A Hybrid Neuro-Efficient Particle Swarm Optimization (EPSO) Algorithm for Economic Load Dispatch Considering Transmission Losses with Non-Smooth and Smooth Cost Function

S.Dhayanand, N Dhyanesh, K S Harshni, S Muthu Vijaya Pandian, T Nandakumar and K.Thanushkodi

***Abstract*— A Hybrid NEURO-EPSO algorithm for solving Economic Load Dispatch Problem (ELD) with non-smooth cost function is presented in this paper. The ELD problem is a highly constrained, large scale, non-linear optimization problem, considering the equality and the inequality constraints. To demonstrate the effectiveness of the proposed algorithm, it is applied to test ELD problem with non-smooth cost function while considering the Valve-Point loading effect. Here we employ an Efficient PSO technique and the Back Propagation Algorithm(NN) to solve the ELD problem, so that faster convergence and more optimized results are obtained compared to other optimization techniques.**

***Index Terms*—Economic Load Dispatch.Effificient Particle swarm optimization, Neural networks.**

I. INTRODUCTION

Economic Load Dispatch (ELD) is defined as the process of allocating generating levels to the generators, so that the load may be supplied, entirely and most economically. 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 with non smooth cost functions considering valve-point loading effect. Comparison with other optimization techniques showed the superiority of the proposed NEURO-EPSO approach and confirmed its potential for solving nonlinear economic load dispatch problems.

Manuscript received March 17, 2009.

First S Dhayanand is a Final year electrical engineering student of V.L.B. Janakiammal College of Engineering and Technology, Coimbatore, Tamil Nadu, India.(Mobile: +91 98947 40059)

Second N Dhyanesh is a Final year electrical engineering student of V.L.B. Janakiammal College of Engineering and Technology, Coimbatore, Tamil Nadu, India.(Mobile: +91 99525 12765)

Third K S Harshni is a Final year electrical engineering student of V.L.B. Janakiammal College of Engineering and Technology, Coimbatore, Tamil Nadu, India.(Mobile: +91 99440 48470)

Fifth S Muthu Vijaya Pandian is a Lecturer in V.L.B. Janakiammal College of Engineering and Technology, Coimbatore, Tamil Nadu, India.(Mobile: +91 98652 59633)

Fourth T Nanda Kumar is a Final year electrical engineering student of V.L.B. Janakiammal College of Engineering and Technology, Coimbatore, Tamil Nadu, India.(Mobile: +91 97866 75470

II. FORMULATION OF ED PROBLEM

A. 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 cost functions are linear, differentiable and convex functions.

The most simplified cost function of each generator can be represented as a quadratic function as given whose solution can be obtained by the conventional mathematical methods.

$$\mathbf{C=\sum F_j(P_j)} \quad \mathbf{(1)}$$

$$\mathbf{F_j(P_j) = a_j+b_jP_j+c_jP_j^2} \quad \mathbf{(2)}$$

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,

$$\mathbf{P_L = \sum B_{oi}P_j} \quad \mathbf{(3)}$$

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

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

$$\mathbf{\sum P_j + P_L = D} \quad \mathbf{(4)}$$

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

$$P_{jmin} < P_j < P_{jmax} \quad (5)$$

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

B. 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.

C. Non-smooth Cost Function with Valve-Point Effects

The generator with multi-valve steam turbines has a very different input-output curve compared with the smooth cost function [6]. Typically, the result of valve point is that, as each steam valve starts to open, ripples occur which should be taken into account, sinusoidal functions are added to the quadratic cost functions as follows:

$$F_j(P_j) = a_j + b_j P_j + c_j P_j^2 + e_j \times \sin(f_j \times (P_{jmin} - P_j)) \quad (6)$$

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

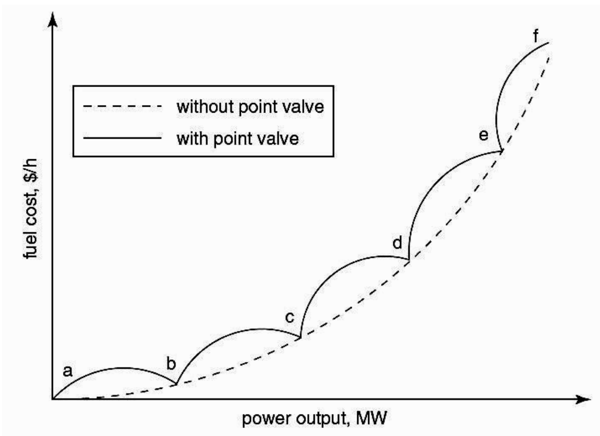


Fig.1 Example cost function with values

III. 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 $\mathbf{Pbest_i} = (x_{i1}^{pbest} \ldots x_{in}^{pbest})$ and $\mathbf{GBest_i} = (x_{i1}^{gbest} \ldots x_{in}^{gbest})$ 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:

$$V_i^{k+1} = \omega V_i^k + c_1 rand1 \times (P_{besti}^k - x_i^k) + c_2 rand_2 \times (G_{best}^k - x_i^k) \quad (7)$$

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 i through iteration k.
$Gbest^k$	best position of group through out k

Each individual moves from the current position to the next one by the modified velocity in (7) using the following equation [8]:

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

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

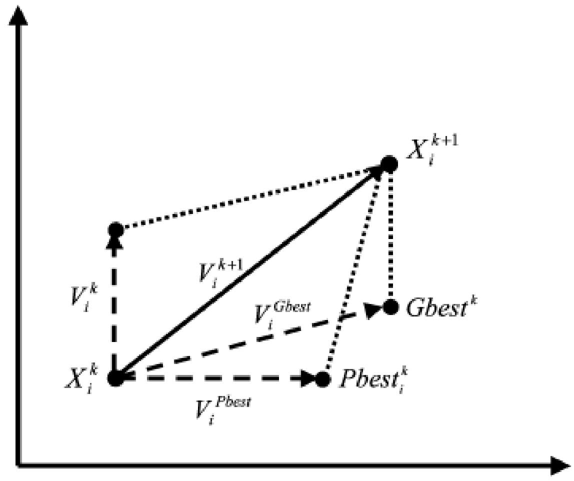


Fig. 2 Search mechanism of PSO

A. 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 (EPSO) 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 algorithm are described.

B. Initialization of Individuals

In the initialization process, a set of individuals (i.e., generation outputs) is created at random. Therefore, individual ith position at iteration 0 can be represented as the vector of

$$\mathbf{X_i^0 = (P_{i1}^0, \ldots\ldots, P_{in}^{\ 0})}$$

where

n is the number of generators. [3]The velocity of individual i is given by

$$\mathbf{V_i^{\ 0} = (v_{i1}^0, \ldots\ldots, v_{in}^{\ 0})}$$

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 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 $\sum \mathbf{P_{ij}^0}$ 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:

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

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).

C. 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, c_1 and c_2 should be determined in advance.
The weighting function is defined as follows

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

where

$\mathbf{w_{max}}$ final weight
$\mathbf{w_{min}}$ initial weight
$\mathbf{iter_{max}}$ maximum iteration number
iter current iteration number

D. 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:

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

To resolve the equality constraint problem without intervening with the dynamic process inherent to the PSO algorithm, we propose the following 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 $\sum \mathbf{P_{ij}^0}$ 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

E. Update of Pbest and Gbest

The Pbest of each individual at iteration k+1 is updated as follows:

$$\mathbf{P_{besti}^{k+1} = x_i^{k+1} \quad if\ TC_i^{k+1} < TC_i^k}$$
$$\mathbf{P_{besti}^{k+1} = P_{besti}^{k} \quad if\ TC_i^{k+1} \geq TC_i^k}$$

Where

$\mathbf{TC_i}$ - the object function evaluated at the position of individual i.

Additionally, **Gbest** at iteration k+1 is set as the best evaluated position among $\mathbf{Pbest_i^{\,k+1}}$

F. Simulated results for analysis of ELD Problem with Non Smooth Cost Functions with Valve point effect

Three unit system:

The input data for standard three unit system [3] for a load demand of 850 MW with valve point loading effect is given in Table1.

Table 1:Input data for 3 units

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

PSO Parameters:
Generations=100
Population size=150
Maximum inertia weight, w_{max} = 1.0
Minimum inertia weight, w_{min} = 0.5
Acceleration constants, c1=c2=2

TABLE 2: OUTPUT DATA FOR 3 UNITS-EPSO

Unit	Output(MW)
1	486.09
2	164.87
3	200.00

Losses: 0.93 MW
Optimal Cost: 8461.22 $/hr

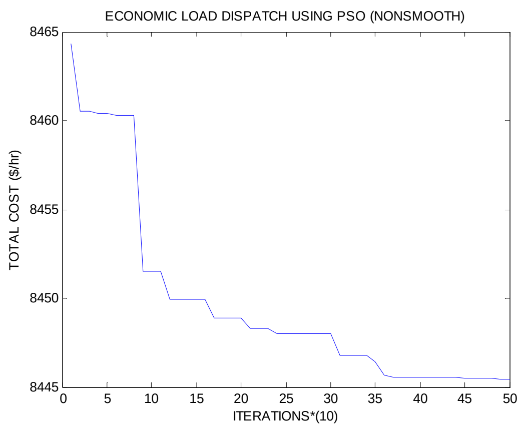


Fig. 3 Converge plot for 3 unit system with Valve Point Effect

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

Ten unit system

The input data for the 10 unit sample system with valve point loading effect is given below.

TABLE 3: INPUT DATA FOR 10 UNITS

Units	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	21.0	1313.6	100	0.084	165	460
3	0.00039	20.8	604.97	100	0.084	73	390
4	0.00070	23.9	471.6	150	0.063	60	300
5	0.00079	21.6	480.29	120	0.077	73	243
6	0.00056	17.8	601.75	100	0.084	57	160
7	0.00211	16.5	502.7	200	0.042	20	130
8	0.00480	23.2	639.4	200	0.042	47	170
9	0.10908	19.5	485.6	200	0.042	20	80
10	0.00951	22.5	692.4	200	0.042	55	55

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 4 gives the power output values of individual generators of 10 unit system for a **demand of 1036 MW** as follows

TABLE 4: OUTPUT DATA FOR 10 UNITS-EPSO

UNIT	POWER OUTPUT MW
1	150.00
2	135.00
3	73.00
4	60.00
5	**198.63**
6	160.00
7	130.00
8	47.00
9	**34.06**
10	55.00

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

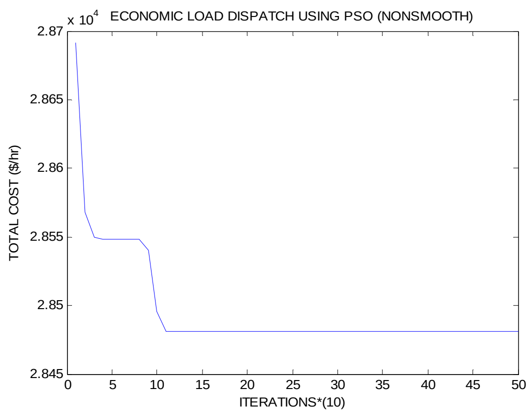


Fig.4 Convergence plot for 10 unit system with Valve Point Loading Effect

IV. NEURAL NETWORKS

An artificial neural network is a mathematical or computational model based on biological neurons. They are information processing paradigms. It consists of a set of interconnected group of artificial neurons. In most cases an artificial neural network is an adaptive network. It is composed of a highly interconnected processing elements called neurons working in unison to solve specific problems. ANN’s like people learn by example. Each neural network can be configured for a particular problem say classification, pattern recognition etc., through a learning process. Learning in biological neurons means the process of adjusting their synaptic connections. This holds good for artificial neural networks also.

A. Multilayered Feed Forward Network

A multi-layered feed-forward Neural Net has an input layer, an output layer and at least one hidden layer. This type of neural net can be utilized to map input patterns into desirable output patterns. To achieve the desired mapping the neural network has to be trained. The network is presented with the training patterns and the network is trained when the error is minimized.

B. Back Propagation Algorithm (NN)

The back propagation algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights which minimizes the error function is considered to be a solution of the learning problem. Since this method requires computing the gradient of the error function at each iteration step, we must guarantee the continuity and differentiability of the error function.

C. Neural Network Training

The ANN is trained to provide ELD results within a maximum tolerance of 1 MW in the generations of the units and the trained network is tested for the similar accuracy for every 1% change in the total load demand. The inputs and the outputs of the training patterns have been appropriately normalized for training the neural net.

Here the sigmoid activation function is employed, number of hidden layer used is one and the number of neurons in each layer will be equal to that of the number of generating units.

D. Simulated Results for NN

Three Unit System

Input data is same as that of Table 1

TABLE 5: OUTPUT DATA FOR 3 UNITS-NEURAL NETWORKS

Unit	Output(MW)
1	536.27
2	114.87
3	200

Losses: 1.64 MW
Optimal Cost: 8438.16 $/hr

Ten Unit System

Input data is a same as that of Table3

TABLE 6: OUTPUT DATA FOR 10 UNITS-NEURAL NETWORKS

UNIT	POWER OUTPUT MW
1	150.00
2	135.00
3	73.00
4	60.00
5	195.63
6	160.00
7	130.00
8	47.00
9	37.06
10	55.00

Losses: 6.72 MW
Optimal Cost: 27, 978.46 $/hr

V. PROPOSED HYBRID SYSTEM

The efficient pso technique and the neural network(back propagation algorithm) explained earlier is hybridized in a unique manner to produce this new system named as Neuro-EPSO

E. Algorithm for Hybrid Neuro-EPSO

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 selected generation is normalized by using binary sigmoid activation function.
Step 6) The output of the BPN is denormalized.
Step 7) The value of the last element of an individual is obtained by subtracting $\sum \mathbf{P_{ij}}^{\mathbf{0}}$ from the total system demand.If the demand is satiafied then go to step-9.
Step 8) If i=no. of individuals then go to step 7; otherwise i=i+1 and go to Step2
Step 9) Stop the modification procedure

F. Hybrid Results

Three Unit System

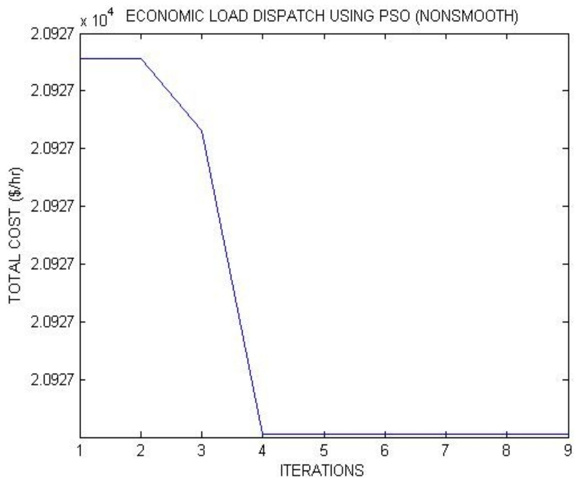
The hybrid Neuro-EPSO algorithm is now applied for a 3 unit system whose input data is the same as that of table 1 and the results are presented below.

TABLE 7: OUTPUT FOR 3 UNIT SYSTEMS- HYBRID

Unit	Output(MW)
1	486.08
2	164.87
3	200

Demand = 850 MW
Losses = 0.95 MW
Elapsed time =0.18 sec

Fig.5 Plot for 3 Unit System Using NN-EPSO Algorithm



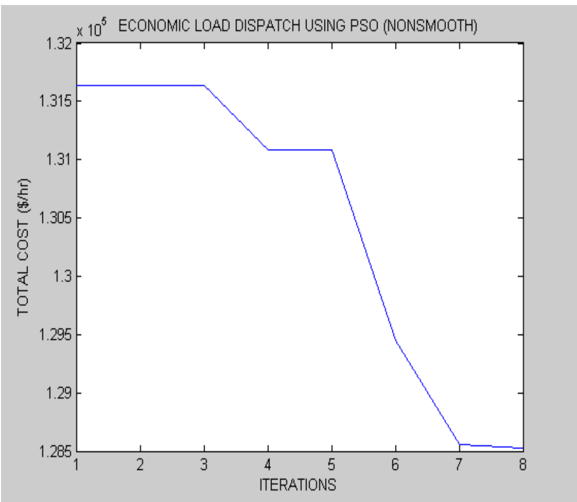
Ten Unit System
Input data is same as that of table 3

TABLE 8: OUTPUT FOR 3 UNIT SYSTEMS- HYBRID

Unit	Output (MW)
1	150
2	135
3	73
4	131.17
5	144
6	119
7	73
8	93
9	68
10	55

Demand = 1036 MW
Losses = 5.17 MW
Elapsed Time = 2.343 sec

Fig.6 Plot For 10 Unit System Using NN-EPSO Algorithm



Forty unit system

TABLE 9: INPUT DATA FOR 40 UNIT SYSTEM

Generator	Pjmin	Pjmax	ai	bi	ci	ei	fi
1	36	114	0.00690	6.73	94.705	100	0.084
2	36	114	0.00690	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.01140	5.35	148.89	120	0.077
6	68	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	94	375	0.00515	12.9	635.20	200	0.042
12	94	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	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.01140	5.35	148.89	120	0.077
31	60	190	0.00160	6.43	222.92	150	0.063
32	60	190	0.00160	6.43	222.92	150	0.063
33	60	190	0.00160	6.43	222.92	150	0.063
34	90	200	0.00010	8.95	107.87	200	0.042
35	90	200	0.00010	8.62	116.58	200	0.042
36	90	200	0.00010	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

TABLE 10: OUTPUT FOR 3 UNIT SYSTEMS- HYBRID

Unit	Output (MW)
1	114
2	114
3	120
4	190
5	97
6	140
7	300
8	300
9	300
10	300
11	375
12	375
13	500
14	500
15	500
16	500
17	409.273
18	225

19	508
20	458
21	356
22	394
23	355
24	525
25	310
26	448
27	72
28	131
29	75
30	67
31	151
32	112
33	139
34	90
35	129
36	104
37	36
38	89
39	104
40	550

Method	P1 MW	P2 MW	P3 MW	PD MW	LOSS MW	OPTIMAL COST $/hr	CPU TIME SEC
EPSO	486.09	164.87	200	850	0.93	20927.807	0.48
NN	536.27	114.87	200	850	0.94	21094.87	0.27
NN-EPSO	**486.08**	**164.87**	**200**	**850**	**0.95**	**20926.3688**	**0.18**

Demand = 10500 MW
Losses = 62.27 MW
Elapsed Time = 6.954 sec

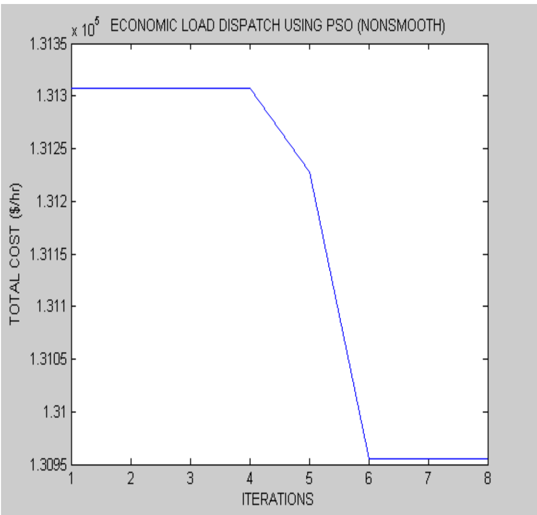


Fig.7Convergence Plot For 40 Unit System Using NN-EPSO Algorithm

It can be inferred by comparing the convergence plot of EPSO and the Hybrid NN-EPSO algorithm that the hybrid algorithm gives the most optimum cost in the least number of iterations.

Hence it can be deduced that the NN-EPSO algorithm is the superior most of all the three algorithms.

This is again clearly brought out in an easy to peruse manner in the table below.

TABLE 11: COMPARISON OF EPSO, NN, NEURO- EPSO FOR 3 UNITS

VI. CONCLUSION

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

REFERENCES:

[1] A. J. Wood, and B. F. Wollenberg, "Power Generation, Operation, and Control", New York: John Wiley & Sons, Inc., 1984.
[2] Kennedy J. and Eberhart R." Swarm Intelligence", Academic Press, 1st ed., San Francisco, CA: Morgan Kaufmann, 2001.
[3] J.B.Park, K.S.Lee, K.Y.Lee, "A particle swarm optimization for economic dispatch with non-smooth cost functions", IEEE Trans. Power systems, vol.20, Feb.2005.
[4] Zwe-Lee Gaing, "Particle Swarm optimization to solving economic dispatch considering the generator constraints", IEEE Trans. Power systems, vol.18, Aug.2003.
[5] H. T. Yang, P. C. Yang, and C. L. Huang, "Evolutionary programming based economic dispatch for units with Non-smooth fuel cost functions, " IEEE Trans. Power Systems, vol. 11, no. 1, pp. 112–118, Feb. 1996.
[6] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming Techniques for economic load dispatch", IEEE Trans. Evol. Comput, vol. 7, pp. 83–94, Feb. 2003.
[7] B.H.Chowdhury and S.Rahman, "A review of recent advances in economic dispatch ", IEEETrans. Power Systems, Vol.5, no.4, pp. 1248- 1259, Nov.1990.
[8] Abido M. A, "Optimal design of power-system stabilizers using particle swarm optimization, " IEEE Trans. Energy Conv., vol. 17, no. 3, pp. 406– 413, Sept.2002.
[9] Kassabalidis I. N, M. A. El-Sharkawi, R. J. Marks, L. S. Moulin, and A. P. A. da Silva, "Dynamic security border identification using enhanced particle swarm optimization, " IEEE Trans. Power Systems., vol. 17, pp. 723–729, Aug. 2002.
[10] T.Sree Renga Raja, N.S.Marimuth and and N.Albert Sing, "A Novel Neural Network for Economic Load Dispatch with Environmental Constraints"International Journal of Electrical and Power Engineering, 1(1) 7-12 2007, Medwell Journals.
[11] G.H.Sen and S.N.Yeh "Particle Swarm Optimization for Economic Power Dispatch with Valve Point Effects." 2006 IEEE PES Transmission and Distribution Conference and Exposition Latin Amercica, Venezuela.
[12] .Y.Lee, June Ho Park and Arthit Sode Yome, "Adaptive Hopfield Neural Networks for Economic Load Dispatch" IEEE Trans. Power Systems., vol. 13, no.2, May.1998.
[13] [11] Nanda J, Sachan A, Pradhan L, Kothari M.L., Rao A.K, Lai, L.L, Prasad M., "Application of Neural Networks to Economic Load Dispatch" Advances in Power System Control, Operation and Management, 1997. APSCOM-97. Fourth International Conference on (Conf. Publ. No. 450), vol. 13, no.2, May.1998.
[14] [12] Deepak Mishra, Amit Shukla, Prem.K.Kalra"OR Neuron Based Hopfield Neural Network for solving Economic Load Dispatch" Neural Information Processing, Vol. 10, No. 11, November 2006

S.DHAYANAND was born in Tiruchirapalli, Tamil Nadu, India, on the 9th of January 1988, Dhayanand is a final year under graduate student at

V.L.B.Janakiammal College of Engineering and Technology Coimbatoere, Tamil Nadu, India, currently pursuing his bachelor's degree (B.E) in Electrical and Electronics Engineering and will receive the degree in may 2009.

He has published a paper titled "Fractional Frequency Transmission System with Automatic Cycloconveter Control" at the National Systems Conference, Manipal Institute of Technology, Manipal, Karnataka, India.His current research interests include power systems and image processing.

N.DHYANESH was born in Coimbatore, Tamil Nadu, India, on the 1st of July 1988. Dhyanesh is a final year under graduate student at V.L.B.Janakiammal College of Engineering and Technology Coimbatoere, Tamil Nadu, India, currently pursuing his bachelor's degree (B.E) in Electrical and Electronics Engineering and will receive the degree in may 2009.

He has published a paper titled "Fractional Frequency Transmission System with Automatic Cycloconveter Control" at the National Systems Conference, Manipal Institute of Technology, Manipal, Karnataka, India.His current research interests include power systems.

HARSHNI SREEDHAR was born in Chennai, Tamil Nadu, India, on the 3rd of May 1988, Harshni is a final year under graduate student at V.L.B.Janakiammal College of Engineering and Technology Coimbatoere, Tamil Nadu, India, currently pursuing her bachelor's degree (B.E) in Electrical and Electronics Engineering and will receive the degree in may 2009.

She has published a paper titled "Fractional Frequency Transmission System with Automatic Cycloconveter Control" at the National Systems Conference, Manipal Institute of Technology, Manipal, Karnataka, India.Her current research interests include power systems and Digital Signal Processing.

Ms.Sreedhar is a member of the Indian Knowledge Commission and the Berkeley Electronic Press socities.

MR.S.MUTHU VIJAYA PANDIAN born in Karaikudi, Tamil Nadu, India on the 16th of june 1978.He received his B.E. in Electrical and electronics engineering from Mohammad Sathak Engineering college, Tamil Nadu India in 1999.He then recived his M.B.A from Madurai Kamarajar University, Tamil Nadu, India in 2002 and his M.E. in Power systems from Government College of Technology, Coimnbatore, Tamil Nadu, India in 2004 and his currently pursuing his Phd under the guidance of Dr.Thanushkodi, syndicate member Anna university Chennai.

He is currently working as a lecturer in V.L.B.Janakiammal college of engineering ant technology.He has published a paper titled "An Efficient Particle Swarm Optimization for Economic Load Dispatch considering Valve point effects" in the WSEAS journal.His current research interests include Power sytems and Neural networks.

T.NANDAKUMAR was born in Tiruchirapalli, Tamil Nadu, India, on the 5th of August 1987, Nandakumar is a final year under graduate student at V.L.B.Janakiammal College of Engineering and Technology Coimbatoere, Tamil Nadu, India, currently pursuing his bachelor's degree (B.E) in Electrical and Electronics Engineering and will receive the degree in may 2009.

His current research interests include power systems and image processing.