which the search algorithm is inspired by the process of marriage in real honey bee. Honey bee has been applied to model agent based systems [18]. In a recent work, Abbass [19, 20] developed an optimization algorithm based on the honey bee marriage process. This paper presents an improved version of the honey bee mating optimization (HBMO) algorithm for design of multi-machine PSSs. The effectiveness of the proposed HBMOPSS is tested on a multi-machine power system under different operating conditions and results are demonstrated through nonlinear time simulation. Results evaluation shows that the proposed method achieves good robust performance for damping low frequency oscillations under different operating conditions.

2. Honey Bee Mating Optimization Algorithm

The honey bee is one of the social insects that can just survive as a member of colony. The activity of honey bee suggests many characteristics like together working and communication. A honey bee colony normally includes of a single egg-laying queen with which it's life-span is more than other bees; that with depend upon that seasons usually have more than 60,000 workers or more. A colony may contain a queen during its life-cycle. That is named monogynous one. Only the queen is fed by royal jelly. The Nurse bee take care of this gland and feed it to queen. The royal jelly causes the queen bee biggest bee in the hive. Several hundred drones live with queen and its workers. Queen bee life-span is about 5 or 6 years, whereas rest of the bees, especially worker bees, oven their period of living do not reach to 1 year. The drones die after mating process [20].

The drones act in father function in the colony, which are haploid and amplify or multiply their mother's genome without changing their genetics combinations, but mutation. So, drones are agents that anticipate one of the mother's gametes and by the sake of that female can do genetically like males. Broods, that be cared by workers, improve from fertilized or unfertilized eggs. They represent potential queens and prospective drones, respectively. In marriage process, the queens in mating period, their mate flight of the nest to the far places. Insemination ends with the gradual death of drones, and by the sake of that queens receive the mating sign. Any drone can take part in mating process just one time, but the queens mate several times. These features make bee mating very interesting among insects. A drone mates with a queen probabilistically using an annealing function like this [21]:

$$\Pr ob(D) = \exp(-\Delta f \,/\, S(t)) \tag{1}$$

Where *Prob(D)* is probability of adding drone's sperm *D* to queen's spermatheca, *Δ(f)* is perfect difference of fitness *D* and queen, and *s(t)* is speed of the queen at time *t*. The mating is high either when queen's speed level is high, or when drone's fitness is equal with queens. After every transition, speed of queen will decrease according to the following equations:

$$s(t+1) = \alpha \times s(t) \tag{2}$$

$$E(t+1) = E(t) - \gamma \tag{3}$$

Where, α is a factor ϵ (0, 1) and γ is the amount of energy, *E(t)* reduction after each transition. Firstly, speed of queen randomly generated. A number of mating flights are realized.

The queens play the most important function in mating process in nature and also HBMO algorithm. The spermateca is a place for sperm of drones and queen's, all drones, however are originally haploid; after that a mating done successfully, the drone's sperm is stored in the queen's spermatheca. A brood is reproduced by coming of some genes of drones into the brood genotype. Therefore, an HBMO algorithm would be constructed by the following five important stages [21]:

1. The algorithm starts with mating flight, where a queen selects drones probabilistically from the spermatheca. A drone is selected from list randomly for the creation of broods.
2. Creating of new broods by combining of drone's genotypes with the queens.
3. Using of workers to lead local searching on broods.
4. Adaptation of worker's ability, based on the improvement of broods.
5. Substitution of worker queens by stronger and aptitude broods.

However, when all queens completed their mating flight, start breeding. After all broods have been generated, they are sorted according to their fitness. The best brood is replaced by the worst queens until all of queens are better and there is no only needing to broods. After completing of mating, remaining broods finally killed in order to new mating process begin. The main steps in the HBMO algorithm are presented in Figure 1. Main difference (or one of them) HBMO algorithm from classic evolutionary algorithms is that be storing of many different drone's sperm in spermatheca by queen cause which the queen uses of them to create new solution for fittest of broods. The computational flow chart of HBMO algorithm is shown in Figure 2.

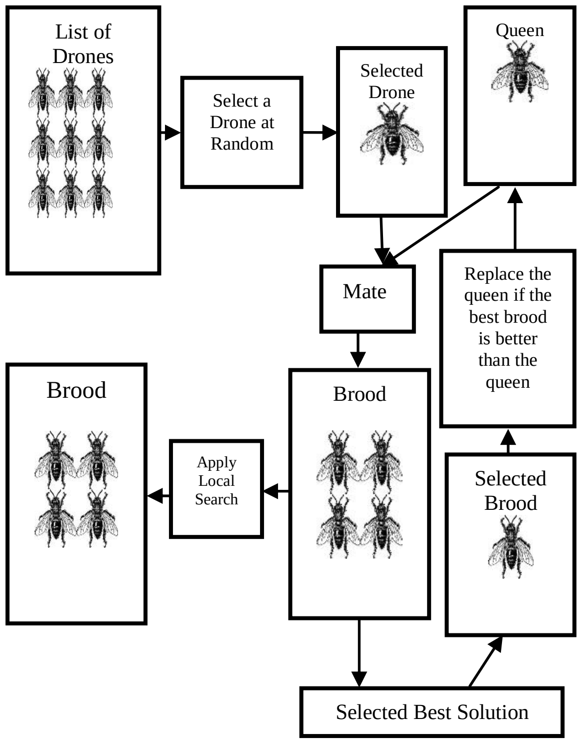

Figure 1. The HBMO algorithm [20]

3. Problem Statement

3.1 Power system model

The aim of this study is to determine the parameters of power system stabilizers for damping oscillations. For this reason appropriate modeling of the power system has a main role on better designing of stabilizers. The complex nonlinear model related to an *n*–machine interconnected power system, can be described by a set of differential- algebraic equations by assembling the models for each generator, load, and other devices such as controls in the system, and connecting them appropriately via the network algebraic equations. The generator in the power system is represented by Heffron-Philips model. In this study, the two-axis model [22] given in Appendix A is used for time domain simulations.

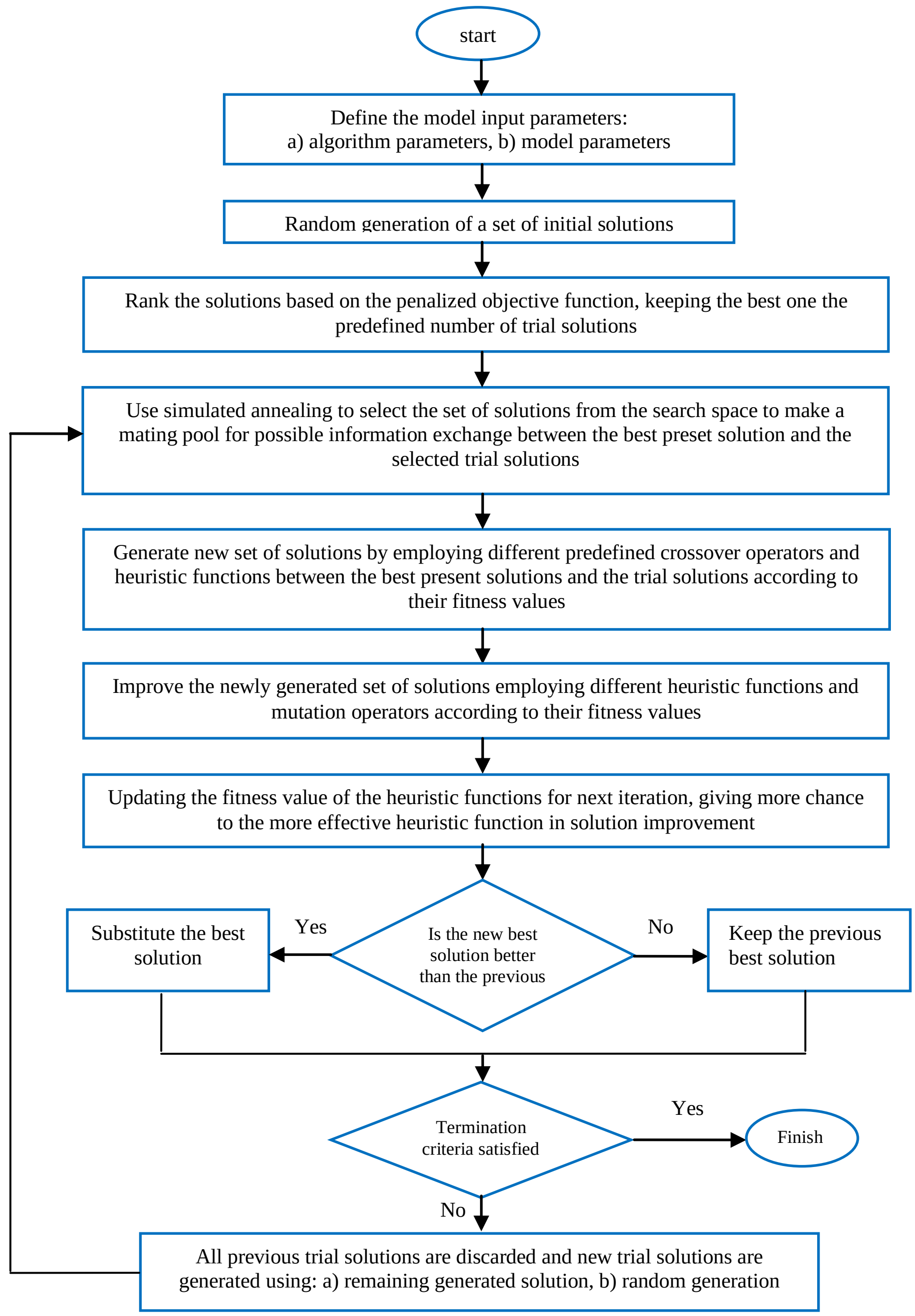

Figure 2. Flowchart of the HBMO algorithm

3.2 PSS structure

The operating function of a PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. A widely speed based used conventional PSS is considered throughout the study [10-13]. The transfer functions of the *i*th PSS is [23]:

$$U_i = K_i \frac{sT_w}{1+sT_w}\left[\frac{(1+sT_{1i})(1+sT_{3i})}{(1+sT_{2i})(1+sT_{4i})}\right]\Delta\omega_i(s) \tag{4}$$

Where, $\Delta\omega_i$ is the deviation in speed from the synchronous speed. This type of stabilizer consists of a washout filter, a dynamic compensator. The output signal is fed as a supplementary input signal, U_i, to the regulator of the excitation system. The washout filter, which essentially is a high pass filter, is used to reset the steady-state offset in the output of the PSS. The value of the time constant T_w is usually not critical and it can range from 0.5 to 20 s. In this study, it is fixed to 10 s. The dynamic compensator is made up to two lead-lag stages and an additional gain. The adjustable PSS parameters are the gain of the PSS, K_i, and the time constants, T_{1i}-T_{4i}. The required phase lead can be derived from the lead-lag block even if the denominator portion consisting of T_{2i} and T_{4i} gives a fixed lag angle. Thus, to reduce the computational burden in this paper, the values of T_{2i} and T_{4i} are kept constant at a reasonable value of 0.05 s and tuning of T_{1i} and T_{3i} are undertaken to achieve the net phase lead required by the system. In this paper, the problem of robust PSS design is formulated as an optimization problem and HBMO is employed to solve this problem. Robustness is achieved by considering several operating conditions and system configurations simultaneously.

3.3 Objective function

To acquire an optimal combination, this paper employs HBMO algorithm [20] to improve optimization synthesis and find the global optimum value of fitness function. For our optimization problem, objective function is time domain-based objective function [17]:

$$J = \sum_{j=1}^{NP}\sum_{i=1}^{n}\int_0^{tsim} t\left|\Delta\omega_i\right|dt \tag{5}$$

Where, speed deviations ($\Delta\omega$), of machines are considered for evaluation of the J. The t_{sim} is the time range of simulation, n is the number of machines and NP is the total number of operating points for which the optimization is carried out. It is aimed to minimize this fitness function in order to improve the system response in terms of the settling time and overshoots. The advantage of this selected objective function is that minimal dynamic plant information is needed. The design problem can be formulated as the following constrained optimization problem, where the constraints are the PSS parameter bounds:

$$\begin{aligned}&\text{Minimize}\,J\ \text{subject to}\\ &K_i^{\min} \le K_i \le K_i^{\max}\\ &T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max}\\ &T_{3i}^{\min} \le T_{3i} \le T_{3i}^{\max}\end{aligned} \tag{6}$$

The proposed approach employs HBMO algorithm to solve this optimization problem and search for optimal or near optimal set of PSSs parameters (K_i, T_{1i} *and* T_{3i} *for* $i=1,2,\ldots,m$) where, m is the number of machines in the multi-machine environment.

4. Case Study

In this study, the three-machine nine-bus power system shown in Figure 3 is considered. Detail of the system data are given in Ref. [22]. To assess the effectiveness and robustness of the proposed method over a wide range of loading conditions, three different cases designated as nominal, light and heavy loading are considered. The generator and system loading levels at these cases are given in Tables 1 and 2.

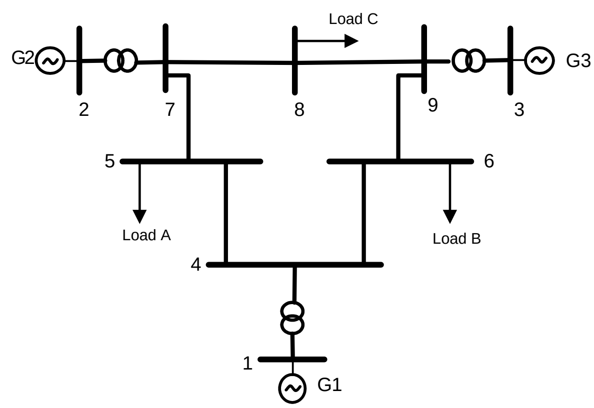

Figure 3. Three-machine nine-bus power system

Table 1. Generator operating conditions (in pu)

Gen	Nominal		Heavy		Light	
	P	Q	P	Q	P	Q
G_1	0.72	0.27	2.21	1.09	0.36	0.16
G_2	1.63	0.07	1.92	0.56	0.80	-0.11
G_3	0.85	-0.11	1.28	0.36	0.45	-0.20

Table 2. Loading conditions (in pu)

Load	Nominal		Heavy		Light	
	P	Q	P	Q	P	Q
A	1.25	0.5	2.0	0.80	0.65	0.55
B	0.90	0.30	1.80	0.60	0.45	0.35
C	1.0	0.35	1.50	0.60	0.50	0.25

4.1 PSSs design using HBMO

The PSS is connected to all machines in the test system. In the proposed method, we must tune the PSSs parameters optimally to improve the overall system dynamic stability in a robust way under different operating conditions. The optimization of PSS parameters is carried out by evaluating the objective function as given in (5), which considers a multiple of operating conditions. The operating conditions considered are:

i) Nominal case of the system

ii) Heavy loading of the system

iii) Light loading of the system

In order to acquire better performance, number of size of spermatecha , number of variables, maximum number of mating flight, Nqueen, Nbrood, and Nworkers is chosen as 150, 9, 100, 1, 50 and 3000, respectively. In order to facilitate comparison with genetic algorithm (see the Appendix B), the design and tuning of stabilizers were used. Results of PSSs parameter set values are given in Table 3.

4.2 Nonlinear time-domain simulation

To investigate the power system performance with proposed algorithm based designed stabilizers, two classes of disturbances are studied. These classes are chosen to represent the large, as well as small power system disturbances**:**

Table 3. Optimal PSSs parameters using HBMO and GA

Controller parameters	GA			HBMO		
	PSS_1	PSS_2	PSS_3	PSS_1	PSS_2	PSS_3
K	59.78	14.15	25	50.51	16.06	29.23
T_1	0.1258	0.1403	0.1187	0.0713	0.0832	0.1602
T_3	0.0801	0.1743	0.1891	0.1226	0.2148	0.1175

Scenario 1

In this scenario, to evaluate the performance of the proposed method a disturbance of 0.1 pu input torque is applied to the 2^{th} machine after 0.5 second, respectively. The study is performed at three different operating conditions. The results are shown in Figures 4-6**.**

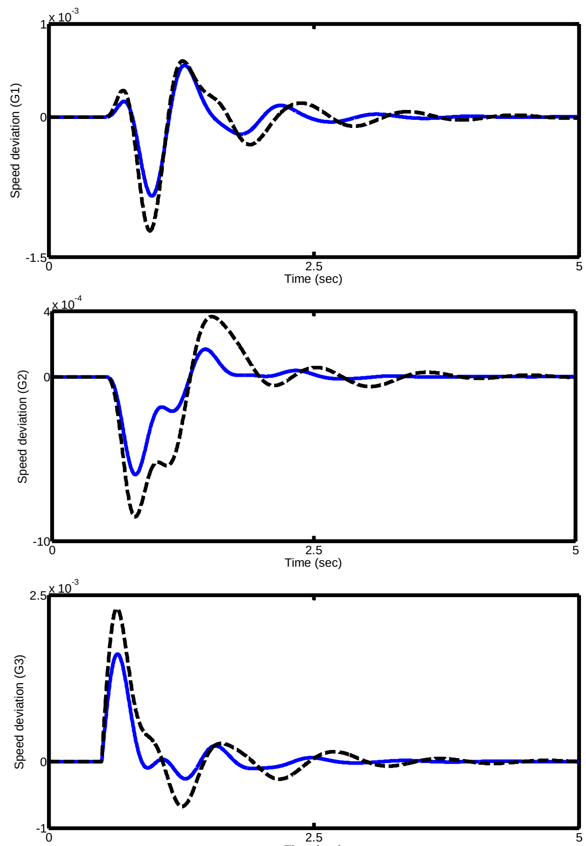

Figure 4. Dynamic responses for Δω in scenario 1 with nominal loading condition: Solid (HBMOPSS) and Dashed (GAPSS)

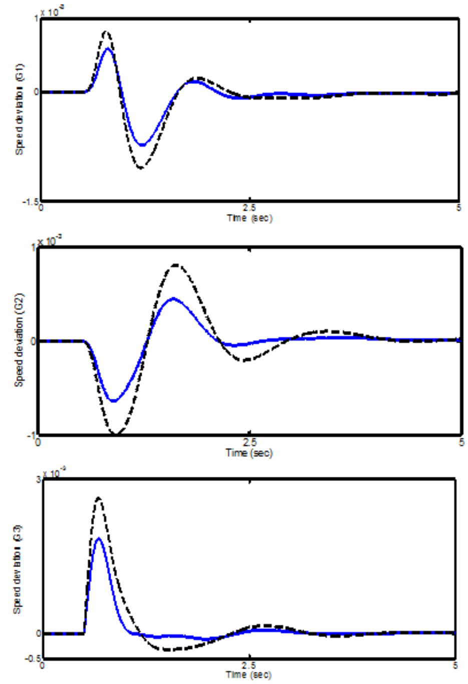

Figure 5. Dynamic responses for Δω in scenario 1 with light loading condition: Solid (HBMOPSS) and Dashed (GAPSS)

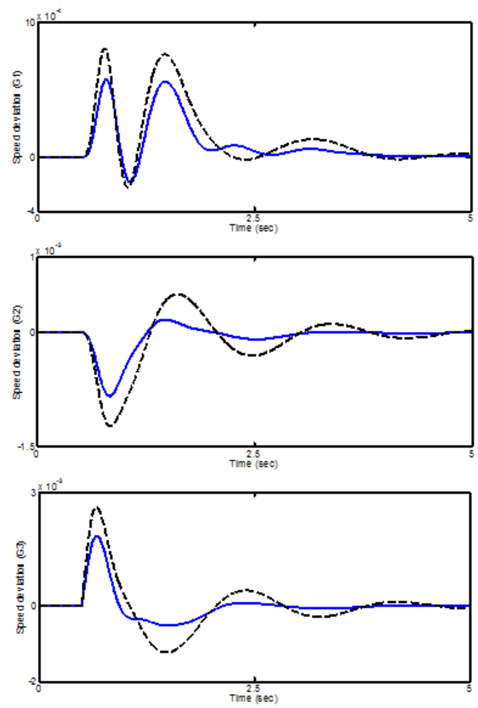

Figure 6. Dynamic responses for Δω in scenario 1 with heavy loading condition: Solid (HBMOPSS) and Dashed (GAPSS)

Figure 4 shows the speed deviations of G_1 , G_2 and G_3 , respectively, under nominal condition. For case under heavy loading condition, the simulation results are shown in Figure 5, respectively. It can be concluded that the proposed PSS achieves robust performance and damps the oscillations very well over a wide range of operating conditions. The simulation results in Figure 6, respectively, shows the speed deviations of generators under light loading conditions. It is clear that the proposed PSSs provide good damping characteristics to low-frequency oscillations and greatly enhance the dynamic stability of power system.

Scenario 2

In this scenario, the performance of the proposed PSSs under transient conditions is verified by applying a 6-cycle three-phase fault at t = 0.5 sec, at bus 7 at the end of line 5-7 is considered [22]. The fault is cleared by permanent tripping of the faulted line. The speed deviations of generators G_2 and G_3 under the nominal, light and heavy loading conditions are shown in Figures 7-9. It can be seen that the HBMO based PSSs achieves good robust performance and provides superior damping in comparison with the genetic algorithm.

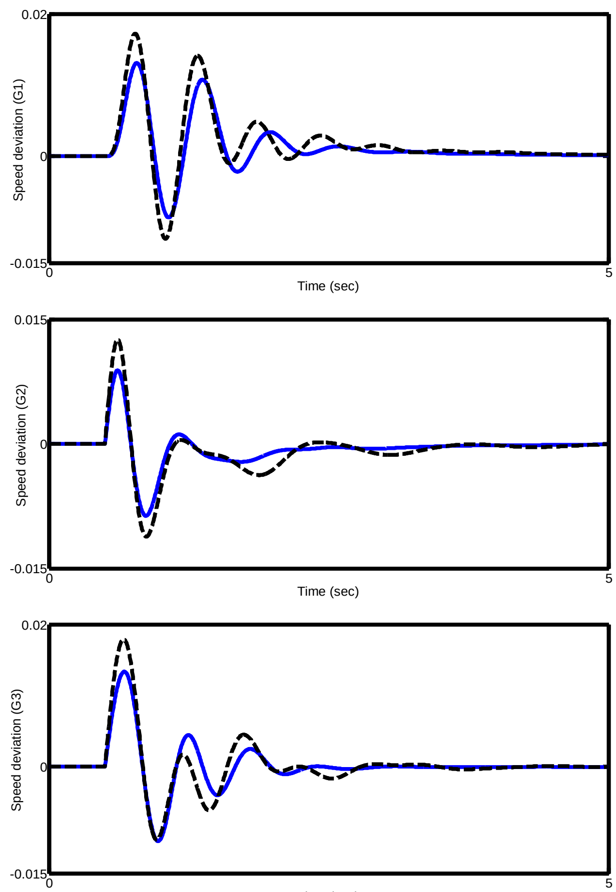

Figure 7. Dynamic responses for Δω in scenario 2 with light loading condition: Solid (HBMOPSS) and Dashed (GAPSS)

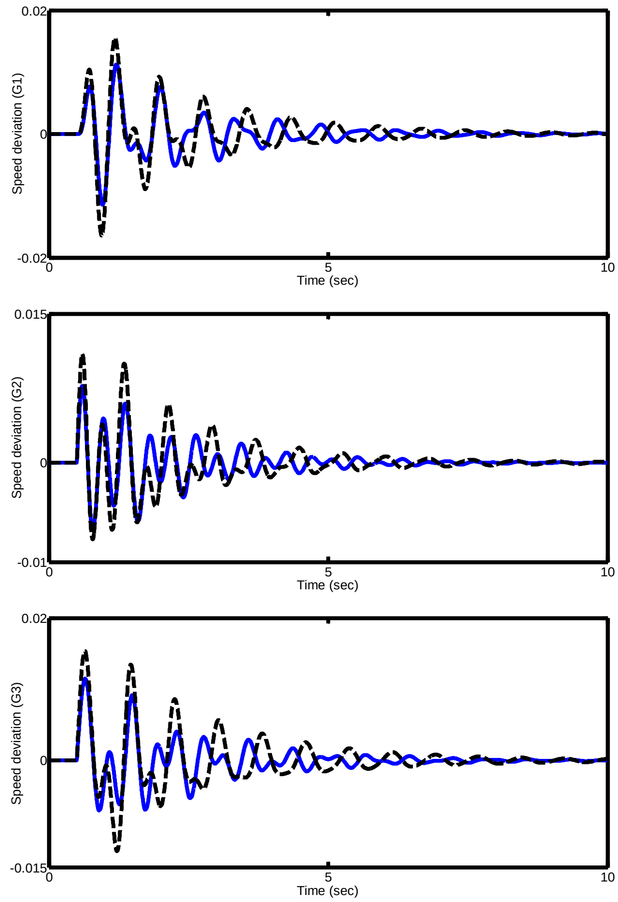

Figure 8. Dynamic responses for Δω in scenario 2 with nominal loading condition: Solid (HBMOPSS) and Dashed (GAPSS).

To evaluate the effectiveness of the supplementary controller, a Figure of Demerit (FD) used as a performance index expressed by:

$$FD = (OS \times 500)^2 + (US \times 1000)^2 + T_s^2, \tag{7}$$

Where, Overshoot (OS), Undershoot (US) and settling time of rotor angle deviation of the second machine is considered for the evaluation of the FD. It is worth mentioning that the lower the value of FD index is the better the system response in terms of time-domain characteristics. Numerical results of the performance robustness for all cases in both two considered scenarios are listed in Table 4. It can be seen that the values of these system performance characteristics with the proposed HBMO based tuned PSSs are much smaller in comparison with the GA based tuned PSSs.

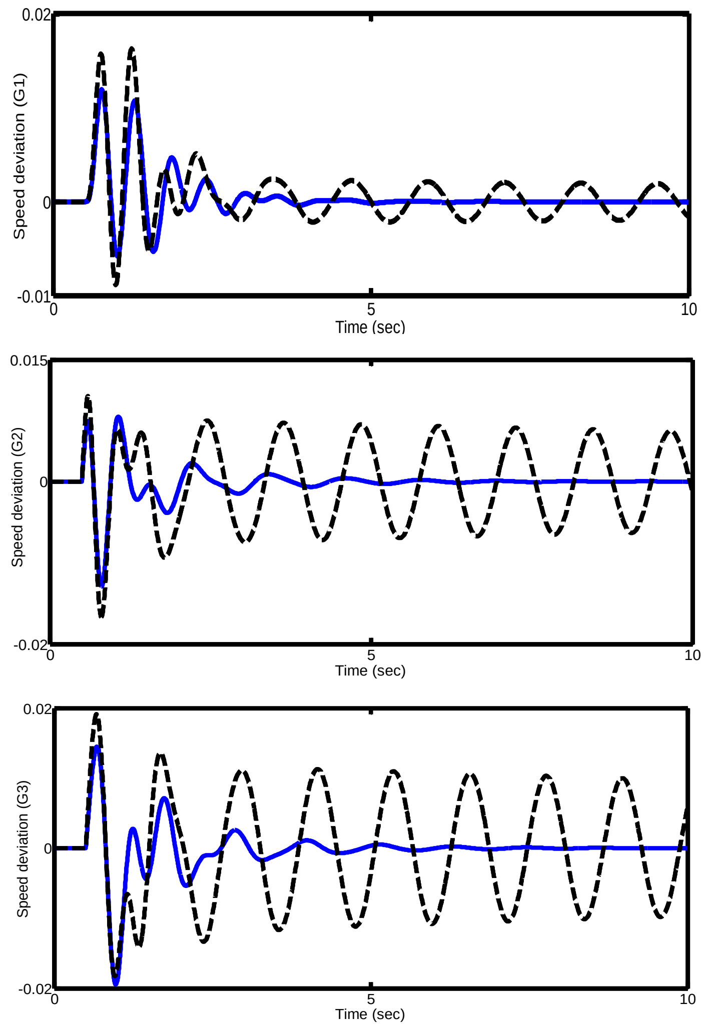

Figure 9. Dynamic responses for Δω in scenario 2 with heavy loading condition: Solid (HBMOPSS) and Dashed (GAPSS)

Table 4. Values of FD index in different operating conditions and scenarios

Method	Scenario 1			Scenario 2		
	Nom.	Heavy	Light	Nom.	Heavy	Light
GAPSS	2.01	4.62	5.11	34.33	54.66	40.23
HBMOPSS	0.945	2.051	2.836	15.32	28.98	25.45

5. Conclusions

In a multi-machine environment, the sequential tuning of PSS (*i.e.*, CPSS) parameters does not guarantee the robustness of the PSS with variable operating condition, location, and severity of faults. For this reason, in this paper, PSSs parameters tuning problem is converted to an optimization problem which is solved by a honey bee mating optimization algorithm. The honey-bee mating process has been considered as a typical swarm-based approach to optimization, in which the search algorithm is inspired by the process of real honey-bee mating. The effectiveness of the proposed method is tested on a multi-machine power system for a wide range of loading conditions. Time-domain simulations show that the oscillations of synchronous machines can be quickly and effectively damped for power systems with the proposed PSSs over a wide range of loading conditions and provides superior damping in comparison with the genetic algorithm.

APPENDIX A

Machine models

$$\dot{\delta}_i = \omega_b(\omega_i - 1) \tag{A.1}$$

$$\dot{\omega}_i = \frac{1}{M_i}(P_{mi} - P_{ei} - D_i(\omega_i - 1)) \tag{A.2}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}) \tag{A.3}$$

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \tag{A.4}$$

$$T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})\, i_{di}\, i_{qi} \tag{A.5}$$

Where,

δ	rotor angle
ω	rotor speed
P_m	mechanical input power
P_e	electrical output power
E'_q	internal voltage behind x'_d
E_{fd}	equivalent excitation voltage
T_e	electic torque
T'_{do}	time constant of excitation circuit
K_A	regulator gain
T_A	regulator time constant
v_{ref}	reference voltage
v	terminal voltage

APPENDIX B

Genetic algorithms are stochastic search techniques based on the mechanism of the natural selection and survival of the fittest [24]. Further, they combine function evaluation with randomized and/or well-structured exchange of information among solutions to arrive at the global optimum. The architecture of the GA implementation can be segregated into three constituent phases, namely: initial population generation, fitness evaluation and genetic operations. The GA control parameters, such as population size, crossover probability and mutation probability are selected, and an initial population of the binary strings of the finite length is randomly generated. Given a random initial population GA operates in cycles called generations, as follows [25]:

- Each member of the population is evaluated using a fitness function.

- The population undergoes reproduction in a number of iterations. One or more parents are chosen stochastically, but strings with higher fitness values have higher probability of contributing an offspring.

- Genetic operators, such as crossover and mutation are applied to parents to produce offspring.

- The offspring are inserted into the population and the process is repeated.

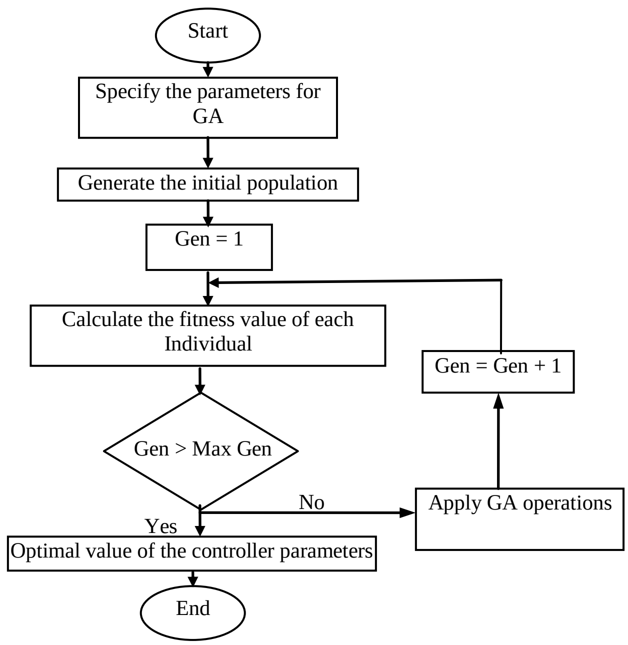

Figure 10. Flowchart of the Genetic algorithm

The crossover is the kernel of genetic operations. It promotes the exploration of new regions in the search space using randomized mechanism of exchanging information between strings. Two individuals placed in the mating pool during the reproduction are randomly selected. A crossover point is then randomly selected and information from one parent up to the crossover point is exchanged with the other parent. Performance method is illustrated below for the simple crossover technique used in this paper.

Parent 1: 1011↓ 1110 $\Rightarrow$ Offspring 1: 10111011

Parent 2: 1010 ↓1011 $\Rightarrow$ Offspring 2: 1010 1110

Another process also considered in this work is the mutation process of randomly changing encoded bit information for a newly created population individual. Mutation is generally considered as a secondary operator to extend the search space and cause escape from a local optimum when used prudently with the selection and crossover schemes [26].

In order to obtain the optimal set of controller parameters, the time domain simulation is performed and the fitness function as given in Eq. (5) is optimized. The computational flow chart of the GA is shown in Figure 10. While applying GA, a number of parameters are required to be specified. Optimization is terminated by the pre-specified number of generations for the genetic algorithm.

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Authors

Ali Nazari received the B.S. and MSc degree in Electrical Engineering from Shahid Rajaee University, Tehran, Iran, in 2000 and 2011 respectively. His areas of interest in research are application of artificial intelligence to power system control design and power system stability.

Amin Safari received the B.Sc. and M.Sc. degrees in Electrical Engineering in 2007 and 2009, respectively. Currently, he is a Ph.D. student of Power Electrical Engineering, Iran University of Science and Technology, Tehran, Iran. His areas of interest in research are Application of artificial intelligence to power system control design, FACTS device and fuzzy sets and systems. He has published more than 60 papers in international journals and conference proceedings. He joined to Islamic Azad University, Ahar branch, Iran, as lecture in 2009.