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Parameter optimization of multimachine power system stabilizers using genetic local search

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Abstract

A genetic local search (GLS) algorithm for optimal design of multimachine power system stabilizers (PSSs) is presented in this paper. The proposed approach hybridizes the genetic algorithm (GA) with a heuristic local search in order to combine their strengths and overcome their shortcomings. The potential of the proposed approach for optimal parameter settings of the widely used conventional lead–lag PSSs has been investigated. Unlike the conventional optimization techniques, the proposed approach is robust to the initial guess. The performance of the proposed GLS-based PSS (GLSPSS) under different disturbances, loading conditions, and system configurations is investigated for different multimachine power systems. Eigenvalue analysis and simulation results show the effectiveness and robustness of the proposed GLSPSS to damp out local as well as interarea modes of oscillations and work effectively over a wide range of loading conditions and system configurations.

Keywords: PSS; Genetic algorithm; Local search; Dynamic stability

1. Introduction

Power systems experience low-frequency oscillations due to disturbances. The oscillations may sustain and grow to cause system separation if no adequate damping is available [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 power system stabilizer (PSS) design problems. These include optimal control, adaptive control, variable structure control, and intelligent control [3–5].

Despite the potential of modern control techniques with different structures, power system utilities still prefer the conventional lead–lag PSS structure [6–8]. The reasons behind that might be the ease of on-line tuning and the lack of assurance of the stability related to some adaptive or variable structure techniques. Kundur et al. [8] have presented a comprehensive analysis of the effects of the different conventional PSS parameters on the overall dynamic performance of the power system. It is shown that the appropriate selection of conventional lead–lag PSS parameters results in satisfactory performance during system upsets.

Different techniques of sequential design of PSSs are presented in Refs. [9,10] to damp out one of the electromechanical modes 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 stabilizer 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 Refs. [11–13] 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 the reduction procedure of the system order. 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. A gradient procedure for optimization of PSS parameters is presented in Ref. [14]. Unfortunately, the optimization process requires heavy computational burden and suffers from slow convergence.

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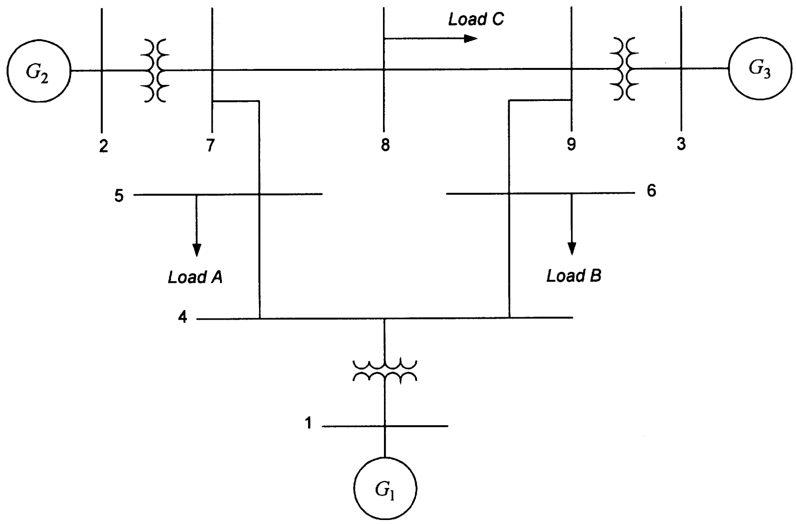

Fig. 1. Single-line diagram of three-machine nine-bus system.

In addition, the search process is susceptible to be trapped in local minima and the solution obtained will not be optimal.

Recently, heuristic search algorithms such as genetic algorithm (GA) [15,16], tabu search algorithm [17], and simulated annealing [18] have been applied to the problem of PSS design. The results are promising and confirm the potential of these algorithms for the optimal settings of PSS parameters. Unlike other optimization techniques, GA works with a population of strings that represent different potential solutions. Therefore, GA has implicit parallelism that enables it to search the problem space globally and the optima can be located more quickly when applied to complex optimization problem. Unfortunately, recent research has identified some deficiencies 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 premature convergence of GA represents a major problem.

In this paper, a hybrid off-line tuning approach to PSS design problem is developed and presented. In this approach, GA is hybridized with a local search algorithm to enhance its capability of exploring the search space and overcome the premature convergence. The design problem is formulated as an optimization problem with mild constraints and an eigenvalue-based objective function. Then genetic local search (GLS) algorithm is employed to solve this optimization problem and search for the optimal settings of PSS parameters. The proposed design approach has been applied to different multimachine power systems. Eigenvalue analysis and simulation results have been carried out to assess the effectiveness and robustness of the proposed GLSPSS to damp out the electromechanical modes of oscillations and enhance the dynamic stability of power systems.

2. Problem statement

2.1. 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

Table 1
Generator loadings in pu

Gen	Case 1		Case 2		Case 3	
	P	Q	P	Q	P	Q
G_1	0.72	0.27	2.21	1.09	0.33	1.12
G_2	1.63	0.07	1.92	0.56	2.00	0.57
G_3	0.85	−0.11	1.28	0.36	1.50	0.38

Table 2
Loads in pu

Load	Case 1		Case 2		Case 3	
	P	Q	P	Q	P	Q
A	1.25	0.50	2.00	0.80	1.50	0.90
B	0.90	0.30	1.80	0.60	1.20	0.80
C	1.00	0.35	1.50	0.60	1.00	0.50

Table 3
The optimal settings of the proposed GLSPSS

	k	T_1	T_3
G_2	8.7586	0.1574	0.1697
G_3	0.0782	0.6049	0.6748

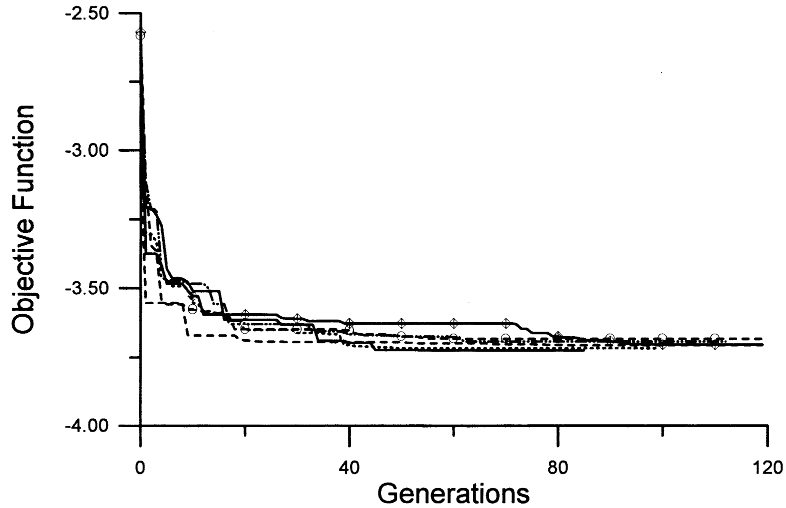

Fig. 2. Objective function convergence with different initializations.

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:

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

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

A widely used conventional lead–lag PSS is considered in this study. It can be described as [1,2]

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

where T_w is the washout time constant, U_i is the PSS output signal at the ith machine, and $\Delta\omega_\tau$ is the speed deviation of this machine. The time constants T_w, T_2, and T_4 are usually prespecified [11]. The stabilizer gain K_i and time constants T_{1i} and T_{3i} still need to be optimized.

2.2. Objective function and PSS tuning

To increase the system damping to electromechanical modes, an objective function J defined below is considered.

$$J = \max\{\mathrm{Re}(\lambda_i),\ i \in \text{set of electromechanical modes}\} \tag{4}$$

Where $Re(\lambda_i)$ is the real part of the ith eigenvalue associated with electromechanical modes. This objective function is proposed to shift these eigenvalues to the left of s-plane in order to improve the system damping factor and settling time and insure some degree of relative stability.

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

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

Subject to

$$K_i^{\min} \le K_i \le K_i^{\max} \tag{6}$$

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

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

Typical ranges of these parameters are [0.01–50] for K_i and [0.1–1.0] for T_{1i} and T_{3i} [1]. The time constants T_w, T_2, and T_4 are set as 5, 0.05, and 0.05 s, respectively [16].

The proposed approach employs GLS 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. Genetic local search

3.1. Overview

GA is an exploratory search and optimization procedure that is devised on the principles of natural evolution and

Table 4
Electromechanical mode eigenvalues without PSSs

Case 1	Case 2	Case 3
−0.011 ± j9.068	−0.021 ± j8.907	0.377 ± j8.865
−0.778 ± j13.86	−0.519 ± j13.83	−0.336 ± j13.69

Table 5
Electromechanical mode eigenvalues with the proposed GLSPSSs

Case 1	Case 2	Case 3
−3.726 ± j8.132	−2.398 ± j7.577	−2.649 ± j8.186
−3.724 ± j18.957	−4.079 ± j19.07	−3.910 ± j18.75

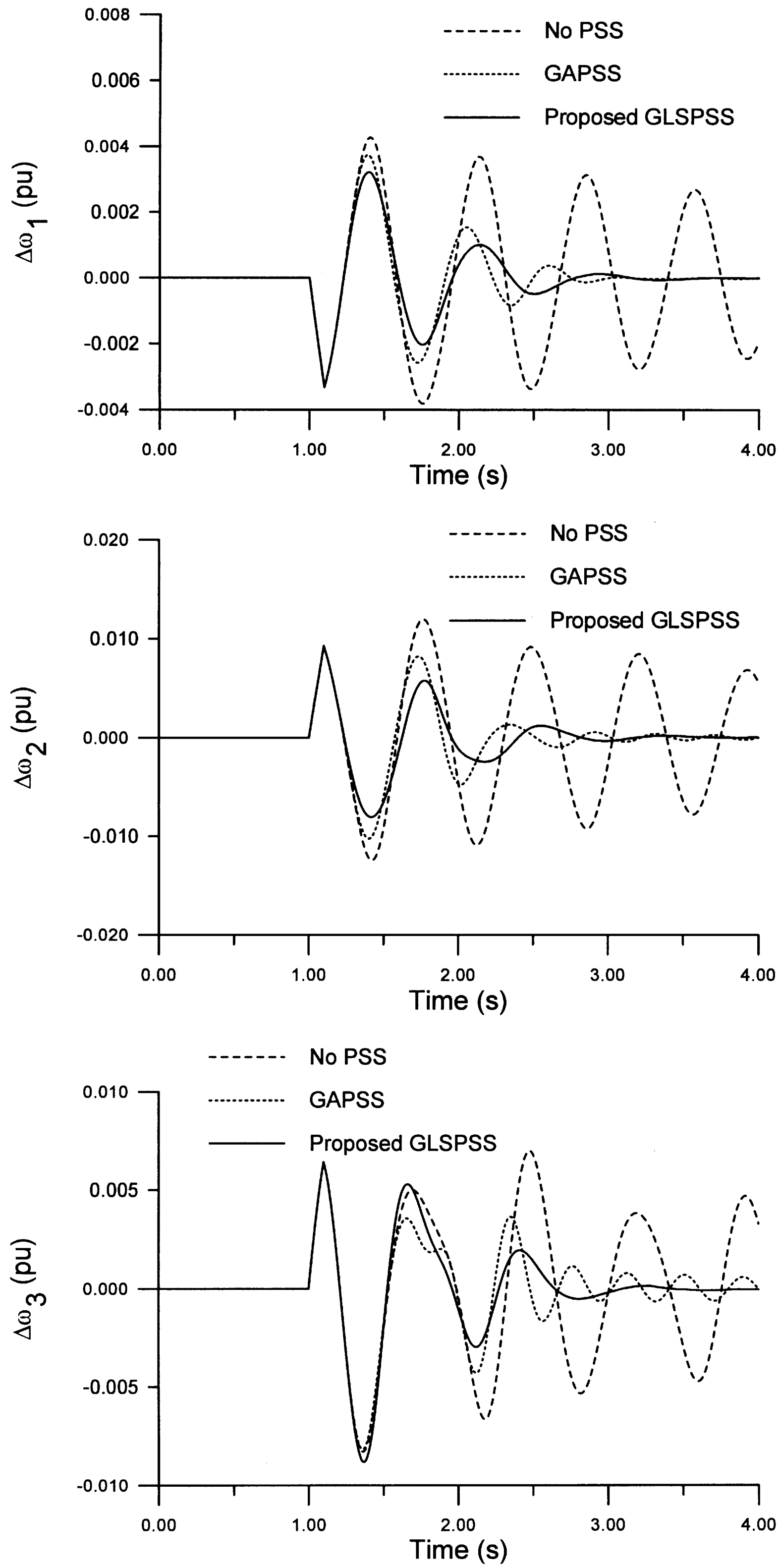

Fig. 3. System response under fault disturbance with case 2.

population genetics. Unlike other optimization techniques, GA works with a population of strings that represent different potential solutions, each corresponding to a sample point from the search space. For each generation, all the populations are evaluated based on a certain objective function. The fittest strings have more chances of evolving to the next generation.

Typically, the GA starts with little or no knowledge of the

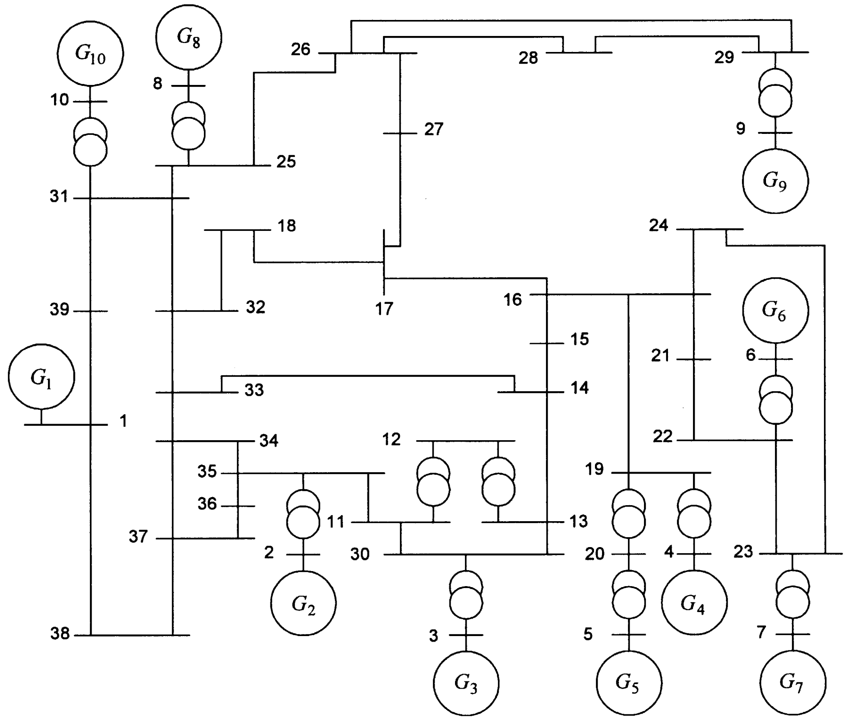

Fig. 4. Single-line diagram of 10-machine 39-bus system.

correct solution depending entirely on responses from interacting environment and their evolution operators to arrive at optimal solutions. In general, GA includes three basic operations: *reproduction*, *crossover*, and *mutation* [20]. These operations can be defined as follows.

Reproduction is a process in which a new generation of population is formed by selecting the fittest individuals in the current population. This is the survival of the fittest mechanism. Strings selected for reproduction are copied and entered to the mating pool.

Crossover is the most dominant operator in GA. It is responsible for producing new offsprings by selecting two strings from the mating pool and exchanging portions of their structures. The new offsprings may replace the weaker individuals in the population. With the crossover operation, GA is able to acquire more information with the generated individuals and the search space is thus extended and more complete. The probability of crossover is set arbitrarily (typically 0.6–0.9 [20]). The crossover will be applied if a random number generated between 0 and 1 is less than the preset value of crossover probability.

Mutation is an operation to alter the value of a random position in a string to avoid a loss of important information at a particular position. Generally, mutation is a local operator, which is applied with a very low probability. Similar to crossover, the mutation probability is set arbitrarily (typically 0.001–0.01 [20]).

Recent research has identified some deficiencies 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 premature convergence of GA represents a major problem. This problem occurs when the population of chromosomes reaches a configuration such that crossover no longer produces offsprings that can outperform their parents. Under such circumstances, all standard forms of crossover simply regenerate the current parents. Any further optimization relies solely on bit mutation and can be quite slow. At this stage, hill-climbing heuristics should be employed to search for improvement [21].

In this study, a hybrid GLS technique is presented to integrate the use of GA and local search in order to combine their different strengths and overcome their shortcomings. It is important to clarify that the proposed approach brings the parallelism capabilities of GA to the hill-climbing capabilities of local search in the sense that the local search concepts are imbedded in GA operations.

Table 6
The optimal settings of the proposed GLSPSSs

	k	T_1	T_3
G_2	31.134	0.870	0.636
G_3	45.406	0.522	0.555
G_4	30.792	0.875	0.893
G_5	48.241	0.185	0.123
G_6	37.146	0.650	0.978
G_7	6.207	0.429	0.291
G_8	25.904	0.781	0.903
G_9	46.725	0.190	0.137
G_{10}	32.551	0.983	0.997

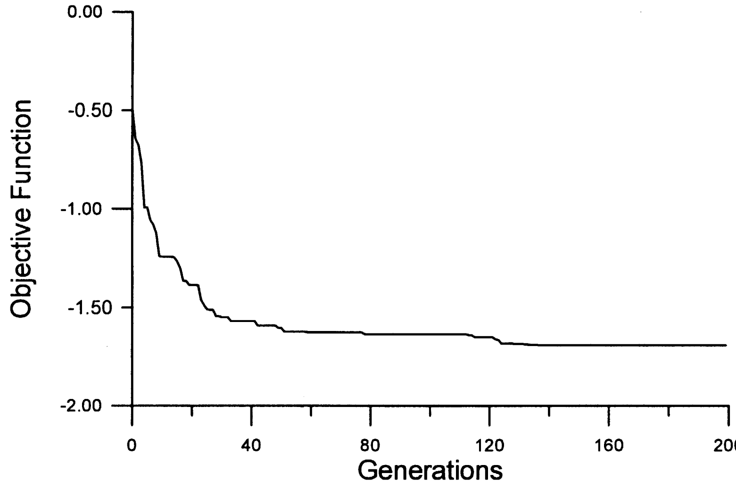

Fig. 5. Objective function convergence.

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

- Alike GA, GLS has implicit parallelism. This property ensures GLS to be less susceptible to getting trapped on local minima.
- GLS uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, it can easily deal with non-differentiable objective functions that are the real-life optimization problems. Additionally, this property relieves GLS of assumptions and approximations, which are often required by traditional optimization methods for many practical optimization problems.
- GLS uses probabilistic transition rules to make decisions, not deterministic rules. Hence, GLS is a kind of stochastic optimization algorithm that can search a complicated and uncertain area to find the global optimum. This makes GLS more flexible and robust than conventional methods.
- GLS employs local optimization concepts in generation production to overcome the premature convergence of GA.

3.2. GLS algorithm

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

Step 1: Set the generation counter $k = 0$ and generate randomly n initial solutions, $X_0 = \{x_i,\ i = 1, \ldots, n\}$. The ith initial solution x_i can be written as $x_i = [p_1 \ldots p_j \ldots p_m]$, where the jth optimized parameter p_j is generated by randomly selecting a value with uniform probability over its search space $[p_j^{\min}, p_j^{\max}]$. These initial solutions constitute the parent population at the initial generation X_0. Each individual of X_0 is evaluated using the objective function J. Set $X = X_0$.
Step 2: Optimize locally each individual in X. Replace each individual in X by its locally optimized version. Update the objective function values accordingly.
Step 3: 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 4: Check the stopping criteria. If one of them is satisfied then stop, else set $k = k + 1$ and go to Step 5.
Step 5: Set the population counter $i = 0$.
Step 6: Draw randomly, with uniform probability, two solutions x_1 and x_2 from X. Apply the genetic crossover and mutation operators obtaining x_3.
Step 7: Optimize locally the solution x_3 obtaining x_3^*.
Step 8: Check if x_3^* is better than the worst solution in X and different from all solutions in X then replace the worst solution in X by x_3^* and the value of its objective by that of x_3^*.
Step 9: If $i = n$ go to Step 3, else set $i = i + 1$ and go back to Step 6.

In this study, the search will terminate if one of the following criteria is satisfied: (a) the number of generations

Table 7
Electromechanical mode eigenvalues without PSSs

Case 1	Case 2	Case 3
0.191 ± j5.808	0.195 ± j5.716	0.152 ± j5.763
0.088 ± j4.002	0.121 ± j3.798	0.095 ± j3.837
−0.028 ± j9.649	0.097 ± j6.006	0.033 ± j6.852
−0.034 ± j6.415	−0.032 ± j9.694	−0.026 ± j9.659
−0.056 ± j7.135	−0.104 ± j8.015	−0.094 ± j8.120
−0.093 ± j8.117	−0.109 ± j6.515	−0.100 ± j6.038
−0.172 ± j9.692	−0.168 ± j9.715	−0.171 ± j9.696
−0.220 ± j8.013	−0.204 ± j8.058	−0.219 ± j8.000
−0.270 ± j9.341	−0.250 ± j9.268	−0.259 ± j9.320

Table 8
Electromechanical mode eigenvalues with the Proposed GLSPSSs

Case 1	Case 2	Case 3
−1.693 ± j2.927	−1.162 ± j3.281	−1.400 ± j2.679
−1.694 ± j11.04	−1.676 ± j10.99	−1.684 ± j11.05
−1.694 ± j11.75	−1.678 ± j11.71	−1.690 ± j11.74
−1.706 ± j10.07	−1.756 ± j9.193	−1.716 ± j9.757
−1.732 ± j13.31	−1.673 ± j13.09	−1.717 ± j13.23
−2.022 ± j9.934	−1.882 ± j10.12	−1.807 ± j10.09
−1.830 ± j10.85	−1.904 ± j10.47	−1.831 ± j10.84
−1.819 ± j9.020	−2.397 ± j8.952	−2.319 ± j7.639
−2.087 ± j3.472	−1.806 ± j3.058	−2.255 ± j3.597

since the last change of the best solution is greater than a prespecified number; and (b) the number of generations reaches the maximum allowable number.

To assess the effectiveness and robustness of the proposed PSS design approach, two different examples of multimachine power systems have been considered and examined under different loading conditions and system configurations.

4. Example 1: three-machine system

4.1. Test system and proposed GLSPSS design

In this example, the three-machine nine-bus power system shown in Fig. 1 is considered. Details of the system data are given in Ref. [22]. 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 case 1. The generator and system loading levels at this case are given in Tables 1 and 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 objective function convergence is shown in Fig. 2. It is clear that unlike the conventional methods [11–13], 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 other traditional methods.

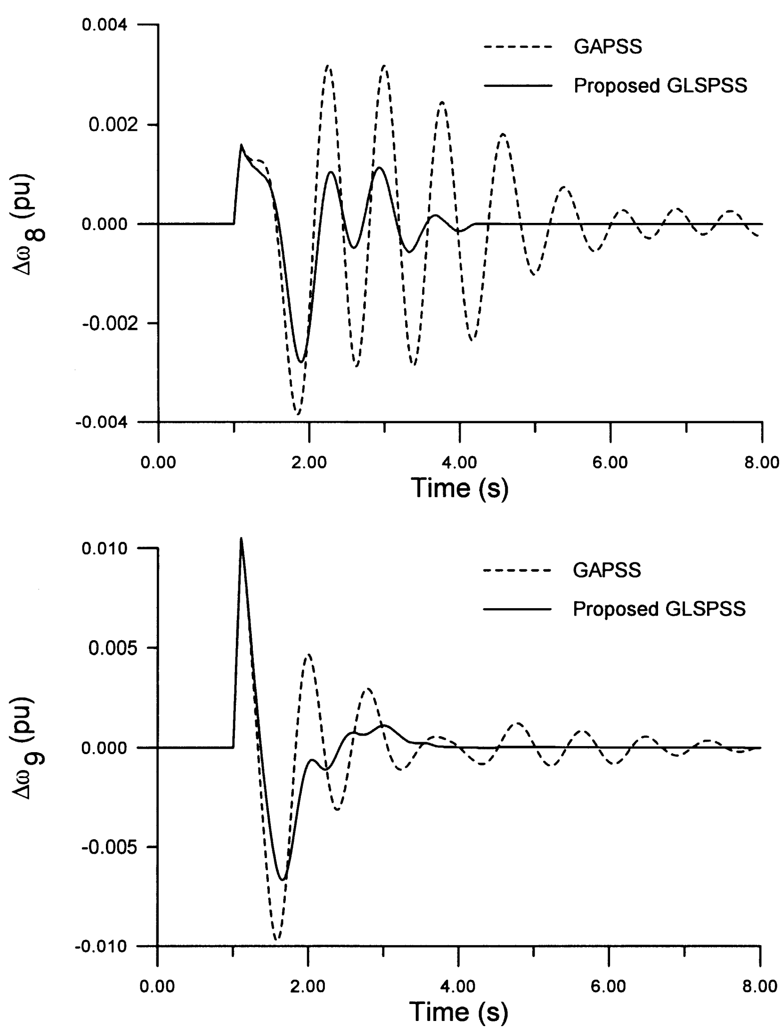

Fig. 6. System response for six-cycle fault disturbance with case 1.

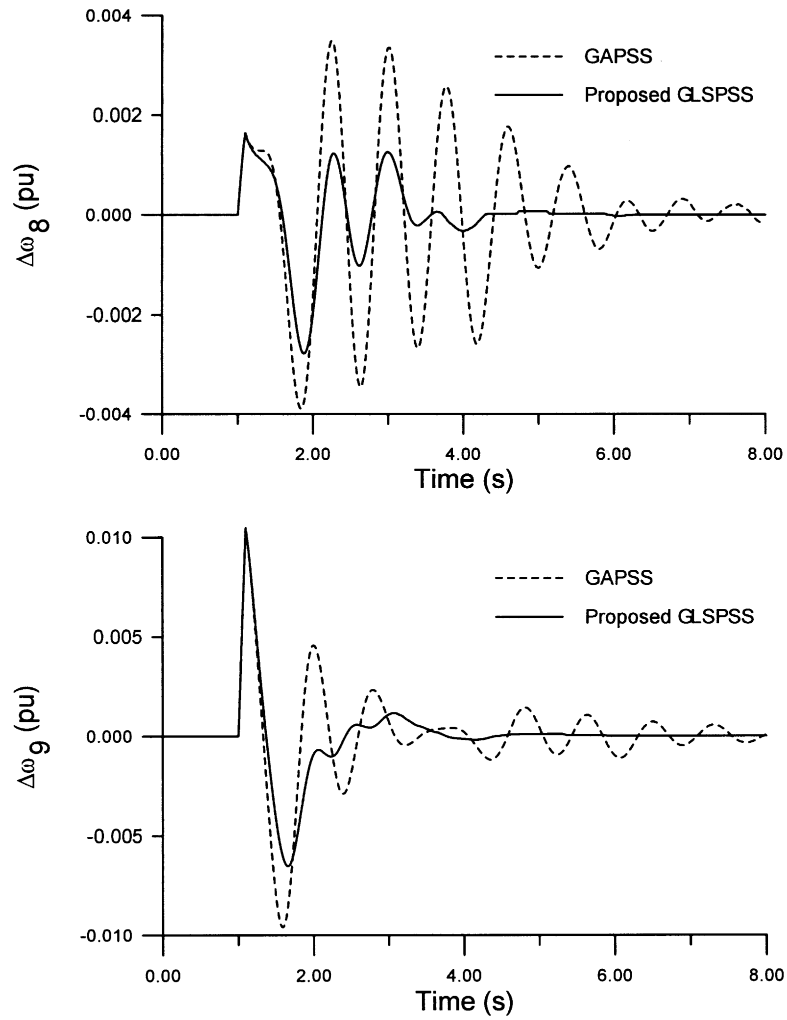

Fig. 7. System response for six-cycle fault disturbance with case 2.

4.2. Eigenvalue analysis and simulation results

To demonstrate the effectiveness and robustness of the proposed GLSPSS over a wide range of loading conditions, two different cases designated as cases 2 and 3 are considered. The generator and system loading levels at these cases are given in Tables 1 and 2, respectively. Eigenvalue analysis shows that the system has two local electromechanical modes of oscillations. Without PSSs, these modes, given in Table 4, are poorly damped and some of them are unstable. The electromechanical modes with the proposed GLSPSSs are given in Table 5. It is obvious that the eigenvalues have been shifted to the left in the *s*-plane and system damping to the electromechanical modes is greatly improved.

For further illustration, a six-cycle three-phase fault disturbance at bus 7 at the end of lines 5–7 is considered for time-domain simulations. The performance of the proposed GLSPSSs is compared to that of GA-based PSS given in Ref. [23]. The system response under the fault disturbance with case 2 is shown in Fig. 3. It is clear that the system performance with the proposed GLSPSSs is much better and the oscillations are damped out much faster. This illustrates the superiority of the proposed GLSPSS over that designed using GA. It can be concluded that, the proposed GLSPSSs are quite efficient to damp out the low-frequency oscillations.

5. Example 2: New England power system

5.1. Test system and proposed GLSPSS design

The 10-machine 39-bus New England power system shown in Fig. 4 is considered in this example. Generator G_1 is an equivalent power source representing parts of the US–Canadian interconnection system. Details of the system data are given in Ref. [24]. In this study, all generators except G_1 are equipped with the proposed GLSPSSs, which leads to 27 optimized parameters. The final values of the optimized parameters are given in Table 6. The objective function convergence is shown in Fig. 5.

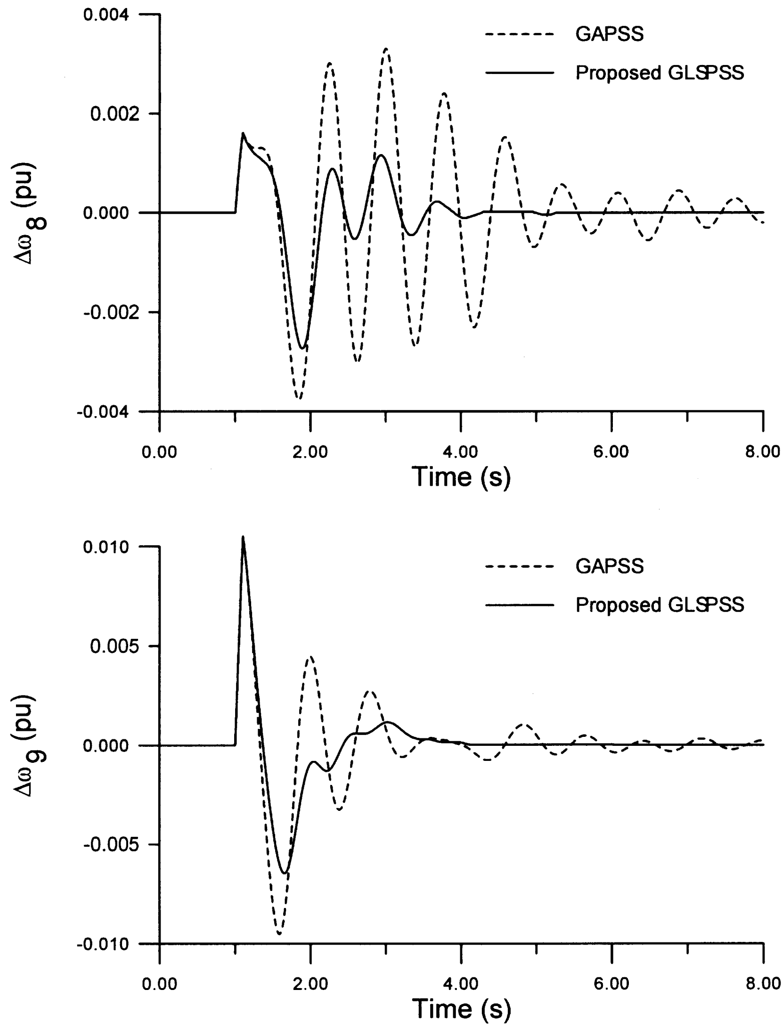

Fig. 8. System response for six-cycle fault disturbance with case 3.

5.2. Eigenvalue analysis and simulation results

It is worth mentioning that the optimization process has been carried out at the operating condition specified as case 1. To demonstrate the effectiveness of the proposed GLSPSS, two additional cases that represent different system configurations are considered. Specifically, case 2 represents the outage of lines 21–22 while case 3 represents the outage of lines 14–15. The system has nine electromechanical modes of oscillations and some of them are classified as interarea modes. Without PSSs, both local and interarea modes are given in Table 7. It is clear that these modes are poorly damped and some of them are unstable. The electromechanical modes with the proposed GLSPSSs are given in Table 8. It is obvious that the eigenvalues have been shifted to the left in the *s*-plane and the system damping to the electromechanical modes is greatly improved. In comparison with the results of GA reported in Ref. [16], it is clear that the proposed GLSPSSs outperform the GAPSSs and the system damping of electromechanical modes is significantly enhanced. This confirms the superiority of GLS approach to search for the optimal PSS parameters.

For further illustration, a six-cycle three-phase fault disturbance at bus 29 at the end of lines 26–29 is considered for the time simulations. The performance of the proposed GLSPSSs is compared to that of GAPSSs given in Ref. [16]. The speed deviations of G_8 and G_9 are shown in Figs. 6, 7, and 8 with cases 1, 2, and 3 respectively. It is clear that the system performance with the proposed GLSPSSs is much better and the oscillations are damped out much faster. This illustrates the superiority of the proposed GLS design approach to get an optimal or near optimal set of PSS parameters. In addition, the proposed GLSPSSs are quite efficient to damp out the local modes as well as the interarea modes of oscillations.

6. Conclusions

In this study, a genetic local search algorithm is proposed to the PSS design problem. The proposed design approach hybridizes GA with a local search to combine their different strengths and overcome their drawbacks. The potential of the proposed design approach has been demonstrated by applying it to two examples of multimachine power systems with different disturbances, loading conditions, and system configurations. Optimization results show that the proposed approach solution quality is independent of the initialization step. Eigenvalue analysis reveals the effectiveness and robustness of the proposed GLSPSS to damp out local as well as interarea modes of oscillations. In addition, the simulation results show that the proposed GLSPSSs can work effectively and robustly over a wide range of loading conditions and system configurations.

Acknowledgements

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