Particle Swarm Optimization for Multimachine Power System Stabilizer Design

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Abstract: In this paper, a novel evolutionary algorithm based approach to optimal design of multimachine Power System Stabilizers (PSSs) is proposed. The proposed approach develops and employs 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 and loading conditions is tested and examined. Eigenvalue analysis and nonlinear simulation results show the effectiveness of the proposed PSOPSSs to damp out the electromechanical oscillations and work effectively over a wide range of loading conditions.

Keywords: PSS, particle swarm optimization, dynamic stability.

1. INTRODUCTION

Power systems are experiencing low frequency oscillations due to disturbances. The oscillations may sustain and grow to cause system separation if no adequate damping is available. To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems [1-9].

Different techniques of sequential design of PSSs are presented [3] 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 [4] 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 [5]. Unfortunately, the problem of the PSS design is a *multimodal* optimization problem therefore local optimization techniques are not suitable for such a problem. In general, conventional optimization methods that make use of derivatives and gradients are not able to locate or identify the global optimum.

Recently, heuristic search algorithms such as genetic algorithm (GA) [6-7], tabu search algorithm [8], and simulated annealing [9] have been applied to the problem of PSS design. The results are promising and confirming 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 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 [10]. This degradation in efficiency is apparent in applications with highly *epistatic* objective functions, *i.e.*, where the parameters being optimized are highly correlated. In addition, the premature convergence of GA degrades its performance and reduces its search capability.

Particle swarm optimization (PSO) has been proposed and introduced as a new evolutionary computation technique in [11-12]. This technique combines social psychology principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms such as fish schooling and bird flocking. Generally, PSO is characterized as simple in 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, PSO algorithm is employed to solve this optimization problem. Eigenvalue analysis and nonlinear simulation results have been carried out to assess the effectiveness of the proposed PSSs under different disturbances and loading conditions. In addition, the performance of the proposed PSOPSS is compared to that of recent approaches reported in the literature.

2. 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 $X = [\delta, \omega, E_q^{'}, E_{fd}]^T$ and U is the PSS output signals.

In the design of PSSs, the linearized incremental models around an equilibrium point are usually employed [1-2]. Therefore, the state equation of a power system with n machines and n_{PSS} stabilizers can be written as:

$$\Delta \dot{X} = A\,\Delta X + B\,U \qquad (2)$$

where A is $4n\times4n$ 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. ΔX is $4n\times1$ state vector while U is $n_{PSS}\times1$ input vector.

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

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

where T_w is the washout time constant, U_i is the PSS output signal at the i^{th} machine, and $\Delta\omega_i$ is the speed deviation of this machine. The time constants T_w, T_2, and T_4 are usually prespecified [4]. The stabilizer gain K_i and time constants T_{1i} and T_{3i} are remained to optimize.

B. *Objective Functions*

To increase the system damping, two eigenvalue-based objective functions are considered as follows.

$J_1=max\{Real(\lambda_i): \lambda_i\in \lambda s$ of electromechanical modes$\}$ (4)

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

where $Real(\lambda_i)$ and ζ_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 is aimed to *Maximize* J_2 in order to increase the damping of electromechanical modes. In this study, these objectives are optimized individually. The problem constraints are the optimized parameter bounds. Therefore, the design problem can be formulated as the following optimization problem.

Optimize J (6)

Subject to

$K_i^{min} \le K_i \le K_i^{max}$ (7)

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

$T_{3i}^{min} \le T_{3i} \le T_{3i}^{max}$ (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 5s, 0.05s, and 0.05s respectively.

The proposed approach employs PSO algorithm to solve this optimization problem and search for optimal set of PSS parameters, $\{K_i, T_{1i}, T_{3i}, i=1,2,\ldots,n_{PSS}\}$.

3. PARTICLE SWARM OPTIMIZATION

A. *Overview*

Like evolutionary algorithms, PSO technique conducts search using a population of particles. Each particle represents a candidate solution to the problem. In a PSO system, particles change their positions by flying around in a multi-dimensional search space until a relatively unchanging positions 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 [11]. 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.

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

- 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.
- PSO uses objective function information to guide the search in the problem space. Therefore, PSO can easily deal with non-differentiable objective functions.
- PSO uses probabilistic transition rules, 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.
- Unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space.

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 $X_j(t)=[x_{j,1}(t), \ldots, x_{j,m}(t)]$, 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.*, $pop(t)=[X_1(t), \ldots, X_n(t)]^T$.
- ***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 [11].
- ***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 $V_j(t)=[v_{j,1}(t), \ldots, v_{j,m}(t)]$, where $v_{j,k}(t)$ is the velocity component of the j^{th} particle w.r.t. 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 trade-off between the global and local exploration abilities of the particles [12] 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.

- ***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 such that $J(X_j^*(t)) \leq J(X_j(\tau))$, $\tau \leq t$. For simplicity, assume that $J_j^* = J(X_j^*(t))$. For the j^{th} particle, individual best can be expressed as $X_j^*(t)=[x_{j,1}^*(t), \ldots, x_{j,m}^*(t)]$.
- ***Global best,*** $X^{**}(t)$,: It is the best position among all individual best positions achieved so far. Hence, the global best can be determined as $J(X^{**}(t)) \leq J(X_j^*(t))$, $j=1,\ldots,n$. For simplicity, assume that $J^{**}=J(X^{**}(t))$.
- ***Stopping criteria:*** These are the conditions under which the search will terminate. In this study, the search will stop 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; or **(b)** the number of iterations reaches the maximum allowable number.

In this study, the basic PSO has been developed by incoporating the following modifications: -

- An annealing procedure has been incorporated in order to to make uniform search in the initial stages and very locally search in the later stages. A decrement function for decreasing the inertia weight given as $w(t)=\alpha\, w(t-1)$, α is a decrement constant smaller than but close to 1, is proposed in this study.
- A feasibility check procedure of the particle positions has been imposed after the position updating to prevent the particles from flying outside the feasible search space.
- 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 [11]. To ensure uniform velocity through all dimensions, the maximum velocity in the k^{th} dimension is proposed as:

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

N is a chosen number of intervals in the k^{th} dimension.

In 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. The PSO technique can be described in the following steps.

Step 1 (Initialization): Set the time counter t=0 and generate randomly n particles, $\{X_j(0), j=1, \ldots, n\}$, where $X_j(0)=[x_{j,1}(0), \ldots, x_{j,m}(0)]$. $x_{j,k}(0)$ 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, $\{V_j(0), j=1, \ldots, n\}$, where $V_j(0)=[v_{j,1}(0), \ldots, v_{j,m}(0)]$. $v_{j,k}(0)$ 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 $J_j^*=J_j$, $j=1, \ldots, n$. Search for the best value of the objective function J_{best}. Set the particle associated with J_{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:

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

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. 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 $J_j<J_j^*$, $j=1, \ldots, n$, 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.*, $min \in \{j; j=1, \ldots, n\}$. 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, 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. Initially, several runs have been done with different values of the PSO key parameters such as the initial inertia weight and the maximum allowable velocity. 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. Other parameters are chosen as: number of particles n=50, decrement constant α=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 systems are considered. 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* that represent different loading conditions and system configurations are considered. It is worth mentioning that the nonlinear system model is used in time-domain simulations.

4. SIMULATION RESULTS

A. Test System and PSS design

In this example, the 3-machine 9-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 given 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}, and T_{3i}, i=2,3. These parameters are optimized at the operating point specified as *base case*. The generator and system loading levels at this case are given in Table 1 and Table 2 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 3. The convergence of objective functions is shown in Fig. 2. It is clear that, unlike the conventional methods, the proposed approach finally leads to the optimal solution regardless the initial one. Therefore, the proposed approach can be used to improve the solution quality of classical methods.

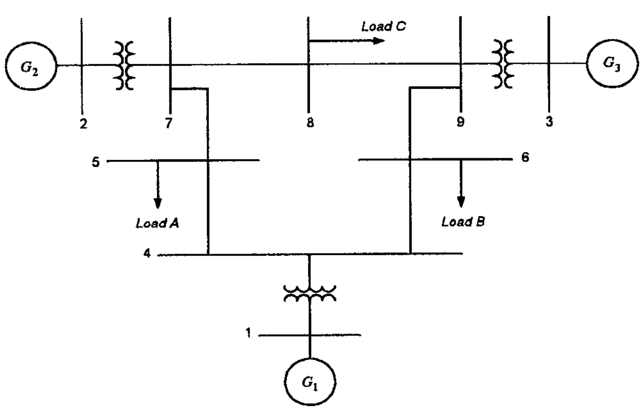

Fig. 1: Three-machine nine-bus power system

Table 1: 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 2: 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

Table 3: The 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

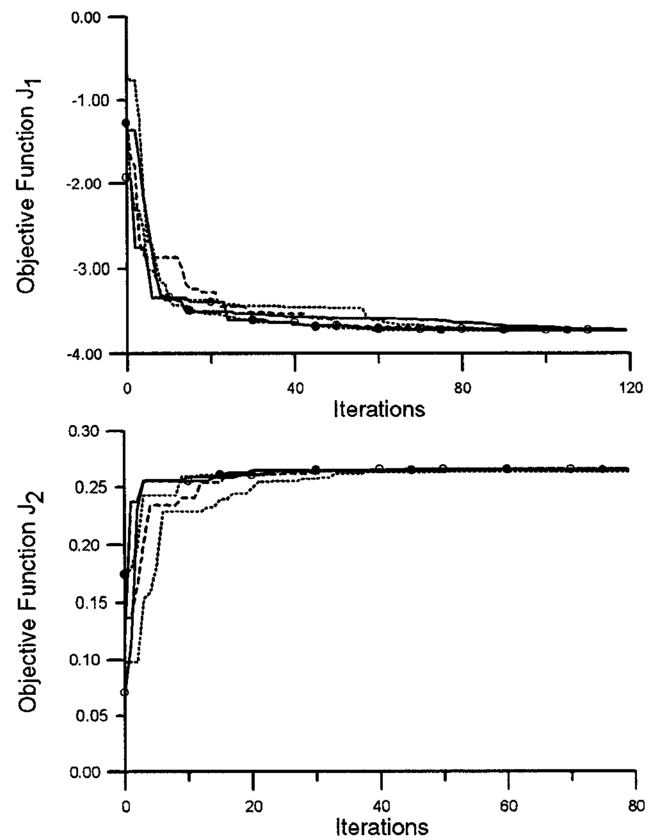

Fig. 2: Convergence of objective functions with different initializations

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 Table 1 and Table 2 respectively. The electromechanical mode eigenvalues and the corresponding damping ratios without PSSs for all cases are given in Table 4. 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 Table 5 and 6 respectively. It is obvious that the system damping with the proposed PSOPSSs is greatly improved and enhanced.

For further illustration, a 6-cycle three-phase fault at bus 7 at the end of line 5-7 is considered. The speed deviation of G_3 are shown in Fig. 3. The performance of the proposed PSOPSSs is compared to that of GA based PSS (GAPSS) given in [13]. It is clear that the proposed PSOPSSs outperform the GAPSSs and provide good damping characteristics and enhance greatly power system stability.

Table 4: Eigenvalues and damping ratios without PSSs

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

Table 5: Eigenvalues and damping ratios with PSOPSSs (J_1 settings)

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

Table 6: Eigenvalues and damping ratios with PSOPSSs (J_2 settings)

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

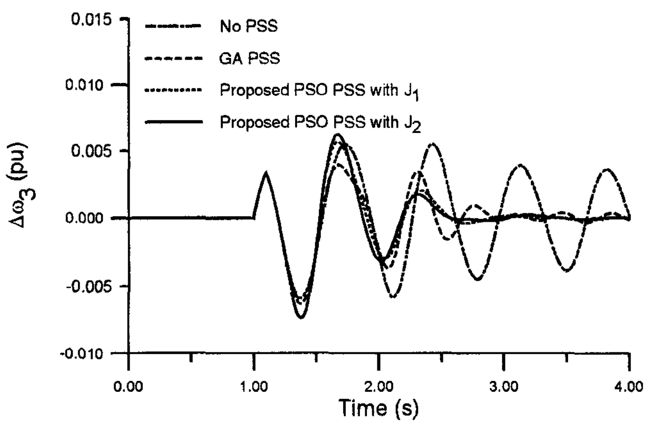

Fig. 3: System response to 6-cycle fault disturbance

5. EXAMPLE 2: NEW ENGLAND POWER SYSTEM

A. *Test System and PSS Design*

In this example, the 10-machine 39-bus New England system shown in Fig. 4 is considered. G_1 is an equivalent power source representing parts of the U.S.-Canadian interconnection system. Details of the system data are in [14].

For illustration and comparison purposes, is 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,...,10 *i.e.*, the number of optimized parameters is 27 in this example. PSO algorithm has been applied to search for settings of these parameters so as to optimize each objective function. The final values of the optimized parameters are given in Table 7.

Table 7: The 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

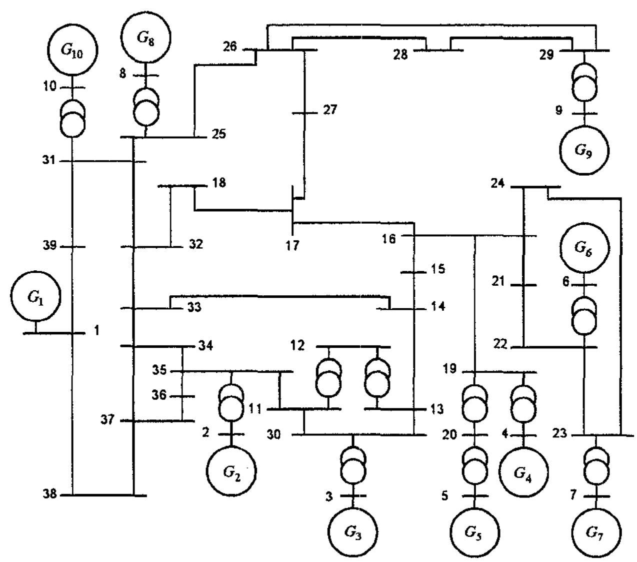

Fig. 4: Single line diagram for New England system

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; and *Case 2*; outage of line 14-15.

The electromechanical modes without PSSs are given in Table 8. It is clear that these modes are poorly damped and some of them are unstable. The electromechanical modes and the corresponding damping ratios with the proposed PSOPSSs for J_1 and J_2 settings are given in Tables 9 and 10 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.

For time-domain simulations, a 6-cycle three-phase fault at bus 29 at the end of line 26-29 has been applied and the faulty line is tripped of for 1.0s befor successful reclosure. The performance of the proposed PSOPSSs is compared to that of GAPSSs given in [13] and gradient-based PSSs given in [5]. Due to space limitations, only the speed deviation of G_9 is shown in Fig. 5. It can be seen that the gradient based PSSs are not able to stabilize the system under the fault disturbance. 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 get optimal set of PSS parameters.

6. CONCLUSIONS

In this study, a novel particle swarm optimization based approach to optimal design of multimachine PSSs is presented. The proposed design approach employs PSO to search for optimal settings of conventional lead-lag PSS parameters. The proposed approach has been applied to two different examples of multimachine power systems with different loading conditions and system configurations. The main features of the proposed approach can be summarized as: -

1. The proposed PSSs are of decentralized nature since only local measurements are employed as the stabilizer inputs. This makes the proposed PSOPSS easy to tune and install. In addition, the proposed stabilizers are of widely-used lead-lag structure which can be easily implemented and examined by power utilities.
2. The results show the potential of PSO technique for optimal design of PSS.
3. The solution quality of the proposed approach is independent of the initialization step. Therefore, the proposed approach can be used to improve the quality of the solutions of other classical optimization methods.
4. Eigenvalue analysis reveals the effectiveness of the proposed PSOPSSs to damp out electromechanical modes of oscillations.
5. Nonlinear time simulation results show that the proposed PSOPSSs can work effectively over a wide range of loading conditions and system configurations.

Table 8: 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*

Table 9: Eigenvalues and damping ratios with 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 10: Eigenvalues and damping ratios with 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*

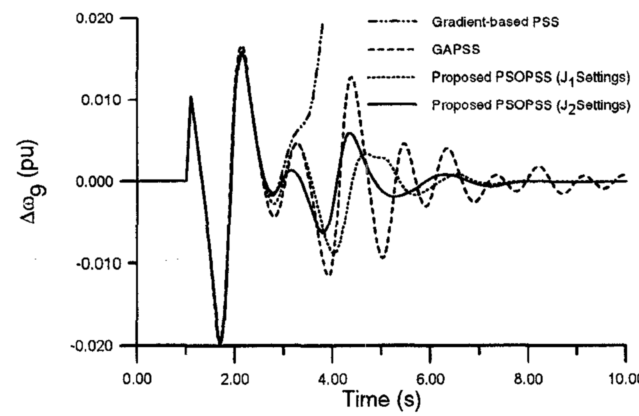

Fig. 5: System responses with fault disturbance

7. ACKNOWLEDGEMENT

The author acknowledges the support of King Fahd University of Petroleum & Minerals, Saudi Arabia.

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