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Full Length Research Paper

Tuning of power system stabilizers using particle swarm optimization with passive congregation

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Power System Stabilizers (PSSs) are the most well-known and efficient devices to damp the power system oscillations caused by interruptions. This paper introduces a novel algorithm to determine the PSS parameters, using the multi-objective optimization approach called particle swarm optimization with the passive congregation (PSOPC). The tuning of the PSS parameters is usually formulated as the objective function with constraints, including the damping ratio and damping factor. Maximization of the damping factor and the damping ratio of power system modes are taken as the goals or two objective functions, when designing the PSS parameters. The optimization procedure handles the problem-specific constraints using a penalty function. This could enhance the diversity of the swarm and lead to a better outcome. The two-area multi-machine power system, under a wide range of system configurations and operation conditions is investigated, to illustrate the performance of the proposed approach. In this paper, the performance of the proposed PSOPC is compared to the Standard Particle Swarm Optimization (SPSO) and Genetic Algorithm (GA) in terms of parameter accuracy and computational time. The results verify that, the PSOPC is a much better optimization technique, in terms of accuracy and convergence, compared to PSO and GA. Furthermore, nonlinear simulation and eigenvalue analysis based results also confirm the efficiency of the proposed technique.

Key words: Passive congregation, design power system stabilizers (PSS), penalty function, particle swarm optimization.

INTRODUCTION

Constantly increasing intricacy of electric power systems, has enhanced interests in developing superior methodologies for Power System Stabilizers (PSSs). Transient and dynamic stability considerations are among the main issues in the reliable and efficient operation of power systems. Low Frequency Oscillation (LFO) modes have been observed when power systems are interconnected by weak tie-lines (Liu et al., 2004; Messina et al., 1998). The LFO mode, with weak damping, is also called the electromechanical oscillation mode, and it usually happens in the frequency range of 0.1 to 2 Hz. PSSs are the most efficient devices for damping both local mode and inter-area mode small signal LFOs by increasing the system damping, thus enhancing the dynamic stability of the power systems (Anderson and Fouad, 1997). The generators are equipped with PSS, which provides supplementary feedback and stabilizes the signal in the excitation system (Demello and Concordia, 1969). The problem of PSS design is to tune the parameters of the stabilizer so that the damping of the system's electromechanical oscillation modes is increased. This must be done without adverse effects on other oscillatory modes, such as those associated with the exciters or the shaft torsional oscillations. The stabilizer must also be so designed, that it has no adverse effects on a system's recovery from a severe fault. The concept and parameters of PSS have been considered in various studies (Klein et al., 1991;

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Kundur, 1999). The PSS has been usually used for mitigating the influences of LFO modes (Ishimaru et al., 2004).

Currently, many generating plants prefer to use Conventional Lead-Lag Structure of PSS (CPSS), due to the ease of online tuning and reliability (Hongesombut et al., 2004). CPSSs are greatly being used in the power systems, and this may be pursuant to some problems behind utilizing the new methods. Intelligent optimization based methods have been initiated to solve the problems of PSS design (Arredondo, 1997; Dubey and Gubey, 2005; Viveros et al., 2005; Mishra et al., 2007; Wang et al., 2009). Two main techniques used for the parameter tuning of PSS in the power system are sequential tuning and simultaneous tuning. To achieve a set of optimal PSS parameters under different operating conditions, the tuning and testing of PSS parameters must be repeated under different operating conditions of the system. The simultaneous tuning of PSS parameters is generally formulated as a very large scale nonlinear non-differentiable optimization problem (Cai and Erlich, 2002). This type of optimization problem is very difficult to solve by applying traditional differentiable optimization algorithms. Many random investigating techniques, for instance, Genetic Algorithm (GA) and simulated annealing (SA), Tabu search (TS), evolutionary programming (EP), have recently gained acceptance due to their effectiveness and the ability to investigate the near-global optimal results in problem space. Abdel-Magid and Abido (1999, 2000, 2002, 2003) have used the TS, SA, EP and GA to optimize the parameters of the PSSs. The problem of the robust PSS design is formulated as a multi-objective optimization problem to solve it. Modifying damping ratio and damping factor of the lightly damped or un-damped electro-mechanical modes are two objectives. It has been observed that, taking just one of the objectives into account may yield an unacceptable result for another objective. The objective function is devised to optimize the desired damping factor and/or the desired damping ratio of the lightly damped and un-damped modes. In this way, only the unstable or lightly damped oscillation modes are relocated. Zhang and Coonick (2000) have suggested frequency domain based methods for the same purpose which appears to be more appropriate than the others. They proposed a list of objectives and used GA to optimize them. While GA is satisfactory in finding near-global optimal result of the problem, it often yields revisiting the same sub-optimal solution; it needs a very long run time that may be several minutes or even several hours depending on the size of the system under study.

Particle Swarm Optimization (PSO) is a type of random search algorithm that simulates the evolutionary process of nature and shows the excellent characteristic in solving some complex optimization problems. PSO has some attractive characteristics compared to GA and other similar evolutionary techniques. First, this method requires very few parameters to adjust, and thus it is convenient for algorithm parameter optimization where the large amount of computations is required. Secondly, PSO can discover the optimal solutions with a faster convergent speed, because it has just two computations formulae for iteration (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998). Optimization of PSS parameters using standard PSO were reported by Abido (2002), Panda and Ardil (2008). In addition, the design of a particle swarm optimization-based lead-lag power system stabilizer (PSOLLPSS) and particle swarm optimization-based fuzzy logic power system stabilizer (PSOFLPSS) were presented to damp oscillations of the multi-machine system (El-Zonkoly et al., 2009). In recent times, many researchers have been undertaken to modify the act of the Standard PSO (SPSO) to improve its performance.

One of the best improvements on this method has been done by He et al. (2004). He improved the PSO with the passive congregation (PSOPC), which can enhance the convergence rate and the accuracy of the SPSO efficiently. Passive congregation is an important biological force which preserves swarm integrity. It helps each swarm member in receiving a multitude of information from other members, and thus decreases the possibility of a failed attempt at detection or a meaningless search. Furthermore, PSOPC has shown a faster convergence rate than other evolutionary algorithms such as genetic algorithms, and it has very few parameters to adjust. Moreover, by introducing passive congregation, the information sharing mechanism is improved, and the optimization result is more accurate.

Hence, in this study, particle swarm optimizer with the passive congregation is used to determine the optimal gain and time constants of PSSs for the multi-machine system. The algorithm handles the constraints by using a penalty function. The effectiveness of the proposed PSOPC is investigated on a two-area power system under various operating conditions during eigenvalue analysis and some performance indices. The results show that the proposed method achieves good performance for damping LFOs under various operating conditions rather than the SPSO and GA. This provides an excellent negotiation opportunity for the system manager, manufacturer of the PSS and customers to pick out the desired PSS from a set of optimally designed PSSs.

This paper is organized as follows. The proposed controller structure and problem formulation are described next. This is followed by a brief overview of GA, PSO and PSOPC optimization techniques are presented. The power system under study and simulation results are provided, discussed and finally, conclusions

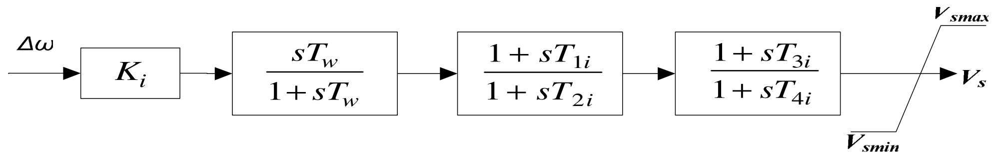

Figure 1. Structure of power system stabilizer.

are given.

PROBLEM FORMULATION

Power system model

In this study, each generator is modeled as a two-axis, six-order model. For all operating conditions, the power system with generators, PSSs, and excitation systems can be modeled by a set of nonlinear differential equations as:

$$\dot{x} = f(x,u) \tag{1}$$

where x = [Δδ, Δω, Eq′, ψd″, Ed′, ψq″] and u are the vector of state variables and the vector of the PSS output signals, respectively.

In the PSS design, the power system is usually linearized in terms of a perturbed value in order to perform the small signal analysis. Therefore, the system in (1) is linearized around an equilibrium operating point of the power system. Equation (2) describes the linear model of the power system:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{2}$$

where A is the power system state matrix, B is the input matrix, C is the output matrix, D is the feed-forward matrix. From (2), the eigen values $\lambda j = \sigma j \pm i\omega j$ of the total system can be evaluated.

Structure of power system stabilizer

The function of a PSS is to generate appropriate torque on the rotor of the machine, in such a way that, the phase lag between the exciter input and the machine electrical torque is compensated. In this study extensively used speed based PSS design is considered where the stabilizing signal is assumed to be proportional to the speed perturbation. The structure of PSS is shown in Figure 1. It consists of a gain block with gain Ki, a signal washout block and two-stage phase compensation blocks. Hence, the transfer function of the ith PSS is given by:

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

where Δωi and Ui are the perturbations of the synchronous speed and the output voltage signal respectively, which are added to the excitation system reference perturbation. The signal was hout block acts as a high-pass filter, with the time constant Tw that allows the signal associated with the oscillations in rotor speed to pass unchanged, and it does not allow the steady state changes to modify the terminal voltages. From the view of the washout function, the value of Tw is generally not critical and may be in the range of 0.5 to 20 s. In this study, it is fixed as 10 s. The phase compensation blocks with time constants T1, T2 and T3, T4 supply the suitable phase-lead characteristics to compensate for the phase lag between the input and the output signals. The five PSS parameters consisting of the four time constants T1 to T4 and the gain K need be optimally chosen for each generator to guarantee optimal system performance under various system configurations and disturbances.

Objective function

During an unstable condition, the declining rate of the power system oscillation is determined by the highest real part of the eigenvalue (damping factor) in the power system and the magnitude of each oscillation mode is determined by its damping ratio. Hence, the objective functions naturally contain the damping ratio and the damping factor in the formulation for the optimal setting of PSS parameters. Therefore, for the optimal tuning of PSS parameters, a multi-objective function may be formulated as follows:

$$\text{Maximize: } F_1 = \min(\text{abs}(\delta_k)) \tag{4}$$

$$\text{Maximize: } F_2 = \min(\zeta_k) \tag{5}$$

$$\text{Minimize: } f(x) = (F_1 + \varpi . F_2)^{-1} = [\min(\text{abs}(\delta_k)) + \varpi . \min(\zeta_k)]^{-1} \tag{6}$$

Subject to

$$\begin{cases} \sigma_j < 0 \\ \alpha < \omega_k < \beta \\ \xi_j \geq \xi_{min} \end{cases} \tag{7}$$

and also

$$\begin{cases} K_{i\,min} \leq K_i \leq K_{i\,max} \\ T_{1i,min} \leq T_{1i} \leq T_{1i,max} \\ T_{2i,min} \leq T_{2i} \leq T_{2i,max} \\ T_{3i,min} \leq T_{3i} \leq T_{3i,max} \\ T_{4i,min} \leq T_{4i} \leq T_{4i,max} \end{cases} \tag{8}$$

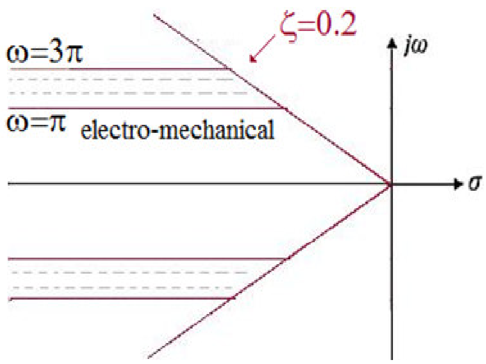

Figure 2. Region of eigenvalue location for objective function F.

where k=1, 2, 3 represent the number of electromechanical modes of oscillation and j=1, 2, 3,…, n. n is the total number of eigen values. i=1, 2, 3, 4 is the number of PSSs. σk is the real part of the kth electro-mechanical mode and ξk =− σk /√ σk ²+ωk ² is the damping ratio of the kth electro-mechanical mode. ξmin is considered experimentally as 0.2. Figure 2 shows the expected performance of the multi-objective function F. Observe that all the oscillation modes can be relocated by the above multi-objective function. In (7), α and β are empirically considered limits of frequency for the electro-mechanical modes. ϖ is a weight for combining both damping factor and damping ratio. The constraint set is made up of bounds of PSS parameters, which can be formulated as (8).The proposed approach employs PSOPC to solve this optimization problem and search for an optimal set of PSS parameters.

Overview of applied optimization methods

Here, we describe an overview of some optimization methods used in this work, to compare the performance of the proposed PSOPC, namely GA and SPSO. After highlighting the operation GA, the procedure of SPSO is given on which the PSOPC is developed.

Genetic algorithm

GA is inspired by biological systems' improved fitness through evolution. The genetic algorithm is advanced by Holland (1975). It is an optimization approach based on the concepts of genetics and natural reproduction and the evolution of the living creatures, in which an optimum solution evolves through a series of generations. A solution to a given problem is represented in the form of a string, called 'chromosome'/solution vector, consisting of a set of elements, called 'genes', that hold a set of values for the optimization variables (Goldberg, 1989).

GAs work with a random population of solution vectors (chromosomes). The fitness of each chromosome is determined by evaluating it against an objective function. To simulate the natural "survival of the fittest" process, best chromosomes exchange information (through crossover or mutation) to produce offspring chromosomes. The offspring solution vectors are then evaluated and used to evolve the population if they provide better solution vectors than weak population members. Usually, the process is continued for a large number of generations/iterations to obtain a best-fit (near-optimum) solution vector. More details on the mechanism of GAs can be found in Goldberg (1989). Four main parameters affect the performance of GAs: population size, number of generations, crossover rate, and mutation rate. Larger population size (that is, hundreds of chromosomes) and large number of generations (thousands) increase the likelihood of obtaining a near-global optimum solution, but substantially increase processing time.

Crossover among parent chromosomes is a common natural process and traditionally is given a rate that ranges from 0.6 to 1.0. In crossover, the exchange of parents' information produces an offspring. As opposed to crossover, mutation is a rare process that resembles a sudden change to an offspring. This can be done by randomly selecting one chromosome from the population and then arbitrarily changing some of its information. The benefit of mutation is that it randomly introduces new genetic material to the evolutionary process, perhaps thereby avoiding stagnation around local minima. A small mutation rate less than 0.1 is usually used. A flowchart for the GA algorithm is shown in Figure 3.

Particle swarm optimization

Particle swarm optimization is a population based stochastic optimization method (Kennedy and Eberhart, 1995). It explores for the optimal solution from a population swarm of moving particle vectors, based on a fitness function. Each ith particle vector represents a potential answer and has a position (Xik) and a velocity (Vik) at the kth iteration in the problem space. Each ith vector keeps a record of its individual best position (Pik), which is associated with its own best fitness it has achieved so far, at any kth step in the iteration process. This value is known as pbesti. Moreover, the optimum position among all the particles obtained so far in the swarm is stored as the global best position (Pgk). This location is called gbest. The new velocity of particle will be updated according to the following equation:

$$V_i^{k+1} = w \times V_i^k + c_1 \times r_1 \times (P_i^k - X_i^k) + c_2 \times r_2 \times (P_g^k - X_i^k) \quad (9)$$

where w is an inertia weight in the first part that represents the memory of a particle during a search, c1 and c2 are positive numbers illustrating the weights of the acceleration terms that guide each particle toward the individual best and the swarm best positions respectively, r1 and r2 are uniformly distributed random numbers in (0, 1), and N is the number of particles in the swarm. The second and the third parts of (10) represent cognitive part and social part respectively. The inertia weighting function in (9) is usually calculated using the following equation:

$$w = w_{max} - (w_{max} - w_{min}) \times iter / iter_{max} \quad (10)$$

where wmax and wmin are the maximum and minimum values of w respectively, itermax is the maximum number of iterations and iter is the current iteration number. The first term in (9) enables each particle to perform a global search by exploring a new search space. The last two terms in (9) enable each particle to perform a local search around its individual best position and the swarm best position. Each particle changes its position based on the updated velocity according to the following equation and Figure 4:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (11)$$

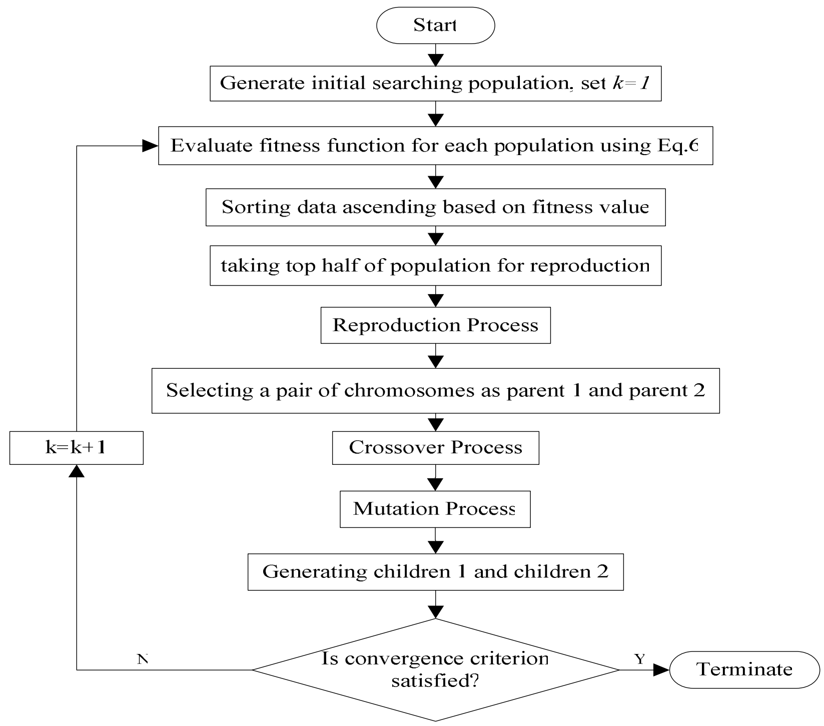

Figure 3. Algorithm of genetic algorithm.

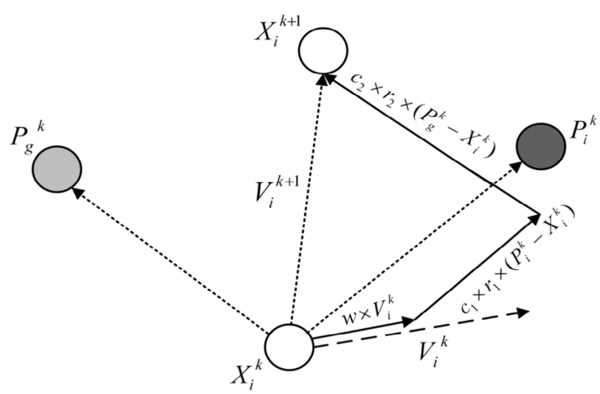

Figure 4. Position update of particle in PSO.

As the PSO's equations reveal, unlike the traditional optimization algorithms, such as Newton's method, the PSO algorithm does not need a mathematical model of the problem. The only information required by the PSO to search for the optimum solution is the evaluation of fitness function.

Particle swarm optimization with passive congregation

In this study, a modified particle swarm optimization with the passive congregation (PSOPC) is proposed to optimally tune PSS in multi-machine power systems. The theory of PSOPC creates an additional part at the end of the velocity update in (9) of SPSO, known as passive congregation part. The basic idea is that individuals need to monitor both their environment and their surroundings. Thus, each group member receives a multitude of information from other members, which may decrease the possibility of a failed attempt at detection or a meaningless search. This kind of information exchange can be realized by a model called passive congregation. Passive congregation is an attraction of an individual to other group members but not display of social behavior. Social congregations usually happen in a group where

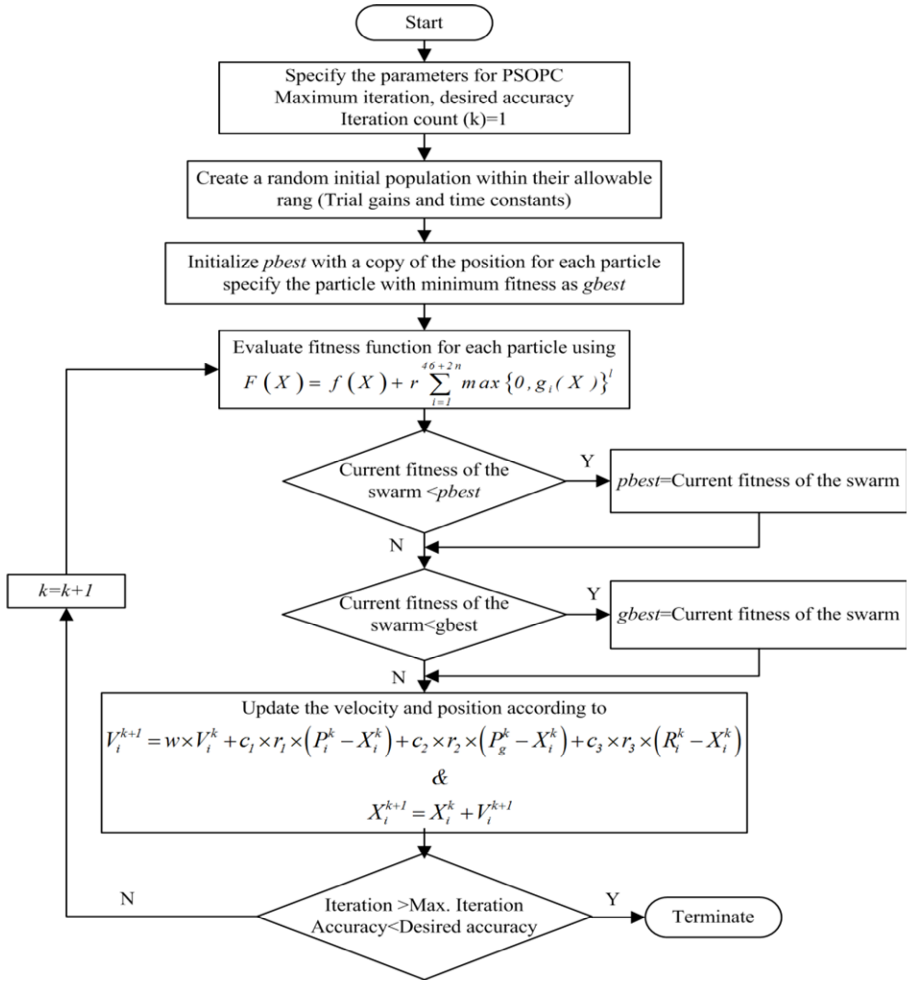

Figure 5. Flowchart of the PSOPC used for the optimization of PSS parameters.

the members are related (sometimes highly related). A variety of inter-individual behaviors are displayed in social congregations, necessitating active information transfer.

From the definitions given earlier, the third part of (9):c2 × r2 × (Pik − Xik) can be defined as passive congregation. However, Pg is the best solution the swarm has found so far, which can be regarded as the place with most food. Fish schooling is one of the representative types of passive congregation and the PSO is inspired by it. Adding the passive congregation model to the SPSO may increase its performance. The update velocity equation in hybrid PSO with the passive congregation (PSOPC) is defined as:

$$V_i^{k+1} = w \times V_i^k + c_1 \times r_1 \times (P_i^k - X_i^k) + c_2 \times r_2 \times (P_g^k - X_i^k) + c_3 \times r_3 \times (R_i^k - X_i^k) \quad (12)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (13)$$

where Rik is a particle selected randomly from the swarm, c3 is the passive congregation coefficient, and r_3 is a uniform random sequence in the range of 0 to 1. It must be noted that each particle obtains passive additional information from another particle that is selected at random. This could increase the diversity of the swarm and lead to an improved result. The particle will oscillate around the weighted mean of global and local best.

On the one hand, if the previous best position and the neighborhood best position are near each other the particle will achieve a local exploration. On the other hand, if the previous best position and the neighborhood best position are far apart from each other, the particle will achieve a more investigative exploration. During the exploration, the neighborhood and previous best position will change and the particle will move from local search back to global search. The restriction factor method, balances the need for local and global search depending on what social conditions are in place. The detailed procedure for updating the position and velocity of individuals for PSOPC algorithm is presented in Figure 5.

Constraint optimization using PSOPC

General constrained nonlinear optimization problem can be defined as follows:

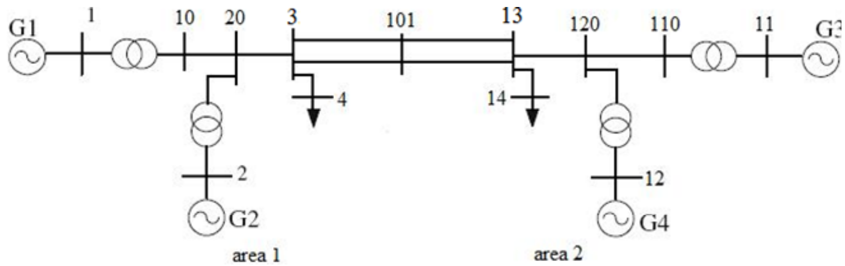

Figure 6. Single line diagram of a two area system.

$$\begin{aligned} \min imize \quad & f(X) \\ subject\ to \quad & g_i(X) \le 0 \quad i = 1,2,...,p \\ & h_j(X) = 0 \quad j = 1,2,...,m \\ & L_k \le X_k \le U_k \quad k = 1,2,...,n \end{aligned} \quad (14)$$

where X is an n dimensional vector of design variables, f(X) is the objective function. g(X) and h(X) are the inequality and equality constraints respectively. L_k, U_k are lower and upper band constraints.

A careful inspection of PSO algorithm reveals that, only the objective function is used to see if the new particle position is more favorable than the previous one. A number of approaches have been taken in the evolutionary computing field to do constraint handling. These methods can be grouped into four categories: methods that preserve the feasibility of solutions, penalty-based methods, methods that clearly distinguish between feasible and unfeasible solutions and hybrid methods. The common approach is penalty method. Penalty methods add a penalty to the objective function to decrease the quality of infeasible solutions.

In this work, the penalty-based method proposed in (Yang et al., 1997) is used and the constraint optimization problem in (14) is replaced with the alternative unconstrained problem as follows:

$$F(X) = f(X) + r\sum_{i=1}^{p+m} q_i(X)^l \quad (15)$$

where f(X) is the original objective function of the problem in (14), r is a penalty factor and l is the power of the penalty function. The function qi(X) is a relative violated function of the constraints, as follows:

$$q_i(X) = \begin{cases} max\{0, g_i(X)\} & 1 \le i \le p \\ \left|h_{i-p}(X)\right| & p+1 \le i \le p+m \end{cases} \quad (16)$$

The parameters r and l are problem dependent and r should be a suitably positive large constant. In the present study, the values set for r and l are 1000 and 2, respectively.

According to Equations (7) and (8), a total of 46+2n inequality constraints should be considered in the optimization of the PSS parameters. Finally, the main objective function may be obtained by substituting the objective function of Equation (6) and inequality constraints presented in Equations (7) and (8), into Equation (15). Therefore, the final objective function (fitness function) for optimal tuning of PSS using PSOPC can be formulated in the following form:

$$F(X) = f(X) + r\sum_{i=1}^{46+2n} max\{0, g_i(X)\}^l \quad (17)$$

The implementation procedure of the proposed PSOPC for the optimal design of PSS parameters is shown as a flowchart in Figure 5.

SIMULATION RESULTS

Power system under study

To demonstrate the application and robustness of PSOPC in tuning PSS, a two-area multi-machine power system (Rogers, 2000) is simulated by using the power system toolbox (PST) (Chow and Rogers, 1993). The single line diagram of the system is shown in Figure 6. In this system, there are two generation areas and two loads interconnected by transmission lines. Each area has two generators. All the generators are equipped with identical speed governors and turbines, which includes exciters, AVRs, and PSSs. The generators and their controls are assumed to be identical. The system is quite heavily stressed, and it has 400 MW flowing on the tie-lines from area 1 to area 2.

The simple model shows the fundamental electromechanical oscillations that are inherent in interconnected power systems. There are three different electromechanical modes of oscillation, which includes two local modes of oscillation corresponding to each area, and one inter-area mode. This system is unstable without PSS and therefore, PSS must be installed with appropriate parameters. Participation factors are useful measures for indicating the best generator for power system stabilizer placement. They show the sensitivity of an eigenvalue to a change in the diagonal elements of the state matrix. If mechanical damping could be applied

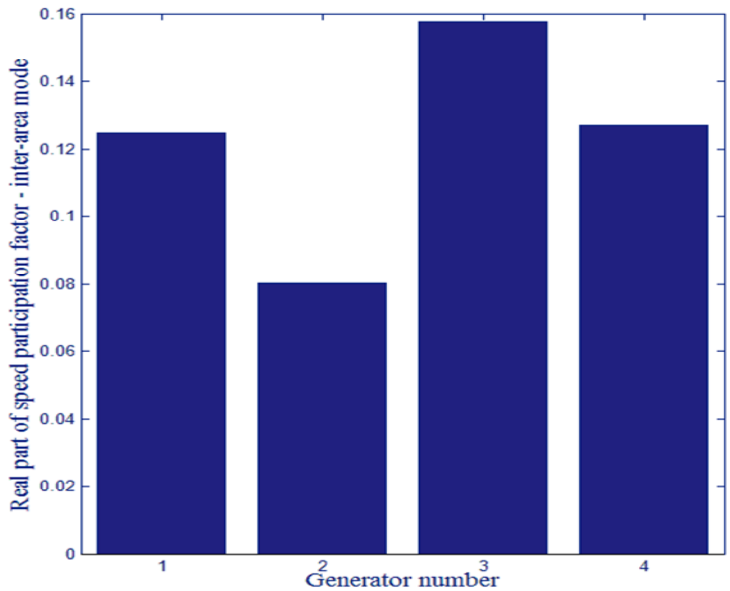

Figure 7. Real part of generator speed participation factors.

to the shaft of a generator, it would appear in the state equations as a negative coefficient on the diagonal of the state matrix in the row, corresponding to the speed change of the generator. If the real part of the participation factor is positive, a damping torque at the corresponding generator's shaft will add the damping to the mode. A bar chart of the real parts of participation factor for the inter-area mode is shown in Figure 7. In this case, all the participation factors are real and positive and a damping torque at any of the generators will add to the damping of the inter-area mode. To analyze the LFO in the system, the following cases representing various operating conditions are studied:

Case 1: Base case (all lines in service).
Case 2: Loss of a line between bus 3 and bus 101.
Case 3: Loss of a line between bus 13 and bus 101.
Case 4: Loss of either of these lines.

Furthermore the above conditions are individually studied with:

1. Without any PSSs.
2. Conventional PSS (CPSS) having the parameters K = 10.00, T1 = 0.05 s, T2 = 0.015 s, T3 = 0.05 s, and T4 = 0.01 s, respectively for all four generators.
3. The PSS parameters optimized using the GA algorithm
4. The PSS parameters optimized using the SPSO algorithm change rows of the state matrix.
4. The PSS parameters optimized using the PSOPC algorithm.

PSOPC-based PSS design and eigenvalue analysis

The optimal tuning of five PSS parameters namely, Ki, T1i to T4i is performed by the PSOPC. Since there are four PSSs, twenty parameters need be optimized. Fortunately, these parameters have upper and lower limits as shown in Table 1. These limits help in reducing the computational times significantly. In this work, the values of α and β are considered as π and 3π, respectively. The weight parameter ϖ is set to be 10, which is derived from the experiences of many experiments conducted on this problem. The optimization procedure following the methods described above was carried out by a specially prepared computer program coded in MATLAB. All the programs were executed on a 2.10 GHz Pentium IV processor with 2GB of Random Access Memory (RAM). To achieve optimum performance in the proposed methodology, the parameters for the three algorithms need to be carefully adjusted. The optimization procedure was terminated when one of the following stopping criteria was met: (i) the maximum number of generations is reached; (ii) after a given number of iterations, there is no significant improvement of the solution.

Table 2 shows the specified parameters for the three algorithms PSOPC, SPSO and GA that are used in this study. First, the system is run without PSS for the four cases mentioned before. Then PSSs are connected to all the four generators and GA, SPSO, and the PSOPC algorithms are used separately to find out the optimum parameters for the PSSs. The final values of the

Table 1. Lower and upper limits of PSS parameters.

Parameters	T1	T2	T3	T4	Kpss
Lower limit	0.01	0.01	0.01	0.01	1
Upper limit	2	2	2	2	50

Table 2. Parameters used for GA, SPSO and PSOPC algorithm.

Parameters	GA	SPSO	PSOPC
Swarm size	25	25	25
itermax	250	250	250
C1	-	2	2
C2	-	2	1
C3	-	-	0.4
wmin	-	0.4	0.45
wmax	-	0.9	0.95
Crossover probability	0.95	-	-
Mutation probability	0.10	-	-

Table 3. Searched gains and time constants of PSSs by the GA, SPSO and PSOPC.

	Unit	K	T1	T2	T3	T4
	G1	11.934	0.0512	0.0241	0.0500	0.0567
	G2	17.033	0.1907	0.0161	0.1021	0.0348
GA optimized parameters	G3	26. 308	0.0675	0.0231	0.0731	0.0364
	G4	15.099	0.0356	0.0151	0.0715	0.0384
	G1	22.5477	0.0489	0.0201	0.0825	0.6231
	G2	12.9182	0.1070	0.0491	0.1032	0.0700
SPSO optimized parameters	G3	27.8645	0.0653	0.0251	0.0800	0.2180
	G4	11.0024	0.0512	0.0235	0.0699	0.3011
	G1	24.4382	0.0834	0.0153	0.0500	0.1670
	G2	15.8664	0.5070	0.0440	0.0487	0.0650
PSOPC optimized parameters	G3	26.3067	0.0675	0.0160	0.0541	0.0158
	G4	23. 4433	0.0356	0.0100	0.0389	0.0100

optimized parameters with the objective function F by the three methods (PSOPC, SPSO and GA) are presented in Table 3. It shows the values of the parameters corresponding to the best fitness achieved by each algorithm after 10 trials. The principal eigen values and the damping ratios obtained for all operating conditions with no PSS, CPSS and after application of various optimization methods in the system are given in Table 4. The bolded values represent the greatest damping factor, and the values enclosed in square frames represent the smallest damping ratio values. For the system without PSS, it can be observed that some of the modes are weekly damped and for some operating conditions the system is unstable. The unstable cases are highlighted in Table 4. The addition of PSSs improves the damping in the system oscillations. The results clearly show that the performance of PSOPC optimized PSSs is better than SPSO and GA optimized PSSs and CPSS.

All damping factors are smaller than -1.0 and all damping ratios are greater than 0.2 when the proposed

Table 4. Eigenvalues and damping ratios with and without PSSs for four cases.

	Case 1	Case 2	Case 3	Case 4
	0.044387 ± 4.0309i, -0.0110	-0.0231 ± 3.297i, -0.0700	0.0413 ± 3.3227, -0.0124	0.0014 ± 2.5144i, -0.00057
Without PSSs	-0.55258 ± 7.302i, 0.07546	-0.5477 ± 7.2853i, 0.0750	-0.5720 ± 7.2695i, 0.0784	-0.5784 ± 7.2473i, 0.0796
	-0.55317 ± 7.383i, 0.07471	-0.5643 ± 7.3284i, 0.0768	-0.5412 ± 7.3456i, 0.0735	-0.5355 ± 7.2801i ,0.0734
	-0.52484 ± 3.8483i, 0.1351	-0.4636 ± 2.9055i, 0.1576	-0.4511 ± 2.9236i, 0.1525	-0.4469 ± 1.7633i, 0.2457
With CPSS	-3.2505 ± 8.2795i, 0.36545	-2.8394 ± 7.8648i, 0.3396	-2.9202 ± 7.7275i, 0.3535	-2.6431 ± 8.0318i, 0.3126
	-3.248 ± 8.5995i, 0.35333	-3.0725 ± 7.9076i, 03622	-2.9536 ± 8.0302i, 0.3452	-2.9310 ± -8.2929i, 0.3332
	-0. 9499 ± 3.5917i, 0.255	-0. 8084 ± 3.4146i, 0.2342	-0.8002 ± 3. 304i, 0.2353	-0.8653 ± 3. 558i, 0.2368
With GA	-4.0428 ± 5.8045i, 0.5716	-3.7688 ± 6.0058i, 0.5315	-3.8675 ± 5.9526i, 0.6866	-3.59805 ± 6.2598i, 0.6586
	-5.5160 ± 5.22030i, 0.7108	-5.1901 ± 5.6320i, 0.6777	-5.0132 ± 5.7291i, 0.5760	-5.1746 ± 5.8396i, 0.5788
	-0. 9944 ± 3.6930i, 0.2600	-0. 8168 ± 3.5782i, 0.2225	-0.8105 ± 3.5297i, 0.2237	-0. 7829 ± 3.5290i, 0.2170
With SPSO	-5.4132 ± 5.8041i, 0.7148	-5.2506 ± 5.8287i, 0.6693	-5.3782 ± 57275i, 0.6845	-5.2328 ± 5.9824i, 0.6584
	-5.5969 ± 5.4586i, 0.6914	-5.2227 ± 6.0117i, 0.6558	-5.0100 ± 6.1150i, 0.6338	-5.1627 ± 6.1754i, 0.6414
	-1.2134 ± 3.5317i , 0.3258	-1.1412 ± 3.5233i, 0.3081	-1.1324 ± 3.5222i, 0.3060	-1.1254 ± 3. 5175i, 0.3047
With PSOPC	-6. 3034 ± 4.7931i, 0.7977	-5.9715 ± 4.9960i, 0.7670	-5.8049 ± 5.1216i, 0.7499	-5.9465 ± 5.3284i, 0.7448
	-7.2232 ± 5.9910i, 0.7697	-6.4870 ± 6.5369i, 0.7044	-6.6810 ± 6.3634i, 0.7241	-6.1758 ± 6.8565i, 0.6693

method is applied. The results from the SPSO show that, the minimum damping ratio and the maximum damping factor, under all cases are better than the results obtained by the use of CPSS and GA. Also, the results from the PSOPC are better than those from SPSO. It means that the addition of passive congregation part can increase the system dynamic stability. The principal eigen values are drawn in the s-plane, shown in Figure 8. In Figure 8, it not only shows that the proposed PSOPC can shift the unstable or lightly damped oscillation modes but also shift other oscillation modes more to the left in the s-plane.

Nonlinear time-domain simulation

A number of time domain simulations have been performed to demonstrate the efficiency of tuning of PSS parameters, using the proposed PSOPC method. In these tests, to evaluate the effectiveness of the PSOPC based tuned PSS using the proposed multi-objective function, a 200-ms three-phase fault is applied at bus 3 and a fault between the bus 3 and bus 101 is cleared in 0.05 s at the near end. After a further 0.05 s, remote end circuit breaker at bus 101 is operated for the complete clearance in each case. From Figures 9 to 12, line powers from bus 3 to 101 are shown for illustration. Observe that with the optimally tuned parameters using PSOPC, the system reaches the steady state slightly faster than using other tuning methods under any system operating condition. The speed deviations of generators G1, G2, G3 and G4 under the fault at bus 3 are shown in Figures 13 to 16, respectively.

These time domain simulations are also in well

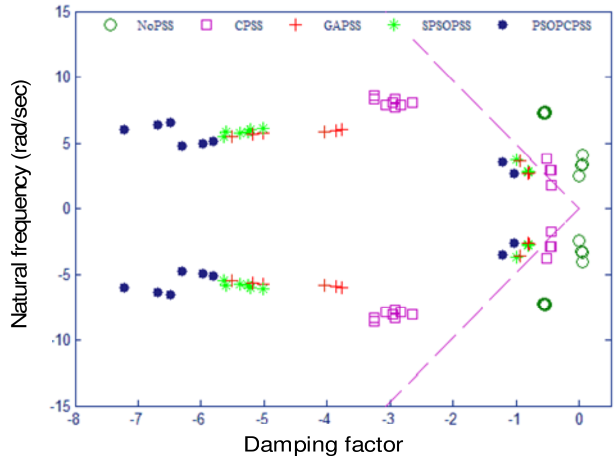

Figure 8. The searched eigenvalues with the objective function for the four cases.

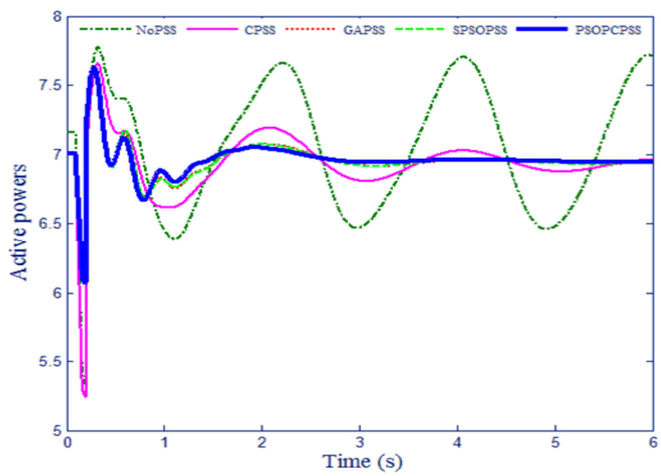

Figure 9. The line powers from bus 3 to 101 for the case 1.

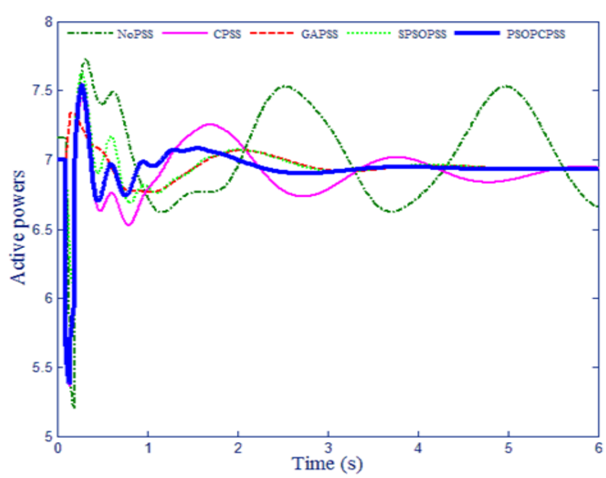

Figure 10. The line powers from bus 3 to 101 for the case 2.

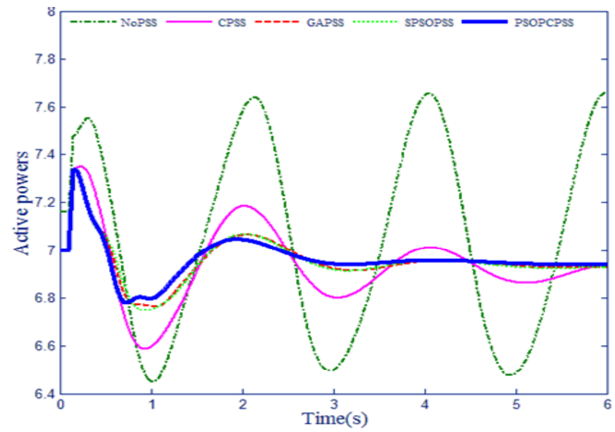

Figure 11. The line powers from bus 3 to 101 for the case 3.

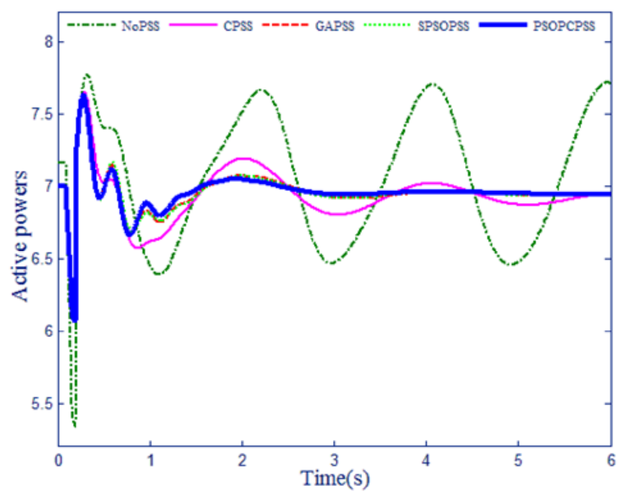

Figure 12. The line powers from bus 3 to 101 for the case 4.

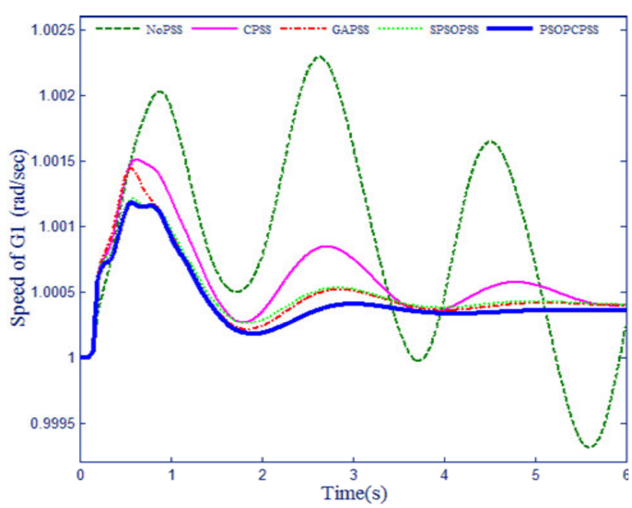

Figure 13. Speed response of generator G1.

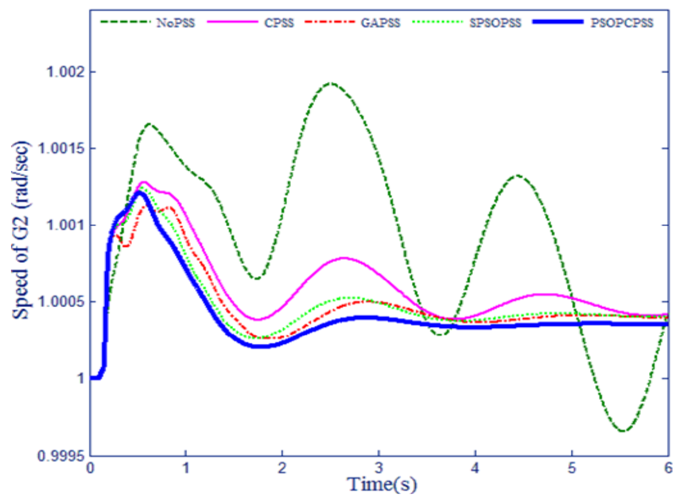

Figure 14. Speed response of generator G2.

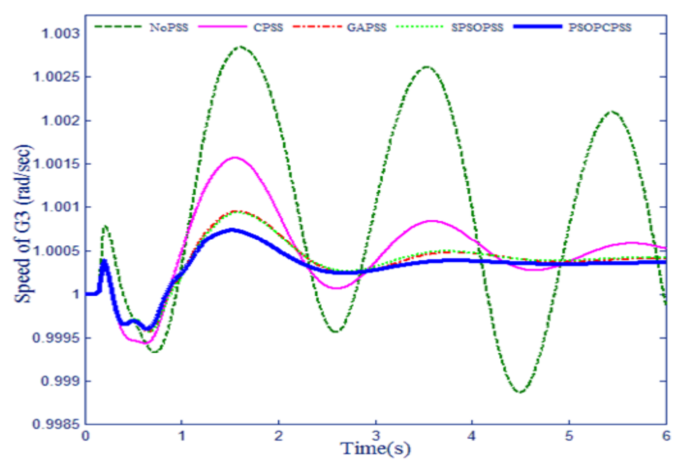

Figure 15. Speed response of generator G3.

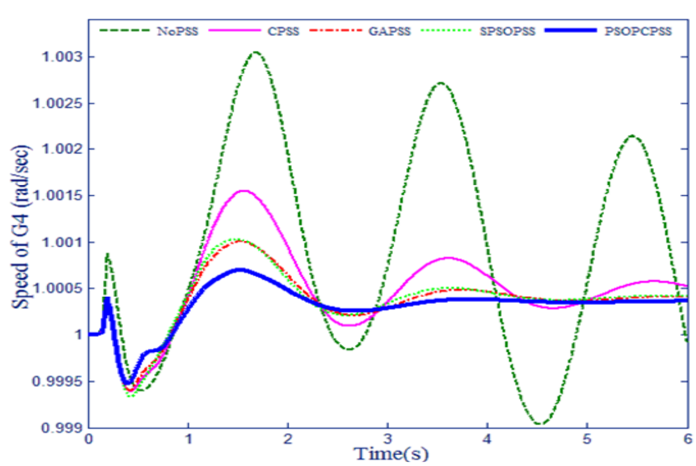

Figure 16. Speed response of generator G4.

Table 5. Iterations and time required by GA, SPSO and PSOPC algorithms.

	Best result			Average result			Worst result		
	GA	SPSO	PSOPC	GA	SPSO	PSOPC	GA	SPSO	PSOPC
Iterations	195	120	35	217	140	41	240	160	47
Elapse time (s)	54000	25694	6247	56936	27847	6600	59872	30000	6953
Best fitness value	0.9145	0.8710	0.8047	0.9655	0.9016	0.8351	1.0165	0.9322	0.8656

agreement with the results of eigenvalue analysis. The addition of PSSs improves the damping in the system oscillations. It can be seen that the PSSs tuned using the proposed method achieve good results and provide superior damping, in comparison to the case when either SPSO or GA is used. All of these figures represent large signal stability of the test systems with optimum PSSs. Furthermore, it seems that PSOPC based PSSs show better performances in most of the cases. It is clear that the newly proposed method is quite efficient to damp out the local modes, as well as the inter-area modes of oscillations. This illustrates the potential and the superiority of the proposed design approach to get the optimal set of PSS parameters.

DISCUSSION

In order to have a fair comparison among all the three algorithms, same number of iterations and same ranges of the parameters are used. To compare the accuracies of these algorithms, a maximum number of iteration cycles are considered as a stopping condition and the results obtained from these algorithms are compared. The values of different variables relevant for each algorithm are summarized in Table 2. For all the algorithms, the initialization is done randomly within the limits of the PSS parameters. The best fitness value achieved by each algorithm is a measure of the strength of the algorithm. Each algorithm is run for 10 times and the average elapsed time is considered as a criterion for the computational time. Table 5 illustrates the results obtained by PSOPC, SPSO and GA algorithms. The results indicate the iteration count, elapse time and the convergence of the solution or success is met. It is clearly obvious that, the proposed algorithm requires extremely fewer iterations and less computational time to reach a predefined threshold as compared to other algorithms.

Hence, it can be concluded that the PSOPC is the best among the aforementioned algorithms, in terms of accuracy and convergence speed. Furthermore, Table 5 compares the best fitness values achieved by the algorithms in 10 trials. It can be observed that as a whole, the performance is the best for the PSOPC. The fitness achieved by it is 0.8047. This is the lowest among the three algorithms. Also, the worst result obtained by the PSOPC is even better than the best result obtained by GA and SPSO. The result shows that, using PSOPC for optimal tuning of PSSs has faster convergence rate compared to SPSO and GA, as it can be seen that the elapsed time for PSOPC is the least, which is approximately a quarter of the computation times for SPSO and GA. In addition, the fitness value versus iteration characteristics for each algorithm is depicted in Figure 17. Here the fitness corresponds to the average fitness of the 10 trials. Figure 17 confirms the success of the optimization process by using PSOPC algorithm.

Conclusion

In the present paper, an application of a hybrid PSO with the passive congregation algorithm to determine the optimal tuning of PSSs parameters is introduced. The design problem of PSSs parameters selection is converted into an optimization problem which is solved by the PSOPC technique with the eigen value-based multi-objective function. Maximization of the minimum damping ratio and minimum damping factor of dominant oscillatory modes are employed as two objectives to optimize the PSS parameters. Eigenvalue analysis shows acceptable damping of system modes, particularly the low-frequency modes, when the PSSs are tuned by PSOPC.

Time domain simulations also show that, the oscillations of synchronous machines can be rapidly damped for power systems with the proposed PSSs over a wide range of conditions. Besides, the comparative performances of three optimization algorithms, namely PSOPC, SPSO and GA for finding the optimal parameters of power system stabilizers in a multi-machine have been presented. Based on ten trial runs, it is observed that, the PSOPC consistently performs the best in solving the tuning problem. This indicates the efficiency of the proposed PSOPC algorithm in tuning PSS and stabilizing the system under LFOs.

NOMENCLATURE: ***Δ,*** rotor angle; *w,* inertial weight; ***Δω,*** speed deviation; ***iter,*** the current iteration number; T_1, T_2, T_3, T_4, lead/lag time constants of *PSS;* ***G,*** the maximum

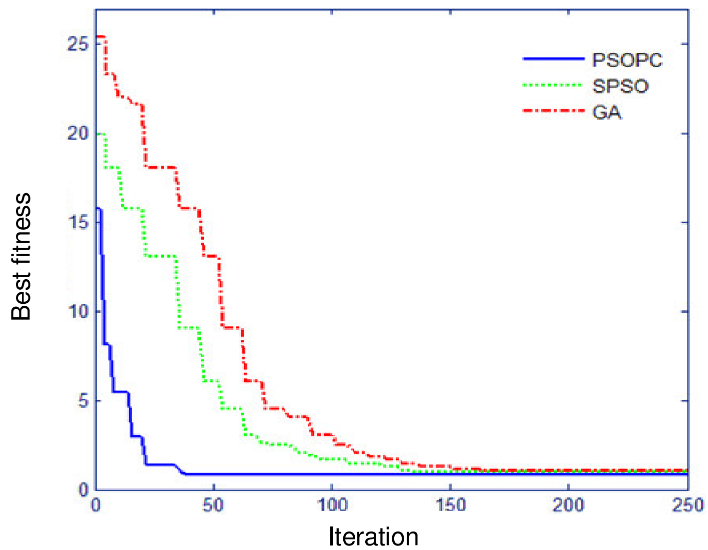

Figure 17. Average best fitness vs. iteration curve.

number of iterations; ***ξ,*** damping ratio; ***$pbest_i$*** pbest of agent I; ***$ξ_{min}$,*** expected damping; ***gbest,*** gbest of group; ***ʃ,*** damping factor; ***r,*** random number between 0 and 1; ***E_q,*** *q*-axis component of stator voltage; ***g(X),*** inequality constraints; ***E_d,*** *d*-axis component of stator voltage; ***h(X),*** equality constraints; ***$ψ_d$,*** *d*- axis component of stator flux linkage; ***L_k,*** lower band constraints; ***$ψ_q$,*** *q*-axis component of stator flux linkage; ***U_k,*** upper band constraints; ***K_i,*** the power system stabilizer gain; ***$q_i(X)$,*** relative violated function of the constraints; ***T_w,*** the time constant of the signal washout block; ***l,*** the power of the penalty function; ***V_s,*** the output voltage of the phase compensator; ***k,*** the number of electromechanical modes; □**,** weight constant.

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