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Hybrid Chaotic Particle Swarm Optimization Based Gains for Deregulated Automatic Generation Control

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***Abstract*— Generation control is an important objective of power system operation. In modern power system, the traditional automatic generation control (AGC) is modified by incorporating the effect of bilateral contracts. This paper investigates application of chaotic particle swarm optimization (CPSO) for optimized operation of restructured AGC system. To obtain optimum gains of controllers, application of adaptive inertia weight factor and constriction factors is proposed to improve performance of particle swarm optimization (PSO) algorithm. It is also observed that chaos mapping using logistic map sequence increases convergence rate of traditional PSO algorithm. The hybrid method presented in this paper gives global optimum gains of controller with significant improvement in convergence rate over basic PSO algorithm. The effectiveness and efficiency of the proposed algorithm have been tested on two area restructure system.**

***Keywords* — Automatic generation control, deregulation, bilateral contracts, chaotic particle swarm optimization, logistic mapping, particle swarm optimization.**

I. INTRODUCTION

AUTOMATIC generation control (AGC) in a power system is a control to area’s generation due to load changes to maintain tie-line flows and frequency at their scheduled value. In a practically interconnected power system, the generations normally consist of a combination of thermal, hydro, nuclear and gas power generation.

Nanda et al [3] are the first to present analysis of AGC of an interconnected hydrothermal system in continuous-discrete mode with classical controller. Most of the researchers have focused to optimize the PI controller gains using artificial neural network (ANN), Hybrid-neuro-fuzzy [9], genetic algorithm (GA) and hybrid genetic algorithm-simulated annealing (GA-SA). The PI controller improves steady state error simultaneously with little or no overshoot.

After deregulation, AGC has become more challenging to ensure reliability and security together with economic efficiency. In the restructured environment, vertically integrated utilities no longer exist. Kumar et al [2] have presented an AGC model for power system under deregulated environment. Their model does not include the detail of governor and turbine dynamics and there is no mention of the controller structures and their strategy to find the optimum gains.

There are several Gencos (generation companies) and Discos (distribution companies) in deregulated structure. A Disco has freedom to have contracts with any Gencos for transaction of power. A Disco may have a contract with Genco of any other control area; such transaction is called bilateral transaction. All transactions have to be cleared through independent system operator (ISO). These ISO control many of the ancillary services. To visualize the implementation of contracts Donde and Pai [1] proposed Disco participation matrix (DPM). The critical parameters in order to tune such a system are found to be the feedback integral gains, proportional gain as well as the frequency biases of each area. These bias constant determines the relative importance attached to the frequency error feedback.

The main objective of this paper is to find optimum gain value of controller with proper bias constant. The classical optimization method of finding the gains with an appropriate performance index is not enough convenient because of it space complexity. Particle swarm optimization (PSO) is a population based swarm intelligence algorithm. In the recent year PSO become much more popular in different kind of application because of it easy implementation. However, the traditional PSO highly depend on its parameter and suffers the problem of being trapped in local optima. With multidimensional functions when local optima are found in region where fitness function varies rapidly, PSO fails at this stage.

To solve this problem, the chaotic PSO (CPSO) method has been introduced. Most of the works concerned with optimization algorithms using chaotic sequences for solving design problem. To enhance the performance of PSO, Acharjee et al [9] proposed CPSO algorithm. Due to non repetitive nature of chaos, it can carry out overall searches at higher speed. Chaos is a characteristic of non-linear system.

In this paper, an alternative hybrid method is proposed. This method combines the PSO with chaos sequence generated by logistic map. The application of chaotic sequences instead of random sequences in PSO diversifies the population of particles and improves the performance of PSO.

In the view of the above, the following are the main objectives of the proposed work:

1. To obtain optimize gains of controller and frequency bias by hybrid chaotic particle swarm (HCPSO) optimization for AGC of two area interconnected system.
2. To obtain dynamic response of AGC problem in MATLAB.
3. To compare the performance of the HCPSO based controller to the PSO based controller.

The rest of the paper is organized as follow: In section II the two area system model is developed. In section III hybrid chaotic particle swarm optimization is discussed in brief and implementation of HCPSO based controller is presented in section IV. Section V shows the results with discussion and conclusions are drawn in section VI.

II. Restructure System Model

In restructure environment, Gencos sell power to various Discos at competitive price. Discos may or may not have contracts with Gencos in their own area. This makes various combinations of Gencos-Discos contracts [1]. In this paper, two area systems with each area having two Gencos and two Discos in it as shown in Fig1 is used.

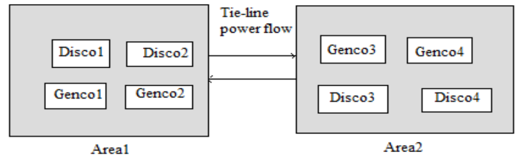

Fig.1. Schematic of a two-area system in restructures environment

The MATLAB simulation model of a two area AGC system in deregulated environment is shown in Fig. 2

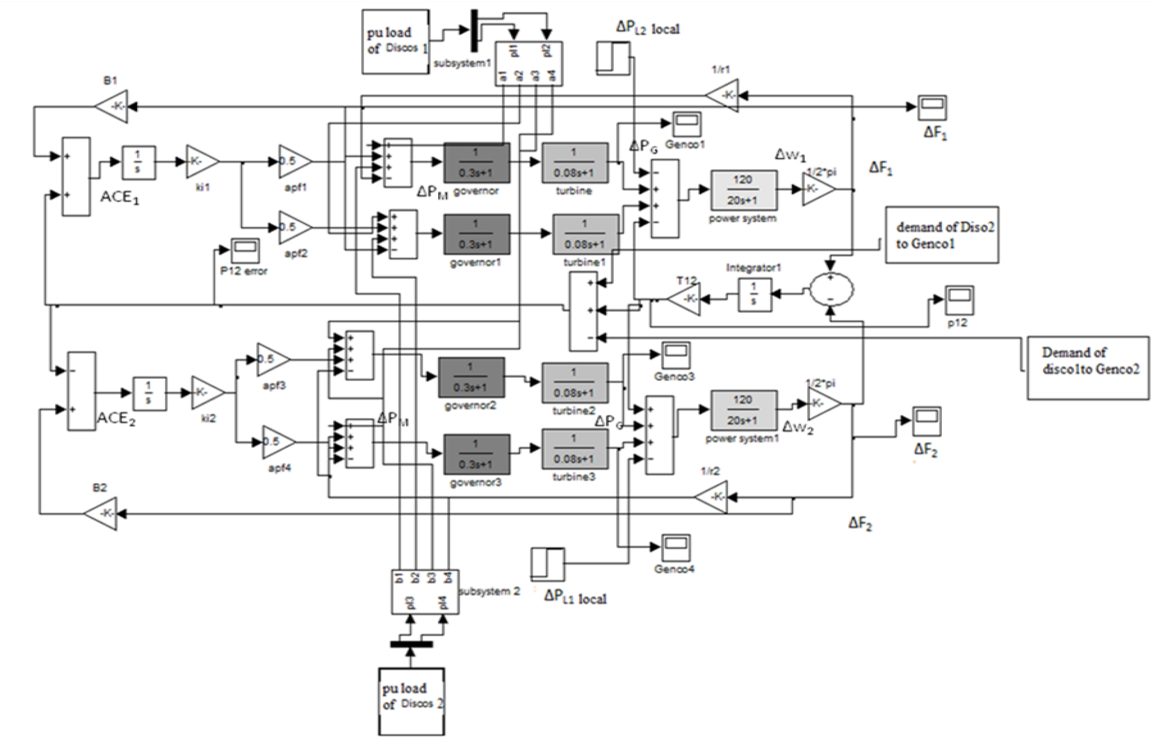

Fig.2. Two area AGC system block diagram with deregulation in MATLAB simulink.

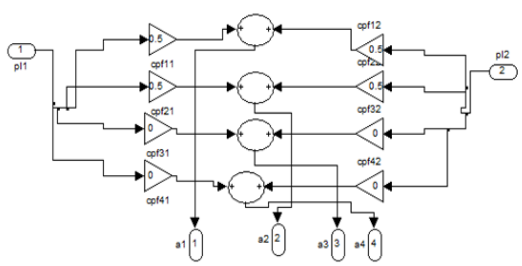

Fig 3 Block diagram representation of subsystem1

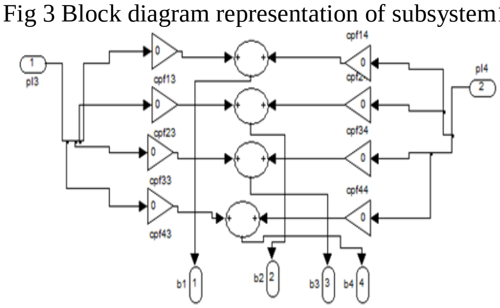

Fig 4 Block diagram representation of subsystem2

A Disco demands a load power to particular Gencos. Whenever Discos demand a load changes, it is reflected as a local loads (ΔP_{L1} and ΔP_{L2}) of corresponding Discos area. These demands are met by Gencos under regulation of contracts participation factors (cpfs) defined as:

$$cpf_{ij} = \frac{j^{th}\ \text{Disco power demand out of}\ i^{th}\ \text{Genco}}{j^{th}\ \text{Disco's total power demand}} \quad (1)$$

These cpfs sets the Discos participation matrix (DPM). In DPM the number of columns is equal to the number of Discos and number of rows equal to number of Gencos. Each cpf in DPM is a fraction of a load contracted by Discos towards Gencos. The sum of all the entries in a column is unity. For two area system with two Gencos and Discos, corresponding DPM will become

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$$DPM = \begin{array}{c} \text{Discos} \longrightarrow \\ \begin{bmatrix} cpf_{11} & cpf_{12} & cpf_{13} & cpf_{14} \\ cpf_{21} & cpf_{22} & cpf_{23} & cpf_{24} \\ cpf_{31} & cpf_{32} & cpf_{33} & cpf_{34} \\ cpf_{41} & cpf_{42} & cpf_{43} & cpf_{44} \end{bmatrix} \end{array} \begin{array}{c} \text{Gencos} \\ \downarrow \end{array}$$

The scheduled steady state power flow on the tie-line is:

$\Delta P_{tie,ij\ schduled} =$ (demand of Disco in area j from Genco in area i) – (demand of Disco in area i from Genco in area j (2)

In the proposed work, the scheduled power on the tie-line from area 1 to area 2 is:

$$\Delta P_{tie\ 1-2\ scheduled} = \sum_{i=1}^{2}\sum_{j=3}^{4} cpf_{ij}\Delta P_{Lj} - \sum_{i=3}^{4}\sum_{j=1}^{2} cpf_{ij}\Delta P_{Lj} \qquad (3)$$

Hence, the tie-line power error is:

$$\Delta P_{tie,ij\ error} = \Delta P_{tie,ij\ actual} - \Delta P_{tie\ ij\ scheduled} \qquad (4)$$

This error signal is used to generate ACE signal as:

$$ACE_i = B_i \Delta f_i + \Delta P_{tie,ij\ error} \qquad (5)$$

Since there are many Gencos in each area, ACE has to be distributed among them in proportion to their participation in the AGC. Area participation factors (apfs) distribute ACE to several Gencos such that $\sum_{j=1}^{n} apf_j = 1$, where n is number of Gencos.

The closed loop system in Fig. 2 can be express in state space form as:

$$\dot{x} = Ax + Bu \qquad (6)$$

Where x is state vector (x= [Δw_1, Δw_2, ΔP_{G1}, ΔP_{G2}, ΔP_{G3}, ΔP_{G4}, ΔP_{M1}, ΔP_{M2}, ΔP_{M3}, ΔP_{M4}, $\int ACE_1 dt$, $\int ACE_2 dt$, $\Delta P_{tie,1-2}$]^T) and u is the vector of power demands of Discos (u=[ΔP_{L1}, ΔP_{L2}, ΔP_{L3}, ΔP_{L4}]^T).

III. Chaotic Particle Swarm Optimization

A. General PSO

PSO is a population based stochastic search algorithm. Kennedy and Eberhart developed PSO in 1995 [11]. PSO randomly initialized the swarm of particles in the search space associated with randomized velocities. Particle's position and velocities are adjusted and the function evaluated with the new coordinates at each time step (iteration).

Each particle of PSO keeps track of its coordinates in search space which are associated with best solution it has achieved so far. This is called pbest. The overall best value obtained so far called gbest. The particle velocities constantly adjusted according to the position of particles as:

$$v_i^{k+1} = wv_i^k + c_1 r_1\left(pbest_i^k - x_i^k\right) + c_2 r_2\left(gbest_i^k - x_i^k\right) \qquad (7)$$

Where,

c_1, c_2 are constriction factors. The maximum step size in the direction of the global best particle is regulated by c2, and c1 regulates the step size in the direction of the pbest value.

r_1 and r_2 are random function in the range [0, 1].

x_i^k is position of particle at k^{th} iteration.

'w' is inertia weight for velocity of i^{th} particle. A suitable value of w provides better optimal solution. In each iteration weight 'w' is varied as:

$$w = w_{max} - \frac{(w_{max} - w_{min})}{itermax} iter \qquad (8)$$

Where itermax is maximum number of iteration and iter is the current iteration. w_{max} and $w_{min,}$ the upper and lower limit of inertia weights respectively.

The position of each particle is updated using velocity vector as:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \qquad (9)$$

In PSO particles may be flying over regions of importance. The probability of a particle stumbling in to a valley, especially in high dimensional space may be extremely low. A problem which they address with some success by incorporating "acceleration" terms in to the basic PSO algorithm. It is possible to imagine situation in which the swarm may fly over a region of importance and in this process miss out on finding the global minimum. In this paper a simple modification to the PSO by chaos sequences is studied which mutate a small no of particles in each iteration. Lowering the mutation rate allows the CPSO to balance enough individuals away from the false minimum. Following section presents various modifications in traditional PSO.

B. Approach 1(CPSO1):

The parameters r1 and r2 in equation (7) are important control parameter. The use of chaotic sequence in PSO can be useful to escape from local minima than general PSO method.

Chaotic sequence based on logistic map is used as:

$$z1^{k+1} = a * z1^k * \left(1 - z1^k\right) \qquad (10)$$

Where, 'a' is the value for which logistic map attracted. Another logistic map uses the same equation to generate variable $z2^k$ in range [0, 1]. If initialize z1= 0.6 and set a = 4, the variation in z1 is shown in Figure 5.

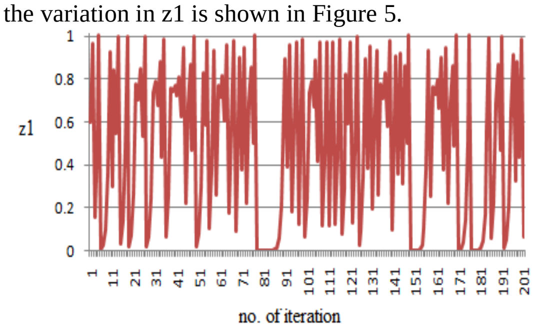

Fig. 5 variation in z1 with number of iteration

Other parameters are remaining same as in equation (7). Hence, velocity of particles is updated as:

$$v_i^{k+1} = wv_i^k + c_1 z1^k\left(pbest_i^k - x_i^k\right) + c_2 z2^k\left(gbest_i^k - x_i^k\right) \qquad (11)$$

The position of particles is modified same as in equation (9)

C. Approach 2 (CPSO2):

General PSO depends on its parameter. In PSO after certain iterations, the parameters sets are approximately identical and no improvement is noticed [8]. Optimization based on chaotic sequence can be better way to provide diversity in population. A chaotic sequence for inertia weight and constriction factor for optimization of gains is

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used.

(i). Adaptive inertia weight factor (AIWF) [9]:

In each, iteration same value of inertia weight is set for all particles. Therefore difference among particles is omitted. This adaptive method states that the better particle should tend to exploit its neighbor particles. This strategy provides the large selection pressure. The AIWF is obtained as [8]:

$$w_i^k = w_{min} + \frac{f_{pbest}^k \,|f_i^k - f_{pbest}^k|}{f_i^k \,|f_i^k - f_{gbest}^k|} \qquad (12)$$

w_i^k is inertia weight of i^{th} population at k^{th} iteration. w_{min} is minimum inertia weight, f_{pbest}^k is fitness function of pbest solution at k^{th} iteration, f_i^k fitness function of i^{th} population at k^{th} iteration and f_{gbest}^k fitness function of gbest solution at k^{th} iteration.

(ii). Adaptive constriction factors:

Since c1 and c2 controls the maximum step size. Constriction factor are highly depended on fitness function of current iteration, pbest and gbest solutions. This factor can be determined as:

$$c1_i^k = sqrt\left(\frac{f_i^k}{f_{pbest}^k}\right) \qquad (13)$$

$$c2_i^k = sqrt\left(\frac{f_i^k}{f_{gbest}^k}\right) \qquad (14)$$

So, velocity up gradation modified as:

$$v_i^{k+1} = w_i^k v_i^k + c1_i^k r_1\left(pbest_i^k - x_i^k\right) + c2_i^k r_2\left(gbest_i^k - x_i^k\right) \qquad (15)$$

D.Approach 3 (HCPSO)

Proposed HCPSO in this paper is an attempt to combine the advantages of CPSO1 and CPSO2 to update the velocity of particles. The proposed methodology updates the velocity of particles as given in following equation.

$$v_i^{k+1} = w_i^k v_i^k + c1_i^k z1_i^k\left(pbest_i^k - x_i^k\right) + c2_i^k z2_i^k\left(gbest_i^k - x_i^k\right) \quad (16)$$

IV. Implementation Of HCPSO Based Controller

The gain parameter and frequency bias are to be so selected that some degree of relative stability, damping, minimum overshoot, minimum undershoot and minimum settling time are achieved. So to satisfy all these requirement, select optimization function as:

$$F_{min} = 10 * \sum_i (\lambda_0 - \lambda_i)^2 + 10 * \sum_i (\xi_0 - \xi_i)^2 + 0.01 * \sum_i (\lambda_{imag})^2 \qquad (17)$$

Where λ_0 = -1, if $\lambda_i \geq 0$. λ_i is the real part of the i^{th} Eigen value. Eigen values in each test system are computed from 'A' by model analysis (eq. 5). The relative stability is determined by λ_0. By optimization, closed loop system poles are pushed further left of $j\omega$ axis with reduction of imaginary part also.

ξ_i is the damping ratio of the i^{th} Eigen value, if imaginary part of the i^{th} Eigen value > 0.0 and ξ_0 =0.2 (minimum damping ratio).

λ_{imag} is imaginary part of i^{th} Eigen value, if $\lambda_i \geq -1.0$.

A. The algorithm:

step1 Choose the population size and number of iteration.

step2 Select the value of speed regulation parameter, power system time constant of ith area.

step3 Generate randomly 'n' particles for gains and frequency biases with uniform probability over the optimized parameter search space [xmin, xmax]; similarly generate initial velocities of all particles as:

step4 Run AGC model and calculate the fitness function for each particle (eq.17) at kth iteration.

step5 Calculate gbest value and pbest value.

step6 Calculate fitness function at gbest and pbest solution.

step7 Calculate AIWF (eq. 12), constriction factor (eq. 13-14) and z1, z2 (eq. 10).

step8 Update velocity of each particle (eq.16).

step9 Based on updated velocities, each particle changes its position according to equation (9). If a particle is violates the position limit in any dimension, set its position at the proper limit.

step10 If the last change of the best solution is greater than a pre specified number or the number of iteration reaches the maximum iteration, stop the process, otherwise go to step 4.

B. Case studies:

(i). Case 1: basic case

(i) Consider load changes occurred only in area 1 and assuming that each area equally participate i.e. apf_1= apf_2= apf_3= apf_4=0.5. Hence load demanded by each Disco1 and Disco2 is 0.1 pu MW. Therefore DPM becomes [1]:

$$DPM = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \text{ and } Disco = \begin{bmatrix} 0.1 \\ 0.1 \\ 0 \\ 0 \end{bmatrix} pu\ MW$$

There are no contracts of power between a Genco in one area and a Disco in another area. Therefore scheduled steady state power flow over the tie-line is zero. In steady state, generation of a Genco must match the demand of the Discos according to contracts, i.e. Genco1 and Genco2 must supply 0.1 pu MW and Genco2 and Genco3 supply '0' pu MW power.

(ii) Case 2 Normal case:

In this case, all the Discos contracts with the Gencos for power according to following DPM. Each Discos demands 0.1 pu MW power from Gencos and each Genco participate in AGC as defined by apf_1=0.75, apf_2=0.25, apf_3=0.5, apf_4=0.5.

$$DPM = \begin{bmatrix} 0.5 & 0.25 & 0 & 0.3 \\ 0.2 & 0.25 & 0 & 0 \\ 0 & 0.25 & 1.0 & 0.7 \\ 0.3 & 0.25 & 0 & 0 \end{bmatrix}$$

The steady state generated power of the Gencos is:

$$Gencos\ power = \begin{bmatrix} 0.105 \\ 0.045 \\ 0.195 \\ 0.055 \end{bmatrix} pu\ MW$$

The scheduled power on the tie-line in direction from area 1 to area 2 (eq 3) is -0.05 pu MW.

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V. RESULTS AND DISCUSSION

Proposed HCPSO is implemented on two areas AGC scheme is implemented. Both the areas are assumed to be identical. The comparative time responses of the restructure system are presented through figures 9-23. The area's frequency deviation, the generated power of various Gencos, and actual power flow in the tie-lines for step load change in Discos for the two cases with I-type controller clearly illustrated that the HCPSO tuned system has quit fast frequency response compared to CPSO1 and CPSO2.

Fig 6 depicts the plot of $f_{best}^{\ k}$ (corresponding to gbest^k) against number of iteration for population size 20. The HCPSO algorithm based solution converged fast with minimum value of fitness function compare to other PSO algorithms.

Table 3-4 shows that the HCPSO based system has generation of a Genco matches the demand of the Disco with minimum error. In Fig. 11 and Fig. 16, the actual generated power of Gencos reaches the desired values in the steady state. In case1, Genco3 and Genco4 are not contracted by any Disco for transaction of power; hence, their change in generated power is zero in the steady state.

In Fig. 17-21, PI controller acts fast to the generator inputs while maintaining an acceptable overshoot and settling time on frequency deviation signal in each area.

Table-1 gives the comparative optimum value of gain and frequency bias for I-type controller and Table-2 gives optimum value of gains (K_p, K_i) and frequency bias using fitness function (eq.14). It is shown that for different cases HCPSO give the best optimized parameters values.

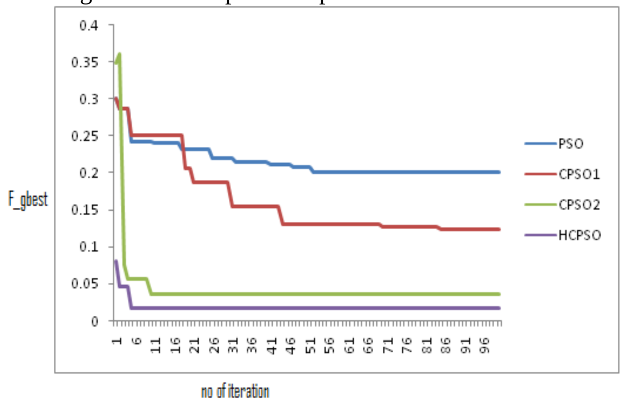

Fig 6 Convergence of algorithms for population size = 20.

Table-1 optimum value for I-type controller gains and frequency biases

Algorithms	Case1			Case2		
	Ki	B	Fitness function	Ki	B	Fitness function
PSO	0.9626	1.0161	0.091	1.3035	0.8006	6.4275
CPSO1	0.7509	0.2561	0.066	0.7529	0.2585	6.407
CPSO2	0.8042	0.2862	0.074	0.6601	1.1881	0.1772
HCPSO	0.8092	0.2688	0.06	0.7649	0.2249	0.0132

Table-2 optimum value for PI-type controller gains and frequency biases

Algorithms	Case1				Case2			
	Kp	Ki	B	Fitness function	Kp	Ki	B	Fitness function
PSO	0.7323	0.5766	0.3416	0.1245	0.3563	0.4242	0.5891	0.1172
CPSO1	0.5093	0.8839	0.2699	0.1068	0.4522	0.8824	0.2701	0.1044
CPSO2	0.0383	0.8343	0.4434	0.085	0.5066	0.8909	0.267	0.1066
HCPSO	0.0183	0.9504	0.3451	0.0844	0.0021	0.5031	0.0188	0.081

Table-3 steady state values of generated power for I-type controller

Generated power	algorithms	Case1			Case2		
		Computed value	Resulted actual value	error	Computed value	Resulted actual value	Error
Genco1	PSO	0.1	0.1007	0.0007	0.105	0.1056	0.0006
	CPSO1		0.1	0.0		0.1051	0.0001
	CPSO2		0.09857	0.0014		0.1049	0.0001
	HCPSO		0.1	0.0		0.105	0.000
Genco2	PSO	0.1	0.1007	0.0007	0.045	0.04485	0.00015
	CPSO1		0.1	0.0		0.0448	0.0002
	CPSO2		0.09857	0.0014		0.0492	0.00008

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	HCPSO		0.1	0.0		0.045	0.0
Genco3	PSO	0.0	-0.00056	0.00056	0.195	0.1946	0.0004
	CPSO1		-0.00005	0.00005		0.195	0.0
	CPSO2		0.001537	-0.00154		0.1951	0.0001
	HCPSO		-0.00004	0.00004		0.195	0.0
Genco4	PSO	0.0	-0.00056	0.00056	0.055	0.05457	0.00043
	CPSO1		-0.00005	0.00005		0.05498	0.00002
	CPSO2		0.001537	-0.00154		0.05507	0.00007
	HCPSO		-0.00004	0.00004		0.05498	0.00002

Table-4 steady state values of generated power for PI-type controller

Generated power	algorithms	Case1			Case2		
		Computed value	Resulted actual value	error	Computed value	Resulted actual value	Error
Genco1	PSO	0.1	0.09988	0.00012	0.105	0.1049	0.0001
	CPSO1		0.1001	0.0001		0.105	0.0
	CPSO2		0.0999	0.0001		0.1051	0.0001
	HCPSO		0.0999	0.0001		0.105	0.0
Genco2	PSO	0.1	0.09988	0.00012	0.045	0.04492	0.00008
	CPSO1		0.1001	0.0001		0.04501	0.00001
	CPSO2		0.0999	0.0001		0.04489	0.00011
	HCPSO		0.0999	0.0001		0.04499	0.00001
Genco3	PSO	0.0	0.00011	0.00011	0.195	0.1951	0.0001
	CPSO1		-0.00008	-0.00008		0.195	0.0
	CPSO2		0.000007	0.000007		0.195	0.0
	HCPSO		0.000004	0.000004		0.195	0.0
Genco4	PSO	0.0	0.00011	0.00011	0.055	0.0551	0.0001
	CPSO1		-0.00008	-0.00008		0.055	0.0
	CPSO2		0.000007	0.000007		0.05499	0.00001
	HCPSO		0.000004	0.000004		0.05504	0.000004

Transient system's responses for case1 with I-type controller:

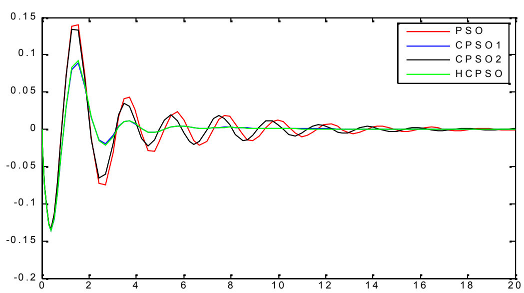

Fig.7. Frequency deviation ΔF_1 in rad/sec.

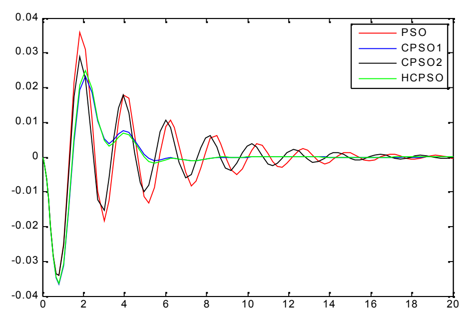

Fig. 9 Tie-line power ΔP_{12} (pu MW)

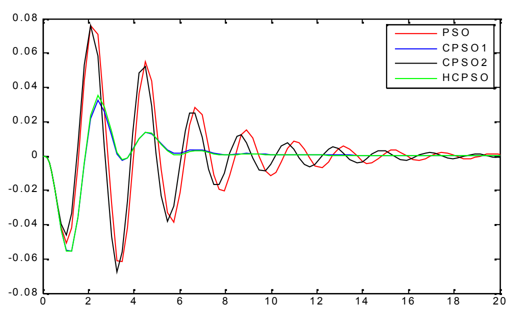

Fig.8. Frequency deviation ΔF_2 (rad/sec.)

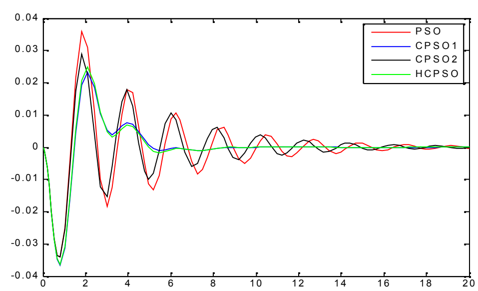

Fig 10 Tie-line power error $\Delta P_{12error}$ (pu MW)

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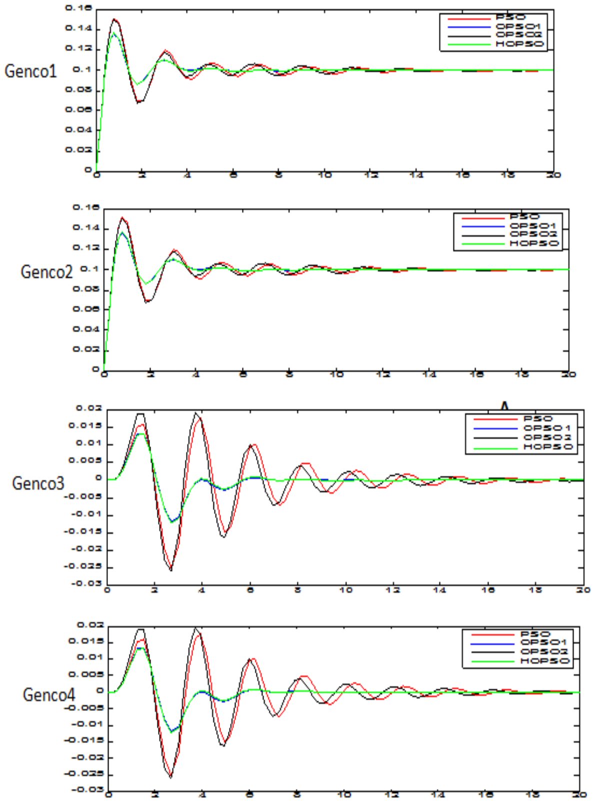

Fig 11 Generated power (pu MW)

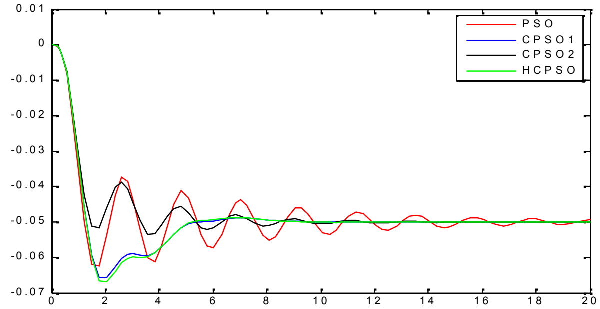

Fig 14 tie-line power flow ΔP_{12} (pu. MW)

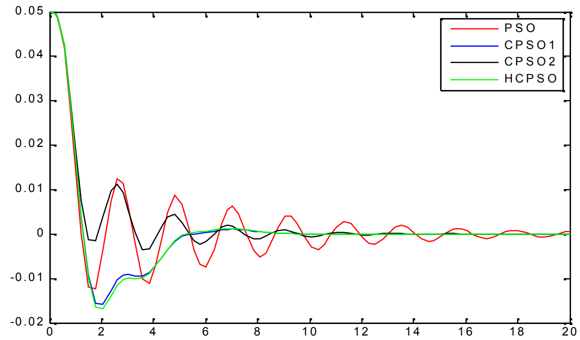

Fig 15 tie-line power error $\Delta P_{12\ error}$ (pu MW)

Transient system's responses for case2 with I-type control

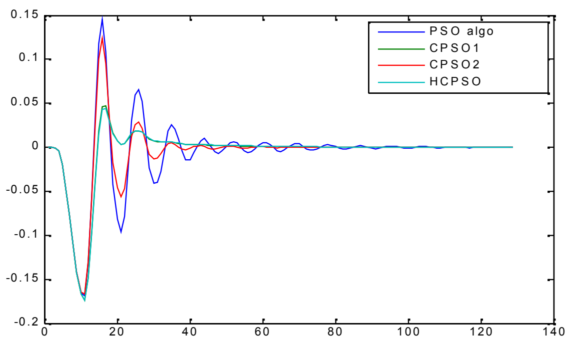

Fig 12 frequency deviation ΔF_1 (rad/sec)

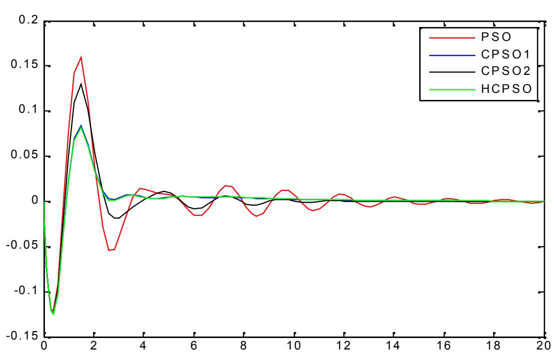

Fig 13 frequency deviation ΔF_2 (rad/sec)

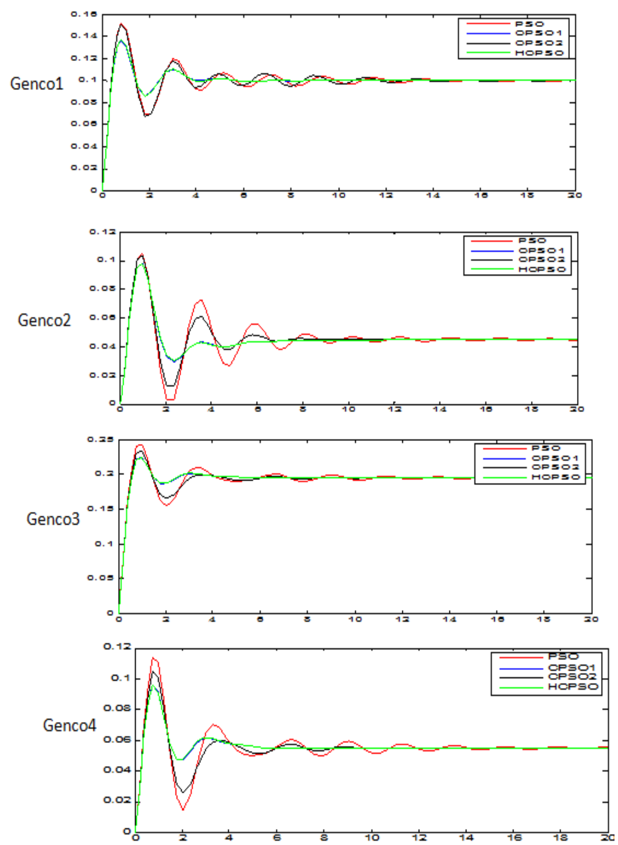

Fig 16 generated power (pu MW)

Comparative transient system's responses of I-type and PI-type controller

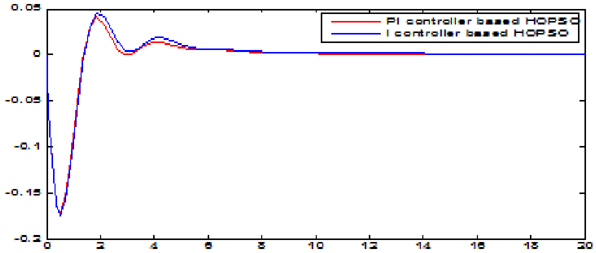

Fig 17 frequency deviation ΔF_1 (rad/sec)

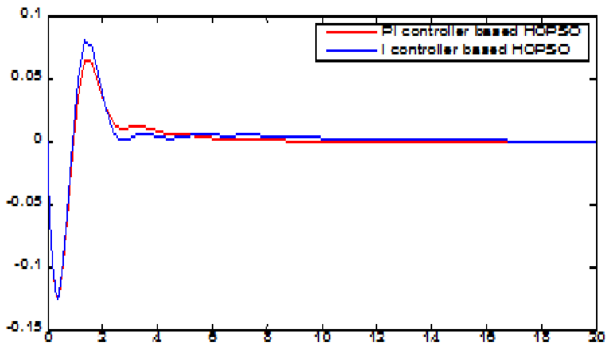

Fig 18 frequency deviation ΔF_2 (rad/sec)

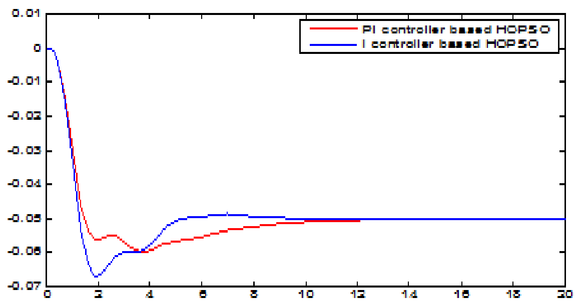

Fig 19 tie-line power flow ΔP_{12} (pu MW)

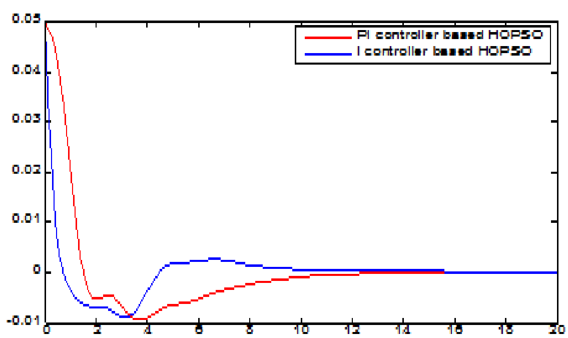

Fig 20 area control error of area1 (ACE1)

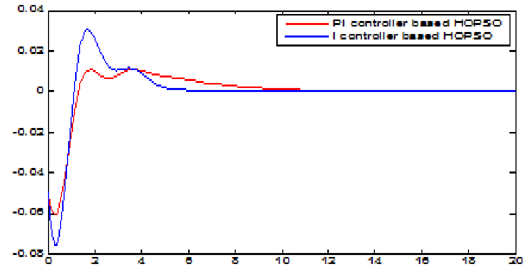

Fig 21 area control error of area2 (ACE2)

VI. Conclusion

This paper used HCPSO based algorithm to solve optimization problem, which is faster and effective method for optimization of gains and frequency bias for two areas automatic generation control in restructure environment. It is observed that the number of required iteration for convergence decreased. The proposed approach utilizes the global and local best values to search optimal setting of the state variables. From the results, it has been shown that HCPSO have ability to search better optimum solution of gains. This paper has successfully applied HCPSO to the optimization of gains of controller.

Appendix

Nominal parameters of two area test system:

H_1= H_1= 5 seconds
D_1= D_2= 8.33×10^{-3}P.U. MW/Hz
R_1= R_1=2.4 Hz/P.U. MW
Th_1= Th_2=80 ms
Tt_1= Tt_2=0.3 seconds
Kp_1= Kp_2=120HzP.U. MW
Tp_1= Tp_2=20 seconds
P_s=0.145P.U. MW/Radian

Parameters for HCPSO algorithm:

Initial population= 30
Maximum iteration= 100
W_{min}= 0.1

Parameters for PSO algorithm:

Maximum iteration= 100
W_{max}= 0.6, W_{min}= 0.1
C_1= C_2= 1.5

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