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A multiobjective tuning approach of power system stabilizers using particle swarm optimization

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Abstract: This work presents an optimal tuning approach of power system stabilizers (PSSs) using multiobjective particle swarm optimization. Two types of PSSs are investigated, the conventional speed-based PSS type and a dual-input PSS type that uses the accelerating power as an additional input. The tuning problem of these PSSs is formulated as a minimization problem of a vector objective function characterizing the damping and the transient performance of the closed-loop system. A 3-machine 9-bus power system example is considered, and the speed-constrained multiobjective particle swarm optimization algorithm is used to solve the optimization problem. The results show that trade-offs exist between the 2 objective functions of the problem, and that the best trade-off is obtained with the dual-input PSS. The performance of the resulting PSSs is illustrated through numerical simulations considering different scenarios.

Key words: Power system stabilizer, optimal design, multiobjective optimization, speed-constrained multiobjective particle swarm optimization, multimachine power system

1. Introduction

Power systems are constantly subjected to different types of disturbances and uncertainties, such as small and large variations of the system parameters and 3-phase faults. In this regard, the use of power system stabilizers (PSSs) can greatly enhance the system stability in addition to the automatic voltage regulator (AVR) [1]. Fixed-structure and fixed-parameter PSSs such as PID (proportional integral derivative) and lead-lag PSS have been shown to be very effective in damping the power system oscillations, providing an excellent cost/performance ratio. However, the tuning of such devices becomes complicated for multimachine power systems because of the complexity and the nonlinearity of these systems. Therefore, an optimal and efficient tuning approach is required to guarantee optimal performance.

The parameters of a fixed-structure and fixed-parameter PSS can be judicially tuned using metaheuristics such as genetic algorithms (GAs), particle swarm optimization (PSO), and simulated annealing (SA). These methods are known to be very efficient optimization techniques for solving difficult and nonlinear problems [2]. The tuning problem of PSSs can be regarded as an optimization problem that involves one or multiple objective functions. Considerable works have been devoted to single-objective problems in which objective functions are usually defined using time-based criteria [3–5], closed-loop eigenvalues [6–10], or some H_2 and H_∞ norm-based functions [11,12].

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In a more explicit manner, multiobjective optimization problems are considered, where 2 or more performance criteria can be considered and handled separately [5–9]. As a result, multiple noncompetitive solutions are found instead of a unique and perfect solution. The PSS tuning problem that considers multiple objectives has already been tackled in the literature [13–19]. To deal with this problem, metaheuristic-based multiobjective optimization methods were used. For example, the authors in [13,14] proposed multiobjective design approaches of a lead-lag PSS using the well-known nondominated sorting genetic algorithm-II (NSGA-II) and the strength Pareto evolutionary algorithm 2 (SPEA2). The design objectives are based on the closed-loop system eigenvalues to characterize the system's rapidity and damping. Another approach in [15] uses a micro-GA to solve a multiobjective problem considering an eigenvalued and an H_∞-based objective function. In [16–18], a set of optimal controllers was generated using NSGA-II considering multiple objective functions, such as the minimization of the speed deviation and the terminal voltage variation. In [19], the PSS tuning is formulated as a mixed H_2/H_∞ design problem where the H_2 and H_∞ norms are used to characterize the transient performance and the robustness of the closed-loop system, respectively. To solve this problem, a PSO-based algorithm called the speed-constrained multiobjective optimization algorithm (SMPSO) is used, and it is shown to be more efficient than NSGA-II. Nevertheless, all these works considered only classical types of PSSs, such as PID and lead-lag PSSs, whereas other types can be considered, such as the dual-input PSS.

In this paper, the tuning problem of the classical speed-based type and a dual-input PSS type is addressed using SMPSO and applied to a 3-machine, 9-bus system. The design problem is formulated as a minimization problem of 2 objective functions that separately characterize the damping and the transient performance of the overall closed-loop system. The optimization results show that the problem has multiple optimal solutions, and also that the best trade-off is obtained when using the dual-input PSS.

The rest of the paper is organized as follows. Section 2 presents the system under study, the types of PSSs to be used, and the formulation of the multiobjective optimal tuning problem of PSSs. Section 3 reviews the basic concepts of multiobjective optimization and presents the SMPSO algorithm. In Section 4, the optimization results and some illustrative simulations are given. Finally, Section 5 concludes the work.

2. Problem statement

2.1. System under study

The power system example considered in this work is the 9-bus, 3-machine system shown in Figure 1, which consists of 3 generators and 3 loads. The optimal locations for installing PSSs to damp out the electromechanical modes of oscillations are known to be at generators 2 and 3 [6]. The differential equations governing the dynamics of each generator are given in the Appendix, and the parameters of this system can be found in [1].

2.2. Types of PSS under study

Two types of PSS are investigated in this work. The first type is the classical speed-based PSS, whose transfer function is given in Eq. (1). This PSS consists of 2 phase compensation stages, a washout stage and a constant gain stage. In this study, we consider $T_w = 10$ s and $T_2 = T_4 = 0.01$ s. Therefore, the parameters to be found are the time constants T_1 and T_3, and the gain K.

$$U_{PSS} = \left[K \cdot \frac{T_w}{1+T_wS} \cdot \frac{1+T_1S}{1+T_2S} \cdot \frac{1+T_3S}{1+T_4S} \right] \cdot \Delta\omega \tag{1}$$

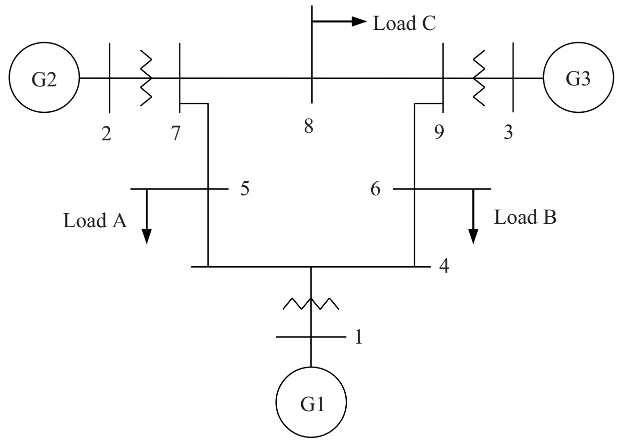

Figure 1. Three-machine, 9-bus system.

The second type of PSS is the dual-input PSS given by Eq. (2). The input signals of this PSS are the speed deviation and the accelerating power, which is equal to the difference between the mechanical and electrical power of the generator. This PSS is composed of 2 classical PSS systems for each input. In this study, we consider for simplicity $T_{w1} = T_{w2} = 10$ s, $T_2 = T_4 = T_6 = T_8 = 0.01$ s, $T_1 = T_3$, and $T_5 = T_7$. Therefore, the remaining unknown parameters are T_1, T_5, K_1, and K_2.

$$U_{PSS} = \left[K_1 \cdot \frac{T_{w1}}{1+T_{w1}S} \cdot \frac{1+T_1S}{1+T_2S} \cdot \frac{1+T_3S}{1+T_4S}\right] \cdot \Delta\omega + \left[K_2 \cdot \frac{T_{w2}}{1+T_{w2}S} \cdot \frac{1+T_5S}{1+T_6S} \cdot \frac{1+T_7S}{1+T_8S}\right] \cdot \Delta P_e \qquad (2)$$

2.3. Multiobjective tuning of PSS

The tuning problem of PSSs for the 3-machine, 9-bus power system can be mathematically formulated as a minimization problem of a vector objective function that separately measures the damping and the transient performance of the closed-loop system. In this study, the following objective functions are considered:

$$f_1 = \max_i(\sigma_i), \qquad (3)$$

$$f_2 = -\min_i(\xi_i), \qquad (4)$$

where ξ_i and σ_i represent, respectively, the damping ratio and the real part of the ith eigenvalue of the closed-loop system. For simplicity, only the linearized model of the system based on nominal conditions is used. In fact, the 2 objective functions represent conflicting performance criteria, since f_1 measures the attenuation speed of the electromechanical oscillations, while f_2 measures the maximum overshoots. Note that the difference between this formulation and the one proposed in [14] is that the objective function f_1 here concerns only the complex closed-loop eigenvalues, which are related to the electromechanical modes. The evaluation of the proposed objective functions is simple and time-saving, since no numerical simulations are required and only one linearized model is used.

3. Multiobjective particle swarm optimization

3.1. Multiobjective optimization

A multiobjective optimization problem is the problem of optimizing (minimizing or maximizing) a vector function. In this work, we consider a minimization problem that can be mathematically expressed as follows:

$$\min_{x \in X} F(x) = (f_1(x), f_2(x), \ldots, f_m(x)), \tag{5}$$

$$\text{subject to } g_i(x) \leq 0, \quad i = 1, \ldots, k,$$

where m is the number of objective functions; x is the vector of the design parameters, also called the decision variables; and g_i, $i = 1, \ldots, k$ are k constraints related to the problem.

Usually the problem does not have a unique and perfect solution but rather a set of optimal solutions known as the Pareto-optimal set. The set of the corresponding objective vectors is called the Pareto front. Additionally, a solution x is said to dominate $y$if and only if $F(x)$ is partially less than $F(y)$, i.e.:

$$\forall\, i,\ f_i(x) \leq f_i(y) \ \ \wedge \ \ \exists\, i,\ f_i(x) < f_i(y) \tag{6}$$

Therefore, a solution is Pareto-optimal if it is nondominated by all the feasible solutions of the search space. The set of the nondominated solutions found at any stage of the optimization process is called the nondominated set, and the corresponding objective vectors constitute the nondominated front.

3.2. Particle swarm optimization

PSO is a metaheuristic and global optimization technique proposed by Kennedy and Eberhart [20]. It is inspired by the social behavior of individual organisms living together in groups to look for food and avoid predators. The PSO algorithm considers a set of potential solutions (swarm), which are considered as moving particles in the decision space. The position of a particle is represented by all the decision variables of the problem, and the movement of this particle regarding one decision variable, x, is governed by the following equations:

$$v(t+1) = wv(t) + r_1 c_1 (p_{best} - x(t)) + r_2 c_2 (g_{best} - x(t)), \tag{7}$$

$$x(t+1) = x(t) + v(t+1), \tag{8}$$

where $x(t)$ and $v(t)$ represent the position and the velocity of the particle at iteration t, respectively; p_{best} is the best position of the particle up to t and g_{best} is the best position in the swarm; r_1 and r_2 are random numbers in the range $[0,\ 1]$; and w, c_1, and c_2 are the confidence coefficients that control the behavior of the particle.

In comparison with GAs and other global metaheuristics, PSO is easy to implement and can produce better solutions in less computation time. In the case of multiobjective optimization, many PSO-based methods have been proposed in the literature. The choice of a method depends mainly on the problem to solve. In this work, the so-called SMPSO algorithm is used. This algorithm is known to be one of the most powerful methods for multiobjective optimization.

3.3. Speed-constrained multiobjective particle swarm optimization

SMPSO was proposed by Nebro et al. [21] and is based on another algorithm called OMOPSO (optimized multiobjective particle swarm optimization). The difference between the 2 algorithms is that SMPSO uses a constriction operator to control the velocities of the particles in order to enhance the exploration of the search space and produce more efficient solutions. The constriction operator is given by:

$$\chi = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}}, \tag{9}$$

where:

$$\phi = \begin{cases} c_1 + c_2 & \text{if } c_1 + c_2 > 4 \\ 0 & \text{if } c_1 + c_2 \leq 4 \end{cases}. \tag{10}$$

The velocities resulting from Eq. (7) are then multiplied by the constriction operator and bounded using the following equation:

$$v(t) = \begin{cases} \delta & \text{if } v(t) > \delta \\ -\delta & \text{if } v(t) \leq -\delta \\ v(t) & \text{otherwise} \end{cases}, \tag{11}$$

where:

$$\delta = \frac{U - L}{2}, \tag{12}$$

in which U and L represent the upper and lower bounds of the variable x, respectively.

The procedure of SMPSO can be described by Figure 2. The algorithm starts by initializing the positions and the velocities of the swarm particles. Another set of particles, called the archive, is also initialized with the nondominated solutions of the swarm. The algorithm is then run for a predefined number of iterations. At each iteration, the velocities and the positions of the swarm particles are updated according to Eqs. (7) and (8), and then a mutation operator is applied to 15% of them. The archive and the memory of the best positions are updated according to Pareto-dominance, taking into account the newly generated particles. On the other hand, if the size of the archive exceeds a predefined limit, the solutions that are less crowded in the objective space are kept in the archive. The final solutions of the algorithm are represented by the archive particles of the last iteration.

4. Results and discussion

This section presents the optimization results of the proposed multiobjective design approach for the 3-machine, 9-bus system considering both the classical speed-based PSS and the dual-input PSS. Additionally, some simulation results are presented in order to illustrate the performance of the resulting PSSs and to demonstrate the effectiveness of the proposed tuning approach.

The multiobjective design of power system stabilizers for the 3-machine, 9-bus power system presented above is formulated as a follows:

$$\text{Minimize } F(x) = \begin{pmatrix} \max_i(\sigma_i) \\ -\min_i(\xi_i) \end{pmatrix}, \tag{13}$$

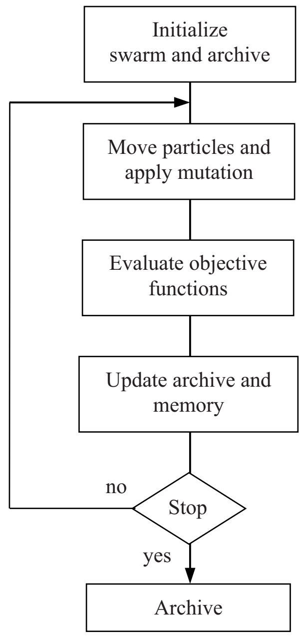

Figure 2. Flowchart of SMPSO.

subject to:

$$\begin{cases} \min\limits_{i}(\xi_i) \geq \xi_c \\ \max\limits_{i}(\sigma_i) \leq \sigma_c \end{cases}, \tag{14}$$

where $x = (K_1^2, K_2^2, T_1^2, T_3^2, K_1^3, K_2^3, T_1^3, T_3^3)$ is the vector of decision variables, which represent the unknown parameters of the dual-input PSSs. Here, the first 4 variables correspond to the parameters of the PSS related to generator 2, and the other variables concern generator 3. In the case of a single-input PSS, the variables K_1 and K_2 are replaced by one variable, K. Furthermore, it was found that the most efficient way to represent these variables is the pole-zero representation. Therefore, this representation is adopted in this work. The bounds of the decision variables are given in Table 1. Note that gains K, K_1, and K_2 hereafter correspond to the gains of the pole-zero form and not to those initially used in Eqs. (1) and (2).

Table 1. Bounds of the decision variables.

Variables	Lower	Upper
Zeros	–100	0
K	1	5000
K_1	1	5000
K_2	–15	15

The previous problem is a constrained problem, which means that any feasible solution must satisfy all the constraints of the problem. The constraints considered in this work impose a minimal value on each objective function. These constraints, which are formulated in Eq. (14), can be handled in the optimization process by assigning a large number to the objective values of the infeasible solutions. In this way, any infeasible solution is dominated by all the feasible solutions regardless of their objective values, and if 2 infeasible solutions are to be compared, the one with the lowest degree of constraint violation is selected. In this study, we consider $\xi_c = 0.5$ and $\sigma_c = -4$ in order to guarantee satisfactory damping and good attenuation speed.

The algorithm SMPSO is implemented using the same parameters as in [21] except for the swarm size and the number of iterations, which are set here to 500 and 10,000, respectively. On the other hand, in order to evaluate the objective functions of a particle, the corresponding PSSs are first used to compute the closed-loop model, and then the resulting eigenvalues are used to evaluate the objective functions.

At the end of the optimization process, only 50 uniformly distributed solutions are selected to represent the approximation set. Furthermore, in order to improve the distribution of the nondominated solutions, the rejection of extra solutions of the archive is performed using the truncation method, which is employed by the algorithm SPEA2 [22]. Note that the archive has the same size as the swarm.

4.1. Optimization results

The final nondominated fronts using the 2 considered types of PSS are illustrated in Figure 3. It is shown that trade-offs exist between the 2 objective functions of the problem, which means that these functions are conflicting performance criteria and cannot be improved simultaneously. As a result, multiple optimal solutions are found at the end of the optimization process, so that no solution can be said to be better than another one. Additionally, it is shown that the dual-input PSS outperforms the single-input PSS according to Pareto-dominance.

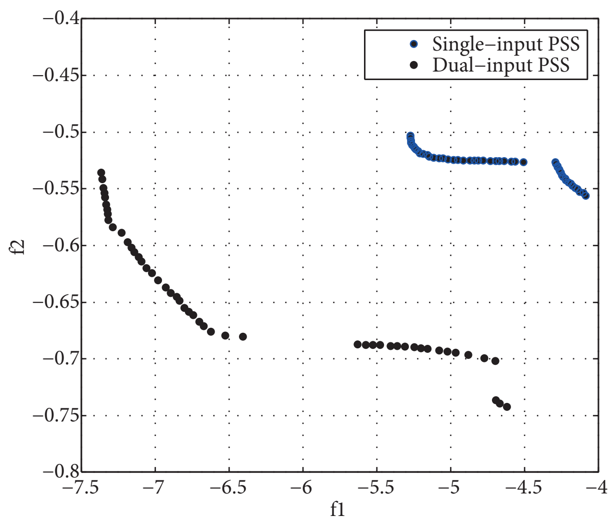

Figure 3. Nondominated fronts produced by SMPSO.

4.2. Simulation results

To illustrate the performance of the resulting dual-input PSSs, different simulations have been carried out using the nonlinear model of the 3-machine, 9-bus system considering nominal, heavy, and light loading conditions. Three scenarios are chosen for simulation. The first scenario is a 0.05 p.u. step decrease in the terminal voltage reference of generators 2 and 3. The second scenario is a 0.01 step increase in the mechanical power of generators 2 and 3, and the third scenario is a short-circuit occurring at bus 7 at the end of the line 5-7 during 0.15 s, followed by line tripping.

For simplicity, only 2 optimal PSSs are used in the simulations. These PSSs are those that provide the best performance according to each objective function of the nondominated front shown in Figure 3. The parameters of such PSSs are given in Table 2. Additionally, the PSSs proposed in [6] are used for comparison purposes. These PSSs are designed using GAs for the same 3-machine, 9-bus system considered in this work.

Table 2. Parameters of the selected dual-input PSSs.

Minimized function	Generator #	PSS parameters
f_1	2	T_1 = 0.12 s T_5 =0.035 s K_1 =21.8 K_2 =–0.32
	3	T_1 = 0.073 s T_5 =0.087 s K_1 =32.1 K_2 =0.02
f_2	2	T_1 = 0.093 s T_5 =0.022 s K_1 =26.1 K_2 =–0.08
	3	T_1 = 0.022 s T_5 =0.019 s K_1 =85.7 K_2 =2.80

To assess the performance of the selected PSSs, 3 performance indices are used: the integral time-weighted absolute error (ITAE), the settling time to measure the transient performance of the controlled system, and the peak value for measuring the damping performance. Note that the ITAE index is computed considering the system response from the peak time. The settling time is evaluated considering a speed deviation range of 10^{-3} rad/s, and the peak value for scenario 3 is defined as the minimum value of the system response. These indices are evaluated for each machine of the power system considering nominal, heavy, and light loading conditions [6]. The average performances of the 3 machines are then evaluated. Note that the output variables of the system are the speed deviations in the COI (center of inertia) referenced system of the 3 generators of the system.

The results of these tests are summarized in Tables 3–5, where GAPSS stands for the PSSs designed using the GA -approach proposed in [6], and DIPSS1 and DIPSS2 stand for the designed PSSs using the proposed approach minimizing f_1 and f_2, respectively. It is shown that the 2 dual-input PSSs outperform the GA-based PSSs, which means that the proposed PSSs are more robust with regard to perturbations and changes in loading conditions. On the other hand, it is shown that the selected PSSs do present a trade-off between damping and transient performance, since none of these PSSs can provide the best results for all considered performance indices and scenarios.

Table 3. Comparison results for scenario 1.

Loading	PSS type	ITAE ($\times 10^{-1}$)	Peak ($\times 10^{-1}$)	Settling time (s)
Nominal	GAPSS	4.17	3.00	11.57
	DIPSS1	1.10	2.60	3.55
	DIPSS2	1.78	1.46	3.73
Heavy	GAPSS	3.42	4.49	9.25
	DIPSS1	0.72	2.45	2.19
	DIPSS2	1.20	1.32	3.30
Light	GAPSS	3.80	2.12	12.54
	DIPSS1	1.36	2.05	4.81
	DIPSS2	2.22	1.29	4.93

To illustrate the previous results, the speed-deviation responses of the 3 generators of the system are given in Figures $4-12$. These simulations are carried out considering heavy loading conditions. It is shown that despite the perturbations, the system stability is enhanced and the electromechanical oscillations are damped out quickly, especially when using the dual-input PSSs. It is also shown that the performances of the selected dual-input PSSs are traded-off against each other, according to which the objective function is minimized. In this regard, when minimizing f_1 the overall transient performance of the system is improved, while the minimization of f_2 improves the damping of the electromechanical oscillations. Nevertheless, a compromise solution among all the provided nondominated solutions can be selected according to the preferences of the decision maker.

Table 4. Comparison results for scenario 2.

Loading	PSS type	ITAE ($\times 10^{-2}$)	Peak ($\times 10^{-2}$)	Settling time (s)
Nominal	GAPSS	3.39	2.48	2.97
	DIPSS1	0.95	1.48	1.87
	DIPSS2	1.88	0.77	2.34
Heavy	GAPSS	1.78	2.50	2.36
	DIPSS1	0.38	1.48	1.17
	DIPSS2	0.64	0.77	1.43
Light	GAPSS	6.02	2.65	4.00
	DIPSS1	2.61	1.69	3.20
	DIPSS2	4.91	0.97	3.57

Table 5. Comparison results for scenario 3.

Loading	PSS type	ITAE	Peak	Settling time (s)
Nominal	GAPSS	7.63	2.34	12.56
	DIPSS1	2.21	2.57	4.87
	DIPSS2	2.30	2.21	5.78
Heavy	GAPSS	11.37	3.22	15.03
	DIPSS1	5.16	3.88	5.70
	DIPSS2	5.87	3.09	8.63
Light	GAPSS	1.03	0.71	6.82
	DIPSS1	0.42	0.85	4.79
	DIPSS2	0.47	0.69	5.45

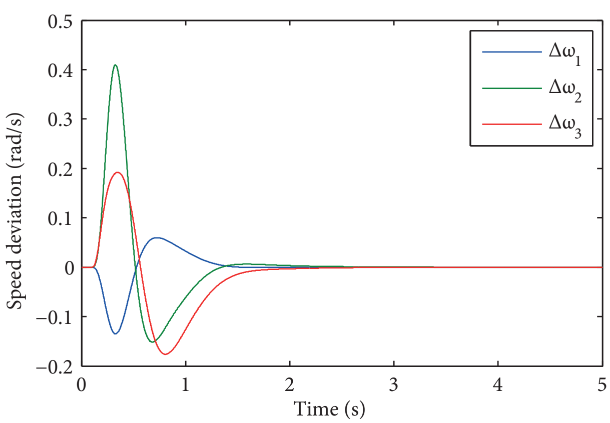

Figure 4. System response for scenario 1 using DIPSS1.

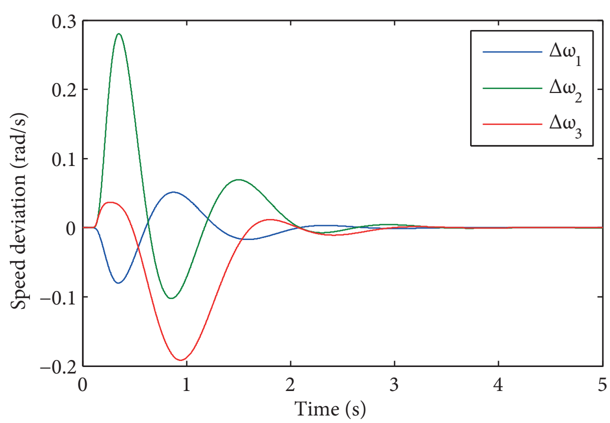

Figure 5. System response for scenario 1 using DIPSS2.

5. Conclusion

This work presents an optimal multiobjective design approach of PSSs for multimachine power systems using multiobjective particle swarm optimization. The design problem is formulated as a minimization problem of 2 objective functions, which characterize the damping and the transient performance of the closed-loop system. The proposed objective functions are simple to evaluate and consider only one operating point. Two types of PSSs are investigated, the classical single-input PSS type and a dual-input PSS that uses the accelerating power as an additional input. The results show that trade-offs exist between the 2 objective functions of the

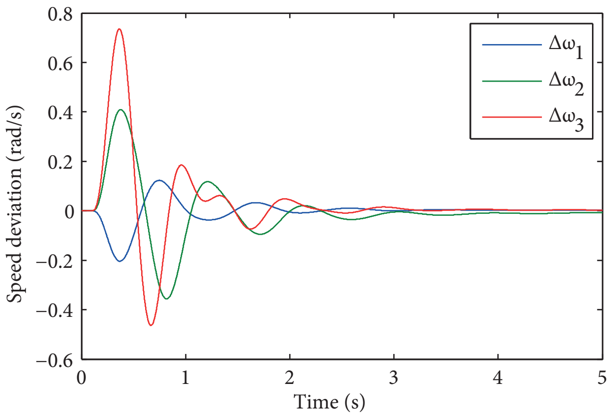

Figure 6. System response for scenario 1 using GAPSS.

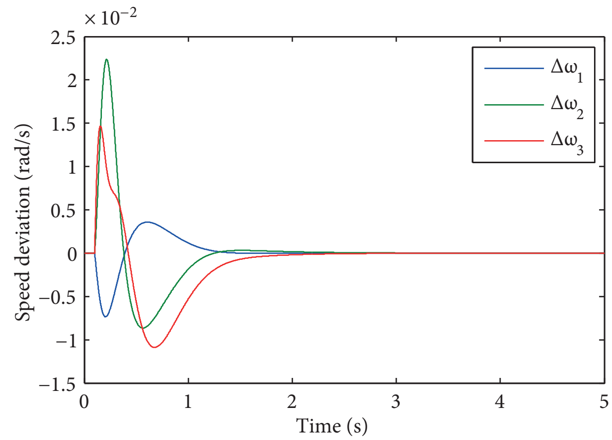

Figure 7. System response for scenario 2 using DIPSS1.

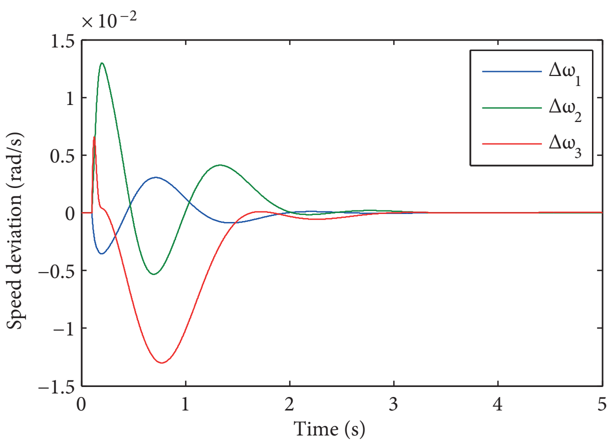

Figure 8. System response for scenario 2 using DIPSS2.

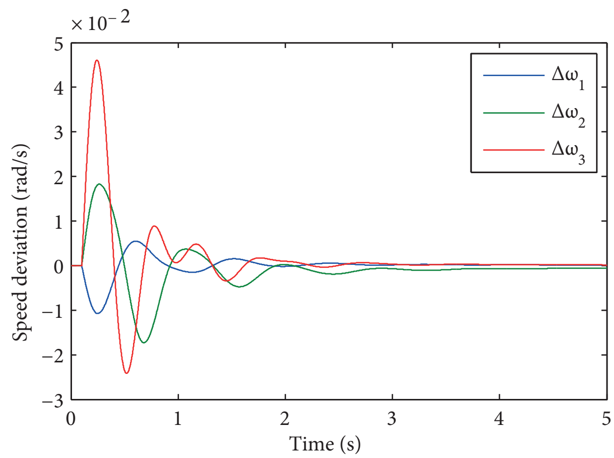

Figure 9. System response for scenario 2 using GAPSS.

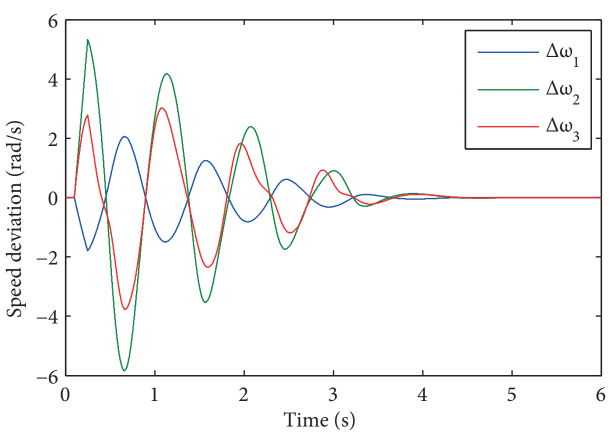

Figure 10. System response for scenario 3 using DIPSS1.

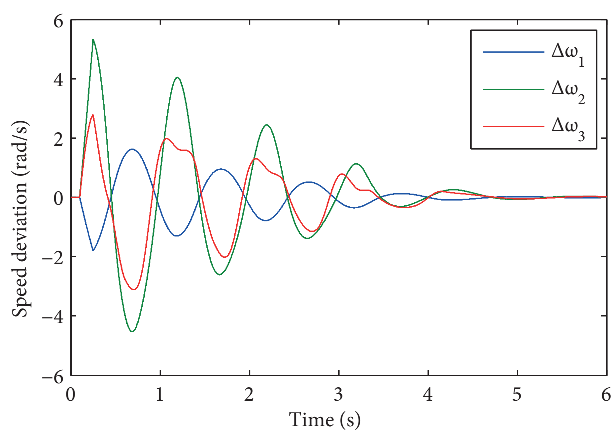

Figure 11. System response for scenario 3 using DIPSS2.

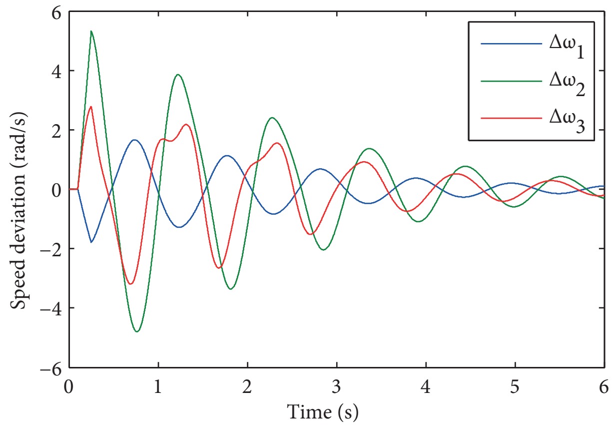

Figure 12. System response for scenario 3 using GAPSS.

problem, and also that the dual-input PSS can provide better results than the single-input PSS according to Pareto-dominance. A future work may investigate other types of PSS and consider a higher number of objective functions.

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Appendix

The dynamic model of a generator with an AVR is given by the following equations:

$$\dot{\delta} = \omega - \omega_0, \tag{A.1}$$

$$\dot{\omega} = -\frac{D}{M}(\omega - \omega_0) + \frac{\omega_0}{M}(P_m - P_e), \tag{A.2}$$

$$\dot{E}'_q = \frac{1}{T'_{d0}}(E_f - E'_q - (X_d - X'_d)I_d), \tag{A.3}$$

$$\dot{E}'_d = \frac{1}{T'_{q0}}(-E'_d + (X_q - X'_q)I_q), \tag{A.4}$$

$$\dot{E}'_f = \frac{1}{T_A}(K_A(U_{ref} - U_t + U_{PSS}) - E_f) \tag{A.5}$$

$$P_e = E'_q I_q + E'_d I_d + (X'_q - X'_d)I_q I_d, \tag{A.6}$$

$$U_t = \sqrt{(E'_d + X'_q I_q)^2 + (E'_q - X'_d I_d)^2} \tag{A.7}$$

Nomenclature

δ	Power angle
ω	Shaft speed
ω_0	Synchronous speed
P_m	Mechanical input power
P_e	Real electrical power
Q_e	Reactive electrical power
D	Damping constant
M	Inertia coefficient
E'_d	Transient EMF in the d-axis
E'_q	Transient EMF in the q-axis
E_f	Equivalent EMF in the excitation coil
T'_{d0}	d-axis transient short-circuit time constant
T'_{q0}	q-axis transient short-circuit time constant
I_d	d-axis current
I_q	q-axis current
X_d	d-axis reactance
X_q	q-axis reactance
X'_d	d-axis transient reactance
X'_q	q-axis transient reactance
U_t	Generator terminal voltage
U_{ref}	Terminal voltage reference
K_A	Gain of the AVR
T_A	Time constant of the AVR
U_{PSS}	PSS output voltage