Optimal PSS Design in a Multimachine Power System via Bacteria Foraging Optimization Algorithm

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Abstract- This paper proposes Bacteria Foraging Optimization Algorithm (BFOA) based power system stabilizer (PSS) for the suppression of oscillations in multimachine power system. The proposed design problem of PSS over a wide range of loading conditions is formulated as an optimization problem. BFOA is employed to search for optimal controller parameters by minimizing the time domain objective function. The performance of the proposed technique has been evaluated with the performance of Genetic Algorithm (GA) to demonstrate the superior efficiency of the proposed BFOA in tuning PSS controller. Simultaneous tuning of the Bacteria Foraging based PSS (BFPSS) gives robust damping performance over wide range of operating conditions in compare to optimized PSS controller based on GA (GAPSS) and conventional PSS (CPSS).

Key-Words: - Bacteria Foraging; Genetic Algorithm; Power System Stabilizer; Low Frequency Oscillations; Power System Stability; Multimachine System

1. Introduction

Stability of power systems is one of the most important aspects in electric system operation. This arises from the fact that the power system must maintain frequency and voltage levels, under any disturbance, like a sudden increase in the load, loss of one generator or switching out of a transmission line during a fault [1]. Since the development of interconnected large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2–3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. Moreover, low frequency oscillations present limitations on the power transfer capability. To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation system. PSSs augment the power system stability limit and extend the power transfer capability by enhancing the system damping of low frequency oscillations associated with the electromechanical modes [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 power system stabilizers 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 was 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 presented in [9]. A technique based on PSO is developed in [10] for tuning the parameters of a fixed structure PSS. The use of simulated annealing and PSO to design robust PSS for power systems working at various operating conditions are investigated in [11]. A comprehensive assessment of the effects of PSS based damping controller has been carried out in [12]. The design problem of this controller is transformed into an optimization problem. PSO based optimal tuning algorithm is used to optimally tune the parameters of the PSS. A systematic procedure for simultaneous tuning of multiple PSS for enhancing power system stability is presented in [13]. A GA is introduced in [14] to the PSS design problem. A new method for power system stabilizing by using lead lag compensator based on pole assignment and pole shifting techniques is discussed in [15]. Multi-objective design of multimachine PSSs using PSO is discussed in [16]. Optimal locations and design of robust multimachine PSSs using GA is illustrated in [17]. 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 [18]. Multi-objective design of multimachine PSSs using PSO is introduced in [19]. A new design procedure for simultaneous coordinated designing of the TCSC damping controller and PSS in multimachine power system is presented in [20]. A new robust control strategy to synthesis of robust proportional-integral-derivative (PID) based PSS is addressed in [21]. The design of a simple, yet robust controller for power system stabilization, using Kharitonov's stability theory is introduced in [22]. A speed control of induction motor and DC Permanent Magnet Motor is designed via PSO in [23-24]. Bacterial Foraging Optimization Algorithm (BFOA) as new optimization algorithm is discussed in [25] for optimal designing of PI controller based LFC in two area interconnected power system to damp power system oscillations. Moreover, this technique has been extended to design FACTS controllers [26-31].

Recently, global optimization technique like GA has attracted the attention in the field of controller parameter optimization [32]. Unlike other techniques, GA is a population based search algorithm, which works with a population of strings that represent different solutions. Therefore, GA has implicit parallelism that enhances its search capability and the optima can be located swiftly when applied to complex optimization problems. Unfortunately recent research has identified some deficiencies in GA performance [33]. This degradation in efficiency is apparent in applications with highly *epistatic* objective functions (i.e. where parameters being optimized are highly correlated). Also, the premature convergence of GA degrades its performance and reduces its search capability.

BFOA is proposed as a solution to the above mentioned problems and drawbacks [26]. Moreover, BFOA due to its unique dispersal and elimination technique can find favourable regions when the population involved is small. These unique features of the algorithms overcome the premature convergence problem and enhance the search capability. Hence, it is suitable optimization tool for power system controllers.

This paper proposes a new optimization algorithm known as BFOA for damping of power system electromechanical oscillations. BFOA is used for tuning the PSS controller parameter for multimachine power system. The design problem of the proposed controller is formulated as an optimization problem and BFOA is employed to search for optimal controller parameters. By minimizing the time domain objective function, in which the deviations in speed are involved; stability performance of the system is improved. Simulations results assure the effectiveness of the proposed controller in providing good damping characteristic to system oscillations over a wide range of loading conditions and system parameters. Also, these results validate the superiority of the proposed method in tuning PSS compared with GA, and conventional one.

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 that are stronger get 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 [33-34].

A. 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 $\varphi(j)$ multiplied by step length of that bacterium $C(i)$. In case of swimming, this random length is predefined.

B. 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.

C. 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.

D. 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 [33-34].

3. Problem statement

A. Power system model

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

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

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

$$\dot{X} = AX + Bu \tag{2}$$

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.

B. 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:

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

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 PSSs parameters are the gain of the PSSs, 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. To reduce the computational burden in this study, 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.

C. System under Study

Fig. 1 shows the single line diagram of the test system used. Details of system data are given in [35]. 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).

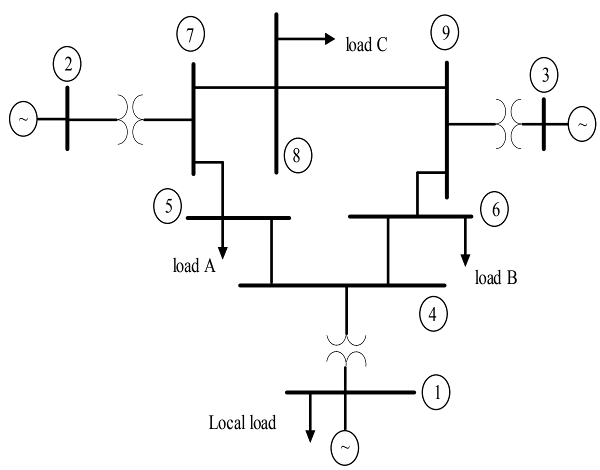

Figure 1. System under study.

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)

	Light		Normal case		Heavy	
Generator	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	-.1086	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

The parameters of the PSSs may be selected to minimize the following objective function:

$$J = \int_{0}^{\infty} t\left(\left|\Delta w_{12}\right| + \left|\Delta w_{23}\right| + \left|\Delta w_{13}\right|\right) dt \qquad (4)$$

Where $\Delta w_{12} = \Delta w_1 - \Delta w_2$, $\Delta w_{23} = \Delta w_2 - \Delta w_3$, and $\Delta w_{13} = \Delta w_1 - \Delta w_3$.

This index is based on the Integral of Time multiple Absolute Error (ITAE). The advantage of this selected performance index is that minimal dynamic plant information is needed. Based on this objective function J optimization problem can be stated as: Minimize J subjected to:

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

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

$$T_{3i}^{\min} \le T_{3i} \le T_{3i}^{max} \qquad (5)$$

Typical ranges of the optimized parameters are [1-100] for K_i and [0.06-1.0] for T_{1i} and T_{3i}.

This study focuses on optimal tuning of PSSs using BFOA algorithm. The aim of the optimization is to search for the optimum controller parameters setting that reflect the settling time and overshoots of the system. Moreover, all PSSs are designed simultaneously, taking into consideration the interaction among them. Also, they have simply and decentralized nature since only local measurements are employed as the stabilizer inputs. This makes the proposed BFPSS easy to implement and tune.

5. Bacteria foraging algorithm

In this paper, optimization using BFOA is carried out to find the parameters of PSSs controller. The algorithm of the proposed technique involves two steps.

[Step- 1] Initialization

i) p is the number of parameters to be optimized.

ii) S is the number of bacteria to be used for searching the total region.

iii) N_S is the swimming length after which tumbling of bacteria will be undertaken in a chemotactic loop.

iv) N_C is the number of iteration to be undertaken in a chemotactic loop. ($N_C > N_S$).

v) N_{re} is the maximum number of reproduction to be undertaken.

vi) N_{ed} is the maximum number of elimination and dispersal events to be imposed over the bacteria.
vii) P_{ed} is the probability with which the elimination and dispersal will continue.
viii) P (1-p, 1-S, 1) is the location of each bacterium which is specified by random numbers on [-1, 1].
ix) The value of C (*i*) which is assumed to be constant in this case for all the bacteria to simplify the design strategy.
x) The values of $d_{attract}$, $\omega_{attract}$, $h_{repelent}$ and $\omega_{repelent}$.

[Step-2] Iterative algorithm for optimization

This section models the bacterial population chemotaxis, swarming, reproduction, elimination and dispersal (initially, j=k=l=0). For the algorithm updating θ^i automatically results in updating of P.
[1] Elimination-dispersal loop: l=l+1
[2] Reproduction loop: k=k+1
[3] Chemotaxis loop: j=j+1
a) For i=1, 2,…, S, calculate cost function value for each bacterium i as follows.

- Compute value of cost function $J(i,j,k,l)$.

Let $J_{sw}(i,j,k,l) = J(i,j,k,l) + J_{cc}(\theta^i(j,k,l), P(j,k,l))$.
J_{cc} is defined by the following equation

$$J_{cc}(\theta, P(j,k,l))) = \sum_{i=1}^{S} J_{cc}(\theta, \theta^i(j,k,i))$$
$$= \sum_{i=1}^{S}\left[-d_{attract}\, exp\left(-\omega_{attract}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right]$$
$$+ \sum_{i=1}^{S}\left[h_{repelent}\, exp\left(-\omega_{repelent}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right]$$
(6)

- Let $J_{last} = J_{sw}(i,j,k,l)$ to save this value since one may find a better cost via a run.
- End of For loop

b) For i=1, 2,….S take the tumbling/swimming decision.

- Tumble: generate a random vector $\Delta(i) \in \Re^p$ with each element $\Delta_m(i)$ m=1,2,…p,
- Move: Let $\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\dfrac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$

Fixed step size in the direction of tumble for bacterium i is considered.
Compute $J(i,j+1,k,l)$ and

$$J_{sw}(i,j+1,k,l) = J(i,j+1,k,l) + J_{cc}(\theta^i(j+1,k,l), P(j+1,k,l))$$

Swim
i) Let m=0 (counter for swim length).
ii) While $m < N_S$ (have not climbed down too long)

- Let m=m+1
- If $J_{sw}(i,j+1,k,l) < J_{last}$ (if doing better), let $J_{last} = J_{sw}(i,j+1,k,l)$ and let $\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\dfrac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$ and use this $\theta^i(j+1,k,l)$ to compute the new $J(i,j+1,k,l)$
- Else, let $m = N_S$. This is the end of the while statement.

iii) Go to next bacterium (i+1) if $i \neq S$
[4] If j< N_c, go to [step 3]. In this case, continue chemotaxis, since the life of the bacteria is not over.
[5] Reproduction

a) For the given k and l, and for each i=1, 2,..S, let $J^i_{health} = \min_{j \in \{1...N_c\}} \{J_{sw}(i,j,k,l)\}$ be the health of the bacterium i(a measure of how many nutrients it got over its life time and how successful it was at avoiding noxious substance). Sort bacteria in order of ascending cost J_{health}.
b) The $S_r = S/2$ bacteria with highest J_{health} values die and other S_r bacteria with the best value split.

[6] If k< N_{re}, go to [step 2]. In this case, one has not reached the number of specified reproduction steps, so one starts the next generation in the chemotactic loop.
[7] Elimination-dispersal: for $i = 1,2,....,N$, with probability P_{ed}, eliminate and disperse each bacterium, and this result in keeping the number of bacteria in the population constant. To do these, if you eliminate a bacterium, simply disperse one to a random location on the optimization domain. If $l <$ N_{ed}, then go to [step 2]; otherwise end.

The detailed mathematical derivations as well as theoretical aspect of this new concept are presented in [33-34].

6. Results and simulations

In this section different comparative cases are examined to show the effectiveness of the proposed BFOA method for optimizing controller parameters.

Fig. 2. shows the variations of objective function with two different optimization techniques. The objective functions decrease monotonically over generations of GA and BFOA. The final value of the objective function is J_t=0 for both algorithms, indicating that all modes have been shifted to the left of S-plane and the proposed objective function is satisfied. Moreover, BFOA converges at a faster rate (54 generations) compared to that for GA (93 generations).

Computational time (CPU) of both algorithms is compared based on the average CPU time taken to converge the solution. The average CPU for BFOA is 28.34 second while it is 49.82 second for GA. It is clear that average convergence time for BFOA is less than GA. The higher computational time for GA is due to its characteristics to simultaneously deal with a population of points (solutions), thus leading to the disadvantage of requiring a relatively large number of functions evaluations and large computational time respectively.

Table (3), shows the system eigenvalues, and damping ratio of mechanical mode with three different loading conditions. It is clear that the system with CPSS is suffered from small damping factor (σ=-0.19,-0.24,-0.33) for light, normal, and heavy loading respectively. Moreover, BFPSS shift substantially the electromechanical mode eigenvalues to the left of the S-plane and the value of the damping factor with the proposed BFPSS is significantly improved to be (σ=-1.05,-1.12,-1.48) for light, normal, and heavy loading respectively. Hence compared to the CPSS and GAPSS, BFPSS greatly enhances the system stability and improves the damping characteristics of electromechanical modes. Results of PSSs parameter set values based on the time domain objective function using BFOA, GA, and conventional method are given in Table (4). It is worth mentioning that the lower the value of these indices 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 characteristics with the proposed BFPSS are much smaller compared to that GAPSS and CPSS. This demonstrates that the overshoot, undershoot settling time and speed deviations of all machines are greatly reduced by applying the proposed BFOA based tuned PSSs.

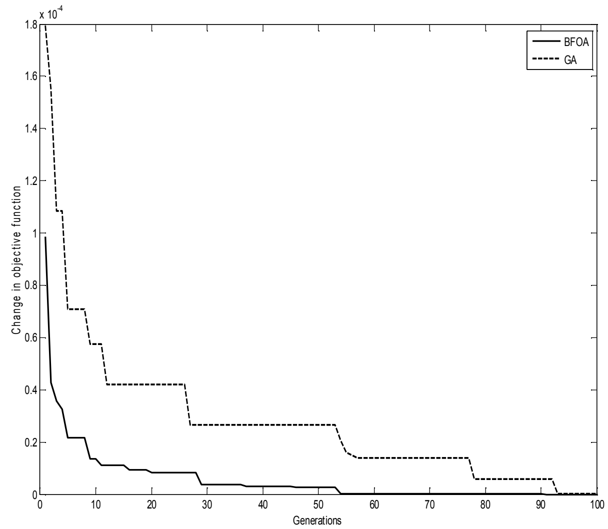

Figure 2. Variations of objective function.

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

	CPSS	GAPSS	BFPSS
Light load	-3.24 ± 5.20j, 0.52 -2.35 ± 4.15j, 0.49 -0.19 ± 0.69j, 0.26	-3.48 ± 8.22j, 0.39 -3.72 ± 6.46j, 0.5 -1.04 ± 0.71j, 0.83	-3.56 ± 7.96j, 0.41 -3.68 ± 5.74j, 0.547 -1.05 ± 0.69j, 0.84
Normal load	-3.32 ± 5.34j, 0.52 -2.41 ± 4.42j, 0.47 -0.24 ± 0.75j, 0.30	-3.59 ± 8.79j, 0.38 -4.25 ± 7.14j, 0.51 -1.09 ± 0.61j, 0.87	-3.76 ± 8.66j, 0.4 -3.99 ± 6.14j, 0.54 -1.12 ± 0.60j, 0.88
Heavy load	-3.09 ± 5.25j, 0.50 -1.96 ± 4.32j, 0.41 -0.33 ± 0.89j,0.34	-3.76 ± 8.94j, 0.39 -3.50 ± 6.76j, 0.46 -1.46 ± 0.78j, 0.88	-3.81 ± 8.63j, 0.40 -3.59 ± 5.88j, 0.52 -1.48 ± 0.77j, 0.89

Table (4) Parameters of PSSs for different

	CPSS	GAPSS	BFPSS
PSS1	K=14.4386 T_1=0.2652 T_3=0.8952	K=26.6544 T_1=0.4684 T_3=0.4428	K=27.8403 T_1=0.3889 T_3=0.4115
PSS2	K=5.1659 T_1=0.5242 T_3=0.2032	K=8.3287 T_1=0.1918 T_3=0.1249	K=7.3789 T_1=0.3065 T_3=0.1035
PSS3	K=8.3287 T_1=0.5817 T_3=0.4268	K=7.2317 T_1=0.2356 T_3=0.2955	K=7.9287 T_1=0.2890 T_3=0.3030

Table (5) Performance index for different controllers.

Controller type	Operating condition		
	Light	Normal	Heavy
CPSS	7.9349e-4	7.8086e-4	0.0013
GAPSS	1.2167e-4	1.373e-4	1.6492e-4
BFPSS	7.1961e-5	8.1201e-5	1.0684e-4

A. Step response for light load condition:

Figs. 3-5, show the response of $\Delta\omega_{12}$, $\Delta\omega_{23}$, and $\Delta\omega_{13}$ to a 0.1 step increase in mechanical torque of generator (1) for light loading condition. From these Figures, It can be seen that the BFOA based tuned PSSs using the time domain objective function achieves good robust performance and provides superior damping in comparison with the other methods. Moreover, the mean settling time of these oscillations is approximately 2.3 second with BFPSS and 2.9 second for GAPSS so the designed controller is capable of providing sufficient damping to the system oscillatory modes. Also, the system with CPSS can't reach steady state value till 8 second.

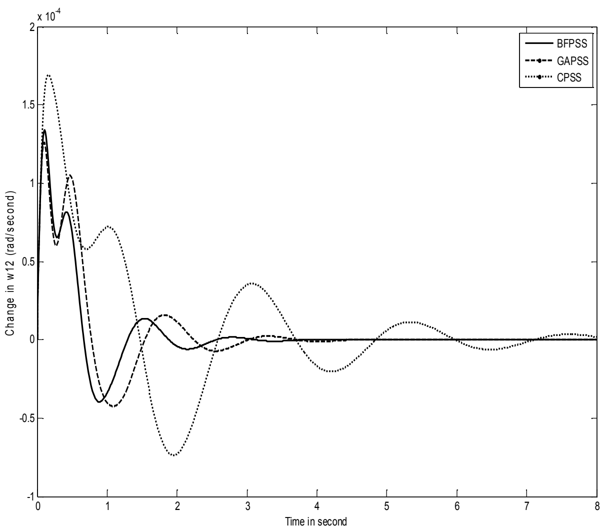

Figure 3. Change in $\Delta\omega_{12}$ for light load.

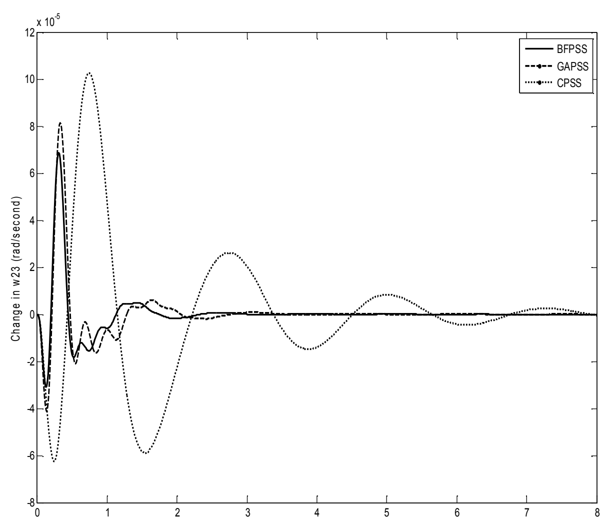

Figure 4. Change in $\Delta\omega_{23}$ for light load.

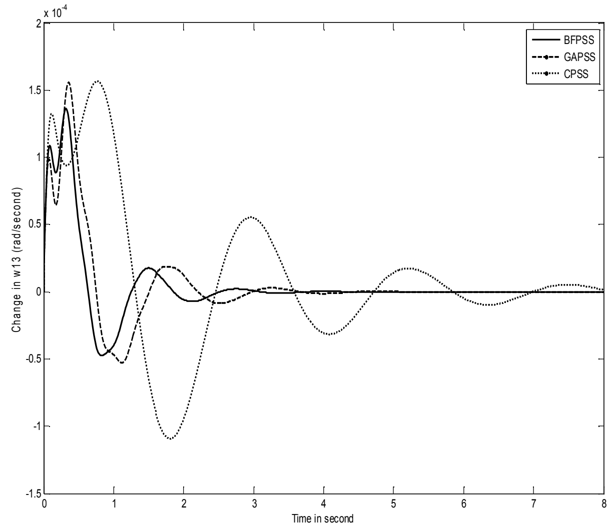

Figure 5. Change in $\Delta\omega_{13}$ for light load.

B. Response for normal load condition:

Figs. 6-8, show the response of $\Delta\omega_{12}$, $\Delta\omega_{23}$, and $\Delta\omega_{13}$ for normal loading condition. These figures indicate the capability of the BFPSS in reducing the settling time and damping power system oscillations. Moreover, the mean settling time of these oscillations is T_s =2.4, 2.8, and 6.7 second for BFPSS, GAPSS, and CPSS respectively so the proposed BFPSS is capable of providing sufficient damping to the system oscillatory modes compared with GAPSS and CPSS.

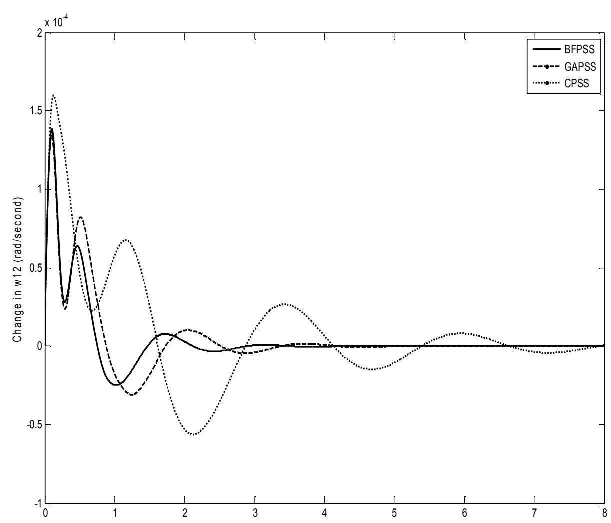

Figure 6. Change in $\Delta\omega_{12}$ for normal load.

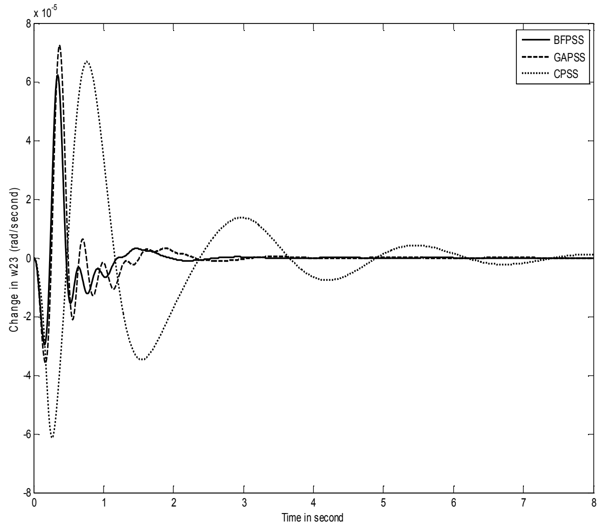

Figure 7. Change in $\Delta\omega_{23}$ for normal load.

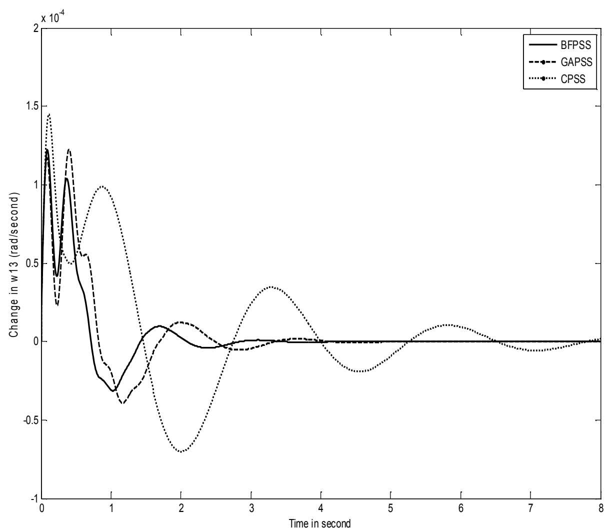

Figure 8. Change in $\Delta\omega_{13}$ for normal load.

C. Response for heavy load condition:

Figs. 9-11, 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 BFPSS shows good damping characteristics to low frequency oscillations and the system is more quickly stabilized than GAPSS. The mean settling time of oscillation is T_s =2.14, and 3.1 second for BFPSS and GAPSS respectively. Moreover, the system is suffered from high oscillation and large settling time for CPSS case. Hence, the proposed BFPSS extend the power system stability limit and the power transfer capability.

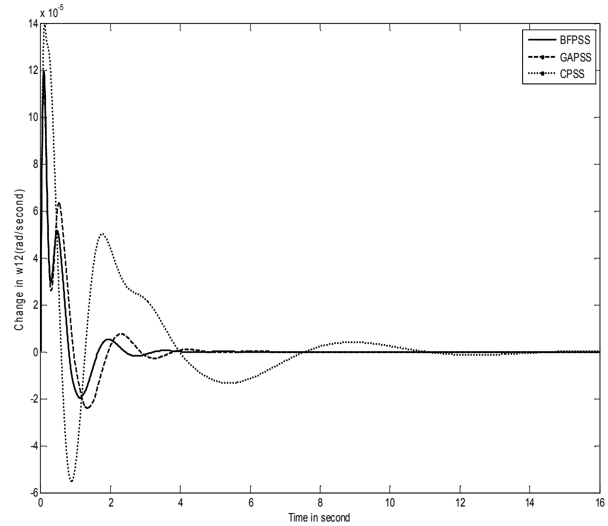

Figure 9. Change in $\Delta\omega_{12}$ for heavy load.

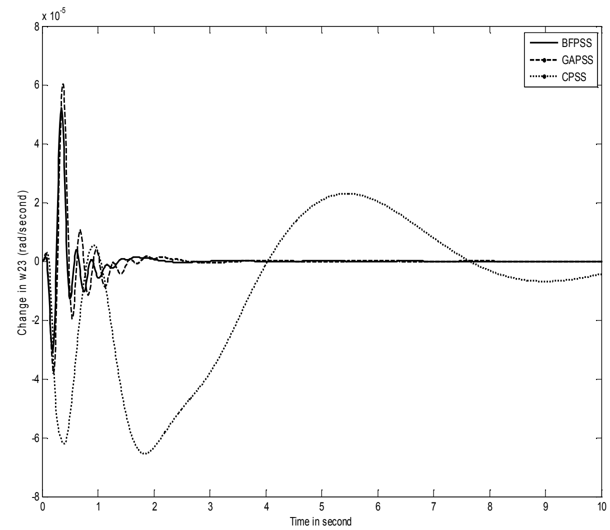

Figure 10. Change in $\Delta\omega_{23}$ for heavy load.

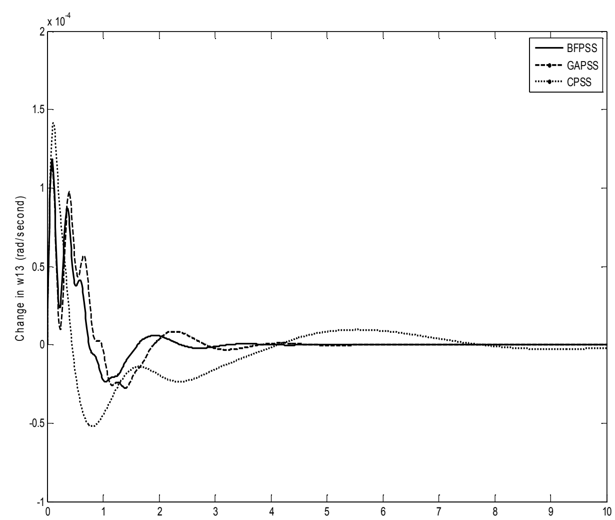

Figure 11. Change in $\Delta\omega_{13}$ for heavy load.

D. Line Removal:

To evaluate the effectiveness and robustness of the proposed BFPSS, the performance of the system with the proposed BFPSS is compared to GAPSS and CPSS under large disturbance. Fig. 12 shows the response of $\Delta\omega_{12}$ due to removal line 5-7. It is clear that, the oscillations are increased rapidly and system is unstable with CPSS. Moreover, the system with BFPSS is stabilized more rapidly than GAPSS. Hence, the performance of BFPSS achieves robust performance and provides superior damping in comparison with the other controllers. Moreover, this controller has a simple architecture and the potentiality of implementation in real time environment.

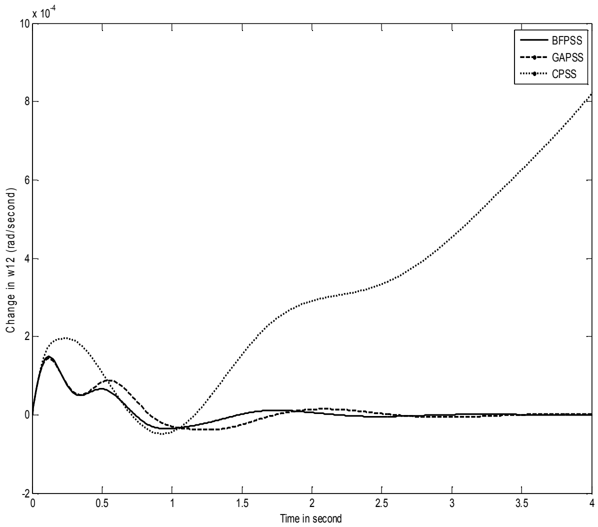

Figure 12. Change in $\Delta\omega_{12}$ for removal line 5-7 with normal load condition.

7. Conclusions

In this paper, a robust design of the PSS for stabilization of multimachine power system oscillations is proposed. The design problem of the proposed controller is formulated as an optimization problem and BFOA is employed to search for optimal controller parameters. By minimizing the time domain objective function, in which the deviations in speed are involved; stability performance of the system is improved. Simulations results assure the effectiveness of the proposed BFPSS in providing good damping characteristic to system oscillations over a wide range of loading conditions and system configuration. Also, these results validate the superiority of the proposed method in tuning controller compared with GA and conventional one over wide range of operating conditions, and system configuration.

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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) Genetic parameters: Max generation=150; Population size=50; Crossover probabilities=0.75; Mutation probabilities =0.1.