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Application of Particle Swarm Optimization with Variable learning factors and inertia weight factor in a Deregulated Economic Dispatch

[1] John Valder, [2] Dr. Abdul Khadar A

[1] Research Scholar, Department of Electrical & Electronics Engineering, Ballari Institute of Technology and Management, Ballari, Karnataka, India
[2] Associate Professor & Assistant Head, Department of Electrical & Electronics Engineering, Ballari Institute of Technology and Management, Ballari, Karnataka, India

Abstract : This paper emphasizes the characteristics and effectiveness of PSO in attaining the optimal solution in economic dispatch of thermal units in a deregulated market. Economic dispatch plays a major role in the arena of complex power system achieving minimum fuel costs of thermal units while satisfying the equality and non-equality constraints. The merits of deregulation due to competitive bidding like market efficiency and cost minimization with faster time is exclusively anticipated in the competitive system at present. The robustness of the PSO is tested by altering the learning factors and inertia factors and the results are being assessed with two test cases for 3 thermal units with population size of 1000 and 5000 using a demand of 850 MW and two test cases with 1000 MW for 3 and 8 thermal units with a similar population size. The outcome show that PSO has the ability and effectiveness in reaching optima by selecting proper learning and inertia weight factors.
Keywords: Economic Dispatch, particle swarm optimization, deregulation

1. INTRODUCTION

Exponentially increasing energy demand, scarcity of energy resources, depleting fossil fuels demands economic dispatch in today's power system[16]. Ever increasing electricity demand and a complex power system need an open market resulting into a deregulated environment. The significance of deregulation in the power system coupled with knowledge-based information and technologies can help to revive the benefits to the supplier and the end user[24]. When the utility companies are no longer a monopoly due to deregulation, it exhibits a competitive market for the participants and the consumers. It enables the market efficiency and reduces the costs to the supplier directly benefitting end users with a reduced energy price[25].The thermal units competing in the deregulated energy market are called as bidders which must meet the demand optimally through a process called as auction. Auction based[21] economic dispatch necessitated to achieve the optimal solution while the bidder's minimum fuel requirements is fulfilled. In this context, solution for the operation power system by economic dispatch forms an amicable part as visible by the interest shown by various researchers. Power systems analysis combines a highly nonlinear and computationally difficult environment with a need for optimality. Heuristic methods, has the apparent ability to adapt to nonlinearities and discontinuities found commonly in large systems. Economic dispatch defines the necessity of the power system to commit the units within operating limits such that the total cost is minimized while fulfilling the demand and satisfying the operating constraints both the equality and non-quality [1] constraints. Any positive corrections in scheduling the units helps to save significant amount which helps to transfer the savings to the consumers. Deregulated power system initiates a vital role in achieving minimal costs offering a competitive bidding among the various bidders. The task of obtaining the optimal solutions by the most available mathematical methods such as dynamic programming, linear programming, homogenous linear programming, and nonlinear programming techniques[2], [3]–[7] requires the cost characteristics of each generator to be approximated by a simple quadratic function. However, due to the local optimality stucking of these methods deprive an optimal outcome and suffer from the distotions of dimensionality and local optimality[1]. The resemblance of swarm of bird and fish schooling [8] was adopted by Russell Eberhart and James Kennedy in the form of particle swarm optimization (PSO). The survival of the species in a swarm is maximised by the PSO by mimicking the behaviour of the individuals. In PSO,own experience and others experience is used by the individual to make his decisions[8]. Compared to other conventional and heuristic methods, PSO are assumed to be as easier concept, simpler implementation, stronger to control parameters, effective memory capability, efficient in maintaining the diversity of the swarm[13] and computational efficiency. As compared to other meta heuristic algorithms, PSO evaluation is simple as it takes no or fewer assumptions for optimizing the solution process[14]. It takes measure of quality as improvement of the solution by taking a iterative optimization[15] It is a stochastic-based search technique based on artificial life and social psychology, as well as in engineering and computer science. The utilization of a "population," called particles, which moves through the problem search space with given velocities and in each iteration, velocities are randomly adjusted considering the tangible best location for the particle itself and the surrounding best position [4,9] (both of them expressed according to a predefined fitness function). Then, the flow of each particle naturally evolves to an optimal or near-optimal solution. The existing property of the PSO does not require any crossover and mutation probabilities. Speed of the particle pushes the search process and the most finer particle carries the information to the next particle in the swarm[15] with a faster speed. Its ability to obtain faster convergence rate to global solution and greater potential to achieve global solutions to economic dispatch problems is visible by the enormous work and acknowledgements by the researchers worldwide[17,18].

This paper considers the effect of change of learning factors and inertia weight on the quality of the convergence characteristics of PSO. The strength of the learning factors to replicate the enhanced features are proven[19].The selection of identical learning factors to achieve successful convergence of the PSO is evident in[19]. An extensive work needs to be extended to determine the nature of asymmetric learning factors. The effect of addition of inertia weight factor to balance the global exploration and local exploitation was introduced[10] and validated with decreasing inertia weights. Several authors have attempted to attain the fast convergence using random inertia weights and decreasing inertia weights[20]. Two cases have been chosen in this paper by considering two different population sizes. Case 1 is considered with similar and varying learning factors but with increasing inertia weights. .Case 2 takes into account varying and similar learning factors and constant inertia weights. Both the cases simulated with a population size of 1000 and 5000 respectively.

2. PROBLEM FORMULATION

In the bidding process of the deregulated market, the seller cost of the thermal plants is the bidden cost[22,23] as given in equation (1) and the incremental cost function bidding cost is given in equation (2).

$$F_i(P_{gi}) = a_i + b_i P_{gi} + c_i P_{gi}^2 \qquad (1)$$

where a_i, b_i and c_i are the coefficients of the cost of the ith generating system.
Bidden cost function or the incremental cost is

$$IC_i(P_{gi}) = b_i + 2c_i P_{gi} \qquad (2)$$

The economic dispatch problem for deregulated environment can be defined as follows,
Minimize the bidden cost function,

$$F = \sum_{i=1}^{N_g} F_i(P_{gi}) \qquad (3)$$

Where $F_i(P_{gi})$ is the bidden cost of the *i*th generating(seller) unit, P_{gi} the real output of the *i*th unit, and N_g is the number of (sellers)units in the system.
The net power generated by all units in the system is because of the total load in the system and the network loss. The power generated by each unit should exist between its maximum output power and minimum output power, that is:

$$\sum_{i=1}^{N_g} P_{gi} = P_{D+} P_L \qquad (4)$$

$P_{imin} < P_{gi} < P_{imax}$, $i \in [1, N_g]$ (5)

P_{gi} is the algebraic sum of the system generation, P_D is the total system demand, P_l is the transmission losses.

Neglecting the transmission losses and considering the generator capacity limits, economic dispatch problem is formulated[22].

3. SOLUTIONS METHODS USED: PARTICLE SWARM OPTIMIZATION

PSO algorithm with a predetermined amount of swarm or particles explore with certain position and velocity move in a known search space. Each of the particle thus exploring is a possible solution. The objective function has to utilise the optimization process such that each particle during the process knows its best positon known as Personal Best(Pbest). Similarly, the best position attained by the group or the other particles is called as Global Best(Gbest)

Velocity equation is given below,

$$V_j(i) = \omega V_j(i-1) + c_1 r_1 [P_{bestj} - X_j(i-1)] + c_2 r_2 [G_{best} - X_j(i-1)] \quad (6)$$

$where, j = 1, 2 \ldots, Ng$

$here$
$c1, c2\ are\ cognitive\ and\ social\ learning\ factors$
$r1, r2\ are\ uniformy\ distributed\ randoms\ in\ range\ 0\ and\ 1$
$\omega\ is\ the\ inertia\ weight\ factor$

Position update equation is given below

$$X_j(i) = X_j(i-1) + V_j(i) \quad (7)$$

Here the particles (X) are the generator values and the fitness are the equation (1) which is cost minimization. The global best value is identified using the PSO algorithm. The steps considered are

1. Initialize the swarm population (control variable 'X' (generated power Pg)) as Ng.
2. Take initial population of X within the power limit and initial velocity of the particle V_j
3. as zero.
4. Each population fitness (Fuel cost F) is calculated. Find the new velocities and increment the count.
5. The Personal Best (Pbest) of each population due to fitness are assigned to each X value. The lower cost of X value is taken as Global Best (Gbest). Calculate the velocity function as represented by the equation (6).
6. Update the value of X shown by equation (7).
7. Go to step 3 and repeat until the stop criteria. Stopping criteria is the total number of iterations. The final result is the final Gbest value.

4. RESULTS AND DISCUSSION

This section presents the results of simulation of two sets of 3 and 8 test thermal units subjected to test the performance of PSO in a deregulated set up. The effectiveness of the algorithm in the pursuit of optimal solution is evaluated with two test cases of population size of 1000 and 5000 with 10 runs by taking constant inertia weight factor and variable learning factors and variable learning and inertia weight factors. The thermal units were subjected to a load demand of 850 MW, 1200 MW and 450 MW respectively.

Case study 1

The thermal unit's parameters used in the test case[21] are given in table 1 and table 2. .In this test case the learning factors were varied from 0.5 to 1.25 and inertia weight factor was maintained constant at 0.1 with a swarm population size(PS) of 1000 and with 1000 iterations and the results are examined with a population size of 5000 maintaining the other factors similar. The total system load is 850 MW. It is evident from the results that as the learning factors were reduced with a reduction in the learning factors (0.5) and irrespective of the inertia weights, the saving in fuel will be little higher. However, at higher learning factors, the influence of inertia weights does not affect the optimal solution much in multiple runs. As the population size is increased in the search space to 5000, the algorithm gives similar effective optimal values for the other test factors considered. It is evident that by a proper selection of the learning and inertia weight factors as done by various researchers, optimal solution can be fine-tuned. Table 2 presents best optimal values of 3 seller systems with cost minimization in a simulation process of 10 runs. Figures 1 to 8 show the convergence characteristics of the 3-seller system with a constant inertia weight factor. It is seen that at lower learning factors and lesser population size, there is a tendency of the algorithm deviating drastically from the least costs whereas as visible in the figures tested with higher population deviation of the least costs across each runs are lesser and stable. The table 3 gives a comparatively optimal cost for different learning factors while satisfying the constraints set by the experimental set up for a demand of 850 MW. It can be inferred from the table 3 that the generating units share the load optimally in addition to minimizing the cost as desired by the parameters concerned.

Table 1. 3 Seller Test System parameters

Unit	P_{gmi} (MW)	Pg_{max} (MW)	a $	b $/MW	c $/MW^2
1	100	600	562	7.92	0.001562
2	100	400	310	7.85	0.00194
3	50	200	78	7.97	0.00482

Table 2. 8 Seller Test System parameters

Unit	P_{gmi} (MW)	Pg_{max} (MW)	a $	b $/MW	c $/MW^2
1	20	100	100	7.92	0.001562
2	20	100	100	7.92	0.001562
3	20	100	100	7.92	0.001562
4	20	100	100	7.92	0.001562
5	20	100	100	7.92	0.001562
6	20	100	100	7.92	0.001562
7	20	100	100	7.92	0.001562
8	20	100	100	7.92	0.001562

Case study 2

This test is done with variable learning factors and variable inertia weight factors. The two learning factors were identical. The two sets of tests were done with population sizes of 1000 and 5000 respectively. The system load taken is 850 MW. It is evident that higher values of learning factors(2) and higher inertia weight factors(2) with a reduced population resulted in the requirement of higher runs to achieve the optimal value. The mean value of the least cost was observed to be higher as compared with higher population. The best cost values of the 3 seller system tested with 10 run are tabulated in table 3. Figure 9 to 14 show the convergence characteristics of the PSO algorithm with higher learning factors and higher inertia weight factors. The table 4 records the optimal loads shared as obtained by the optimal schedule for the parameters shown in the table 1. The optimal cost obtained with different learning factors satisfies the sharing of the load with different runs.

Case study 3

In this scenario, the load has been increased to 1000 MW while the learning factors were kept identical and inertial factor was maintained constant. The test results with lower learning factors tend to deviate the limits set on the thermal units while the optimal values are achieved without local minima at most of the higher values. The convergence characteristics of the 3-seller system with PSO algorithm with an increased load demand are shown in the figures 15 to 18. iI is evident from the convergence characteristics that higher learning factors improve the search for optimality while at lower the learning factors with increased load, the systems tend to deviate from the constraints set by the units.

Case study 4

The 8 seller systems are subjected to a load demand of 1000 MW with similar learning factors to observe the effectiveness of the PSO algorithm in arriving at the optimal situation. It is to be noted that with the above load, the 8-seller system in majority of the runs, converges optimally while giving the minimum costs. The convergence characteristics of the 8-seller system are shown in the figures 19 to 25. The system parameters of the 8-seller system are shown in the table 2.
The table 5 gives the results obtained from the simulation of the 8 seller loads with optimal costs in different runs.

Table 3 Effect of learning factors and inertia weight factors in PSO with 3 seller test system with a load demand, Pd=850 MW

Case	Population	c1	c2	ω	Pg1 (MW)	Pg2 (MW)	Pg3 (MW)	Cost $/hr
1	1000	0.5	0.5	0.1	349.4633	337.7681	162.799	8205.60
2	1000	0.75	0.75	0.1	371.9161	337.8086	140.3058	8196.90
3	1000	1	1	0.1	374.2324	346.5275	129.2707	8195.70
4	1000	1.25	1.25	0.1	374.8897	347.3022	127.8387	8195.60
5	5000	0.5	0.5	0.1	412.7588	313.1161	124.1556	8196.10
6	5000	0.75	0.75	0.1	383.5628	336.3891	130.0786	8195.10
7	5000	1	1	0.1	383.3596	332.6841	133.9868	8195.50
8	5000	1.25	1.25	0.1	402.1484	317.7843	130.0978	8195.60

Table 4 Effect of varying learning factors and inertia weight factors in PSO with 3 seller test system with a load demand, Pd=850 MW

Case	Population	c1	c2	ω	Pg1 (MW)	Pg2 (MW)	Pg3 (MW)	Cost $/hr
1	1000	0.75	0.75	0.09	304.5367	346.2911	125.5796	8195.30
2	1000	1	1	0.1	374.2324	346.5275	129.2707	8195.70
3	1000	1.25	1.25	0.15	375.6897	348.2449	126.0959	8195.50
4	1000	2	2	0.2	262.2838	399.9296	187.8171	8250.40
5	5000	0.75	0.75	0.09	387.8666	350.7525	111.4114	8195.70
6	5000	1	1	0.1	383.3596	332.6841	133.9868	8195.50
7	5000	1.25	1.25	0.15	387.747	350.5834	111.7001	8195.70
8	5000	2	2	0.2	387.8893	350.7846	111.3567	8195.80

Table 5 Effect of learning factors and inertia weight factors in PSO with 3 seller test system with a load demand, Pd=1000 MW.

Case	Population	c1	c2	ω	Pg1 (MW)	Pg2 (MW)	Pg3 (MW)	Cost $/hr
1	1000	0.5	0.5	0.1	475.6892	380.9801	143.3613	9583.8
2	1000	0.75	0.75	0.1	465.8433	291.2160	232.9712	9583.7
3	1000	1	1	0.1	469.3256	382.3542	148.3507	9583.6
4	1000	1.25	1.25	0.1	471.3374	381.9198	146.7733	9583.7
5	5000	0.5	0.5	0.1	453.1545	406.832	140.0440	9584.1
6	5000	0.75	0.75	0.1	479.5230	379.2922	141.2154	9584.1
7	5000	1	1	0.1	480.0932	379.9268	140.0105	9584.2
8	5000	1.25	1.25	0.1	481.0384	380.9677	138.0345	9584.3

Table 6 Effect of learning factors and inertia weight factors in PSO with 8 seller test system with a load demand, Pd=1000 MW.

Case	Population	c1	c2	ω	Pg1 (MW)	Pg2 (MW)	Pg3 (MW)	Pg4 (MW)	Pg5 (MW)	Pg6 (MW)	Pg7 (MW)	Pg8 (MW)	Cost $/hr
1	1000	0.5	0.5	0.1	33.7367	89.0585	25.9879	38.3894	39.6619	52.7749	98.8242	71.5970	4320.2
2	1000	0.75	0.75	0.1	37.7961	39.9356	50.1512	51.5126	56.9268	65.9956	60.4381	87.2746	4406.5
3	1000	1	1	0.1	50.9039	52.8882	66.9335	72.5250	63.3522	37.1112	65.6498	40.6666	4405.6
4	1000	1.25	1.25	0.1	35.9484	51.3584	57.6014	44.2324	56.9031	67.2429	63.0852	73.6587	4405.4

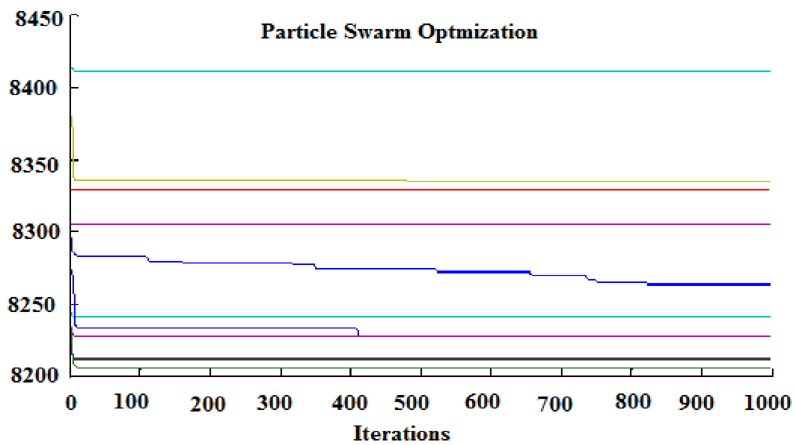

Figure 1 Convergence characteristics of PSO 3 seller system (c1=0.5,c2=0.5, ω=0.1,PS:1000

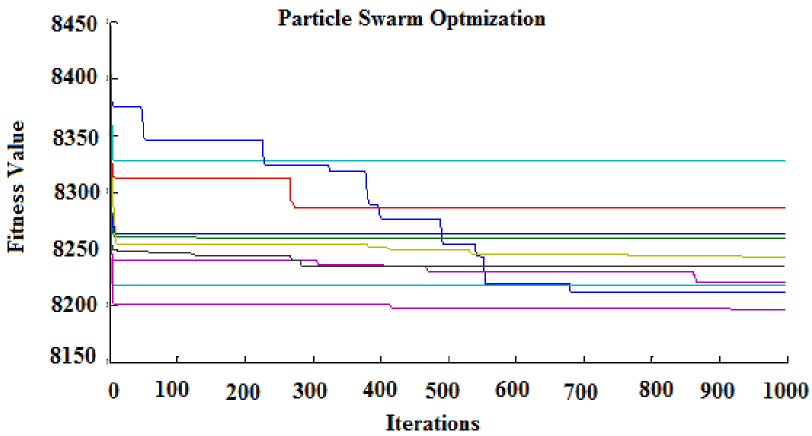

Figure 2 Convergence characteristics of PSO 3 seller system (c1 = 0.75, c2 = 0.75, ω =0.1, PS:1000)

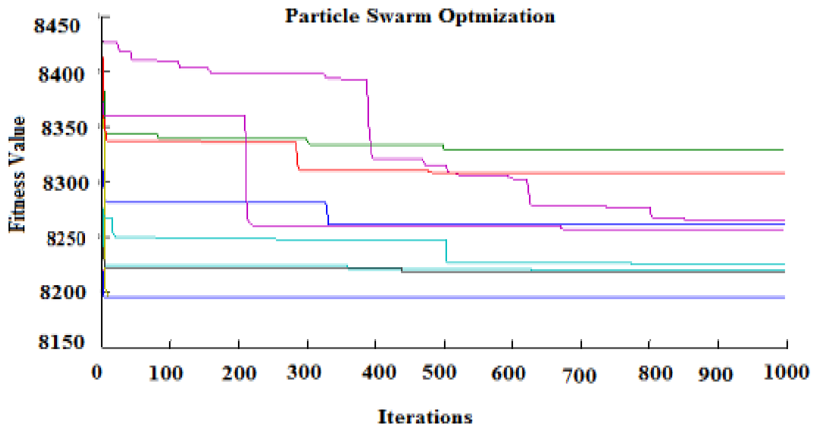

Figure 3 Convergence characteristics of PSO 3 seller system

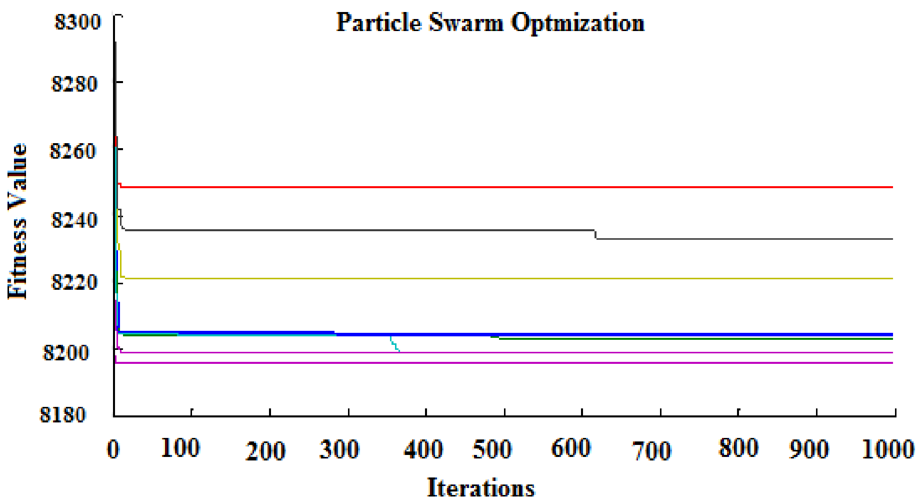

Figure 4 Convergence characteristics of PSO 3 seller system
(c1 = c2 = 1, ω =0.1, PS:1000

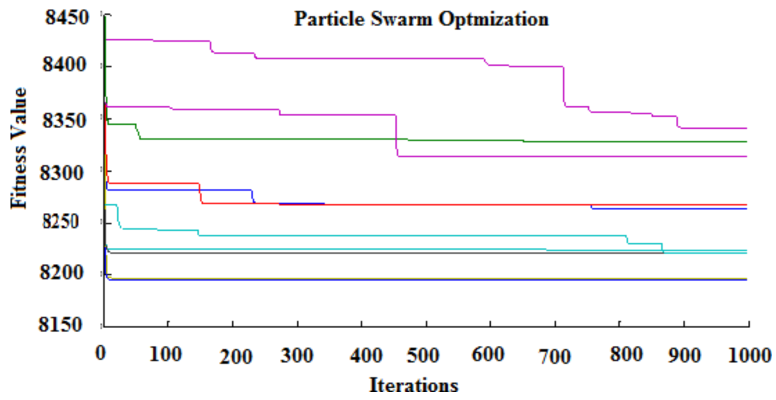

Figure 5 Convergence characteristics of PSO 3 seller system

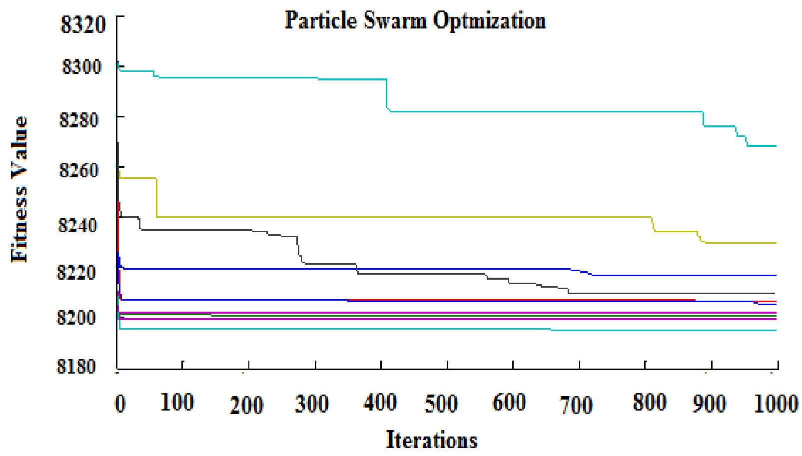

Figure 6 Convergence characteristics of PSO 3 seller system
(c1 = 0.75, c2 = 0.75, ω =0.1, PS:5000)

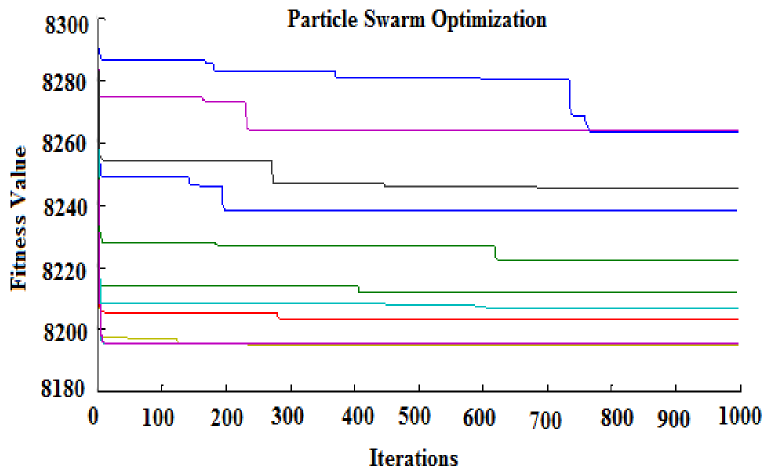

Figure 7 Convergence characteristics of PSO 3 seller system
(c1 = 1, c2 = 1, ω =0.1, PS:5000)

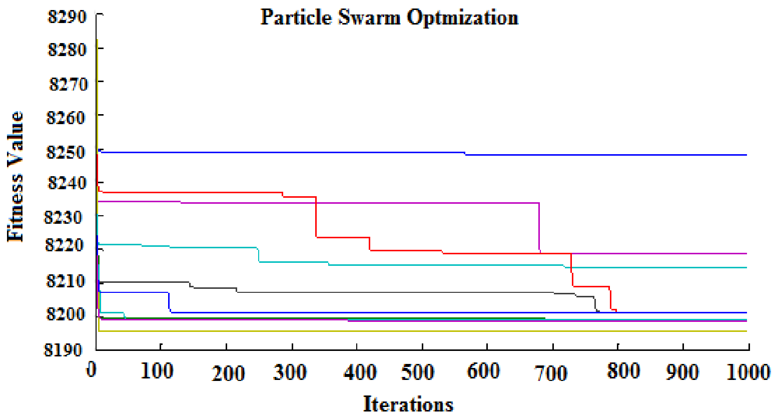

Figure 8 Convergence characteristics of PSO 3 seller system
(c1 = 1.25, c2 = 1.25, ω =0.1, PS:5000)

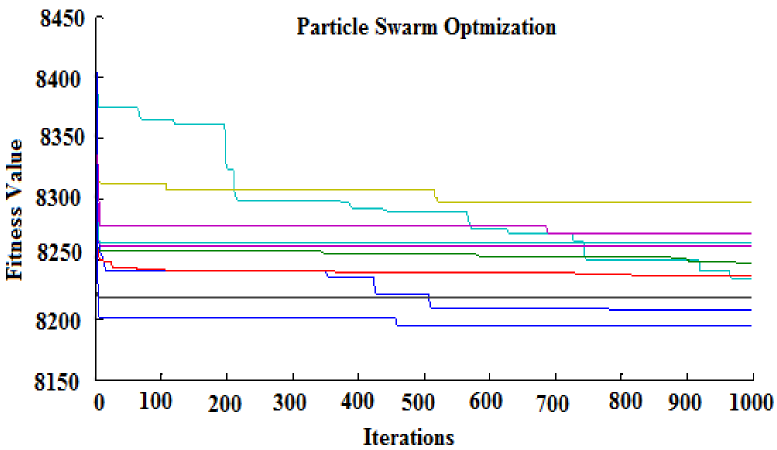

Figure 9 Convergence characteristics of PSO 3 seller system
(c1 = 0.75, c2 = 0.75, ω =0.09, PS:1000)

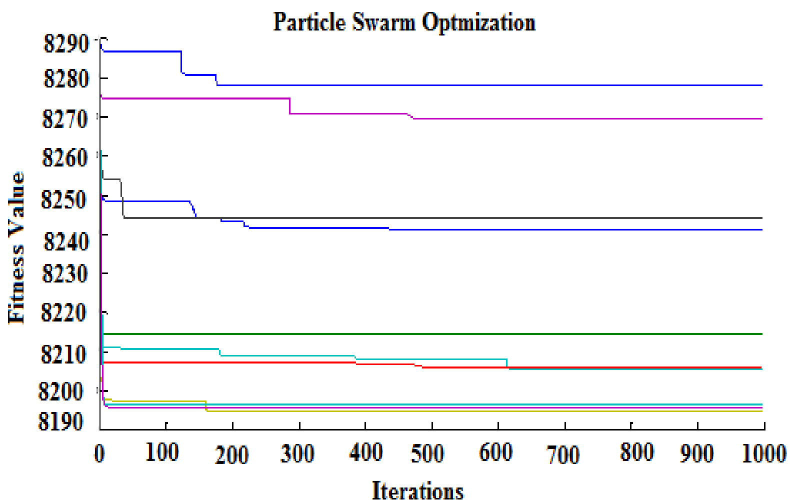

Figure 10 Convergence characteristics of PSO 3 seller system
(c1 = 0.75, c2 = 0.75, ω =0.09, PS:5000)

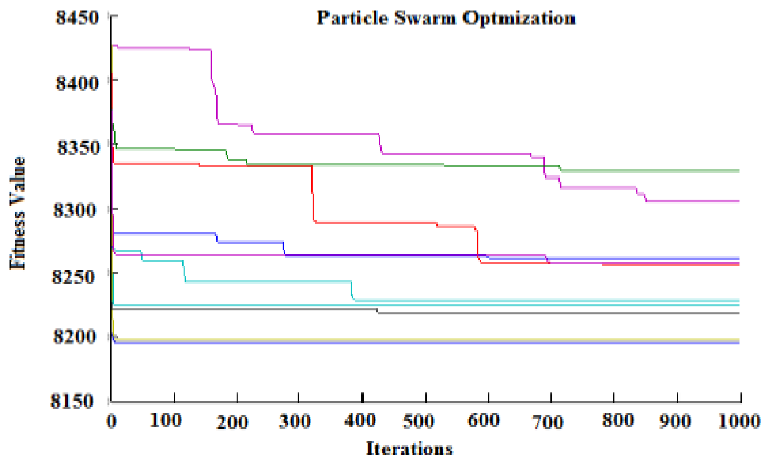

Figure 11 Convergence characteristics of PSO 3 seller system
(c1 = 1.25, c2 = 1.25, ω =0.15, PS:1000)

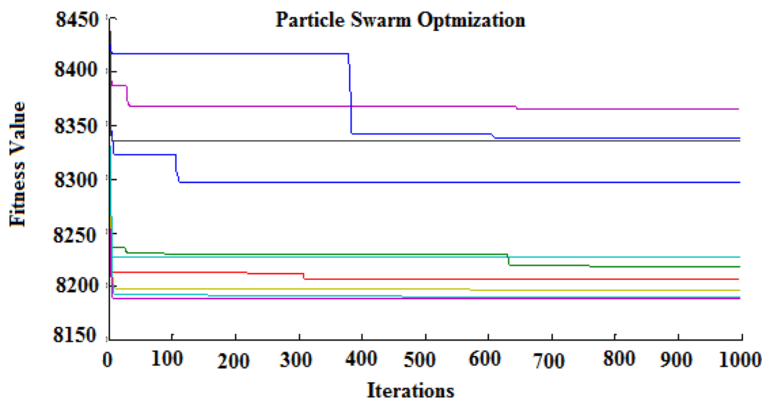

Figure 12 Convergence characteristics of PSO 3 seller system
(c1 = 1.25, c2 = 1.25, ω =0.15, PS:5000)

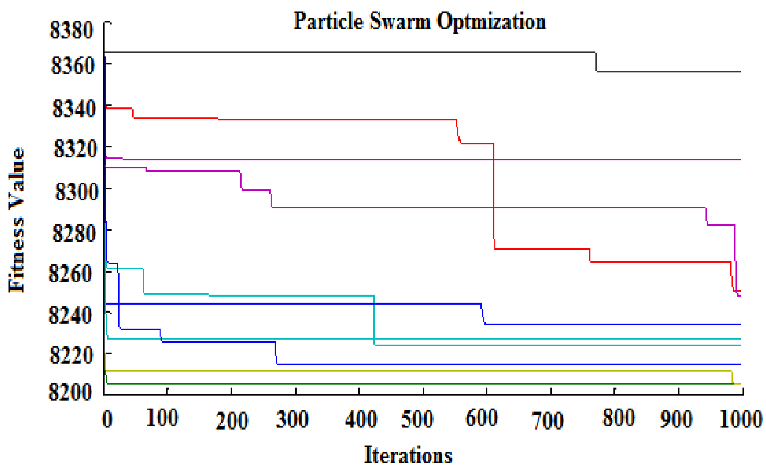

Figure 13 Convergence characteristics of PSO 3 seller system
(c1 = 2, c2 = 2, ω =0.2, PS:1000)

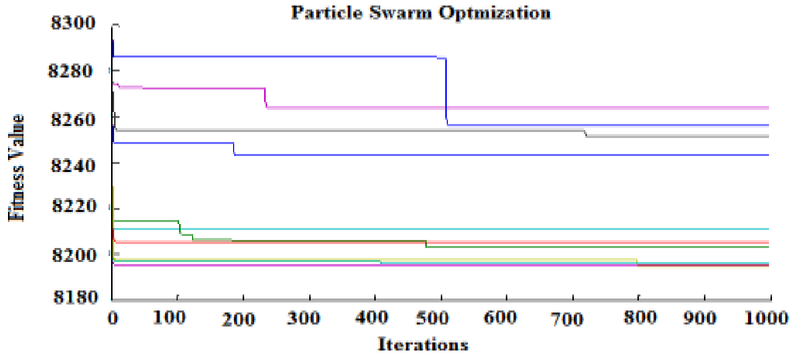

Figure 14 Convergence characteristics of PSO -3 seller system
(c1 = 2, c2 = 2, ω =0.2, PS:5000)

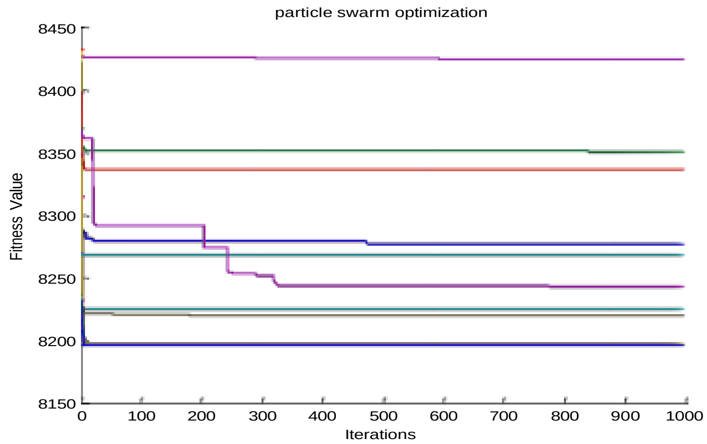

Figure 15 Convergence characteristics of PSO -3 seller system
(c1 = 0.5, c2 = 0.5, ω =0.1, PS:1000, PD=1000 MW)

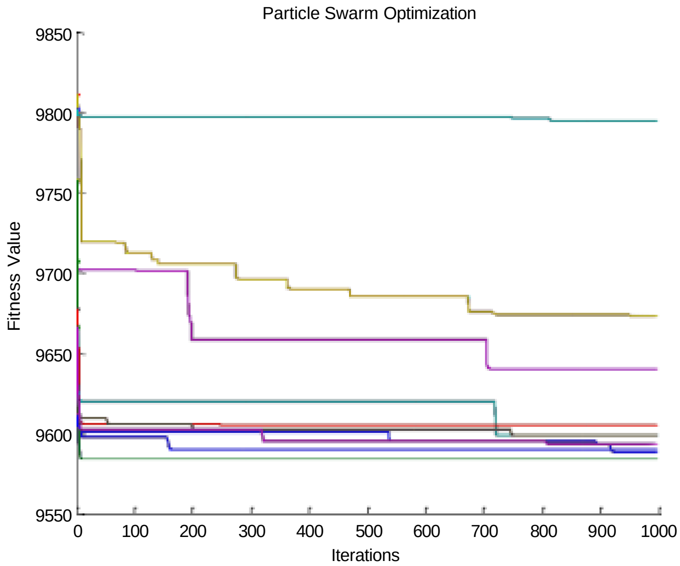

Figure 16 Convergence characteristics of PSO -3 seller system
(c1 = 0.75, c2 = 0.75, ω =0.1, PS:1000, PD=1000 MW)

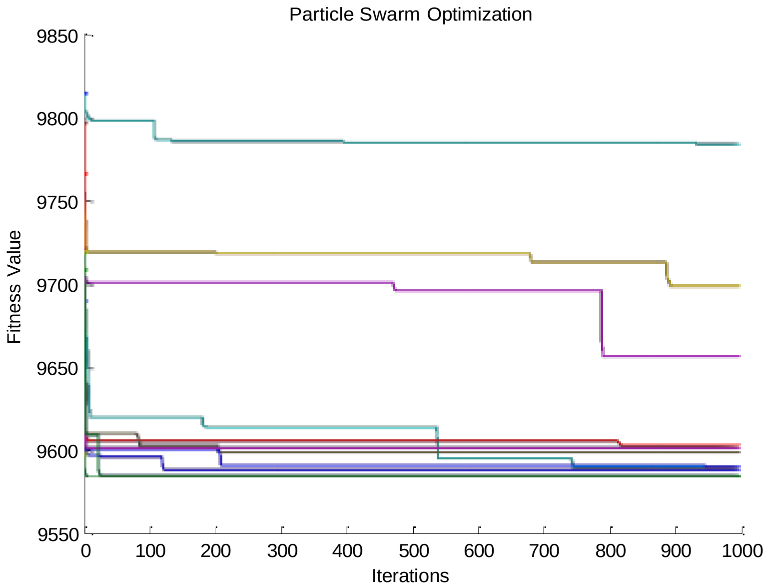

Figure 17 Convergence characteristics of PSO -3 seller system
(c1 = 1, c2=1, ω =01, PS:1000, PD=1000 MW)

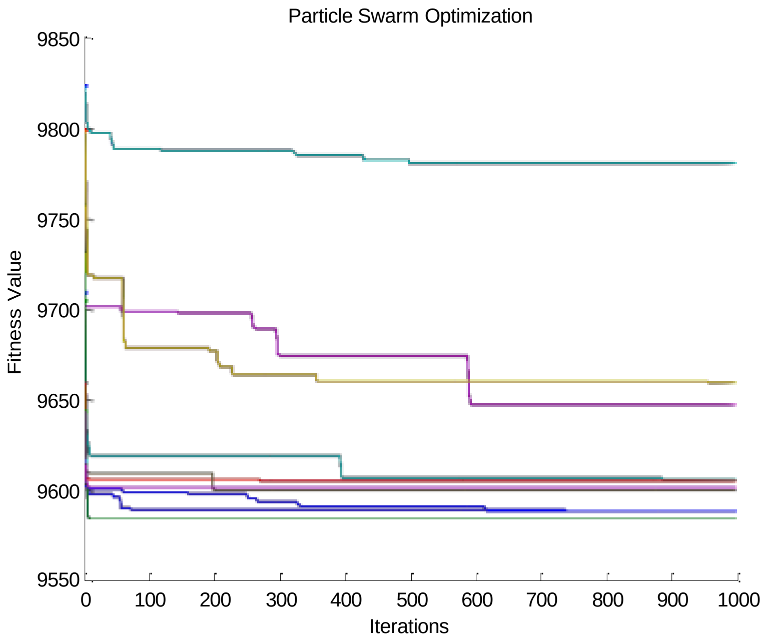

Figure 18 Convergence characteristics of PSO -3 seller system
(c1 = 1.25, c2=1.25, ω =01, PS:1000, PD=1000 MW)

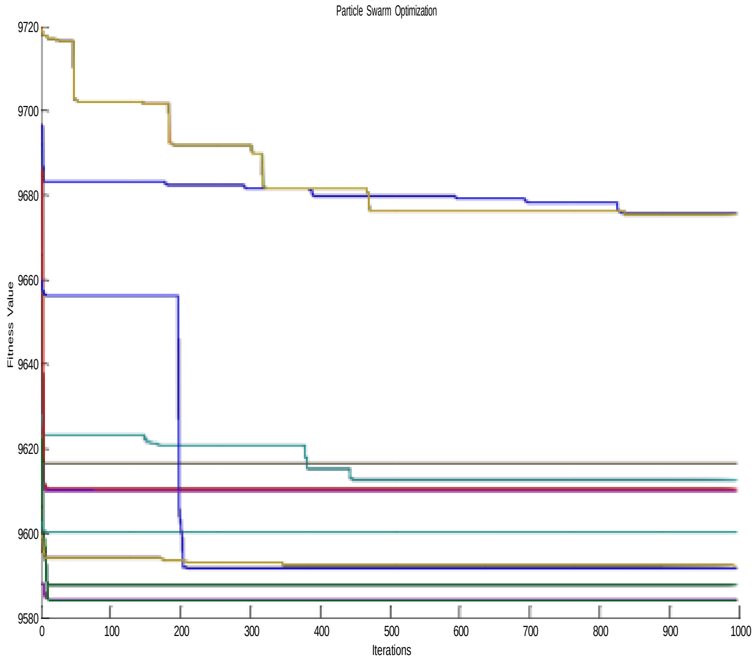

Figure 19 Convergence characteristics of PSO -3 seller system (c1 =c2 =0.5, ω =01, PS:5000, PD=1000 MW)

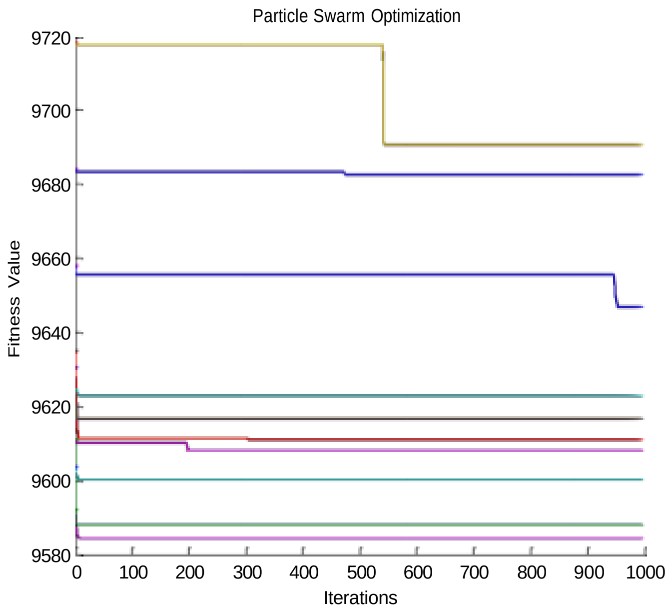

Figure 20 Convergence characteristics of PSO -3 seller system (c1 =c2 =0.75, ω =01, PS:5000, PD=1000 MW)

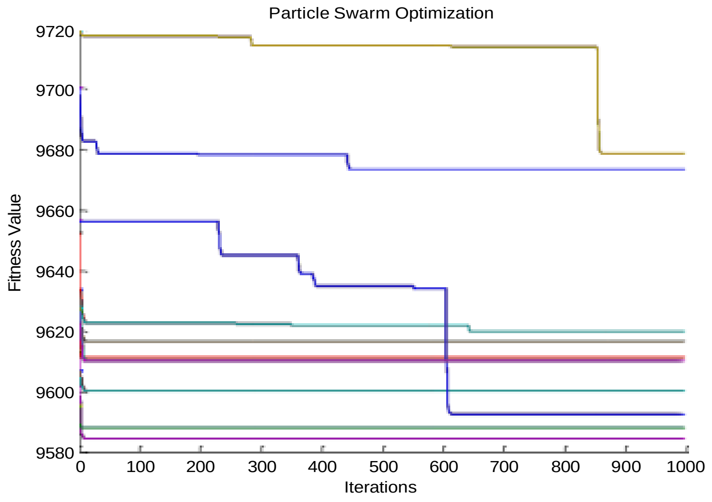

Figure 21 Convergence characteristics of PSO -3 seller system (c1 = 1, c2=1, ω =01, PS:5000, PD=1000 MW)

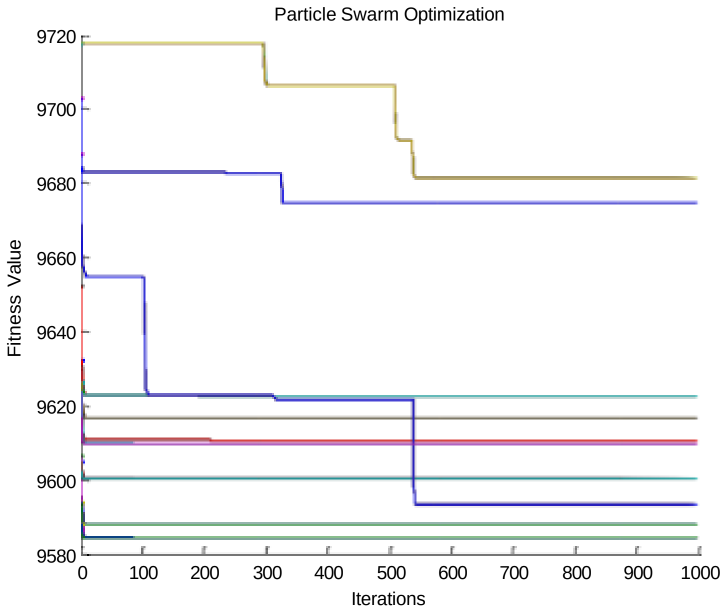

Figure 22 Convergence characteristics of PSO -3 seller system (c1 = 1.25, c2=1.25, ω =01, PS:5000, PD=1000 MW)

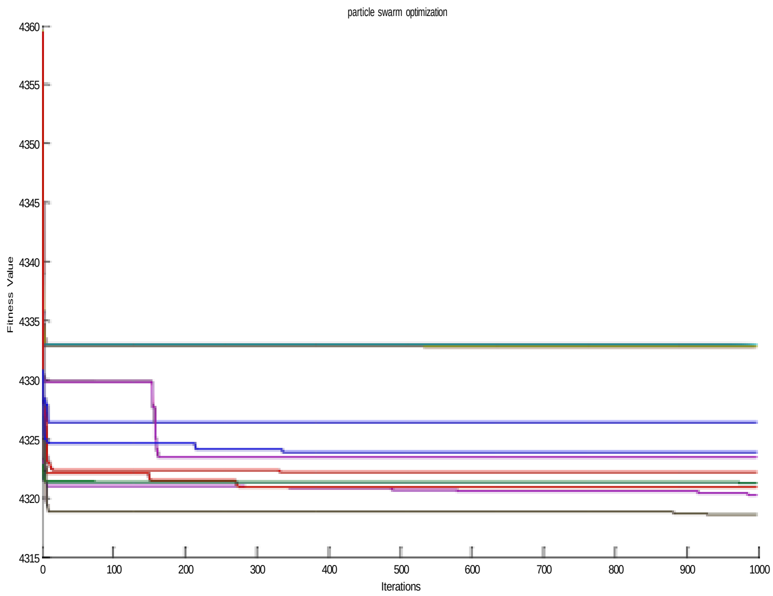

Figure 23 Convergence characteristics of PSO -8 seller system
(c1 = 0.5, c2=0.5, ω =0.1, PS:5000, PD=1000 MW)

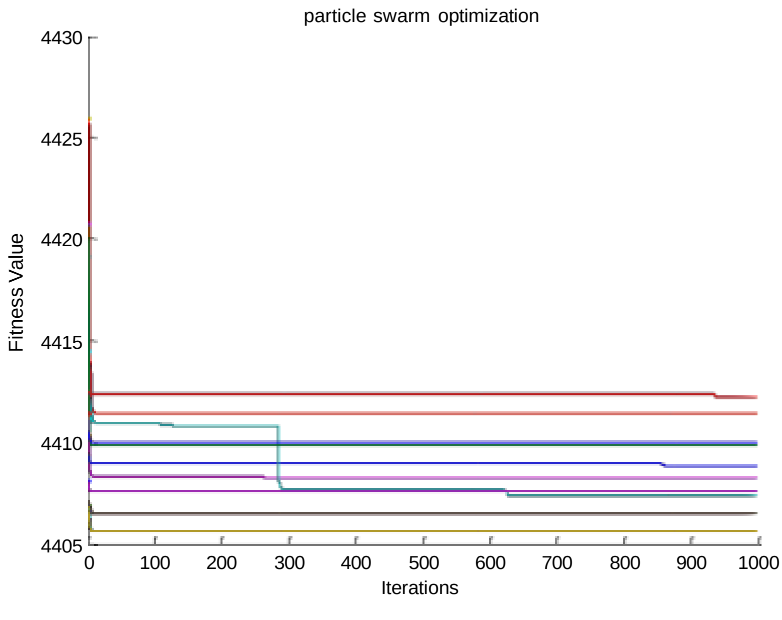

Figure 24 Convergence characteristics of PSO -8 seller system
(c1 = 0.75, c2=0.75, ω =0.1, PS:5000, PD=1000 MW)

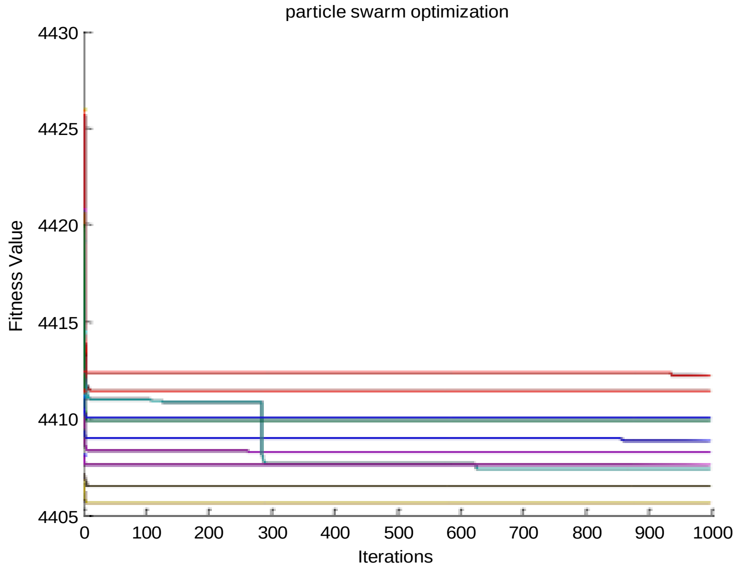

Figure 25 Convergence characteristics of PSO -8 seller system (c1 =c2 =1, ω =01, PS:5000, PD=1000 MW)

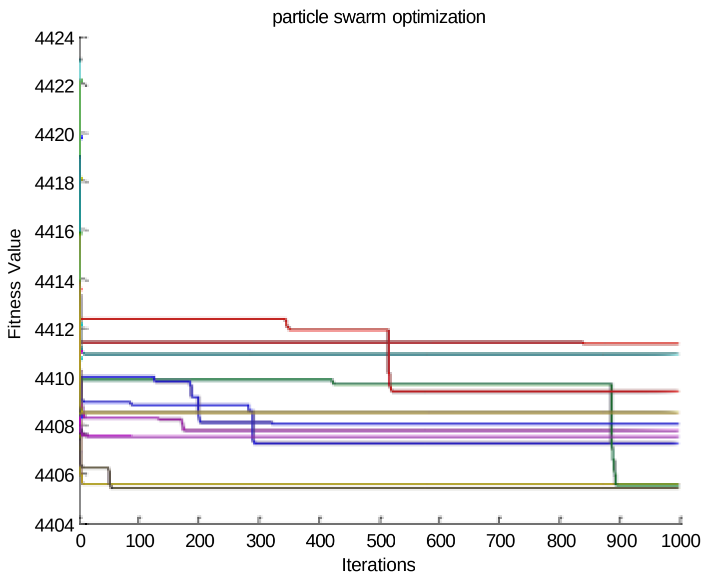

Figure 26 Convergence characteristics of PSO -8 seller system (c1 = 1.25, c2=1.25, ω =0.1, PS:5000, PD=1000 MW)

5. CONCLUSION

Particle Swarm Optimization is one of the simplest and efficient heuristic algorithms effectively implemented in the economic dispatch to obtain optimal solutions. Modified by the researchers in the pursuit of optimization over the years since its inception [26] PSO has shown encouraging results. The experimental simulations carried out by the authors by randomly selecting the learning factors and inertia weight factors yielded effective optimization in all the cases by considering the 3-seller system and 8 seller system in a deregulated environment with the inclusion of 3 different load scenarios namely 450 MW, 850 MW and 1000 MW respectively. The selection of the load plays an important criterion in the selection of learning factors as evident from the convergence characteristics. The convergence characteristics does not have multiple local optima as the increase in the learning factors. However, selection of the larger population resulted in a mean improvement in the resultant minimized cost values. A comprehensive analysis can be done in the future work to relate this random selection of factors through established mathematical relation and test for optimality and can be competitively utilized in comparison to other available algorithms. A more meaningful response can be achieved by considering the valve point effects with suitable samples selected from various test benches to improve the effectiveness.

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