Optimal Design of Power System Stabilizers Using Evolutionary Programming

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***Abstract*—The optimal design of power system stabilizers (PSSs) using evolutionary programming (EP) optimization technique is presented in this paper. The proposed approach employs EP to search for optimal settings of PSS parameters that shift the system eigenvalues associated with the electromechanical modes to the left in the s-plane. Incorporation of EP algorithm in the design of PSSs significantly reduces the computational burden. The performance of the proposed PSSs under different disturbances, loading conditions, and system configurations is investigated for a multimachine power system. The eigenvalue analysis and the nonlinear simulation results show the effectiveness and robustness of the proposed PSSs to damp out the local as well as the interarea modes of oscillations and work effectively over a wide range of loading conditions and system configurations.**

***Index Terms*—Dynamic stability, evolutionary programming, PSS design.**

NOMENCLATURE

ρ	first derivative w.r.t. time d/dt;
δ	torque angle;
ω, $\Delta\omega$	speed and speed deviation, respectively;
M, D	inertia constant and damping coefficient, respectively;
ω_b	synchronous speed;
E'_q	internal voltage behind x'_d;
E_{fd}	equivalent excitation voltage;
i_d, i_q	stator currents in d and q axis circuits, respectively;
v_d, v_q	stator voltages in d and q axis circuits, respectively;
V, V_{ref}	terminal and reference voltages, respectively;
x_d	synchronous reactance in d-axis;
x'_d	d-axis transient reactance;
T'_{do}	time constant of excitation circuit;
T_m, T_e	mechanical torque and electric torque, respectively;
K_A, T_A	regulator gain and time constant, respectively;
U	PSS control signal.

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I. INTRODUCTION

WITH the increased loading of long transmission lines, transient and dynamic stability after a major fault are increasingly important, and they can become a transmission power-limiting factor. Since the development of interconnection of large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2 to 3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. Moreover, low-frequency oscillations present limitations on the power-transfer capability. To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems. PSSs augment the power system stability limit and extend the power-transfer capability by enhancing the system damping of low-frequency oscillations associated with the electromechanical modes [1], [2].

DeMello and Concordia [2] 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 the PSS design problem. These include optimal control, adaptive control, variable structure control, and intelligent control [3]–[6].

Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead-lag power system stabilizer (CPSS) structure [7]–[9]. The reasons behind that might be the ease of online tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques.

Kundur *et al.* [9] have presented a comprehensive analysis of the effects of the different CPSS parameters on the overall dynamic performance of the power system. It is shown that the appropriate selection of CPSS parameters results in satisfactory performance during system upsets.

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 [10]–[12] to damp out the electromechanical modes one at a time. Generally, the dynamic interaction effects among various modes of the machines are found to have significant influence on the stabilizer settings. Therefore, considering the application of stabilizers to one machine at a time may not finally lead to an overall optimal choice of PSS parameters. Moreover, the stabilizers designed to damp one mode can produce adverse effects in other modes. In addition, the optimal sequence of design is a very involved question.

The sequential design of PSSs is avoided in [13]–[16], where various methods for simultaneous tuning of PSSs in multimachine power systems are proposed. Unfortunately, the proposed techniques are iterative and require heavy computational burden due to the system reduction procedure. This results in time-consuming computer codes. In addition, the initialization step of these algorithms is crucial and affects the final dynamic response of the controlled system. Hence, different designs assigning the same set of eigenvalues were simply obtained by using different initializations. Therefore, a final selection criterion is required to avoid long runs of validation tests on the nonlinear model. Other techniques, such as mathematical programming [17], have been applied to the problem of tuning PSSs. The problem has been formulated as a quadratic and linear programming problem. However, this formulation is carried out at the expense of some conservativeness, and the number of constraints becomes unduly large. A gradient procedure for optimization of PSS parameters is presented in [18]. The optimization process requires computations of sensitivity factors and eigenvectors at each iteration. This gives rise to heavy computational burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima, and the solution obtained will not be optimal. 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, which are well elaborated upon, 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 are, in general, not able to locate or identify the global optimum, but for real-world applications, one is often content with a "good" solution, even if it is not the best. Consequently, heuristic methods are widely used for global optimization problems. In this paper, evolutionary programming (EP), as a promising heuristic algorithm, is proposed for a PSS design problem.

Recently, evolutionary algorithms such as genetic algorithms (GAs) and EP have received much attention for global optimization problems [19], [20]. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection. Even though several successful applications have been reported, recent research has identified some inefficiency in GA performance [19]. 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 encoding and decoding processes of each solution use a lot of computing time. The new generation of GA after mutation and crossover may lose advantages obtained in the last generation. On the other hand, the competition in the combined old generation and mutated old generation avoids such a problem in an EP algorithm. On the other hand, EP has been shown to be more robust to *epistatic* objective functions and is more efficient than GA on many function optimization problems [19]. In addition, the convergence theory for EP is well established, and EP has been proven to asymptotically converge to the global optimum with probability one under elitist selection [19]. Another strong feature of the EP algorithm is that a complicated mathematical model is not required, and the problem constraints can be easily incorporated [20]. In power systems, EP has been applied to a number of power system optimization problems with impressive successes [21]–[23]. However, to the best of the authors' knowledge, the potential of the EP algorithm to PSS design has yet to be exploited.

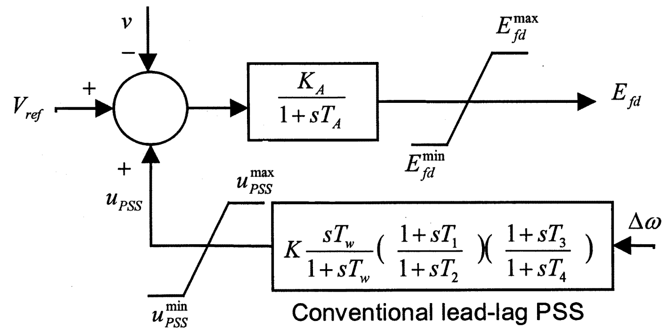

Fig. 1. IEEE-type-ST1 excitation system with conventional lead-lag PSS.

In this paper, a novel approach to PSS design by an eigenvalue shift technique using the EP algorithm is proposed. The problem of PSS design is formulated as an optimization problem, and the EP algorithm is employed to solve this optimization problem with the aim of getting optimal settings of the PSS parameters. The proposed design approach has been applied to the New England power system. The eigenvalue analysis and the nonlinear simulation results have been carried out to assess the effectiveness of the proposed PSSs under different disturbances, loading conditions, and system configurations.

II. Problem Statement

A. Power System Model

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. The nonlinear model is given in the Appendix.

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 m stabilizers can be written as

$$\dot{X} = AX + BU \tag{2}$$

where A is a $4n \times 4n$ matrix and equals $\partial f/\partial X$, whereas B is a $4n \times m$ matrix and equals $\partial f/\partial U$. Both A and B are evaluated at a certain operating point. X is the $4n \times 1$ state vector, whereas U is the $m \times 1$ input vector.

B. PSS Structure

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 is the washout time constant, U_i is the PSS output signal at the ith machine, and $\Delta\omega_\iota$ is the speed deviation of this machine. The time constants T_w, T_2, and T_4 are usually prespecified. The optimal values of the stabilizer gain K_i and the time constants T_{1i} and T_{3i} are to be determined. The IEEE-type-ST1 excitation system shown in Fig. 1 is considered in this study.

C. Objective Function

To formulate the optimization problem, an objective function J, which will be defined, is considered.

$$J = \sum_{\sigma_i \geq \sigma_0} (\sigma_0 - \sigma_i)^2 \tag{4}$$

where σ_i is the real part of the ith eigenvalue, and σ_0 is a chosen threshold. The value of σ_0 represents the desirable level of system damping. This level can be achieved by shifting the dominant eigenvalues to the left of $s = \sigma_0$ line in the s-plane. This also ensures some degree of relative stability. The condition $\sigma_i \geq \sigma_0$ is imposed on the evaluation of J to consider only the unstable or poorly damped modes that mainly belong to the electromechanical ones.

The problem constraints are the parameter bounds. Therefore, the design problem can be formulated as the following optimization problem:

$$\text{Minimize} \quad J \tag{5}$$

$$\text{Subject to} \quad K_i^{\min} \leq K_i \leq K_i^{\max} \tag{6}$$

$$T_{1i}^{\min} \leq T_{1i} \leq T_{1i}^{\max} \tag{7}$$

$$T_{3i}^{\min} \leq T_{3i} \leq T_{3i}^{\max}. \tag{8}$$

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

III. Proposed Approach

A. Overview

EP is an exploratory search and optimization procedure that was devised on the principles of natural evolution and population genetics. Unlike conventional optimization techniques, EP works with a population of points that represent different potential solutions, each corresponding to a sample point from the search space. For each generation, all of the population points are evaluated based on a certain objective function. The fittest points have more chances of evolving to the next generation. The advantages of EP over other traditional optimization techniques can be summarized as follows.

- EP searches the problem space using a population of trials representing possible solutions to the problem and not a single point, (i.e., EP has implicit parallelism). This property ensures that EP is less susceptible to getting trapped on local minima, and therefore, EP can reach to a global or near-global optimal solution.
- EP uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, EP can easily deal with nonsmooth, noncontinuous, and nondifferentiable objective functions that are the real-life optimization problems. Additionally, this property relieves EP of assumptions and approximations, which are often required by traditional optimization methods for many practical optimization problems.
- EP uses probabilistic transition rules to make decisions: not deterministic rules. Hence, EP is a kind of stochastic optimization algorithm that can search a complicated and uncertain area to find the global optimum. This makes EP more flexible and robust than conventional methods.

Typically, the EP starts with little or no knowledge of the correct solution, depending entirely on responses from interacting environment and their evolution operators to arrive at optimal or near optimal solutions.

B. EP Algorithm

In the EP algorithm, the population has $2n$ candidate solutions. Each candidate solution is an m-dimensional real-valued vector, where m is the number of optimized parameters. The EP algorithm can be described in the following steps.

- ***Step 1 (Initialization)***: Set the generation counter $k = 0$, and generate randomly n trial solutions $\{x_i, i = 1, \ldots, n\}$. The ith trial solution x_i can be written as $x_i = [p_1, \ldots, p_m]$, where the jth optimized parameter p_j is generated by randomly selecting a value with uniform probability over its search space $\left[p_j^{\min}, p_j^{\max}\right]$. These initial trial solutions constitute the parent population at the initial generation $k = 0$. Each individual in the initial population is evaluated using the objective function J. Search for the minimum value of the objective function $J_{\min}$. Set the solution associated with $J_{\min}$ as the best solution x_{best}, with an objective function of J_{best}.
- ***Step 2 (Mutation)***: Each parent x_i produces one offspring x_{n+i} as follows.
  a) Perturb each optimized parameter p_j by a Gaussian random variable $N\left(0, \sigma_j^2\right)$. The standard deviation σ_j specifies the range of the optimized parameter perturbation in the offspring. σ_j is given according to the following equation:

$$\sigma_j = \beta \times \frac{J(x_i)}{J_{\max}} \times \left(p_j^{\max} - p_j^{\min}\right) \tag{9}$$

  where β is a scaling factor, and $J(x_i)$ is the objective function of the trial solution x_i.
  b) Using the perturbations described, the offspring x_{n+i} can be determined as

$$x_{n+i} = x_i + \left[N\left(0, \sigma_1^2\right), \ldots, N\left(0, \sigma_m^2\right)\right], \quad i = 1, \ldots, n. \tag{10}$$

  If any optimized parameter violates its specified range, its value will be set at the appropriate limit. The generated offsprings along with the parents constitute the current population with $2n$ individuals.

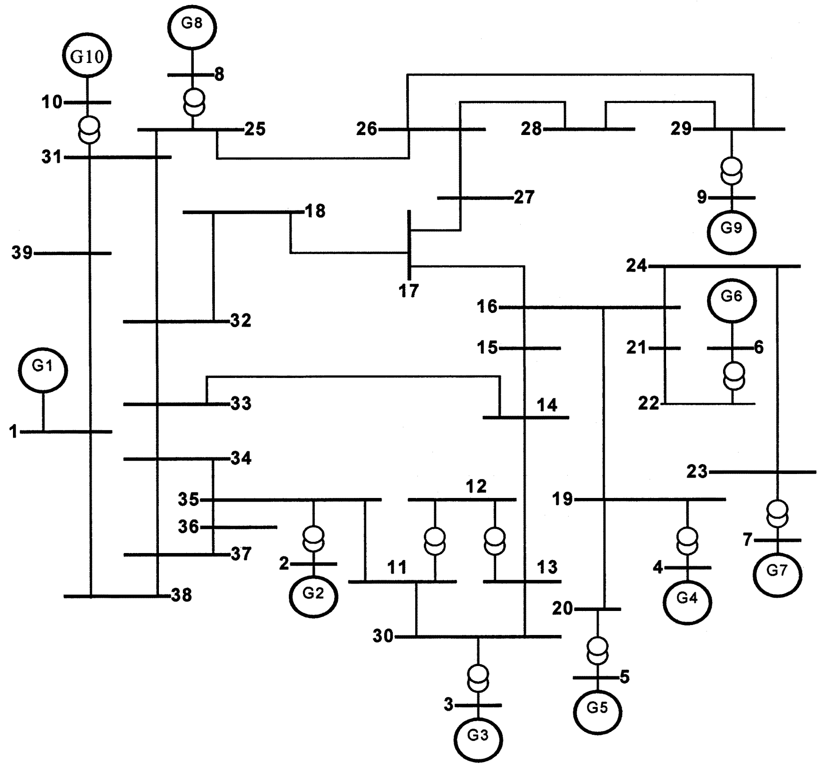

Fig. 2. Single-line diagram for a New England system.

- ***Step 3 (Statistics)***: The objective functions of the offsprings are evaluated. The minimum objective function $J_{\min}$, the maximum objective function $J_{\max}$, and the average objective function J_{ave} of all individuals are calculated.
- ***Step 4 (Updating the Best Solution)***: If $J_{\min} > J_{\text{best}}$, go to Step 5, or else, update the best solution x_{best}. Set $J_{\text{best}} = J_{\min}$, and go to Step 5.
- ***Step 5 (Tournament)***: Each member in the population x_i is compared with q opponents that are selected at random from the population $q \leq 2n - 1$. A weight value W_i of each individual x_i is calculated according to the following competition rule:

$$W_i = \sum_{t=1}^{q} W_t \tag{11}$$

and

$$W_t = \begin{cases} 1, & \text{if } U > \frac{J(x_i)}{J(x_i)+J(x_r)} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where U is a uniform random number ranging over $[0, 1]$, and x_r is a randomly selected individual from the current population. After getting the competition weights of all $2n$ individuals, these individuals are ranked in a descending order, based on their weights.
- ***Step 6 (Selection)***: The first n individuals with higher weights are selected along with their objective functions to represent the parents of the next generation. Set the generation counter $k = k + 1$.
- ***Step 7 (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 generations since the last change of the best solution is greater than a prespecified number.
  b) The number of generations reaches the maximum allowable number.
  c) The ratio $J_{\text{ave}}/J_{\max}$ is very close to 1. If one of these criteria is satisfied then stop, else, go back to Step 2.

C. Application of EP to PSS Design

The EP algorithm described before has been applied to search for optimal or near optimal settings of the PSS optimized parameters. In our implementation, the search will terminate if the following occur.

1) The best solution does not change for more than 20 generations.
2) The number of generations reaches 100.
3) The ratio $J_{\text{ave}}/J_{\max} \geq 0.999$.

One more stopping criterion has been implemented in this study since the search will terminate if the value of the objective function reaches *zero* (i.e., all of the dominant eigenvalues are shifted to the left of $s = \sigma_0$ line).

IV. Results and Discussions

A. Test System

In this study, the ten-machine, 39-bus New England power system shown in Fig. 2 is considered. Each machine has been represented by a fourth-order nonlinear model. Generator G_1

TABLE I
OPTIMAL VALUES OF THE PROPOSED PSS PARAMETERS

Gen#	k	T_1	T_3
G_2	23.162	0.368	0.365
G_3	47.485	0.496	0.502
G_4	46.826	0.508	0.986
G_5	9.472	0.158	0.381
G_6	45.417	0.430	0.939
G_7	18.755	0.268	0.102
G_8	39.767	0.889	0.914
G_9	45.728	0.214	0.124
G_{10}	26.870	0.999	0.749

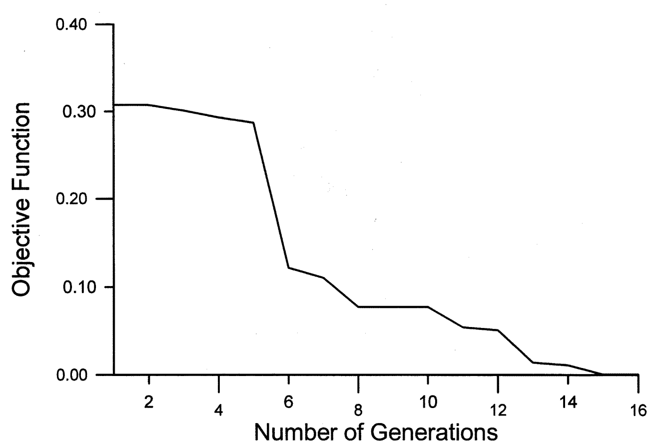

Fig. 3. Objective function variations.

TABLE II
EIGENVALUES WITHOUT PSSS

Base Case	*Case 1*	*Case 2*
0.191 ±j 5.808	**0.195 ±j 5.716**	**0.189 ±j 5.811**
0.088 ±j 4.002	**0.121 ±j 3.798**	**0.006 ±j 3.113**
-0.034 ±j 6.415	**0.097 ±j 6.006**	**0.001 ±j 6.180**
-0.028 ±j 9.649	-0.032 ±j 9.694	-0.028 ±j 9.650
-0.056 ±j 7.135	-0.104 ±j 8.015	-0.032 ±j 7.105
-0.093 ±j 8.117	-0.109 ±j 6.515	-0.091 ±j 8.115
-0.172 ±j 9.692	-0.168 ±j 9.715	-0.172 ±j 9.693
-0.220 ±j 8.013	-0.204 ±j 8.058	-0.218 ±j 8.024
-0.270 ±j 9.341	-0.250 ±j 9,268	-0.269 ±j 9.342

TABLE III
EIGENVALUES WITH THE PROPOSED PSSS

Base Case	*Case 1*	*Case 2*
-1.008 ±j 9.279	-0.968 ±j 9.181	-1.003 ±j 9.276
-1.023 ±j 7.269	-0.867 ±j 7.215	-1.091 ±j 8.890
-1.108 ±j 3.095	-0.876 ±j 3.058	-0.694 ±j 2.243
-1.154 ±j 8.912	-0.952 ±j 8.804	-1.203 ±j 6.915
-1.701 ±j 8.828	-2.480 ±j 7.213	-1.714 ±j 8.885
-1.725 ±j 12.965	-1.709 ±j 12.742	-1.724 ±j 12.962
-1.816 ±j 13.608	-1.804 ±j 13.549	-1.815 ±j 13.603
-2.103 ±j 11.247	-2.139 ±j 11.185	-2.106 ±j 11.248
-3.543 ±j 15.280	-3.610 ±j 14.720	-3.552 ±j 15.284

is an equivalent power source representing parts of the U.S.-Canadian interconnection system. Details of the system data are given in [24]. The number and location of PSSs can be investigated using the participation factor method [25] and the sensitivity of the PSS effect method [26]; see [6]. However, for illustration and comparison purposes, we assume that all generators except G_1 are equipped with PSSs.

B. PSS Design

In this example, 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). T_w, T_2, and T_4 are set to be 5, 0.05, and 0.05 s, respectively. Typical bounds of the optimized parameters are [0.01–50] for K_i and [0.1–1.0] for T_{1i} and T_{3i} [27]. Here, σ_0 is chosen to be -1.0. The EP algorithm has been applied to search for settings of these parameters in order to shift the eigenvalues of electromechanical modes to the left of the line $s = -1.0$ in the s-plane. The final values of the optimized parameters are given in Table I. The convergence rate of the objective function J with the number of generations is shown in Fig. 3.

C. Simulation Results

To demonstrate the effectiveness of the proposed PSSs under severe conditions and critical line outages, two different operating conditions in addition to the base case are considered. These conditions are extremely hard from the stability point of view [28]. They can be described as

1) base case;
2) case 1, outage of line 21–22;
3) case 2, outage of line 1–38.

The electromechanical modes without PSSs for the three cases are given in Table II. It is clear that these modes are poorly damped, and some of them are unstable. The electromechanical modes with the proposed PSSs are given in Table III. It can be seen that the electromechanical modes of the base case with the proposed PSSs have been shifted to the left of $s = -1.0$ line. It is obvious that the system damping greatly improved and enhanced all cases.

A six-cycle three-phase fault disturbance at bus 29 at the end of line 26–29 is considered for the nonlinear time simulations. The performance of the proposed PSSs is compared with that of conventional PSSs with the gradient-based settings given in [18]. The speed deviation of G_6 and G_8, along with their stabilizing signals, are shown in Figs. 4–6 for the base case, case 1, and case 2, respectively. It is clear that the system performance with the proposed PSSs is much better and that the oscillations are damped out much faster. It is worth mentioning that the control effort is limited to ± 0.2 pu to avoid unrealistic values. Although the robustness issue has been considered in the design process of conventional PSSs of [18], the proposed PSS is more robust, as shown in results of cases 1 and 2. This reflects the potential of the proposed approach to search for the global rather than the local optimum. In addition, the proposed PSSs are quite efficient to damp out the local modes, as well as the interarea modes of oscillations. This illustrates the superiority of the proposed PSS design approach to get an optimal or near-optimal set of PSS parameters.

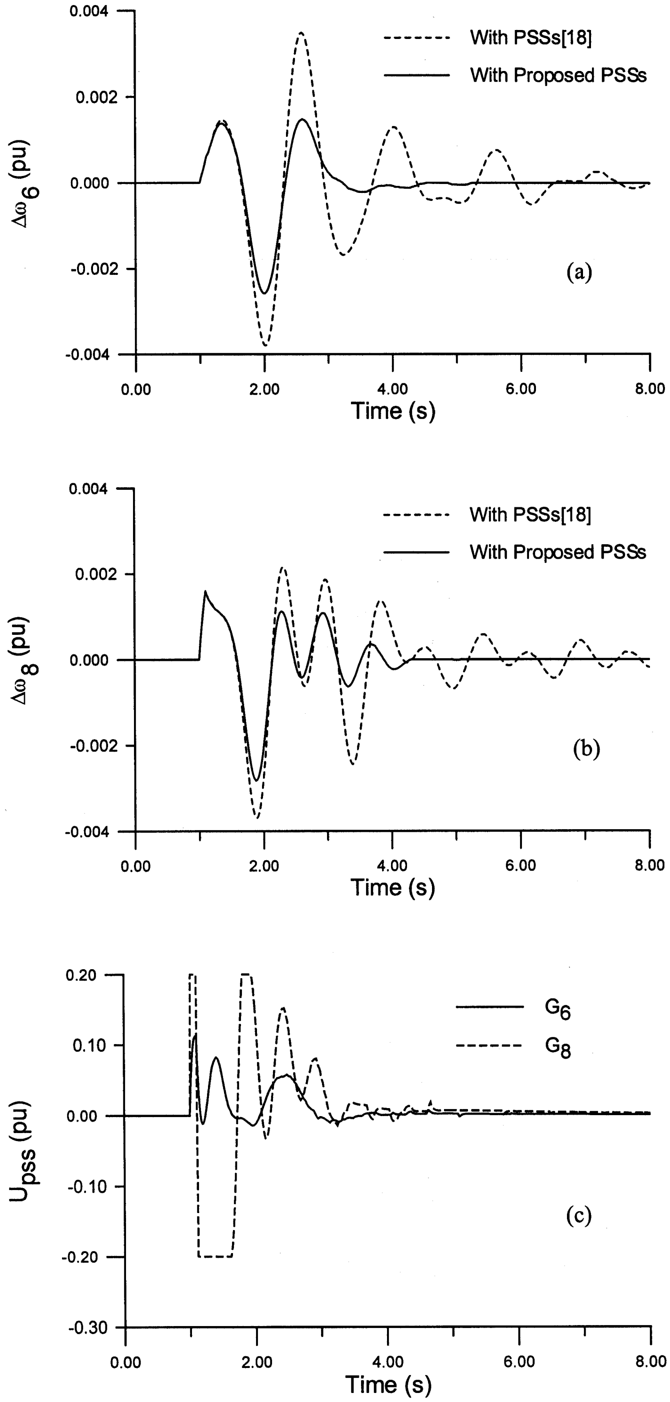

Fig. 4. System responses with the base case.

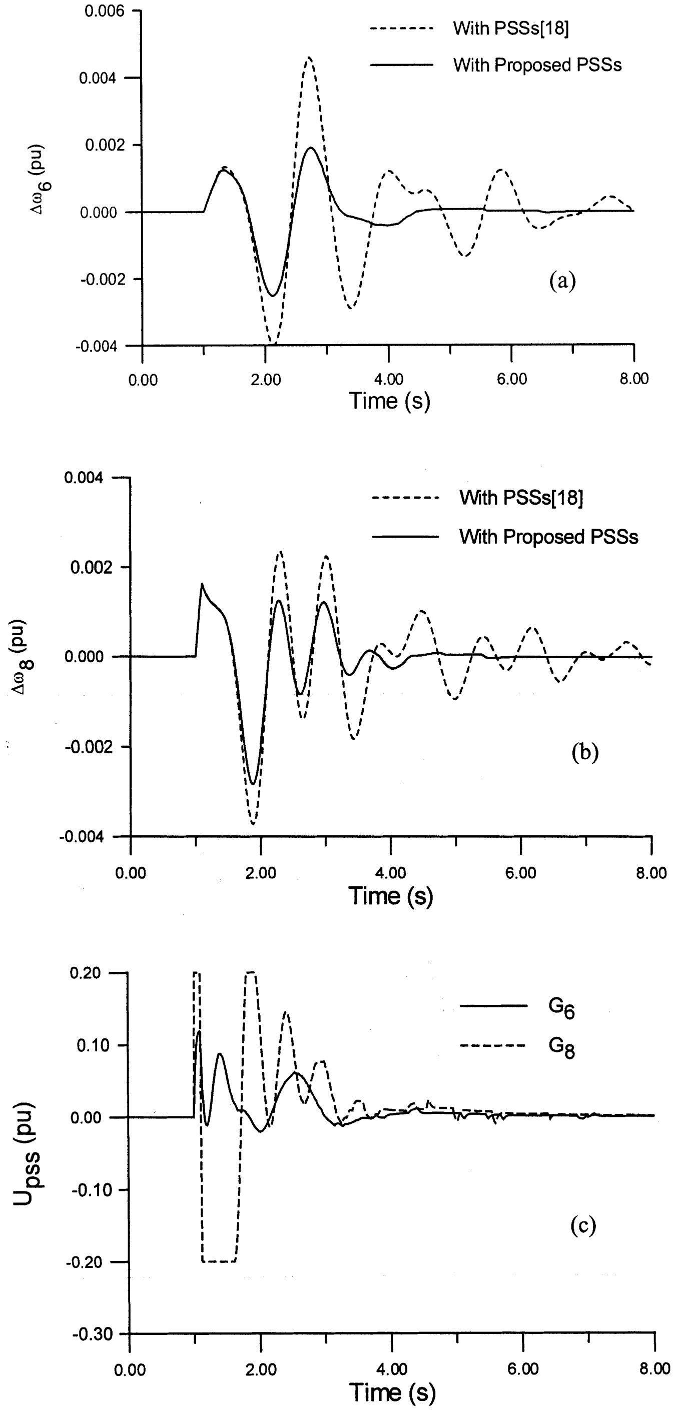

Fig. 5. System responses with case 1.

Due to space limitations and to offer clear perceptiveness about the system responses, two performance indices that reflect the settling time and overshoots are introduced. They are defined as

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

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

where n is the number of machines, and t_{sim} is the simulation time. It is worth mentioning that the lower the value of these indices is, the better the system response in terms of the settling time and overshoots. The values of these indices with the different cases are given in Table IV. It is clear that the values of these indices with the proposed PSSs are much smaller compared with the corresponding values, with the PSSs given in [18]. This demonstrates that the settling time and the speed deviations of all units are greatly reduced by applying the proposed PSSs.

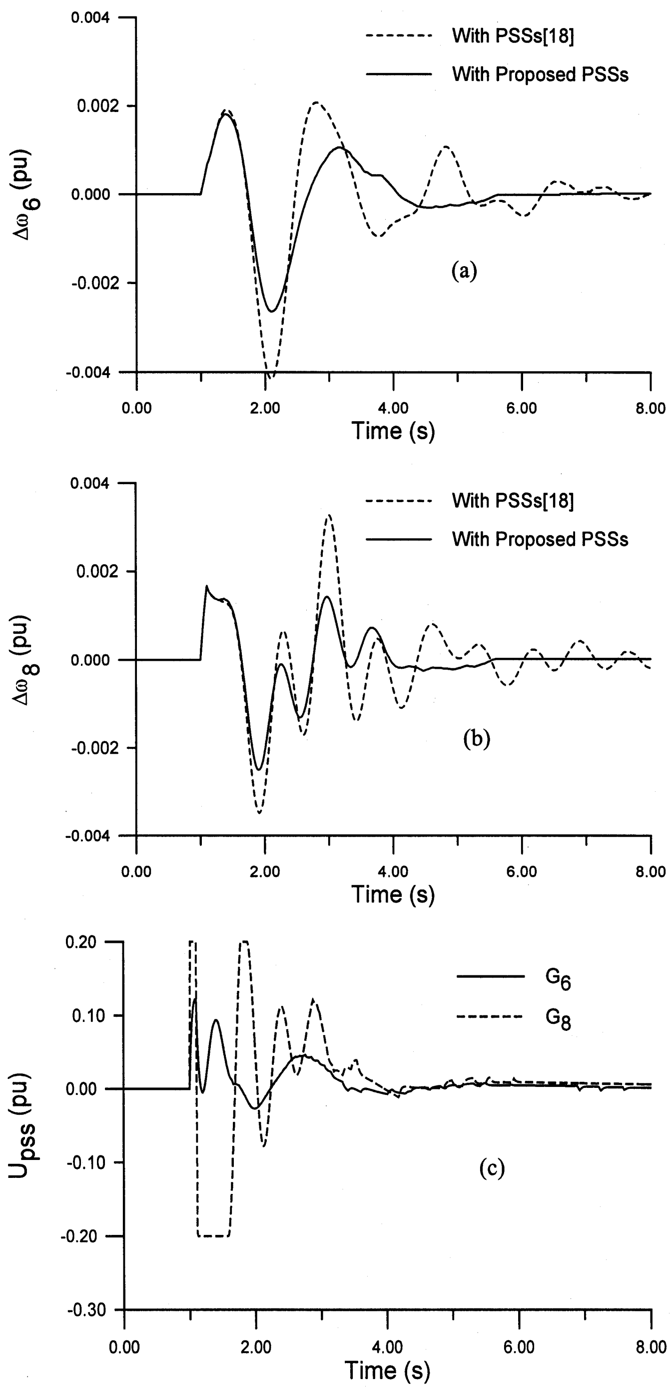

Fig. 6. System responses with case 2.

TABLE IV
VALUES OF THE PERFORMANCE INDICES

Fault of	PI_1		PI_2	
	PSS [18]	Prop. PSS	PSS [18]	Prop. PSS
Base	2.4277	0.5573	1.0491	0.5631
Case 1	3.3486	0.8335	1.0858	0.6068
Case 2	2.3882	0.8045	1.1032	0.6297

V. CONCLUSIONS

In this study, the evolutionary programming algorithm is proposed for the PSS design problem. The proposed design approach employs EP to search for optimal settings of conventional lead-lag PSS parameters. The proposed approach has been applied to a single machine infinite bus system and a multimachine power system with different disturbances, loading conditions, and system configurations. The main features of the proposed approach can be summarized as follows.

1) The proposed PSSs are of decentralized nature since only local measurements are employed as the stabilizer inputs. This makes the proposed PSS easy to tune and install.
2) All PSSs are designed simultaneously, taking into consideration the interaction among them.
3) Since eigenvector calculations and sensitivity analysis are not required to evaluate the proposed objective function, heavy computations of the design process are avoided.
4) The eigenvalue analysis reveals the effectiveness of the proposed PSSs to damp out local as well as interarea modes of oscillations.
5) The nonlinear time simulation results confirm that the proposed PSSs can work effectively over a wide range of loading conditions and system configurations.

APPENDIX
iTH MACHINE MODEL

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

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

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

$$\dot{E}_{fd_i} = \frac{K_{ai}(V_{refi} - V_i - U_i) - E_{fdi}}{T_{ai}} \tag{A.4}$$

$$T_{ei} = v_{qi}i_{qi} + v_{di}i_{di}. \tag{A.5}$$

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