Economic Load Dispatch Solutions using New Particle Swarm Intelligence

Yajvender Pal Verma and Ashwani Kumar

Abstract-- **In this paper new particle swarm optimization (NPSO) technique is being used to solve non-convex economic load dispatch (ELD) problems. Unlike classical particle swarm optimization (PSO) method the NPSO remembers both best and worst visited position of the particles which helps in exploring the search space effectively. Some nonlinear characteristics of the generators such as ramp rate limits, valve point effects and non linear cost functions are considered. The local random search is also being combined to expedite the solution finding. The technique has been applied to three generator test system for various cost functions. The optimum values of parameters selected were obtained and verified. The NPSO was found efficient in terms of convergence rate and optimal cost for Economic Dispatch problem.**

Index Terms**—Economic load dispatch, ramp rate limit, particle swarm optimization.**

I. Introduction

Electric power industry is changing rapidly and the traditional monopolistic environment is moving to a competitive power supply market. Determining the operating strategies to meet the demand for electricity for a specific planning horizon is one of the most important concerns under the current commercial pressure [1]. A major challenge for all power utilities is not only to satisfy the consumer demand for power, but to do so at minimal cost. Any given power system can be comprised of multiple generating stations, each of which has its own characteristic operating parameters. The cost of operating these generators does not usually correlate proportionally with their outputs; therefore the challenge for power utilities is to try to balance the total load among generators that are running as efficiently as possible.

In a typical power system multiple generators having unique cost-per hour characteristics are used to meet the total consumer demand. The things become complex when utilities try to account for the transmission loss and seasonal changes [2]. The objective is to minimize the total cost of generation (including fuel cost, emission cost, operating/maintenance cost plus network losses cost) meeting various operational constraints. The generators are to be coordinated in such a way that lowest cost generators are used as much as possible and expensive generators are to be operated when demand increases[3].

The ELD problem has been solved by many traditional techniques. The ramp rate limits inclusion makes the problem different from the static Economic load dispatch [4], [5], [6]. Dynamic Economic Dispatch problem is also introduced and solved by discretization of the entire dispatch period into a number of small time periods. To achieve the overall cost reduction, static economic dispatch (ED) in each time period is solved subject to the power balance constraint at that time and the additional time dependent dynamic constraints [7], [8], [9], [10].

Economic load dispatch is the fundamental optimization problem in power system and it must include ramp rate limits, prohibited operating zones, valve point effects and multi fuel options to make a complete economic dispatch problem[11][12]. In this paper the new particle swarm optimization technique is being applied to the generator system having non smooth characteristics of cost. The technique remembers the previously visited best and worst positions of the swarm particles that help in expediting the search process. The local random search is also being included to speed up the search and explore the search space effectively. The technique was applied on 3-bus system to demonstrate the effectiveness of the technique. The coding was done in turbo C++ and PSO was implemented for economic dispatch problems.

II. Overview of New Particle Swarm Optimization

Natural creatures sometime behave as a Swarm. One of the main streams of artificial life researches is to examine how natural creatures behave as a Swarm and reconfigure the Swarm models inside the computer. Dr. Eberhart and Kennedy develop PSO, based on analogy of the Swarm of birds and fish school. Each individual exchanges previous experiences among themselves [13]. PSO as an optimization tool provides a population based search procedure in which individuals called particles change their position with time. In a PSO system, particles fly around in a multi dimensional search space. During flight each particles adjust its position according its own experience and the experience of the neighboring particles, making use of the best position encountered by itself and its neighbors.

In the multidimensional space where the optimal solution is sought, each particle in the swarm is moved toward the optimal point by adding a velocity with its position. The

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velocity of a particle is influenced by three components, namely, inertial, cognitive, and social. The inertial component simulates the inertial behavior of the bird to fly in the previous direction. The cognitive component models the memory of the bird about its previous best position, and the social component models the memory of the bird about the best position among the particles .The particles move around the multidimensional search space until they find the optimal solution. The modified velocity of each agent can be calculated using the current velocity and the distance from Pbest and Gbest as given below.

$$V_{ij}^{t} = w \times V_{ij}^{t-1} + C_{1g} \times r_1 \times \left(Pbest_{ij}^{t-1} - X_{ij}^{t-1}\right) + C_2 \times r_2 \times \left(Gbest_{i}^{t-1} - X_{ij}^{t-1}\right) \quad (1)$$

$i=1,2,\ldots,N_D$
$j=1,2,\ldots,N_{par}$

Using the above equation, a certain velocity, which gradually gets close to Pbest and Gbest, can be calculated. The current position (searching point in the solution space), each individual moves from the current position to the next one by the modified velocity in (1) using the following equation:

$$X_{ij}^{t} = X_{ij}^{t-1} + V_{ij}^{t} \quad (2)$$

$i=1,2,\ldots,N_D$
$j=1,2,\ldots,N_{par}$

where,

t	Iteration count,
V_{ij}^{t}	Dimension *i* of the velocity of particle *j* at iteration *t*,
X_{ij}^{t}	Dimension *i* of the position of particle *j* at iteration *t*,
w	Inertia weight,
C_1, C_2	Acceleration coefficients,
$Pbest_{ij}^{t}$	Dimension *i* of the own best position of particle *j* until iteration *t*,
$Gbest_{i}^{t}$	Dimension *i* of the best particle in the swarm at iteration *t*,
N_D	Dimension of the optimization problem (Number of decision variables),
N_{par}	Number of particles in the swarm,
r_1,r_2	Two separately generated uniformly distributed random numbers in the range [0, 1].

The following weighting function is usually utilized:

$$\omega = \omega_{\max} - \left(\left(\omega_{\max} - \omega_{\min}\right) \div Iter_{\max} \times Iter\right) \quad (3)$$

where,

ω_{max}, ω_{min}	initial and final weights,
$Iter_{max}$	maximum iteration number
$Iter$	current iteration number.

A new variation in the classical PSO is achieved by splitting the cognitive component of the classical PSO into two different components [19]. The first component can be called good experience component. That is, the bird has a memory about its previously visited best position. This component is exactly the same as the cognitive component of the basic PSO. The second component is given the name bad experience component. The bad experience component helps the particle to remember its previously visited worst position. To calculate the new velocity, the bad experience of the particle is also taken into consideration. This gives the new model of the PSO as below. The new velocity update equation is given by:

$$V_{ij}^{t} = w \times V_{ij}^{t-1} + C_{1g} \times r_1 \times \left(Pbest_{ij}^{t-1} - X_{ij}^{t-1}\right) + C_{1b} \times r_2 \times \left(X_{ij}^{t-1} - Pworst_{ij}^{t-1}\right) + C_2 \times r_3 \times \left(Gbest_{i}^{t-1} - X_{ij}^{t-1}\right) \quad (4)$$

$i=1,2,\ldots,N_D$
$j=1,2,\ldots,N_{par}$

C_{1g}	Acceleration coefficient, which accelerates the particle toward its best position,
C_{1b}	Acceleration coefficient, which accelerates the particle away from its worst position,
$Pworst_{ij}^{t}$	Dimension *i* of the own worst position of particle j until iteration *t*,
r_1,r_2,r_3	Three separately generated uniformly distributed random numbers in the range [0, 1].

The positions are updated using (2). The inclusion of the worst experience component in the behavior of the particle gives additional exploration capacity to the swarm. By using the bad experience component, the bird (particle) can bypass its previous worst position and always try to occupy a better position.

III. Problem Formulation

The basic ED becomes a nonconvex optimization problem if the practical operating conditions are included. The basic cost function used is:

$$\text{Min} \quad F_T = \sum_{i=1}^{N_G} F_i\left(P_{Gi}\right) \quad (5)$$

$$\sum_{i=1}^{N_G} F_i(P_{Gi}) = \sum_{i=1}^{N_G} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \quad (6)$$

where,

$\boldsymbol{F_T}$	Total generation cost ($/hr),
$\boldsymbol{F_i}$	Cost function of generator *I* ($/hr),
$\boldsymbol{a_i}$,$\boldsymbol{b_i}$, $\boldsymbol{c_i}$	Cost Coefficients of Generator *i*,
$\boldsymbol{P_{Gi}}$	Power of Generator *i* (MW).
$\boldsymbol{N_G}$	Number of Generators.

1) *Active Power Balance Equation*

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{N_G} P_{Gi} = P_{Load} + P_{Loss} \quad (7)$$

where P_{Load} is the total load in the system (MW), and P_{Loss} is the network loss (MW) that can be calculated by matrix loss formula. However, the transmission losses considered are governed by the following equation:

$$P_{Loss} = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \quad (8)$$

where,

B_{ij} , B_{0i} , B_{00} are the B-matrix coefficients, P_j is the power in the line.

2) Minimum And Maximum Power Limits:

Generation output of each generator should lie between maximum and minimum limits. The corresponding inequality constraints for each generator are

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max} \quad (9)$$

where

P_{Gimin} and P_{Gimax} are the minimum and maximum output of generator *i,* respectively.

3) Generator Ramp Rate Limits

If the generator ramp rate limits are considered, the effective real power operating limits are modified as follows:

$$Max\left(P_{Gi\ \min}, P_{Gi}^{0} - DR_i\right) \le P_{Gi} \le \min\left(P_{Gi\ \max}, P_{Gi}^{0} + UR_i\right) \quad (10)$$

$i=1,2,\ldots,N_G$

where

P_{Gi}^{0} is the previous operating point of generator i.

DR_i and UR_i are the down and up ramp limit of the generator i, respectively.

4.) Valve Point Effect (VPE)

The valve opening process of multivalve steam turbines produces a ripple-like effect in the heat rate curve of the generators, and it is taken into consideration in the ED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoidal component as follows:

$$F_i\left(P_{Gi}\right) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left|e_i \sin\left(f_i\left(P_{Gi\ \min} - P_{Gi}\right)\right)\right| \quad (11)$$

where,

F_T total generation cost,

F_i cost function of generator *i*,

a_i, b_i, c_i, ei , fi Cost Coefficients of Generator *i*

P_{Gi} Power of Generator *i*,

NG Number of Generators.

PGi_{min} Minimum limit of Power Generation for Generator *i*

The objective of Economic Dispatch VPE is to minimize F_T *with* the constraints from (6) to (11).

IV. Development and Implementation of NPSO

The objective of this paper is to solve a constrained ED problem using NPSO algorithm to obtain efficiently a high quality solution within practical power system operation. The NPSO was applied to mainly to determine the optimal generation power of each unit thus minimizing the total cost of generation.

A. *Particle representation*:

Each individual with in the population represents a candidate solution for solving ED problems. The real power generations are used to form the swarm. The real power output P_G of all generators is represented as the positions of the particles in the swarm. If N_G are generators, and there are N_{par} particles in the swarm, the complete swarm is represented as a matrix as follows:

$$Swarm=[X_1,X_2,\ldots\ldots\ldots,X_j,\ldots..X_{Npar}] \quad (12)$$

Where Xj is the position vector of the particle j . It represents one of the possible solutions for the optimization problem. The element Xij of Xj is the ith position component of particle j, and it represents the real power generation of generator i of the possible solution j.

B *Initialization of the Swarm*:

Initial values for the swarm are assigned randomly within the effective real power operating limits. The initialization also takes in to account the real power limits and ramp rate limits. The velocities of the particles are initialized as follows:

$$\left(P_{Gi\ \min} - \xi - X_{ij}^{initial}\right) \le V_{ij}^{initial} \le \left(P_{Gi\ \max} + \xi - X_{ij}^{initial}\right) \quad (13)$$

j = 1, 2, …………. , Ng

i = 1, 2, ……………, Npar

Where ξ is small positive number.

The velocities obtained ensure the new particles within constraints limits. The penalty can also be imposed in case of violation.

C. *Initialization of the Best and Worst Positions:*

The best position of a particle is the position, which gives the minimum PF_T , and the best position out of all the Pbests is taken as Gbest. In this technique the particle's worst position (Pworst) is used. In the beginning the Pbest and Pworst for all the particles are taken as the same as the initial positions. The PF_T at Gbest is taken as F_{Gbest}^{0} .

D Moving the Particles:

The particles in the swarm are moved to new positions with the help of new velocities. The new velocities are calculated using (4) and the position of the particles are updated using (2) where N_D is taken as N_G. If any Xij violates the effective real power operating limit constraints, its value is taken as the limiting value.

E. Updating the Best and Worst positions:

The particles are evaluated in the new positions by PF_T. Then Pbest and Pworst of particle j are updated as follows:

$$Pbest_j^t = X_j^{t-1} + V_j^t \text{ if } PF_{Tj}^t < PF_{Tj}^{t-1}$$

$$Pbest_j^t = Pbest_j^{t-1} \text{ if } PF_{Tj}^t \ge PF_{Tj}^{t-1}$$

$$Pworst_j^t = X_j^{t-1} + V_j^t \text{ if } PF_{Tj}^t > PF_{Tj}^{t-1}$$

$$Pworst_j^t = Pbest_j^{t-1} \text{ if } PF_{Tj}^t \le PF_{Tj}^{t-1} \quad (14)$$

where PF_{Tj}^{t} is the penalized objective function value of particle j at iteration t. The best position out of all the new Pbests is taken as $Gbest^t$, and PF_T at $Gbest^t$ is taken as F^t_{Gbest} .

F. *Employing LRS Procedure*:

If F^t_{Gbest} is better than F^{t-1}_{Gbest} the LRS subroutine is invoked. The Y^0 and F^0_{best} for the LRS are taken as $Gbest^t$ and F^t_{Gbest} , respectively. If Fopt obtained from LRS is better than F^t_{Gbest} , $Gbest^t$ and F^t_{Gbest} are replaced with Y_{opt} and F_{opt} , respectively.

Local random Search (LRS)

The algorithms like GA, EP, SA, and PSO do well for small dimensional and less complicated problems. However, they fail to locate global minima for the complex multiminima functions. Although they locate the promising area, they fail to exploit the promising area to get good quality solutions [14], [15] With a single algorithm, it is difficult to control and to strike a balance between exploration of whole search space to locate the promising area and exploitation of the promising area to get global minima. Several hybrid methods have been proposed by combining the metaheuristic methods with simple local search algorithms.

This paper uses a simple LRS procedure, which is a modification of a direct search technique proposed in [16]. The initial search point is taken as Y^0 , and the objective function value at Y^0 is $F^0_{best.}$.

The steps followed for LRS are given below:

Step 1) The initial local search range is selected around Y^0 as follows:

$$Y^{\min} = P_{G\min} + \left(Y^0 - P_{G\min}\right)\times\beta \tag{15}$$

$$Y^{\max} = P_{G\max} - \left(P_{G\max} - Y^0\right)\times\beta \tag{16}$$

$$R^0 = Y^{\max} - Y^{\min} \tag{17}$$

where Y^{min} and Y^{max} are the lower and upper boundaries of the local search region; β is the local area parameter; P_{Gmin} and P_{Gmax} are the vectors of power generation limits; and R^0 is the initial local search range. The iteration count m is set to 1. Y^0_{best} (best search point at the beginning of LRS) and Y_{opt} (optimum search point) are set to Y^0.

Step 2) The N_L local search points are randomly generated as follows:

$$Y_n^m = Y_{best}^{m-1} + R^{m-1}\times r\left(N_D,1\right) \tag{18}$$

n=1,2,…., N_L

where $r(N_D,1)$ is a random number vector of length N_D , whose elements are randomly generated between -1and 1. If any local search point violates the limits, it is forced within the boundaries.

Step 3) For each local search point, the objective function values are calculated. Then the minimum objective function among all is taken as F^m_{best} , and the corresponding Y is taken as Y^m_{best} . The optimum values are updated as follows:

If $F^m_{best} < F^{m-1}_{best}$ then $F_{opt} = F^m_{best}$ and $Y_{opt} = Y^m_{best}$

Otherwise

$F_{opt} = F^{m-1}_{best}$ and $Y_{opt} = Y^{m-1}_{best}$

Step 4) The search range is reduced as

$$R^m = R^{m-1}\times\left(1-\alpha\right) \tag{19}$$

where α is the range reduction parameter.

Step 5) If maximum iteration for local search ($iter_{LRS}$) is not reached, the iteration count is incremented by one and the above procedure is repeated from step 2). Otherwise, Y_{opt} and F_{opt} are taken as the optimum results found by the LRS algorithm.

F. *Stopping Criterion*:

There are different criteria available to stop a stochastic optimization algorithm. Tolerance, number of function evaluations, and maximum number of iterations are some examples and we have considered the convergence of the total final cost and Gbest as our stopping criteria.

V. Numerical Examples and Results

The conventional PSO and NPSO –LRS were applied to a system of 3-units to verify the feasibility and efficiency of the methods. In the case study taken, the ramp rate limits and valve point effects have also been considered. The solutions were obtained by considering different parameters and for different number of iterations. The B-coefficient matrix of power system networks was used to find the transmission line loss and satisfy the transmission capacity constraints. The software was developed in C++ and compiled using the Borland C++ Version 4.5 compiler and Turbo C++ IDE.

Case Study

Example: Three-unit System: The data of 3-bus system considered have been used for deciding power generation on various generators and total cost of generation by taking maximum and minimum power limits of generation, ramp rate limits, cost coefficients, load demand and various constraints of the system [16]. Initially the powers for two generators are chosen randomly and then using basic equations of ELD, the generation for the third generator is calculated which satisfies all the constraints. The NPSO is applied and losses are calculated from the B-matrix coefficients using (8).

The Values of some of the other constants used are as below:

Beta=0.4 *C1g* = 1.6 *C2* = 2
Alpha=0.05 C1b = 0.4 *C1* = 2
Wmax=0.9 *Wmin*=0.4 *Absiln* = .001
Rand1 = 0.5 *Rand2* = 0.5

NPSO code is user friendly in which the values of various parameters are entered by the user. Various cases of parameters variation such as (random numbers, load demand, VPE etc) have been considered and their effects on the output were studied and summarized below:

1. *Variation in random numbers (r_1, r_2, and r_3):*

The values for random numbers do not have much effect on the total cost for the system but the Gbest increases with increase in the value for random numbers Table I. To demonstrate the effect of these random numbers on total cost and Gbest the load demand taken considered is 400 MW for IEEE 30-bus system data. This helps in choosing the appropriate values of random numbers for optimization in PSO method.

TABLE I

GBEST VARIATION WITH DIFFERENT RANDOM NUMBERS

r_1	r_2	r_3	Total Cost ($/hr)	Gbest
0.1	0.2	0.1	4844.2	71.9634
0.5	0.5	0.5	4844.2	89.9635
0.9	0.9	0.9	4844.2	89.9635

2. PSO and NPSO_LRS for different load demands:

The conventional PSO was applied to 3-bus data [16] and generation pattern, Gbest and total cost were obtained Table II. The demand on the system was varied and generation pattern of generators and total operating cost given by quadratic function (6) were calculated.

TABLE II

GENERATION PATTERN, GBEST AND TOTAL COST WITH LOAD DEMAND BY PSO

Pd (MW)	PLoss (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Cost ($/hr)	Gbest (MW)
600	18	50	100	468	6222.6250	50
700	21	50	100	571	7195.5459	50
800	24	124	100	600	8130.1123	100
900	27	200	127	600	9078.3594	127

The NPSO with Local random Search (LRS) was applied to 3-bus system with the same variation in load for some standard parameters taken and some modified results were obtained both for total cost and Gbest. Table III.

TABLE III

GENERATION PATTERN, GBEST AND TOTAL COST WITH LOAD DEMAND BY NPSO-LRS

Pd (MW)	PLoss (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Total Cost ($/hr)	Gbest (MW)
600	18.72	50	100	468.71	6219.3330	50
700	22.98	50	100	572.98	7114.8384	50
800	23.94	123.94	100	600	8129.5752	100
900	28.49	50	278.491	600	9010.4843	50

Considering both best and worst positions along with LRS have helped in reducing the total cost of generation. A graphical comparison has been shown in Figure 1.

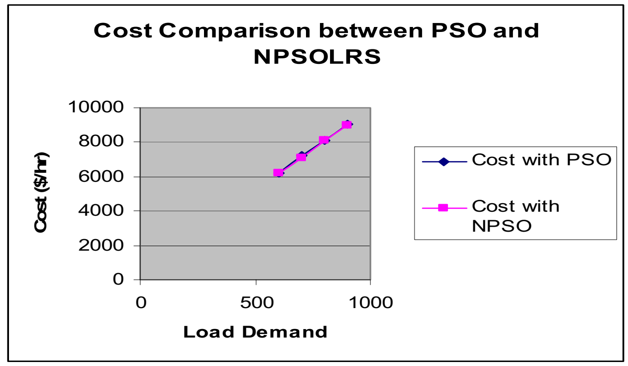

Fig.1. VARIATION OF COST WITH LOAD DEMAND FOR PSO AND NPSO METHOD

3. NPSO with Valve Point Effect.

The practical ED problem takes in to account the VPE and other constraints hence valve point effect was also introduced and cost function was modified equation (11).The losses were calculated using B-coefficient matrix for each iteration and generation for all generators was obtained for different number of iterations. The numbers of trials were carried out and the following patterns of generation for various generators were obtained Table IV. It was found that the convergence of the method is fast and solution converges in less than 20 iteration.

TABLE IV

GENERATION PATTERN, GBEST AND TOTAL COST WITH LOAD DEMAND BY PSO

Pd (MW)	PLoss (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Total Cost ($/hr)	Gbest (MW)
600	18.7148	50	100	468.7	6463.333	50
700	22.9875	50	100	572.9	7431.838	50
800	23.9414	123.9	100	600	8290.575	100
900	28.4908	50	278.4	600	9209.484	50

The programs were run for different number of iterations and a comparison of total generation cost is being tabulated in Table V below for a load demand of 900 MW on three bus system taken.

TABLE V

CONVERGENCE COMPARISON OF DIFFERENT METHODS

Itr.No	Total Cost($/hr)		
	PSO	NPSO	NPSOVPE
5	9235.45	9456.98	9702.67
10	9110.03	9289.56	9521.28
15	9104.89	9124.41	9346.56
20	8982.35	9010.48	9209.485
25	8912.07	9010.48	9209.485
30	8843.07	9010.48	9209.485

The NPSO is found to be converging fast as compared to the conventional PSO method. A graphical representation of their convergence trend is also being shown below in the figure2.

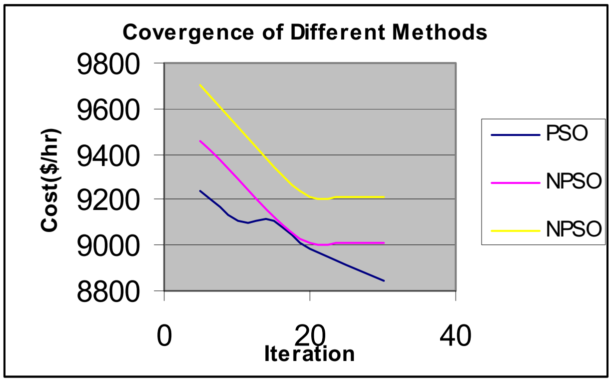

Fig.2 Convergence comparison of different methods

The PSO was also applied to IEEE 30 bus data and a generation schedule (table VI) and costs were obtained as shown below. The PSO was found converging fast as compared to GA. The cost obtained by PSO for a load of 250MW is 721.675 $/hr. The cost obtained using GA [18] was 807.51 $/hr for standard load on the system.

TABLE VI

GENERATION SCHEDULE FOR SIX GENERATORS SYSTEM

Gen. no	GA (MW)	PSO (MW)
1	171.04	105.5
2	49.32	60
3	22.39	30
4	26.37	25
5	12.51	17
6	12.22	20

V. CONCLUSIONS

This paper presents PSO and NPSO with local random search to solve ELD problems. The superior features such as stable convergence characteristics and good computation efficiency have been demonstrated by its application to 3-bus system. The non-linear characteristics such as valve point effects, ramp rate limits, and equality and inequality constraints have been considered for practical generation operation. The convergence for nonconvex characteristics of generators depends upon parameter selection, which is obtained by suitable experiments. A comparison has also been given to select the random numbers for fast convergence and optimum solution. The NPSO-LRS converges fast as compared to other conventional methods as well as PSO used and optimal value of Gbest is being obtained. Since the system is dynamic in nature, losses are being considered at each update for position and velocity and calculated considering the equality constraints and iteration is stopped after new positions start lying between a certain ranges.

V. REFERENCES

[1] H.H.Balci and F.Jorge, "Scheduling Electric Power Generators Using Particle Swarm Optimization Combined With the Lagrangian Relaxation Method", *Department of Industrial and Systems Engineering Auburn University, Auburn*, AL, 36849, USA

[2] M.Pelarski and R.Gerhart, Advisor: Hossein Salehfar, "Genetic Algorithm Power System Economic Dispatch Optimization" *FALL* 1996.

[3] http://www.acsatlanta.com/pages/ems_ed.html.

[4] X. S. Han, H. B. Gooi, and D. S. Kirschen, "Dynamic Economic Dispatch: Feasible and Optimal Solutions," *IEEE Transaction on Power Systems*, vol. 16, No. 1, pp. 22-28, Feb. 2001.

[5] W. R. Barcelo and P. Rastgoufard, "Dynamic Economic Dispatch Using the Extended Security Constrained Economic dispatch Algorithm," *IEEE Transaction on Power Systems,* Vol. 12, No. 2, pp. 961-967,May1997.

[6] Z. LEE Gaing, "Particle Swarm Optimization to solving the economic Dispatch considering the generator constraints," *IEEE Transaction on Power systems*, vol. 18, no.3, pp.1187-1195, Aug 2003.

[7] J.Y, Fan L Zhang, "Real-Time Economic Dispatch with Line Flow and Emission Constraints Using Quadratic Programming," *IEEE Trans. on Power System,* vol. 13, no. 2, pp.320-325, *1998*.

[8] W Ongsakul, N. Uangpayoongsak, "Constrained dynamic economic dispatch by simulated annealing genetic algorithm," *IEEE Power Engineering Society lnt. Conf/wenee* on, 20-24, May, 2001.

[9] R. W. Ferrem and *S* M Shahidehpour, "Dynamic economic dispatch in deregulated systems," *Electrical Power & Energy System,* vol. 19, no. 7, pp. 433-439.

[10] Bo Zhao, Chuangxin Guo and Yijia Cao, "Dynamic Economic Dispatch In Electricity Market Using Particle Swarm Optimization Algorithm," *Proceedings of the 5Ih World Congress on Intelligent Control and Automation, College of Electrical Engineering University of Zhejiang Hangzhou, Zhejiang Province*, June 15-19, 2004, Hangzhou. P.R. China, available at zhaobozju@zju,edu.cn.

[11] C. Wang, S. M. Shahidehpour "Effects Of Ramp-Rate Limits On Unit Commitment And Economic Dispatch", *IEEE Transactions on Power Systems*, Vol. 8, No. 3, August, 1993.

[12] Jong-Bae Park, Yun-Won Jeong, Hyun-Houng Kim and Joong-Rin Shin,"An Improved Particle Swarm Optimization For Economic Dispatch With Valve Point Effect" *International Journal of Innovations in Energy Systems and Power*, Vol. 1, no. 1 (November 2006).

[13] E. Bonabeau, M. Dorigo, and G. Theraulaz, Swarm Intelligence: From Natural to Artificial Systems, *Oxford Press*, 1999.

[14] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Trans. Evol. Comput.*, vol. 7, no. 1, pp. 83–94, Feb. 2003.

[15] J.-B. Park, K.-S. Lee, J.-R. Shin, and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 34–42, Feb. 2005.

[16] R. Luss and T. H. I. Jaakola, "Optimization by direct search and systematic reduction of the size of the search region," *AIChE J.*, vol. 19, no. 4, pp. 760–766, 1973.

[17] H. Yoshida, K. Kawata, Y. Fukuyama, S.Takayama, and Y. Nankashi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment," *IEEE Transactions on Power Systems*, Vol.15, pp.1232-1239, Nov 2000.

[18] R.Khanna, Y.P.Verma, A.Gupta,"Genetic algorithm approach to optimal power flow" *Modelling Measurement & control,* Vol.77, no.7-8, pp.33-43, 2004.

[19] A. Immanuel Selvakumar, "A New Particle Swarm Optimization Solution to Nonconvex Economic Dispatch Problems", *IEEE Transactions on Power Systems,* Vol. 22, No. 1, February 2007

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