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An efficient heuristic optimization technique for robust power system stabilizer design

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Abstract

Design of a power system stabilizer (PSS) using simulated annealing (SA) heuristic optimization technique is presented in this paper. Two different PSSs are proposed, namely, simulated annealing based PSS (SPSS) and robust SPSS (RSPSS). The proposed approach employs SA to search for optimal or near optimal settings of (RSPSS). The proposed approach employs SA to search for optimal or near optimal settings of PSS parameters. An objective function that shifts the system eigenvalues associated with the electromechanical modes to the left in the s-plane is proposed. The robustness of the proposed SPSS and RSPSS over a wide range of loading conditions and system parameter uncertainities is investigated. The nonlinear simulation results show the effectiveness of the proposed PSSs to damp out the low frequency oscillations and work effectively over a wide range of loading conditions and system parameter uncertainities. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: PSS; Simulated annealing; Dynamic stability

1. Introduction

For many years, low frequency oscillations have been observed when large power systems are interconnected via relatively weak tie lines. In the past two decades, the utilization of supplementary excitation control signals for improving the dynamic stability of power systems has received much attention [1,2]. Nowadays, the conventional power system stabilizer (CPSS) is widely used by power system utilities. 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 [3–6].

Despite the potential of modern control techniques, power system utilities still prefer the conventional lead-lag power system stabilizer (CPSS) structure [7,8]. The reasons behind that might be the decentralized nature and the ease of on-line tuning of CPSS and the lack assurance of the stability related to some adaptive or variable structure techniques.

Kunder 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. In addition, Gibbard [10] demonstrated that the CPSS provide satisfactory damping performance over a wide range of system loading conditions. The robustness nature of the CPSS is due to the fact that the torque-reference voltage transfer function remains more or less invariant over a wide range of system conditions. The robustness nature of the CPSS is due to the fact that the torque-reference voltage transfer function remains more or less invariant over a wide range of operating conditions and system configurations. Abdel-Magid et al. [11] presented a genetic algorithm based approach to PSS design problem. It is shown that the optimal selection of PSS parameters results in a robust performance of PSS.

Several PSS design techniques have been reported in the literature. Generally, most of these techniques are based on eigenvalue assignment [12–15]. Unfortunately, the proposed techniques are iterative and require heavy computation burden due to system reduction procedure. Mathematical programming [16]

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have been applied to the problem of tuning of PSSs. The problem has been formulated as both 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 [17]. 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. Recently, H_∞ based techniques and sequential loop closure method [18,19] have been applied to PSS design problem. However, the importance and difficulties in the selection of weighting functions of H_∞ optimization problem have been reported. On the other hand, the order of the H_∞ based stabilizer is as high as that of the plant. This gives to complex structure of such stabilizers and reduces their applicability. Although the sequential loop closure method is well suited for on-line tuning, there is no analytical tool to decide the optimal sequence of the loop closure. Hence, PSS design approach based on SA optimization technique is proposed in this paper to avoid the shortcomings of the earlier methods.

SA algorithm [20,21] is a promising heuristic algorithm for handling the combinatorial optimization problems. It has been theoretically proved that SA algorithm converges to the optimal solution [20]. Another strong feature of SA algorithm is that a complicated mathematical model is not required and the

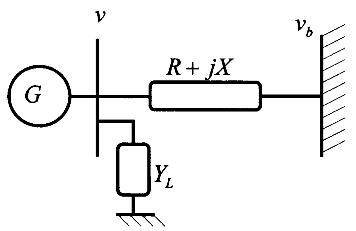

Fig. 1. Single machine infinite bus system with local load.

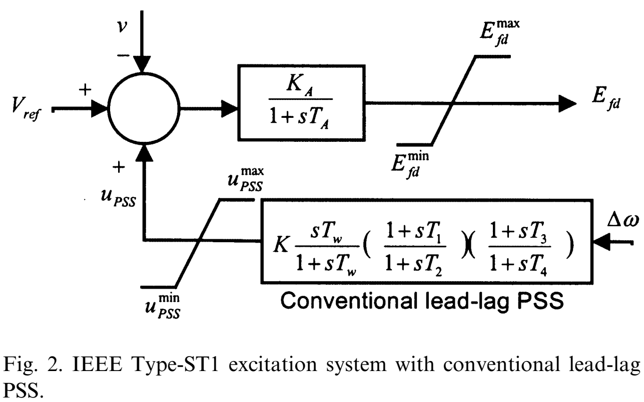

Fig. 2. IEEE Type-ST1 excitation system with conventional lead-lag PSS.

problem constraints can be easily incorporated [20]. In power systems, SA has been applied to a number of power system optimization problems with impressive successes [22,23]. However, the potential of SA algorithm to PSS design has not been exploited.

In this paper, a novel approach to PSS design by eigenvalue shift technique using SA algorithm is proposed. The problem of PSS design is formulated as an optimization problem. Then, SA algorithm is employed to solve this optimization problem with the aim of getting optimal settings of PSS parameters. Based on the number of operating conditions considered in the design process, two different stabilizers are proposed. The eigenvalue analysis and the nonlinear stimulation results have been carried out to assess the robustness and the effectiveness of the proposed PSSs under different disturbances, loading conditions, and system configurations.

2. Power system model

In this study, a single machine infinite bus system shown in Fig. 1 is considered. The generator is connected to the infinite bus via a transmission line. The impedance is $Z=R+jX$ and the generator has a local load of admittance $Y_L=g+jb$. The generator is represented by the third-order model comprising of the electromechanical swing equation and the generator internal voltage equation (Eqs. (1) and (2)). The swing equation is divided to the following equations

$$\rho\delta=\omega_b(\omega-1) \tag{1}$$

$$\rho\omega=\frac{(P_m-P_e-D(\omega-1))}{M} \tag{2}$$

where, P_m and P_e are the input and the output powers of the generator respectively; M and D are the inertia constant and damping coefficient respectively; δ and ω are the rotor angle and speed respectively; ρ is the derivative operator d/dt. The output power of the generator can be expressed in terms of the d-axis and q-axis components of the armature current, i, and terminal voltage, v, as

$$P_e=v_d i_d+v_q i_q \tag{3}$$

the internal voltage, E'_q equation is

$$\rho E'_q=\frac{(E_{fd}-(x_d-x'_d)i_d-E'_q)}{T'_{do}} \tag{4}$$

Here, E_{fd} is the field voltage; T'_{do} is open circuit field time constant; x_d and x'_d are d-axis transient reactance of the generator respectively.The IEEE Type-STI excitation system shown in Fig. 2 is considered in this study. It can be described as

$$\rho E_{fd} = \frac{(K_A(V_{ref} - v + u_{PSS}) - E_{fd})}{T_A} \tag{5}$$

where, K_A and T_A are the gain and time constant of the excitation system respectively; V_{ref} is the reference voltage. As shown in Fig. 2, a conventional lead-lag PSS is installed at the feedback loop to generate a stabilizing signal u_{PSS}. In Eq. (5), the terminal voltage v can be expressed as

$$v = (v_d^2 + v_q^2)^{1/2} \tag{6}$$

and;

$$v_d = x_q i_q \tag{7}$$

$$v_q = E'_q - x'_d i_d \tag{8}$$

where x_q is the q-axis reactance of the generator.

3. Problem formulation

3.1. Linearized power system model

In the design of PSS damping controller, the linearized incremental model around a nominal operating point is usually employed [1,2]. Linearizing the expressions of i_d and i_q and substituting into the linear form of Eqs. (1)–(8) yield the following linearized power system model

$$\begin{bmatrix} \rho\Delta\delta \\ \rho\Delta\omega \\ \rho\Delta E'_q \\ \rho\Delta E_{fd} \end{bmatrix} = \begin{bmatrix} 0 & 377 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 \\ -\frac{K_4}{T'_{do}} & 0 & -\frac{K_3}{T'_{do}} & \frac{1}{T'_{do}} \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E'_q \\ \Delta E_{fd} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{K_A}{T_A} \end{bmatrix} u_{PSS} \tag{9}$$

Here, the control vector u_{PSS} is the PSS output signal. The values of K_1–K_6 depend on system parameter and loading conditions. Expressions of these constants K_1–K_6 are given in [1].

3.2. PSS structure

A widely used conventional lead-lag PSS is considered in this study. Its structure is shown in Fig. 2. In this structure, T_W is the washout time constant and $\Delta\omega$ is the speed deviation. The time constants T_W, T_2, and T_4 are usually prespecified. The stabilizer gain K and time constants T_1 and T_3 are remained to be determined.

4. Simulated annealing algorithm

4.1. Overview

Simulated annealing is an optimization technique that simulates the physical annealing process in the field of combinatorial optimization. Annealing is the physical process of heating up a solid until it melts, followed by slow cooling it down by decreasing the temperature of the environment in steps. At each step, the temperature is maintained constant for a period of time sufficient for the solid to reach thermal equilibrium.

Metropolis et al. [21] proposed a *Monte Carlo* method to simulate the process of reaching thermal equilibrium at a fixed value of the temperature T. In this method, a randomly generated perturbation of the current configuration of the solid is applied so that a trial configuration is obtained. Let E_C and E_t denote the energy level of the current and trial configurations respectively. If $E_t < E_c$, then a lower energy level has been reached, and the trial configuration is accepted and becomes the current configuration. On the other hand, if $E_t \geq E_C$ the trial configuration is accepted as current configuration with probability proportional to $\exp(-\Delta E/T)$, $\Delta E = E_t - E_C$. The process continues until the thermal equilibrium is achieved after a large number of perturbations.

By gradually decreasing the temperature T and repeating Metropolis simulation, new lower energy levels become achievable. As T approaches zero least energy configurations will have a positive probability of occurring.

4.2. SA algorithm

At first, the analogy between a physical annealing process and a combinatorial optimization problem is based on the following [20]:

- Solutions in an optimization problem are equivalent to configurations of a physical system.
- The cost of a solution is equivalent to the energy of a configuration.In addition, a control parameter C_p is introduced to play the role of the temperature T.The basic elements of SA are briefly stated and defined as follows:

Table 1
Loading conditions and parameter uncertainties

Loading condition (P, Q) in pu	Parameter uncertainties
(1.0, 0.015) nominal	30% increase of line reactance X
(1.1, 0.1) heavy	25% decrease of machine inertia M
(0.7, −0.3) leading power factor	30% decrease of field time constant T'_{do}

- *Current, trial, and best solutions*, x_{current}, x_{trial}, and x_{best}: these solutions are sets of the optimized parameter values at any iteration.
- *Acceptance criterion*: at any iteration, the trial solution can be accepted as the current solution if it meets one of the following criteria; (a) $J(x_{\mathrm{trial}}) < J(x_{\mathrm{current}})$; (b) $J(x_{\mathrm{trial}}) > J(x_{\mathrm{current}})$; and $\exp(-(J(x_{\mathrm{trial}}) - J(x_{\mathrm{current}}))/C_{\mathrm{p}}) \geq$ rand(0,1). Here, rand(0,1) is a random number with domain [0,1] and $J(x_{\mathrm{trial}})$and $J(x_{\mathrm{current}})$ are the objective function values associated with x_{trial} and x_{current} respectively. Criterion (b) indicates that the trial solution is not necessarily rejected if its objective function is not as good as that of the current solution with hoping that a much better solution becomes reachable.
- *Acceptance ratio*: at a given value of C_{p} an n_1 trial solutions can be randomly generated. Based on the acceptance criterion, an n_2 of these solutions can be accepted. The acceptance ratio is defined as n_2/n_1.
- *Cooling schedule*: it specifies a set of parameters that governs the convergence of the algorithm. This set includes an initial value of control parameter C_{p0} a decrement function for decreasing the value of C_{p}, and a finite number of iterations or transitions at each value of i.e. the length of each homogeneous *Markov chain*. The initial value of C_{p} should be large enough to allow virtually all transitions to be accepted. However, this can be achieved by starting off at a small value of C_{p0} and multiplying it with a constant α larger than 1, i.e. $C_{\mathrm{p0}} = \alpha C_{\mathrm{p0}}$. This process continues until the acceptance ratio is close to 1. This is equivalent to heating up process in physical systems. The decrement function for decreasing the value of is given by $C_{\mathrm{p}} = \mu C_{\mathrm{p}}$ where μ is a constant smaller than but close to 1. Typical values lie between 0.8 and 0.99 [20].
- *Equilibrium condition*: it occurs when the current solution does not change for a certain number of iterations at a given value of C_{p}. It can be achieved by generating a large number of transitions at that value.
- *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 *Markov chains* since the last change of the best solution is greater than a prespecified number; or (b) the number of *Markov chains* reaches the maximum allowable number.

The general algorithm of SA can be described in steps as follows:

Step 1: Set the initial value of C_{p0} and randomly generate an initial solution x_{initial} and calculate its objective function. Set this solution as the current solution as well as the best solution, i.e. $x_{\mathrm{initial}} = x_{\mathrm{current}} = x_{\mathrm{best}}$.

Step 2: Randomly generate an n_1 of trial solutions in the neighborhood of the current solution.

Step 3: Check the acceptance criterion of these trial solutions and calculate the acceptance ratio. If acceptance ratio is close to 1 go to step 4; else set $C_{\mathrm{p0}} = \alpha C_{\mathrm{p0}}$, $\alpha > 1$, and go back to step 2.

Step 4: Set the chain counter $k_{\mathrm{ch}} = 0$.

Step 5: Generate a trial solution x_{trial}. If x_{trial} satisfies the acceptance criterion set $x_{\mathrm{current}} = x_{\mathrm{trial}}$, $J(x_{\mathrm{current}}) = J(x_{\mathrm{trial}})$, and go to step 6; else go to step 6.

Step 6: Check the equilibrium condition. If it is satisfied go to step 7; else go to step 5.

Step 7: Check the stopping criteria. If one of them is satisfied then stop; else set $k_{\mathrm{ch}} = k_{\mathrm{ch}} + 1$ and $C_{\mathrm{p}} = \mu C_{\mathrm{p}}$, $\mu < 1$, and go back to Step 5.

5. The proposed design approach

5.1. Loading conditions and parameter uncertainties

In this study, two different SA based PSSs are proposed as follows.

1. *The Proposed SPSS:* in this case, the PSS parameters are optimized at the nominal operating condition given in Table 1, i.e. only one loading condition is considered for PSS parameter tuning. The system parameters are set at their nominal values given in the Appendix A and no parameter uncertainties are considered in this case.
2. *The Proposed RSPSS:* in this case, the PSS parameters are optimized over a wide range of operating conditions and system parameter uncertainties. Three loading conditions represent nominal, heavy, and leading power factor are considered. Each loading condition is considered without and with the parameter uncertainties given in Table 1. Hence, the total number of points considered for the design process is 12.

5.2. Proposed objective function

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

$$J = \sum_{\sigma_i \geq \sigma_0} (\sigma_0 - \sigma_i)^2 \tag{10}$$

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 insures also some degree of relative stability. The condition $\sigma_i \geq \sigma_0$ is imposed on J evaluation to consider only the unstable or poorly damped modes which are mainly belonging to the electromechanical ones. For the proposed SPSS, there is only one eigenvalue considered in J calculation. However, the summation has been carried out over 12 eigenvalues with the proposed RSPSS.

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

$$\text{Minimize } J \tag{11}$$

Subject to

$$K^{\min} \leq K \leq K^{\max} \tag{12}$$

$$T_1^{\min} \leq T_1 \leq T_1^{\max} \tag{13}$$

$$T_3^{\min} \leq T_3 \leq T_3^{\max} \tag{14}$$

The proposed approach employs SA algorithm to solve this optimization problem and search for optimal or near optimal set of PSS parameters, $\{K, T_1, T_3\}$.

Table 2
Optimal parameters for the proposed SPSS and RSPSS

Proposed stabilizer	K	T_1	T_3
SPSS	19.049	0.1393	0.2634
RSPSS	33.387	0.1418	0.2131

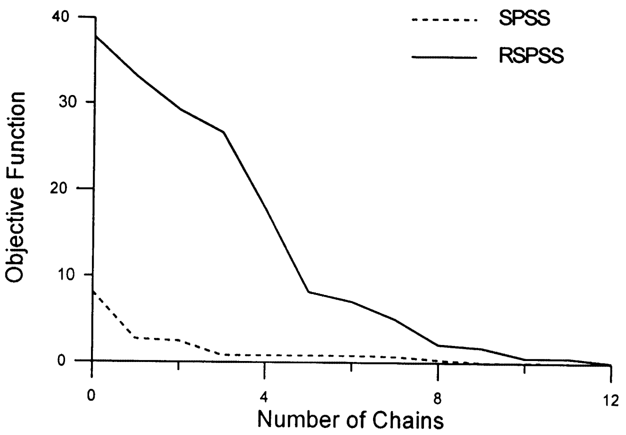

Fig. 3. Convergence of the objective functions for the proposed SPSS and RSPSS.

5.3. Application of SA to PSS design

The SA algorithm has been applied to search for optimal settings of the PSS optimized parameters. In our implementation, σ_0 is chosen to be -2.0, i.e. all the electromechanical mode eigenvalues are shifted to the left of $s = -2.0$ vertical line in the s-plane. Also, the search will terminate if one of the following conditions is satisfied; (1) best solution does not change for more than 20 chains; (2) number of chains reaches 100; or (3) value of the objective function reaches zero, i.e. all the electromechanical mode eigenvalues are shifted to the left of $s = -2.0$ line. It is imperative to point out that, at each iteration during the optimization process, the electromechanical mode eigenvalue is identified using participation factors method [24] to evaluate the objective function.

The optimal PSS parameters obtained for the proposed SPSS and RSPSS are given in Table 2. The convergence rates of the objective functions for the proposed SPSS and RSPSS are shown in Fig. 3. It is clear that the proposed approach shifts the electromechanical mode eigenvalues to the left of $s = -2.0$ line in *few chains*. This confirms the potential of SA algorithm to search for optimal values of the tuning parameters.

6. Robustness of the proposed stabilizers

To assess the robustness of the proposed SPSS and RSPSS, they are tested over a wide range of operating conditions and system parameter uncertainties. The operating range is specified as $P \in [0.1, 1.2]$ pu and $Q \in [-0.4, 0.4]$ pu. At each operating condition within the specified range, the electromechanical mode eigenvalue is identified using participation factors method [24] and located in the s-plane. The results with the proposed SPSS and RSPSS as well as that of CPSS given in [1] are shown in Figs. 4–7. Two important observations can be drawn from these results. First, the proposed SPSS is more robust compared with CPSS. It also provides more damping to the electromechanical mode. In addition, the stability region with the CPSS is much smaller than those of the proposed stabilizers. Moreover, the CPSS fails to stabilize the system at some operating conditions and parameter uncertainties as shown in Fig. 5(a). This demonstrates the potential of the proposed SA-based approach to the PSS design problem. Second, considering different operating conditions and parameter uncertainties in the PSS design problem results in the extension of the stability margin and robustness as shown in Figs. 4(c)–7(c).

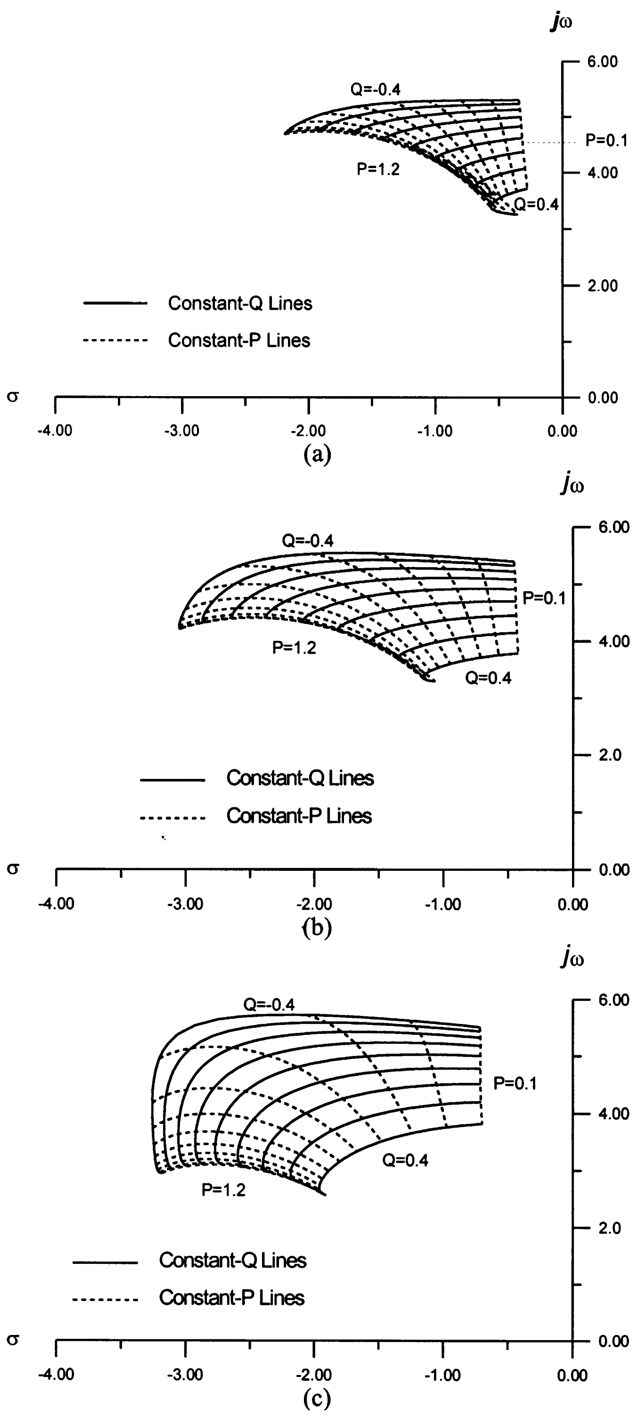

Fig. 4. Location of the electromechanical mode eigenvalue without parameter uncertainties, (a) with CPSS; (b) with the proposed SPSS; (c) with the proposed RSPSS.

7. Nonlinear simulation results

To evaluate the effectiveness of the proposed SPSS and RSPSS, nonlinear time domain simulations have been carried out at four different operating conditions with different disturbances as given in Table 3. The system responses are shown in Figs. 8–11. It is clear that the proposed SPSS and RSPSS outperform the CPSS. The oscillations with the proposed stabilizers are damped out much faster. Also, the first swing is much reduced as shown in Fig. 8. This extends the power system stability limit and increase its power transfer capability.

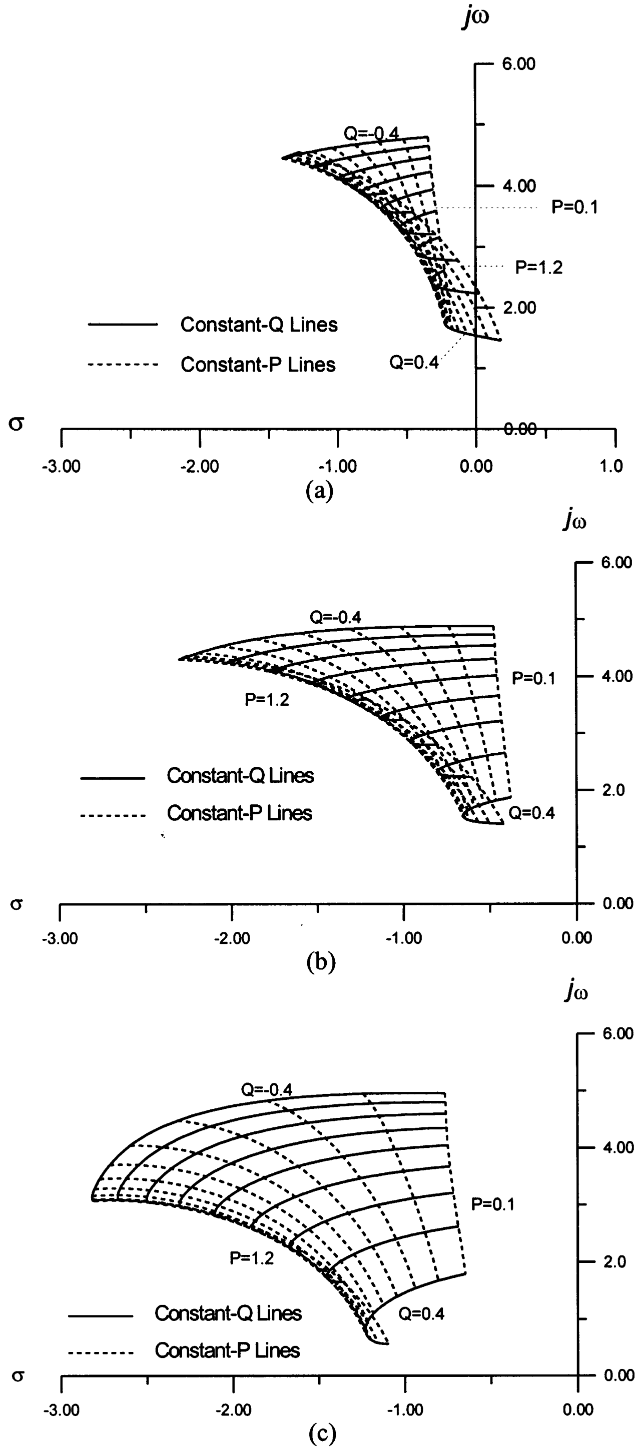

Fig. 5. Location of the electromechanical mode eigenvalue with 40% uncertainity of X, (a) with CPSS; (b) with the proposed SPSS; (c) with the proposed RSPSS.

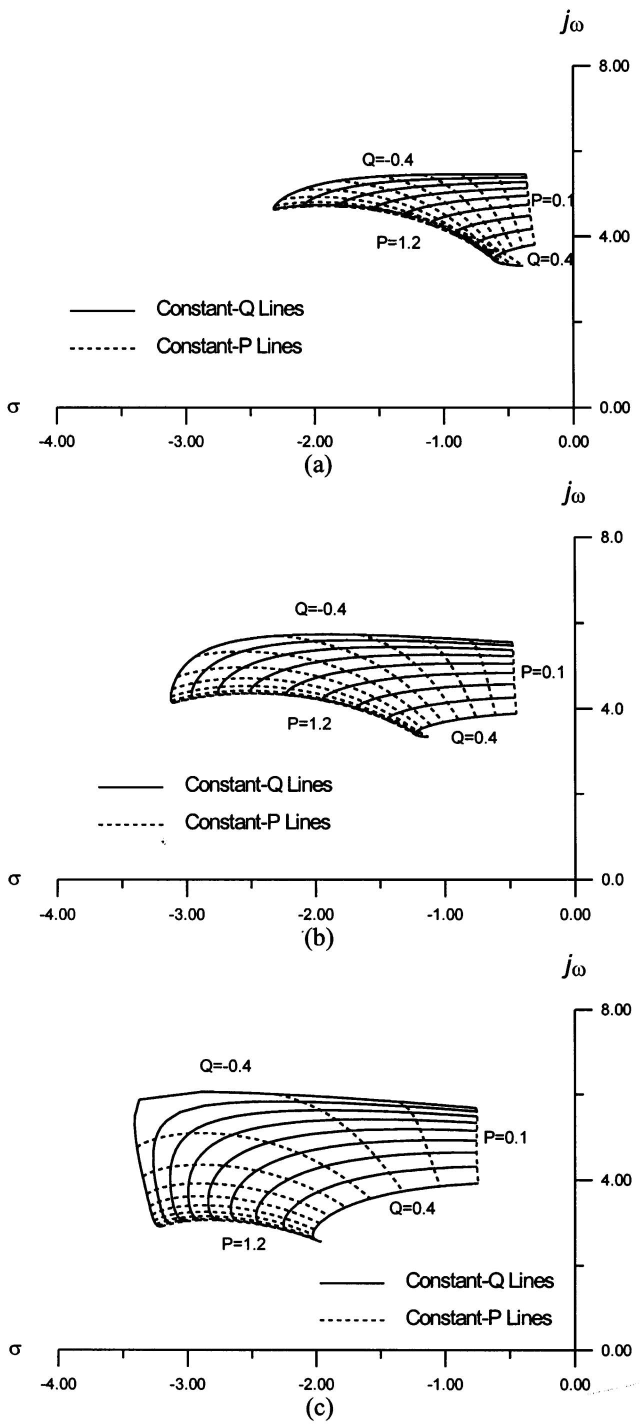

Fig. 6. Location of the electromechanical mode eigenvalue with -5% uncertainity of M, (a) with CPSS; (b) with the proposed SPSS; (c) with the proposed RSPSS.

8. Conclusions

In this study, a novel approach based on the simulated annealing algorithm is proposed to the PSS design problem. The proposed design approach employs SA to search for optimal settings of conventional lead-lag PSS parameters. Heavy computations of the design process are avoided with the proposed approach. Two different PSSs, SPSS and RSPSS, are designed based on the number of operating conditions considered in the optimization process. The robustness and effectiveness of the proposed SPSS and RSPSS are investigated. The results show that the proposed stabilizers are robust

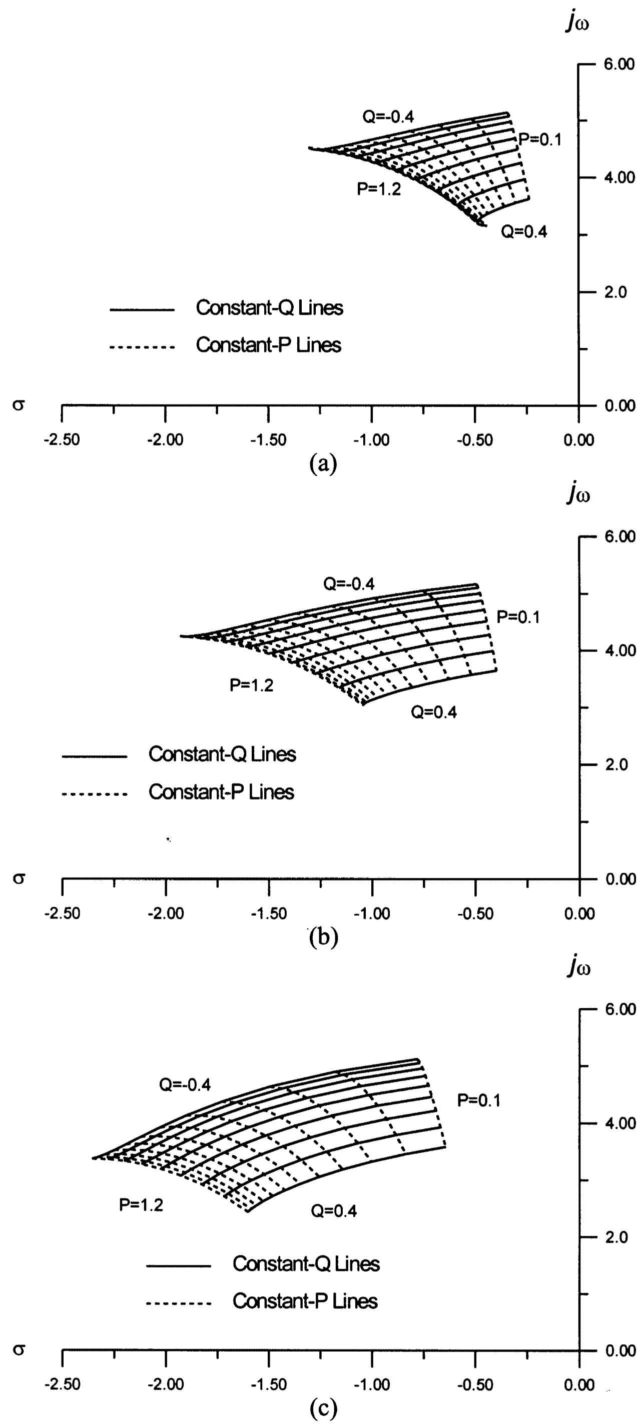

Fig. 7. Location of the electromechanical mode eigenvalue with -50% uncertainity of T'_{do}, (a) with CPSS; (b) with the proposed SPSS; (c) with the proposed RSPSS.

Table 3
Loading conditions and disturbances for nonlinear time simulations

Loading condition (P, Q) in pu	Associated disturbance
(1.0, 0.3)	10% pulse of T_m and -10% of M
(1.0, 0.015)	3-phase fault for six cycles at the infinite bus
(1.1, 0.4)	3-phase fault for three cycles at the infinite bus
(1.1, -0.4)	3-phase fault for six cycles at the infinite bus

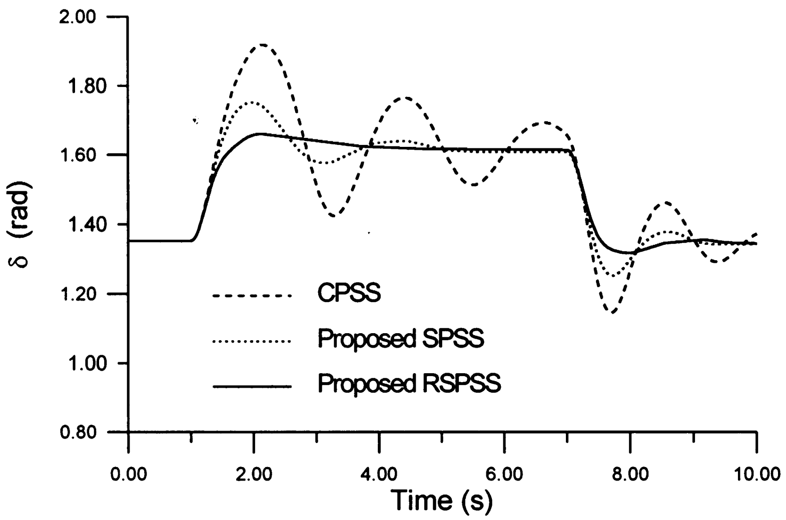

Fig. 8. System response with 10% pulse of T_m and -10% of M disturbance for 6 s and (1.0, 0.3).

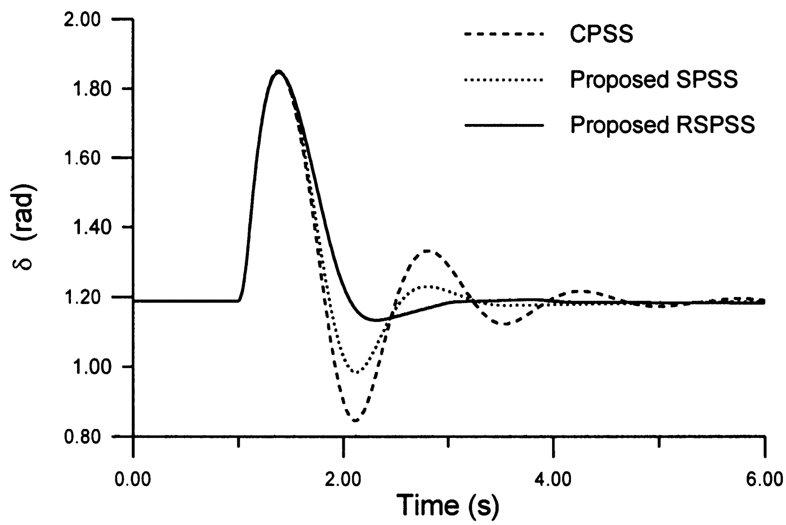

Fig. 9. System response with 6-cycle fault disturbance and (1.0, 0.015).

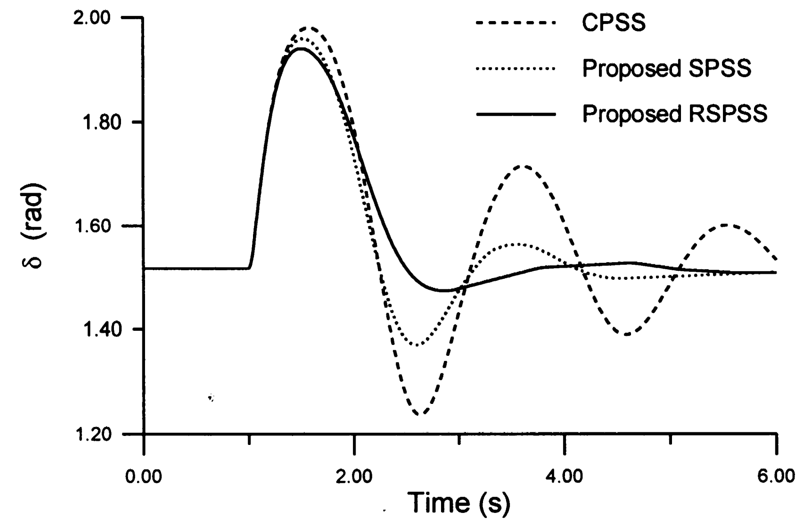

Fig. 10. System response with 3-cycle fault disturbance and (1.1, 0.4).

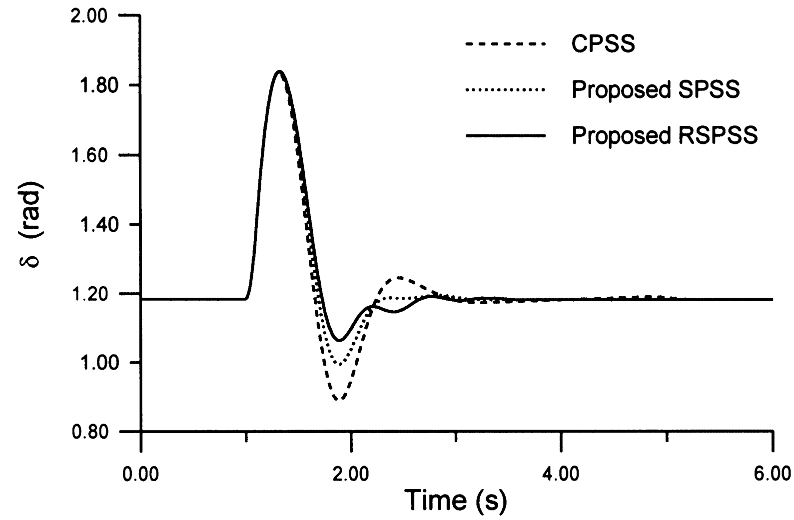

Fig. 11. System response with 6-cycle fault disturbance and (1.1, −0.4).

and effective over a wide range of operating conditions and parameter uncertainties.

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Appendix A

The system data are as follows: $M = 9.26$ s; $T'_{do} = 7.76$; $D = 0.0$; $x_d = 0.973$; $x'_d = 0.19$; $x_q = 0.55$; $R = -0.034$; $X = 0.997$; $g = 0.249$; $b = 0.262$; $K_A = 50$; $T_A = 0.05$; $|u_{PSS}| \leq 0.2$ pu; $|E_{fd}| \leq 7.3$ pu.

All resistances and reactances are in pu and time constants are in seconds.

References

[1] Y.N. Yu, Electric Power System Dynamics, Academic Press, 1983.
[2] F.P. deMello, C. Concordia, Concepts of synchronous machine stability as affected by excitation control, IEEE Trans. PAS 88 (1969) 316–329.
[3] S.M. Osheba, B.W. Hogg, Performance of state space controllers for turbogenerators in multimachine power systems, IEEE Trans. PAS 101 (9) (1982) 3276–3283.
[4] D. Xia, G.T. Heydt, Self-tuning controller for generator excitation control, IEEE Trans. PAS 102 (1983) 1877–1885.
[5] Y. Cao, L. Jiang, S. Cheng, D. Chen, O.P. Malik, G.S. Hope, A nonlinear variable structure for power system stability, IEEE Trans. Energy Conversion 9 (3) (1994) 489–495.
[6] Y.L. Abdel-Magid, M.A. Abido, S. Al-Baiyat, A.H. Mantawy, Simultaneous stabilization of multimachine power systems via genetic algorithms, IEEE Trans. on Power Systems, 14 (4) (1999) 1428–1439.
[7] E. Larsen, D. Swann, Applying power system stabilizers, IEEE Trans. PAS 100 (6) (1981) 3017–3046.

[8] G.T. Tse, S.K. Tso, Refinement of conventional P55 design in multimachine system by modal analysis, IEEE Trans. PWRS 8 (2) (1993) 598–605.
[9] P. Kundur, M. Klein, G.J. Rogers, M.S. Zywno, Application of power system stabilizers for enhancement of overall system stability, IEEE Trans. PWRS 4 (2) (1989) 614–626.
[10] M.J. Gibbard, Robust design of fixed-parameter power system stabilizers over a wide range of operating conditions, IEEE Trans. PWRS 6 (2) (1991) 794–800.
[11] Y.L. Abdel-Magid, M. Bettayeb, M.M. Dawoud, Simultaneous stabilization of power systems using genetic algorithms, IEE Proc. Gen. Trans. Distrib. 144 (1) (1997) 39–44.
[12] S. Lefebvre, Tuning of stabilizers in multimachine power systems, IEEE Trans. PAS 102 (2) (1983) 290–299.
[13] C.M. Lim, S. Elangovan, Design of stabilizers in multimachine power systems, IEE Proc. 132 (3) (1985) 146–153.
[14] C.L. Chen, Y.Y. Hsu, Coordinated synthesis of multimachine power system stabilizer using an efficient decentralized modal control (DMC) algorithm, IEEE Trans. PWRS 2 (3) (1987) 543–551.
[15] Y.N. Yu, Q. Li, Pole-placement power system stabilizers design of an unstable nine-machine system, IEEE Trans. PWRS 5 (2) (1990) 353–358.
[16] J.J. da Cruz, L.C. Zanetta, Stabilizer design for multimachine power systems using mathematical programming, Int. J. Electr. Power Energy Systems 19 (8) (1997) 519–523.
[17] V.A. Maslennikov, S.M. Ustinov, The optimization method for coordinated tuning of power system regulators, Proc. Twelfth Power System Computation Conference PSCC, Dresden, 1996, pp. 70–75.
[18] T.C. Yang, Applying H_∞ optimisation method to power system stabilizer design parts 1 and 2, Int. J. Electr. Power Energy Systems 19 (1) (1997) 29–43.
[19] T.C. Yang, A new decentralised stabilisation approach with application to power system stabilizer design, IFAC/IFORS/IMACS Symp. Large Scale Systems, 1995.
[20] E. Aarts, J. Korst, Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing, Wiley, 1989.
[21] N. Metropolis, A. Rosenbluth, M. Rosenbluth, A. Teller, E. Teller, Equation of State Calculations by Fast Computing Machines, J. Chem. Phys. 21 (1953) 1087–1092.
[22] R. Romero, R. Gallego, A. Monticelli, Transmission system expansion planning by simulated annealing, IEEE Trans. PWRS 11 (1) (1996) 364–369.
[23] K. Wong, C. Fung, Simulated annealing based economic dispatch algorithm, IEE Proc. C 140 (6) (1993) 509–515.
[24] Y.Y. Hsu, C.L. Chen, Identification of optimum location for stabilizer applications using participation factors, IEE Proc. C 134 (3) (1987) 238–244.