DEMAND BASED MUTATED PARTICLE SWARM OPTIMIZATION FOR NON-CONVEX ECONOMIC DISPATCH PROBLEM

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Abstract: This paper proposes a new approach to solve practical Economic Dispatch (ED) problem that includes non-smooth cost function by Particle Swarm Optimization method (PSO) with mutation strategy. A new constraint handling mechanism was implemented to meet the equality constraint effectively. This technique effectively reduces the demand error. In this method, by using the mutation strategy the particles can easily attain the global or near global optimum solution without being trapped local optimum point. The robustness of the proposed method was tested in practical ED problem by considering valve point effect, unit ramp rate limit, prohibited operating zone and network losses. The effectiveness of the system was verified using two different test system such as 6-unit and 15-unit system. The results of the proposed method were compared with the conventional PSO approaches.

Keywords: economic dispatch, optimization, particle swarm optimization, equality constraint, mutation strategy

1.Introduction

The most paramount and demanding segment in power system planning and operation is scheduling the committed generators while satisfying the practical constraints in the form of equality and inequality constraints. The effective scheduling of generating unit leads to cost minimization. Traditionally, various mathematical programming methods such as lagrangian multipliers [1], the interior point method [2], the gradient method [3], decomposition technique [4], the base point and participation factors method [5], etc. have been applied to solve the ED problem by treating the cost curve as a linear quadratic function. This approximation lead to infeasible solution for practical ED problem due to the nonlinear characteristics of the constraints like Valve Point Effect (VPE), Prohibited Operating Zone (POZ), Spinning Reserve (SR), Ramp Rate Limit (RRL), Network losses and Multiple Fuels type ED Problem (MFEDP). In the past decades several meta heuristics algorithms were suggested for solving nonlinear ED problem. They include Genetic Algorithm (GA) [6-9], Particle Swarm Optimization [10-16,21,34], Differential evaluation (DE) [16], Biogeography Based Optimization (BBO) [17], Simulated Annealing (SA) [18], Firefly Algorithm (FA) [19], Ant Colony Optimization (ACO) [20], Whale

Optimization Algorithm[30,31] , Polar Bear Optimization (PBO) [32], Grasshopper Optimization (GO) [33], Grey Wolf Optimization (GWO) [35] etc.

In this paper a modified structure of PSO is used for nonsmooth economic dispatch problem. The mechanism used here to deal with the equality and inequality constraints is, among the initialized population, one generator of each individual is treated as the slag generator, so that the output power of the slag generator is calculated as the difference between the demand and the sum of all generator output excluding the slag generator. However, the calculated value can violate the inequality constraints. So, this mechanism can be repeated until the calculated slag generator power satisfies the inequality constraint (i.e., the power lies between the minimum and maximum power generation). Mutation strategy is implemented here to reach the global minimum effectively. The particles moved to the mutation process after applying the PSO algorithm in each iteration. The position of each particles can be changed here to reach the best position.

2.Formulation of ED Problem

2.1 ED problem with smooth cost function

The ED problem determines the optimal power generation of the units that participates in supplying the load by satisfying all the equality and inequality constraints. In general, the smooth cost function curve of each thermal generating unit in quadratic form is represented by

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{1}$$

The objective function of ED problem is formulated to minimize the total generating cost of N_G generating unit as,

$$Min\ \ TC = \sum f_i(P_i) \tag{2}$$

where

TC : total generation cost

$\mathcal{N}$: set of generating unit

$a_i, b_{i,}, c_i$: fuel cost coefficient generating unit i

P_i : real power output of generating unit i

2.2 Constraints of ED Problem

2.2.1 Equality Constraint

While minimizing the cost, the real power output of the set of generating unit should meet system demand and losses.

$$\sum_{i\in\mathcal{N}} f_i(P_i) = D + P_{Loss} \tag{3}$$

D is the total system demand. By kron's loss formula, P_{Loss} is given by

$$P_{Loss} = \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} P_i B_{i,j} P_j + \sum_{i\in\mathcal{N}} B_{0i} P_i + B_{00} \tag{4}$$

$B_{i,j}, B_{0i}, B_{00}$ are loss coefficient.

2.2.2 Inequality Constraints

2.2.2.1 Generator Limit Constraint

The real power generation of each unit should be in the minimum and maximum power generation capacity. This frame the inequality constrains to satisfy by each generator.

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{5}$$

where P_i^{min}, P_i^{max} is the minimum and maximum generation capacity of generator i.

2.2.2.2 Ramp Rate Limit Constraint

The generation range of every unit is also constrained by it's up and down ramp rate limits:

If power output increases

$$P_i - P_i^0 \leq UR_i \tag{6}$$

If power output decreases

$$P_i^0 - P_i \leq DR_i \tag{7}$$

P_i^0 is the prior power supplied by generator i, UR_i , DR_i is the up and down ramp limit of generator i.

2.2.2.3 Prohibited Operating Zone Constraint

Prohibited Operating Zone divide the operating region into sub region with minimum and maximum limits as shown in fig 1. Each generating unit should operate within the sub region. That is, the following inequality constraint should be satisfied

$$P_i \in \begin{Bmatrix} P_i^{min} \leq P_i \leq P_{i,1}^{LB} \\ P_{i,z-1}^{UB} \leq P_i \leq P_{i,z}^{LB} \\ P_{i,z}^{UB} \leq P_i \leq P_i^{max} \end{Bmatrix}, \quad z = 2,3\,...\,N_i^{POZ} \tag{8}$$

$$i = 1,2\ ...\,N_G^{POZ}$$

where $P_{i,z}^{UB}, P_{i,z}^{LB}$ are the upper and lower bound of zth prohibited operating zone of generator i. N_i^{POZ} is the number of prohibited operating zone of generator i. N_G^{POZ} is the number of generator with prohibited operating zone.

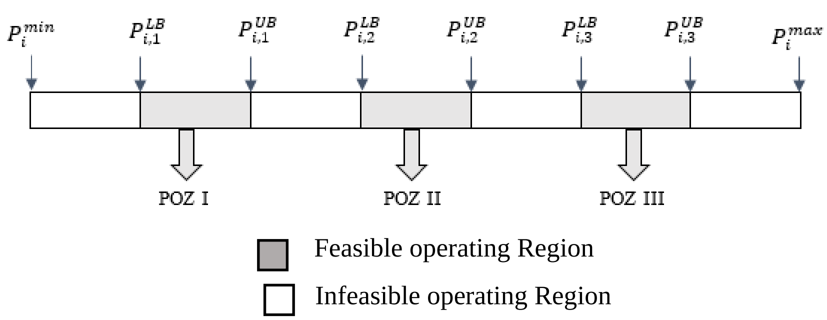


Fig.1. Representation of three prohibited operating zone

2.3 ED problem with non-smooth cost function

In ED problem, the generator with multi valve steam turbine added the rectified sinusoidal component with the basic quadratic fuel cost equation as

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin\left(f_i * \left(P_i^{min} - P_i\right)\right)\right| \quad (9)$$

where e_i, f_i are the fuel cost coefficient of generator i. The ripples are added to the cost functions when each steam valve starts to open is shown the Fig 2.

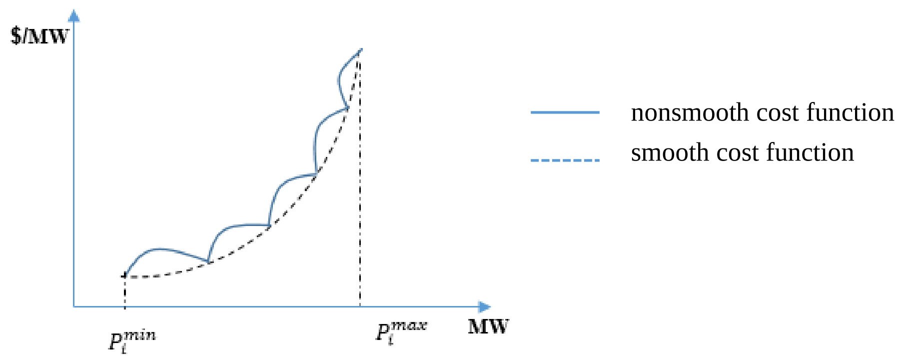


Fig.2. Graphical representation of smooth and nonsmooth cost function

3. Overview of Particle Swarm Optimization (PSO)

Kennedy and Eberhart first addressed the PSO algorithm in 1995, which simulates the social behavior of animals, such as fish schooling, birds flocking and swarm theory. Among the various meta heuristics method PSO has been extensively used to figure out the practical ED problem considering Valve Point Loading (VPL), Prohibited Operating Zone (POZ), Ramp Rate Limit (RRL), Spinning Reserve (SR) in the form of equality and inequality constraints.

In PSO, the fixed number of particles is randomly initialized in multidimensional search space. Each particle moves around in the multidimensional space to find the optimal solution by updating its velocity with its location by tracking their own best position indexed as *Pbest* and the best position obtained among all particle indexed as *Gbest.*

For particle i, the velocity and position updating rule is given by

$$v_{i,j}^{t+1} = w * v_{i,j}^t + c_1 * Rand(0,1) * \left(Pbest_{i,j}^t - x_{i,j}^t\right) + c_2 * Rand(0,1) * \left(Gbest^t - x_{i,j}^t\right) \quad (10)$$

$$i = 1,2,3\ldots N$$

$$j = 1,2,3\ldots \mathcal{N}$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \quad (11)$$

where

$v_{i,j}^t$: dimension $\mathcal{N}$ of the velocity of particle i at iteration t

$x_{i,j}^t$: dimension $\mathcal{N}$ of the position of particle i at iteration t

w : inertia weight

c_1, c_2 : acceleration coefficient

$Pbest_{i,j}^{t}$: dimension $\mathcal{N}$ of the own best position of particle i

$Gbest^{t}$: dimension $\mathcal{N}$ of the best position among all particle

$\mathcal{N}$: dimension (No. of generators) of the problem

N : size of population

$Rand(0,1)$: uniformly distributed random numbers in the range [0, 1]

4. Demand based PSO (D-PSO) approach for ED Problem

In this part a new approach to implement the PSO algorithm is described. This section gives the idea to deal with inequality and equality constraints. It is quite difficult to deal with the demand constraint, though the power generation lies within the generation limit. Demand based PSO (D-PSO) is suggested here to handle the equality constraint. It describes how the system demand should meet the power generation plus system losses.

4.1Initialization and structure of the particle.

In this Initialization process each particle is randomly initialized by satisfying the equality (3) and inequality constraints (5), (6), (7) & (8). Each particle is represented as a set of variables (output of generating unit). The position of particle i at initial stage in MW is $x_i^0 = \{x_{i,1}^0, x_{i,2}^0 \ldots . x_{i,\mathcal{N}}^0\}$, same as the velocity is $v_i^0 = \{v_{i,1}^0, v_{i,2}^0 \ldots . v_{i,\mathcal{N}}^0\}$. Even though we can generate the particle with in its generating limit, it is a big deal to initialize the particle to satisfy the equality constraint. i.e., the summation of all the variables of particle i $(\sum_{i\in\mathcal{N}} f_i(P_i))$ should be equal to the system demand D and losses. To carry out the Initialization the following process should be followed.

4.1.1 Process I: Initialization of particle by neglecting the losses

The following procedure is suggested to meet the equality constraints by neglecting the losses.

Step 1: Select any particle say $i = 1$, In which randomly select one variable (i.e., generator among $\mathcal{N}$ number of variables and set as $\mathcal{J} = 1$

Step 2: Randomize the variable by satisfying the equality constraint (3).

Step 3: If $\mathcal{J} = \mathcal{N} - 1$ then go to Step 4 else $\mathcal{J} = \mathcal{J} + 1$.

Step 4: Subtract the demand D from the sum of all variable of particle i $(\sum_{i\in\mathcal{N}-1} f_i(P_i))$, which gives the value of the variable $\mathcal{N}$ of particle i. If the value satisfies the inequality constraint (5), (6), (7) & (8) then go to step 5 else go to Step 1 and repeat the process.

Step 5: If $i = N$ go to Step 6 else $N = N + 1$and go to Step1.

Step 6: Stop the process.

4.1.2 Process II: Initialization of particle by considering the losses

In practical ED problem the losses should be considered for accurate solution. In this work system losses is also considered in the equality constraint. To satisfy the equality constraints in addition to process I the following steps also carried out.

Step 1: Randomly select an particle and set $i = 1$

Step 2: Calculate P_{Loss} using (4)

Step 3: Compute $violation = \sum_{i\in\mathcal{N}} f_i(P_i) - P_{Loss} - D$.

If $violation = 0$ go to step 6 otherwise go to Step 4

Step 4: Add the $violation$ value to any one variable (say $\mathcal{J} = 1$) which can be choosen as slack (i.e., slack generator).

$$P_{i,j}^{0} = P_{i,j}^{0} + violaion$$

If the variable does not lie between the maximum/minimum power generation capacity $\left[P_i^{min}, P_i^{max}\right]$ then go to step 5 else move to step 6.

Step5: If $\mathcal{J} = \mathcal{N}$ then go to section 3.1.1 and carryout process I then move on to Process II.

Step6: If $i = N$ go to Step 7 else $N = N + 1$and go to Step 2.

Step 7: Stop the initialization process.

Followed by the initialization of the positions of particles$\left(P_{i,j}^{0}\right)$, the velocity is also initialized randomly within the boundary. Based on the evaluation process the initial $Pbest_{i,j}^{0}$and $Gbest^{0}$ is determined.

4.2 Velocity updation

In order to update the position $P_{i,j}^{t+1}$in the next section it is necessary to update the $v_{i,j}^{t+1}$ using (10). For this calculation the value of w should be calculated as follows

$$w = w^{max} - \left({(w^{max} - w^{min})}/{Iter^{max}}\right) * Iter \tag{12}$$

where

w^{max}, w^{min} : maximum and minimum weights

$Iter^{max}$: maximum iteration number

$Iter$: present iteration number

4.3 Position update satisfying the inequality constraint

The position of each variable j of particle i can be modified using (11). It is necessary to examine whether the resultant position $P_{i,j}^{t+1}$ should satisfy the inequality constraints (5), (6), (7) & (8). It is not guarantee that the calculated position always satisfies the inequality constraints. Checking process can be carried out by three Rules

Rule 1: Check for variables Ramp Rate Limit:

In order to satisfy the Ramp rate constraint, check and assign the value based on the equation given below

$$P_{i,j}^{t+1} \in \left\{\begin{matrix} P_{i,j}^{t+1} & if\ P_{i,j}^{t+1} - P_i^0 \le UR_i & (for\ generation\ increases) \\ UR_i & if\ P_{i,j}^{t+1} - P_i^0 \ge UR_i & \\ P_{i,j}^{t+1} & if\ P_i^0 - P_{i,j}^{t+1} \le DR_i & (for\ generation\ decreases) \\ DR_i & if\ P_i^0 - P_{i,j}^{t+1} \ge DR_i & \end{matrix}\right\} \tag{13}$$

Rule 2: Check for variables generation limit:

The power generation limit can be satisfied using,

$$P_{i,j}^{t+1} \in \left\{\begin{matrix} P_{i,j}^{t+1} & if P_i^{min} \le P_{i,j}^{t+1} \le P_i^{max} \\ P_i^{min} & if P_i^{min} < P_{i,j}^{t+1} \\ P_i^{max} & if P_{i,j}^{t+1} > P_i^{max} \end{matrix}\right\} \tag{14}$$

Rule 2: Check for variables Prohibited Operating Zone limit

$$P_{i,j}^{t+1} = P_{i,j}^{(LB)_z} \quad if\ P_{i,j}^{(LB)_z} \le P_{i,j}^{t+1} \le P_{i,j}^{(UB)_z} \tag{15}$$

The aforementioned rules guarantee that the generating values always satisfies the inequality constraints. The problem of equality constrains can be resolved by using the following procedure. In this process the PSO can be applied for $\mathcal{N}-1$ particle instead of $\mathcal{N}$ particle.

Step 1: Select any particle say $i=1$, In which randomly select one variable (i.e., generator) and set as $\mathcal{J}=1$

Step 2: modify the value of particle using (11), (12)

Step 3: carry out section 3.3 for inequality constraints.

Step 4: if $\mathcal{J}=\mathcal{N}-1$ go to Step 5 else $\mathcal{J}=\mathcal{J}+1$ and go to step 2

Step5:The value of particle $\mathcal{N}$ can be found by subtracting the sum of remaining $\mathcal{N}-1$ particles (i.e.,($\sum_{i\in\mathcal{N}-1} f_i(P_i)$) from the demand D. If the value satisfies the inequality constraints go to Step 6. Else go to step 1 and repeat the procedure until the value of particle $\mathcal{N}$ satisfy the inequality constraints without applying the rules in section 3.3.

Step 6: Stop the process

4.4 Updation of $Gbest$ and $Pbest$

The best particle position and the best variable position of each particle can be estimated using

$$Pbest_i^{t+1} = P_i^{t+1} \quad if\ TC_i^{t+1} > TC_i^t$$
$$Pbest_i^{t+1} = Pbest_i^{t} \quad if\ TC_i^{t+1} < TC_i^t \tag{16}$$

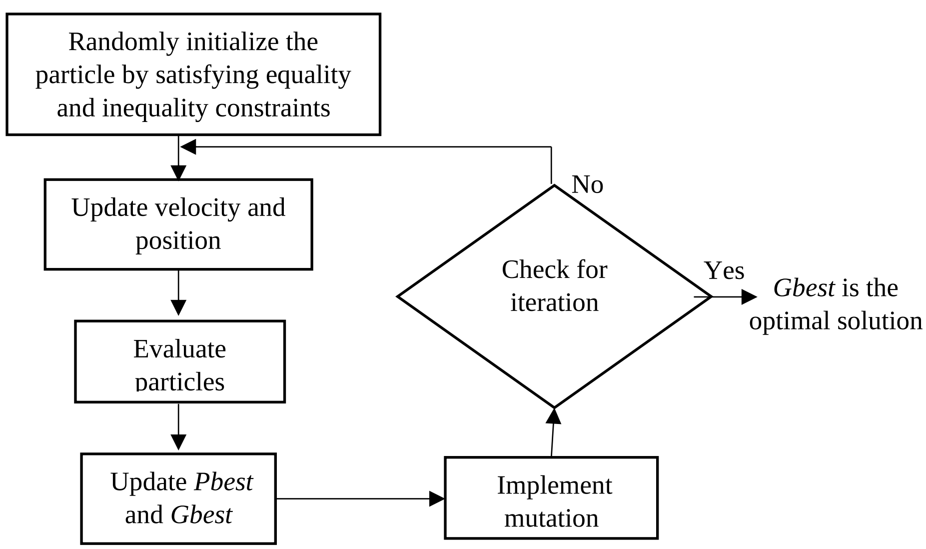
$Gbest$ is the best evaluation value among $Pbest_i^{t+1}$ at the current iteration.

4.5 Stopping criteria

The algorithm is terminated if it reaches the predefined maximum number of iterations.

5. Implementation of D-PSO using Mutation Strategy (D-MPSO) for ED Problem

In this section a new strategy is followed to improve the performance of D-PSO and to reach the global minimum consistently. The whole process can be accomplished by the following steps.



5.1 Mutation Strategy

In general, particles wander around the multidimensional search space with a motive to find optimal solution. During this process the particles tend to move towards the optimal solution. The main problem faced by D-PSO is to direct the movement of swarm towards the optimal solutions. This approach is limited to achieve the near global solution. To improve the performance of D-PSO and to attain the exact global solution a mutated strategy is incorporated here. In each iteration four particles $P_{1,}\, P_{2,}\, P_{3,}\, P_4$ can be selected randomly from the population N. The variables (generations) of the all particles is modified using the selected population variables.

$$P_{i,j(mut)}^{t+1} = P_{1,j}^{t+1} + \begin{pmatrix} (Rand_1[0,1])(1 - Rand_2[0,1])\left(P_{2,j}^{t+1} - P_{3,j}^{t+1}\right) + \\ (Rand_3[0,1])(1 - Rand_4[0,1])\left(Gbest - P_{4,j}^{t+1}\right) \end{pmatrix} \quad (17)$$

Let us consider the existing variables$P_{i,j(old)}^{t+1}$ and the modified variables $P_{i,j(mut)}^{t+1}$ of particle i at iteration $t+1$ is represented by

$$P_{i,j(old)}^{t+1} = \left[P_{i,1(old)}^{t+1}, P_{i,2(old)}^{t+1}, P_{i,1(old)}^{t+1} \cdots P_{i,\mathcal{N}(old)}^{t+1}\right] \quad (18)$$

$$P_{i,j(mut)}^{t+1} = \left[P_{i,1(mut)}^{t+1}, P_{i,2(mut)}^{t+1}, P_{i,3(mut)}^{t+1} \cdots P_{i,\mathcal{N}(mut)}^{t+1}\right] \quad (19)$$

The modified variables $P_{i,j(mut)}^{t+1}$ is mixed with the existing variables $P_{i,j}^{t+1}$ using

$$P_{i,j(new)}^{t+1} = \begin{Bmatrix} P_{i,1(mut)}^{t+1}, & if\ Rand_5[0,1] \leq Rand_6[0,1] \\ P_{i,1(old),}^{t+1} & otherwise \end{Bmatrix} \quad (20)$$

The new values are the input population of next iteration. The above strategy is used to escape from the local optima solution. It has the capability to change the position of each particle randomly towards the global point.

6. Results and Analysis

To validate the performance of the proposed D-MPSO method, it has been applied to various test system. Test system can be either with objective function as convex or non-convex. Evaluation can be carried out in test system either by including prohibited operating zone and ramp rate limit or not. To make the assessment two test strategies are applied to ED problem.

Test Strategy 1: D-PSO The classical PSO with demand based approach without mutation strategy.

Test Strategy 2: D-MPSO The classical PSO with demand based approach with mutation strategy.

The test strategies are applied to two standard systems which consist of 6 and 15 generating unit. Prohibited operating zone, ramp rate limit and transmission losses are considered in this case study. The B loss coefficient matrix and input data for the test strategies are taken from [10]. For the two test strategies the standard values are taken for PSO i.e., $c_1 = 2, c_2 = 2, w^{max} = 0.9$ and $w^{min} = 0.4$.

6.1 Effect of population size:

The effect of optimal population size on problem dimensional increases the problem complexity. For this case, to evaluate the effect of population size on the performance of D-MPSO algorithm four different population (30, 50, 100 and 150) are chosen. Table 1 shows the execution results of D-MPSO algorithm for 50 independent runs (each run is carried out for 1000 iterations). Population size 100 reaches near the optimal solution effectively and more consistently. Among 50 trials it reaches optimal value 46 times for 6-unit and 44 times for 15-unit system.

Table 1. Effect of population size on D-MPSO

Test System	Population size	No.of. hits to global minimum	Total fuel cost ($)		
			Maximum cost	Minimum cost	Average cost
6-unit System	30	32	15440.70505	15456.83088	15445.63898
	50	35	15440.71347	15456.82746	15445.25153
	100	46	15440.67421	15456.82128	15441.47842
	150	45	15440.69320	15456.82314	15441.40699
15-unit System	30	32	32560.51918	32687.49833	32575.45073
	50	38	32560.68364	32693.77881	32571.11400
	100	44	32560.34401	32580.81987	32561.77244
	150	38	32560.36190	32666.32792	32572.59625

6.2 Effect of randomly selected particles in mutation strategy

To evaluate the performance of D-MPSO in mutation process, four different particles were selected among the population and each combination was executed for 50 independent trails. Due to space limitations some of the results were displayed for reference.

Table 2 Effect of randomly selected particles (P_1, P_2, P_3, P_4) for mutation strategy for 6-unit system

Sl.no	Randomly selected particles (P_1, P_2, P_3, P_4)	Best Value	Worst value	Average value	No.of. hits to global minimum (15440.5-15441)
1	1,2,3,4	15440.682	15456.825	15442.426	42
2	2,3,4,5	15440.697	15456.825	15442.306	41
3	3,4,5,6	15440.687	15456.825	15442.068	45
4	**5,6,7,8**	**15440.674**	**15456.821**	**15441.478**	**47**
5	1,3,5,7	15440.716	15456.822	15442.345	45
6	50,51,52,53	15440.693	15456.826	15443.015	43
7	90,91,92,93	15440.696	15456.826	15441.494	46
8	93,94,95,96	15440.717	15456.822	15442.405	44
9	1,2,90.95	15440.695	15456.822	15441.482	45
10	1,40,70,90	15440.689	15456.824	15442.385	44

From Table 2 for 6-unit system D-MPSO succeed in achieving global minimum by selecting the 5, 6, 7 and 8 particles for mutation. Whereas in 15-unit system the particle 1, 3, 5 and 7 produce the best results as depicted in table 3.

Table 3. Effect of randomly selected particles (P_1, P_2, P_3, P_4) for mutation strategy for 15-unit system

Sl.no	Randomly selected particles (P_1, P_2, P_3, P_4)	Best value	Worst value	Average value	No.of. hits to global minimum (32560-32562)
1	1,2,3,4	32,560.344	32580.838	32562.696	40
2	2,3,4,5	32560.369	32663.525	32566.686	38
3	3,4,5,6	32560.391	32675.200	32567.964	43
4	5,6,7,8	32560.476	32658.169	32564.590	40
5	1,3,5,7	32560.280	32580.765	32562.583	45
6	50,51,52,53	32560.393	32581.068	32563.441	40
7	90,91,92,93	32560.338	32660.300	32564.550	40
8	93,94,95,96	32560.409	32580.909	32562.850	38
9	1,2,90.95	32560.300	32580.937	32563.244	39
10	1,40,70,90	32560.357	32581.364	32564.088	39

6.3 Convergence Characteristics

In order to find the effectiveness of the proposed D-PSO and D-MPSO methods, the convergence test was carried out with same initial population size and iteration number. Fig 3 & 4 shows the superiority of D-MPSO over D-PSO. The mutation strategy steers the D-MPSO algorithm towards the global optimum efficiently and consistently.

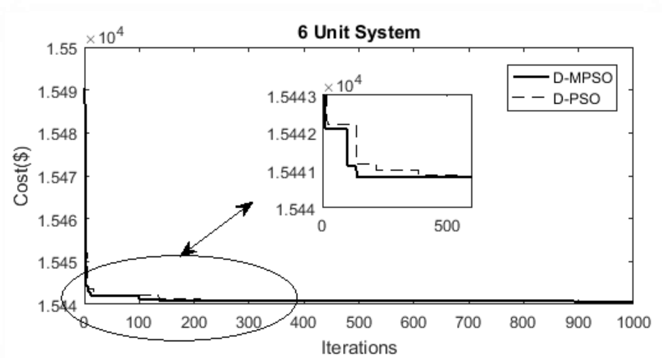


Fig.3. Convergence curve for 6-unit system

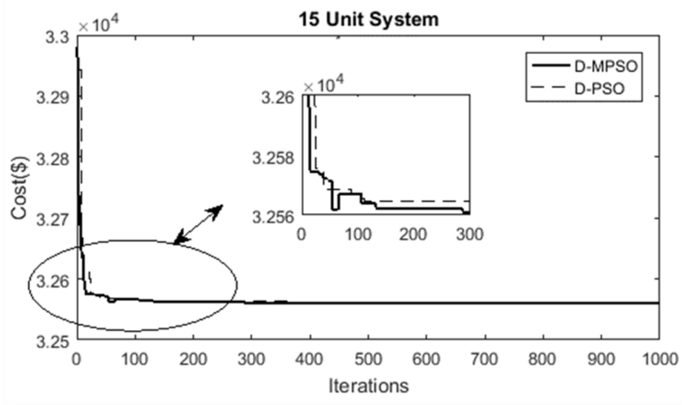


Fig.4. Convergence curve for 15-unit system

6.4 Robustness of the proposed method

To ensure the robustness of the proposed D-MPSO method over D-PSO method for the test strategies, the frequency of convergence for 50 randomly initiated trails are listed in Table 5. The comparision plot of best solution obtained by each trial is showed in Fig 5 & 6. Almost in all the trial D-MPSO producing better solution than D-PSO. D-MPSO method effectively reach the global minimum point due to the mutation statergy. Thus verifying that the proposed method provides excellence in ED problem for generating optimal power generation.

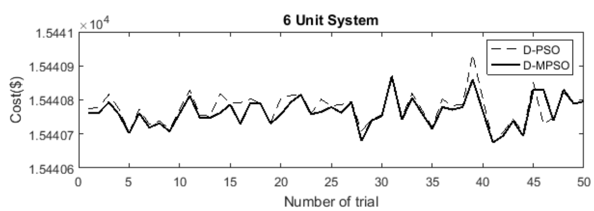


Fig.5. Distribution of generation cost of test strategies for 6-unit system

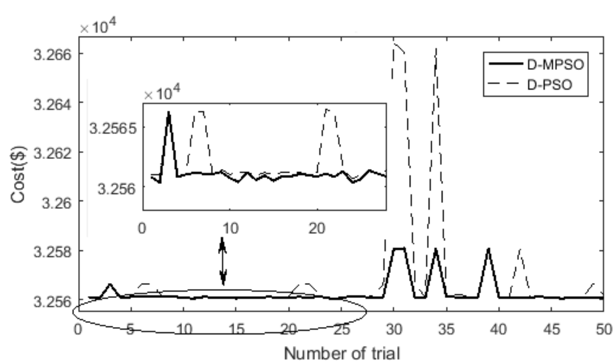


Fig.6. Distribution of generation cost of test strategies for 15-unit system

Table.5. Frequency of convergence for 6 & 15-unit

6-Unit system										
Methods	**Range of costs ($)**									
	15457-15456	15456-15448	15448-15447	15447-15446	15446-15445	15445-15444	15444-15443	15443-15442	15442-15441	15441-5440.5
D-MPSO	1	0	0	0	0	0	0	0	2	47
D-PSO	2	0	0	0	0	0	0	6	11	31
15-Unit system										
Methods	**Range of costs ($)**									
	32665-32581	32581-32580	32580-32567	32567-32566	32566-32565	32565-32564	32564-32563	32563-32562	32562-32561	32561-32560
D-MPSO	0	4	0	2	0	0	0	0	13	31
D-PSO	2	0	0	8	0	0	0	0	24	16

6.5 Evaluation of dynamic behavior.

The dynamic behavior of the optimal search algorithm can be evaluated by monitoring the mean and standard deviation of the evaluation function in each iteration. The mean μ and standard deviation σ can be calculated using

$$\mu = \frac{\sum_{i=1}^{N} f(P_i)}{N}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f(P_i) - \mu)^2}$$

Fig 7 & 8 shows the mean and standard deviation of 6 and 15-unit system respectively. The D-MPSO records the superiority by producing lower mean and standard deviation.

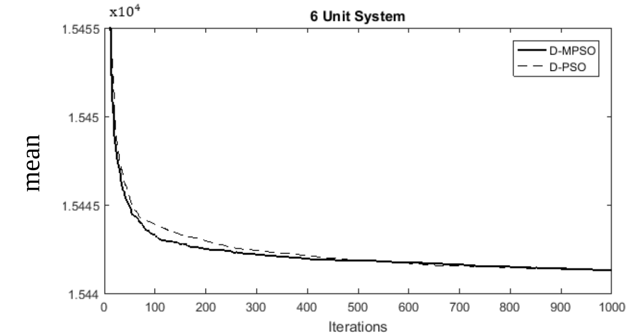


Fig.7 (a). Mean distribution curve for 6-unit system.

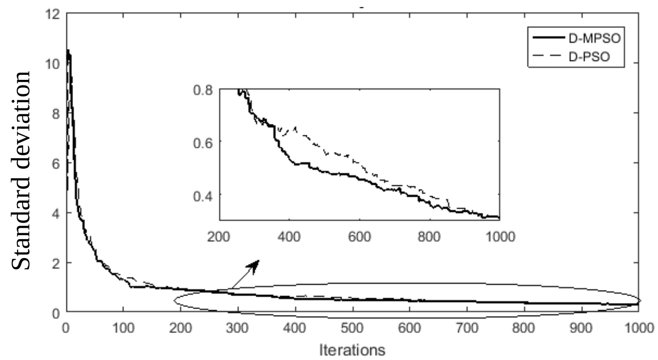


Fig.7 (b). Standard deviation curve for 6-unit system

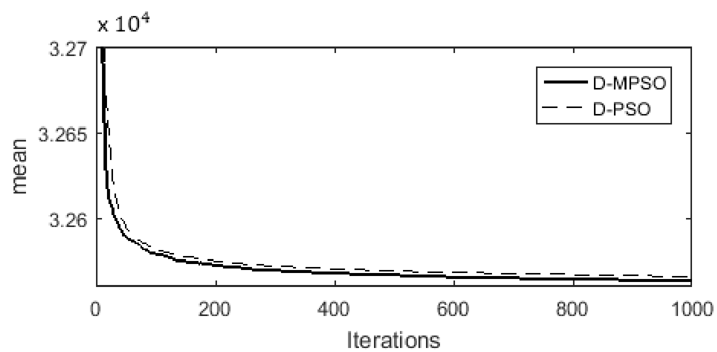


Fig.8 (a). Mean distribution curve for 15-unit system

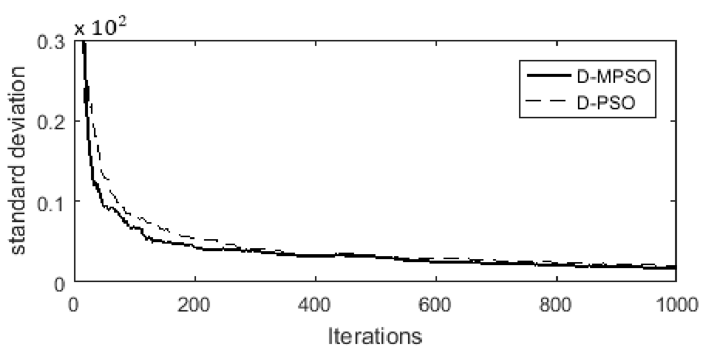


Fig.8 (b). Standard distribution curve for 15-unit system

The best power output of 6 and 15 generating unit for the two proposed PSO methods are compared with PSO [10], NPSO-LRS [12], ST-IRDPSO [15], SOH-PSO [24], RDPSO [25], and CTLBO [23] in table 6 & 7. In 6-unit system the optimal cost is calculated for the demand of 1263MW and the best cost obtained so far is 15,441.697 [$] reported in [23]. In 15-unit system, 2630WM is taken as a demand and the so far obtained best cost is 32,652.33 [$] reported in [25]. The minimum cost obtained by D-MPSO method for 6-unit system is 15440.674 [$] and for 15-unit system is 32560.280 [$], which produce better results when compared to the existing approaches. The power loss obtained in D-PSO and D-MPSO are less when compared to the results in literature. Compared to D-PSO, D-MPSO guarantee to generate best optimal scheduling with minimum operating cost and minimum network loss. Fig 3 & 4 shows that the obtained generation cost of D-MPSO is lesser than the D-PSO method. This proves the better convergence characteristics of D-MPSO. The minimum average power of D-MPSO shows the superiority of the proposed method over various methods listed in the literature.

Table. 6 Comparison of best power output for 6-unit system

Unit power output	Methods							
	PSO [10]	NPSO-LRS [12]	ST-IRDPSO [15]	SOH-PSO [24]	RDPSO [25]	CTLBO [23]	D-PSO	D-MPSO
P_1	447.4970	446.9600	447.5131	438.21	445.254`	449.498	443.67	444.03
P_2	173.3221	173.3944	173.2975	172.58	172.791	173.481	170.41	170.22
P_3	263.4745	262.3436	263.4668	257.42	263.528	264.970	261.09	261.45
P_4	139.0594	139.5120	139.0360	141.09	141.068	127.461	150.00	150
P_5	165.4761	164.7089	165.4843	179.37	163.857	173.842	164.61	163.78
P_6	87.1280	89.0162	87.16047	86.88	88.8558	86.239	85.16	85.45
Total power output (MW)	1276.01	1275.94	1275.958	1275.55	1275.35	1275.49	1274.97	1274.96
Total losses (MW)	12.9584	12.9361	12.958	12.55	12.3598	12.490	11.97	11.96
Minimum cost($/hr)	15,450	15,450	15449.894	15,446.02	15,442.75	15,441.69	15440.72	15440.674
Maximum cost($/hr)	15,492	15,452	NA	15,609.64	15,445.29	15,441.97	15456.82	15456.821
Average cost($/hr)	15,454	15,450.5	15450.70	15,497.35	15445.02	15,441.76	15441.49	15441.478

Table.7. Comparison of best power output for 15-unit system

Unit power output	Methods								
	GA [10]	PSO [10]	SOH-PSO	CPSO [27]	RDPSO [25]	CSO [26]	MIQCQP [28]	D-PSO	D-MPSO
P_1	415.3108	439.1162	455.00	450.05	454.8093	455.00	455.00	451.939	454.975
P_2	359.7206	407.9727	455.00	454.04	379.9742	380.00	380.00	455.000	455.00
P_3	104.4250	119.6324	130.00	124.82	129.8458	130.00	130.00	130.000	130.00
P_4	74.9853	129.9925	130.00	124.82	129.9152	130.00	130.00	130.000	130.00
P_5	380.2844	151.0681	170.00	151.03	169.0867	170.00	170.00	218.256	218.314
P_6	426.7902	459.9978	459.96	460.00	459.6428	460.00	460.00	460.000	460.00
P_7	341.3164	425.5601	430.00	434.53	429.9559	429.99	430.00	465.00	465.00
P_8	124.7867	98.5699	117.53	148.41	73.2746	71.95	72.13	86.341	86.378
P_9	133.1445	113.4936	77.90	63.61	49.7381	58.907	58.54	25.00	25.00
P_{10}	89.2567	101.1142	119.54	101.13	160.00	159.99	160.00	29.878	25.00
P_{11}	60.0572	33.9116	54.50	28.656	79.8596	80.00	80.00	69.92	71.709
P_{12}	49.9998	79.9583	80.00	20.612	79.3174	80.00	80.00	80.00	80 .00
P_{13}	38.7713	25.0042	25.00	25.001	26.1522	25.00	25.00	25.00	25.00
P_{14}	41.9425	41.4140	17.86	54.418	18.7287	15.00	25.00	15.00	15.00
P_{15}	22.6445	35.6140	15.00	20.625	15.0645	15.00	15.00	15.00	15.00
Total power output (MW)	2668.4	2662.4	2662.2	2662.1	2655.365	660.85	2670.67	2656.34	2656.37
Total losses (MW)	38.2782	32.4306	32.28	32.130	25.3696	30.85	30.66	26.34	26.37
Minimum cost($/hr)	33,113	32,858	32,751	32835	32,652.3	32,706.6	32,704.45	32,561.17	32560.280
Maximum cost($/hr)	33,337	33,331	32,945	33,318	32,959.7	NA	NA	32664.28	32580.765
Average cost($/hr)	33,228	33,039	32,878	33,021	32,744.5	NA	NA	32568.80	32562.696

7. Conclusion

In this paper a new method, D-MPSO was proposed for solving ED problem with valve point loading effect, prohibited operation zone, ramp rate limit and network losses. Two powerful strategies were followed in order to deal with this non-convex, non-differentiable and non-smooth ED problem and to bias the optimization for better convergence. Strategy 1: An efficient constraint handling procedure based on demand concept was mainly imposed to ignore the violations in power balance constraints. This concept has influence in particle initialization and position updating process of PSO. Strategy 2: In order to reach the global minima and not to be trapped by local minima, using mutation strategy the position of each particle can be modified at the end of velocity and position updation process in PSO. To disclose the effectiveness of the proposed method, it can be applied to comprehensive realistic power system. From the statistical data obtained from 50 trials it has been proven that the proposed D-MPSO can easily escape from premature convergence and generate better quality solution with optimum cost.

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