Solution of Non-Convex Economic Load Dispatch Problem with Valve Point Loading Effects Using PSO

*G. Sreenivasan, **Dr. C. H. Saibabu, ***Dr. S. Sivanagaraju.
*Reseach scholor, JNTUniversity Kakinada, Kakinada
** Professor&Director(Admissions), JNTU Kakinada, Kakinada, AP, INDIA.
*** Associate Professor, Dept. of Electrical Engineering, JNTU Kakinada, Kakinada, AP, INDIA.

ABSTRACT: *Economic Load Dispatch (ELD) is an important optimization task in power system operation for allocating generation among the committed units such that the constraints imposed are satisfied and the operating cost is minimized. This paper presents an application of Particle swarm optimization (PSO) technique to solve non-liner, non-convex ELD problem for the determination of the global or near global optimum dispatch solution. To illustrate the effectiveness of the proposed approach, a test system consisting of 40-thermal generating units, with incorporation of load balance constraints, operating limits, valve point loadings, is considered and tested. the comparison of numerical results demonstrate the performance and applicability of the proposed method.*

Keywords: *Economic Load Dispatch(ELD),non-convex problem, valve point loading effect, particle swarm optimization*

I. INTRODUCTION

In the traditional ELD problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient-based method, etc. Most of power system optimization problems including economic load dispatch (ELD) have complex and nonlinear characteristics with heavy equality and inequality constraints. The fuel cost functions of generating units can be modeled in a more practical fashion by including the valve-point effects. Thus, the practical ELD problem is represented as a non-smooth optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Many recent works have been around Artificial Intelligence (AI) methods, on par with the development of AI optimization theories, such as Artificial Neural Networks (ANN), Simulated Annealing (SA), Genetic Algorithms (GA), Differential Evolution (DE), Evolutionary Programming (EP), and hybrid methods [3-5]. ELD algorithms for thermal unit system involving combined cycle units presented in [6]. Online solving of economic dispatch problem using neural network approach and comparing it with classical methods were presented in [7]. The evolutionary Algorithms (EAs) are different from the conventional optimization methods, and they do not need to differentiate cost function and constraints. Theoretically, like SA, EAs converge to the global optimum solution. EAs, including Evolutionary Programming (EP), Evolutionary Strategy (ES), and GA are AI methods of optimization based on the mechanics of natural selection, such as mutation, recombination, reproduction, crossover, selection, etc [8]. Many researchers exerted lot of work to improve many optimization and intelligent techniques to solve ELD problems such as GA [11], Hopfield solution [19] and SA [10,22]. N Amjadi, H Nasiri-rad [21] presented a more realistic model for the ED problem considering more practical constraints and non-linear characteristics than previous works in the area. K P Wong, Y W Wong [22] developed and presented the implementation of basic and incremental GA algorithms for determination of the global or near global optimum solution for the economic dispatch problem. A Y saber et al [23] proposed higher order cost function for (a)better curve fitting of running cost (b)less approximation (c)more practical results. There constraint management is incorporated and extra concentration is needed for the higher order cost function of single or multiple fuel units. S Y Lim et al [24] proposed a novel approach to solve the non-smooth ELD Problem with valve point effect by introducing constriction factor concept in the algorithm.

In this paper, an algorithm based on Particle Swarm Optimization technique is proposed as methodology for solving convex and non-convex Economical Load Dispatch problem. In this proposed approach the ELD problem is solved by considering the smooth and non-smooth cost co-efficients, representing the effects of valve point loading, and unit constraints. The results obtained through the approach are analyzed and compared with those existed methods represented in literature.

The proposed algorithm has been implemented in MATLAB 7.0 version on Pentium IV, 2.4 GHZ Personnel Computer with 1 GB RAM.

II. PROBLEM FORMULATION

The Primary concern of an ELD problem is the minimization of its objective function. The total cost generated that meets the demand and satisfies all other constraints associated is selected as the objective function. In general, the ELD problem can be formulated mathematically as a constrained optimization problem with an objective function of the form

$$\text{Minimize } C = \sum_{i=1}^{n} C_i\left(P_{Gi}\right) \qquad \ldots(1)$$

Where

$C_i(P_{Gi})$ is the fuel cost function of the i^{th} unit,
P_{Gi} is the power generated by the i^{th} unit,
n is the total number of generating units,
C is the total generation cost subject to power balance constraints.

This objective function is modeled in two ways as i) Classical Smooth Fuel Cost Function and ii) Non- Smooth Fuel Cost Function.

2.1 Classical Smooth Fuel Cost Functions

Generally, the fuel cost of a thermal generation unit is considered as a second order polynomial function (neglecting valve-point effects) and this is called classical and smooth fuel cost function. It is represented as

$$C_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^{\ 2} \qquad \dots(2)$$

Where a_i b_i, and c_i are the fuel-cost coefficients of the i^{th} unit.

2.2 Non – Smooth Fuel Cost Functions

In present scenario, the input-output characteristics of modern generating units are inherently highly non-linear due to valve point loadings, ramp rate limits etc., further they may have multiple local minimum points in the cost functions. For such combinatorial optimization problems, the conventional methods are failing to obtain the global optimal solutions while considering non-Linear characteristics of the units for the solution techniques as they have no restrictions on the shape of the fuel cost curves.

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore the cost function should be modified to consider the valve point effects. This valve point effect leads to non-smooth, non-convex input-output characteristics as shown in fig.1

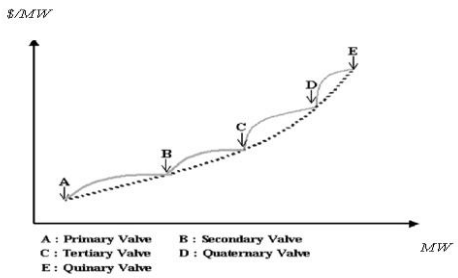

Fig. 1 Input-output characteristics of steam turbine generators with Valve- Point Effects

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:

$$C_i\left(P_{Gi}\right) = a_i + b_i P_{Gi} + c_i P_{Gi}^{\ 2} + \left| e_i \times sin\left(f_i \times \left(P_{Gi_{\min}} - P_{Gi} \right)\right)\right| \qquad \dots(3)$$

Where e_i and f_i are the fuel cost-coefficients of the i^{th} unit reflecting valve-point loading effects.

These classical and non-classical models either with smooth or non smoothed fuel cost functions are subjected to the following equality and inequality constraints.

2.3 Equality Constraints

These constraints are also known as power balance constraints. The total power generated must supply the total load demand and the transmission losses, and expressed as

$$\sum_{i=1}^{n} P_{Gi} = P_D + P_{TL} \qquad \dots (4)$$

Where P_D is the total system load demand and
P_{TL} is the total transmission line losses.

According to Kron's formula, the total transmission line losses can be calculated by the following expression

$$P_{TL} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{Gi}^T B_{ij} P_{Gj} + \sum_{i=1}^{n} P_{Gi} B_{oi} + B_{oo} \qquad \dots(5)$$

Where B_{ij}, B_{oi} and B_{oo} are the transmission line loss coefficients
P_{Gi}^T is the vector transpose of all generating plants net MW.
B_{ij} is the square matrix of same dimension as P_{Gi}
B_{oi} is a vector of same length as P_{Gi} and
B_{oo} is a constant

2.4 Inequality Constraint

Each generator is constrained between its minimum and maximum generation limits, and represented as inequality constraints as.

$$P_{Gi,min} \le P_{Gi} \le P_{Gi,max}, \quad \text{for} \quad i = 1,2,\ldots\ldots n \qquad \ldots(6)$$

Where $P_{Gi,min}$ and $P_{Gi,max}$ are the minimum and maximum power outputs of the i^{th} generating unit.

III. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is one of the most recent developments in the category of combinatorial metaheuristic optimizations. This method has been developed under the scope of artificial life where PSO is inspired by the natural phenomenon of fish schooling or bird flocking. PSO is basically based on the fact that in quest of reaching the optimum solution in a multi-dimensional space, a population of particles is created whose present coordinate determines the cost function to be minimized. After each iteration the new velocity and hence the new position of each particle is updated on the basis of a summated influence of each particle's present velocity, distance of the particle from its own best performance, achieve so far during the search process and the distance of the particle from the leading particle, i.e. the particle which at present is globally the best particle producing till now the best performance i.e. minimum of the cost function achieved so far. Let *x* and v denote a particle position and its corresponding velocity in a search space, respectively. Therefore, the i^{th} particle is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ in the 'd' dimensional space. The best previous positions of the i^{th} particles recorded and represented as $pbest_i = (pbest_{i1}, pbest_{i2}, .\ pbest_{id})$. The index of the best particle among all the particles in the group is represented by the $gbest_d$. The rate of the velocity for i^{th} particle is represented as $v_i=(v_{i1}, v_{i2}, \ldots, v_{id})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_{id}$ to $gbest_d$ as shown in the following formulae:

$$v_{id}^{k+1}=w x v_{id}^{k}+c_{1}\, x\, rand(\,)x(pbest- x_{id}^{k})+c_2 x rand(\,)x(gbest_d-x_{id}^{k}) \qquad \ldots\ (7)$$

$$x_{id}^{k+1}=x_{id}^{k}+ v_{id}^{\ k+1} \qquad \ldots.(8)$$

$$\text{for } i=1,2,\ldots,N_p,\ d=1,2,\ldots\ldots\ N_g$$

where, N_P is the number of particles in a group, Ng the number of members in a particle, k the pointer of iterations, *w* the inertia weight factor, c_1, c_2 the acceleration constants, rand( ) the uniform random value in the range [0,1], v_i^k the velocity of a particle 'i' at iteration k, $v_d^{min}\le v_{id}^{k}\le v_d^{max}$ and x_i^k is the current position of a particle 'i' at iteration k. In the above procedures, the parameter v^{max} determined the resolution, with which regions are to be searched between the present position and the target position. If v^{max} is too high, articles might fly past good solutions. If v^{max} is too small, particles may not explore sufficiently beyond local solutions. The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward the pbest and gbest positions. Low values allow particle to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward or past, target regions. Hence, the acceleration constants c_1 and c_2 were often set to be 2.0 according to past experiences. Suitable selection of inertia weight '*w*' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, '*w'* often decreases linearly from about 0.3to -0.2 during a run. In general, the inertia weight *w* is set according to the following equation:

$$w = w_{\max} - \frac{w_{max} - w_{min}}{iter_{max}}\ x\ iter \qquad \ldots.(9)$$

Where,

ω_{max} : Initial value of inertia weight,

ω_{min} : Final value of inertia weight,

$Iter_{max}$: Maximum iteration number,

Iter : Current iteration number.

IV. PROPOSED PSO FOR ELD PROBLEMS

In this section, a new approach is designed to implement the PSO algorithm in solving the ELD problems. Especially, it is suggested how to deal with the equality and inequality constraints of the ELD problems in the process of modifying each individual's search point in the PSO algorithm. The dynamic process of the PSO algorithm can be summarized as follows:

Step i : Initialization of a group at random

Step ii : Velocity and position update

Step iii : Update of Pbest and Gbest

Step iv : Go to step ii until satisfying stopping criteria.

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

i) Initialization: In the initialization process, a set of individuals is created at random. The structure of an individual for ELD problem is composed of a set of elements (i.e., generation outputs). Therefore, individual i's position at iteration 0 can be represented as the vector $X_i^0 = (P_{i1}, \ldots, P_{in})$ where *n* is the number of generators in the ELD problem. The velocity of individual *i* (i.e., $V_i^0 = (V_{i1}, \ldots, V_{in})$) corresponds to the generation update quantity covering all generators. The elements of position and velocity have the same dimension, i.e., MW in this case. Note that it is very important to create a group of individuals satisfying the equality constraint eqn.(4) and inequality constraint eqn.(6). That is, summation of all elements of individual '*i*' (*i.e.,* $\sum_{J=1}^{n} P_{ij}$) should be equal to the total system demand P_D and the created element *j* of individual '*i*' at random (i.e., P_{ij}) should be located within its boundary. Although the element *j* of individual '*i*' ,created at random satisfying the inequality constraint by mapping [0,1] into [P_{min}, P_{max}], it is necessary to develop a new strategy to handle the equality constraint. To do this, the following procedure is suggested for any individual in a group:

Step 1: Set *j* = 1.
Step 2: Select an element (i.e., generator) of an individual at random.
Step 3: Create the value of the element (i.e., generation output) at random satisfying its inequality constraint.

Step4: If *j = n-1* then go to *Step 5* ; otherwise *j = j+1* and go to *Step2*.

Step5: The value of the last element of an individual is determined by subtracting $\sum_{J=1}^{n-1} P_{ij}$ from the total system demand P_D. If the value is in the range of its operating region then go to *Step* 6; otherwise go to *Step* 1.

Step6: 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:

$$(P_{ij,min} - \varepsilon) - P^{o}_{ij} \le v_{ij} \le (P_{ij,max} + \varepsilon) - P^{o}_{ij} \quad \cdots (10)$$

Where ε is a small positive real number. The velocity element *j* of individual '*i*' is generated at random within the boundary. The developed initialization scheme always guarantees to produce individuals satisfying the constraints as well as not to deviate from the concept of the PSO algorithm. The initial *P*best$_i$ of individual '*i*' is set as the initial position of individual '*i*' and the initial *G* best is determined as the position of an individual with minimum pay off of eqn (1).

ii) 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 eqn(2). In this velocity updating process, the values of parameters such as ω, c_1, and c_2 should be determined in advance. The weighting function is defined as eqn (9).

iii) Position Modification Considering Constraints: The position of each individual is modified by eqn(3) based on its updated velocity. The resulting position of an individual is not always guaranteed to satisfy the inequality constraints due to over/under velocity. 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. Fig.2 illustrates how the position of element *j* of individual '*i*' is adjusted to its maximum when over-velocity situation occurs. The similar strategy is used for individual's position adjustment to its minimum point.

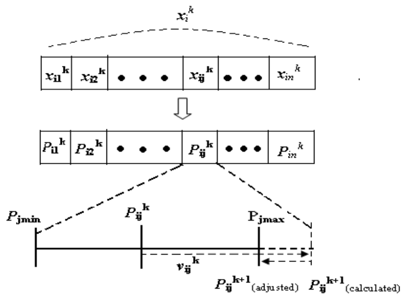

Fig. 2 Adjustment strategy for an individual's position within boundary.

Although the aforementioned method always produces the position of each individual satisfying the inequality constraints given in eqn (6), the problem of equality constraint still remains to be resolved. Therefore, it is necessary to develop a new strategy such that the summation of all elements in an Individual (i.e., $\sum_{J=1}^{n} P_{ij}$) is equal to the total system demand. To resolve the equality constraint problem without intervening the dynamic process inherent in the PSO algorithm, the following heuristic procedures are proposed:

Step 1: Set j = 1. Let present iteration be k.
Step 2: Select an element (i.e., generator) of individual *i* at random and store in an index array *A*(*n*).
Step 3: Modify the value of element *j* (i.e., output of generator *j*) using eqns.(2) and (3), and the position adjustment strategy to satisfy its inequality constraint as follows:

$$\begin{aligned} P_{ij}^{k+1} &= P_{ij}^{k} + v_{ij}^{k+1} && \text{if } P_{ij,min} \le P_{ij}^{k} + v_{ij}^{k+1} \le P_{ij,max} \\ &= P_{ij,\min} && \text{if } P_{ij}^{k} + v_{ij}^{k+1} < P_{ij,,min} \\ &= P_{ij,\max} && \text{if } P_{ij}^{k} + v_{ij}^{k+1} > P_{ij,,min} \end{aligned} \quad \ldots(12)$$

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 individual *i* is determined by subtracting $\sum_{j=1}^{n-1} P_{Gij}$ from P_D. If the value is not within its boundary then adjust the value using eqn.(12 and go to *Step* 6, otherwise go to *Step* 8.

Step 6: Set $l = 1$

Step 7: Readjust the value of element *l* in the index array $A(n)$ to the value satisfying equality condition i.e., $P_D - \sum_{\substack{J=1 \\ J \neq l}}^{n} P_{ij}$. If the value is within its boundary then go to *Step* 8; otherwise, change the value of element-*l* using eqn(12).
Set $l = l+1$, and go to *Step* 7. If $l = n+1$, go to *Step* 6.

Step 8: Stop the modification procedure

iv) Update of P_{best} and G_{best}: The P_{best} of each individual at iteration $k+1$ is updated as follows:

$$Pbest_i^{k+1} = X_i^{k+1} \quad \text{if} \quad TC_i^{k+1} < TC_i^k$$
$$Pbest_i^{k+1} = Pbest_i^k \quad \text{if} \quad TC_i^{k+1} > TC_i^k \qquad \ldots(9)$$

Where,TC_i is the objective function evaluated at the position of individual ' *i* '. Also, *Gbest* at iteration *k*+1 is set as the best evaluated position among $Pbest_i^{k+1}$.

v) Stopping criteria: The proposed method in terminated if the iteration approaches to the predefined maximum iteration.

IV. RESULTS AND ANALYSIS

The performance of the proposed PSO algorithm is verified on a test system consisting of 40-units which has been adopted from [15] with modifications to incorporate the effects of valve point loadings. The proposed method is illustrated with two following cases:

Case -1: Without Valve point effects and
Case -2: With Valve point effects

At each test system, 50 trails were performed using the proposed method to observe the solution quality, convergence characteristic, and execution time. The PSO parameters used in solving the problem are given in Table-1.

Table 1. PSO parameters and their setting values

PSO Parameters	**Setting values**
Population size	20
Number of generations	200
Initial weight function, w_{max}	0.9
Final weight function, w_{min}	0.4
Limit of change in velocity of each number in an individual, V_{pd}^{max}	$0.5\ _{Pd}^{max}$
Limit of change in velocity of each number in an individual, V_{pd}^{min}	$-0.5\ _{Pd}^{min}$
Acceleration constants c_1 and c_2	2

The optimal scheduling and fuel cost comparisons for case-1 & case-2 are given in Table 2. The minimum fuel cost obtained by proposed PSO method for case-1 is 119364.55 $/hr and by GA is 119683.12 $/hr. The minimum fuel cost obtained by proposed PSO method for case-2 is 119558.61$/hr. For case-2,The cost obtained by GA and EP are 119732.25 $/hr and 123488.29 $/hr respectively. The convergence characteristics of proposed technique for case-1 and case-2 are shown in fig.3. The results obtained by proposed technique are compared with existing methods and found satisfactorily in terms of execution time and net saving. For case-1, the execution time for proposed PSO technique is 0.98 sec and for existing GA method is 12.52 sec. The net saving in cost by the proposed technique is 318.57 $/hr when compared to GA. For case-2, the execution time for proposed technique is 1.03 sec and for existing EP method the execution time is 1955.20 sec. The net saving in cost by the proposed technique is 173.64 $/hr when compared to GA and 3929.68 $/hr when compared to EP. It is also observed that, the PSO is a very robust and efficient algorithm in terms of control parameters such as the number of particles in a group and condition of initial group generated at random. Although the required number of iterations reacting the global solution is different when the number of particles or the random initial group is changed, the PSO guarantees the convergence to the global solution for the examples taken. It is also observed that the solutions provided by the proposed PSO always satisfy the equality and inequality constraints for all the cases.

Table 2 Optimal scheduling and fuel cost comparisons of 40 – unit system

Generation of units (MW)	Case-1		Case-2		
	GA method	Proposed method	Existing GA [26]	Existing EP[15]	Proposed method
PG_1	114	114	108.76409	--	114.00
PG_2	114	114	114.0000	--	114.00
PG_3	120	120	117.63920	--	120.00
PG_4	190	190	190.0000	--	190.00
PG_5	97	97	97.0000	--	97.00
PG_6	140	140	140.0000	--	140.00
PG_7	300	300	300.0000	--	300.00
PG_8	300	300	300.0000	--	300.00
PG_9	300	300	300.0000	--	300.00
PG_{10}	188.73	300.00	136.5658	--	300.00
PG_{11}	126.69	375.00	94.7871	--	375.00
PG_{12}	98.94	267.46	94.3880	--	375.00
PG_{13}	260.63	500.00	127.9169	--	216.62
PG_{14}	322.95	241.81	311.1454	--	304.55
PG_{15}	161.66	421.01	282.7689	--	496.07
PG_{16}	319.28	500.00	203.2046	--	363.25
PG_{17}	482.21	500.00	500.0000	--	391.70
PG_{18}	455.66	340.48	500.0000	--	477.43
PG_{19}	515.08	242.00	550.0000	--	345.43
PG_{20}	547.89	408.28	550.0000	--	512.06
PG_{21}	538.14	547.80	550.0000	--	439.88
PG_{22}	550.00	550.00	550.0000	--	526.37
PG_{23}	539.58	520.60	550.0000	--	524.65
PG_{24}	549.42	550.00	550.0000	--	269.04
PG_{25}	513.83	378.55	550.0000	--	523.29
PG_{26}	541.32	527.77	550.0000	--	534.34
PG_{27}	10.82	18.70	14.03671	--	11.31
PG_{28}	17.80	12.42	11.9778	--	13.56
PG_{29}	17.80	10.00	11.3036	--	10.00
PG_{30}	76.81	62.67	97.0000	--	72.67
PG_{31}	188.73	60.00	190.0000	--	133.60
PG_{32}	180.09	190.00	190.0000	--	189.86
PG_{33}	183.90	125.92	190.0000	--	155.49

PG_{34}		191.18	186.19	200.0000	--	200.00
PG_{35}		199.68	158.81	200.0000	--	199.99
PG_{36}		190.86	180.54	200.0000	--	132.85
PG_{37}		97.70	55.95	107.5014	--	35.86
PG_{38}		101.77	49.91	110.0000	--	93.92
PG_{39}		105.85	25.00	110.0000	--	51.20
PG_{40}		550.00	518.14	550.0000	--	550.00
Demand (MW)		10500.00	10500.00	10500.00	10500.00	10500.00
Fuel Cost ($/hr)	Best	119683.12	119364.55	119732.25	123488.29	119558.61
	Average	121330.20	119558.61	--	124793.48	121308.69
	Worst	133352.26	123793.77	--	126902.89	126270.07
Execution Time (Sec)		12.52	0.98	--	1955.20	1.03
Net Saving ($/hr)		-	318.57	--		173.64

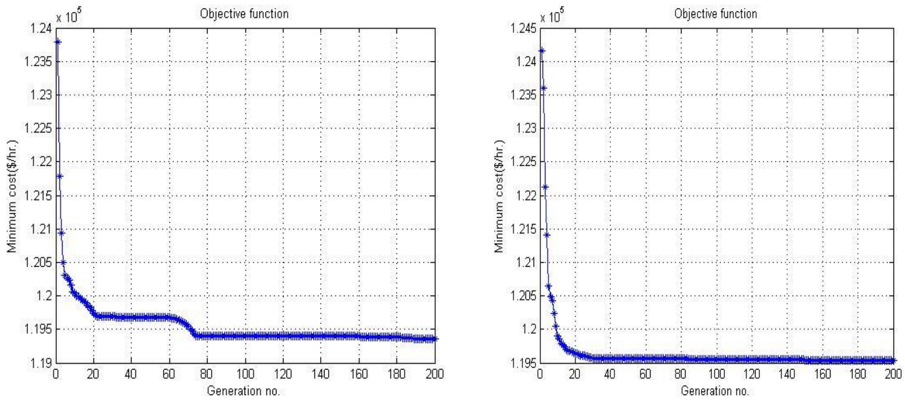

Fig 3 Convergence Characteristics of PSO Algorithm for Case-1 and Case-2 of 40-unit system

V. CONCLUSIONS

In this paper the PSO method is successfully employed to solve the Economic Load Dispatch (ELD) problem with generator constraints and valve point loading effects. The PSO Algorithm has been demonstrated to have superior features, including high quality solutions, stable convergence characteristics and good computation efficiency. The non-linear characteristics of the generator such as valve point loading effects and non-smooth cost functions are considered for practical generator operations in the proposed method. The results show that the proposed method was indeed capable of obtaining higher quality solution efficiently in non-linear, non-convex ELD Problems within a reasonable computation time and iteration numbers when compared to the existing methods given in literature.

REFERENCES

[1]. Wood,A.J .,and Wollenberg,B.F.: "Power Generation, Operation And Control" (Wiley, New York,1984)
[2]. Irving,M.R., and Sterling.M.J.H. "Economic Dispatch Of Active Power With Constraint Relaxation", IEE Proc.C.1983, 130,(4), Pp.172-177.
[3]. Nanda,J., Kothari,D.P., And Srivastava,S.C.: "New Optimum Power-Dispatch Algorithm Using Fletcher's Quadratic Programming Method", Iee Proc.C.1989,136,(3),Pp.153-161.
[4]. Berry.P.E., and Dunnett,R.M., "Contingency Constrained Economic Dispatch Algorithm For Transmission Planning', IEE Proc.C, 1989,136,(4),Pp.238-244.
[5]. Lee,K.Y.,Park,Y.M., and Ortis,M.S,: "Fuel-Cost Minimization For Both Real And Reactive-Power Dispatches", IEEE Proc. C , 1984,131.
[6]. Lin,C.E., and Viviani,G.L.: "Hierarchical Economic Dispatch For Piecewise Quadratic Cost Functions", IEEE Trans.,1984.Pas-103,(6),Pp.1170-1175.

[7]. Wong,K.P., And Doan,K. "A Recursive Economic Dispatch Algorithm For Assessing The Cost Of Thermal Generator Schedules', IEEE Trans.,1992,Pwrs-7,(2),Pp.577-583.
[8]. IEEE Committee Report: "Practices In The Economic Operation Of Power Systems", IEEE Trans.,1971,Pas-90,Pp.1768-1775.
[9]. Liang,Z.X., And Glover , J.D. "A Zoom Feature For A Dynamic Programming Solution To Economic Dispatch Including Transmission Losses', IEEE Trans.,1992,Pwrs-7,(2),Pp.544-550.
[10]. Wong,K.P., And Fung,C.C, "Simulated-Annealing Based Economic Dispatch Algorithm," IEEE Proc.C, 1993,140,(6),Pp.509-515.
[11]. Walters,D.C., And Sheble,G.B. "Genetic Algorithm Solution Of Economic Dispatch With Valve Point Loading", IEEE Trans. On Power Systems, Vol. PWRS-8,No,3,Aug 1993, Pp. 1325-1332.
[12]. Hong-Tzer Yang,Pai-Chuan Yang ,Ching-Lien Huang, "Evolutionary Programming Based Economic Dispatch For Units With Non-Smooth Fuel Cost Functions". IEEE Transaction On Power Systems, Vol.11, No.1, February 1996
[13]. L.L.Lai, "Evolutionary Programming For Economic Load Dispatch Of Units With Non Smooth Input-Output Characteristic Function", Intelligent System Applications in Power Engineering –Evolutionary Programming and Neutral Networks. Chichester, U.K.:Wiley ,1998 , Ch.8.
[14]. 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 Syst.,Vol.11,Pp.112-118,Feb.1996.
[15]. Nidul Sinha, R.Chakrabarti, and P.K.Chattopadhyay, "Evolutionary Programming Techniques For Economic Load Dispatch", IEEE Transactions on Evolutionary Computation, Vol.7,No.1,February 2003.
[16]. J.B.Park,K.S.Lee,J.R.Shin and K.Y.Lee, "A Particle Swarm Optimization for Economic Dispatch with Non-Smooth Cost Funnction", IEEE Trans.Power Syst.,Vol.20,No.1,Pp.34-42,Feb.2005.
[17]. C.E.Lin And G.L.Viviani, "Hierarchical Economic Dispatch For Piece-Wise Quadratic Cost Functions," IEEE Trans. Power App.Syst.,Vol.Pas-103,No.6,Pp.1170-1175,June 1984.
[18]. C.L.Chen And C.L.Wang, "Branch-And –Bound Scheduling For Thermal Generating Units," IEEE Trans. Energy Convers., Vol.8,No.2,Pp.184-189, June.1993.
[19]. Leandro Dos Santos Coelho And Viviana Cocco Mariani , "Combining Of Chaotic Differential Evolution And Quadratic Programming For Economic Dispatch Optimization With Valve-Point Effect," IEEE Transactions On Power Systems,Vol.21,No.2,May 2006.
[20]. T.A.A.Victoire And A.E.Jeyakumar, "Hybrid PSO-SQP For Economic Dispatch With Valve –Point Effect," Elect.Power Syst.Res.,Vol.71,No.1,Pp.51-59,Sep.2004.
[21]. N.Amjady, H.Nasiri-Rad , "Economic Dispatch Using An Efficient Real-Coded Genetic Algorithm",IET Gener.Transm. Distrib., 2009, Vol.3, Issue 3,Pp 266-278.
[22]. K.P.Wong, Y.W.Wong, "Genetic And Genetic/Simulated-Annealing Approaches To Economic Dispatch" IEEE Proc. -Gener. Transn .Distrib., Vol.141,No.5,September 1994.
[23]. Ahmed Yousuf Saber, Atsushi Yona, And Masatake Higashi, "Economic Load Dispatch Of Higher Order Cost Polynomials Using Modified Particle Swarm Optimization",2007 IEEE,Pp.1203-1208.
[24]. Shi Yao Lim, Mohammad Montakhab, And Hassan Nouri, "Economic Dispatch of Power System Using Particle Swarm Optimization With ConstrictionFactor",International Journal of Innovations in Energy Systems and Power;Vol.4,No.2,October 2009.
[25]. S.Muthu Vijaya Pandian,K.Thanushkodi, "An Evolutionary Programming Based Efficient Particle Swarm Optimization For Economic Dispatch Problem With Valve-Point Loading", EuropeanJournal ofScientificResearch,Vol.52,No.3,2011,Pp.385-397.
[26]. Attia A.El-Fargany, "Solution of Economic Load Dispatch problem with smooth and non-smooth fuel cost functions including line losses using Genetic Algorithm," International journal of Computer and Electrical Engineering,Vol.3,No.5,October 2011.

About The Authors

*__G. Sreenivasan__ received his graduation in 1996, Masters in 2001 from JNTUniversity college of Engineering, Anantapur and pursuing Ph.D at JNTUniversity, Kakinada. Presently he is working as Associate Professor in the department of Electrical and Electronics Engineering, Intell Engineering College, Anantapur since 2001. His area of interest is applications of GA and PSO to Power System Operation and Control. He has published research papers in 6 international and 3 national journals and has publications in national and international conferences. He has participated several workshops conducted by various engineering colleges at south India.He authored the text book, "Power System Operation and Control" under the publication of Pearson Education, New Delhi. He is the life member of ISTE and IE.

** **Dr. CH. SaiBabu** received his graduation from Andhra university, Masters from REC, Warangal and Ph.D from JNTU, Hyderabad. He is the Professor in the Department of Electrical and Electronics Engineering and Director of Admissions at JNT University, Kakinada. He has about 20 publications in international journals and 44 national and international conferences. He authored a text book, "Elements of Power Electronics" published by S.Chand and Co. He is the member of AICTE team and Member of governing council for various affiliated engineering colleges of JNTU, Kakinada.

*** **Dr. S. Sivanagaraju** received his graduation in 1998, Masters in 2000 from IIT, Kharagpur and his Ph.D from JNT University, Hyderabad in 2004. He is working as Associate Professor and Head of the Electrical and Electronics Engineering department, JNT University, Kakinada, Andhra Pradesh. He has received 2 National awards (Panditmadan Mohan malaviya Memorial prize award and Best paper prize award) form the Institute of Engineers (India) for the year 2003 – 2004. He is also a referee for the IEEE proceedings – generation, transmission and distribution and international journal of emerging electric power systems. He has about 50 publications in national and international journals and conferences to his credit. His areas of interest are in Distribution Automation, Genetic Algorithm Applications to Distribution Systems and Power Systems.