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Analysis of PSO Strategies for Non-Convex Economic Load Dispatch

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Abstract

Economic load dispatch (ELD) is a problem in power system which determines individual contribution of each generation unit to meet the required demand satisfying generator constraints. Cost function for each unit in ELD problems are approximately represented by quadratic function and solved using mathematical methods. These methods require marginal cost information to find global optimal solution. The cost characteristics of generating units are non-convex because of prohibited operating zones, valve point loading effect, ramp rate limits etc. Thus problem becomes complex which challenges to optimum solution. Thus method providing optimized cost is needed. So Particle Swarm Optimisation (PSO) technique is adopted. To get best results, PSO strategies are implemented. Strategies are based on parameters used in the standard PSO algorithm. Results are provided with analysis and are compared with standard PSO which seems to give better convergence characteristics.

1. Introduction

Electric energy is the most popular artificial form of energy achieved from natural sources because it is transported easily at high efficiency and reasonable cost with large interconnection of the electric networks, the energy crisis in the world and continuous rise in prices, it is very essential to reduce the running costs of electric energy. A saving in the operation of the power system brings about a significant reduction in the operating cost as well as in the quantity of fuel consumed [1]. The ELD problem is one of the fundamental issues in power system operation. ELD problems can be solved by using methods like, lambda iterative method, piecewise linear programming, base point and participation factor method and gradient method etc. [2].

Large turbine generating units with multi-valve steam turbines exhibit a large variation in the input-output characteristic functions. In steam turbine, when each steam admission valve opens creates ripple-like in heat rate curve. Thus heat rate curve becomes non-smooth. The conventional method fails to find solution for such problem. The problem is known as valve point loading effect problem [3]. When a generating unit is off-line due to fault occurs in shaft bearing or vibrations of machine or its accessories, during the working schedule, makes cost curve with number of discontinuities. The discontinuities are also known as prohibited operating zone. The prohibited regions show discontinuities in cost curve, constituting a non-convex solution space, and problem becomes non-convex economic load dispatch problem (NCELD) [3]. For optimum scheduling, electric utilities are adjusted. Thus output of generator cannot be adjusted whenever load changes. Hence previous hour generation restrict the operating region of the entire on-line unit. This fact gives rise to ramp rate limits. Characteristic becomes nonlinear also suffers from problem of dimensionality and excessive evaluation at each stage [3]. In case of the nonlinear characteristics of the units, there is a demand for techniques that do not have restrictions on the shape of fuel cost curves [3]. Hence the PSO technique can generate superior solutions within shorter calculation time and stable convergence characteristic than other stochastic methods without considering shape of cost curve. NCELD finds optimum fitness value during the search. To overcome this difficulty, parameters used in PSO algorithm, are adapted gives rise to new strategies. It helps to improve rate of convergence. Within few iteration, the algorithm provides the diversity of problems to be solved with global optimal solution.

In 1995, Kennedy and Eberhart first introduced the PSO method, motivated by social behaviour of organisms. It was modelled by a simplified social system, and becomes strong to solve continuous nonlinear optimization problems [4].

Objective of this paper include (i) to analyse the solution of NCELD problem by implementing various PSO strategies; (ii) to analyse the effect of nonlinearly varying inertia weight factor on NCELD and (iii) to extend algorithm of crazy particle PSO strategy for non-linear decrease in velocity. The objective also includes to see the effect of non-linear decrease in crazed velocity for performance of individual unit with the global best performance. The solutions obtained using these strategies gives near optimum solution. The results obtained are found in good agreement with results reported earlier.

2. Problem statement

To satisfy changing consumer load demand, ELD generate sufficient electricity with minimum cost under various constraints.

2.1. Objective Function

The objective is to minimize fuel cost of thermal power plant. The quadratic cost function is considered here as objective function to determine least cost.

$$\text{Minimize} \quad F_T = \sum_{i=1}^{n} F_i P_i \tag{1}$$

$$F_T = F_i P_i = A_i P_i^2 + B_i P_i + C_i \tag{2}$$

F_T -Total generation cost,
F_i - Cost function of generator i,
P_i - Power of generator i,
n - Number of generators
A_i, B_i, C_i are the cost coefficients of generator.

2.2. Constraints

The constraints considered to solve ELD problem are,

2.2.1. Power Balance Equation:

a) Without transmission loss

$$\sum_{i=1}^{n} P_{gi} = P_D \tag{3}$$

b) With transmission loss

$$\sum_{i=1}^{n} P_{gi} = P_D + P_L \tag{4}$$

P_L -Total transmission line losses
P_D -Total system demand

The constraint of power balance equation using transmission loss is solved by concept of dependent loading [5]. Loading of any one of the units is selected as the dependent loading P_d and its present value is replaced by the value calculated by the equation,

$$P_d = P_D + P_L - \sum_{\substack{i=1 \\ i \neq d}}^{n} P_i \tag{5}$$

With known power demand, transmission losses and summation of remaining generator loadings excluding considered loading as dependent loading, satisfies equations (3) and (4).

2.2.2. Transmission Loss:

The accurate form of the loss formula, Kron's formula.

$$P_L = B_{00} + \sum_{i=1}^{NG} B_{i0} P_{gi} + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{ji} \tag{6}$$

Where P_{gi} and P_{gj} are the real power injections at the i^{th} and j^{th} buses respectively. With certain assumed conditions B_{00}, B_{i0} and B_{ij} are constants. NG is number of generation units.

2.2.3. Minimum and maximum power limits:

Each generator's maximum and minimum limits should be satisfied by generation output [6]. The corresponding inequality constraints for each generator are

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \tag{7}$$

Where P_{gi}^{min} and P_{gi}^{max} are the minimum and maximum output.

2.2.4. Generator ramp rate limits

The assumption of generator output adjusted instantaneously simplifies the ELD problem, although it does not consider the operating process of generation unit. The operation of on-line generation unit is restricted by ramp rate limit [3]. The three possible operating conditions of generation unit can be considered as (a) steady state operation (b) increasing generating power operation and (c) decreasing generating power operation. Fig1. represent all three cases respectively.

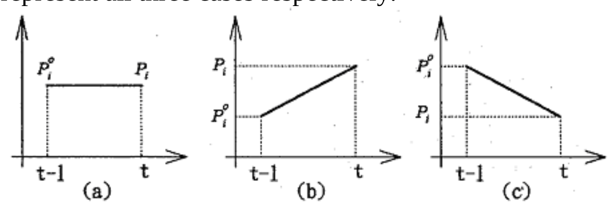


Figure 1: Three possible situations of an on-line unit

The operating conditions are given by following inequality constraints,

i) If generation increases

$$P_i - P_i^o \leq UR_i \tag{8}$$

ii) If generation decreases

$$P_i^o - P_i \leq DR_i \tag{9}$$

where P_i^0 is the previous output power of unit i.
DR_i and UR_i are the down ramp and up ramp limits

Rearranging (8), (9) and (10), then constrained optimization problem is modified as follows,

$$\text{Max}\left(P_i^{min}, P_i^o - DR_i\right) \leq P_i \leq \text{Min}(P_i, P_i^o + UR_i) \tag{10}$$

2.2.5 . Generator prohibited operating zones

The operating zone of a generating unit may not be available always for power generation due to limitations in practical operating constraints [3] as shown in Fig.2

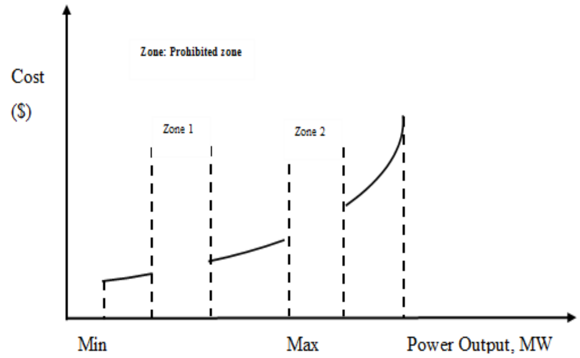


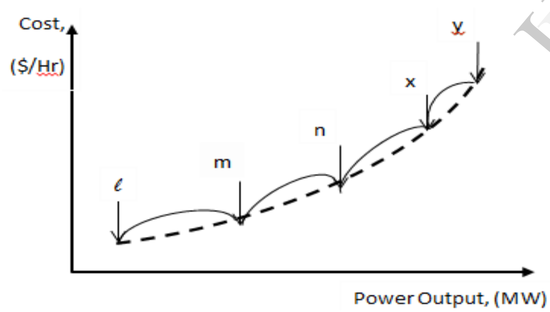
Figure 2: Cost functions with 2 prohibited operating zones

$$P_i \in \begin{cases} P_i^{min} \le P_i \le P_{i1}^L \\ P_{ik-1}^U \le P_i \le P_{ik}^L \\ P_{izi}^U \le P_i \le P_i^{max} \end{cases} \qquad (11)$$

where $P^l i,k$, and $P^u ik$, are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. $N_{PZ,i}$ is the number of prohibited zones of unit *i*.

2.2.6 Valve Point Effects

The generating unit containing multi-valve steam turbines creates variation in the fuel-cost functions. Since the valve point results in the ripples as shown inFig.3.



l :primary valve m:Secondary valve
n:Tertiary valve x: Quaternary valve
y: Quinary valve

Figure 3: Valve Point effects

The valve-point effect, so due to ripples sinusoidal functions are added to the quadratic functions. Therefore, quadratic functions equation should be replaced follows [6]:

$$\hat{F}_i(P_i) = F_i(P_i) + \left| e_i \sin * \left(f_i * \left(P_i^{min} - P_i \right) \right) \right| \qquad (12)$$

Where e_i and f_i are the coefficients of unit *i* reflecting valve point effects.

3. Particle swarm optimization

PSO is a population based optimization method, motivated by group activities of bird flocking or fish schooling. The system is initialized with a population (solutions) of random solutions and searches for optima by updating generations. PSO simulates the behaviors of bird flocking. A group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO is used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles [7].

In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained by any particle in the population. This best value is a global best and called gbest. A particle from population is the local best is p-best. The particle having pbest and gbest, updates its velocity and positions with following equation (14) and (15).

$$V_i^{k+1} = \omega V_i^k + C_1 r_1 \left(Pbest_i^k - x_i^k \right) + C_2 r_2 \left(Gbest^k - x_i^k \right) \qquad (13)$$

$$P_{gid}^{t+1} = P_{gid}^t + v_{id}^{k+1} \qquad (14)$$

In the above equation, the first bracket term is called particle memory influence. The second bracket term is called swarm influence. V_i^k which is the velocity of i^{th} particle at iteration 'k' must lie in the range

$V_d^{min} \le V_d^i \le V_d^{max}$

$$V_d^{max} = +0.5 * P_{g\,max} \qquad (15)$$

$$V_d^{min} = -0.5 * P_{g\,min} \qquad (16)$$

The constants C_1 and C_2 pull each particle towards pbest and gbest positions. The acceleration constants C_1 and C_2 are often set to be 1.5 to 2.2. In general, ω_{max}= 0.9 and ω_{min}= 0.4. The inertia weight ω is set according to the following equation,

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{iter_{max}} * iter \qquad (17)$$

ω is the inertia weighting factor
ω_{max} - maximum value of weighting factor
ω_{min} - minimum value of weighting factor
$iter_{max}$ - maximum number of iterations
iter - current number of iteration

4. Strategies implemented to PSO

To solve complex ELD problems are becoming challenge as it contains valve point effects, prohibited zones, ramp rate limits etc. Because of chances of occurrence of premature convergence in PSO solution, it needs to find some modifications. Hence various PSO strategies are discussed and analyzed with examples to avoid limitations.

4.1 Inertia weight PSO (IWPSO)

4.1.1 LDWPSO:

In standard PSO (SPSO) algorithm, ω is decreasing linearly. This linearly decreasing inertia weight (LDWPSO) is given by the formula (17) [8].

4.1.2 MPSO:

To avoid low precision in solution of SPSO algorithm by equation (17), Qing-he et al.[8] has proposed a modified PSO (MPSO) algorithm in which nonlinearly varying inertia weight ω is defined as in equation (18),

$$\omega_i^{k+1} = \omega_{max} - (\omega_{max} - \omega_{min}) \left(\frac{iter}{iter_{max}}\right)^{0.5} \qquad (18)$$

4.1.3 NPSO:

To avoid local optimum and slow convergence in (17) and (18), new method of decreasing inertia weight (NPSO) [9] is given as,

$$\omega_i^{k+1} = \omega_{max} - (\omega_{max} - \omega_{min}) \left(\frac{iter}{iter_{max}}\right)^{0.5} \left(\frac{Fb^k}{Fit_i^k}\right)^m \qquad (19)$$

Where Fb^k is the optimal global solution, Fit^k_i is the local optimal solution, and m=2.

4.2 Constriction factor PSO (CFPSO)

4.2.1 CFPSO$_1$:

To ensure the convergence of SPSO, use of constriction factor (K) is proposed by Lim, *et al*. [10]. In SPSO velocity updating equation is given as,

$$V_i^{k+1} = K\left(V_i^k + C_1 r_1 (Pbest_i^k - x_i^k) + C_2 r_2 (Gbest^k - x_i^k)\right) \qquad (20)$$

Where,

$$K = \frac{2}{|2-\varphi-\sqrt{\varphi^2-4\varphi}|}, \varphi = c_1 + c_2 \ , \ \varphi > 4 \qquad (21)$$

Where C_1=C_2=2.05.

4.2.2 CFPSO$_2$:

To get the fast convergence of SPSO, Khamsawang *et.al* [11] has proposed velocity as,

$$V_i^{k+1} = K\left(\omega * V_i^k + C_1 r_1 (Pbest_i^k - x_i^k) + C_2 r_2 (Gbest^k - x_i^k)\right) \qquad (22)$$

4.3 Time Varying Acceleration Coefficients (PSO_TVAC)

To enhance the global search capability of PSO algorithm, Chatrvedi *et al.* [12] has proposed the concept of TVAC. By decreasing cognitive component (C_1) and increasing social component (C_2) premature convergence of PSO can be avoided. Selection of C_1 and C_2 for velocity updating equation (14) as follows,

$$C_1 = (C_{1f} - C_{1i}) \frac{iter}{iter_{max}} + C_{1i} \qquad (23)$$

$$C_2 = (C_{2f} - C_{2i}) \frac{iter}{iter_{max}} + C_{2i} \qquad (24)$$

Where, C_{1i}, C_{1f}, C_{2i} and C_{2f} are initial and final values of cognitive and social components.

4.4 Crazy Particle PSO (CRPSO)

Global search ability over SPSO, with the help of CRPSO method is proposed by Chatterjee *et. al*. [13]. The velocity updated with crazed velocity is as follows,

Position and velocity updating:

$$V_i^{k+1} = r_2 V_i^k + (1 - r_2) C_1 r_1 (Pbest_i - x_i^k) + (1 - r_2) C_2 (1 - r_1)(gbest - x_i^k) \qquad (25)$$

Change in velocity is modelled as in (26),

$$V_i^{k+1} = r_2 * sign\, r_3 . V_i^k + (1 - r_2) C_1 r_1 (Pbest_i - x_i^k) + (1 - r_2) C_2 (1 - r_1)(gbest - x_i^k) \qquad (26)$$

In (25), sign (r_3) is defined as in (27).

$$sign(r_3) = \begin{cases} -1 & (r_3 \le 0.05) \\ 1 & (r_3 > 0.05) \end{cases} \qquad (27)$$

Inclusion of craziness:

The particles may be crazed in accordance with (28), before updating its position.

$$V_i^{k+1} = V_i^k + Pr(r_4) * sign(r_4) * V_i^{craziness} \qquad (28)$$

Where, $Pr(r_4)$ and sign r_4 are defined, respectively as,

$$Pr(r_4) = \begin{cases} 1 & (r_4 \le P_{craz}) \\ 0 & (r_4 > P_{craz}) \end{cases} \qquad (29)$$

$$sign(r_4) = \begin{cases} 1 & (r_4 \ge 0.5) \\ -1 & (r_4 < 0.5) \end{cases} \qquad (30)$$

Random numbers r1, r2, r3 and r4 are chosen randomly. It should lie between 0 to 1. Suitable selection of parameters [15], may provide superior results to PSO.

4.5 Variations of $V_i^{creziness}$ (CP_1, CP_2, CP_3) :

CRPSO algorithm [13] uses decreased in crazed velocity linearly in the range of 10 to 1 (CP_1). To see the effect of non-linear decrease in crazed velocity (CP_2) equation (32) is proposed here. The effects of non-linear decrease in crazed velocity (CP_3); for individual performance of the unit with respect to global optimal solution is proposed here by equation (33),

4.5.1 CP_1:

$$V_i^t = V_i^{creziness,max} - \frac{\left(V_i^{creziness,max} - V_i^{creziness,min}\right)}{iter_{max}} * iter \quad (31)$$

4.4.6 $CP2$:

$$V_i^t = V_i^{creziness,max} - \left(V_i^{creziness,max} - V_i^{creziness,min}\right) * \left(\frac{iter}{iter_{max}}\right)^{0.5} \quad (32)$$

4.5.3 CP_3:

$$V_i^t = V_i^{creziness,max} - \left(V_i^{creziness,max} - V_i^{creziness,min}\right) * \left(\frac{iter}{iter_{max}}\right)^{0.5} * \left(\frac{F_b^t}{Fit_i^t}\right)^2 \quad (33)$$

5. Case studies

To obtain the result programs are developed in MATLAB and spread sheet. The results of the above strategies are presented for three, six and thirteen units system.

Example 5.1: Three Unit Thermal System [3]

Table 1: Data with valve point effect

Unit	a_i	b_i	C_i	e_i	f_i	P_i^{min}	P_i^{max}
1	0.001562	7.92	561	300	0.0315	100	600
2	0.001940	7.85	310	200	0.042	100	400
3	0.004820	7.97	78	150	0.063	50	200

Table 2: B-Coefficients for three units system

B_{ij} =	0.0000676	0.00000953	-0.0000057
	0.00000953	0.00005210	0.00000901
	-0.00000507	0.00000901	0.00029400
B_{oi} =	-0.0007760	-0.0000342	0.01890
B_{oo} =			0.040357

For the system load of 850MW.

Example 5.2: Six Unit Thermal System load for 1263 MW with prohibited zones and ramp rate limits [3].

Table 3: Operating limits for six units system

Unit	a_i ($)	b_i ($/MW)	C_i($/MW^2)	P_i^{min}	P_i^{max}
1	0.007	240	7	100	500
2	0.0095	200	10	50	200
3	0.009	220	8.5	80	300
4	0.009	200	11	50	150
5	0.008	220	10.5	50	200
6	0.0075	190	12	50	120

Table 4: B-Coefficients for six units system

B_{ij} =	0.0017	0.0012	0.0007	-0.0001	-0.0005	-0.0002
	0.0012	0.0014	0.0009	0.0001	-0.0006	-0.0001
	0.0007	0.0009	0.0031	0.0000	0.001	-0.0006
	-0.0001	0.0001	0.0000	0.0024	-0.0006	-0.0008
	-0.0005	-0.0006	-0.001	-0.0006	0.0129	-0.0002
	-0.0002	-0.0001	-0.0006	0.0008	-0.0002	0.015
B_{oi} =	-0.0003908	-0.0001297	0.000704719	0.0000591	0.0002161	0.0006635
B_{oo} =						0.056

Table 5: Prohibited operating zones and ramp rate limits

Unit	P_i^o	UR_i (MW/h)	DR_i (MW/h)	Prohibited zone (MW)
1	440	80	120	[210,240][350,380]
2	170	50	90	[90,110][140,160]
3	200	65	100	[150,170][210,240]
4	150	50	90	[80,90][110,120]
5	190	50	90	[90,110][140,150]
6	110	50	90	[75,85][100,105]

Example 5.3: Thirteen Unit System load for 1800MW with valve point loading [14].

6. Results:

6.1 Results with IWPSO for three, six & thirteen units are shown in Table 6.

Table 6: Results of IWPSO

Units		IWPSO			SPSO [3]
		LDWPSO	MPSO	NPSO	
3	Fuel Cost	8251.36	8251.17	8251.51	8234.07
	Iterations	10	10	10	50
6	Fuel Cost	15444.47	15451.14	15451.11	15451.31
	Iterations	10	10	10	50
13	Fuel Cost	18160.8	18165.1	18165.17	18151.072
	Iterations	20	20	20	50

Convergence obtained by IWPSO for three, six and thirteen units systems are observed. For three units, Fig.4,5 and 6 shows that LDWPSO converges faster also time required to reach minimum cost is less. The ratio of global and local optimal value of cost is very small hence change in MPSO and NPSO characteristics is very small.

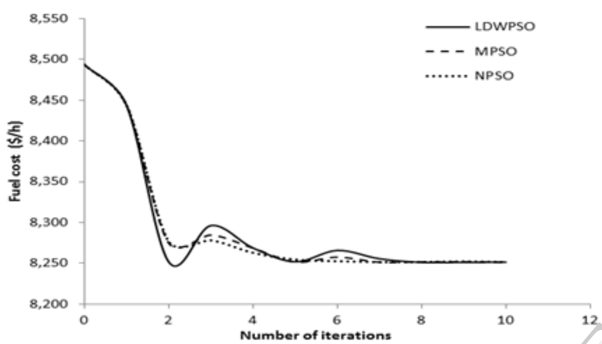


Figure 4: Convergence of three units for IWPSO

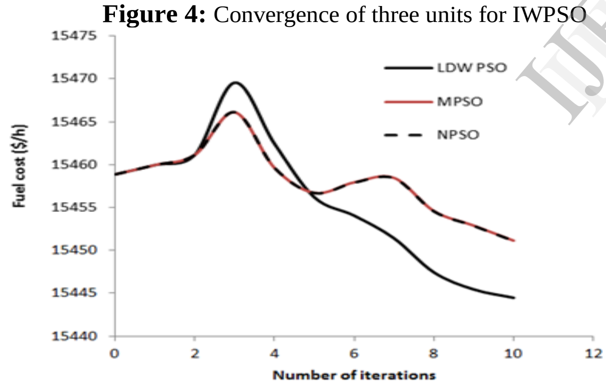


Figure 5: Convergence of six units for IWPSO

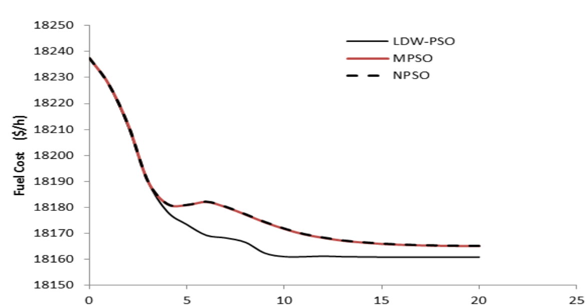


Figure 6: Convergence of thirteen units for IWPSO

6.2 Results with CFPSO for three and six units are given in Table 7.

Table 7: Results for Constriction factor

Units		CFPSO		SPSO [3]	$CFPSO_1$
		$CFPSO_1$	$CFPSO_2$		
3	Fuel Cost	8234.07	8251.06	8234.07	8234..07
	Iterations	50	50	50	50
6	Fuel Cost	15444.76	15444.86	15451.31	-
	Iterations	20	20	50	-

Fig.7 and 8 shows convergence for CFPSO for three and six units. It is seen that $CFPSO_2$ shows faster convergence. In Fig.7, for three units system, $CFPSO_1$ gives minimum cost than $CFPSO_2$. Hence the method is superior to SPSO.

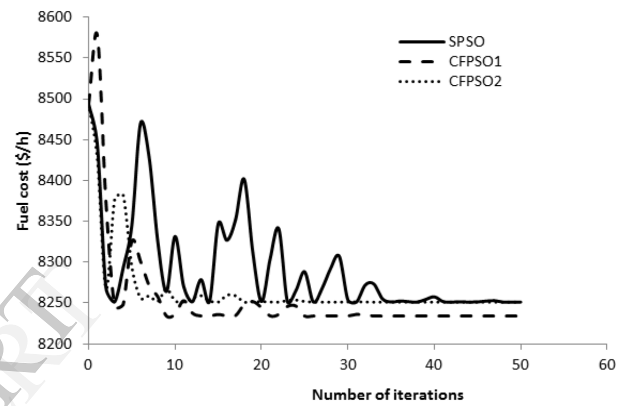


Figure 7: Convergence of three units for CFPSO

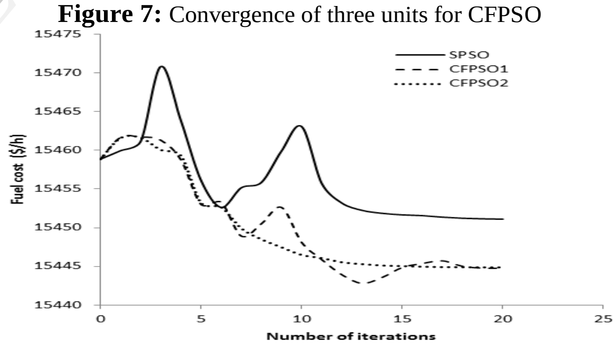


Figure 8: Convergence of six units for CFPSO

6.3 Table 8 shows result obtained with PSO_TVAC for three, six and thirteen units.

Table 8: Results for PSO_TVAC

Units		PSO_TVAC	PSO_TVAC [12]
3	Fuel Cost	8498.84	8440.901
	Iterations	25	50
6	Fuel Cost	15445.72	-
	Iterations	20	-
13	Fuel Cost	18171.38	17963.879
	Iterations	20	50

PSO_TVAC for three, six and thirteen units shows convergence in Fig.9,10 and 11. For each iteration cost obtained for PSO_TVAC is less than SPSO. Convergence of PSO_TVAC is faster also time required to reach minimum cost is less. Hence PSO_TVAC is better solution than SPSO for NCELD problems.

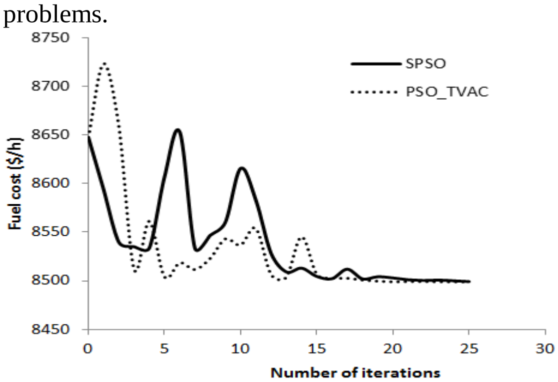


Figure 9: Convergence of three units for PSO_TVAC

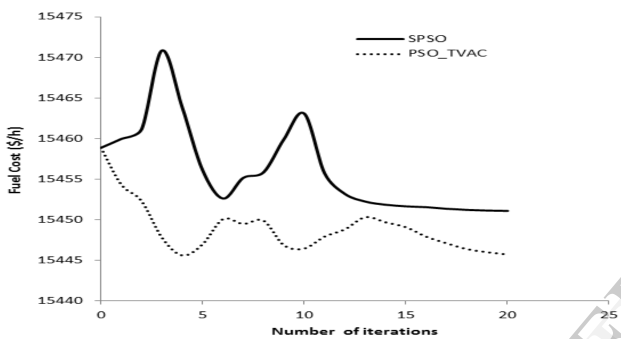


Figure 10: Convergence of six units for PSO_TVAC

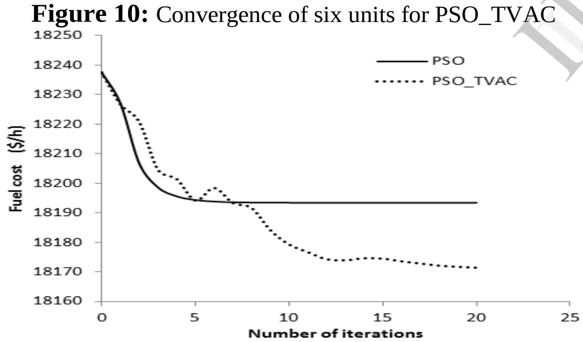


Figure 11: Convergence of thirteen units for PSO_TVAC.

6.4 Results with PSO_TVAC for three, six & thirteen units are shown in Table 9.

Table 9: Results for CRPSO

Units		CRPSO	CRPSO [12]
3	Fuel Cost	8499.2	8440.901
	Iterations	25	50
6	Fuel Cost	15450.2	15449.3394
	Iterations	20	50
13	Fuel Cost	18135.86	18152.197
	Iterations	20	50

Convergence for CRPSO of three, six and thirteen units is shown in Fig.12, 13 and 14. For three and thirteen units system it is clearly seen that CRPSO converges faster in less time. Number of iterations required to converge are less. For six units system, characteristics of CRPSO are deflecting but still show less costs than SPSO. Hence CRPSO gives better solution than SPSO for NCELD problems. More number of iterations will improves the result and smoothen the cost characteristics.

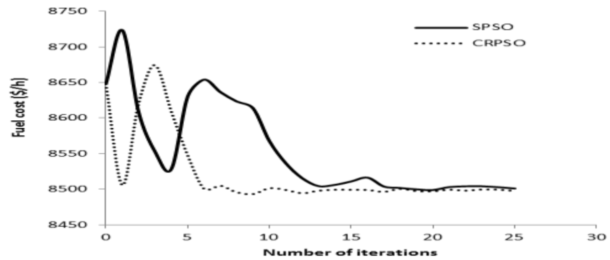


Figure 12: Convergence of three units for CRPSO

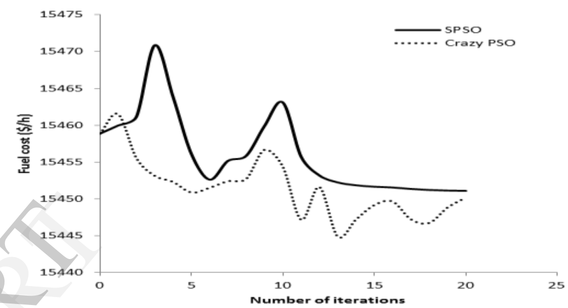


Figure 13: Convergence of six units for CRPSO

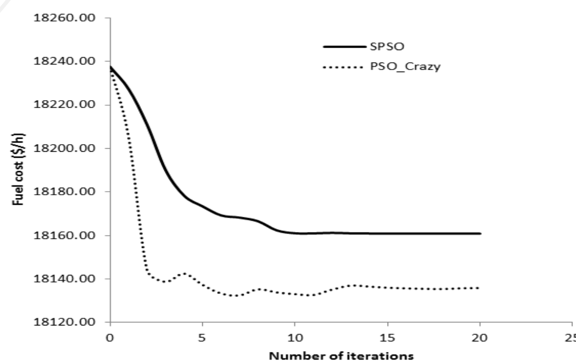


Figure 14: Convergence of thirteen units for CRPSO

6.5 Table 10 gives result obtained for CP_1, CP_2 & CP_3 for thirteen units system.

Table 10: Results for CP_1, CP_2, CP_3

Units		CP_1	CP_2	CP_3	CP1 [12]
13	Fuel Cost	18135.86162	18130.77083	18139.135	18152.197
	Iterations	20	20	20	50

Convergence of CP_1, CP_2, and CP_3 is shown in Fig.15. It indicates faster convergence than SPSO. Less number of iterations is required to reach minimum cost for CP_1, CP_2, and CP_3. Time required to converge for CP_1, CP_2, and CP_3 is very less. Cost obtained at each iteration is very less than SPSO. CP_2 gives better performance as compared to CP_1 and CP_3.

Hence this method finds best solution for NCELD problem.

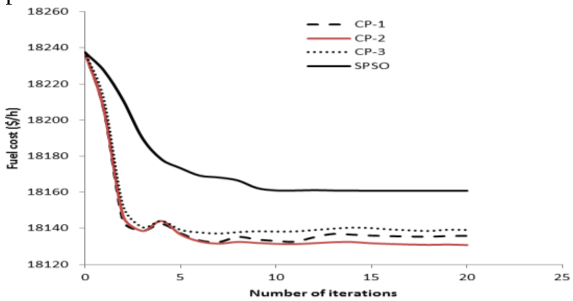


Figure 15: Convergence of thirteen units for CP_1, CP_2, CP_3

7. Solution quality

Strategies used are tested with their solution quality by knowing mean value, convergence characteristics and computational efficiency [2].Result obtained for mean value of CRPSO and PSO_TVAC are shown in Fig. 16 and Fig. 17 respectively for thirteen unit system.

7.1 Mean value:

Least generation cost is the main aim of ELD. So as to get it, firstly after each iteration the mean value is calculated for selected population size and then maximum, minimum and average costs out of performed iterations is calculated for standard PSO and adopted strategy. To calculate mean value formula is given as,

$$\mu = \frac{\sum_{i=1}^{ps} f(P)_i}{PS} \quad (34)$$

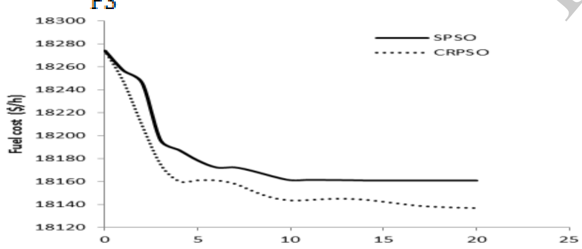


Figure 16: Mean value of SPSO and CRPSO of thirteen units

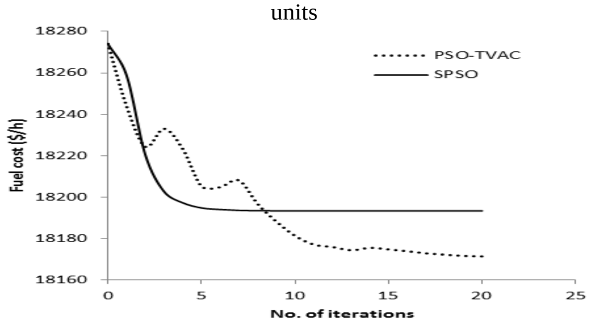


Figure 17: Mean value of SPSO and PSO_TVAC of thirteen units

For CRPSO mean value shows better results than SPSO.

7.2 Convergence characteristics:

Convergences of three, six and thirteen units are plotted for all strategies earlier. By knowing their costs at each iteration, it can be concluded that convergence of all strategies are superior to SPSO.

7.3 Computational efficiency:

Different algorithms are applied to NCELD problems. By knowing cost values at each iteration for different strategies, least cost is recorded with less computational time. Suggested strategies are consistent for ELD problems. It ensures the computational efficiency of all strategies to solve ELD problem.

8. Conclusions

PSO strategies available in literature are implemented to NCELD for three, six and thirteen units system. CFPSO ensures the convergence of algorithm. In PSO_TVAC, accelerating coefficients are active till the last iteration so convergence is faster than SPSO. Crazed velocity enhances the rate of convergence by giving lower cost at each iteration. Varying $V_i^{creziness}$ improves the results within vary few iterations by providing lowest cost than SPSO. Varying crazed velocity non- linearly (CP_2) gives better solution as compared to both linearly (CP_1) and considering effect of local and global solution varying crazed velocities (CP_3). It is also found that the problem of premature convergence is avoided using PSO strategies for NCELD. The results obtained are also in good agreement with the results reported earlier.

9. References

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