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CLPO Solution for Dynamic Economic Dispatch with nonsmooth Fuel Cost Functions

K. Mahadevan, J. Booma, R. Joseph Rathish and D. Arun Prasad

K. Mahadevan is with the Department of Electrical & Electronics Engineering, P.S.N.A. College of Engineering & Technology, Dindigul, 624 622, INDIA (mob: 9865615300; e-mail: mahadevand@rediffmail.com).
J. Booma is with the Department of Electrical & Electronics Engineering, P.S.N.A. College of Engineering & Technology, Dindigul, 624 622, INDIA (e-mail: boomakumar2005@gmail.com).
R. Joseph Rathish is with the Department of Electrical & Electronics Engineering, P.S.N.A. College of Engineering & Technology, Dindigul, 624 622, INDIA (e-mail: rathishjoseph@gmail.com).
D. Arun Prasad is with the Department of Electrical & Electronics Engineering, P.S.N.A. College of Engineering & Technology, Dindigul, 624 622, INDIA (e-mail: sdarunprasad@gmail.com).

**Corresponding Author: Mobile: +91-9865615300 E-mail: mahadevand@rediffmail.com*

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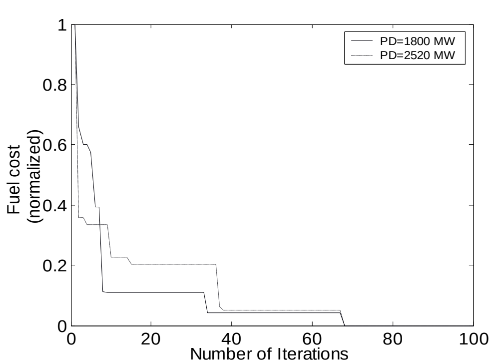

ABSTRACT

Dynamic economic dispatch (DED) is a method to schedule the online generator outputs with the predicted load demands over a certain period of time so as to operate an electric power system most economically. Normally in all economic dispatch (ED) problems, it is assumed that the incremental cost curves of the units are monotonically increasing piece-wise linear function. In fact, discontinuity may also be observed in thermal power plants due to valve point loading. As the conventional optimization methods require the objective functions in continuous differentiable form, they fail to solve these types of problems. This paper presents a new approach using Comprehensive Learning Particle Swarm Optimization (CLPSO), a variant of Particle Swarm Optimization (PSO), for solving the DED problem of generating units having non-smooth fuel cost functions. In this approach, each particle learns from different particles' historical information for different dimensions for a few generations. This strategy ensures that the diversity of the swarm is preserved to discourage premature convergence. The proposed method is implemented for solving few example dispatch problems having non-smooth fuel cost functions as either in the form of sine function model into the objective function or with prohibited operating zones. The results of CLPSO are compared with those of Evolutionary Programming (EP), Genetic Algorithms (GA) and simple PSO. The simulation results show that the proposed CLPSO method is indeed capable of finding higher quality solution efficiently in non-convex ED problems.

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1. INTRODUCTION

The process of scheduling generation to minimize the operating cost is called economic dispatch. In this calculation, the generation costs are represented as curves, usually piecewise linear, and the overall calculation minimizes the operating cost by finding a point where the total output of the generations equals the total power that must be delivered and where the incremental cost of power generation is equal for all generators. However, if a generator is at its upper or lower limit, that generator's incremental cost is different. Various mathematical programming methods and optimization techniques have been applied to ED. Most of these are calculus-based optimization algorithms that are based on successive linearization and use the first and second differentiations of objective function and its constraint equations as the search directions [1]. They usually require the heat input-electric power output characteristics of generators to be of monotonically increasing nature or of a piecewise linearity. However, large modern generating units with multi-valve steam turbines exhibit a large variation in the input-output characteristic functions. The valve-point effects, owing to wire drawing as steam admission valve starts to open, typically produce a ripple-like heat rate curve. Moreover, to keep thermal gradients inside the turbine within safe limits and to avoid shortening the life, the rate of increase/decrease of the power output of generating units is limited within a range. Such ramp rate constraints make the conventional ED problem as a dynamic one. The conventional optimization methods are not suitable to solve such a problem. Hence, more general approaches are needed without restrictions on the shape of fuel cost functions.

Dynamic programming (DP) solution is one of the approaches to solving the inherently non-linear and discontinuous ED problem [2]. However, the dimensions of the problem would become extremely large with the increase of the variables (curse of dimensionality). Methods such as Simulated Annealing (SA) [3], GA [4] and EP [5, 6] have been proposed to solve such nonsmooth ED problems. P. Attaviriyanupap *et al.* have applied Hybrid EP to solve DED problem [7]. These methods have the advantage of searching the solution space more thoroughly. However, the main difficulty is their sensitivity to the choice of parameters, such as temperatures in SA, the cross over and mutation probabilities in GA and scaling factor in EP.

Particle swarm optimization, first introduced by Kennedy and Eberhart [8], is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [8]–[12]. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods [9]–[12]. Although the PSO seems to be sensitive to the tuning of some weights or parameters, many researches are still in progress for proving its potential in solving complex power system problems [11]. Researchers including Yoshida *et al.* have presented a PSO for reactive power and voltage control considering voltage security assessment. The feasibility of their method is compared with the reactive tabu system (RTS) and enumeration method on practical power system, and has shown promising results [13]. Naka *et al.* have presented the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem [14]. Z.L. Giang has solved ED problem with generator constraints using simple PSO [15]. J.B. Park *et al.* [16] have proposed a modification in PSO to deal equality and inequality constraints of ED problem with nonsmooth fuel cost functions.

In this paper, a new PSO variant, called CLPSO is employed, which alleviates the problem of premature convergence in PSO. In this approach, each particle learns from different particles' historical information for different dimensions for a few generations. This strategy ensures that the diversity of the swarm is preserved to discourage premature convergence. The proposed method is implemented for solving few example dispatch problems having nonsmooth fuel cost functions as either in the form of sine function model into them or with prohibited operating zones. The results of CLPSO are compared with that of EP, GA and simple PSO.

This paper is organized as follows: The DED problem formulation is given in Section II. An introduction to CLPSO is given in Section III. Application of CLPSO method to DED problem is given in Section IV. Numerical tests and their results on five test systems from the literature are given in Section V. Finally, a conclusion is made in Section VI.

2. PROBLEM FORMULATION

The dynamic ED problem can be described as an optimization process with the following objective function and constraints:

$$\min F = \sum_{h=1}^{H}\sum_{i=1}^{N} F_{ih}(P_{ih}) \qquad (1)$$

The fuel cost functions of the generating units are generally characterized by second-order polynomials as

$$F_{ih}(P_{ih}) = a_i + b_i P_{ih} + c_i P_{ih}^2 \qquad (2)$$

To model the steam admission valve point effect, a recurring rectified sinusoidal contribution is added to the second-order polynomial function to represent the input-output equation [4]. Thus (1) becomes

$$\min F = \sum_{h=1}^{H}\sum_{i=1}^{N} \left(a_i + b_i P_{ih} + c_i P_{ih}^2 + \left|e_i \sin\left(f_i\left(P_{ih} - P_{i(\min)}\right)\right)\right|\right) \qquad (3)$$

The cost is optimized with the following power system constraint

$$\sum_{i=1}^{N} P_{ih} - P_{Dh} - P_L = 0 \quad ,h=1,\ldots,H \qquad (4)$$

The inequality constraint on real power generation P_i of each generator i is

$$P_{i(\min)} \le P_i \le P_{i(\max)} \qquad (5)$$

The ramp rate constraint imposed on it is

$$P_{ih} - P_{i(h-1)} \le UR_i \quad ,i=1,\ldots,N$$
$$P_{i(h-1)} - P_{ih} \le DR_i \quad ,i=1,\ldots,N \qquad (6)$$

The input-output curve of a generator may also be represented with prohibited operating zones. These are also due to steam valve operation or vibration in shaft bearing. Since it is not easy to determine the prohibited zone by actual performance testing or operation records, the best economy is achieved by avoiding operation in areas that are in actual operation. To solve such ED problems with prohibited operating zones (3) is rewritten as (1) and so is subjected to (4), (5) and (6). The feasible operating zones of unit i can be described as follows:

$$\begin{aligned} &P_{i(\min)} \le P_i \le P_{i,1}^{l} \\ &P_{i,j-1}^{u} \le P_i \le P_{i,j}^{l} \qquad , j=2,3,\ldots,n_i \qquad (7) \\ &P_{i,n_i}^{u} \le P_i \le P_i^{\max} \end{aligned}$$

where $P_{i,j}^{l}$ and $P_{i,j}^{u}$ are the lower and upper bounds of the j-th prohibited operating zone of unit i and n_i is the number of prohibited zones of unit i.

The notations used above are,

F	:	the operating cost,
H	:	number of hours in the study horizon,
N	:	the number of generating units,
P_{ih}	:	the power output of i-th generating unit at h-th hour,
$F_{ih}(P_{ih})$	:	the fuel cost function of i-th unit at h-th hour,
P_{Dh}	:	the demand at h-th hour,
P_L	:	the transmission losses in the system,
UR_i	:	ramp-up rate of i-th generating unit,
DR_i	:	ramp-down rate of i-th generating unit,
$P_{i(\min)}$	:	minimum generation capacity of i-th generating unit,
$P_{i(\max)}$	:	maximum generation capacity of i-th generating unit.

3. COMPREHENSIVE LEARNING PSO

Particle swarm optimization developed by Eberhart and Kennedy [17] is one of the evolutionary computation techniques. PSO, like GA, is a population based optimization algorithm. The swarm initially has a population of random solutions. Each potential solution, called particle, is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of its previous best position, called *pbest* and corresponding fitness.

The swarm remembers another value called *gbest*, which is the best solution discovered by the swarm. Velocity and position of the particles are changed according to the equations (8) and (9) respectively.

$$V_j(d) = wV_j(d) + c_1 * rand * (Pbest(d) - X_j(d)) + c_2 * rand * (gbest(d) - X_j(d)) \quad (8)$$

$$X_j(d) = X_j(d) + V_j(d) \quad (9)$$

where $V_j(d)$ and $X_j(d)$ represent the velocity and position of *d*-th dimension of *j*-th particle respectively and *rand* is a uniform random number in the range [0,1].

Though there are numerous PSO variants, premature convergence is still the main deficiency of the most PSO based algorithms[18]. In the original PSO, each particle learns from its *pbest* and *gbest* simultaneously and its social learning factor is restricted to only *gbest*. Furthermore, all particles in the swarm learn from the *gbest* even if the current *gbest* is far from the global optimum. In such situations, particles may easily be attracted and trapped into an inferior local optimum if the search environment is complex with numerous local solutions.

As the fitness value of a particle is decided by all dimensions, a particle which has discovered the value corresponding to the global optimum in one dimension may have a low fitness value because of the poor solutions in other dimensions. This good genotype may be lost in this situation. In order to prevent this, different novel learning strategies are adopted [18]. It differs in two main aspects compared to many present PSO variants:

1) Instead of learning from two exemplars namely the *pbest* and *gbest* in every iteration in the original PSO as in equation (8), each dimension of a particle learns from just one exemplar for a few iterations.

2) Instead of learning from the *pbest* and *gbest* for all dimensions, each dimension of a particle in general learns from a different *pbest* for different dimensions for a few iterations.

In CLPSO, for each particle, besides its own *pbest*, other particles' *pbest*s are used as exemplars. Each particle learns from potentially all particles' *pbests* in the swarm. During the search process, it is not known which dimensions of each particle's *pbest* are good or bad. Therefore, each dimension of a particle has equal chance to be learnt by other particles. For each particle, some dimensions of other particles' *pbest*s are randomly chosen according to a probability P_c, called learning probability, as social exemplars to be learnt from, while other dimensions learn from its *pbest*, as cognitive exemplar. Here, for each particle, a different velocity updating is used:

$$V_j(d) = w * V_j(d) + rand * (pbest_{fi(d)}(d) - X_j(d)) \quad (10)$$

Where, $pbest_{fi(d)}(d)$ could be any particle's *pbest* or its own *pbest*, and the decision depends on P_c. P_c decides which dimension will learn from the other particle's *pbest* and which dimension will follow the particle's own *pbest*. Each particle has its own P_c, which could be different from that of other particles. For each dimension of particle *j*, a random number is generated. If this random number is larger than P_c of *j*-th particle, then this dimension will learn from its own *pbest*, otherwise it will learn from another particle's *pbest*. When a dimension of one particle learns from other particle's *pbest* is as follows: 1) Two particles are randomly chosen out of the population, which excludes the particle being updated, 2) The fitness values of these two particles' *pbest* are compared, and 3) Then the winner's *pbest* is used as the exemplar for that dimension. If all exemplars of a particular particle are its own *pbest*, then one dimension is randomly selected to learn compulsorily from other particle's *pbest*.

The weighting function *w* is determined by an annealing procedure, which makes uniform search in the initial stages and very local search in the latter stages. The weighting function w_k for *k*-th iteration is determined by

$$w_k = \frac{(w_o - 0.2) \times (\max\_iter - k)}{\max\_iter} + 0.2 \qquad w_o = 0.9 \quad (11)$$

During the process, the velocity of each particle is clamped according to the following equation (12).

$$V_j(d) = \min(V_{\max}(d), \max(-V_{\max}(d), V_i(d)) \quad (12)$$

and $V_{\max}$ is set as 0.25 ($X_{\max}$ – $X_{\min}$), after experimentation.

This learning strategy from different particles' *pbests* for different dimensions increases the particles' initial diversity and enables the swarm to overcome premature convergence problem.

4. CLPSO IMPLEMENTATION IN ED PROBLEM

Step 1: Initialization

A set of candidate solutions, called 'particles', is randomly created in *d*-dimensional space. This set is referred to as 'swarm'. This initial vector is denoted as X_j. For example, the position of *j*-th individual can be represented as

$$X_j = [P_{j1}, P_{j2}, \ldots P_{jd}] \qquad j = 1,2,\ldots,m \qquad (13)$$

and the velocity is described as,

$$V_j = [V_{j1}, V_{j2}, \ldots V_{jd}] \qquad j = 1,2,\ldots,m \qquad (14)$$

where *m* is the population size and *d* is the number of generators.

Step 2: Fitness function

Fitness function is directly called from the objective function. Each individual's fitness value is compared with its *pbest*. The best value among the *pbests* in the swarm is denoted as *gbest*.

Step 3: Velocity modification

The velocity of each particle is modified according to (10).

Step 4: Position modification

The position of each individual is modified according to (9).

Step 5: Constraints handling

The new position of particles found in previous step must satisfy all the operating constraints.

Equality constraint (4) is handled by

$$P_{1h} = P_{Dh} - \sum_{i=2}^{N} P_{ih} \qquad , h = 1, 2, \ldots, H \qquad (15)$$

The capacity constraints of the first unit are handled by adding them into the objective function using penalty factor (ψ_1). A dummy variable $P_{1\lim}$ is used to find the amount of violation of equality constraint and is defined as

$$P_{1\lim} = \begin{cases} P_{1\min} & \text{if} \quad P_{1h} < P_{1\min} \\ P_{1\max} & \text{if} \quad P_{1h} > P_{1\max} \\ P_{1h} & \text{otherwise} \end{cases} \qquad (16)$$

The capacity constraints and operating ramp rate constraints are simultaneously handled by adding another penalty factor (ψ_2) into the objective function. Here another dummy variable $P_{r\lim}$ is used to find the amount of violation and is defined as

$$P_{r\lim} = \begin{cases} \max\left(P_{1\min}, P_{i(t-1)} - DR_i\right) & \text{if} \quad P_{1h} < P_{i(t-1)} - DR_i \\ \min\left(P_{1\max}, P_{i(t-1)} - UR_i\right) & \text{if} \quad P_{1h} > P_{i(t-1)} - UR_i \\ P_{ih} & \text{otherwise} \end{cases} \qquad (17)$$

The penalty factors ψ_1 and ψ_2 are added into (1) to form a generalized objective function as

$$\min F = \sum_{h=1}^{H}\sum_{i=1}^{N} F_{ih}(P_{ih}) + \sum_{h=1}^{H} \psi_1 \left|P_{1h} - P_{1\lim}\right| + \sum_{h=2}^{H}\sum_{i=1}^{N} \psi_2 \left|P_{ih} - P_{r\lim}\right| \qquad (18)$$

The above generalized objective function is used as fitness function.

If the problem is considered with prohibited operating zones, instead of introducing a penalty term into the objective function for each of the unit loadings falling within the prohibited operating zones, the following procedure is adopted.

The mid-points of the prohibited zones for each generator are calculated. For a generator level $P_i^{'}$ lying between $P_{i,n}^{u}$ and $P_{i,n}^{l}$, the mid-points of the prohibited operating zone is

$$M_{i,n} = \frac{P_{i,n}^{u} + P_{i,n}^{l}}{2} \quad \text{for } n = 1,2,3,\ldots n_i \qquad (19)$$

And

$$P_i^{'} = P_{i,n}^{l} \quad \text{if} \quad P_i^{'} < M_{i,n}$$

$$P_i^{'} = P_{i,n}^{u} \quad \text{if} \quad P_i^{'} > M_{i,n}$$

Step 6: Individual best update & global best update

If the fitness value of each individual is better than the previous *pbest*, the current value is set to be *pbest*. If the best *pbest* is better than *gbest*, the value is set to be *gbest*.

Step 7: Stopping criteria

If the number of iterations reaches set value, then the individual that generates the latest *gbest* is the optimum generation output power of each unit with minimum total cost.

5. NUMERICAL RESULTS

To assess the feasibility and efficiency of the proposed method, it has been applied to five example test problems from the literature, in which the generating units are having nonsmooth fuel cost functions. The first two test systems, one with 13 units and another with 40 units are considered without ramp rate limits. The third example, 10-unit system, considered with ramp rate limits is studied over a study horizon of 24 hours. These three systems' objective functions are modeled with sine function to reflect valve-point loading effect. The next two systems are studied with prohibited operating zones. For the purpose of comparison, the study horizon is considered for one hour only in these two test systems. The program was coded in MATLAB and the simulations were carried out on a Pentium III, 850MHz, 128 RAM PC.

A. ED problems having nonsmooth cost functions with sine function model

Firstly, the CLPSO method is applied to two ED problems, one with 13 generators and another with 40 generators where valve-point loading effects are included as sine function model for both problems. The input data for 13-generator system are taken from [19] and those for 40-generator from [20]. For 13-generator system, the total demand is 1800MW and 2520MW as in [20] and [21]. Transmission losses are not considered.

The control parameters used in CLPSO method are as follows:

population size 50
number of iterations 100

The results obtained from the CLPSO method are shown in Table I. A comparison between the CLPSO method and other methods such as CEP, FEP, MFEP and IEP for a demand of 1800MW and GA, EP and IEP for a demand of 2520MW are made in Tables II and III respectively. As seen in the tables II and III, the proposed method is able to produce better results. Fig.1 shows the fuel cost variation for these two demands in this example.

Table I : Generation Output for 13-Unit System

Unit	Demand (1800 MW)	Demand (2520 MW)
1	628.321	628.275
2	223.951	298.379
3	298.000	298.986
4	60.000	159.558
5	60.000	159.143
6	60.000	159.717
7	109.863	159.643
8	60.000	159.621
9	109.865	159.732
10	40.000	76.937
11	40.000	113.728
12	55.000	55.000
13	55.000	91.281
Cost ($)	17972.92	24177.73
CPU time (sec)	30.32	50.87

Table II : Comparison of minimum cost($) of various methods in 13-Unit system (for a demand of 1800 MW)

CEP	FEP	MFEP	IFEP	CLPSO
18048.21	18018.00	18028.09	17994.07	17972.92

Table III : Comparison of minimum cost($) of various methods in 13-Unit system (for a demand of 2520 MW)

GA1	GA2	EP	IEP	CLPSO
24416.26	24404.58	24395.50	24395.50	24177.73

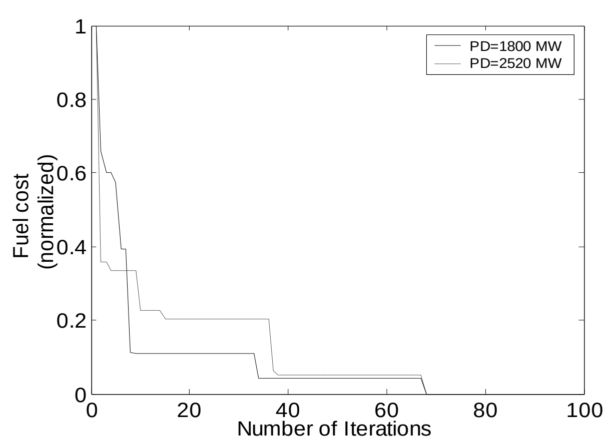

Fig.1. Fuel cost variation of example 1.

For the 40-generator test system the demand is 10500 MW as in [16, 20].

The control parameters used in CLPSO method for this 40-generator test system are as follows:

Population size	200
Number of iterations	200

The results obtained by the proposed method for 10500 MW demand along with other two demands such as 9000 MW and 7500 MW are shown in Table IV. A comparison of results is made in Table V for the demand 10500 MW. It is evident from Table V, the CLPSO method has provided better solution than various EP methods and Modified PSO method. A substantial cost reduction of $725 is realized against PSO in this test case due to the introduction of learning strategy in PSO proposed in this paper. Fig.2 shows the fuel cost variation for these three demands in this example.

Table IV : General output for 40-unit system

Unit	Generation (MW)		
1	112.520	113.995	111.067
2	112.573	113.11	109.782
3	97.410	60.000	60.000
4	180.011	179.242	80.000
5	90.190	86.298	47.000
6	139.980	102.777	68.000
7	299.957	261.028	254.911
8	285.132	284.908	283.395
9	284.505	283.389	283.389
10	130.036	130.000	130.000
11	94.611	94.000	94.000
12	94.262	94.000	94.000
13	215.852	125.016	125.000
14	394.202	125.000	125.000
15	394.318	125.000	125.000
16	304.666	125.000	125.000
17	489.431	309.561	220.000
18	489.658	403.092	220.000
19	511.066	511.597	242.000
20	510.447	421.535	242.000
21	523.364	525.476	523.62
22	523.541	525.976	513.342
23	523.53	524.487	524.593
24	523.264	525.538	521.209
25	523.234	523.341	522.717
26	523.452	524.232	431.747
27	10.252	10.000	10.000
28	10.014	10.615	10.000
29	10.572	10.300	10.000
30	88.086	89.081	88.884
31	190.000	160.039	190.000
32	189.935	161.648	160.416
33	190.000	159.972	160.12
34	199.100	168.285	90.000
35	200.000	161.77	90.000
36	199.648	165.851	90.000
37	110.000	91.393	106.603
38	109.900	92.123	89.485
39	109.946	109.806	85.72
40	511.335	511.519	242
Total generation (MW)	10500	9000	7500
Total Cost ($)	121527.17	103330.27	88532.14
CPU time (sec)	728.1	434.6	520.9

Table V : Comparison of minimum cost of various methods in 4—unit system

CEP	FEP	MFEP	IFEP	MPSO	CLPSO
123488.29	122679.71	122647.57	122624.35	122252.26	121527.17

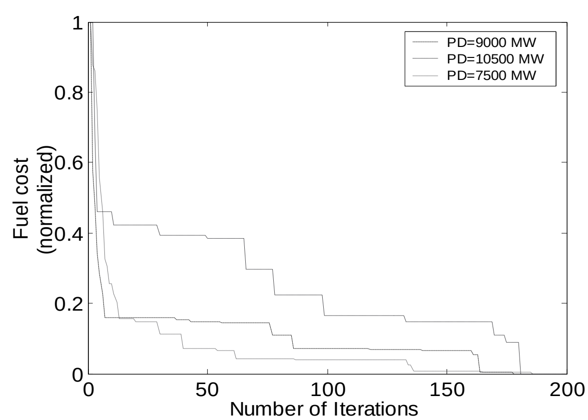

Fig.2. Fuel cost variation of example 2

B. DED problem having nonsmooth cost functions with sine function model

The proposed method is applied to obtain DED solution for a test system, which has 10 generating units. The study horizon is taken as 24 hours. The generator characteristics data and demand data are taken from [7]. Line losses are neglected.

The parameters used in CLPSO method are with population size as 500 and number of iterations set as 500.

Table VI shows the generation output of each generator at each hour by the proposed method and Fig.3 shows its fuel cost variation. A comparison is made with earlier reported results in Table VII. As seen in Table VII, CLPSO performs better than EP and hybrid EP in finding the minimum solution.

Table VIII lists the maximum cost, minimum cost, and average cost obtained, and average CPU time taken of CLPSO method for the first three example problems.

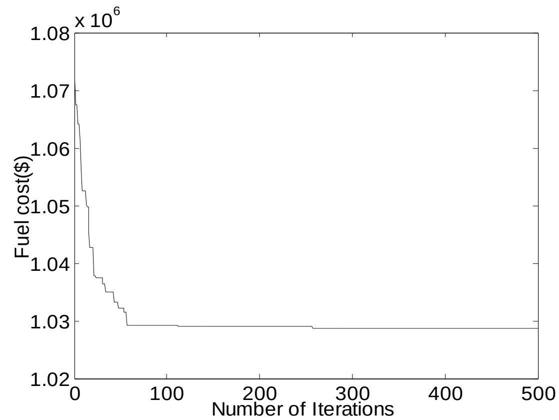

Fig.3. Fuel cost variation of example 3.

Table VI: Generation output for 10-unit 24-hour system

P/Hour	1	2	3	4	5	6	7	8	9	10	11	12
P_1	150.23	227.87	303.56	302.47	379.69	449.17	380.71	457.34	454.34	457.34	457.29	461.57
P_2	137.08	135.82	214.14	222.86	223.95	222.17	299.22	379.04	458.73	458.47	459.46	459.46
P_3	186.84	184.34	133.45	194.86	260.44	297.22	301.63	308.72	296.22	308.07	339.38	316.69
P_4	61.03	62.96	60.46	110.21	120.52	119.74	122.80	77.90	119.74	164.88	185.85	234.64
P_5	123.92	123.67	171.89	171.22	137.23	173.32	222.65	173.41	203.59	223.08	222.59	233.69
P_6	124.54	123.20	123.00	158.74	141.85	121.92	122.93	126.63	136.92	148.63	140.02	159.52
P_7	129.47	99.47	128.89	123.26	94.13	121.65	129.40	129.00	131.65	129.63	129.45	129.67
P_8	47.50	76.50	47.07	47.01	47.04	47.06	47.57	48.52	47.06	76.21	104.37	116.55
P_9	20.39	21.17	20.54	20.37	20.15	20.75	20.09	20.44	20.75	50.69	52.59	53.21
P_{10}	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00
P_D	1036	1110	1258	1406	1480	1628	1702	1776	1924	2072	2146	2220
Cost/h	28316.0	30514.9	33575.0	36927.9	38782.7	41506.7	43004.9	44973.0	48476.9	52276.3	54111.0	55903.0

P/Hour	13	14	15	16	17	18	19	20	21	22	23	24
P_1	455.86	382.16	302.32	226.32	227.23	303.81	382.14	461.96	456.57	379.89	301.39	226.58
P_2	397.61	396.68	396.50	316.61	309.96	321.42	395.99	396.6	319.46	308.64	230.01	222.22
P_3	306.21	315.03	285.72	305.79	307.23	304.54	257.37	307.49	296.32	258.81	196.56	175.30
P_4	241.96	193.43	180.55	131.82	120.28	140.64	190.6	240.41	227.17	179.23	130.6	122.54
P_5	222.47	222.46	173.4	222.35	174.06	173.61	173.95	222.87	220.02	175.00	126.43	122.75
P_6	125.77	122.8	118.97	120.14	122.43	123.54	122.66	158.65	122.36	74.75	123.45	99.38
P_7	129.04	128.83	128.61	99.04	95.04	106.88	129.04	129.83	129.88	129.42	100.6	92.81
P_8	87.32	86.07	85.09	56.18	47.16	76.75	47.3	47.25	47.17	47.14	47.67	47.38
P_9	50.76	21.54	49.84	20.75	21.61	21.81	21.95	51.94	50.05	20.12	20.29	20.04
P_{10}	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00
P_D	2072	1924	1776	1554	1480	1628	1776	2072	1924	1628	1332	1184
Cost/h	51510.3	48164.0	44925.6	40435.7	38202.0	42368.9	45017.6	51565.6	48431.5	42002.3	35570.7	32174.0

Total cost: 1028737$ CPU time: 988 sec.

Table VII: Comparison of minimum cost of various methods in 10-unit 24-hour system

Method	SQP	EP	Hybrid EP	CLPSO
Minimum Cost ($)	1051163	1048638	1035748	1028737

Table VIII: Statistical results of ED problems with sine function modeled nonsmooth fuel cost function (50 Trials)

Test system	13 Unit System		40 Unit System			10 Unit 24 Hour System
Dem. (MW)	1800	2520	10500	9000	7500	
Max. Cost $)	18214.47	25682.61	123714.59	104721.65	90610.54	1071885
Min. Cost $)	17972.92	24177.734	121527.172	103330.27	88532.14	1028737
Avg. Cost ($)	18012.86	24812.39	122489.28	103991.52	89417.64	1050290
Avg. CPU time(sec)	36.84	49.62	818.3	452.1	518.9	1012.6

C. ED problems with prohibited operating zones

In this example a test system which contains six thermal units are considered and all the six units have prohibited operating zones as well as ramp rate limits. The power loss is taken into account by the use of loss-formula coefficients. The input data is taken from [15].The system load demand is 1263 MW as in [15]. Table IX presents the results obtained by the proposed CLPSO method along with the results of GA and PSO reported in [15, 22]. Table XI lists the maximum, minimum, and average costs obtained and average CPU time taken. Fig.4 shows the fuel cost variation in this example.

In the next example, a 15-generator system is considered, however, with only the units 2, 5, 6 and 12 to have prohibited operating zones. The unit characteristics data, loss-formula coefficients are taken from [15]. The system load demand is 2630 MW. As the ramp rate limits and the presence of prohibited operating zones restrict the operating range of units, the search area is getting reduced and even a small population size is enough for a global search.

The parameters used in CLPSO method for these two examples are as follows:

population size	50
number of iterations	100

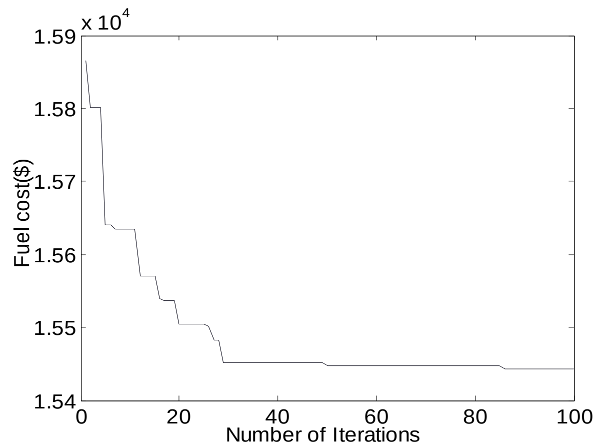

Fig.4. Fuel cost variation of example 4.

Table X shows the results obtained by the CLPSO method for this test case and a reproduction of GA, PSO results found in [22] for comparison. It is to be noted that, the dispatch levels of 6-Unit system by the CLPSO method are closer with PSO method, whereas they are at quite different levels in 15-Unit system, because, the presence of prohibited zones in all six units narrows down the solution space and in 15-Unit case their presence is available in only four generating units. Fig.5 shows the fuel cost variation in this example.

Table IX : Comparison of various methods in 6-unit system

Unit	CLPSO	GA[15]	PSO[15]
1	445.9774	474.4970	447.4970
2	173.4263	178.8066	173.3221
3	264.1014	262.2089	263.4745
4	139.3423	134.2826	139.0594
5	165.4098	151.9039	165.4761
6	87.1534	74.1812	87.1280
Demand	1275.4106	1276.03	1276.01
Ploss (MW)	12.4106	13.0217	12.9584
Cost ($)	15442.66	15459	15450
CPU time (sec)	6.78	21.31	14.89

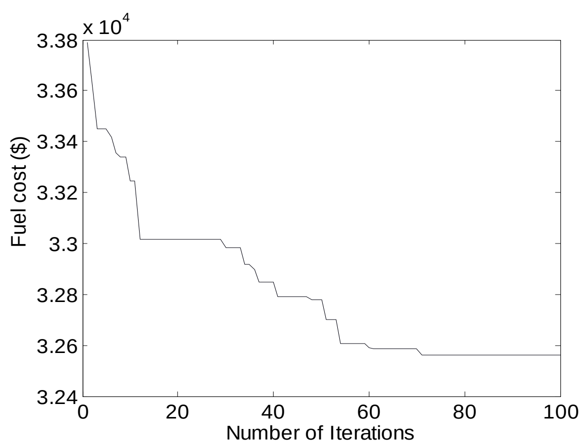

Fig.5 Fuel cost variation of example 5.

Table X : Results and comparison of various methods in 15-unit system

Unit	CLPSO	GA	PSO
1	455.0000	455.0000	450.2978
2	419.9997	440.0000	440.0000
3	130.0000	119.1179	118.1179
4	130.0000	117.9836	122.4839
5	268.5836	270.0000	270.0000
6	460.0000	324.8959	284.0404
7	430.0000	314.1524	430.0000
8	63.3506	140.3805	151.2743
9	25.6830	113.2752	111.3938
10	60.2372	128.6250	75.1117
11	80.0000	63.2303	50.4559
12	77.1371	44.1564	44.6579
13	25.0000	77.2804	47.3174
14	15.0000	25.7138	37.1838
15	15.0000	34.0248	35.0895
Demand (MW)	2654.9912	2668.3	2667.4
Ploss (MW)	24.9912	38.2499	37.3329
Cost ($)	32560.92	33,149	33,020
CPU time (sec)	19.6	26.7	24.72

Table XI shows the maximum cost, minimum cost, and average cost obtained and average time taken by the CLPSO method in the 6-Unit system and 15-Unit system having prohibited operating zones.

Table XI : Statistical Results of ED problems with prohibited operating zones

Test system	6 Unit System	15 Unit System
Demand (MW)	1263	2630
Maximum Cost ($)	15818.71	33191.63
Minimum Cost ($)	15442.66	32560.92
Average Cost ($)	15616.55	32866.73
Average CPU time (sec)	7.21	20.54

6. CONCLUSION

In this paper, a new methodology, Comprehensive Learning Particle Swarm Optimization is proposed to solve ED problems. In this method, each particle learns from different exemplars for different dimensions for a few iterations. This learning strategy enables the swarm to overcome premature convergence. This method yields outstanding performance on ED problems of either static dispatch or dynamic dispatch. The proposed method is implemented in five example test problems having nonsmooth fuel cost functions as either in the form of sine function model into the objective function or with prohibited operating zones. The results of the proposed method are compared with those of evolutionary programming (EP), genetic algorithms (GA) and simple PSO. From the results it is observed that the proposed CLPSO method performs better than GA, EP and PSO in terms of higher quality solution in non-convex ED problems.

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