An Efficient Particle Swarm Optimization (EPSO) for Economic Dispatch Problems With Transmission Losses for Both Smooth and Non-smooth Cost functions

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Abstract: An Efficient Particle Swarm Optimization (EPSO) technique, employed to solve Economic Dispatch (ED) problems including losses in power system is presented in this paper. With practical consideration, ED will have nonsmooth cost functions with equality and inequality constraints that make the problem, a large-scale highly constrained nonlinear optimization problem. The proposed method expands the original PSO to handle a different approach for satisfying those constraints. In this paper, an Efficient Particle Swarm Optimization (EPSO) 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 non smooth 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 with losses.

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 excluding losses [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 as 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 (including losses) 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 minimize the cost of generation subject to relevant system constraints. Cost equations are obtained from the heat rate characteristics of the generating machine. Smooth costs functions 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]:

$$C=\sum F_j(P_j) \qquad (1)$$

$$F_j(P_j) = a_j+b_jP_j+c_jP_j^2 \qquad (2)$$

where

C	total generation cost
Fj	cost function of generator j
aj bj cj	cost coefficients of generator j
Pj	power output of generator j

While minimizing the total generation cost, the total generation should be equal to the total system demand plus the transmission network loss.

The transmission loss is given by the equation,

$$P_L = \sum B_{oi}P_j$$

where B_{oi} is the loss co-efficient matrix.

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

$$\sum P_j + P_L = D \qquad (2)$$

where D is the total demand needed by the load or consumer.

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

$$P_{jmin}<P_j<P_{jmax} \qquad (3)$$

where P_{jmin}, P_{jmax} are the minimum and maximum output of individual generators.

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:

$$F_j(P_j) = a_j+b_jP_j+c_jP_j^2+e_j\times\sin(f_j\times(P_{jmin}-P_j)) \qquad (4)$$

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

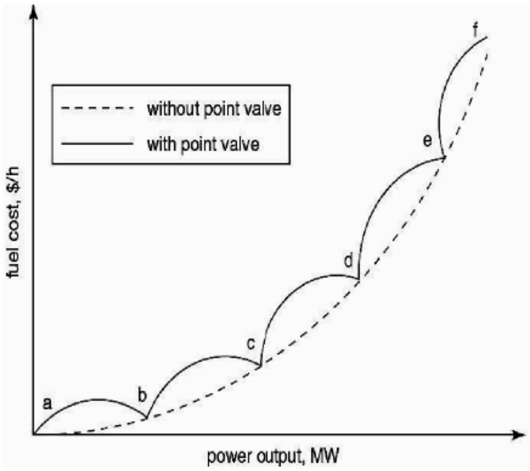


Fig.1 Example cost function with 5 valves

3. Implementation of PSO for ED Problems

The PSO algorithm searches in parallel using a group of individuals, in a physical dimensional search space, the position and velocity of individual i are represented as the vectors **Xi = (xib……….xin)** and **Vi = (vib……….vin)** respectively , in the PSO algorithm. Let $\mathbf{Pbest_i} = (x_{i1}^{pbest} \ldots\ldots x_{in}^{pbest})$ and $\mathbf{GBest_i} = (x_{i1}^{gbest} \ldots\ldots x_{in}^{gbest})$ 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:

$$V_i^{k+1} = \omega V_i^k + c_1 \mathrm{rand}_1 \times \left(\mathrm{Pbest}_i^k - X_i^k\right) + c_2 \mathrm{rand}_2 \times \left(\mathrm{Gbest}^k - X_i^k\right) \quad \textbf{(5)}$$

where

V_i^k	velocity of individual of iteration at k
ω	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 throughout iteration k
$Gbest^k$	best position of group through out iteration k

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

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad \textbf{(6)}$$

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

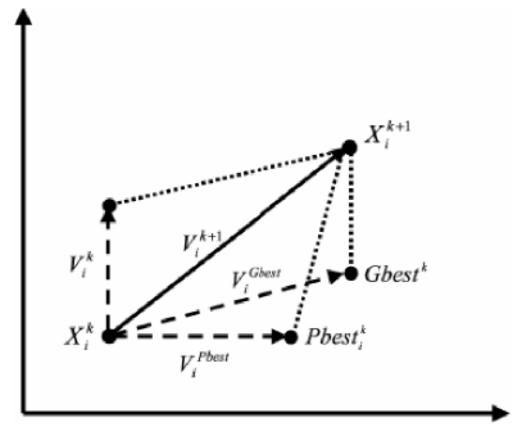


Fig. 2 Search mechanism of PSO

3.1 Efficient PSO for ED problems

In this section, a new approach to implement the PSO algorithm will be described while solving the ED problems considering losses. The main process of the efficient 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) Calculate transmission losses for the obtained Pbest and Gbest
Step 5) Increment the demand with the transmission losses
Step6) 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[th] position at iteration 0 can be represented as the vector of

$$X_i^0 = (P_{i1}^0, \ldots\ldots, P_{in}^0) \quad \textbf{(7)}$$

where
n is the number of generators.

The velocity of individual i is given by

$$V_i^0 = (v_{i1}^0, \ldots\ldots, v_{in}^0) \quad \textbf{(8)}$$

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 j^{th} 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 $\sum \mathbf{P_{ij}}^{\mathbf{0}}$ from the total demand
Step 6) If i=no of individuals go to step 7; otherwise put i=i+1 and go to step 2.
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:

$$(P_{min}-\varepsilon)-P_{ij}^0 < V_{ij}^0 < (P_{max}-\varepsilon)-P_{ij}^0 \quad (9)$$

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 i^{th} individual 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

$$w=w_{max}-(w_{max}-w_{min}/iter_{max})*iter \quad (10)$$

where
w_{max} final weight
w_{min} initial weight
$iter_{max}$ 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 or minimum operating point. Therefore, this can be formulated as follows:

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

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 obtained by subtracting $\sum \mathbf{P_{ij}}^{\mathbf{0}}$ 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:

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

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 $\mathbf{Pbest_i}^{\mathbf{k+1}}$

4 Simulated Result Analyses

To assess the efficiency of the proposed EPSO, it has been applied to ED (with losses) 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 **PD** is the power demand of the system in megawatt (MW) . Table 2 shows the comparison of the results between EPSO and lambda 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}	P_{jmax}	PD
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

Table 2:

Comparison Between EPSO With Losses And Lambda Iteration For 2- Unit Systems.

Method	P1 MW	P2 MW	PD MW	LOSS MW	CPU Time
EPSO	130	130.735	250	10.735	0.1870
Lambda Iteration Method	130	130.735	250	10.735	3.1460

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

Table 3:
Input Data For 3 Unit System

Unit	ai	bi	ci	Pjmin	Pjmax	PD
1.	561	7.92	0.00156	150	600	850
2.	310	7.85	0.00194	100	400	
3.	78	7.97	0.00482	50	200	

EPSO 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:

Comparison Between EPSO With Losses And Lambda Iteration For 3-Unit Systems.

Method	P1	P2	P3	PD	LOSS	CPU Time
EPSO	403.8	342.1	128.3	850	22.79	0.3750
Lambda Iteration Method	403.17	342.60	128.22	850	22.72	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

Comparison Of IEP And EPSO With Losses

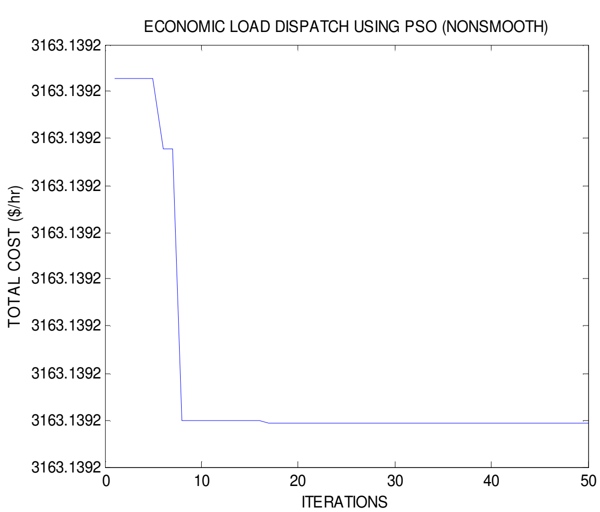
Unit	IEP	EPSO
1	403.17	403.8
2	342.60	342.1
3	128.22	128.3

Parameter	IEP	EPSO
TP	872.79	872.75
TL	22.79	22.75
TC	8194.45	8187.321

*TP: Total Power (MW), TL: Total Losses, 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.

4.1.3 Convergence plot for 3 unit system



4.1.4 Ten unit system

The input data for the 10 unit sample system [6] is given in Table 6 as below,

Table 6:

Input Data For 10 Unit Systems:

Unit	a_i	b_i	c_i	P_{jmin} MW	P_{jmax} MW	PD MW
1	0.00 043	21.60	958.2	150	470	1036
2	0.00 063	21.05	1313.60	135	460	
3	0.00 039	20.81	604.97	73	390	
4	0.00 070	23.90	471.6	60	300	
5	0.00 079	21.62	480.29	73	243	
6	0.00 056	17.87	601.75	57	160	
7	0.00 211	16.51	502.7	20	130	
8	0.00 48	23.23	639.4	47	170	
9	0.10 908	19.58	455.6	20	80	
10	0.00 951	22.54	692.4	55	55	

EPSO 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

Table7:

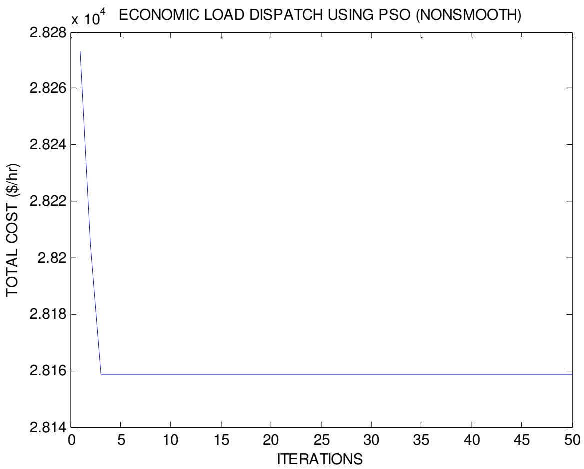
EPSO(Transmission Losses) For 10 Units

Units	EPSO Power output MW
1	160.464
2	147.18
3	77.88
4	60.00
5	164.55
6	160.00
7	130.00
8	66.824
9	20.00
10	55.00

Thus the total generation cost for optimal operation of 10 unit system is **28285.91$/hr**

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

4.1.5 Convergence Plot for 10 Unit Systems



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:

Input Data For 3 Unit Systems

Unit	a_i	b_i	c_i	e_i	f_i	P_{jmin}	P_{jmax}
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

EPSO 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

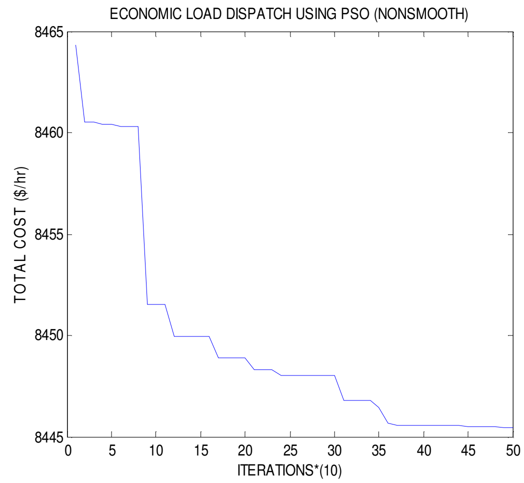
Table 9:
Comparison Of IEP And EPSO With Losses

Unit	IEP	EPSO
1	403.170	403.168
2	340.603	340.6037
3	128.227	128.224

Parameter	IEP	EPSO
TP	872.92	872.86
TL	22.92	22.86
TC	8196.34	8188.13

*TP: Total Power (MW), TL: Total Losses, TC: Total cost ($/hr)

4.2.1.1 Converge 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.

4.2.1 Ten unit system

Table 10:
Input Data For 10 Unit Systems

Unit	a_i	b_i	c_i	e_i	f_i	P_{imin}	P_{imax}
1	0.00043	21.6	958.2	100	0.084	150	470
2	0.00063	21.05	1313.6	100	0.084	165	460
3	0.00039	20.81	604.97	100	0.084	73	390
4	0.00070	23.9	471.6	150	0.063	60	300
5	0.00079	21.62	480.29	120	0.077	73	243
6	0.00056	17.87	601.75	100	0.084	57	160
7	0.00211	16.51	502.7	200	0.042	20	130
8	0.00480	23.23	639.4	200	0.042	47	170
9	0.10908	19.58	485.6	200	0.042	20	80
10	0.00951	22.54	692.4	200	0.042	55	55

EPSO 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

4.2.2 Convergence plot for 10 unit system with Valve Point Loading Effect

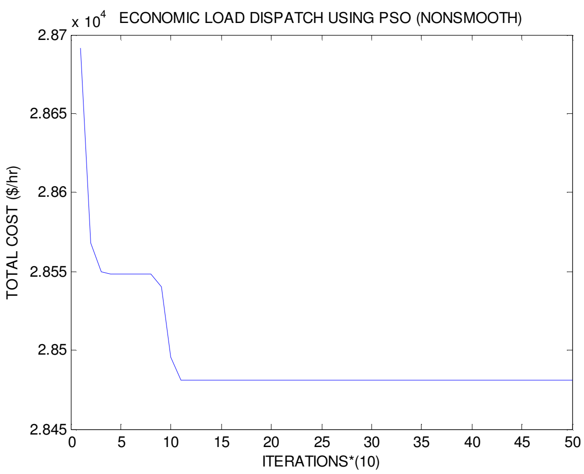


Table 9: EPSO(Transmission Losses) For 10 Unit System

UNIT	POWER OUTPUT MW
1	150
2	135
3	73
4	60
5	198.6362
6	160
7	130
8	47
9	34.0633
10	55

Estimated Losses = 6.29 MW
Optimal Cost = 28,736.67 $/hr

4.3.2 Forty unit system

Table 10:
Input Data For 40 Unit Systems

Unit	a_i	b_i	c_i	e_i	f_i	P_{imin}	P_{imax}
1	0.00690	6.73	94.705	100	0.084	36	114
2	0.00690	6.73	94.705	100	0.084	36	114
3	0.02028	7.07	309.54	100	0.084	60	120
4	0.00942	8.18	369.03	150	0.063	80	190
5	0.0114	5.35	148.89	120	0.077	47	97
6	0.01142	8.05	222.33	100	0.084	68	140
7	0.00357	8.03	287.71	200	0.042	110	300
8	0.00492	6.99	391.98	200	0.042	135	300
9	0.00573	6.60	455.76	200	0.042	135	300
10	0.00605	12.9	722.82	200	0.042	135	300
11	0.00515	12.9	635.20	200	0.042	130	300
12	0.00569	12.8	654.69	200	0.042	94	375
13	0.00421	12.5	913.40	300	0.035	125	500
14	0.00752	8.84	1760.4	300	0.035	125	500
15	0.00708	9.15	1728.3	300	0.035	125	500
16	0.00708	9.15	1728.3	300	0.035	125	500
17	0.00313	7.97	647.85	300	0.035	220	500
18	0.00313	7.95	649.69	300	0.035	220	500
19	0.00313	7.97	647.83	300	0.035	242	550
20	0.00313	7.97	647.81	300	0.035	242	550
21	0.00298	6.63	785.96	300	0.035	254	550
22	0.00298	6.63	785.96	300	0.035	254	550
23	0.00284	6.666	794.53	300	0.035	254	550
24	0.00284	6.66	794.53	300	0.035	254	550
25	0.00277	7.10	801.32	300	0.035	254	550
26	0.00277	7.10	801.32	300	0.035	254	550
27	0.52124	3.33	1055.1	120	0.077	10	150
28	0.52124	3.33	1055.1	120	0.077	10	150
29	0.52124	3.33	1055.1	120	0.077	10	150
30	0.01140	5.35	148.89	120	0.077	47	97
31	0.00160	6.43	222.92	150	0.063	60	190
32	0.00160	6.43	222.92	150	0.063	60	190
33	0.00160	6.43	222.92	150	0.063	60	190
34	0.0001	8.95	107.87	200	0.042	90	200
35	0.0001	8.62	116.58	200	0.042	90	200
36	0.0001	8.62	116.58	200	0.042	90	200
37	0.0161	5.88	307.45	80	0.098	25	110
38	0.0161	5.88	307.45	80	0.098	25	110
39	0.0161	5.88	307.45	80	0.098	25	110
40	0.00313	7.97	647.83	300	0.035	242	550

Power Demand =10500MW.

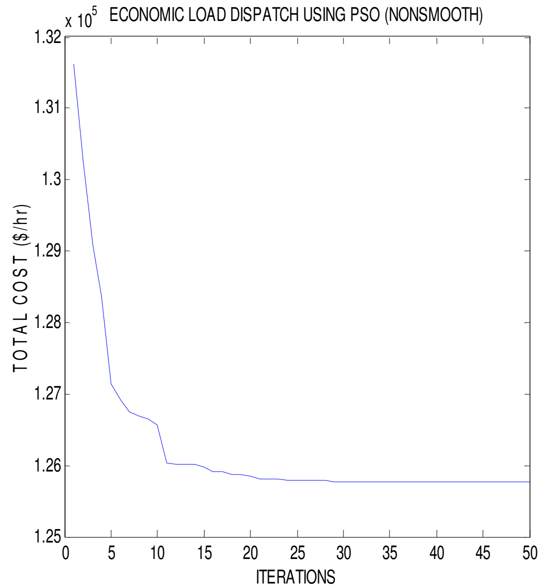
EPSO Parameters:
Generations= 300
Population size= 10
Maximum inertia weight, w_{max} = 0.9
Minimum inertia weight, w_{min} = 0.4
Acceleration Constants, c1=c2= 2

Table 11:
EPSO(Transmission Losses) Results For 40 Unit Systems

UNIT	POWER OUTPUT MW
1	108.050862
2	113.5257021
3	115.2825143
4	188.8629301
5	95.87067372
6	137.2985274
7	290.1661592
8	285.2480313
9	294.6811031
10	285.2480313
11	349.6263277
12	369.2849849
13	466.9895715
14	440.8348903
15	462.1319384
16	455.763579
17	360.211533
18	220
19	550
20	364.5162114
21	550
22	464.2614254
23	502.3040444
24	446.8553429
25	424.9135906
26	379.9197831
27	10
28	37.38369
29	10
30	97
31	60
32	174.4460687
33	196.2311317
34	166.3273326
35	200
36	200
37	69.531618
38	82.13928
39	110
40	514.97533

Estimated Losses = 63.22 MW
Optimal Cost = 133030.533 $/hr

4.2.3.1 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 EPSO 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. Finally we have obtained a rapid and efficient convergence for both smooth and non smooth cost functions using this **EPSO (with Transmission Losses)** method as compared to various other conventional and non-conventional soft computing techniques.

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