# Optimal Design of Power–System Stabilizers Using Particle Swarm Optimization

M. A. Abido

***Abstract*—In this paper, a novel evolutionary algorithm-based approach to optimal design of multimachine power-system stabilizers (PSSs) is proposed. The proposed approach employs a particle-swarm-optimization (PSO) technique to search for optimal settings of PSS parameters. Two eigenvalue-based objective functions to enhance system damping of electromechanical modes are considered. The robustness of the proposed approach to the initial guess is demonstrated. The performance of the proposed PSO-based PSS (PSOPSS) under different disturbances, loading conditions, and system configurations is tested and examined for different multimachine power systems. Eigenvalue analysis and nonlinear simulation results show the effectiveness of the proposed PSOPSSs to damp out the local and interarea modes of oscillations and work effectively over a wide range of loading conditions and system configurations. In addition, the potential and superiority of the proposed approach over the conventional approaches is demonstrated.**

***Index Terms*—Dynamic stability, particle swarm optimization, PSS design.**

## I. Introduction

**P**OWER SYSTEMS experience low-frequency oscillations due to disturbances. The oscillations may sustain and grow to cause system separation if adequate damping is not available. To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems [1]–[3]. DeMello and Concordia [3] presented the concepts of synchronous machine stability as affected by excitation control. They established an understanding of the stabilizing requirements for static excitation systems. In recent years, several approaches based on modern control theory have been applied to PSS design problem. These include optimal control, adaptive control, variable structure control, and intelligent control [4]–[8].

Despite the potential of modern control techniques with different structures, power-system utilities still prefer the conventional lead-lag PSS structure [9]–[11]. The reasons behind that might be the ease of tuning of conventional stabilizer parameters during commissioning and the lack of assurance of the stability related to some adaptive or variable structure techniques.

Kundur *et al.* [11] have presented a comprehensive analysis of the effects of the different conventional PSS (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.

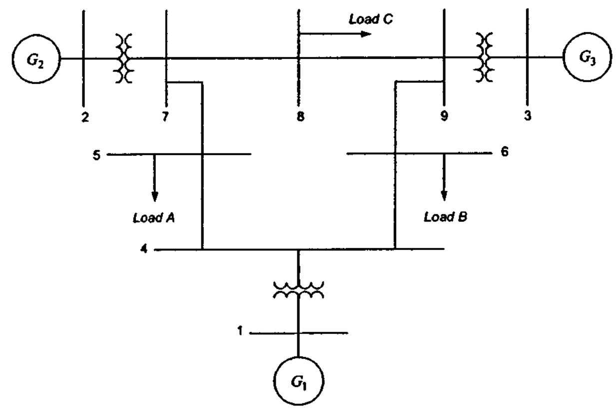

Fig. 1. Three-machine nine-bus power system.

A lot of different techniques have been reported in the literature pertaining to coordinated design problem of CPSS. Different techniques of sequential design of PSSs are presented [12], [13] to damp out one of the electromechanical modes at a time. However, the stabilizers designed to damp one mode can produce adverse effects in other modes. The sequential design of PSSs is avoided in [14]–[16], where various methods for simultaneous tuning of PSSs in multimachine power systems are proposed. Unfortunately, the proposed techniques are iterative and require heavy computation burden due to system reduction procedure. In addition, the initialization step of these algorithms is crucial and affects the final dynamic response of the controlled system. A gradient procedure for optimization of PSS parameters is presented in [17]. Unfortunately, the problem of the PSS design is a multimodal optimization problem (i.e., there exists more than one local optimum). Hence, local optimization techniques are not suitable for such a problem. Moreover, there is no local criterion to decide whether a local solution is also the global solution. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, not able to locate or identify the global optimum.

Recently, a heuristic search algorithms such as genetic algorithm (GA) [18], [19], tabu search algorithm [20], and simulated annealing [21] have been applied to the problem of PSS design. The results are promising and confirm the potential of these algorithms for optimal PSS design. Unlike other optimization techniques, GA is a population-based search algorithm, which works with a population of strings that represent different potential solutions. Therefore, GA has implicit parallelism that

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enhances its search capability and the optima can be located more quickly when applied to complex optimization problems. Unfortunately, recent research has identified some deficiencies in GA performance [22]. This degradation in efficiency is apparent in applications with highly *epistatic* objective functions (i.e., where the parameters being optimized are highly correlated). Also, the premature convergence of GA degrades its performance and reduces its search capability.

A new evolutionary computation technique, called particle swarm optimization (PSO), has been proposed and introduced recently [23]–[26]. This technique combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organizms, such as fish schooling and bird flocking. Generally, PSO is characterized as a simple concept, easy to implement, and computationally efficient. Unlike the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities.

In this paper, a novel PSO-based approach to PSS design is proposed. The problem of PSS design is formulated as an optimization problem with mild constraints and two different eigenvalue-based objective functions. Then, a PSO algorithm is employed to solve this optimization problem. To investigate the potential of the proposed approach, two different examples of multimachine power systems have been considered. Eigenvalue analysis and nonlinear simulation results have been carried out to assess the effectiveness of the proposed PSSs under different disturbances, loading conditions, and system configurations. In addition, the performance of the proposed PSOPSS is compared to that of recent approaches reported in the literature.

## II. Problem Statement

### A. System Model and PSS Structure

A power system can be modeled by a set of nonlinear differential equations as

$$\dot{X} = f(X, U) \tag{1}$$

where $X$ is the vector of the state variables, and $U$ is the vector of input variables. In this study, the two-axis model [2] given in Appendix is used for nonlinear time–domain simulations.

In the design of PSSs, the linearized incremental models around an equilibrium point are usually employed [1]–[3]. Therefore, the state equation of a power system with $n$ machines and $n_{PSS}$ stabilizers can be written as

$$\Delta\dot{X} = A\Delta X + BU \tag{2}$$

where $A$ is $4n \times 4n$ matrix and equals $\partial f/\partial X$, while $B$ is $4n \times n_{PSS}$ matrix and equals $\partial f/\partial U$. Both $A$ and $B$ are evaluated at a certain operating point. $\Delta X$ is $4n \times 1$ state vector, while $U$ is $n_{PSS} \times 1$ input vector.

A widely used conventional lead-lag PSS is considered in this study. It can be described as

$$U_i = K_i \frac{sT_w}{1 + sT_w} \frac{(1 + sT_{1i})}{(1 + sT_2)} \frac{(1 + sT_{3i})}{(1 + sT_4)} \Delta\omega_i \tag{3}$$

where

- $T_w$ washout time constant;
- $U_i$ PSS output signal at the $i$th machine;
- $\Delta\omega_i$ $i$th machine speed deviation from the synchronous speed.

The time constants $T_w, T_2$, and $T_4$ are usually prespecified [14]. The stabilizer gain $K_i$ and time constants $T_{1i}$ and $T_{3i}$ remain to be optimized.

### B. Objective Functions

To increase the system damping to electromechanical modes, two eigenvalue-based objective functions are considered as follows:

$$J_1 = \max\{\text{Real}(\lambda_i) : \lambda_i \in \text{electromechanical modes}\} \tag{4}$$

$$J_2 = \min\{\zeta_i : \zeta_i \in \zeta s \text{ of electromechanical modes}\} \tag{5}$$

where Real$(\lambda_i)$ and $\zeta_i$ are the real part and the damping ratio of the $i$th electromechanical mode eigenvalue, respectively. In the optimization process, it is aimed to Minimize$J_1$ in order to shift the poorly damped eigenvalues to the left in $s$-plane. On the other hand, it aims to Maximize $J_2$ in order to increase the damping of electromechanical modes. The problem constraints are the optimized parameter bounds. Therefore, the design problem can be formulated as the following optimization problem:

$$\text{Optimize } J \tag{6}$$

Subject to

$$K_i^{\min} \le K_i \le K_i^{\max} \tag{7}$$

$$T_{1i}^{\min} \le T_{1i} \le T_{1i}^{\max} \tag{8}$$

$$T_{3i}^{\min} \le T_{3i} \le T_{3i}^{\max}. \tag{9}$$

Typical ranges of the optimized parameters are [0.001–50] for $K_i$ and [0.06–1.0] for $T_{1i}$ and $T_{3i}$ [2]. The time constants $T_w$, $T_2$, and $T_4$ are set as 5 , 0.05, and 0.05 s, respectively [19].

Considering one of the objective functions given in (4) and (5), the proposed approach employs PSO algorithm to solve this optimization problem and search for an optimal set of PSS parameters, $\{K_i, T_{1i}, T_{3i}, i = 1, 2, \ldots, n_{PSS}\}$.

## III. Particle Swarm Optimization

### A. Overview

Similar to evolutionary algorithms, the PSO technique conducts searches using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO system, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. In social science context, a PSO system combines a social-only model and a cognition-only model [23]. The social-only component suggests that individuals ignore their own experience and adjust their behavior according to the successful beliefs of individuals in the neighborhood. On the other hand, the cognition-only component treats individuals as isolated beings. A particle changes its position using these models.

TABLE I
LOADS IN PU ON SYSTEM 100-MVA BASE

| Load | Base Case | | Case 1 | | Case 2 | |
|---|---|---|---|---|---|---|
| | P | Q | P | Q | P | Q |
| A | 1.250 | 0.500 | 2.000 | 0.800 | 1.500 | 0.900 |
| B | 0.900 | 0.300 | 1.800 | 0.600 | 1.200 | 0.800 |
| C | 1.000 | 0.350 | 1.500 | 0.600 | 1.000 | 0.500 |

TABLE II
GENERATOR LOADINGS IN PU ON THE GENERATOR OWN BASE

| Gen. | Base Case | | Case 1 | | Case 2 | |
|---|---|---|---|---|---|---|
| | P | Q | P | Q | P | Q |
| $G_1$ | 0.289 | 0.109 | 0.892 | 0.440 | 0.135 | 0.453 |
| $G_2$ | 0.849 | 0.035 | 1.000 | 0.294 | 1.042 | 0.296 |
| $G_3$ | 0.664 | -0.085 | 1.000 | 0.280 | 1.172 | 0.298 |

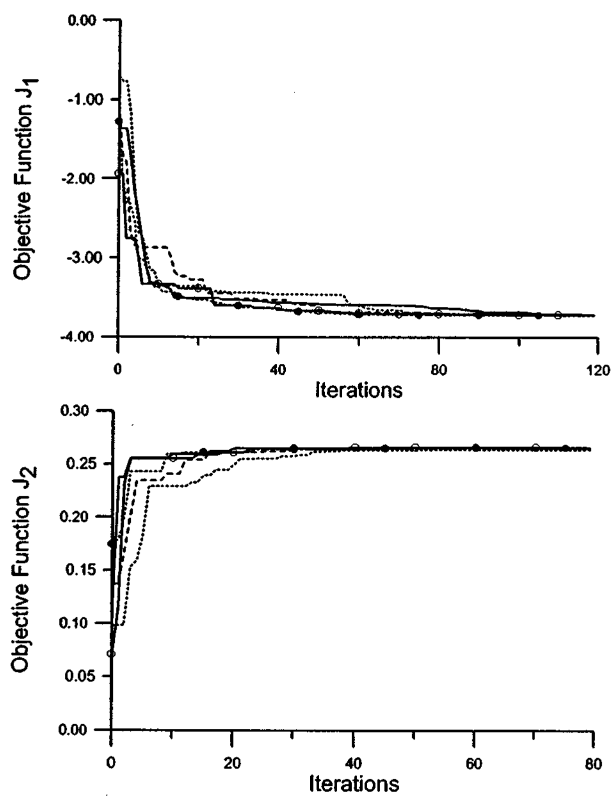


Fig. 2. Convergence of objective functions with different initializations.

The advantages of PSO over other traditional optimization techniques can be summarized as follows.

a) PSO is a population-based search algorithm (*i.e.*, PSO has implicit parallelism). This property ensures PSO to be less susceptible to getting trapped on local minima.
b) PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, PSO can easily deal with nondifferentiable objective functions. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization methods.

TABLE III
OPTIMAL PARAMETERS OF THE PROPOSED PSOPSSs

| Gen. | Objective Function $J_1$ | | | Objective Function $J_2$ | | |
|---|---|---|---|---|---|---|
| | $k$ | $T_1$ | $T_3$ | $k$ | $T_1$ | $T_3$ |
| $G_2$ | 8.255 | 0.201 | 0.137 | 1.742 | 1.000 | 0.090 |
| $G_3$ | 0.082 | 0.631 | 0.629 | 0.041 | 0.602 | 0.265 |

TABLE IV
EIGENVALUES AND DAMPING RATIOS WITHOUT PSSs

| Base Case | Case 1 | Case 2 |
|---|---|---|
| -0.01 ±*j* 9.07, *0.001* | -0.02±*j* 8.91, *0.002* | 0.38 ±*j* 8.87, *-0.034* |
| -0.78 ±*j* 13.86, *0.056* | -0.52 ±*j* 13.83, *0.038* | -0.34 ±*j* 13.69, *0.025* |

TABLE V
EIGENVALUES AND DAMPING RATIOS WITH THE PROPOSED PSOPSS
($J_1$ SETTINGS)

($J_1$ SETTINGS)

| Base Case | Case 1 | Case 2 |
|---|---|---|
| -3.73 ±*j* 8.76, *0.391* | -2.35 ±*j* 7.62, *0.294* | -2.53 ±*j* 8.28, *0.292* |
| -3.74 ±*j* 18.77, *0.195* | -4.11 ±*j* 18.85, *0.213* | -3.93 ±*j* 18.55, *0.207* |

TABLE VI
EIGENVALUES AND DAMPING RATIOS WITH THE PROPOSED PSOPSS
($J_2$ SETTINGS)

($J_2$ SETTINGS)

| Base Case | Case 1 | Case 2 |
|---|---|---|
| -2.15 ±*j* 7.85, *0.264* | -1.62 ±*j* 7.62, *0.208* | -1.51 ±*j* 7.95, *0.187* |
| -3.57 ±*j* 13.02, *0.264* | -2.42 ±*j* 13.62, *0.175* | -2.68 ±*j* 12.92, *0.203* |

c) PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO more flexible and robust than conventional methods.
d) Unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of PSO overcomes the premature convergence problem and enhances the search capability.
e) Unlike the traditional methods, the solution quality of the proposed approach does not rely on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution.

### B. PSO Algorithm

The basic elements of PSO technique are briefly stated and defined as follows.

- ***Particle*** $X(t)$: It is a candidate solution represented by an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. At time $t$, the $j$th particle $X_j(t)$ can be described as $X_j(t) = [x_{j,1}(t), x_{j,2}(t), \ldots, x_{j,m}(t)]$, where $xs$ are the optimized parameters and $x_{j,k}(t)$ is the position of the $j$th particle with respect to the $k$th dimension (*i.e.*, the value of the $k$th optimized parameter in the $j$th candidate solution).

- ***Population*** $pop(t)$: It is a set of $n$ particles at time $t$ (i.e., $pop(t) = [X_1(t), X_2(t), \ldots, X_n(t)]^T$.
- ***Swarm***: it is an apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction [25].
- ***Particle velocity*** $V(t)$: It is the velocity of the moving particles represented by an $m$-dimensional real-valued vector. At time $t$, the $j$th particle velocity $V_j(t)$ can be described as $V_j(t) = [v_{j,1}(t), v_{j,2}(t), \ldots, v_{j,m}(t)]$, where $v_{j,k}(t)$ is the velocity component of the $j$th particle with respect to the $k$th dimension.
- ***Inertia weight*** $w(t)$: It is a control parameter that is used to control the impact of the previous velocities on the current velocity. Hence, it influences the tradeoff between the global and local exploration abilities of the particles [25]. For initial stages of the search process, large inertia weight to enhance the global exploration is recommended while, for last stages, the inertia weight is reduced for better local exploration. The decrement function for decreasing the inertia weight given as $w(t) = \alpha w(t-1)$, where$\alpha$ is a decrement constant smaller than but close to 1, is proposed in this study.
- ***Individual best*** $X^*(t)$: As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best $X^*(t)$. For each particle in the swarm, $X^*(t)$ can be determined and updated during the search. In a minimization problem with objective function $J$, the individual best of the $j$th particle $X_j^*(t)$ is determined so that $J\left(X_j^*(t)\right) \leq J(X_j(\tau))$, $\tau \leq t$. For simplicity, assume that $J_j^* = J\left(X_j^*(t)\right)$. For the $j$th particle, individual best can be expressed as $X_j^*(t) = \left[x_{j,1}^*(t), x_{j,2}^*(t), \ldots, x_{j,m}^*(t)\right]$.
- ***Global best*** $X^{**}(t)$: It is the best position among all of the individual best positions achieved so far. Hence, the global best can be determined such that $J(X^{**}(t)) \leq J(X_j^*(t))$, $j = 1, 2, \ldots, n$. For simplicity, assume that $J^{**} = J(X^{**}(t))$.
- ***Stopping criteria***: These are the conditions under which the search process will terminate. In this study, the search will terminate if one of the following criteria is satisfied: **a)** The number of iterations since the last change of the best solution is greater than a prespecified number; **b)** the number of iterations reaches the maximum allowable number.

The particle velocity in the $k$th dimension is limited by some maximum value, $v_k^{\max}$. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning [23]. The maximum velocity in the $k$th dimension is characterized by the range of the $k$th optimized parameter and given by

$$v_k^{\max} = \frac{\left(x_k^{\max} - x_k^{\min}\right)}{N} \tag{10}$$

where $N$ is a chosen number of intervals in the $k$th dimension.

In a PSO algorithm, the population has $n$ particles that represent candidate solutions. Each particle is an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space. The PSO technique can be described in the following steps.

Step 1) ***(Initialization)***: Set the time counter $t = 0$ and generate random $n$ particles, $\{X_j(0), j = 1, 2, \ldots, n\}$, where $X_j(0) = [x_{j,1}(0), x_{j,2}(0), \ldots, x_{j,m}(0)]$. $x_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the $k$th optimized parameter search space $[x_k^{\min}, x_k^{\max}]$. Similarly, generate randomly initial velocities of all particles, $\{V_j(0), j = 1, 2, \ldots, n\}$, where $V_j(0) = [v_{j,1}(0), v_{j,2}(0), \ldots, v_{j,m}(0)]$. $v_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the $k$th dimension $[-v_k^{\max}, v_k^{\max}]$. Each particle in the initial population is evaluated using the objective function, $J$. For each particle, set $X_j^*(0) = X_j(0)$ and $J_j^* = J_j$, $j = 1, 2, \ldots, n$. Search for the best value of the objective function $J_{\text{best}}$. Set the particle associated with $J_{\text{best}}$ as the global best, $X^{**}(0)$, with an objective function of $J^{**}$. Set the initial value of the inertia weight $w(0)$.

Step 2) ***(Time updating)***: Update the time counter $t = t + 1$.

Step 3) ***(Weight updating)***: Update the inertia weight $w(t) = \alpha w(t-1)$.

Step 4) ***(Velocity updating)***: Using the global best and individual best, the $j$th particle velocity in the $k$th dimension is updated according to the following equation:

$$\begin{aligned} v_{j,k}(t) = w(t) v_{j,k}(t-1) &+ c_1 r_1 \left(x_{j,k}^*(t-1) - x_{j,k}(t-1)\right) \\ &+ c_2 r_2 \left(x_{j,k}^{**}(t-1) - x_{j,k}(t-1)\right) \end{aligned} \tag{11}$$

where $c_1$ and $c_2$ are positive constants and $r_1$ and $r_2$ are uniformly distributed random numbers in [0,1]. Check the velocity limits. If the velocity violated its limit, set it at its proper limit. It is worth mentioning that the second term represents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

Step 5) ***(Position updating)***: Based on the updated velocities, each particle changes its position according to the following equation:

$$x_{j,k}(t) = v_{j,k}(t) + x_{j,k}(t-1). \tag{12}$$

Step 6) ***(Individual best updating)***: Each particle is evaluated according to the updated position. If $J_j < J_j^*$, $j = 1, 2, \ldots, n$, then update individual best as $X_j^*(t) = X_j(t)$ and $J_j^* = J_j$, and go to step 7; else go to step 7.

Step 7) ***(Global best updating)***: Search for the minimum value $J_{\min}$ among $J_j^*$, where $\min$ is the index of the particle with minimum objective function value, i.e.,

$\min \in \{j; j = 1, 2, \ldots, n\}$. If $J_{\min} < J^{**}$ then update global best as $X^{**} = X_{\min}(t)$, and $J^{**} = J_{\min}$ and go to step 8; else go to step 8.

Step 8) ***(Stopping criteria)***: If one of the stopping criteria is satisfied, then stop, or else go to step 2.

### C. PSO Implementation

The proposed PSO–based approach was implemented using the FORTRAN language and the developed software program was executed on a 166-MHz Pentium I PC. Practically, our experience shows that the most effective parameters on PSO performnace are the initial inertia weight and the maximum allowable velocity. Initially, several runs have been done with different values of these two parameters. The results show better performance with initial inertia weight $w(0) \in [0.8–1.2]$ and number of intervals in (10) $N \in [5–10]$. It is worth mentioning that these parameters should be selected carefully for efficient performance of PSO. In our implementation, the initial inertia weight $w(0)$ and the number of intervals in each space dimension $N$ are selected as 1.0 and 8, respectively. It was observed that these values work satisfactorily in all simulation results of this work. Other parameters were set as number of particles $n = 50$, decrement constant $\alpha = 0.98$, $c_1 = c_2 = 2$ and the search will be terminated if **a)** the number of iterations since the last change of the best solution is greater than 50, or **b)** the number of iterations reaches 500.

To demonstrate the effectiveness of the proposed design approach, two different examples of multimachine power systems are considered. In both examples, PSS parameters are optimized at the operating condition designated as *base case*. To assess the robustness of the proposed PSS, two additional cases designated as *case 1* and *case 2*represent different loading conditions while system configurations are considered. It is worth mentioning that the nonlinear system model is used in time-domain simulations.

## IV. Example 1: Three Machine Power System

### A. Test System and PSS Design

In this example, the three-machine nine-bus system shown in Fig. 1 is considered. The rated MVA of $G_1$, $G_2$, and $G_3$ are 247.5, 192, and 128, respectively. Details of the system data are provided in [1]. The participation factor method shows that the generators $G_2$ and $G_3$ are the optimum locations for installing PSSs. Hence, the optimized parameters are $K_i$, $T_{1i}$, $T_{3i}$, and $i = 2, 3$. The range of the optimized parameters was set as [0.001–20] for $K_i$ and [0.06–1.0] for $T_{1i}$ and $T_{3i}$. The optimization process was carried out at the operating point specified as *base case*. The system and generator loading levels at this case are given in Tables I and II, respectively.

To demonstrate the robustness of the proposed approach to the initial solution, different initializations have been considered. The final values of the optimized parameters are given in Table III. The convergence of objective functions is shown in Fig. 2. It is clear that, unlike the conventional methods [12]–[16], the proposed approach finally leads to the optimal solution regardless of the initial one. Therefore, the proposed approach can be used to improve the solution quality of classical methods.

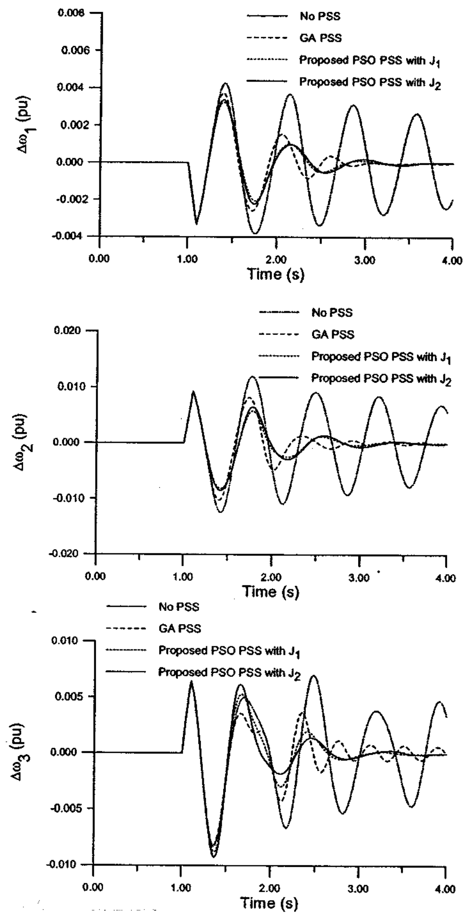


Fig. 3. System response to six-cycle fault with *case 1*.

### B. Eigenvalue Analysis and Simulation Results

To assess the effectiveness and robustness of the proposed PSOPSS over a wide range of loading conditions, two different cases designated as *case 1* and *case 2* are considered. The generator and system loading levels at these cases are given in Tables I and II, respectively. The electromechanical–mode eigenvalues and corresponding damping ratios without PSSs for all cases are given in Table IV. This table shows that the system has two local modes with frequencies of 1.44 and 2.21 Hz in the base case. It is clear that these modes are poorly damped and some of them are unstable. The electromechanical–mode eigenvalues and the corresponding damping ratios with the proposed PSOPSS's for $J_1$ and $J_2$ settings are given in Tables V and VI, respectively. It is obvious that the electromechanical–mode eigenvalues have been shifted to the left in $s$-plane and the system damping with the proposed PSOPSSs greatly improved and enhanced.

For further illustration, a six-cycle three-phase fault disturbance at bus seven at the end of line 5–7 is considered for the nonlinear time simulations. The speed deviations are shown in Fig. 3 with *case 1*. The performance of the proposed PSOPSS is compared to that of GA-based PSS (GAPSS) given in [27]. It is clear that the proposed PSOPSSs outperform the GAPSSs and provide good damping characteristics to low-frequency oscillations and greatly enhance the dynamic stability of power systems.

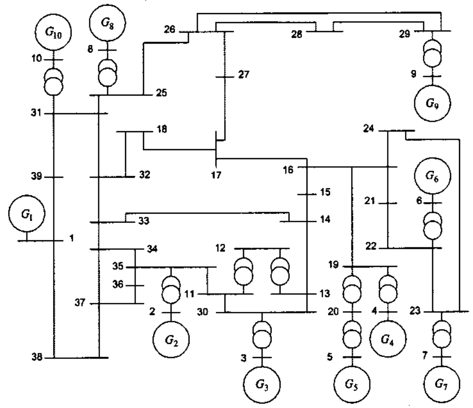

Fig. 4. Single–line diagram for New England system.

TABLE VII
OPTIMAL PARAMETERS OF THE PROPOSED PSOPSSS

| Gen | Objective Function $J_1$ | | | Objective Function $J_2$ | | |
|---|---|---|---|---|---|---|
| | $k$ | $T_1$ | $T_3$ | $k$ | $T_1$ | $T_3$ |
| $G_2$ | 38.462 | 0.728 | 0.603 | 30.644 | 0.638 | 1.000 |
| $G_3$ | 21.538 | 0.719 | 0.785 | 40.633 | 0.673 | 0.324 |
| $G_4$ | 19.716 | 0.953 | 0.592 | 47.775 | 0.530 | 0.977 |
| $G_5$ | 38.040 | 0.131 | 0.251 | 15.536 | 0.810 | 0.140 |
| $G_6$ | 46.057 | 0.477 | 0.857 | 24.872 | 1.000 | 0.834 |
| $G_7$ | 5.1928 | 0.294 | 0.199 | 1.0514 | 1.000 | 0.529 |
| $G_8$ | 23.418 | 1.000 | 1.000 | 23.957 | 1.000 | 1.000 |
| $G_9$ | 49.998 | 0.176 | 0.136 | 24.551 | 0.102 | 0.549 |
| $G_{10}$ | 31.462 | 1.000 | 0.992 | 26.998 | 1.000 | 1.000 |

## V. EXAMPLE 2: NEW ENGLAND POWER SYSTEM

### A. Test System and PSS Design

In this example, the ten-machine, 39-bus New England power system shown in Fig. 4 is considered. Generator $G_1$ is an equivalent power source representing parts of the U.S.-Canadian interconnection system. Details of the system data are given in [28].

For illustration and comparison purposes, it is assumed that all generators except $G_1$ are equipped with PSSs. Hence, the optimized parameters are $K_i$, $T_{1i}$, and $T_{3i}$, $i = 2, 3, \ldots, 10$ (i.e., the number of optimized parameters is 27 in this example). The range of the optimized parameters was set as [0.001–50] for $K_i$ and [0.06–1.0] for $T_{1i}$ and $T_{3i}$. The PSO algorithm has been applied to search for the settings of these parameters in order to optimize the objective function considered. The final values of the optimized parameters are provided in Table VII. The convergence of objective functions is shown in Fig. 5.

### B. Eigenvalue Analysis and Simulation Results

To demonstrate the effectiveness and robustness of the proposed PSOPSSs under severe conditions and critical line outages, two different operating conditions in addition to the *base case* are considered. They can be described as *Case 1*: outage of line 21–22; *Case 2*: outage of line 14–15.

The electromechanical modes without PSSs for the three cases are shown in Table VIII. This table shows that the system has one interarea mode with a frequency of 0.64 Hz and eight local modes with frequencies ranging from 0.92 to 1.54 Hz in the base case. It is clear that these modes are poorly damped and some of them are unstable. The electromechanical–mode eigenvalues and the corresponding damping ratios with the proposed PSOPSSs for $J_1$ and $J_2$ settings are given in Tables IX and X, respectively. It can be seen that the electromechanical mode eigenvalues with the proposed PSSs have been shifted to the left in $s$-plane. It is obvious that the system damping is greatly improved and enhanced for all cases.

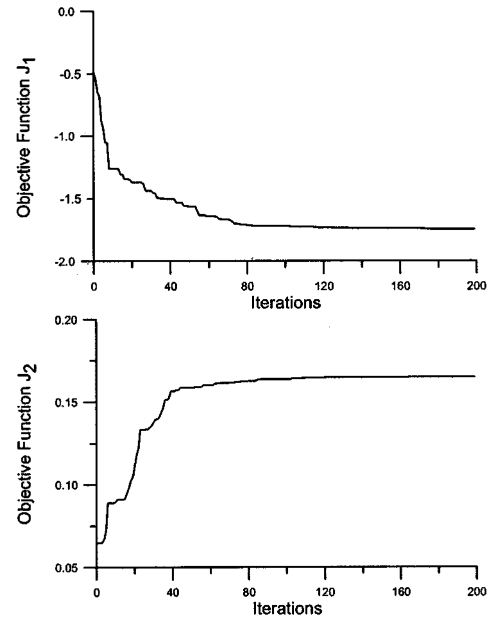


Fig. 5. Objective function convergence.

TABLE VIII
EIGENVALUES AND DAMPING RATIOS WITHOUT PSSS

| Base Case | Case 1 | Case 2 |
|---|---|---|
| **0.191 ±j 5.808, *-0.033*** | **0.195 ±j 5.716, *-0.034*** | **0.152 ±j 5.763, *-0.026*** |
| **0.088 ±j 4.002, *-0.022*** | **0.121 ±j 3.798, *-0.032*** | **0.095 ±j 3.837, *-0.025*** |
| -0.028 ±j 9.649, *0.003* | **0.097 ±j 6.006, *-0.016*** | **0.033 ±j 6.852, *-0.005*** |
| -0.034 ±j 6.415, *0.005* | -0.032 ±j 9.694, *0.003* | -0.026 ±j 9.659, *0.003* |
| -0.056 ±j 7.135, *0.008* | -0.104 ±j 8.015, *0.013* | -0.094 ±j 8.120, *0.012* |
| -0.093 ±j 8.117, *0.011* | -0.109 ±j 6.515, *0.017* | -0.100 ±j 6.038, *0.017* |
| -0.172 ±j 9.692, *0.018* | -0.168 ±j 9.715, *0.017* | -0.171 ±j 9.696, *0.018* |
| -0.220 ±j 8.013, *0.027* | -0.204 ±j 8.058, *0.025* | -0.219 ±j 8.000, *0.027* |
| -0.270 ±j 9.341, *0.029* | -0.250 ±j 9.268, *0.027* | -0.259 ±j 9.320, *0.028* |

For time-domain simulations, two different three-phase faults have been applied to demonstrate the effectiveness and the robustness of the proposed PSOPSSs as follows:

a) a six-cycle three-phase fault at bus 29 at the end of line 26–29;
b) a six-cycle three-phase fault at bus 14 at the end of line 14–15.

These faults have been applied with different cases resulting in the following combination of disturbances:

1) fault (a) with *base case*;
2) fault (a) with *case 1*;
3) fault (a) with *case 2*;
4) fault (a) with *base case* and the faulty line is tripped of for 1.0 s;
5) fault (b) with *base case* and the faulty line is tripped of for 1.0 s.

TABLE IX
EIGENVALUES AND DAMPING RATIOS WITH THE PROPOSED PSOPSSs ($J_1$ SETTINGS)

| *Base Case* | *Case* **1** | *Case* **2** |
|---|---|---|
| -1.754±*j* 2.865, *0.522* | -1.423 ±*j* 3.143, *0.412* | -1.523 ±*j* 2.620, *0.503* |
| -1.756 ±*j* 12.42, *0.140* | -1.564 ±*j* 9.974, *0.155* | -1.658 ±*j* 9.646, *0.169* |
| -1.758 ±*j* 9.703, *0.178* | -1.734 ±*j* 12.38, *0.139* | -1.752 ±*j* 12.41, *0.140* |
| -1.759 ±*j* 9.959, *0.174* | -1.778 ±*j* 10.95, *0.160* | -1.753 ±*j* 10.02, *0.172* |
| -1.762 ±*j* 8.203, *0.210* | -1.799 ±*j* 12.04, *0.148* | -1.768 ±*j* 10.97, *0.159* |
| -1.764 ±*j* 10.98, *0.159* | -1.843 ±*j* 9.937, *0.182* | -1.795 ±*j* 10.97, *0.164* |
| -1.810 ±*j* 10.79, *0.165* | -1.951 ±*j* 9.042, *0.211* | -1.832 ±*j* 7.329, *0.243* |
| -1.829 ±*j* 12.08, *0.150* | -2.124 ±*j* 10.688, *0.195* | -1.834 ±*j* 12.08, *0.150* |
| -2.271 ±*j* 9.826, *0.225* | -2.266 ±*j* 7.489, *0.290* | -2.380 ±*j* 9.818, *0.234* |

TABLE X
EIGENVALUES AND DAMPING RATIOS WITH THE PROPOSED PSOPSSs ($J_2$ SETTINGS)

| *Base Case* | *Case* **1** | *Case* **2** |
|---|---|---|
| -0.782 ±*j* 2.858, *0.264* | -0.691 ±*j* 2.901, *0.232* | -0.730 ±*j* 2.736, *0.258* |
| -1.409 ±*j* 5.130, *0.265* | -0.981 ±*j* 4.496, *0.213* | -1.412 ±*j* 5.075, *0.268* |
| -1.573 ±*j* 8.119, *0.190* | -1.493 ±*j* 9.093, *0.162* | -1.546 ±*j* 9.428, *0.162* |
| -1.762 ±*j* 9.143, *0.189* | -1.674 ±*j* 8.000, *0.205* | -1.556 ±*j* 7.410, *0.206* |
| -1.771 ±*j* 9.730, *0.179* | -2.060 ±*j* 10.24, *0.197* | -2.140 ±*j* 9.648, *0.217* |
| -2.173 ±*j* 12.16, *0.176* | -2.219 ±*j* 12.11, *0.180* | -2.146 ±*j* 10.27, *0.205* |
| -2.178 ±*j* 10.39, *0.205* | -2.237 ±*j* 12.45, *0.177* | -2.169 ±*j* 12.17, *0.175* |
| -2.252 ±*j* 12.51, *0.177* | -2.248 ±*j* 9.323, *0.234* | -2.258 ±*j* 12.49, *0.178* |
| -2.513 ±*j* 13.78, *0.179* | -2.621 ±*j* 13.63, *0.189* | -2.603 ±*j* 13.77, *0.186* |

The performance of the proposed PSOPSSs is compared to that of GAPSSs given in [19] and gradient-based PSSs given in [17]. Due to space limitations, only the speed deviations of $G_8$ and $G_9$ are shown in Figs. 6 and 7 with disturbance 1 and disturbance 4, respectively. Fig. 7 shows that the gradient based PSSs are not able to stabilize the system under disturbance 4. It is clear that the system performance with the proposed PSOPSSs is much better than that of GAPSSs and the oscillations are damped out much faster. In addition, the proposed PSOPSSs are quite efficient to damp out the local modes as well as the interarea modes of oscillations. This illustrates the potential and superiority of the proposed design approach to obtain an optimal set of PSS parameters.

For completeness and clear perceptiveness about the system response for all of the disturbances listed, two performance indices that reflect the settling time and overshoots are introduced and evaluated. These indices are defined as

$$PI_1 = \sum_{i=1}^{n} \int_{t=0}^{t=t_{sim}} (t\Delta\omega_i)^2 \, dt \tag{13}$$

$$PI_2 = \sum_{i=1}^{n} \int_{t=0}^{t=t_{sim}} (\Delta\omega_i)^2 \, dt \tag{14}$$

where $n$ is the number of machines, and $t_{sim}$ is the simulation time. The values of these indices with the disturbances considered are provided in Table XI. It is clear that the values of these indices with the proposed PSOPSSs are much smaller compared to gradient-based PSSs and GAPSSs. This demonstrates that the settling time and speed deviations of all units are greatly reduced by applying the proposed PSOPSSs. Although the robustness has been considered in gradient-based PSS design [17], they fail

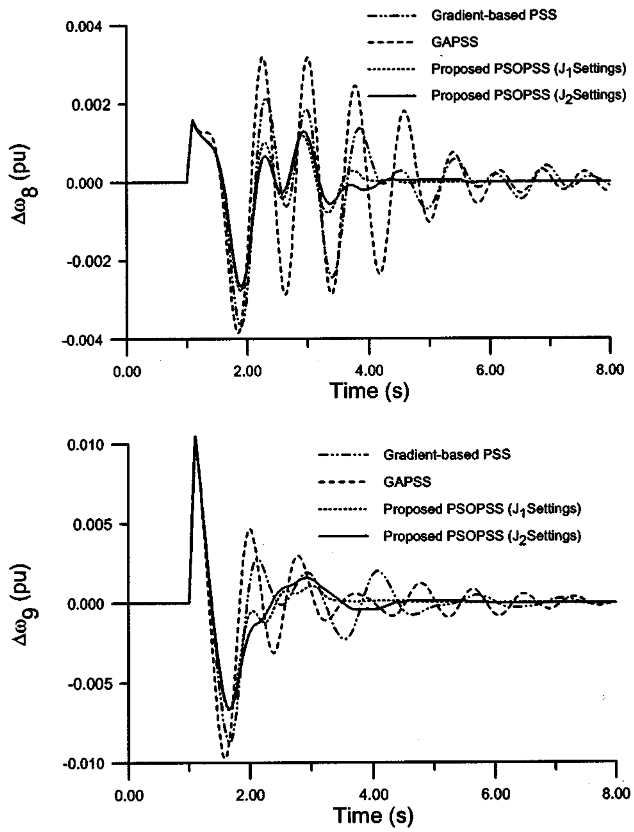


Fig. 6. System responses with disturbance 1.

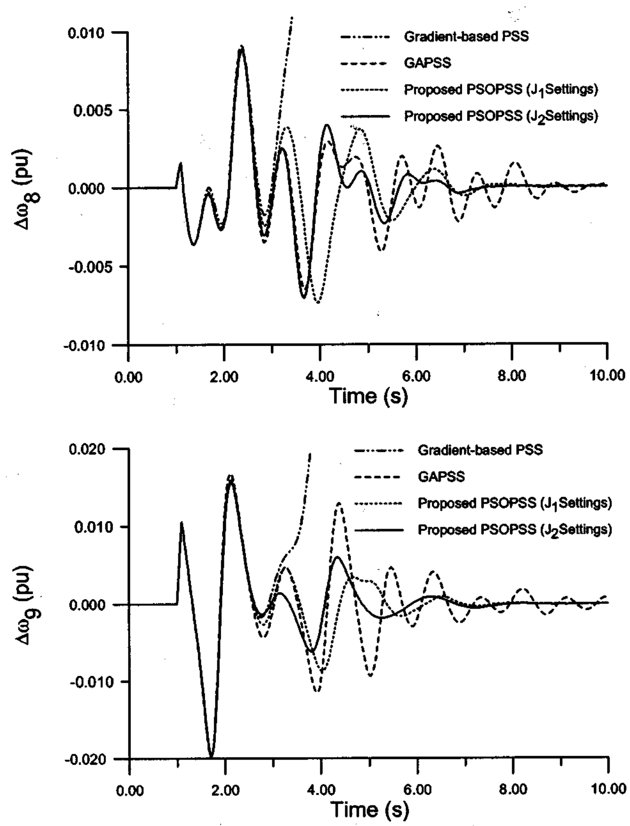


Fig. 7. System responses with disturbance 4.

TABLE XI
PERFORMANCE INDICES WITH DIFFERENT DISTURBANCES

| Disturbance | Gradient-based PSS | | GAPSS | | Proposed PSOPSS | | | |
|---|---|---|---|---|---|---|---|---|
| | $PI_1$ | $PI_2$ | $PI_1$ | $PI_2$ | $PI_1$ | | $PI_2$ | |
| | | | | | $J_1$ | $J_2$ | $J_1$ | $J_2$ |
| 1 | 2.44 | 1.05 | 2.86 | 1.09 | 0.41 | 0.58 | 0.52 | 0.56 |
| 2 | 3.39 | 1.08 | 3.33 | 1.11 | 0.59 | 1.02 | 0.55 | 0.63 |
| 3 | 2.30 | 1.06 | 2.66 | 1.08 | 0.43 | 0.65 | 0.54 | 0.59 |
| 4 | — | — | 65.5 | 8.61 | 55.4 | 28.5 | 8.72 | 6.52 |
| 5 | — | — | 65.2 | 8.64 | 46.4 | 41.4 | 7.50 | 7.25 |

to stabilize the system with disturbances four and five. On the other hand, the proposed PSSs provide good damping characteristics and outperform GAPSS under these severe disturbances.

## APPENDIX

In this work, the $i$th machine model is given as follows:

$$\dot{\delta}_i = \omega_b (\omega_i - 1) \tag{A1}$$

$$\dot{\omega}_i = \frac{(T_{mi} - T_{ei} - D_i(\omega_i - 1))}{M_i} \tag{A2}$$

$$\dot{E}'_{qi} = \frac{(E_{fdi} - (x_{di} - x'_{di}) i_{di} - E'_{qi})}{T'_{doi}} \tag{A3}$$

$$\dot{E}'_{di} = \frac{(-(x_{qi} - x'_{qi}) i_{qi} - E'_{di})}{T'_{qoi}} \tag{A4}$$

$$\dot{E}_{fdi} = \frac{(K_{ai}(V_{refi} - V_i - U_i) - E_{fdi})}{T_{ai}} \tag{A5}$$

$$T_{ei} = E'_{di} i_{di} + E'_{qi} i_{qi} - (x'_{qi} - x'_{di}) i_{di} i_{qi} \tag{A6}$$

| | |
|---|---|
| $d$ and $q$ | direct and quadrature axes, respectively; |
| $\delta$ | rotor angle; |
| $\omega$ | rotor speed; |
| $E'_q$ and $E'_d$ | internal voltages behind $x'_d$ and $x'_q$, respectively; |
| $E_{fd}$ | equivalent excitation voltage; |
| $T_e$ | electric torque; |
| $T'_{do} T'_{qo}$ | time constants of excitation circuit; |
| $K_a$ | regulator gain; |
| $T_a$ | regulator time constant. |

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