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Application and Comparative Performance Analysis of PSO and ABC Algorithms for Optimal Design of Multi-Machine Power System Stabilizers

Serdar EKINCI[1,♠]

[1]*Department of Computer Engineering, Batman University, Batman, Turkey*

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ABSTRACT

This paper presents the application and performance comparison of PSO and ABC optimization techniques, for multi-objective design of power system stabilizers (PSSs) in the multi-machine power system. The design objective is to improve the power system stability. The PSSs parameters tuning problem is converted to an optimization problem with the time domain-based objective function and both PSO and ABC optimization techniques are used to search for optimal stabilizers parameters. The optimized stabilizers are tested on multi-machine electric power system subjected to different disturbances. The performance of both optimization techniques in terms of computational time, convergence rate and solution quality is compared. The eigenvalue analysis, nonlinear time-domain simulation results, critical clearing times and some performance indices studies are introduced and compared in order to demonstrate the effectiveness of both optimization techniques in designing stabilizers, to enhance the dynamic stability of the system. What is more, the potential and superiority of the ABC algorithm over the PSO algorithm are verified.

Keywords: *Artificial Bee Colony (ABC) algorithm; Particle Swarm Optimization (PSO); PSS design; dynamic stability; multi-machine power system.*

1. INTRODUCTION

Two of the most significant design standards for multi-machine power systems are transient stability and damping of electromechanical modes of sustained oscillation [1]. Stability of power systems is known to be one of the most significant aspects in electric system operation. This stems from the fact that the power system must keep frequency and voltage levels in the desired level, under any disturbance, such as a swift rise in the load, loss of one generator or switching out of a transmission line, in the course of a fault. There have been spontaneous system oscillations at very low frequencies in order of 0.2-3.0 Hz, since the enhancement of interconnected large electric power systems. Once they commenced, they would carry on for some time. Under some circumstances, they would keep on growing, triggering system separation in case of deficient damping. In addition, low frequency oscillations set forth limitations on the power-transfer capability [2]. To boost system damping, the generators are outfitted with power system stabilizers (PSSs) which provide supplementary feedback stabilizing signals in the excitation systems [3].

In the last two decades, several heuristic optimization techniques have been proposed in order to solve difficult optimization problems. Most of these methods

♠Corresponding author, e-mail: *ekinciser@yahoo.com*

are inspired by nature and can be classed in two important categories that are evolutionary algorithms and swarm intelligence. Swarm intelligence [4], a branch of natural inspired algorithms, focuses on the behavior of insect in order to develop some heuristics algorithms. Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) techniques are new members of swarm intelligence. These techniques are plain, sturdy and able to solve difficult combinatorial optimization problems.

PSO is one of the recent swarm intelligence methods, which is based on natural flocking and swarming behavior of birds. It was first proposed by Kennedy and Eberhart in 1995 [4]. This algorithm gives high quality solutions within shorter calculation time and stable convergence characteristics. ABC algorithm is a relatively new computation method introduced by Karaboga [5]. It is formed on the basis of the foraging behavior of honey bee swarms. Since its invention in 2005, the ABC, considering its plainness and simplicity of implementation, has held the attention and has been employed to settle several practical optimization problems. Both PSO and ABC optimization techniques are alike in a way that these two techniques are population-based search methods and they search for the optimal solution by updating iterations. As the two approaches are expected to find a solution to a designated objective function but use diverse strategies and computational effort, it is apposite to contrast their performance.

Broadly, the aim of this paper is to compare the computational effectiveness and efficacy of both PSO and ABC optimization techniques for designing PSSs for power system dynamic stability improvement in multi-machine power system. The design problem is formulated as a multi-objective optimization problem and PSS parameters are adjusted using PSO and ABC algorithms. The performance of the PSO-based PSS (PSOPSS) and ABC-based PSS (ABCPSS) are tested on the 10-machine 39-bus New England system. The performance of both optimization techniques with respect to computational time, convergence rate and solution quality are compared. Eigenvalue analysis, nonlinear time-domain simulation, critical clearing times and some performance indices studies have been carried out to assess the effectiveness of the ABCPSS and PSOPSS under severe disturbances. In addition, the performance of the ABCPSS is compared to PSOPSS through the results of these studies.

2. PROBLEM STATEMENT

2.1. Power System Model

In this study, the flux-decay model with static exciter is employed to discuss the synchronous machines. The dynamics of each synchronous machine is formulated as [6]:

$$\frac{d\delta_i}{dt} = \omega_s\left(\omega_i - 1\right) = \omega_s \Delta\omega_i \tag{1}$$

$$\frac{d\omega_i}{dt} = \frac{P_{mi}}{M_i} - \frac{P_{ei}}{M_i} - \frac{D_i(\omega_i - 1)}{M_i} \tag{2}$$

$$\frac{dE'_{qi}}{dt} = -\frac{E'_{qi}}{T'_{doi}} - \frac{(x_{di} - x'_{di})i_{di}}{T'_{doi}} + \frac{E_{fdi}}{T'_{doi}} \tag{3}$$

$$\frac{dE_{fdi}}{dt} = -\frac{E_{fdi}}{T_{ai}} + \frac{K_{ai}}{T_{ai}}\left(V_{refi} + V_{Si} - V_i\right) \tag{4}$$

$$P_{ei} = E'_{qi} i_{qi} + (x_{qi} - x'_{di}) i_{di} i_{qi} \tag{5}$$

2.2. Power System Stabilizers (PSS)

A widely used conventional power system stabilizer (CPSS) is considered throughout the study, as shown in Fig. 1. CPSS comprises three units: phase compensation unit, washout filter, and gain unit. The PSS output signal V_S is a voltage added to the generator exciter input. The rotor speed deviation $\Delta\omega$ is normally employed as the PSS input signal [7]. The high pass washout filter is employed to reset the steady state offset in the PSS output. The value of time constant (T_W) is usually fixed and is considered as 10 s in this study. Also $T_1 - T_4$ and K_P show the time constants and the gain of two stages lead-lag compensator respectively [7]. The optimized parameters are K_P, T_1, T_2, T_3, and T_4 which are referred to as decision variables in the optimization problem.

2.3. Linearized System Model

In the design of PSSs, the linearized incremental models around an equilibrium point are typically used [6]. By the linearized of the power system equations, explained in [6], and by the adding of PSS equations, the linearized power system model yield the following state equation.

$$\Delta\dot{x} = \mathbf{A}\Delta x + \mathbf{B}\Delta u \tag{6}$$

where, $\mathbf{A}$ is the state variables matrix and $\mathbf{B}$ is the input matrix. The state vector Δx is the vector of the state variables and Δu is the vector of input variables. In this study, $\Delta x = \left[\Delta\delta \quad \Delta\omega \quad \Delta E'_q \quad \Delta E_{fd}\right]^T$ and Δu is the PSS output signals. Here, the goal of PSS design is to place the eigenvalues of matrix $\mathbf{A}$ in the left half of the complex plane. Eigenvalues of the system can be evaluated from matrix $\mathbf{A}$:

$$\lambda_i = \sigma_i \pm j\omega_i \tag{7}$$

where $i = 1, 2, \ldots, n$ and n denotes the total number of eigenvalues. The eigenvalues may be real or complex. σ_i and ω_i are the real and imaginary parts of the *i*th eigenvalue. Then, the damping ratio (ξ_i) of the *i*th eigenvalue is defined with the following equation:

$$\xi_i = \frac{-\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \tag{8}$$

2.4. Objective Function and PSS tuning

An objective function that diminishes the overshoots and settling time of the system response is used in this paper. It can be formulized as:

$$J = \sum_{j=1}^{NS}\sum_{i=1}^{m}\int_0^{t_{sim}} (t\omega_{i-1})^2 \, dt \tag{9}$$

where, NS, m, t_{sim} and ω_{i-1} are the total number of scenarios, number of generators, the time range of the simulation and the relative rotor speed of the *i*th generator relative to the first generator. The design problem can be formulated as the following constrained optimization problem, where the constraints are the PSS parameter bounds:

Minimize J subject to

$$\begin{aligned} &K_P^{\min} \le K_P \le K_P^{\max} \\ &T_1^{\min} \le T_1 \le T_1^{\max} \\ &T_2^{\min} \le T_2 \le T_2^{\max} \\ &T_3^{\min} \le T_3 \le T_3^{\max} \\ &T_4^{\min} \le T_4 \le T_4^{\max} \end{aligned} \tag{10}$$

Typical ranges of the optimized parameters are $[0.01-100]$ for K_P and $[0.01-1.0]$ for T_1-T_4 [6]. Considering the objective function given in (9), the proposed approach employs PSO and ABC techniques to solve this optimization problem and search for an optimal set of PSS parameters.

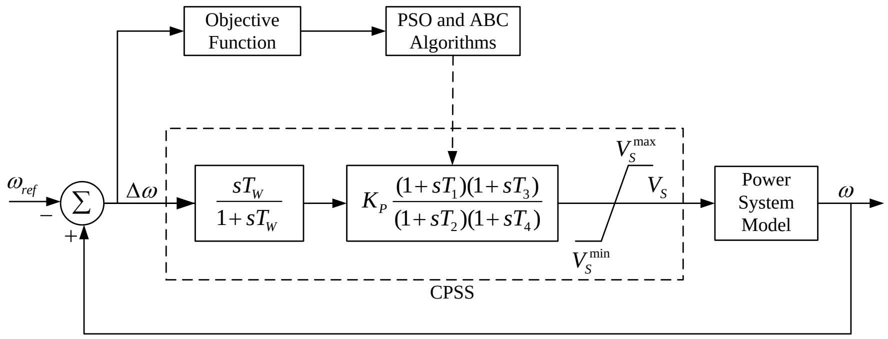

Fig. 1. Block diagram of CPSS parameter optimization using PSO and ABC algorithms.

3. OVERVIEW OF PSO AND ABC OPTIMIZATION TECHNIQUES

3.1. Particle Swarm Optimization (PSO)

The PSO was developed by Kennedy and Eberhart [4] as a swarm-based stochastic optimization method, which is based on social behavior of bird flocking or fish schooling. This method is akin to evolutionary computing in several aspects, but the PSO does not have any evolution operators. The standard PSO algorithm employs a population of particles. The particles fly through the *D*-dimensional domain space of the function to be optimized. The position vector and the velocity vector of the *i*th particle in the *D*-dimensional search space can be defined as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, respectively. Each particle updates its position and velocity based on its own best position (*pbest*) and the best position of the whole swarm (*gbest*). At each time step, after finding the two best values, the particle updates its velocity and position according to its flying trajectory by the following [8]:

$$\begin{aligned} v_{id}^{t+1} = w \times v_{id}^t + c_1 \times r_1 \times (pbest_{id}^t - x_{id}^t) \\ + c_2 \times r_2 \times (gbest_d^t - x_{id}^t) \end{aligned} \tag{11}$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \tag{12}$$

where $i = 1, 2, \ldots, NP$ and NP is the size of the swarm, w represents inertia weight decreased linearly for each iteration, c_1 and c_2 are learning factors which determine the relative influence of cognitive and social components, respectively. r_1 and r_2 are random numbers in the range $[0,1]$. x_{id}^t, v_{id}^t and $pbest_{id}^t$ are the position, velocity and the personal best of *i*th particle in *d*th dimension for the *t*th iteration, respectively. The $gbest_d^t$ is the *d*th dimension of best particle among all particle in the swarm for the *t*th iteration.

3.2. Artificial Bee Colony (ABC)

In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts [9]. First half of the colony contains the employed artificial bees and the second half comprises the onlookers. In other words, the number of employed bees is equivalent to the number of food sources [9]. Onlooker bees wait on the dance area and share the information on the food sources found by employed bees for making a decision to choose better ones and explore around them. If some food sources are not improved for several cycles, the scout bees carry out random searches for discovering new sources. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source indicates the fitness of the associated solution, calculated as follows [10, 11]:

$$fit_i = \frac{1}{1+f_i} \tag{13}$$

An onlooker bee evaluates the fitness values from all the solutions of the employed bees and chooses a solution with a probability value associated with that solution, p_i, which is calculated by the following expression (14) [10, 11]:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{14}$$

where SN is the number of food sources equivalent to the number of employed bees, and fit_i is the fitness of the solution given in (13). To produce a candidate food position from the old one in memory, the ABC utilizes the following equation [10, 11]:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{15}$$

where $k \in \{1, 2, \ldots, SN\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indices, x_{kj} is a randomly chosen solution different from x_{ij}, v_{ij} is the new solution, ϕ_{ij} is a random number in the range $[-1,1]$ and D is the number of optimization parameters.

In the ABC algorithm, a position cannot be enhanced further by a predetermined number of iteration, then that food source is expected to be abandoned. The predetermined number of iteration is a significant control parameter of the ABC algorithm. The scout bees replace new food sources, which are produced irregularly in their dynamic ranges, with the ones that worker bees abandon. The scout bees are going to steer for the new food location by Eq. (16) [10, 11]

$$x_{ij} = x_{\min,j} + rand(0,1)(x_{\max,j} - x_{\min,j}) \tag{16}$$

where $x_{\min,j}$ and $x_{\max,j}$ are the lower and upper limits of the jth optimization variable respectively and $rand(0,1)$ denotes a uniformly distributed random number within $[0,1]$.

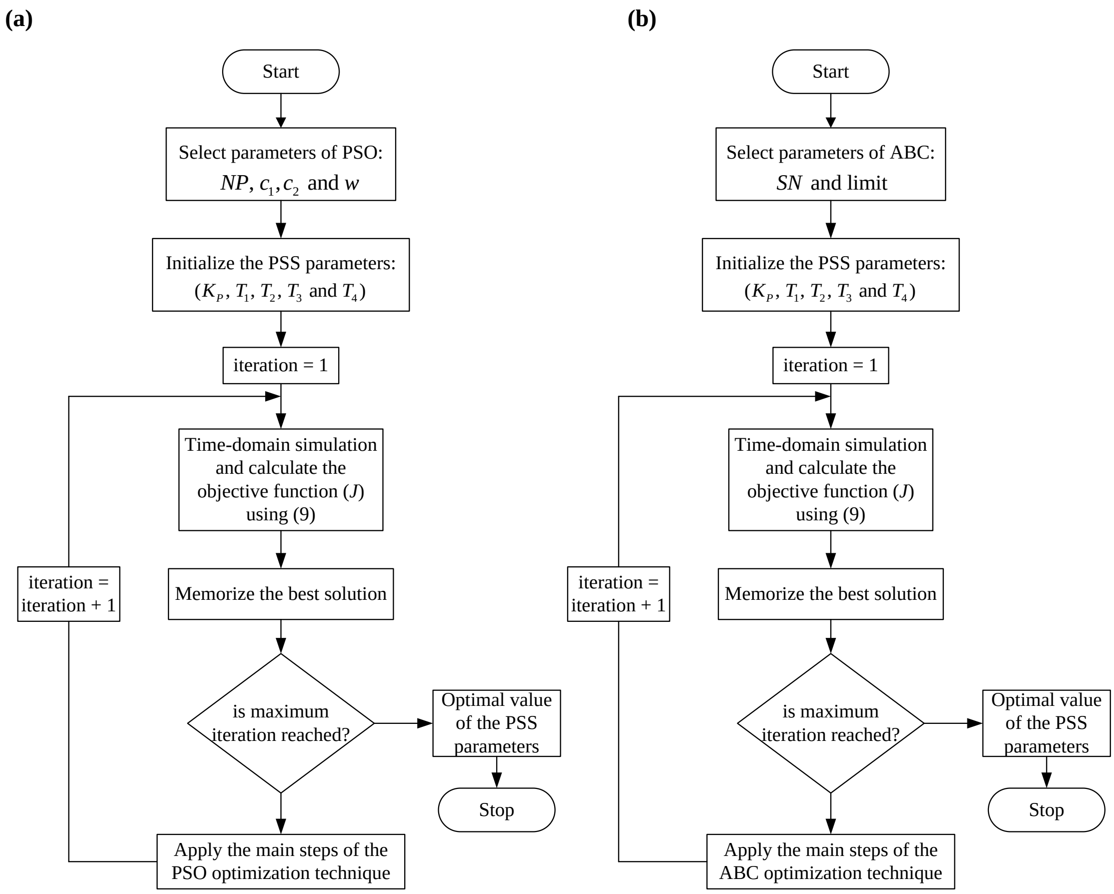

Fig. 2. (a) Flowchart of the PSO algorithm. **(b)** Flowchart of the ABC algorithm.

Table 1. Parameter settings of PSO and ABC algorithms.

Parameters	PSO	ABC
Number of particles/bees	20	20
c_1 and c_2	2.0 and 2.0	Not required
w	Linearly decreasing from 0.9 to 0.4	Not required
Limit number	Not required	100

3.3. Application of PSO and ABC optimization techniques

In time domain simulation of multi-machine power systems, Runge-Kutta 4 technique is used for numerical integration of the differential equations and step of integration is chosen as $\Delta t = 0.01$ s. PSO and ABC algorithms are simulated in an Intel Core processor with 2.10 GHz frequency and 2.00 GB RAM using MATLAB 7.11.0.

The computational flow charts of PSO and ABC algorithms are shown in Fig. 2 (a) and (b), respectively. While applying PSO and ABC, it is required to specify the number of parameters. A suitable choice of the parameters impacts the speed of convergence of the algorithm. Table 1 demonstrations the parameters employed for PSO and ABC optimization techniques. Optimization is terminated by the pre-specified number of iterations for both PSO and ABC. It should be noted that PSO and ABC algorithms are run several times and then the optimal set of PSS parameters is selected.

4. RESULTS AND DISCUSSIONS

4.1. Test System and PSS design

The 10-machine 39-bus New England power system shown in Fig. 3 is considered in this study. This is also the system appearing in [12, 13] and widely used in the literature. Although the number and location of PSSs required can be investigated [14], for illustration and comparison purposes, it is assumed that all generators are equipped with PSSs. In this example, the optimized parameters are K_{Pi}, T_{1i}, T_{2i}, T_{3i}, and T_{4i}, $i = 1, 2\ldots, 10$ and the number of optimized parameters is 50. It is significant to underline that the ABC and PSO algorithms are run a number of times and then optimal set of PSS parameters is selected. The PSO and ABC algorithms are applied to search for the settings of these parameters so as to optimize the multi-objective function considered. The optimization was performed with the total number of iterations set to 200. The final values of the optimized parameters of the PSO and ABC algorithms are given in Table 2.

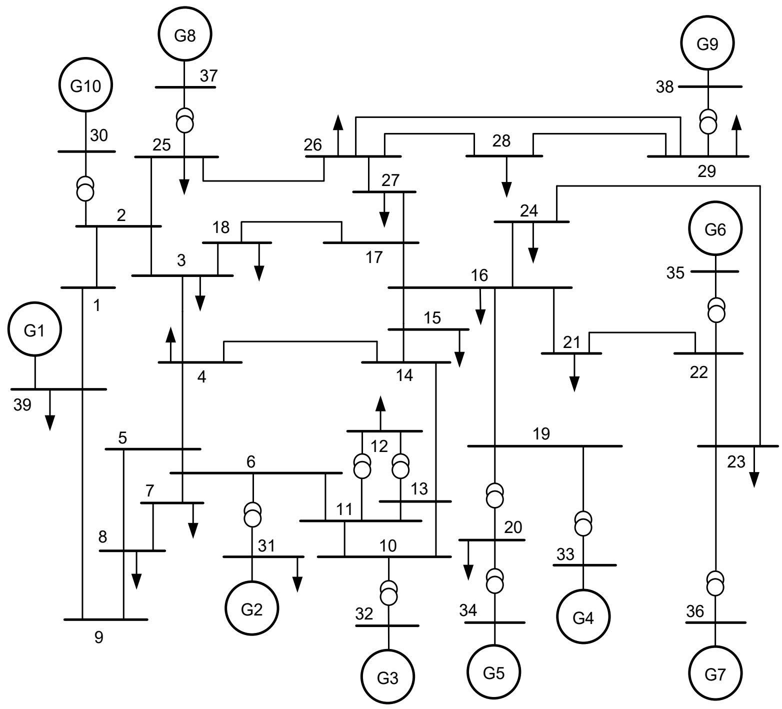

Fig. 3. New England 10-machine 39-bus power system.

Table 2. PSS parameters by using PSO and ABC algorithms.

Method	Gen.	K_P	T_1	T_2	T_3	T_4
PSO	G1	100.00	1.0000	0.3865	1.0000	0.0729
	G2	77.505	1.0000	0.1006	0.6323	0.7681
	G3	31.518	0.8080	0.0987	0.9167	0.5595
	G4	79.386	1.0000	0.0164	1.0000	0.8549
	G5	91.917	0.8012	0.0100	0.4007	0.3878
	G6	24.653	0.6063	0.0433	0.5844	0.3418
	G7	9.9557	1.0000	0.1066	1.0000	0.2686
	G8	14.569	0.2474	0.2542	0.9103	0.1161
	G9	14.225	0.8627	0.0297	0.9479	0.0970
	G10	65.739	0.2626	0.6021	0.2150	0.8810
ABC	G1	100.00	1.0000	0.2870	0.5930	0.0186
	G2	43.233	1.0000	0.1733	0.6999	0.2715
	G3	24.755	1.0000	0.4483	0.9283	0.0100
	G4	71.977	0.3358	0.0100	0.3585	0.0474
	G5	76.217	0.5729	0.2584	0.9718	0.1517
	G6	68.883	1.0000	0.2451	0.8981	0.4970
	G7	65.874	0.5619	0.0541	0.8959	0.5687
	G8	100.00	0.3321	0.0232	0.9525	0.0100
	G9	35.221	0.8939	0.3800	1.0000	0.0100
	G10	25.311	0.0644	1.0000	0.1804	0.9503

4.1.1. Convergence test and computation time

Fig. 4 shows the convergence of ABC and PSO methods for New England power system. It can be inferred from Fig. 4 that PSOPSS takes around 181 iterations to converge, whereas ABCPSS takes only about 159 iterations. It is observed that, ABC appears to attain its final parameter values in less iterations than the PSO.

Table 3 shows a comparison between ABC and PSO algorithms with regard to the computation time. As it can be seen from the table, the computation time of ABC is less than PSO method. This clearly shows that the ABC has got a faster convergence. Thus, systems employing ABC method can save considerable amount of time and therefore are feasible for online optimization with high speed processors.

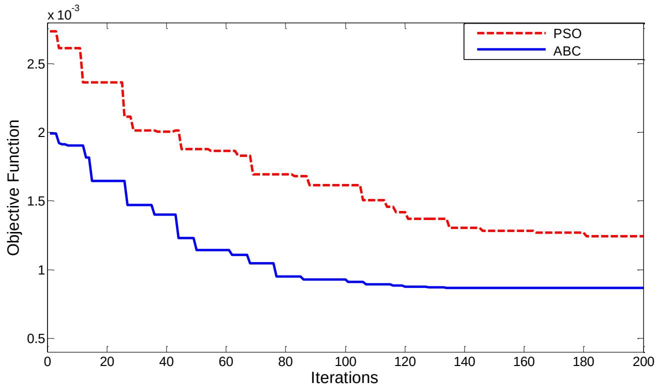

Fig. 4. Objective function variation for PSO and ABC optimization techniques.

Table 3. Computation time comparison of algorithms.

Algorithm	Computation Time (seconds per iteration)
PSO	269.07
ABC	239.82

4.2. Eigenvalue Analysis

The electromechanical mode eigenvalues and the corresponding damping ratios without PSSs and with PSSs (PSOPSS and ABCPSS) are shown in Table 4. Eigenvalue analysis shows that the system has nine electromechanical modes of oscillations and some of them are classified as inter-area modes. It can be seen that without PSS, both local and inter-area modes are poorly damped. It is quite clear that the system eigenvalues associated with the electromechanical modes have been successfully shifted to the left of $s = -0.5$ line with the proposed ABCPSS. This demonstrates that the proposed ABCPSS outperform the PSOPSS and the system damping of electromechanical modes is significantly enhanced. This confirms the superiority of ABC approach to search for the optimal PSS parameters.

Table 4. Eigenvalues and damping ratios of the electromechanical modes.

Without PSS	PSOPSS	ABCPSS
$-0.0477 \pm j7.0372$, 0.0068	$-0.8797 \pm j7.4746$, 0.1169	$-1.1192 \pm j7.3737$, 0.1501
$-0.1508 \pm j6.1434$, 0.0245	$-0.7894 \pm j7.8508$, 0.1001	$-1.0475 \pm j7.7738$, 0.1335
$-0.1514 \pm j7.0925$, 0.0213	$-1.3360 \pm j6.4736$, 0.2021	$-1.5153 \pm j6.5719$, 0.2247
$-0.2220 \pm j8.3659$, 0.0265	$-0.7321 \pm j7.0540$, 0.1032	$-0.9351 \pm j7.9121$, 0.1178
$-0.1898 \pm j5.8445$, 0.0324	$-0.9067 \pm j9.0267$, 0.0999	$-1.4568 \pm j9.6813$, 0.1488
$-0.1556 \pm j6.7077$, 0.0232	$-0.4198 \pm j8.7515$, 0.0479	$-2.0648 \pm j5.0450$, 0.3788
$-0.2351 \pm j8.5438$, 0.0275	$-1.4993 \pm j5.2185$, 0.2761	$-2.3388 \pm j5.4836$, 0.3923
$-0.1813 \pm j8.5091$, 0.0213	$-0.7529 \pm j3.1250$, 0.2342	$-0.8463 \pm j2.8343$, 0.2861
$-0.1041 \pm j3.5444$, 0.0294	$-0.5538 \pm j0.9009$, 0.5237	$-0.6633 \pm j0.6885$, 0.6938

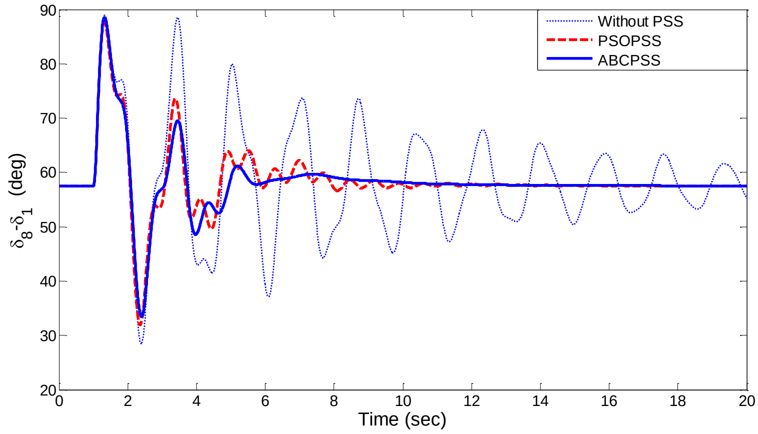

Fig. 5. The relative rotor angle of G_8 under scenario 1.

4.3. Nonlinear Time-Domain Simulation

To evaluate and compare the effectiveness of the PSO and ABC based tuned PSSs using the proposed multi-objective function, two different severe fault scenarios are considered. They can be described as follows:

- **Scenario 1:** In this scenario, a 6-cycle three-phase fault at $t = 1$ s, on bus 2 at the end of line 2-3 is considered for the nonlinear time simulations. The fault cleared without line tripping and the original system is restored upon the clearance of the fault.

•Corresponding author, e-mail: *ekinciser@yahoo.com*

The simulation results on different generators (e.g. G_8 and G_{10}) are presented in Figs. 5-8. Each figure contains three plots for without PSS (dotted line), PSOPSS (dashed line) and ABCPSS (solid line). It is clear from the figures that, the system is oscillatory without PSS under this severe disturbance. Results also demonstrate the effectiveness of the PSS in a large power system. According to Figs. 5-8 tuning PSS parameters by ABC algorithm provides suitable results in more favorable damping for network compared to the use of PSOPSS.

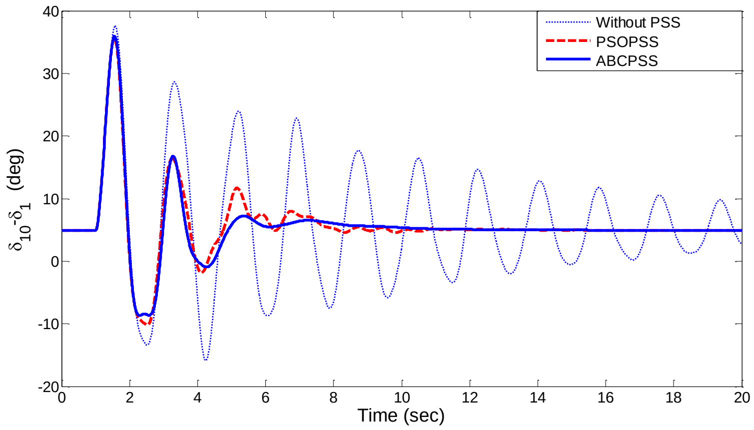

Fig. 6. The relative rotor angle of G_{10} under scenario 1.

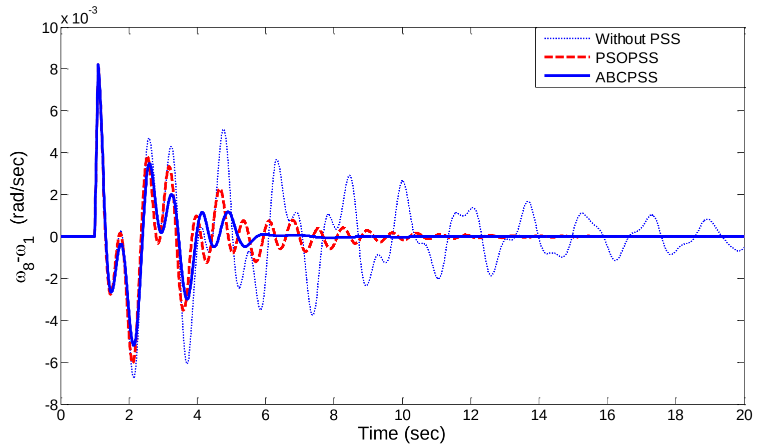

Fig. 7. The rotor speed deviation of G_8 under scenario 1.

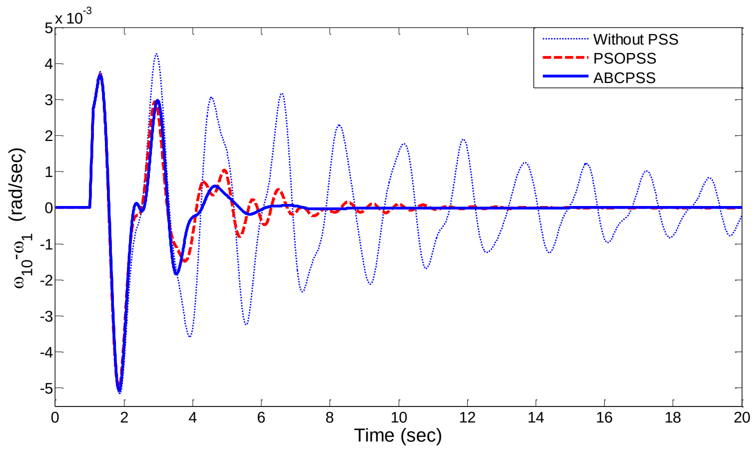

Fig. 8. The rotor speed deviation of G_{10} under scenario 1.

- **Scenario 2:** In this scenario, additional severe disturbance is taken into consideration; that is, a 3-cycle three-phase fault is applied on bus 22 at the end of line 21-22 at $t = 1$ s. The fault is cleared by permanent tripping of the faulted line.

The relative rotor angles and the rotor speed deviations of the different generators (e.g. G_6 and G_7), under the proposed severe scenario are shown in Figs. 9-12. It clearly can be seen that the system performance with the proposed ABCPSS is much superior to that of proposed PSOPSS, as well as the oscillations are damped out at much higher speed. What is more, the proposed ABCPSS are rather effective in damping out the local modes and the inter-area modes of oscillations. This shows the potential and superiority of the proposed ABCPSS to achieve an optimal set of PSS parameters.

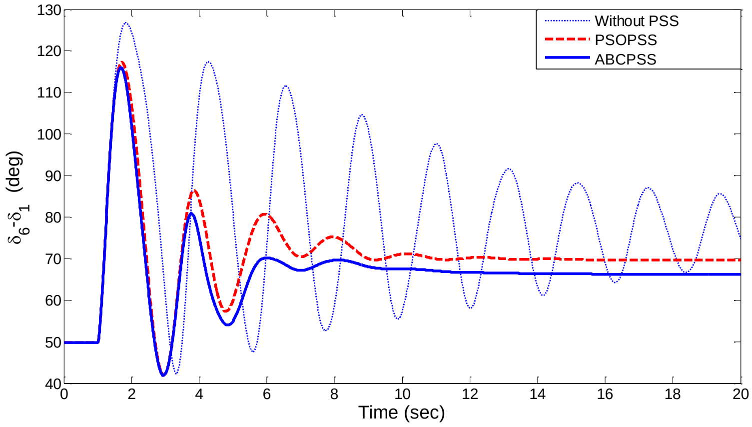

Fig. 9. The relative rotor angle of G_6 under scenario 2.

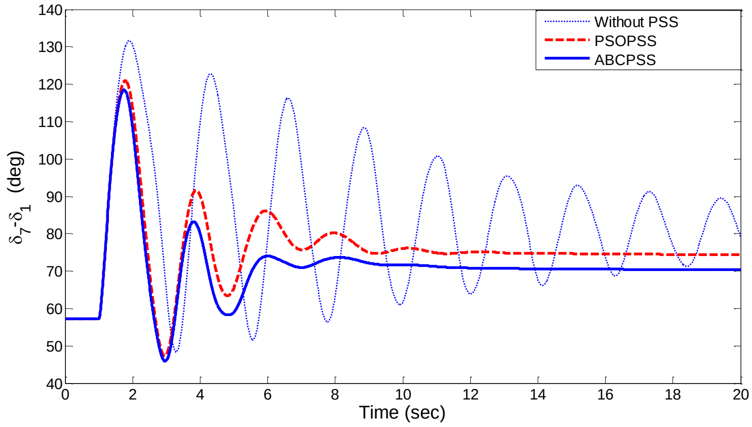

Fig. 10. The relative rotor angle of G_7 under scenario 2.

4.3.1. Comparison of critical clearing time

For a synchronous generator, the critical clearing time is defined as the maximum allowed time duration to clear the fault such that the system maintains transiently stable [15]. For Scenario 1 and Scenario 2, the critical clearing times in s (which is determined by solving the swing equation beyond which the system losses synchronism) are provided in Table 5. From the table it is evident that the proposed ABCPSS have better performance with regard to critical clearing time compared to the proposed PSOPSS.

Table 5. Comparison of critical clearing times.

Fault Type	Faulty Bus	Line	Critical clearing times (s)		
			Without PSS	PSOPSS	ABCPSS
Without line tripping	2	2-3	0.191	0.203	0.206
Tripping of the faulted line	22	21-22	0.071	0.101	0.106

♠Corresponding author, e-mail: *ekinciser@yahoo.com*

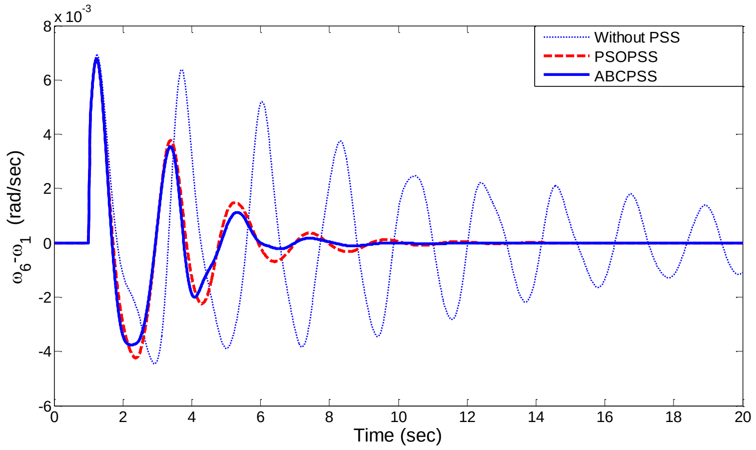

Fig. 11. The rotor speed deviation of G_6 under scenario 2.

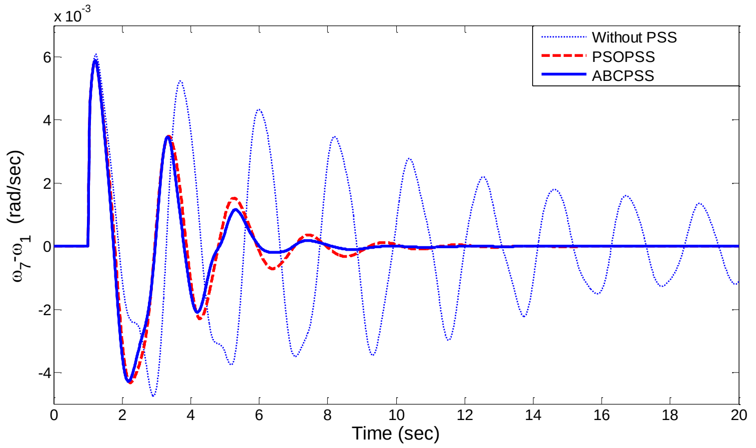

Fig. 12. The rotor speed deviation of G_7 under scenario 2.

4.3.2. Comparison of performance indices of time response

To demonstrate the performance of PSO and ABC optimization techniques, four performance indices that indicate the settling time and overshoots are presented and assessed. These indices are defined as [16]

ISE: Integral of Squared Error:
$$PI_1 = 10000 \times ISE = 10000 \times \sum_{i=2}^{m} \int_0^{t_{sim}} (\omega_i - \omega_1)^2 \, dt \quad (17)$$

IAE: Integral of Absolute Error:
$$PI_2 = 100 \times IAE = 100 \times \sum_{i=2}^{m} \int_0^{t_{sim}} |\,\omega_2 - \omega_1\,| \, dt \quad (18)$$

ITAE: Integral of Time-Weighted Absolute Error:
$$PI_3 = 100 \times ITAE = 100 \times \sum_{i=2}^{m} \int_0^{t_{sim}} t\,|\,\omega_i - \omega_1\,| \, dt \quad (19)$$

ITSE: Integral of Time-Weighted Squared Error:
$$PI_4 = 10000 \times ITSE = 10000 \times \sum_{i=2}^{m} \int_0^{t_{sim}} t\,(\omega_i - \omega_1)^2 \, dt \quad (20)$$

where m is the number of machines and t_{sim} is the simulation time. It is noteworthy to mention that the lower the value of these indices is, the better the system response with reference to time-domain characteristics. Numerical results of the system performance for different fault conditions are given in Table 6. As can be seen from this table the ABC-based stabilizer (ABCPSS) has a better performance than the PSOPSS for all scenarios.

Table 6. Values of the performance indices.

Fault case	Method	PI_1	PI_2	PI_3	PI_4
Scenario 1	PSO	2.0422	7.5948	15.0875	2.4653
	ABC	1.8602	6.6857	10.8873	1.9913
Scenario 2	PSO	1.8684	8.0826	19.9838	3.0337
	ABC	1.6709	7.0850	14.9327	2.4337

5. CONCLUSION

In this research, we have compared the performance of PSO and ABC optimization techniques for optimal design of multi-machine power system stabilizers (PSSs). To achieve optimal tuning of PSS parameters, the design problem of stabilizers is formulated as an optimization problem with the time domain-based objective function and is solved by both PSO and ABC optimization techniques. The proposed stabilizers (PSOPSS and ABCPSS) are applied to a multi-machine power system with different disturbances. Following conclusions can be drawn about the performance comparison of both the algorithms (ABC and PSO).

1. Compared with the PSO technique, the ABC algorithm demonstrates its superiority in computational complexity, convergence rate, solution quality and computational time.

2. The eigenvalue analysis reveals that the ABCPSS improves the damping characteristics of electromechanical modes.

3. The nonlinear simulation results show performance of the ABC-based PSS in improving the critical clearing time of the system and reducing low-frequency oscillations under different disturbances.

4. The system performance characteristics in terms of *ISE*, *IAE*, *ITAE* and *ITSE* indices reveal that compared with the PSO-based PSS, the settling time and speed deviations of the machine are greatly reduced by applying the ABC-based PSS.

From the results obtained in this work, it can be concluded that performance of ABC algorithm is better than PSO algorithm although it uses less control parameters and it can be efficiently used for solving optimization problems in power systems.

CONFLICT OF INTEREST

No conflict of interest was declared by the authors.

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♠Corresponding author, e-mail: *ekinciser@yahoo.com*

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