An Efficient Particle Swarm Optimization for Economic Dispatch Problems With Non-smooth cost functions

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Abstract: - An efficient Particle Swarm Optimization (PSO) technique, employed to solve Economic Dispatch (ED) problems in power system is presented in this paper. With practical consideration, ED will have nonsmooth cost functions with equality and inequality constraints that makes the problem, a large-scale highly constrained nonlinear optimization problem.The proposed method expands the original PSO to handle a different approach for solving those constraints. In this paper, an efficient PSO technique is employed so that faster convergence is obtained for the same results published in IEEE Proceedings. To demonstrate the effectiveness of the proposed method it is being applied to test ED problems, one with smooth and other with nonsmooth cost functions considering valve-point loading effects. Comparison with other optimization techniques showed the superiority of the proposed EPSO approach and confirmed its potential for solving nonlinear economic load dispatch problems.

Key-words: - Economic load dispatch, Particle swarm optimization, Valve point loading effect

1 Introduction

Economic Dispatch (ED) problem is one of the fundamental issues in power system operation. In essence, it is an optimization problem and its main objective is to reduce the total generation cost of units, while satisfying constraints. Previous efforts on solving ED problems have employed various mathematical programming methods and optimization techniques [1]. Recently, Eberhart and Kennedy suggested a Particle Swarm Optimization (PSO) based on the analogy of swarm of bird and school of fish. In PSO, each individual makes its decision based on its own experience together with other individual's experiences [2].The individual particles are drawn stochastically towards the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbors. The main advantages of the PSO algorithm are summarized as: simple concept, easy implementation,and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques.

The practical ED problems with valve-point loading effects are represented as a non smooth optimization problem with equality and inequality constraints. To solve this problem, many salient methods have been proposed such as3 dynamic programming, evolutionary programming, neural network approaches, and genetic algorithm. In this paper, an alternative approach is proposed to the non smooth ED problem using an Efficient PSO (EPSO), which focuses on the treatment of the equality and inequality constraints when modifying each individual's search. The equality constraint (i.e., the supply/demand balance) is easily satisfied by specifying a variable (i.e., a generator output) at random in each iteration as a slag generator whose value is determined by the difference between the total system demand and the total generation excluding the slag generator. However, the inequality constraints in the next position of an individual produced by the PSO algorithm can violate the inequality constraints. In this case, the position of any individual violating the constraints is set to maximum or minimum depending on velocity evaluated [5].

2 Formulation of ED Problem

2.1 ED Problem with Smooth Cost Functions

Economic load dispatch (ELD) pertains to optimum generation scheduling of available generators in an interconnected power system to minimise the cost of generation subject to relevant system constraints. Cost equations are obtained from the heat rate characteristics of the generating machine. Smooth cost functions are are linear, differentiable and convex functions.

The most simplified cost function of each generator can be represented as a quadratic function as given in whose solution can be obtained by the conventional mathematical methods [1]:

$$C = \sum_{j \varepsilon J} F_j(P_j) \quad (1)$$

$$F_j(P_j) = a_j + b_j P_j + c_j P_j^2 \quad (2)$$

where

C	total generation cost
F_j	cost function of generator j
a_j, b_j, c_j	cost coefficients of generator j
P_j	electrical output of generator j
J	set for all generators

While minimizing the total generation cost, the total generation should be equal to the total system demand plus the transmission network loss. However, the network losses are not considered in this paper for simplicity.

The equality constraint for the ED problem can be given by,

$$\sum_{j \varepsilon J} P_j = D \quad (3)$$

where ***D*** is the total system demand

The generation output of each unit should be between its minimum and maximum limits. That is, the following inequality constraint for each generator should be satisfied

$$P_{j\min} \le P_j \le P_{j\max} \quad (4)$$

Where P_{jmin}, P_{jmax} are the minimum, maximum outputs of generator respectively [1].

2.2 ED Problem with Non-smooth Cost Functions

In reality, the objective function of an ED problem has non differentiable points according to valve-point effects. Therefore, the objective function should be composed of a set of non-smooth cost functions. In this paper, one case of non-smooth cost function is considered i.e. the valve-point loading problem where the objective function is generally described as the Superposition of sinusoidal functions and quadratic functions [7].

2.2.1 Non-smooth Cost Function with Valve-Point Effects

The generator with multi-valve steam turbines has very different input-output curve compared with the smooth cost function[6]. Typically, the valve point results in, as each steam valve starts to open, the ripples like in to take account for the valve-point effects, sinusoidal functions are added to the quadratic cost functions as follows:

$$F_j(P_j) = a_j + b_j P_j + c_j P_j^2 + e_j \times \sin(f_j \times (P_{j\min} - P_j)) \quad \textbf{(5)}$$

where e_j, f_j are the coefficients of generator j reflecting valve-point effects.

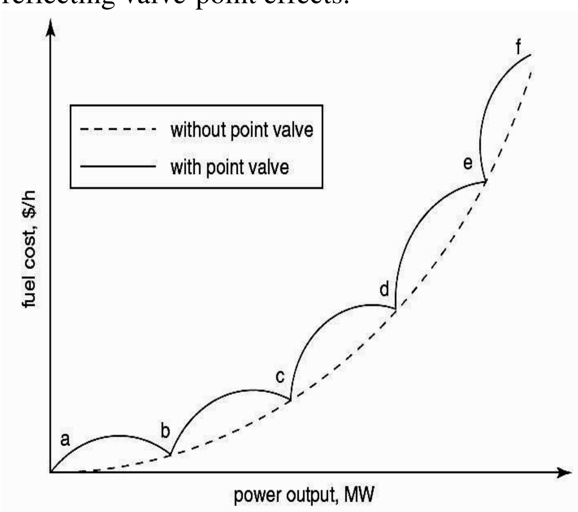


Fig.1 Example cost function with 6 valves

3 Implementation of PSO for ED Problems

The PSO algorithm searches in parallel using a group of individuals , in a physical n dimensional search space, the position and velocity of individual i are represented as the vectors $X_i = (x_{i1},\ldots\ldots,x_{in})$ and $V_i = (v_{i1},\ldots\ldots,v_{in})$, respectively , in the PSO algorithm. Let $\text{Pbest}_i = (x_{i1}^{pbest},\ldots\ldots, x_{in}^{pbest})$ and $\text{Gbest}_i = (x_{i1}^{gbest},\ldots\ldots, x_{in}^{gbest})$, respectively , be the position of the individual i and its neighbors' best position so far[2]. Using the information, the updated velocity of individual i is modified under the following equation in the PSO algorithm:

$$V_i^{k+1} = \omega V_i^k + c_1 \text{rand}_1 \times \left(\text{Pbest}_i^k - X_i^k\right) + c_2 \text{rand}_2 \times \left(\text{Gbest}^k - X_i^k\right) \quad \textbf{(7)}$$

where

V_i^k velocity of individual at iteration k

w weight parameter

c_1, c_2 acceleration factors

$rand_1, rand_2$ random numbers between 0 and 1

X_i^k position of individual i at iteration k

$Pbest_i^k$ best position of individual i until iteration k

$Gbest^k$ best position of the group until iteration k

Each individual moves from the current position to the next one by the modified velocity in (7) using the following equation [2]:

$$X_i^{k+1} = X_i^k + V_i^{k+1}. \quad (8)$$

The search mechanism of the PSO using the modified velocity and position of the individual i based on (7) and (8) is illustrated in Fig. 2

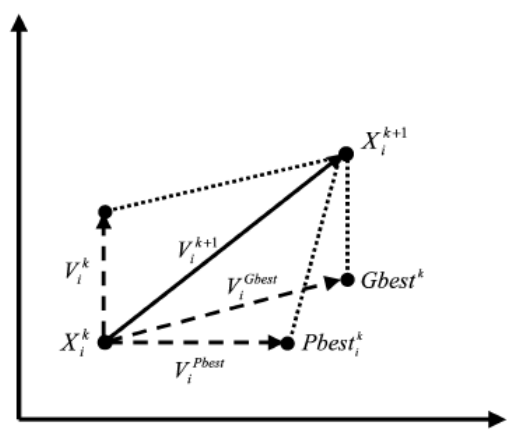


Fig. 2. Search mechanism of PSO

3.1 Efficient PSO for ED problems

In this section, a new approach to implement the PSO algorithm will be described in solving the ED problems. The main process of the modified PSO algorithm can be summarized as follows:

Step 1) Initialization of a group at random while satisfying constraints.
Step 2) Velocity and position updates while satisfying constraints
Step 3) Update of Pbest and Gbest.
Step 4) Go to Step 2 until satisfying stopping criteria.

In the subsequent sections, the detailed implementation strategies of the EPSO are described.

3.1.1 Initialization of Individuals

In the initialization process, a set of individuals(i.e., generation outputs) is created at random. Therefore, individual i's position at iteration 0 can be represented as the vector of $X_i^0 = (P_{i1}^0, \ldots\ldots, P_{in}^0)$ where n is the number of generators.[3]The velocity of individual i (i.e., $V_i^0 = (v_{i1}^0, \ldots\ldots, v_{in}^0)$) corresponds to the generation update quantity covering all generators. The following procedure is suggested for satisfying constraints for each individual in the group:

Step 1) Set j=1,i=1
Step 2) Select the jth element (i.e., generator) of an individual i .
Step 3) Create the value of the element (i.e., generation output) at random satisfying its inequality constraint .
Step 4) If j=n-1 then go to Step 5; otherwise j=j+1 and go to Step 2.
Step 5) The value of the last element of an individual is determined by subtracting
$\sum_{j=1}^{n-1} P_{ij}^0$ *from the total system demand..*
Step 6) If i=no. of individuals then go to step 7; otherwise i=i+1 and go to Step2
Step 7) Stop the initialization process.

After creating the initial position of each individual, the velocity of each individual is also created at random. The following strategy is used in creating the initial velocity:

$$(p_{j\min} - \varepsilon) - p_{ij}^0 \le v_{ij}^0 \le (p_{j\max} + \varepsilon) - p_{ij}^0 \qquad \textbf{(9)}$$

where **ε** is a small positive real number.
The velocity of element j of individual i is generated at random within the boundary [2]. The initial $Pbest_i$ of individual i is set as the initial position of individual and the initial *Gbest* is determined as the position of an individual with minimum payoff of (1).

3.1.2 Velocity Update

To modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage, which is obtained from (7). In this velocity updating process, the values of parameters such as w, c1 and c2 should be determined in

advance.

The weighting function is defined as follows :

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad \textbf{(10)}$$

where,
$\boldsymbol{w_{max}}$, $\boldsymbol{w_{min}}$ - initial, final weights
$\boldsymbol{iter_{max}}$ - maximum iteration number
iter - current iteration number

3.1.3 Position Modification Considering Constraints

The position of each individual is modified by (8). The resulting position of an individual is not always guaranteed to satisfy the inequality constraints due to over/under velocity [4]. If any element of an individual violates its inequality constraint due to over/under speed then the position of the individual is fixed to its maximum/ minimum operating point. Therefore, this can be formulated as follows:

$$P_{ij}^{k+1} = \begin{cases} P_{ij}^k + v_{ij}^{k+1} & \text{if } P_{ij,\min} \le P_{ij}^k + v_{ij}^{k+1} \le P_{ij,\max} \\ P_{ij,\min} & \text{if } P_{ij}^k + v_{ij}^{k+1} < P_{ij,\min} \\ P_{ij,\max} & \text{if } P_{ij}^k + v_{ij}^{k+1} > P_{ij,\max} \end{cases} \qquad (11)$$

To resolve the equality constraint problem without intervening the dynamic process inherent in the PSO algorithm, we propose the following heuristic procedures:

Step 1) Set j=1,i=1. Let the present iteration be k.
Step 2) Select the jth element (i.e., generator) of an individual i.
Step 3) Modify the value of element j using (7), (8), and (11).And satisfy inequality constraint.
Step 4) If j=n-1 then go to Step 5, otherwise j=j+1and go to Step 2.

Step 5) The value of the last element of an individual is determined by subtracting $\sum_{j=1}^{n-1} P_{ij}^{0}$ *from the total system demand.*
Step 6) If i=no. of individuals then go to step 7; otherwise i=i+1 and go to Step2
Step 7) Stop the modification procedure.

3.1.4 Update of Pbest and Gbest
The *Pbest* of each individual at iteration k+1 is updated as follows:

$$\text{Pbest}_i^{k+1} = X_i^{k+1} \quad \text{if } \text{TC}_i^{k+1} < \text{TC}_i^k$$
$$\text{Pbest}_i^{k+1} = \text{Pbest}_i^k \quad \text{if } \text{TC}_i^{k+1} \geq \text{TC}_i^k$$

Where
TC_i - the object function evaluated at the position of individual i
Additionally, *Gbest* at iteration k+1 is set as the best evaluated position among Pbest_i^{k+1}

4 Simulated Result Analysis
To assess the efficiency of the proposed EPSO, it has been applied to ED problems where the objective functions can be either smooth or non-smooth.

4.1 ED Problem with Smooth Cost Functions
The EPSO is applied to an ED problem for standard 2 unit system. The input data for the above system[1] is given in Table 1 and where $\mathbf{P_d}$ is the power demand of the system in megawatt (MW) . Table 2 shows the comparison of the results between EPSO and **λ** iteration.
Software platform used: MATLAB 7.0

4.1.1 Two unit system
Input Data :
Table 1:

Unit	a_i	b_i	c_i	P_{jmin} (MW)	P_{jmax} (MW)	P_d (MW)
1	400	5	0.01	20	200	250
2	600	4	0.015	20	200	

PSO Parameters :
Generations= 100
Population size= 10
Maximum inertia weight, w_{max} = 0.9
Minimum inertia weight, w_{min} = 0.4
Acceleration Constants,c1=c2= 2

Comparison between EPSO and Lambda iteration shown in Table 2 as follows,

Table 2:

Method	P1 (MW)	P2 (MW)	P_d (MW)	CPU TIME (sec)
PSO	130.0000	120.0000	250.0000	0.1870
λ Iteration	130.0345	120.0230	250.0575	3.4160

As seen from Table 2,the EPSO has provided an efficient result when compared with that of **λ** iteration method.

4.1.2 Three unit system
The input data for the standard 3 unit system [1] is given in Table 3. As seen in Table 4, the EPSO has provided the global solution with a very high probability, compared with the lambda-iteration method[3], exactly satisfying the equality and inequality constraints.

Input Data :
Table 3:

Unit	a_i	b_i	c_i	P_{jmin} (MW)	P_{jmax} (MW)	P_d (MW)
1	561	7.92	0.001562	150	600	850
2	310	7.85	0.00194	100	400	
3	78	7.97	0.00482	50	200	

PSO Parameters :
Generations= 100
Population size= 10
Maximum inertia weight, w_{max} = 0.9
Minimum inertia weight, w_{min} = 0.4
Acceleration Constants,c1=c2= 2

Table 4:

Method	P1 (MW)	P2 (MW)	P3 (MW)	P_d (MW)	CPU TIME (sec)
PSO	393.1688	334.6045	122.2267	850.00	0.3750
λ Iteration	393.1727	334.6061	122.2273	850.0061	2.9490

The Table 5 gives the comparison of obtained results of EPSO with numerical method(NM), modified Hopfield neural networks(MHNN), and improved evolutionary programming(IEP).

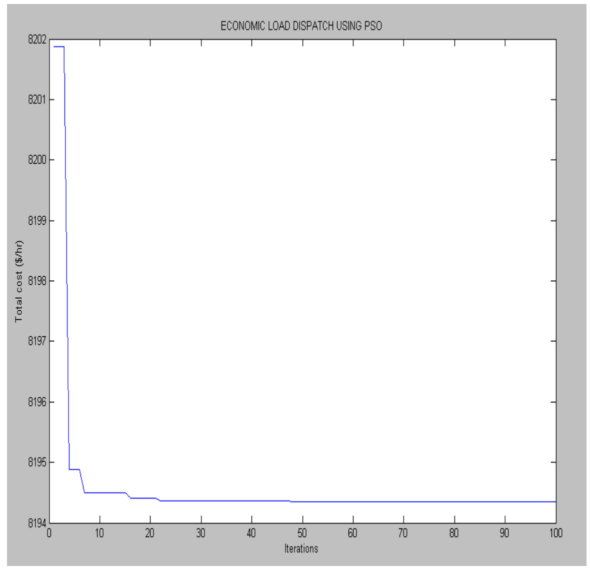
Table 5:

UNIT	NM	MHNN	IEP	EPSO
1	393.172	393.800	393.170	393.1698248
2	334.606	333.100	334.603	334.603754
3	122.227	122.300	122.227	122.2264212
TP	850.006	849.200	850.000	850.000
TC	8194.357	8187.000	8194.35614	8194.356121

*TP:Total Power(MW),TC:Total Cost($/hr)

As visualized from the Table 5, it gives that the proposed EPSO method of optimization is more efficient when compared with other optimization methods.

4.1.2.1 Convergence plot for 3 unit system



4.1.3 Six unit system

The input data for the 6 unit sample system [6] is given in Table 6 as below,

Input Data :

Table 6:

Unit	a_i	b_i	c_i	P_{jmin} (MW)	P_{jmax} (MW)	P_d (MW)
1	240	7.0	0.0070	100	500	1263
2	200	10.0	0.0095	50	200	
3	220	8.5	0.0090	80	300	
4	200	11.0	0.0090	50	150	
5	220	10.5	0.0080	50	200	
6	190	12.0	0.0075	50	120	

PSO Parameters :
Generations= 300
Population size= 10
Maximum inertia weight, w_{max} = 0.9
Minimum inertia weight, w_{min} = 0.4
Acceleration Constants,c1=c2= 2

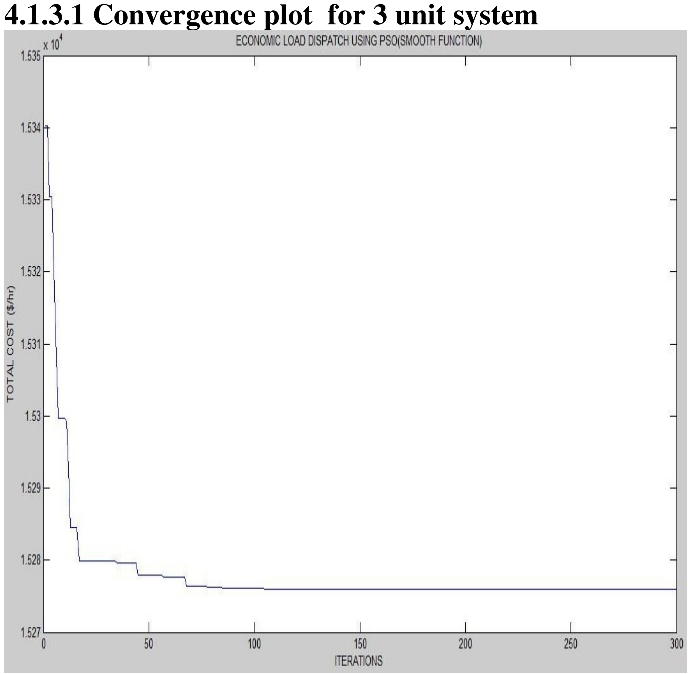
The table 7 gives the power output values of individual generators of 6 unit system as follows,

Table 7:

Unit	Power Output (MW)
1	446.7072691
2	171.2579804
3	264.1056432
4	125.2167933
5	172.118859
6	83.59345494

Thus the total generation cost for optimal operation of 6 unit system is 15275.93039 $/hr.

4.1.3.1 Convergence plot for 3 unit system



4.2 ED Problem with Non Smooth Cost Functions with Valve point effect

4.2.1 Three unit system

Input Data :

The input data for standard three unit system [3] with valve point loading effects is given in Table 8 as below,

Table 8:

Unit	a_i	b_i	c_i	e_i	f_i	$P_{i,min}$	$P_{i,max}$
1	561	7.92	0.001562	300	0.0315	100	600
2	310	7.85	0.001940	200	0.0420	100	400
3	78	7.97	0.004820	150	0.0630	50	200

PSO Parameters :

Generations= 100
Population size= 50
Maximum inertia weight, w_{max} = 1.0
Minimum inertia weight, w_{min} = 0.5
Acceleration Constants,c1=c2= 2

The following Table 9 gives the comparison of efficient PSO (EPSO) with other optimization techniques like genetic algorithms(GA), IEP and evolutionary programming(EP).

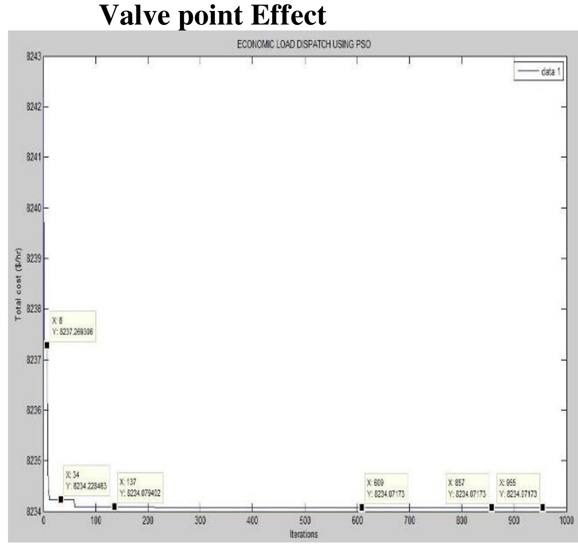
Table 9:

UNIT	GA	IEP	EP	EPSO
1	300.00	300.23	300.26	300.2644952
2	400.00	400.00	400.00	400.00
3	150.00	149.77	149.74	149.7355048
TP	850.00	850.00	850.00	850.00
TC	8237.60	8234.09	8234.07	8234.073073

*TP:Total Power(MW),TC:Total Cost($/hr)

As visualized from the Table 9, it gives that the proposed EPSO method of optimization is more efficient when compared with other optimization methods.

4.2.1.1 Convergence plot for 3 unit system with Valve point Effect



The convergence plot shown above clearly depicts that at how fast the convergence takes place for the proposed EPSO method.

4.2.2 Forty unit system

Input Data :

The input data for the 40 unit sample system with valve point loading effects is given below[13],

Table 10:

Generator	P_{jmin}	P_{jmax}	a_i	b_i	c_i	e_i	f_i
1	3 6	114	0.00690	6.73	94.705	100	0.084
2	3 6	114	0.00690	6.73	94.705	100	0.084
3	6 0	120	0.02028	7.07	309.54	100	0.084
4	8 0	190	0.00942	8.18	369.03	150	0.063
5	4 7	9 7	0.0114	5.35	148.89	120	0.077
6	6 8	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.60	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	9 4	375	0.00515	12.9	635.20	200	0.042
12	9 4	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.40	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.10	801.32	300	0.035
26	254	550	0.00277	7.10	801.32	300	0.035
27	1 0	150	0.52124	3.33	1055.1	120	0.077
28	1 0	150	0.52124	3.33	1055.1	120	0.077
29	1 0	150	0.52124	3.33	1055.1	120	0.077
30	4 7	9 7	0.01140	5.35	148.89	120	0.077
31	6 0	190	0.00160	6.43	222.92	150	0.063
32	6 0	190	0.00160	6.43	222.92	150	0.063
33	6 0	190	0.00160	6.43	222.92	150	0.063
34	9 0	200	0.0001	8.95	107.87	200	0.042
35	9 0	200	0.0001	8.62	116.58	200	0.042
36	9 0	200	0.0001	8.62	116.58	200	0.042
37	2 5	110	0.0161	5.88	307.45	8 0	0.098
38	2 5	110	0.0161	5.88	307.45	8 0	0.098
39	2 5	110	0.0161	5.88	307.45	8 0	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

P_d =10500MW.

PSO Parameters :

Generations= 800
Population size= 150
Maximum inertia weight, w_{max} = 1.0
Minimum inertia weight, w_{min} = 0.1
Acceleration Constants, c1=c2= 2

The table 11 gives the power output values of individual generators of 40 unit system as follows,

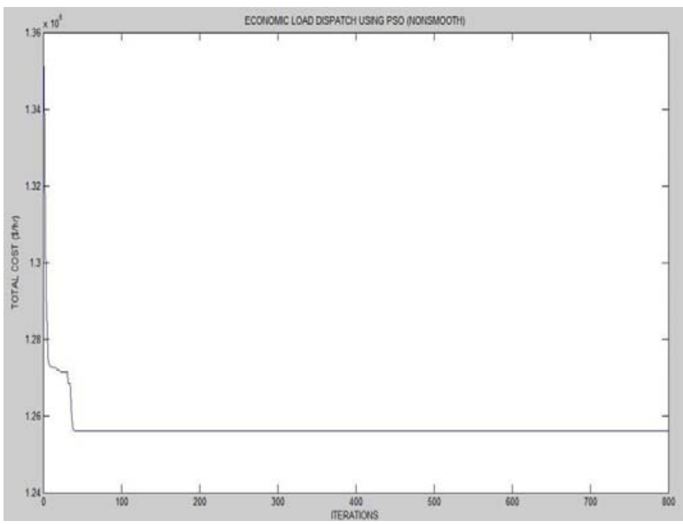
Table 11:

Unit	Power Output (MW)
1	114
2	114
3	60
4	190
5	97
6	140
7	300
8	300
9	290.1619
10	130
11	94
12	94
13	125
14	125
15	394.28
16	394.28
17	500
18	500
19	550
20	550
21	550
22	550
23	550
24	550
25	550
26	550
27	10
28	10
29	10
30	97
31	190

32	190
33	190
34	200
35	200
36	200
37	110
38	110
39	110
40	511.28

Thus the total generation cost for optimal operation of 40 unit system is 124577.273 $/hr

4.2.2.1 Convergence plot for 40 unit system with Valve point Effect



5 Conclusion

This paper presents a new approach to non-smooth ED problems based on the PSO algorithm. A new strategy is incorporated in the PSO framework in order to provide the solutions satisfying the equality and inequality constraints. Although the proposed EPSO algorithm had been successfully applied to ED with valve-point loading effect, the practical ED problems should consider multiple fuels as well as prohibited operating zones. This remains a challenge for future work. Finally we have got an efficient result for smooth cost functions in this EPSO method as compared to the IEEE proceeding results.

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