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PSO BASED PSS DESIGN FOR TRANSIENT STABILITY ENHANCEMENT

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Abstract: *In this paper, optimal tuning the parameters of a power system stabilizer (PSS) controller for the power system transient stability enhancement is introduced. The design problem of the proposed PSS is converted to an optimization problem with the time-domain based objective function which is solved by using particle swarm optimization (PSO) technique with a robust ability in order to find the most promising results. The dynamic performance PSS controller is evaluated on the basis of a multi-machine power system exposed to the diverse disturbances by comparison with the genetic algorithm-based damping controller. By virtue of the nonlinear time-domain simulation and some performance indices studies, the performance of the proposed PSS controller is tested and observed. The results show that the tuned PSO based PSS damping controller by the proposed fitness function has an excellent capability in damping power system low frequency oscillations, as well as it significantly improves the dynamic stability of the power systems. In addition, the results reveal that the performance of the designed controller is better than the genetic algorithm based stabilizer.*
Keywords: *Multi-machine power system, power system stabilizer (PSS), transient stability, particle swarm optimization (PSO), genetic algorithm (GA).*

1. Introduction

Stability of power system is one of the pivotal facets in electric system operation, since the power system is required to maintain its frequency and voltage levels at the nominal values under any disturbance, such as a sudden increase in the load, loss of one generator or switching out of a transmission line during a fault [1]. There have been spontaneous system oscillations at very low frequencies in order of 0.2-3.0 Hz. through the enhancement of interconnection of large electric power systems. They may continue for an extended period of time soon after the initiation. In some instances, they would proceed to grow, causing system separation in case of inadequate damping. In addition, low frequency oscillations present limitations on the power-transfer capability. In order to develop system damping, the generators are provided with Power System Stabilizer (PSS), which yield supplementary feedback stabilizing signals in the excitation system. PSS augments the power system stability limit and extend the power-transfer capability through developing the system damping of low frequency oscillations related to the electromechanical modes [2].

PSS parameter tuning's problem is a complex exercise. Several traditional methods have been reported in the literature apropos of design PSS, such as the eigenvalue assignment, gradient procedure for optimization, mathematical programming, and the modern control theory [2-5]. However, since these traditional techniques are iterative and entail heavy computation burden and slow convergence, they are time consuming. Further, the search process is liable to be trapped in local minima and the acquired solution cannot guarantee the optimal parameters for system [6]. In most cases, proposals concerning PSS parameter tuning are rested upon small disturbance analysis, which necessitates the linearization of the system entailed. Nevertheless, linear techniques may not appropriately acquire the system's complex dynamics, particularly under severe disturbances.

Heuristic population-based optimization techniques like genetic algorithm (GA), tabu search, evolutionary programming and simulated annealing, are the fastest growing optimization technique in recent years because of its capability in solving a special sort of real-world problems symbolized as high dimension, non-linearity, non-differentiability, non-convexity and multi-modal, which constitute the traditional derivative-based technique's deficiency. Heuristic techniques have been applied for PSS parameter optimization [7-15]. In recent years, Particle Swarm Optimization (PSO) technique considered to be an auspicious algorithm in handling the optimization problems. Being inspired by social behavior of bird flocking or fish schooling, PSO is a population based stochastic optimization method [16]. Though PSO has several similarities with Genetic Algorithm (GA), including initialization of population of random solutions and looking

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for the optimal by updating generations, PSO, in contrast to GA, has no evolution operators like crossover and mutation. PSO's most auspicious superiority to GA arises from its algorithmic simplicity, since it employs smaller amount of parameters and facile to carry out [17-18]. In PSO technique, the potential solutions, known as particles, fly through the problem space by tracking the current optimum particles [18]. Therefore, in the present work PSO technique has been used to optimally tune the parameters of the PSS.

In this study, PSS-based damping controller design using PSO algorithm is proposed. The design problem of the proposed controller is transformed into an optimization problem. Then, PSO algorithm is employed to solve this optimization problem with the aim of getting optimal settings of PSS parameters. The optimal location of PSS selected based on Participation Factor (PF) analysis. Proposed controller's effectiveness is verified by a three-machine nine-bus power system under diverse severe disturbances by comparison with the GA based damping controller through the nonlinear time simulation and a number of performance indices. The results analysis reveals that the proposed technique attains the desired performance for damping the low frequency oscillations under a variety of disturbances. It also demonstrates that the proposed method is better than the GA based damping controller.

2. Modeling of Flux Decay Model and Fast Exciter

In this study, we use the flux decay model with static exciter for nonlinear time-domain simulations. The mathematical model comprises differential equations with regard to machine and exciter dynamics, and the algebraic equations corresponding to the stator and network equations [19]. The differential-algebraic equations for the *m* machine, *n* bus system with static exciter as follows:

2.1. Differential Equations

The differential equations of the machine and the exciter are given as in [19] where the various symbols are defined:

$$\frac{d\delta_i}{dt} = \omega_s(\omega_i - 1) = \omega_s \Delta\omega_i \tag{1}$$

$$\frac{d\omega_i}{dt} = \frac{P_{mi}}{M_i} - \frac{E'_{qi} i_{qi}}{M_i} - \frac{(x_{qi} - x'_{di}) i_{di} i_{qi}}{M_i} - \frac{D_i(\omega_i - 1)}{M_i} \tag{2}$$

$$\frac{dE'_{qi}}{dt} = -\frac{E'_{qi}}{T'_{doi}} - \frac{(x_{di} - x'_{di}) i_{di}}{T'_{doi}} + \frac{E_{fdi}}{T'_{doi}} \tag{3}$$

$$\frac{dE_{fdi}}{dt} = -\frac{E_{fdi}}{T_{Ai}} + \frac{K_{Ai}}{T_{Ai}}\left(V_{ref,i} + V_{PSS,i} - V_i\right) \tag{4}$$

for $i = 1, \ldots, m$

2.2. Stator Algebraic Equations

The stator algebraic equations explain the electrical variables pertaining to the stator windings. The stator algebraic equations expressed as [19]

$$V_i \sin(\delta_i - \theta_i) + r_{si} i_{di} - x_{qi} i_{qi} = 0 \tag{5}$$

$$E'_{qi} - V_i \cos(\delta_i - \theta_i) - r_{si} i_{qi} - x'_{di} i_{di} = 0 \tag{6}$$

for $i = 1, \ldots, m$

2.3. Network Equations

In this study, the current-balance form [19] is used and the loads are assumed to be constant impedance and converted to admittances. In power system with *m* generators, the nodal equation can be written as

$$\begin{bmatrix} \bar{I}_1 \\ \vdots \\ \bar{I}_m \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \left[\bar{Y}'\right] \begin{bmatrix} \bar{V}_1 \\ \vdots \\ \vdots \\ \bar{V}_n \end{bmatrix} \tag{7}$$

$$\bar{I}_i = (i_{di} + j i_{qi})\, e^{j(\delta_i - \pi/2)} \qquad i = 1, \ldots, m \tag{8}$$

where $\bar{I}_1, \ldots, \bar{I}_m$ are the complex injected generator currents at the generator buses. Assume that the modified $\bar{\mathbf{Y}}_{\mathbf{bus}}$ represented as $\bar{\mathbf{Y}}'$ be divided as

$$\left[\bar{\mathbf{Y}}'\right] = \begin{array}{c} \\ \mathbf{m} \\ \mathbf{n-m} \end{array} \begin{array}{c} \begin{array}{cc} \mathbf{m} & \mathbf{n\text{-}m} \end{array} \\ \left[\begin{array}{c:c} \bar{\mathbf{Y}}_1 & \bar{\mathbf{Y}}_2 \\ \hdashline \bar{\mathbf{Y}}_3 & \bar{\mathbf{Y}}_4 \end{array}\right] \end{array} \tag{9}$$

Inasmuch as there are no injections at buses $m+1, \ldots, n$, we can leave them out in order to obtain

$$\begin{bmatrix} \bar{I}_1 \\ \vdots \\ \bar{I}_m \end{bmatrix} = \left[\bar{Y}_R\right] \begin{bmatrix} \bar{V}_1 \\ \vdots \\ \bar{V}_m \end{bmatrix} \tag{10}$$

where $\bar{\mathbf{Y}}_{\mathbf{R}} = \bar{\mathbf{Y}}_1 - \bar{\mathbf{Y}}_2 \bar{\mathbf{Y}}_4^{-1} \bar{\mathbf{Y}}_3$ is the desired reduced matrix. The reduced matrices for every network condition (pre-fault, during and after fault) are calculated on account of the power system under study.

2.4. PSS Structure Network

A widely speed based used conventional lead-lag PSS is considered throughout the study [19-20]. It can be described as

$$V_{PSS} = K_{PSS} \frac{sT_W}{1+sT_W} \left[\frac{1+sT_{1PSS}}{1+sT_{2PSS}} \frac{1+sT_{3PSS}}{1+sT_{4PSS}} \right] \Delta\omega \quad (11)$$

The structure comprises a gain block with gain K_{PSS}, as well as a signal washout block and two-stage phase compensation blocks. The input signal of the proposed method is the speed deviation ($\Delta\omega$) and the output is the stabilizing signal (V_{PSS}), which is supplemented to the reference excitation system voltage. The signal washout block serves as a high-pass filter, with the time constant (T_W), high enough to allow signals associated with oscillations in the input signal to pass unchanged. From the washout function's point of view, the value of T_W is not critical and can be within the range of 1 to 20 seconds [2]. The phase compensation block (time constants T_{1PSS}, T_{2PSS} and T_{3PSS}, T_{4PSS}) yields the promising phase-lead characteristics in order to make up for the phase lag between input signals and output signals.

3. PSO Technique

A novel population based optimization approach, known as particle swarm optimization (PSO) approach, was initially presented in [16]. This new approach includes a number of advantages. It is facile, fast and can be coded in few lines as well as its storage requirement is minimal [17].

In addition, this approach is advantageous over evolutionary and genetic algorithms in some ways. First, PSO has memory. In other words, every particle remembers its best solution (local best) and the group's best solution (global best). One further advantage of PSO arises from the fact that the initial population of the PSO is maintained and therefore not required applying operators to the population, a process that is time and memory storage consuming [16-17].

In PSO based method, the trajectory of each individual situated in the search space is modified by dynamically changing each particle's velocity, in line with its own flying experience and other particles' flying experience in the search space. The position and *i*th particle's velocity vectors in the D-dimensional search space is stated as $X_i = x_{i1}, x_{i2}, \ldots, x_{id}$ and $V_i = v_{i1}, v_{i2}, \ldots, v_{id}$. In accordance with a user defined fitness function, suppose that the best position of each particle, which corresponds to the best fitness value (*pbest*) acquired by that particle at time, be $P_i = p_{i1}, p_{i2}, \ldots, p_{id}$, and the global version of the PSO keeps track of the overall best value (*gbest*), and its location, acquired thus far by any particle in the population. So, the new velocities and the positions of particles for the next fitness evaluation are represented as follows [17,21]:

$$v_{id}^{(t+1)} = w * v_{id}^{(t)} + c_1 * r_1(\,) * (p_{id}^{(t)} - x_{id}^{(t)}) + c_2 * r_2(\,) * (p_{gd}^{(t)} - x_{id}^{(t)}) \quad (12)$$

$$x_{id}^{(t+1)} = x_{id}^{(t)} + v_{id}^{(t+1)} \quad (13)$$

where, p_{id} and p_{gd} are *pbest* and *gbest*. The positive constants c_1 and c_2 are the cognitive and social components, which are the acceleration constants responsible for varying the particle velocity towards pbest and gbest, respectively. Variables r_1 and r_2 are chosen as two random functions based on uniform probability distribution functions in the range $[0, 1]$. The inertia weight w responsible for balancing between local and global searches and therefore necessitating less iteration for the algorithm to converge [22]. The inertia weight is given in (12) as follows:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} * iter \quad (14)$$

where, $iter_{\max}$ is the iterations' maximum number and $iter$ is the iteration's current number. Equation (14) describes how the inertia weight is updated, assuming $w_{\max}$ and $w_{\min}$ are the initial and final weights, respectively.

4. Proposed Design Approach

In this section the proposed approach is illustrated as follows. First, the location of the PSS is identified in a multi-machine power system using participation factor technique [23]. Then, PSO technique is proposed in this paper to search for optimal parameters setting.

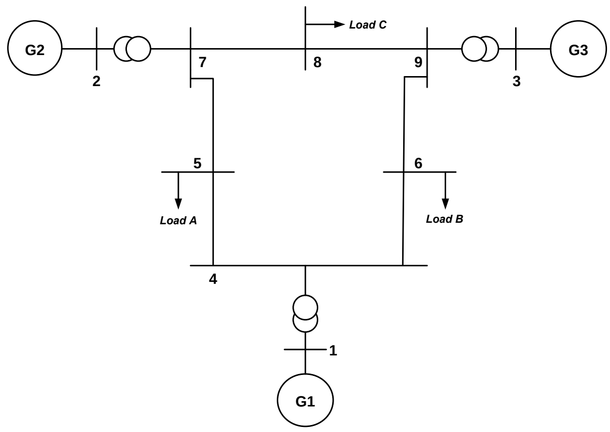

Figure 1. System under study

4.1. Test System and Optimal PSS Location

In this study, three-machine, nine-bus power system shown in Figure 1 is considered. This is also the system appearing in [1] and [19] and widely used in the literature.

The base MVA is 100, and system frequency is 60 Hz. The system data are given in Appendix A. The system has been modeled in the Matlab/SIMULINK environment using (1)-(11).

Table 1. System eigenvalue and participation factor analysis

Eigenvalues	Frequency	Damping Ratio	Machine Participation Factor		
			G1	*G2*	*G3*
-1.3738 ± 11.7499i	1.8828	0.1161	0.0087	0.2388	1
-0.3831 ± 7.8846i	1.2563	**0.0485**	0.4634	1	0.2001

Table 2. Optimal PSS parameters using PSO and GA technique

Type of algorithm	K_{PSS}	T_{1PSS}	T_{2PSS}	T_{3PSS}	T_{4PSS}
PSO	7.0277	0.7526	0.0100	0.5454	0.4598
GA	3.8745	0.2574	0.0278	0.3168	0.0308

The open loop system eigenvalue and participation factor analysis shown in Table 1. The second electromechanical mode has a very low damping ratio equal to (0.0485) in which **Generator no. 2** has the significant participation factor of that mode. Therefore, optimal PSS is located at machine number 2.

4.2. Objective function and PSS tuning

In the likelihood of the above-mentioned lead-lag structured PSS, the washout time constant is usually indicated. This paper uses washout time constant as $T_W = 10$ sec. The stabilizer gain K_{PSS} and the time constants T_{1PSS}, T_{2PSS}, T_{3PSS} and T_{4PSS} are to be determined. It should be noted that the PSS is planned to minimize the power system oscillations following a large disturbance so as to enhance the power system stability. In this paper, the Integral of Absolute Error (**IAE**) of the speed deviations is used as the objective function formulated as

$$J = \int_0^{t_{sim}} (|\omega_2 - \omega_1| + |\omega_3 - \omega_1|).\, dt \qquad (15)$$

where ω_1, ω_2 and ω_3 are the rotor speed of machine 1, 2 and 3 respectively, and t_{sim} is the time range of simulation. By virtue of objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period. It is intended to minimize this objective function so as to enhance the system response with regard to the settling time and overshoots.

The problem restraints are the optimized parameter bounds. Thus, the design problem can be formulated as the following optimization problem:

Minimize J depending on

$$K_{PSS}^{\min} \le K_{PSS} \le K_{PSS}^{\max} \qquad (16)$$

$$T_{1PSS}^{\min} \le T_{1PSS} \le T_{1PSS}^{\max} \qquad (17)$$

$$T_{2PSS}^{\min} \le T_{2PSS} \le T_{2PSS}^{\max} \qquad (18)$$

$$T_{3PSS}^{\min} \le T_{3PSS} \le T_{3PSS}^{\max} \qquad (19)$$

$$T_{4PSS}^{\min} \le T_{4PSS} \le T_{4PSS}^{\max} \qquad (20)$$

Ordinary ranges of these parameters are $0.01-100$ for K_{PSS} and $0.01-1$ for T_{1PSS}, T_{2PSS}, T_{3PSS} and T_{4PSS} [19]. In this study, the optimized parameters are K_{PSS}, T_{1PSS}, T_{2PSS}, T_{3PSS} and T_{4PSS}, and the number of optimized parameters is 5. The proposed approach employs PSO algorithm in order to solve this optimization problem and search for optimal set of PSS parameters. The optimization of the PSS parameters is carried out through assessment of the objective function as given in (15).

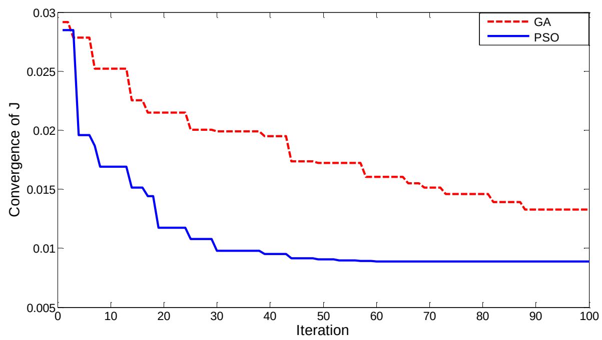

Figure 2. Variation of objective function for GA and PSO algorithms

In order to acquire better performance, swarm size, iteration's number, c_1, c_2, $w_{\max}$ and $w_{\min}$ are selected as 20, 100, 2, 2, 0.9 and 0.4, respectively. It is worth mentioning that PSO algorithm is run numerous times and later optimal set of PSS parameters is chosen. PSS parameter's results set values using both the proposed PSO method and GA method (see Appendix B) are given in Table 2. Figure 2 shows the convergence rate objective function J with the number of generations employing the proposed PSO method and GA method.

5. Nonlinear time-domain simulation

To assess the effectiveness of the proposed PSS, nonlinear time-domain simulation studies are implemented on different severe fault conditions for three cases. The following cases are taken into consideration:

Case 1: In this case, the performance of the proposed controller under transient conditions is substantiated by applying a 6-cycle three-phase fault at $t = 1$ sec, on bus 7 at the end of line 5-7 is considered. The fault cleared without line tripping and the original system is restored upon the clearance of the fault. The system response to this disturbance is given in Figures 3-6. It can be seen from the figures that power system oscillations are insufficiently damped without controller, albeit the system is stable. Stability of the system is maintained and power system oscillations are effectively suppressed with the application of GA based PSS. It is also clear from figures that, unlike GA based PSS, the performance of the PSO based PSS is quite outstanding, and the overshoots and settling time are considerably enhanced in favor of the proposed controller.

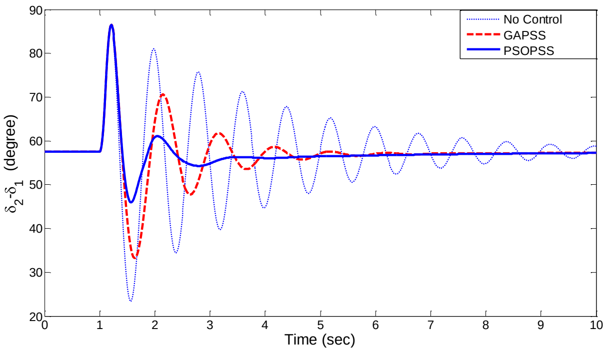

Figure 3. Response of $\delta_2 - \delta_1$ for case 1

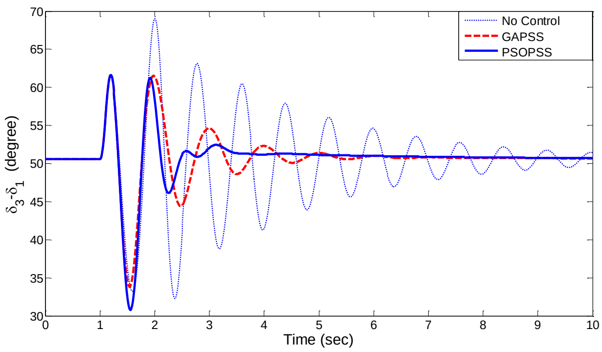

Figure 4. Response of $\delta_3 - \delta_1$ for case 1

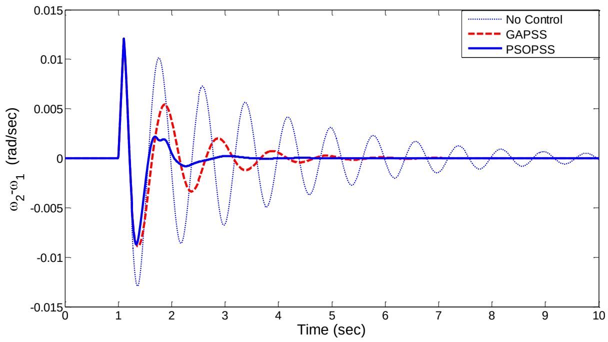

Figure 5. Response of $\omega_2 - \omega_1$ for case 1

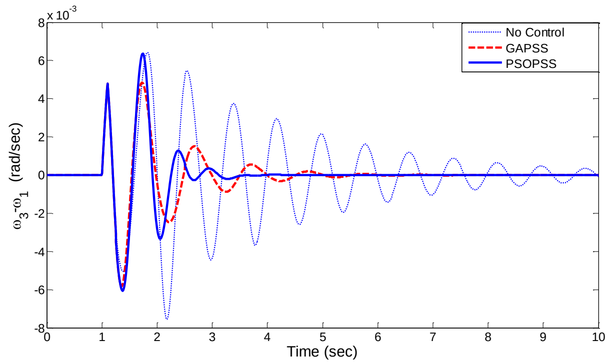

Figure 6. Response of $\omega_3 - \omega_1$ for case 1

Case 2: In this case, additional severe disturbance is taken into consideration; that is, a 6 cycle, three-phase fault is employed at the identical above-mentioned location in case 1. The fault is cleared by permanent tripping of the faulted line. The system response for the above contingency is given in Figures 7-10. It is clear from the figures that the system is unstable without control under severe disturbance. It is also evident that the PSO-based PSS realizes good performance and provides superior damping by comparison with the GA-based PSS.

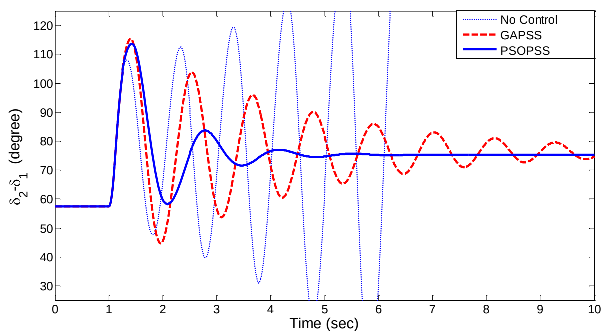

Figure 7. Response of $\delta_2 - \delta_1$ for case 2

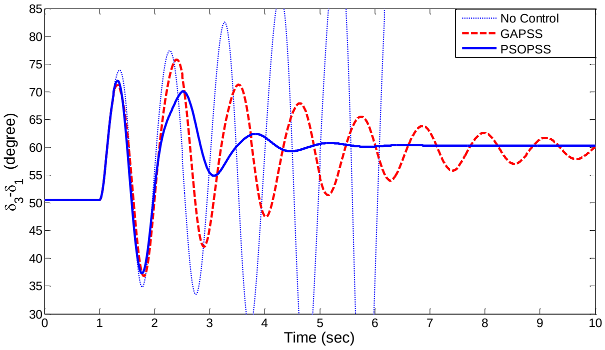

Figure 8. Response of $\delta_3-\delta_1$ for case 2

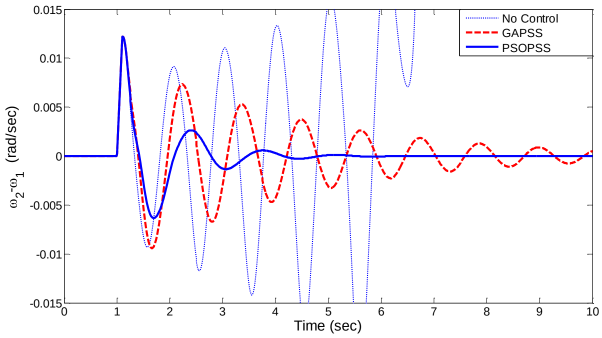

Figure 9. Response of $\omega_2-\omega_1$ for case 2

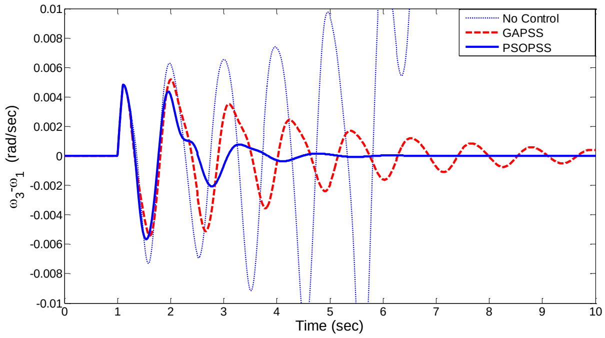

Figure 10. Response of $\omega_3-\omega_1$ for case 2

Case 3: The effectiveness of proposed PSS is also verified under different location and fault clearing time; that is, a 15 cycle three-phase fault is applied on bus 8 at the end of line 8-9 is considered. The fault cleared without line tripping and the original system is restored upon the clearance of the fault. The system response to this disturbance is shown in Figures 11-14. It can be seen from the figures that the system, during the severe disturbances, is unstable without control. In addition, the figures demonstrate that the proposed PSO-based optimized PSS yields the desired dynamic performance and outperforms the GA-based PSS through minimizing the transient errors and then swiftly stabilizing the system.

In order to demonstrate performance of the proposed technique, four performance indices that reflect the settling time and overshoot are introduced. They are expressed as [24]

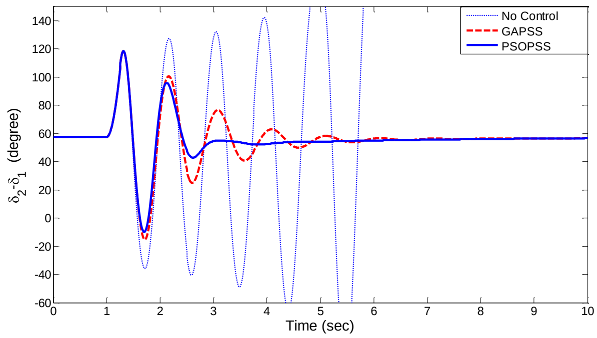

Figure 11. Response of $\delta_2-\delta_1$ for case 3

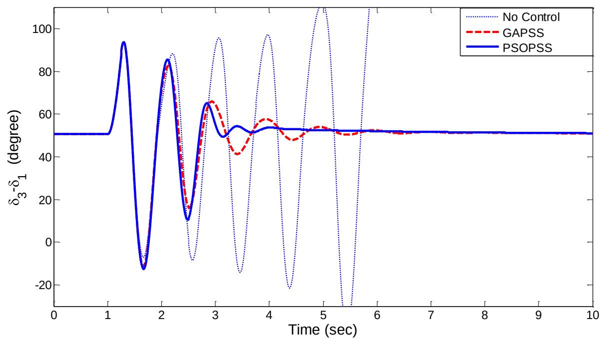

Figure 12. Response of $\delta_3-\delta_1$ for case 3

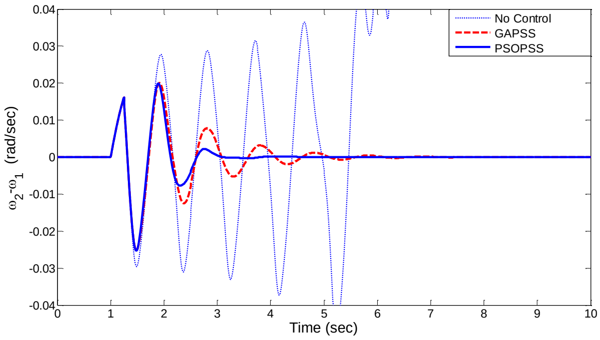

Figure 13. Response of $\omega_2-\omega_1$ for case 3

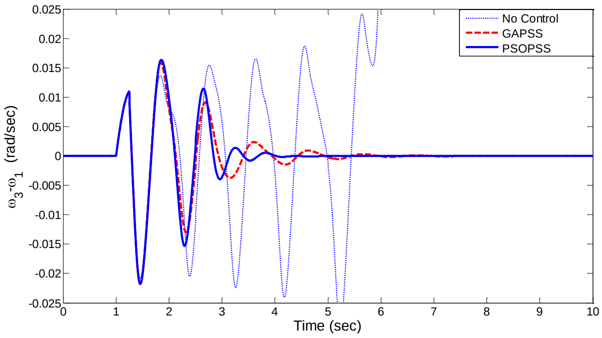

Figure 14. Response of $\omega_3-\omega_1$ for case 3

$$ISE=10^5\times\int_0^{t_{sim}}((\omega_2-\omega_1)^2+(\omega_3-\omega_1)^2).\,dt \qquad (21)$$

$$IAE=10^3\times\int_0^{t_{sim}}(|\omega_2-\omega_1|+|\omega_3-\omega_1|).\,dt \qquad (22)$$

$$ITAE = 10^3 \times \int_0^{t_{sim}} t.(|\,\omega_2 - \omega_1\,| + |\,\omega_3 - \omega_1\,|).\, dt \qquad (23)$$

$$ITSE = 10^5 \times \int_0^{t_{sim}} t.((\omega_2 - \omega_1)^2 + (\omega_3 - \omega_1)^2).\, dt \qquad (24)$$

The values of these indices with the different cases are given in Table 3. It is clear that the values of these indices by the PSO-based tuned PSS are much smaller in compared with GA-based tuned PSS. Indeed, it shows that the settling time and the speed deviations of machine are importantly diminished through employing the proposed PSO-based tuned PSS.

Table 3. Values of performance indices

Fault Case	Algorithm	Compare Index			
		ISE	*IAE*	*ITAE*	*ITSE*
Case 1	GA	5.5314	13.2633	13.7257	3.1155
	PSO	4.2819	8.9001	5.5493	1.7082
Case 2	GA	13.8789	34.7647	92.6242	22.5547
	PSO	5.4911	12.8057	12.4814	2.9242
Case 3	GA	49.7664	44.1104	54.3617	41.3764
	PSO	45.9617	35.7897	32.1148	33.9310

6. Conclusions

A damping controller design for the PSS is employed in this research so as to evaluate the transient stability and damp the power system oscillations after fault effectively. Controller design problem is expressed as an optimization problem, and the PSO algorithm is successfully employed to search for the optimal solution of the design problem. The performance of the proposed controller is demonstrated by a three-machine nine-bus power system through the simulation studies. The nonlinear time-domain simulation results reveal the proposed controller's effectiveness and its ability to yield good damping of low frequency oscillations. The system performance characteristics show that the PSO technique is advantageous over the GA method in terms its computational complexity, solution quality and success rate.

The system performance characteristics regarding ‘ISE’, ‘IAE’, ‘ITAE’ and ‘ITSE’ indices show that by using the proposed PSO based PSS damping controller, the overshoot, settling time and power system low frequency oscillations are immensely diminished during major severe disturbances.

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APPENDIX A

Data for the studied three-machine nine-bus power system. All data are in pu unless specified otherwise. For further information, see Ref. [19].

$H_1 = 23.64$, $H_2 = 6.4$, $H_3 = 3.01$, $D_1 = D_2 = D_3 = 0$,
$x_{d1} = 0.146$, $x_{d2} = 0.8958$, $x_{d3} = 1.3125$,
$x_{q1} = 0.0969$, $x_{q2} = 0.8645$, $x_{q3} = 1.2578$,
$x'_{d1} = 0.0608$, $x'_{d2} = 0.1198$, $x'_{d3} = 0.1813$,
$T'_{do1} = 8.96$, $T'_{do2} = 6.0$, $T'_{do3} = 5.89$

Exciter:

$K_{A1} = K_{A2} = K_{A3} = 100$, $T_{A1} = T_{A2} = T_{A3} = 0.05$

APPENDIX B

Based on the mechanism of the natural selection and survival of the fittest, genetic algorithms are considered as stochastic search methods [25]. Moreover, they integrate function evaluation with randomized and/or well-structured exchange of information amongst the solutions in order to achieve the global optimum point. The architecture of the GA implementation may be divided into following three basic steps: initial population generation, fitness evaluation and genetic operations. The GA control parameters, like population size, mutation probability and crossover probability, are chosen and a first population of the binary strings of the finite length is randomly generated [26]. Given a random initial population GA operates in cycles called generations, as follows [25]:

- Every population member is assessed by employing a fitness function.
- The population undergoes reproduction through several iterations. At least one parent is selected stochastically. Still, strings possessing higher fitness values would have higher probability of contributing an offspring.
- In order to produce offspring, genetic operators, like crossover and mutation, are assigned to parents.
- The offspring are placed in the population and the procedure is rerun.

The time-domain simulation is carried out and the fitness function, as shown in (15), is optimized so as to arrive at the optimal set of controller parameters. While applying GA, parameters' figure must be indicated. Optimization is terminated by the generations' pre-specified figure for the genetic algorithm.

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