

Optimal Power System Stabilizers Design for Multimachine Power System Using Hybrid BFOA-PSO Approach

Ali, E. S.^a and Abd-Elazim, S. M.^b

a- Assistant Professor, Electric Power and Machine Department, Faculty of Engineering, Zagazig University, Zagazig, Egypt, E-mail address: ehabsalimalisalama@yahoo.com

b- Assistant Professor, Electric Power and Machine Department, Faculty of Engineering, Zagazig University, Zagazig, Egypt, E-mail address: sahareldeep@yahoo.com

Abstract- A novel hybrid approach involving Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization Algorithm (BFOA) called Bacterial Swarm Optimization (BSO) is illustrated for designing Power System Stabilizers (PSSs) in a multimachine power system. In BSO, the search directions of tumble behaviour for each bacterium are oriented by the individual's best location and the global best location of PSO. The proposed hybrid algorithm has been extensively compared with the original BFOA algorithm and the PSO algorithm. Simulations results have shown the validity of the proposed BSO in tuning PSSs compared with BFOA and PSO. Moreover, the results are presented to demonstrate the effectiveness of the proposed controller to improve the power system stability over a wide range of loading conditions.

Key-Words: - PSSs; Multimachine Power System; Particle Swarm Optimization; Bacteria Foraging.

1. Introduction

Low frequency oscillations are observed when large power systems are interconnected by weak tie lines. These oscillations may sustain and grow, causing system separation if no adequate damping is available. Moreover, low frequency oscillations present limitations on the power transfer capability [1]. Power system stabilizers (PSSs) are now routinely used in the industry to damp out oscillations. An appropriate selection of PSS parameters results in satisfactory performance during system disturbances [2].

The problem of PSS parameter tuning is a complex exercise. A number of conventional techniques have been reported in the literature pertaining to design problems of conventional PSSs namely: the eigenvalue assignment, mathematical programming, gradient procedure for optimization and also the modern control theory [3]. Unfortunately, the conventional techniques are time consuming as they are iterative and require heavy computation burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima and the solution obtained may not be optimal [4]. The power system stability enhancement via PSS and a thyristor controlled series capacitor (TCSC) based stabilizer when applied independently and also through coordinated application is discussed and investigated in [5]. An augmented fuzzy logic PSS for stability enhancement of power system is presented in [6]. The design of robust PSS which place the system poles in an acceptable region in the complex plane for a given set of operating and system conditions is introduced in [7]. A novel evolutionary algorithm

based approach to optimal design of multimachine PSSs is developed in [8]. This approach employs a particle swarm optimization (PSO) technique to search for optimal settings of PSS parameters. Optimal multi-objective design of robust multimachine PSSs using genetic algorithm (GA) is addressed in [9]. PSSs design using the rule based bacteria foraging (RBBF) optimization techniques is investigated in [10]. A comprehensive assessment of the effects of PSS based damping controller is carried out in [11]. The design problem of the controller is transformed into an optimization problem. PSO based optimal tuning algorithm is used to optimally tune the parameters of the PSS. Optimal locations and design of robust multimachine PSSs using GA is presented in [12]. The possibility of using a linearized power system model to evaluate the stability and estimate the attraction area of the system in a particular operating condition is investigated in [13]. Multi-objective design of multimachine PSSs using PSO is introduced in [14]. A new robust control strategy to synthesis of robust proportional-integral-derivative (PID) based PSS is addressed in [15]. The design of a simple, yet robust controller for power system stabilization, using Kharitonov's stability theory is employed in [16]. A novel algorithm for simultaneous coordinated designing of PSSs and TCSC in a multimachine power system is discussed in [17].

GA has attracted the attention in the field of controller parameter optimization. However, GA is very satisfactory in finding global or near global optimal result of the problem; it needs a very long run time that may be several minutes or even several

hours depending on the size of the system under study. Moreover swarming strategies in bird flocking and fish schooling are used in the PSO and introduced in [18]. However, PSO suffers from the partial optimism, which causes the less exact at the regulation of its speed and the direction. Also, the algorithm cannot work out the problems of scattering and optimization [19-20]. In addition, the algorithm pains from slow convergence in refined search stage, weak local search ability and algorithm may lead to possible entrapment in local minimum solutions. A relatively newer evolutionary computation algorithm, called Bacteria Foraging (BF) scheme has been proposed by [21-24]. The BF algorithm depends on random search directions which may lead to delay in reaching the global solution. A new algorithm BF oriented by PSO is proposed that combine the above mentioned optimization algorithms [25-26]. This combination aims to make use of PSO ability to exchange social information and BF ability in finding a new solution by elimination and dispersal. This new hybrid algorithm called Bacterial Swarm Optimization (BSO) is adopted in this paper to solve the above mentioned problems and drawbacks.

This paper proposes a new optimization algorithm known as BSO for optimal designing of the PSSs controller in a multimachine power system. The performance of BSO has been compared with these of PSO and BFOA in tuning the PSSs controller parameters. The design problem of the proposed controller is formulated as an optimization problem and BSO is employed to search for optimal controller parameters. An eigenvalue based objective function reflecting the combination of damping factor and damping ratio is optimized for different operating conditions. Simulations results assure the effectiveness of the proposed controller in providing good damping characteristic to system oscillations over a wide range of loading conditions. Also, these results validate the superiority of the proposed method in tuning controller compared with BFOA and PSO.

2. Bacteria foraging optimization: A brief overview

The survival of species in any natural evolutionary process depends upon their fitness criteria, which relies upon their food searching and motile behaviour. The law of evolution supports those species who have better food searching ability and either eliminates or reshapes those with poor search ability. The genes of those species who are stronger gets propagated in the evolution chain since

they possess ability to reproduce even better species in future generations. So a clear understanding and modelling of foraging behaviour in any of the evolutionary species, leads to its application in any nonlinear system optimization algorithm. The foraging strategy of *Escherichia coli* bacteria present in human intestine can be explained by four processes, namely chemotaxis, swarming, reproduction, and elimination dispersal [25-26].

2.1 Chemotaxis

The characteristics of movement of bacteria in search of food can be defined in two ways, i.e. swimming and tumbling together known as chemotaxis. A bacterium is said to be 'swimming' if it moves in a predefined direction, and 'tumbling' if moving in an altogether different direction. Mathematically, tumble of any bacterium can be represented by a unit length of random direction $\phi(j)$ multiplied by step length of that bacterium $C(i)$. In case of swimming, this random length is predefined.

2.2 Swarming

For the bacteria to reach at the richest food location (i.e. for the algorithm to converge at the solution point), it is desired that the optimum bacterium till a point of time in the search period should try to attract other bacteria so that together they converge at the desired location (solution point) more rapidly. To achieve this, a penalty function based upon the relative distances of each bacterium from the fittest bacterium till that search duration, is added to the original cost function. Finally, when all the bacteria have merged into the solution point, this penalty function becomes zero. The effect of swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density.

2.3 Reproduction

The original set of bacteria, after getting evolved through several chemotactic stages reaches the reproduction stage. Here, best set of bacteria (chosen out of all the chemotactic stages) gets divided into two groups. The healthier half replaces with the other half of bacteria, which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

2.4 Elimination and dispersal

In the evolution process, a sudden unforeseen event can occur, which may drastically alter the smooth process of evolution and cause the elimination of the set of bacteria and/or disperse

them to a new environment. Most ironically, instead of disturbing the usual chemotactic growth of the set of bacteria, this unknown event may place a newer set of bacteria nearer to the food location. From a broad perspective, elimination, and dispersal are parts of the population level long distance motile behaviour. In its application to optimization, it helps in reducing the behaviour of *stagnation* (i.e. being trapped in a premature solution point or local optima) often seen in such parallel search algorithms. The detailed mathematical derivations as well as theoretical aspect of this new concept are presented in [26-27].

3. Problem Statement

3.1 Power System Model

A power system can be modelled by a set of nonlinear differential equations are:

$$\dot{X} = f(X, U) \quad (1)$$

Where X is the vector of the state variables and U is the vector of input variables. In this study $X = [\delta, \omega, E'_q, E_{fd}, V_f]^T$ and U is the PSS output signal. Here, δ and ω are the rotor angle and speed, respectively. Also, E'_q, E_{fd} and V_f are the internal, the field, and excitation voltages respectively.

In the design of PSS, the linearized incremental models around an equilibrium point are usually employed. Therefore, the state equation of a power system with n machines and m PSSs can be written as:

$$\dot{X} = AX + Bu \quad (2)$$

Where A is a $5n \times 5n$ matrix and equals $\partial f / \partial X$ while B is a $5n \times m$ matrix and equals $\partial f / \partial U$. Both A and B are evaluated at a certain operating point. X is a $5n \times 1$ state vector and U is a $m \times 1$ input vector.

3.2 Structure of PSS

The operating function of a PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. The supplementary stabilizing signal considered is one proportional to speed. A widely speed based used conventional PSS is considered throughout the study [2]. The transfer function of the i^{th} PSS is given by:

$$\Delta U_i = K_i \frac{ST_W}{(1+ST_W)} \left[\frac{(1+ST_{1i})(1+ST_{3i})}{(1+ST_{2i})(1+ST_{4i})} \right] \Delta \omega_i \quad (3)$$

Where $\Delta \omega_i$ is the deviation in speed from the synchronous speed. This type of stabilizer consists of a washout filter, a dynamic compensator. The output signal is fed as a supplementary input signal, U_i to the regulator of the excitation system.

The washout filter, which essentially is a high pass filter, is used to reset the steady state offset in the output of the PSS. The value of the time constant T_W is usually not critical and it can range from 0.5 to 20 second. The dynamic compensator is made up to two lead lag circuits, limiters and an additional gain. The adjustable PSS parameters are the gain of the PSS, K_i and the time constants, $T_{1i} - T_{4i}$. The lead lag block present in the system provides phase lead compensation for the phase lag that is introduced in the circuit between the exciter input and the electrical torque.

3.3 System under Study

Fig. 1 shows the single line diagram of the test system used. Details of system data are given in [27]. The participation matrix can be used in mode identification. Table (1) shows the eigenvalues, and frequencies associated with the rotor oscillation modes of the system. Examining Table (1) indicates that the 0.2371 Hz mode is the interarea mode with G1 swinging against G2 and G3. The 1.2955 Hz mode is the intermachine oscillation local to G2. Also, the 1.8493 Hz mode is the intermachine mode local to G3. The positive real part of eigenvalue of G1 indicates system instability. The system and generator loading levels are given in Table (2).

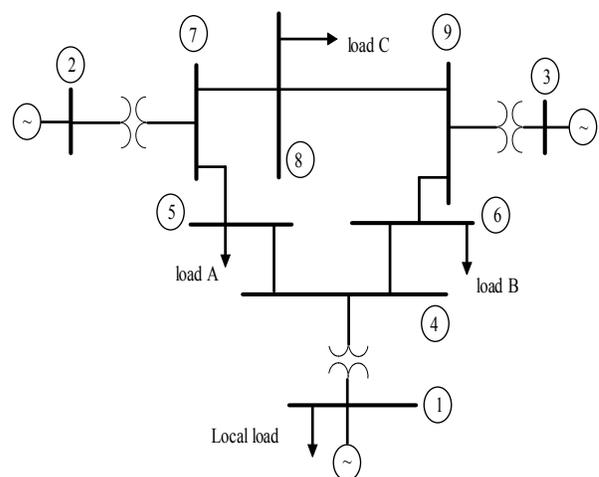


Fig. 1. System under study.

Table (1) The eigenvalues, and frequencies of the rotor oscillation modes of the system.

Generator	Eigenvalues	Frequencies	Damping ratio ζ
G1	$+0.15 \pm 1.49j$	0.2371	-0.1002
G2	$-0.35 \pm 8.14j$	1.2295	0.0430
G3	$-0.67 \pm 11.62j$	1.8493	0.0576

Table (2) Loading of the system (in p.u)

Generator	Light		Normal case		Heavy	
	P	Q	P	Q	P	Q
G1	0.965	0.22	1.716	0.6205	3.57	1.81
G2	1.0	-0.193	1.63	0.0665	2.2	0.713
G3	0.45	-0.267	0.85	-1.086	1.35	0.43
Load	P	Q	P	Q	P	Q
A	0.7	0.35	1.25	0.5	2.0	0.9
B	0.5	0.3	0.9	0.3	1.8	0.6
C	0.6	0.2	1.00	0.35	1.6	0.65
at G1	0.6	0.2	1.00	0.35	1.6	0.65

4. Objective Function

To maintain stability and provide greater damping, the parameters of the PSSs may be selected to minimize the following objective function:

$$J_t = \sum_{j=1}^{np} \sum_{\sigma_{ij} \geq \sigma_0} (\sigma_0 - \sigma_{ij})^2 + \sum_{j=1}^{np} \sum_{\xi_{ij} \geq \xi_0} (\xi_0 - \xi_{ij})^2 \quad (4)$$

This will place the system closed loop eigenvalues in the D-shape sector characterized by $\sigma_{ij} \leq \sigma_0$ and

$\xi_{ij} > \xi_0$ as shown in Fig. 2.

Where, np is the number of operating points considered in the design process, σ and ξ are the real part and the damping ratio of the eigenvalue of the operating point. In this study, σ_0 and ξ_0 are chosen to be -0.5 and 0.1 respectively [9]. To reduce the computational burden in this study, the value of the wash out time constant T_W is fixed to 10 second, the values of T_{2i} and T_{4i} are kept constant at a reasonable value of 0.05 second and tuning of T_{1i} and T_{3i} are undertaken to achieve the net phase lead required by the system. Typical ranges of the optimized parameters are [1- 100] for K and [0.06-1.0] for T_{1i} and T_{3i} . Based on the objective function J_t optimization problem can be stated as: Minimize J_t subjected to:

$$\begin{aligned} K_i^{min} &\leq K_i \leq K_i^{max} \\ T_{1i}^{min} &\leq T_{1i} \leq T_{1i}^{max} \\ T_{3i}^{min} &\leq T_{3i} \leq T_{3i}^{max} \end{aligned} \quad (5)$$

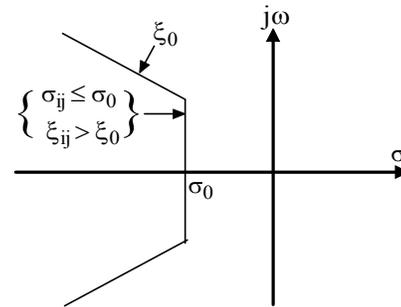


Fig. 2. A D-shape sector in the s-plane.

5. The Bacterial Swarm Optimization Algorithm

PSO is a stochastic optimization technique that draws inspiration from the behaviour of a flock of birds or the collective intelligence of a group of social insects with limited individual capabilities. In PSO a population of particles is initialized with

random positions \vec{X}_i and velocities \vec{V}_i , and a fitness function using the particle's positional coordinates as input values. Positions and velocities are adjusted, and the function is evaluated with the new coordinates at each time step. The velocity and position update equations for the d-th dimension of the i-th particle in the swarm may be given as follows:

$$V_{id}(t+1) = \omega V_{id}(t) + C_1 \phi_1 (V_{lid} - X_{id}(t)) + C_2 \phi_2 (P_{gd} - X_{id}(t)) \quad (6)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (7)$$

On the other hand, the BF is based upon search and optimal foraging decision making capabilities of the Escherichia coli bacteria [25]. The coordinates of a bacterium here represent an individual solution of the optimization problem. Such a set of trial solutions converges towards the optimal solution following the foraging group dynamics of the bacteria population. Chemotactic movement is continued until a bacterium goes in the direction of positive nutrient gradient. After a certain number of complete swims the best half of the population undergoes reproduction, eliminating the rest of the population. In order to escape local optima, an elimination dispersion event is carried out where, some bacteria are liquidated at random with a very small probability and the new replacements are initialized at random locations of the search space. A detailed description of the complete algorithm can be traced in [25-26].

[Step 1] Initialize parameters

$$n, S, N_C, N_{re}, N_{ed}, P_{ed},$$

$$C(i) (i = 1, 2, \dots, N), \phi^i.$$

Where,

- n : Dimension of the search space,
- S : The number of bacteria in population,
- N_C : The number of chemotactic steps,
- N_{re} : The number of reproduction steps,
- N_{ed} : The number of elimination-dispersal events to be imposed over the bacteria,
- P_{ed} : The probability with which the elimination and dispersal will continue,
- $C(i)$: The size of the step taken in the random direction specified by the tumble,
- ω : The inertia weight,
- C_1 : The swarm confidence,
- \rightarrow
- $\theta(i, j, k)$: Position vector of the i -th bacterium, in j -th chemotactic step and k -th reproduction,
- \rightarrow
- V_i : Velocity vector of the i -th bacterium.

[Step 2] Update the following

$J(i, j, k)$: Cost or fitness value of the i -th bacterium in the j th chemotaxis, and the k -th reproduction loop.

\rightarrow
 θ_{g_best} : Position vector of the best position found by all bacteria.

$J_{best}(i, j, k)$: Fitness value of the best position found so far.

[Step 3] Reproduction loop: $k = k + 1$

[Step 4] Chemotaxis loop: $j = j + 1$

[Sub step a] For $i=1, 2, \dots, S$, take a chemotaxis step for bacterium i as follows.

[Sub step b] Compute fitness function, $J(i, j, k)$.

[Sub step c] Let $J_{last} = J(i, j, k)$ to save this value since one may find a better cost via a run.

[Sub step d] Tumble: generate a random vector

$\Delta(i) \in R^n$ with each element $\Delta_m(i), m = 1, 2, \dots, p$, a random number on $[-1, 1]$.

[Sub step e] Move:

$$\text{Let } \theta(i, j+1, k) = \theta(i, j, k) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}.$$

[Sub step f] Compute $J(i, j+1, k)$.

[Sub step g] Swim: one considers only the i -th bacterium is swimming while the others are not moving then

i) Let $m = 0$ (counter for swim length).

ii) While $m < N_S$ (have not climbed down too long)

- Let $m = m + 1$
- If $J(i, j+1, k) < J_{last}$ (if doing better),

Let $J_{last} = J(i, j+1, k)$ and let

$$\theta(i, j+1, k) = \theta(i, j, k) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

and use this $\theta(i, j+1, k)$ to compute the new $J(i, j+1, k)$ as shown in new [sub step f]

- Else, let $m = N_S$. This is the end of the while statement.

[Step 5] Mutation with PSO operator

For $i=1, 2, \dots, S$

- Update the θ_{g_best} and $J_{best}(i, j, k)$
- Update the position and velocity of the d -th coordinate of the i -th bacterium according to the following rule:

$$V_{id}^{new} = \omega V_{id}^{old} + C_1 \varphi_1 \left(\theta_{g_best_d} - \theta_d^{old}(i, j+1, k) \right)$$

$$\theta_d^{new}(i, j+1, k) = \theta_d^{old}(i, j+1, k) + V_{id}^{new}$$

[Step 6] Let $S_r = S/2$

The S_r bacteria with highest cost function (J) values die and other half bacteria population with the best values split (and the copies that are made are placed at the same location as their parent).

[Step 7] If $k < N_{re}$, go to [step 1]. One has not reached the number of specified reproduction steps, so one starts the next generation in the chemotaxis loop.

The detailed mathematical derivations as well as theoretical aspect of this new concept are presented in [25-26].

6. Results and Simulations

In this section, the superiority of the proposed BSO algorithm in designing PSS (BSOPSS) in compare to optimized PSS with BFOA (BFPSS) and optimized PSS controller based on PSO (PSOPSS) is illustrated. Fig. 3. shows the variations of objective function with various optimization techniques. The objective functions decrease monotonically over generations of BFOA, PSO and BSO. The final value of the objective function is $J_t = 0$ for all algorithms, indicating that all modes have been shifted to the specified D-shape sector in

the S-plane and the proposed objective function is satisfied. Moreover, BSO converges at a faster rate (51 generations) compared to that for PSO (64 generations) and BFOA (80 generations).

Table (3), shows the system eigenvalues, and damping ratio of mechanical mode with three different loading conditions. It is clear that the BSOPSS shift substantially the electromechanical mode eigenvalues to the left of the S-plane and the values of the damping factors with the proposed BSOPSS are significantly improved to be ($\sigma = -0.95, -0.94, -1.05$) for light, normal, and heavy loading respectively. Also, the damping ratios corresponding to BSOPSS controllers are almost greater than that corresponding to PSOPSS and BFPSS. Hence, compared to BFPSS and PSOPSS, BSOPSS greatly enhances the system stability and improves the damping characteristics of electromechanical modes. Results of PSSs parameters set values based on the proposed objective function using BFOA, PSO and BSO are given in Table (4).

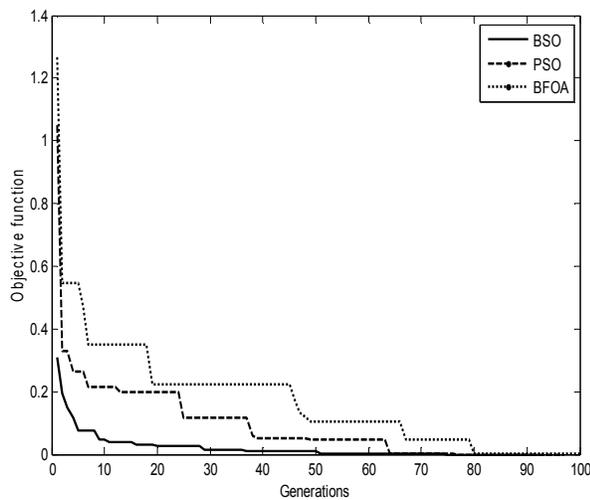


Fig. 3. Variations of objective function.

Table (3) Mechanical modes and ζ under different loading conditions and controllers.

	BFPSS	PSOPSS	BSOPSS
Light load	-3.46 ± 7.27j, 0.43 -2.77 ± 5.99j, 0.42 -0.90 ± 0.71j, 0.78	-3.53 ± 7.37j, 0.43 -6.36 ± 7.07j, 0.67 -0.92 ± 0.67j, 0.81	-3.6 ± 6.01j, 0.51 -6.29 ± 6.70j, 0.68 -0.95 ± 0.63j, 0.83
Normal load	-2.97 ± 6.21j, 0.43 -3.87 ± 6.45j, 0.51 -0.73 ± 0.85j, 0.65	-3.95 ± 8.07j, 0.44 -7.23 ± 7.50j, 0.69 -0.74 ± 0.83j, 0.66	-4.17 ± 8.16j, 0.45 -6.83 ± 7.00j, 0.7 -0.94 ± 0.84j, 0.75
Heavy load	-3.66 ± 6.73j, 0.48 -2.75 ± 5.67j, 0.44 -1.02 ± 0.85j, 0.77	-4.5 ± 7.75j, 0.50 -7.9 ± 6.67j, 0.77 -1.03 ± 0.86j, 0.77	-4.59 ± 7.76j, 0.50 -7.96 ± 5.56j, 0.81 -1.05 ± 0.85j, 0.78

Table (4) Parameters of PSSs for different techniques.

	BFOA	PSO	BSO
PSS1	K=36.3696 $T_1=0.2365$ $T_3=0.2495$	K=26.6544 $T_1=0.4684$ $T_3=0.7428$	K=38.6585 $T_1=0.4153$ $T_3=0.6455$
PSS2	K=7.8812 $T_1=0.4986$ $T_3=0.1921$	K=14.3287 $T_1=0.2918$ $T_3=0.1149$	K=6.4051 $T_1=0.3776$ $T_3=0.9840$
PSS3	K=3.5031 $T_1=0.5031$ $T_3=0.3789$	K=9.2317 $T_1=0.4356$ $T_3=0.3955$	K=2.2337 $T_1=0.2027$ $T_3=0.9160$

6.1 Response for light load condition:

The effectiveness of the performance due to 0.1 step increase in reference voltage of generator 1 is verified. Figs. 4-6, show the response of $\Delta\omega_{12}$, $\Delta\omega_{23}$, and $\Delta\omega_{13}$ due to this disturbance for light loading condition. From these figures, it can be seen that the BSOPSS using the proposed objective function achieves good robust performance, and provides superior damping in comparison with the other controllers. Moreover, the required mean time to suppress these oscillations is approximately 2.1 second with BSOPSS, 2.5 second for PSOPSS, and 2.8 second with BFPSS so the designed controller is capable of providing sufficient damping to the system oscillatory modes.

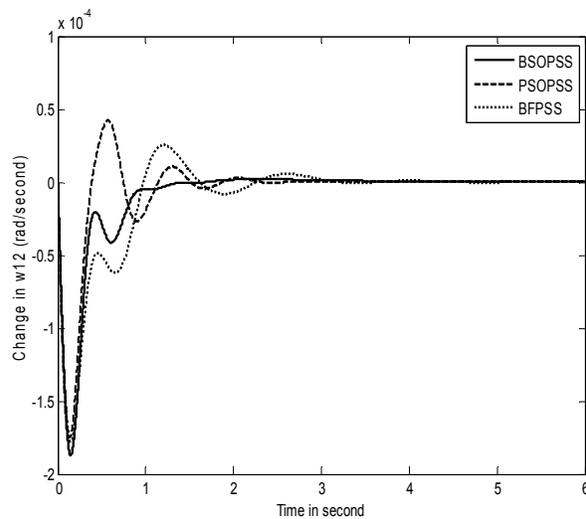


Fig. 4. Change in $\Delta\omega_{12}$ for light load.

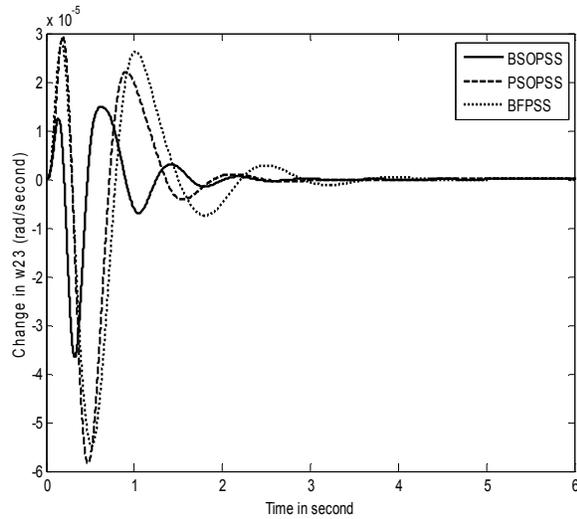


Fig. 5. Change in $\Delta\omega_{23}$ for light load.

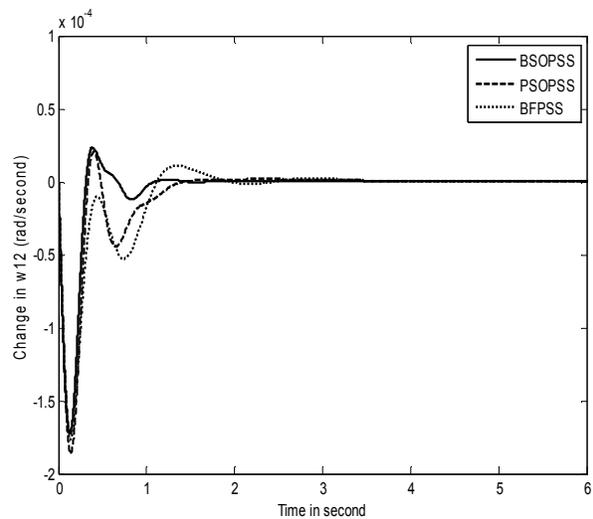


Fig. 7. Change in $\Delta\omega_{12}$ for normal load.

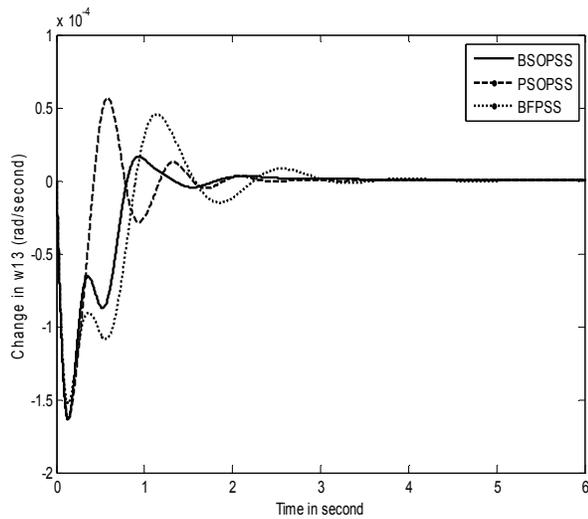


Fig. 6. Change in $\Delta\omega_{13}$ for light load.

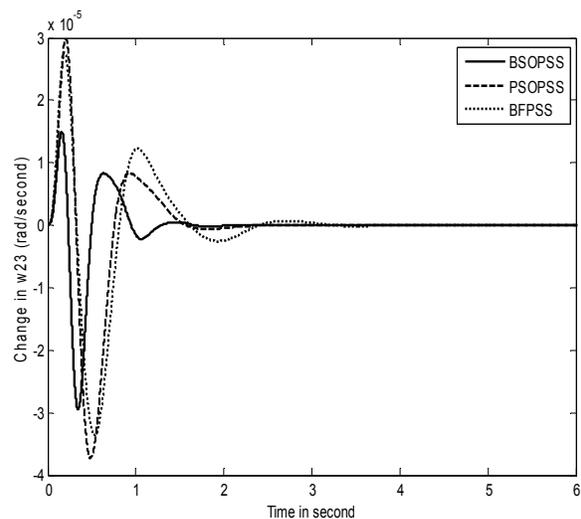


Fig. 8. Change in $\Delta\omega_{23}$ for normal load.

6.2 Response for normal load condition:

Figs. 7-9, show the response of the system to the same disturbance for normal loading condition. These figures indicate the capability of the BSOPSS in reducing the settling time and damping power system oscillations. Moreover, the mean settling time of these oscillations is $T_s=1.1, 1.29,$ and 2.23 second for BSOPSS, PSOPSS, and BFPSS respectively. In addition, the proposed BSOPSS outperforms and outlasts PSOPSS and BFPSS controller in damping oscillations effectively and reducing settling time. Hence, BSOPSS controller greatly enhances the system stability and improves the damping characteristics of power system.

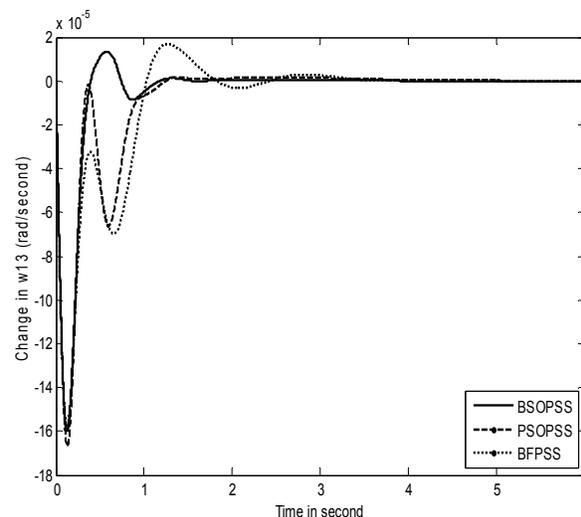


Fig. 9. Change in $\Delta\omega_{13}$ for normal load.

6.3 Response for heavy load condition:

Figs. 10-12, show the system response at heavy loading condition with fixing the controller parameters. From these figures, it can be seen that the response with the proposed BSOPSS shows good damping characteristics to low frequency oscillations and the system is more quickly stabilized than PSOPSS and BFPSS. The mean settling time of oscillation is $T_s = 1, 1.42, \text{ and } 1.96$ second for BSOPSS, PSOPSS, and BFPSS respectively. Hence, the proposed BSOPSS extend the power system stability limit.

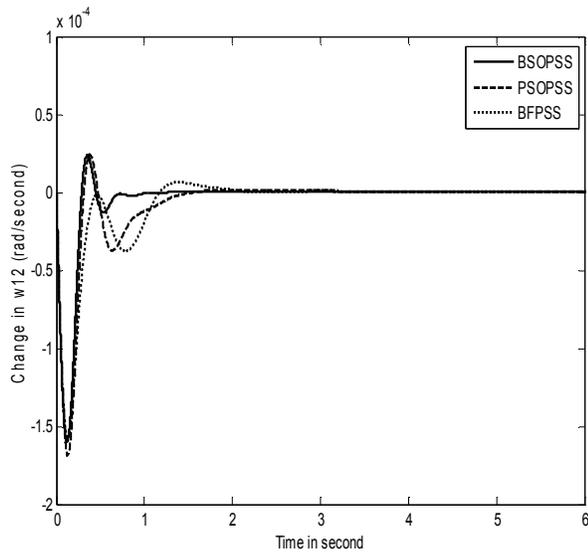


Fig. 10. Change in $\Delta\omega_{12}$ for heavy load.

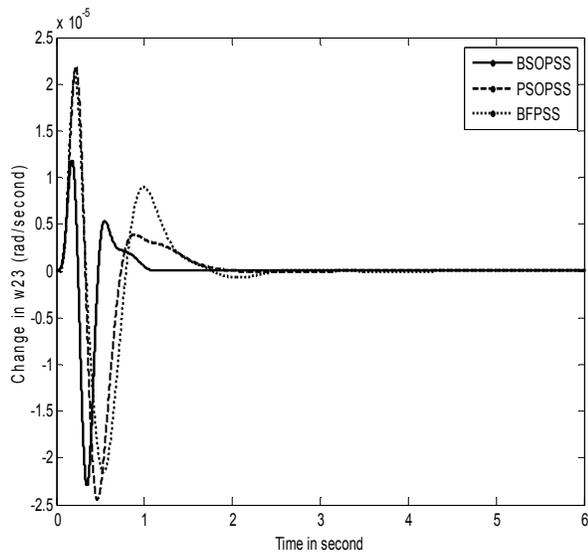


Fig. 11. Change $\Delta\omega_{23}$ for heavy load.

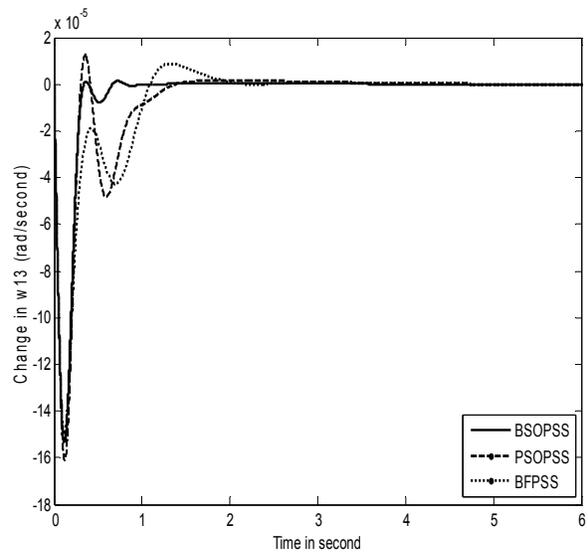


Fig. 12. Change in $\Delta\omega_{13}$ for heavy load.

6.4 Response for severe disturbance:

The effectiveness of the proposed BSOPSS is verified by applying a three phase fault of 6 cycle duration at 1.0 second near bus 7. Figs. 13-14, show the response of $\Delta\omega_{12}$ and $\Delta\omega_{13}$ due to severe disturbance for normal loading condition. From these figures, it is can be seen that the BSO based PSSs using the proposed objective function achieves good robust performance and provides superior damping in comparison with the other methods.

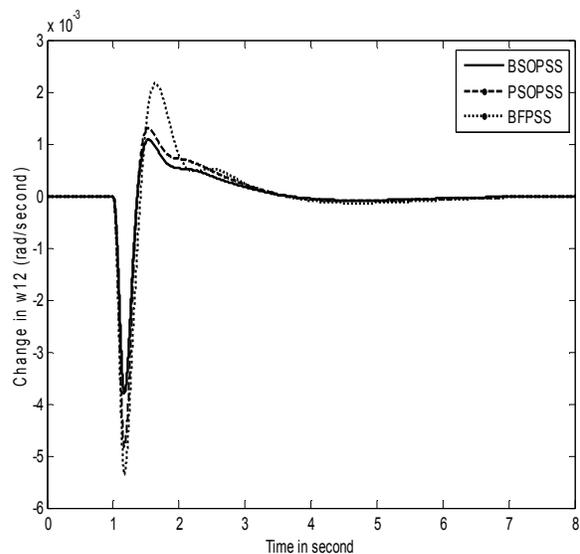


Fig. 13. Change in $\Delta\omega_{12}$ for severe disturbance.

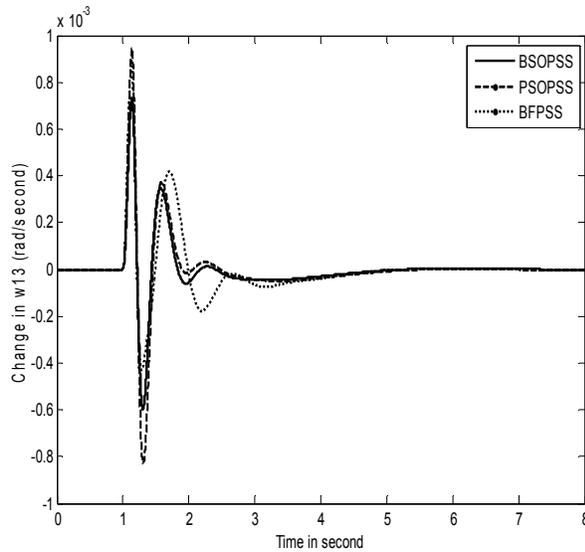


Fig. 14. Change in $\Delta\omega_{13}$ for severe disturbance.

6.5 Robustness and performance index:

To demonstrate the robustness of the proposed controller, a performance index: the Integral of the Time multiplied Absolute value of the Error (ITAE) is being used as:

$$ITAE = \int_0^{30} t(|\Delta w_{12}| + |\Delta w_{23}| + |\Delta w_{13}|) dt \quad (8)$$

It is worth mentioning that the lower the value of this index is, the better the system response in terms of time domain characteristics. Numerical results of performance robustness for all cases are listed in Table (5). It can be seen that the values of these system performance with the BSOPSS are smaller compared to that of PSOPSS and BFPSS. This demonstrates that the overshoot, undershoot, settling time and speed deviations of all units are greatly reduced by applying the proposed BSO based tuned PSSs.

Table (5) Values of performance index.

	ITAE * 10 ⁻⁴		
	BFPSS	PSOPSS	BSOPSS
Light load	1.1240	0.9845	0.5831
Normal load	1.5176	1.1483	0.7715
Heavy load	2.2662	1.5067	1.3347

7. Conclusions

This paper proposes a new optimization algorithm known as BSO, which synergistically couples the BFOA with the PSO for optimal designing of PSSs controller. The design problem of the proposed controller is formulated as an

optimization problem and BSO is employed to search for optimal controller parameters. An eigenvalue based objective function reflecting the combination of damping factor and damping ratio is optimized for different operating conditions. Simulations results assure the effectiveness of the proposed controller in providing good damping characteristic to system oscillations over a wide range of loading conditions. Also, these results validate the superiority of the proposed method in tuning controller compared with PSO and BFOA over wide range of operating conditions.

8. References

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Appendix

The system data are as shown below:

- a) Excitation system: $K_A = 400$;
 $T_A = 0.05$ second; $K_f = 0.025$; $T_f = 1$ second.
- b) Bacteria parameters: Number of bacteria =10; number of chemotatic steps =10; number of elimination and dispersal events = 2; number of reproduction steps = 4; probability of elimination and dispersal = 0.25.
- c) PSO parameters: $C_1 = C_2 = 2.0$, $\omega = 0.9$.