

Implementation of an Innovative Cuckoo Search Optimizer in Multimachine Power System Stability Analysis

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Abstract: Power system stabilizers are implemented in power system networks to mitigate the low frequency inertial oscillations effectively. This paper provides an efficient approach to damp the oscillations experienced in multi-machine power system using an innovative cuckoo search optimization algorithm based controller design, to improve the system stability. The proposed controller design is formulated as a Tri-objective optimization criterion to compute the optimal controller parameters. To show the effectiveness of the proposed controller, time domain simulations under various operating conditions has been carried out. The performance of the cuckoo search controller is compared with conventional lead lag controller and particle swarm optimization based controller designs.

Keywords: Eigen value, Inertial oscillations, Cuckoo search optimization, Particle swarm Optimization, Power system stability.

1. INTRODUCTION

Low frequency inertial oscillations (0.1 to 2 Hz) after a disturbance in a power system, if not properly damped, can lead the system to unstable condition (Yassami *et al.*, 2010). A Power System Stabilizer (PSS) is one of the cost effective damping controller to improve the power system stability. The main objective of PSS is to add damping to the electromechanical oscillations by controlling the generator excitation using auxiliary signal (Masahiko Nambu and Yasuharu Ohsawa, 1996). In recent years, several techniques based on modern control theory have been applied to PSS design. These include variable structure control, adaptive control and intelligent control (Abdallah *et al.*, 1984; Hosseinzadeh and Kalam, 1999; Ghoshal *et al.*, 2009). Despite these techniques, power system researchers still prefer the conventional lead lag controller design (Gibbard, 1991). Conventional PSS are designed using the theory of phase compensation in frequency domain and it can provide effective damping performance only for a particular operating condition and system parameters (Huang *et al.*, 1991).

Also, the fuzzy logic and neural networks had been implemented in damping controller design (You *et al.*, 2002). But these controllers suffer from the following drawbacks: There is no systematic procedure for the fuzzy controller design and also the membership functions of the controller are tuned subjectively, making the design more complex and time consuming. With respect to neural based controller, it is more difficult to understand the behavior of the neural network in implementation.

Recently, as an alternative to the conventional and uncertainty methods, Bio inspired optimization techniques are considered as powerful techniques to obtain optimal solution in power system optimization problems (Abido,

2000; Mishra *et al.*, 2009; Abido and Abdel Magid, 2002; Jalilvand and Daviran Keshavarzi, 2010; Wang *et al.*, 2011). These techniques include Evolutionary programming, Simulated annealing, Bacterial foraging, Harmony search algorithm, Ant colony optimization, Genetic algorithm, Particle swarm optimization and Cuckoo Search optimization algorithm. In this paper, Particle swarm optimization (PSO) and Cuckoo search optimization (CSO) algorithm based PSS designs are implemented in optimizing the power system stabilizer parameters, suitable for multi-machine stability enhancement.

2. MAIN OBJECTIVES OF THE WORK

The following steps will give a clear picture of the main objectives formulated in this paper to improve the stability of the power system:

1. Develop a linearized state space model of the test multi-machine power system model with and without the damping controller implemented in the system.
2. Compute the open loop system eigen values and damping ratios of the weakly damped electromechanical modes of oscillation to analyze the stability of the multi-machine power system.
3. Formulate a Tri-objective optimization criterion to compute the optimal PSS parameters required for better stability.
4. Implement the conventional lead-lag power system stabilizer (CPSS) design, PSOPSS design and proposed CSOPSS design to compute the closed loop eigen values and damping ratios of the weakly damped electromechanical modes of oscillation.
5. Perform a detailed comparative stability analysis based on closed loop eigen values and damping ratios computed in steps 2 and 4, to show the

effectiveness of the PSOPSS and the proposed CSOPSS in enhancing the system stability.

- To show the robustness of the proposed controllers, non linear time domain simulation experiments using MATLAB tool has been implemented with wide variations in system operating conditions and parameters. A detailed comparative oscillation damping analysis has been performed based on the deviation responses obtained from the three damping controller designs.

3. MATHEMATICAL MODELING OF POWER SYSTEM

3.1 Test multi-machine power system modeling

Figure (1) represents the test three machine nine bus power system model taken for modeling and analysis. For analysis and simulation, the Heffron-Phillips block diagram of synchronous generator model was used (Anderson and Fouad, 2008).

The Dynamic model in State Space form is given by

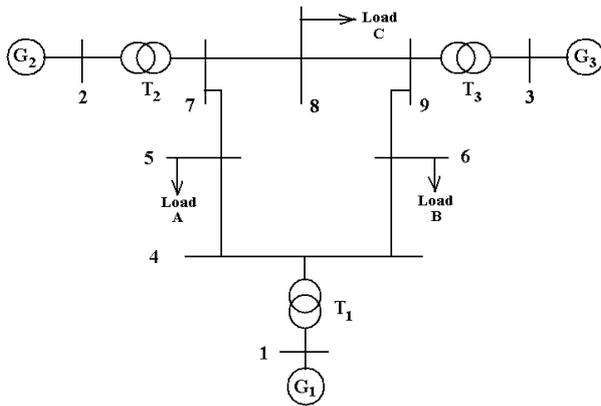


Fig. 1. Three machine nine bus power system model.

$$\dot{x} = Ax + Bu \tag{1}$$

Where x = Vector of State variables.
 A, B = State vector matrix and Input matrix respectively.

The State variables used in the modeling for open loop and closed loop system for each machine are given by,

$$\begin{aligned} [X]_{open} &= [\Delta\omega_j \quad \Delta\delta_j \quad \Delta E'_{qj} \quad \Delta E'_{fdj}]^T \\ [X]_{closed} &= [\Delta\omega_j \quad \Delta\delta_j \quad \Delta E'_{qj} \quad \Delta E'_{fdj} \quad \Delta P_{1j} \quad \Delta U_{Ej}]^T \end{aligned} \tag{2}$$

where $\Delta\omega_j$ = Incremental change in Rotor speed
 $\Delta\delta_j$ = Incremental change in power angle
 $\Delta E'_{qj}$ = Incremental change in generator voltage
 ΔE_{FDj} = Incremental change in field voltage.

ΔP_{1j} and ΔU_{Ej} represents the PSS model variables. The system data used for simulation (Juan Sanchez et al, 1996) are given in Appendix-A. In equation 2, $j= 1, 2, 3$ and it refers to the machine number. The state matrices for the three machines will be individually formulated using the equation

2. $[x]_{open}$ and $[x]_{closed}$ refers to the list of state variables selected for the various machines in the system modeling. The control vector u consists of two inputs to the system namely $[\Delta T_m$ and $\Delta V_{ref}]$. ΔT_m represents the mechanical input torque and ΔV_{ref} represents the reference input voltage. The closed loop state matrices and input matrices (A_{closed} and B_{closed}) developed for the system are given in Appendix-B.

3.2. Power System Stabilizer Structure

The PSS model consists of the Gain block, Phase Compensation block and the washout block. The input to the controller is the Rotor speed Deviation ($\Delta\omega$) and output is the control signal (ΔU_E) given to generator excitation system (Bikash Pal and Balarko Chaudhuri, 2005)..

The transfer function of the PSS model is given by

$$\begin{bmatrix} \Delta U_E \\ \Delta\omega \end{bmatrix} = K_s \begin{bmatrix} s \cdot T_w \\ 1 + sT_w \end{bmatrix} \begin{bmatrix} 1 + sT_1 \\ 1 + sT_2 \end{bmatrix} \tag{3}$$

Where K_s = PSS gain
 T_w = Washout Time constant.
 T_1, T_2 = PSS Time constants

Hence K_s, T_1, T_2 are the PSS parameters which should be computed using CPSS and optimally tuned using PSOPSS and CSOPSS.

4. PROPOSED TRI-OBJECTIVE OPTIMIZATION CRITERION FOR STABILITY

The proposed Tri-objective optimization criterion consists of three objective functions (J_1, J_2 and J_3).

4.1 Eigen Value based Objective Function J_1

The objective function J_1 is set to the maximum of σ_i among the eigen values of electromechanical modes of oscillation, as given in Equation (4).

$$[J_1] = \text{Max}[\sigma_i], \sigma_i \in \sigma_{EMODE} \tag{4}$$

where σ_i = Real part of i^{th} electromechanical mode eigen value.
 σ_{EMODE} = Computed set of electromechanical mode eigen values.

The objective here is to minimize the objective function $[J_1]$, so that the real part of the i^{th} electromechanical eigen value is shifted to better locations in left half of complex s- plane for stability.

4.2 Damping Ratio based Objective Function J_2

In power systems, the rate of decay of electromechanical oscillations is expressed in terms of its damping ratio $[\xi]$. The objective function J_2 is set to minimum of ξ_i among the damping ratios of the electromechanical modes of oscillation, as given in Equation(5).

$$[J_2] = \text{Min}[\xi_i], \xi_i \in \xi_{EMODE} \tag{5}$$

Where ξ_i = Damping ratio of i^{th} electromechanical mode eigen value.

ξ_{EMODE} = set of damping ratios of electromechanical mode eigen values.

The damping ratio for an eigen value $[\sigma \pm j\omega]$ can be computed by

$$[\xi] = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}} \quad (6)$$

The objective here is to maximize $[J_2]$, so that the damping ratio of the weakly damped electromechanical mode of oscillation will be enhanced to make the system more stable.

4.3 Time Domain Simulation based Objective Function J_3

The system electromechanical oscillations are reflected in terms of rotor speed and power angle deviations.

$$[J_3] = \int_0^T [e^2(t)] dt \quad (7)$$

Here, $e(t)$ represents the error deviations in generator speed ($\Delta\omega$) and power angle ($\Delta\delta$). The objective is to minimize $[J_3]$, so that the integral of the squared error deviations are minimized for better stability of the system. The optimization problem including the controller parameter constraints is formulated as follows:

Optimize J [Minimize J_1 , Maximize J_2 , Minimize J_3] subject to

$$K_S^{\text{Min}} \leq K_S \leq K_S^{\text{Max}} \quad (8)$$

$$T_1^{\text{Min}} \leq T_1 \leq T_1^{\text{Max}} \quad (9)$$

$$T_2^{\text{Min}} \leq T_2 \leq T_2^{\text{Max}} \quad (10)$$

The following are the controller gain and time constant limits (minimum and maximum values) taken for algorithm implementation: for the gain ($K_S^{\text{Min}}=1$ and $K_S^{\text{Max}}=70$), time constant ($T_1^{\text{Min}}=0.1$ and $T_1^{\text{Max}}=1$ sec) and ($T_2^{\text{Min}}=0.1$ and $T_2^{\text{Max}}=1$ sec).

5. PROPOSED BIO INSPIRED OPTIMIZATION ALGORITHMS

In this work, the damping performance of PSOPSS and CSOPSS design based controller designs are compared with the conventional lead lag controller design.

5.1 PSO- An overview.

Particle Swarm Optimization is a meta-heuristic technique developed by Eberhart and Kennedy in 1995, which was inspired by the social behavior of bird flocking (Eberhart and Kennedy, 1995; Dash *et al.*, 2009; Magdi Mahmoud *et al.*, 2012). PSO incorporate an initial random population of particles that fly through the problem space with specified velocities and positions. The particles refer to the possible potential solutions taken for computing the optimal value. Here, in this work it refers to the damping controller parameters (K_S , T_1 and T_2). The positions corresponding to the best fitness in the population is called Personal best (i.e.) P_{best} . The overall best value out of all the P_{best} values in the population is called global best (i.e.) g_{best} . The P_{best} and g_{best}

values are determined based on the formulated fitness function.

The velocity of each particle is modified by the following equation:

$$V_i^{K+1} = W \cdot V_i^K + C_1 \cdot \text{rand}_1 \cdot (P_{\text{best}_i} - S_i^K) + C_2 \cdot \text{rand}_2 \cdot (g_{\text{best}} - S_i^K) \quad (11)$$

where V_i^K = Velocity of particle i at iteration K .
 W = Weighting function
 rand = random number between 0 and 1.
 C_j = Weighting factor, $j=1, 2$.
 S_i^K = Current position of particle i at iteration K .

The following weighting function is used in Equation (11).

$$[W] = [W_{\text{Max}}] - \left[\frac{W_{\text{Max}} - W_{\text{Min}}}{\text{iter}_{\text{max}}} \right] \cdot \text{iter} \quad (12)$$

where $W_{\text{Max}}, W_{\text{Min}}$ = Initial and final weight taken.
 iter_{max} = Maximum iteration number.
 iter = Current iteration number.

The current position of the particle is updated using equation (13).

$$S_i^{K+1} = S_i^K + V_i^{K+1} \quad (13)$$

where S_i^{K+1} = updated position of the particle.
 V_i^{K+1} = updated velocity of the particle.

The proposed PSO algorithm implemented in this work to obtain the optimal damping controller parameters is given as follows:

Step 1: Specify the various parameters involved for PSO algorithm implementation (i.e.) swarm size, minimum and maximum limits for PSS parameters (K_S, T_1 and T_2), number of generations, weighting function, termination criteria etc.

Step 2: Initialize a population of particles (possible values of controller parameters) with random positions and velocities in the problem space.

Step 3: Evaluate the fitness function (P) for each particle in the population (i.e) J_1, J_2 and J_3 .

Step 4: For each individual particle, compare the fitness value with its P_{best} value. If the current value (P_i) is better than the P_{best} value, set this value as the P_{best_i} for i^{th} particle. (i.e.) set $P_{\text{best}_i} = P_i$.

Step 5: Identify the particle that has the best fitness value among various P_{best} values. Set this value as g_{best} .

Step 6: If the termination condition ($g > g_{\text{max}}$) is reached, then optimal value of PSS parameters is equal to those obtained in current generation, (i.e.) g_{best} values, otherwise goto step 7.

Step 7: Compute the new velocities and positions of the particles according to Equations (11) and (13).

Step 8: Repeat steps 3-6 until the termination criterion is met.

5.2 Proposed Meta-heuristic CSO algorithm

Cuckoo search (CS) is a Bio inspired optimization algorithm proposed by (Yang and Deb, 2009). It is inspired by the obligate brood parasitism nature of cuckoo species along with the Levy flight behavior of birds and flies in nature. Levy flight represents the flight behavior of animals and birds for food search (Aminreza Noghrehabadi *et al.*, 2011).

The cuckoo species lay their eggs in the nests of other host birds. If a host bird discovers the eggs are not its own, it will throw away these eggs or build a new nest elsewhere.

The following rules will describe the CS algorithm effectively.

- (a). Each cuckoo lays one egg at a time, and will put its egg in the nests, chosen randomly.
- (b). The best nests with good quality of eggs (potential solutions) will be carried over to next generations.
- (c). The number of host nests is fixed, and a host bird will discover an egg with a probability P_a (between 0 and 1). When generating new solutions $x_i^{(t+1)}$, a Levy flight is performed based on the equation(14).

$$x_i^{(t+1)} = x_i^{(t)} + \alpha(t^{-\lambda}) \quad (14)$$

Here, α = step size, normally equal to 1. λ will have values from 1 to 2.5.

The proposed CSO algorithm implemented in this paper to obtain the optimal damping controller parameters is given as follows:

Step 1: Specify the various parameters involved for CSO algorithm implementation (i.e.) number of nests, minimum and maximum limits for PSS parameters (K_s, T_1 and T_2), number of generations, worst nests probability, termination criteria etc.

Step 2: Initialize a population of n host nests in the problem space.

Step 3: Evaluate the fitness function (P_i) for the randomly selected cuckoo (i) by Levy flights. (i.e) J_1, J_2 and J_3 .

Step 4: Choose a nest j among available nests randomly and replace j by new solution, if the fitness (P_i) is greater than fitness (P_j).

Step 5: If the termination condition is reached, then optimal value of PSS parameters is equal to those obtained in current generation, otherwise goto step 6.

Step 6: Abandon a fraction of worse nests with probability P_a .

Step 7: Update the solutions to calculate $x_i^{(t+1)}$ using equation (14).

Step 8: Repeat steps 3-7, until the termination criterion is met.

The cuckoo search algorithm is easier to implement and it provides the global solution required for parameter

optimization in complex engineering problems. In this paper, the cuckoo search algorithm provides an optimal solution for the damping controller parameters, so that the system stability is enhanced to a greater extent possible.

6. SIMULATION RESULTS AND STABILITY ANALYSIS

For all the modeling and simulation, MATLAB tool was used. In this work, the power system stabilizers are installed in the generator 2(131 MVA, 13.8 KV) and generator 3(145 MVA, 14.4 KV), the generator 1 bus is treated as infinite bus system.

The state space modeling of the multimachine system has been performed and the open loop eigen values for various operating conditions are listed in Table1. The damping ratios of the open loop weakly damped electromechanical modes are computed and presented in Table2.

The oscillatory modes are represented by complex eigen values and the weakly damped mode is identified among the real part of the complex eigen values. If the real part is positive, it indicates that the oscillations are growing. If the real part is negative, it indicates that the oscillations are decaying.

The open loop values show that the eigen values are located in right half of complex s plane and also the damping ratios are negative, making the system unstable.

Also, the time domain rotor speed deviation response of generator G2 for $P = 0.63$, $Q = 0.024$, $\Delta P_d = 0.02$ p.u in figure(2), indicate that the deviations are more oscillating in nature and is in need of suitable damping controller for effective damping and stability enhancement.

ΔP_d represent the load change disturbance given to the system. Implementation of CPSS, PSOPSS and CSOPSS using the PSO and CSO parameters (as listed in Table 3) in the multimachine system provides the closed loop eigen values.

Table 2 provides the computed eigen values. The closed loop eigen values indicate that the eigen values are well placed in stable locations in s -plane, thus making the system stable.

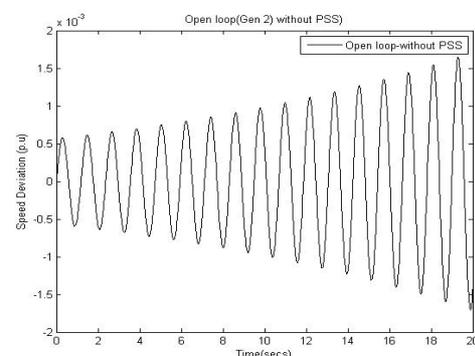


Fig. 2. Open loop speed deviation response of G2 for $P = 0.63$, $Q = 0.024$, $\Delta P_d = 0.02$ p.u.

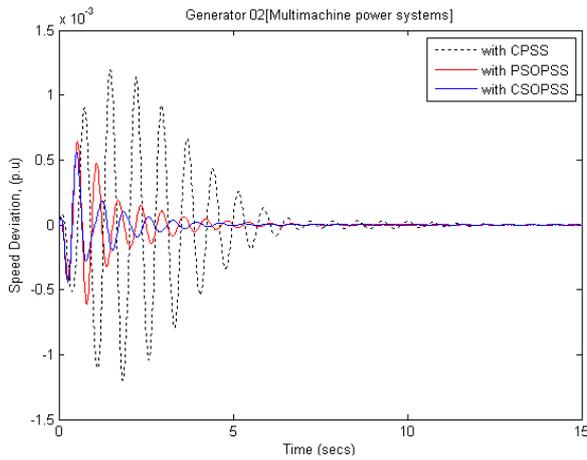


Fig. 3. Speed deviation responses of G2 for P = 0.63, Q = 0.024, ΔPd = 0.02p.u.

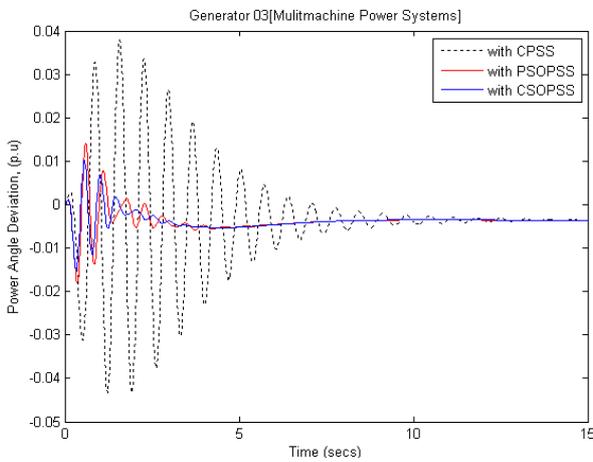


Fig. 4. Power angle deviation responses of G3 for P = 0.63, Q = 0.024, ΔPd = 0.02p.u.

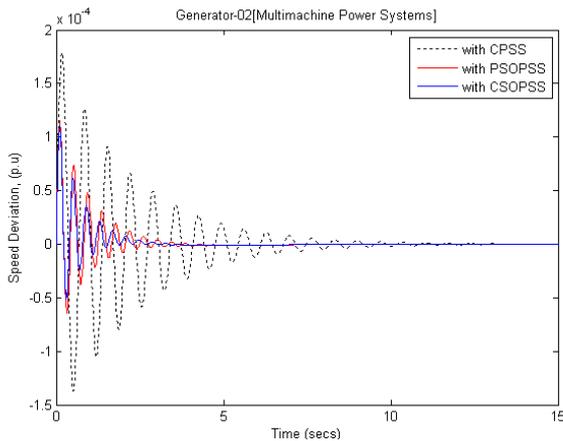


Fig. 5. Speed deviation responses of G2 for P = 0.73, Q = 0.19p.u, ΔPd = 0.04p.u, 15 % increase in M & Tdo' condition

The computed closed loop damping ratios (in Table 2) for weakly damped modes are positive and it is clear that the proposed CSOPSS provide the best possible damping to the system in comparison with the damping values of CPSS and PSOSS. For better damping, the system damping ratios more than 0.05 is recommended. In this work, a damping

threshold (ξ_r)= 0.07 is taken. It is evident that the damping ratios provided by the damping controllers are more than the damping ratio threshold taken for analysis (as per Table 2).

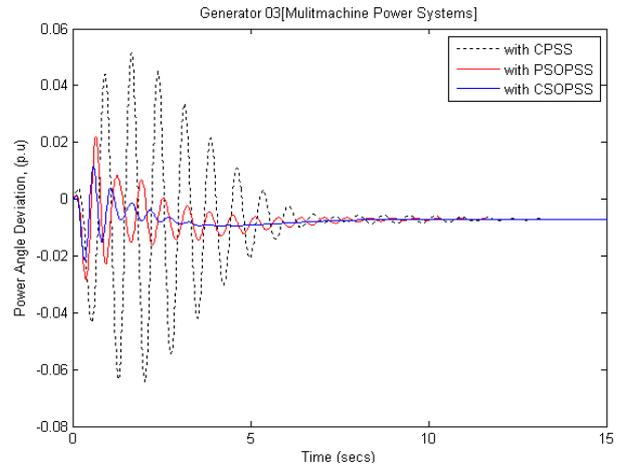


Fig. 6. Power angle deviation responses of G3 for P = 0.73, Q = 0.19p.u, ΔPd = 0.04p.u, 15 % increase in M & Tdo' condition.

Non linear time domain simulation analysis provides the time domain deviation responses for the various controllers. Figure 3 and 4 represent the deviation responses for P = 0.63, Q = 0.024, ΔPd = 0.02p.u condition. From these responses, it is clear that the CSOPSS provide effective damping to the system by damping the deviation overshoots and making the oscillation deviations to settle at a quicker stage compared to CPSS and PSOPSS performance.

Similarly, figure 4 and 5 indicate the speed and power angle deviation responses for P = 0.73, Q = 0.19p.u, ΔPd = 0.04p.u, 15 % increase in M & Tdo' condition. These responses clearly indicate the dominant damping action of proposed CSOPSS in damping the low frequency oscillations effectively, thus satisfying the objective J₃ formulated for stability enhancement.

The following are the dominant features of CSO based controller observed in this paper with regard to stability improvement.

- Better placement of closed loop eigen values in stable locations for all operating conditions involved.
- Provide more damping to the system for all conditions. (i.e.)Damping ratios more than the threshold level (ξ_r = 0.07) and also more than the damping ratios of other controllers.
- Rotor speed and power angle deviation overshoots are minimized and deviations are settled at a quicker time compared to other controllers for all conditions considered.
- Optimal solution got at lesser iterations (generations) compared to PSOPSS (Table 3).

7. CONCLUSION

This paper provides an efficient solution to damp the low frequency electromechanical oscillations experienced in the

multimachine power system model. The salient features of the work carried out in this paper for multimachine system stability enhancement are as follows:

- In this paper, a detailed state space modeling of the test power system has been performed. In order to compute the optimal controller parameters, a tri-objective optimization criterion has been formulated and the proposed algorithms have been implemented effectively.
- The stability analysis has been carried out based on the computed eigen values, damping ratios and also based on the error deviations minimization.
- Also, oscillations damping analysis involving wide variations in operating conditions have been performed based on the damping performance of the proposed controllers.

In all the analysis, the proposed CSO based damping controller provide the best damping performance than CPSS and PSOPSS, so that the multimachine power system stability is improved to a greater level.

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Table 1. Computed Eigen values of multi-machine system for stability analysis.

S.No	Operating conditions(p.u) with variations	Gen	Eigen values for stability analysis			
			Open Loop without PSS	CPSS	PSOPSS	CSOPSS
1	P = 0.63 Q = 0.024 ΔP _d = 0.02p.u	G ₂	-1.229±j 0.9889 0.0214 ± j 5.2379	-9.7515 ± j 15.2319 -0.3042 ± j 3.8751 -0.0769 ; -0.6191	-14.6838 ± j 13.9013 -0.7176 ± j 8.7487 -0.0774 ; -0.222	-18.6309 ± j 16.339 -1.0152 ± j 2.7297 -0.0774 ; -0.6248
		G ₃	-0.3428±j1.6302 0.0849 ± j5.2137	-13.2951 ± j 14.9977 -0.2813 ± j 3.8365 -0.0767 ; -0.7138	-13.9018 ± j 16.8345 -0.5188 ± j 6.4129 -0.0774 ; -0.7834	-16.1001 ± j 16.248 -0.8085 ± j 2.9228 -0.0768 ; -0.7124
2	P = 0.73, Q = 0.19p.u, ΔP _d = 0.04p.u, 15 % increase in M & Tdo'	G ₂	-0.7833±j 1.8542 0.6159 ± j 1.2353	-5.1024 ± j 11.2983 -0.4057 ± j 3.9367 -0.0768 ; -0.1836	-5.4938 ± j 12.3211 -0.6745 ± j 6.0038 -0.0771 ; -0.2273	-6.1058 ± j 11.9011 -1.1242 ± j 2.8056 -0.0773 ; -0.1860
		G ₃	-0.9893 ±j 0.8994 0.1782 ± j 7.0857	-4.6631 ± j 16.1142 -0.5623 ± j 6.8541 -0.0767 ; -0.1925	-11.0186 ± j 15.2466 -0.5182 ± j 5.7611 -0.1953 ; -0.0773	-18.0401 ± j 19.0369 -0.4859 ± j 4.6730 -0.0781 ; 0.2002

Table 2. Computed Optimal PSS parameters and damping ratios.

S.No	Operating Conditions with variations (p.u)	Gen	Optimal damping controller parameters (K _s , T ₁ , T ₂)			Damping ratios of weakly damped electromechanical modes. Damping ratio threshold(ξ _r)= 0.07			
			CPSS	PSOPSS	CSOPSS	Open Loop without PSS	CPSS	PSOPSS	CSOPSS
1	P = 0.63 Q = 0.024 ΔP _d = 0.02p.u	G ₂	12.8555 0.3389 0.14	31.5895 0.3368 0.1085	41.5959 0.6361 0.1438	-0.00408	0.078260	0.081749	0.348582
		G ₃	4.4759 0.2692 0.10	33.5463 0.3069 0.2530	6.1933 0.5511 0.1595	-0.01628	0.073125	0.080635	0.266606
2	P = 0.73, Q = 0.19p.u, ΔP _d = 0.04p.u, 15 % increase in M & Tdo'	G ₂	6.7472 0.6902 0.14	20.0089 0.3221 0.1456	39.2484 0.3558 0.1776	-0.44619	0.102512	0.111643	0.371949
		G ₃	3.0856 0.8694 0.10	25.0594 0.3601 0.1015	63.4766 0.5603 0.1303	-0.02514	0.081763	0.089586	0.103422

Table 3. PSO and CSO parameters implemented for controller design.

S.No	PSO Parameters		CSO Parameters	
1	Swarm Size	60	Number of nests	60
2	No of Generations	33	No of Generations	24
3	No of variables	03	No of variables	03
4	rand ₁ and rand ₂	0.6 and 0.6	Worst nests probability	0.24
5	Weighting function W _{max} and W _{min}	0.9 and 0.5	Step size(α)	1.0
6	Weighting factor C ₁ , C ₂	1.5, 1.5	Levy flight(λ)	2.4
7	Termination Method	Maximum Generations	Termination Method	Maximum Generations

Appendix A

Test multi-machine power system data

Generator 1: 125 MVA, 13.8 KV. Rated power factor = 0.9, $X_d = 1.05$, $X_d' = 0.3$, $X_q = 0.686$, $X_q' = 0.686$, $T_{d0}' = 6.170$, $D = 0$, $M = 10$.

Generator 2: 31 MVA, 13.8 KV. Rated power factor = 0.9, $X_d = 1.010$, $X_d' = 0.36$, $X_q = 0.570$, $X_q' = 0.570$, $T_{d0}' = 7.600$, $D = 0$, $M = 12$.

Generator 3: 145 MVA, 14.4 KV. Rated power factor = 0.9, $X_d = 0.953$, $X_d' = 0.312$, $X_q = 0.573$, $X_q' = 0.573$, $T_{d0}' = 7.070$, $D = 0$, $M = 10$.

Excitation system: IEEE ST1A type, for speed input damping controller

$K_A = 180$, $T_A = 0.05$, $K_F = 0.025$, $T_F = 1.0$, $K_e = 0.15$, $T_e = 0.025$

Appendix B

Closed loop State Matrix and input matrix

$$[A]_{Close} = \begin{bmatrix} 0 & \frac{-K_1}{M} & \frac{-K_2}{M} & 0 & 0 & 0 \\ \omega_b & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{-K_4}{T_{d0}'} & \frac{1}{T_{d0}'K_3} & \frac{1}{T_{d0}'} & 0 & \frac{K_A}{T_A} \\ 0 & \frac{-K_A \cdot K_5}{T_A} & \frac{-K_A \cdot K_6}{T_A} & \frac{1}{T_A} & 0 & 0 \\ 0 & \frac{-K_1}{M} & \frac{-K_2}{M} & 0 & \frac{-1}{T_w} & 0 \\ 0 & \frac{-K_s \cdot K_1 \cdot T_1}{MT_2} & \frac{-K_s \cdot K_2 \cdot T_1}{MT_2} & 0 & \frac{-K_s}{T_2} \left(1 - \frac{T_1}{T_2}\right) & \frac{-1}{T_2} \end{bmatrix}$$

$$[B]_{Close} = \begin{bmatrix} \frac{1}{M} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{K_A}{T_A} & 0 & 0 \end{bmatrix}^T$$