MultiCraft

International Journal of Engineering, Science and Technology
Vol. 3, No. 4, 2011, pp. 130-146

INTERNATIONAL JOURNAL OF ENGINEERING, SCIENCE AND TECHNOLOGY

www.ijest-ng.com

Improved particle swarm optimization approach for nonconvex static and dynamic economic power dispatch

Rajkumari Batham [1], Kalpana Jain [2] and Manjaree Pandit[3*]

[*] *Department of Electrical Engineering, Madhav Institute of Technology and Science Gwalior, INDIA*
[*] *Corresponding Author: manjaree_p@hotmail.com, Tel +91- 0751-2665962, +91-0751-2409380*

Abstract

The cost of power generation in fossil fuel plants is very high and economic dispatch helps in saving a significant amount of revenue. For practical generators the economic dispatch problem gets translated into a complex non-convex, multimodal optimization problem which can not be solved by traditional gradient based optimization methods. The complexity further increases due to the multiple constraints that need to be satisfied. This paper proposes an improved particle swarm optimization approach (IPSO) for solving nonconvex static and dynamic economic dispatch. The classical PSO (CPSO) approach suffers from the problem of premature convergence, particularly for complex multimodal functions. The idea behind IPSO is i) to enhance the search capability of the CPSO by reinitializing the velocity vector whenever saturation sets in and ii) to use a parameter automation strategy to strike a proper balance between local and global search. The performance of IPSO has been tested on five standard test cases. The results are compared with previously published literature and are found to be comparable/or superior.

Keywords: Improved PSO, premature convergence, static/dynamic economic dispatch, prohibited operating zones, ramp rate limits, and valve point loading effects.

1. Introduction

Economic power dispatch is one of the most important functions of modern energy management system. This problem is formulated as a constrained optimization problem with the objective of generation allocation to the power generators to minimize total fuel cost with satisfaction of all operating constraints. Conventional methods usually assume the input-output characteristics of power generators, known as cost curves, to be quadratic or piecewise quadratic, monotonically increasing functions. But modern generating units have a variety of non-linearities in their cost curves due to valve point loading and other effects, which make this assumption inaccurate and the resulting approximate solutions cause a lot of revenue loss over time. On the other hand, evolutionary methods such as genetic algorithms (GA) and particle swarm optimization (PSO), differential evolution (DE) and bacterial foraging (BF) are free from convexity assumptions and perform better due to their excellent parallel search capability. Therefore, these methods are particularly popular for solving non linear, nonconvex, discontinuous optimization problems. This paper focuses on solution of nonconvex ED problem using an improved PSO based method.

Conventional gradient based optimization methods like lamda iteration, base point participation factor, gradient methods etc. rely heavily on the convexity assumption of generator cost curves and hence approximate these curves using quadratic or piecewise quadratic monotonically increasing cost functions (Wood et al.,1984); resulting solutions are inaccurate and cause revenue losses. This assumption is not valid for practical generators because the cost functions of generators have discontinuities and higher order nonlinearities due to valve point loading (Walter et al., 1993, Sinha et al., 2003), prohibited operating zones (Orero et al., 1996) and ramp rate limits of generators (Wang et al., 1993). The practical ED with above nonlinearities translates into a complicated optimization problem having complex and nonconvex characteristics, with multiple minima, making the challenge of obtaining the global minima, very difficult. Dynamic programming (Shoults et al., 1986) has no restriction on the shape of cost curves, but this method is computationally extensive, time consuming and suffers from the problem of dimensionality.

Methods like dynamic programming (Shoults et al., 1986), genetic algorithm (Walter et al., 1993, Sinha et al., 2003, Damousis et al., 2003), evolutionary programming (Sinha et al., 2003), and particle swarm optimization (Selvakumar et al., 2007, Chaturvedi et al., 2008, Park et al., 2007, Victoire et al., 2005, Park et al., 2010) solve nonconvex optimization problems efficiently and often achieve a fast and near global optimal solution. The PSO, which was first introduced by Kennedy and Eberhart (Kennedy, et al., 1995), is a powerful, robust, population based algorithm with inherent parallelism. This method is increasingly gaining acceptance for solving economic dispatch (Chaturvedi et al., 2008, Park et al., 2007, Victoire et al., 2005, Park et al., 2010) and a variety of power system problems, due to its simplicity, superior convergence characteristics and high solution quality. Recent research however has observed that PSO approach suffers from premature convergence, particularly for complex functions having multiple minima (Victoire et al., 2005, Park et al., 2010).

The most important issue with evolutionary techniques is to maintain a proper balance between exploration i.e. global search and exploitation i.e. local search. The performance of evolutionary methods heavily depends on the settings of the tuning parameters; therefore finding optimal parameter setting is a very big challenge. Evolutionary methods also have a tendency to converge very fast to a solution that is quite close to the global minimum. This tendency causes premature convergence. Researchers employ various parameter automation strategies and hybridization of global and local optimization techniques. In reference (Park et al., 2010) performance improvement for nonconvex economic dispatch problem was reported by integrating the PSO with chaotic sequences and crossover operation. The concept of variable scaling factor based on the one-fifth success rule of evolutionary strategies is employed in reference (Chiou et al., 2009). Some researchers have proposed hybrid methods combining the advantages of two evolutionary methods to get improved performance (Bhattacharya et al., 2010).It has been observed by various researchers that the classical PSO (CPSO) very quickly finds a good local solution but gets stuck there for a number of iterations without further improvement. As a result, it becomes tedious to find global best solutions for complicated nonconvex problems having multiple local minima and an irregular search space.

To handle the problem of premature convergence, an improved PSO (IPSO) algorithm is proposed in this paper. The improved PSO employs a two-tier approach to avoid saturation and premature convergence. The improved PSO (IPSO) i) introduces crazy particles with randomized velocities to maintain momentum in the search and to avoid saturation ii) employs a novel parameter automation strategy in which the cognitive and social parameters are dynamically tuned in order to efficiently control the local and global search in such a manner that global convergence is achieved. The performance of the improved PSO (IPSO) is significantly better than the classical PSO (CPSO).

The performance of the proposed IPSO has been tested on a standard test system having prohibited operating zones and ramp rate limits. Five test cases with different complexity levels have been taken. It is observed that the IPSO approach outperforms CPSO. Results are compared with recently published literature (Bhattacharya et al, 2010, Panigrahi et al, 2008, Chen et al, 1995, Naresh et al., 2004) and superiority of IPSO has been established.

2. Nonconvex Economic Dispatch Formulation

The practical static and dynamic NCED problem with generator nonlinearities such as valve point loading effects, prohibited operating zones and ramp rate limits, are solved in this paper using IPSO based approach to find the optimal generation dispatch for different operating conditions.

2.1 Valve point loading effects: The valve-point effects introduce ripples in the heat-rate curves and make the objective function discontinuous, nonconvex and with multiple minima. For accurate modeling of valve point loading effects, a rectified sinusoidal function (Walter et al, 1993) is added in the cost function in this Paper. The fuel input-power output cost function of ith unit is given as

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin(f_i \times (P_{\min} - P_i)) \right| \tag{1}$$

where a_i, b_i and c_i are the fuel-cost coefficients of the i^{th} unit, and e_i and f_i are the fuel cost-coefficients of the i^{th} unit with valve-point effects. The NCED problem is to determine the generated powers Pi of units for a total load of PD so that the total fuel cost, F_T for the N number of generating units is minimized subject to the power balance constraint and unit upper and lower operating limits. The objective is

$$MinF_T = \sum_{i=1}^{N} F_i(P_i)$$; Subject to the constraints given by

$$\sum_{i=1}^{N} P_i - \left(P_D + P_L\right) = 0 \tag{2}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,2,...,N \tag{3}$$

For a given total real load PD the system loss PL is a function of active power generation at each generating unit. To calculate system losses, methods based on penalty factors and constant loss formula coefficients or B-coefficients (Wood et al,1984) are in use. The latter is adopted in this paper as per which transmission losses are expressed as

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \tag{4}$$

For further details, (Wood et al., 1984) may be referred.

2.2 Generator ramp rate limits: When the generator ramp rate limits are considered, the operating limits are modified as follows:

$$Max(P_i^{\min}, P_i^o - DR_i) \le P_i \le Min(P_i^{\max}, P_i^o + UR_i) \tag{5}$$

The previous operating point of ith generator is P_i^o and DR_i and UR_i are the down and up ramp rate limits respectively.

2.3 Prohibited operating zones: The cost curves of practical generators are discontinuous as whole of the unit operating range is not always available for allocation. In other words, the generating units have prohibited operating zones due to some faults in the machines or their accessories such as pumps or boilers etc. (Orero et al, 1996). A unit with prohibited operating zones has discontinuous input-output characteristics. This feature can be included in the NCED formulation as follows:

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i1}^{L} \\ P_{ik-1}^{U} \le P_i \le P_{ik}^{L} \\ P_{izi}^{U} \le P_i \le P_i^{\max} \end{cases} \tag{6}$$

Here z_i are the number of prohibited zones in ith generator curve, k is the index of prohibited zone of ith generator, P_{ik}^{L} is the lower limit of kth prohibited zone, and P_{ik-1}^{U} is the upper limit of kth prohibited zone of ith generator

2.4 Nonconvex dynamic economic load dispatch(NCDED): Dynamic Economic Load dispatch deals with sharing the system load including system losses among the available generators in such a way that all equality and inequality constraints are met and the cost of operation is minimized for each time interval.

In order to solve dynamic load dispatch problem, ramp-rate limit must be considered. The dynamic economic load dispatch (DELD) model can be described as follows: -

$$\begin{cases} \min\ f(t) = \sum_{i=1}^{N} F(P_i(t)) \\ \sum_{i=1}^{N} P_i(t) = P_D(t) + P_L(t) \\ P_{i\min} \le P_i(t) \le P_{i\max} \\ -DR_i \le P_i(t) - P_i(t-1) \le UR_i \end{cases} \tag{7}$$

Where N is total numbers of committed units; P_i (t) is active power output of the ith unit at time t. The fuel cost function f(t)is given by

$$f(t) = \sum_{i=1}^{N} F(P_i(t)) = \sum_{i=1}^{N} (a_i + b_i P_i(t) + c_i P_i^2(t)) + \left| e_i \times Sin\{ f_i \times (P_{i\min} - P_i(t)\} \right| \tag{8}$$

Here a_i, b_i and c_i are cost coefficients, Pi min is minimum output, DR_i is down ramp rate limit, UR_i is up ramp rate limit of the ith unit; $P_D(t)$ is load demand at time interval t; $P_L(t)$ is network loss at time interval t.

3. Particle Swarm Optimization

Various conventional as well as modern methods have been employed for solving the non-linear, non-convex, discontinuous economic dispatch problem. The particle swarm optimization method has become quite popular for solving complex problems during the last couple of years. Its excellent random parallel search capability and constraint handling mechanism make it very efficient for locating good solution in the complex search domain.

3.1 Classical Particle swarm optimization (CPSO): The PSO (Kennedy, et al., 1995) is a population based modern heuristic search method inspired by the movement of a flock of birds searching for food. It is a simple and powerful optimization tool which scatters random particles i.e. solutions into the problem space. These particles, called swarms collect information from each other through an array constructed by their respective positions. The particles update their positions using the velocity of particles. Position and velocity are both updated in a heuristic manner using guidance from a particle's own experience and the experience of its neighbors.

The position and velocity vectors of the ith particle of a d-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, ...x_{id})$ and $V_i = (v_{i1}, v_{i2}, ...v_{id})$ respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $pbest_i = (p_{i1}, p_{i2}........p_{id})$. The particle tries to modify its position using the current velocity and the distance from $pbest$ and $gbest$. The modified velocity and position of each particle for fitness evaluation in the next iteration are calculated using the following equations (Kennedy, et al., 1995):

$$v_{id}^{k+1} = C[w * v_{id}^{k} + c_1 * rand_1 * \left(pbest_{id} - x_{id}\right) + c_2 * rand_2 * \left(gbest_{gd} - x_{id}\right)] \tag{9}$$

$$x_{id}^{k+1} = x_{id} + v_{id}^{k+1} \tag{10}$$

Here w is the inertia weight parameter which controls the global and local exploration capabilities of the particle. Constant C is constriction factor, c_1, c_2 are cognitive and social coefficients, and $rand_1, rand_2$ are random numbers between 0 and 1. A larger inertia weight factor is used during initial exploration and its value is gradually reduced as the search proceeds. The time-varying inertial weight is given by (Eberhart et al., 1999).

$$w = \left(w_{\max} - w_{\min}\right) \times \frac{\left(iter_{\max} - iter\right)}{iter_{\max}} + w_{\min} \tag{11}$$

where $iter_{\max}$ is the maximum number of iterations. Constant c_1 pulls the particles towards local best position whereas c_2 pulls it towards the global best position. Usually these parameters are selected in the range of 0 to 4. To improve the convergence of PSO algorithm, the constriction factor *C* is also used. (Eberhart et al, 1999).For further details, (Kennedy et al., 1995; Eberhart et al., 1999) may be referred.

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad \text{where } 4.1 \le \varphi \le 4.2 \tag{12}$$

As φ increases, the factor C decreases and convergence becomes slower because population diversity is reduced. The value of C is also decreased iteratively similar to w.

3.2 Improved PSO: The proposed IPSO employs a two-tier strategy to combat premature convergence phenomenon in PSO. By the combined use of i) *crazy particles* and ii) *time varying acceleration coefficients* (TVAC) it is ensured that a) population diversity is maintained and b) A proper balance is maintained between exploration (global search) and exploitation(local search). The idea behind using *crazy particles* is to randomize the velocities of some of the particles, (referred to as "crazy particles"), selected by applying a certain probability. In (Victoire et al, 2005), the probability of craziness ρ_{cr} is defined as a function of inertia weight,

$$\rho_{cr} = w_{\min} - \exp\left(-\frac{w^k}{w_{\max}}\right) \tag{13}$$

Then velocities of particles are randomized as per the following logic:

$$v_j^k = \begin{cases} rand(o, v_{\max}); if \rho_{cr} \geq rand(0,1) \\ v_j^k, otherwise \end{cases} \tag{14}$$

If the PSO algorithm tends to saturate in the beginning then a high value of ρ_{cr} is used to create crazy particles, and a comparatively lower value is used at later stages of search.

The time-varying inertia weight (TVIW) can locate good solutions at a significantly faster rate but its ability to fine tune the optimum solution is weak, due to the lack of diversity at the end of the search. It has been observed by most researchers that in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently. Kennedy and Eberhart (Kennedy et al, 1995) stated that a relatively higher value of the cognitive component, compared with the social component, results in roaming of individuals through a wide search space. On the other hand, a relatively high value of the social component leads particles to a local optimum prematurely. Normally studies keep each of the acceleration coefficients at 2, in order to make the mean of both stochastic factors in (7) equal to one, so that particles would over fly only half the time of search.

In population-based optimization methods, the policy is to encourage the individuals to roam through the entire search space, during the initial part of the search, without clustering around local optima. During the latter stages, however convergence towards the global optima should be encouraged, to find the optimum solution efficiently. In TVAC, this is achieved by changing the acceleration coefficients c1 and c2 with time in such a manner that the cognitive component is reduced while the social component is increased as the search proceeds. A large cognitive component and small social component at the beginning, allows particles to move around the search space, instead of moving towards the population best prematurely. During the latter stage in optimization, a small cognitive component and a large social component allow the particles to converge to the global optima. The acceleration coefficients are expressed as (Ratnaweera et al., 2004):

$$c_1 = \left(c_{1f} - c_{1i}\right)\frac{iter}{iter_{\max}} + c_{1i} \tag{15}$$

$$c_2 = \left(c_{2f} - c_{2i}\right)\frac{iter}{iter_{\max}} + c_{2i} \tag{16}$$

The velocity is calculated by substituting eq. (14) and (15) in eq. (7) to get

$$v_{id}^{k+1} = C[w \times v_{id}^k + \left(\left(c_{if} - c_{1i}\right)\frac{iter}{iter_{\max}} + c_{1i}\right) \times rand_1 \times (pbest_{id} - x_{id}) + \left(\left(c_{2f} - c_{2i}\right)\frac{iter}{iter_{\max}} + c_{2i}\right) \\ \times rand_2 \times (gbest_{gd} - x_{id})] \tag{17}$$

where c_{1i}, c_{1f}, c_{2i} and c_{2f} are initial and final values of cognitive and social acceleration factors respectively.

4. Implementation of IPSO for static/dynamic ED solution

The step by step procedure for implementation of the IPSO algorithm for solving static and dynamic economic dispatch problem with valve point loading effect prohibited operating zones and ramp rate limits is given below. The flowchart for this algorithm is given in Figure. 1.

4.1 Solution of constrained static and dynamic nonconvex economic dispatch using IPSO

Most of the PSO algorithms suffer from the problem of premature convergence in the early stages of the search and henceforth are unable to locate the global optimum (Selvakumar et al., 2007, Chaturvedi et al., 2008, Park et al., 2007, Victoire et al., 2005, Park et al., 2010). The proposed IPSO algorithm employs a two-tier strategy to improve the performance of classical PSO. First, the crazy particles, whose probability can be controlled, do not allow saturation to set in. The idea is to randomize the velocities to maintain momentum in the optimization process and improve the solution quality. Secondly, the cognitive and social acceleration coefficients are iteratively controlled to keep a balance between global and local search. The IPSO algorithm achieves significantly better results as compared to the classical PSO. The implementation consists of the following steps.

Step 1- Initialization of the swarm: For a population size *P*, the particles are randomly generated in the range 0-1 and located between the maximum and the minimum operating limits of the generators. If there are *N* generating units, the i^{th} particle is represented as $P_i = \left(P_{i1}\ ,P_{i2}\ ,P_{i3}\ \text{..........}\ \text{..........}\ ...P_{iN}\right)$. The j[th] dimension if the i[th] particle is allocated a value of P_{ij} as given below to satisfy the constraint given by eq. (3) Here, r is a random number, r$\in$[0,1].

$$P_{ij} = P_{j\min} + r(P_{j\max} - P_{j\min}) \tag{18}$$

For generators with ramp rate limits, the initialization is based on eq. (5). For limiting the operation within the prohibited zones, the particles are clamped at their respective lower or upper zone limits, (whichever is nearer to the particle position) as per eq. (6).

Step 2- Evaluation of swarm population: The merit of each individual particle in the swarm is found using a fitness function called evaluation function. The evaluation function should be such that cost is minimized while constraints are satisfied. The popular penalty function method employs functions composed of squared or absolute violations to reduce the fitness of the particle in proportion to the magnitude of the violation. Large values for penalty parameters ill condition the penalty function while very small values do not allow the violations to contribute effectively in penalizing a particle. Therefore, the penalty parameters are chosen carefully to distinguish between feasible and infeasible solution. Hence, the penalty parameters, are chosen such that an infeasible solution is awarded fitness worse than the weakest feasible string. Since two infeasible strings are not treated equally, the string further away from the feasibility boundary, is more heavily penalized. Thus, a constrained optimization problem is converted to unconstrained optimization problem.

The evaluation function $f(P_i)$ is defined to minimize the non smooth cost function given by eq.(1) for a given load demand P_D while satisfying the constraints given by eq. (2, 3) as:

$$f(P_i) = \sum_{i=1}^{N} F_i(P_i) + \alpha\left[\sum_{i=1}^{N} P_i - (P_D + P_L)\right]^2 + \beta\left[\sum_{k=1}^{n_i} P_i(violation)_k\right]^2 \tag{19}$$

where α is the penalty parameter for not satisfying load demand and β represents the penalty for a unit loading falling within a prohibited operating zone.

Step-3: *Initialization of pbest and gbest*: The fitness values obtained above for the initial particles of the swarm are set as the initial *pbest v*alues of the particles. The best value among all the *pbest* values is identified as *gbest*.

Step- 4: *Generation of crazy particles:* To control excessive roaming of particles, velocity is restricted between $-V_j^{\max}$ and $+V_j^{\max}$ .Here, R is selected such that $V_j^{\max}$ lies between 15-20% of the range of the variable. The maximum velocity limit for the j^{th} generating unit is computed as: $V_j^{\max} = \dfrac{P_{j.\max} - P_{j\min}}{R}$ (20)

The velocity vector is randomized using eq. (11) and (12).

Step-5: *Updating the swarm*: The particle position vector is updated using eq. (16). The values of the evaluation function are calculated for the updated positions of the particles. If the new value is better than the previous p*best*, the new value is set to *pbest.* Similarly, value of *gbest* is also updated if the best pbest is better than the stored value of *gbest*.

Step- 6: *Stopping criteria*: A stochastic optimization algorithm is stopped either based on the tolerance limit or maximum number of iterations. In this Paper maximum number of iterations is adapted as the stopping criterion after which the positions of *gbest* are stored as the optimal solution.

5. Test Results and Analysis

A novel improved PSO (IPSO) algorithm is proposed in which a dual strategy is employed to avoid saturation and premature convergence of the population, particularly for complex functions. The idea here is i) to exercise proper control over the global and local exploration of the swarm during the optimization process by using TVAC ii) to reinitialize the velocity vector whenever it stagnates causing saturation.

The performance of the IPSO is compared here with the classical PSO. It is observed that all the IPSO performs significantly better that the classical PSO for complex functions. Simulations were carried out using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz. with 1 GB RAM.

5.1 Description of test systems

A system with three thermal generating units (Wood et al, 1984, Chen et al, 1995) is used to demonstrate the performance of the proposed IPSO algorithm. The system cost coefficients and other data is given in the Appendix section. The system has many complexities and constraints such as i) Valve point loading (VPL) ii) Prohibited operating zone (POZ)and iii) Transmission losses in addition to the generating capacity constraints and power balance equation. The optimal solutions are computed under five different conditions; the first three test cases are solved for static economic dispatch while the last two test cases are solved for dynamic economic dispatch.

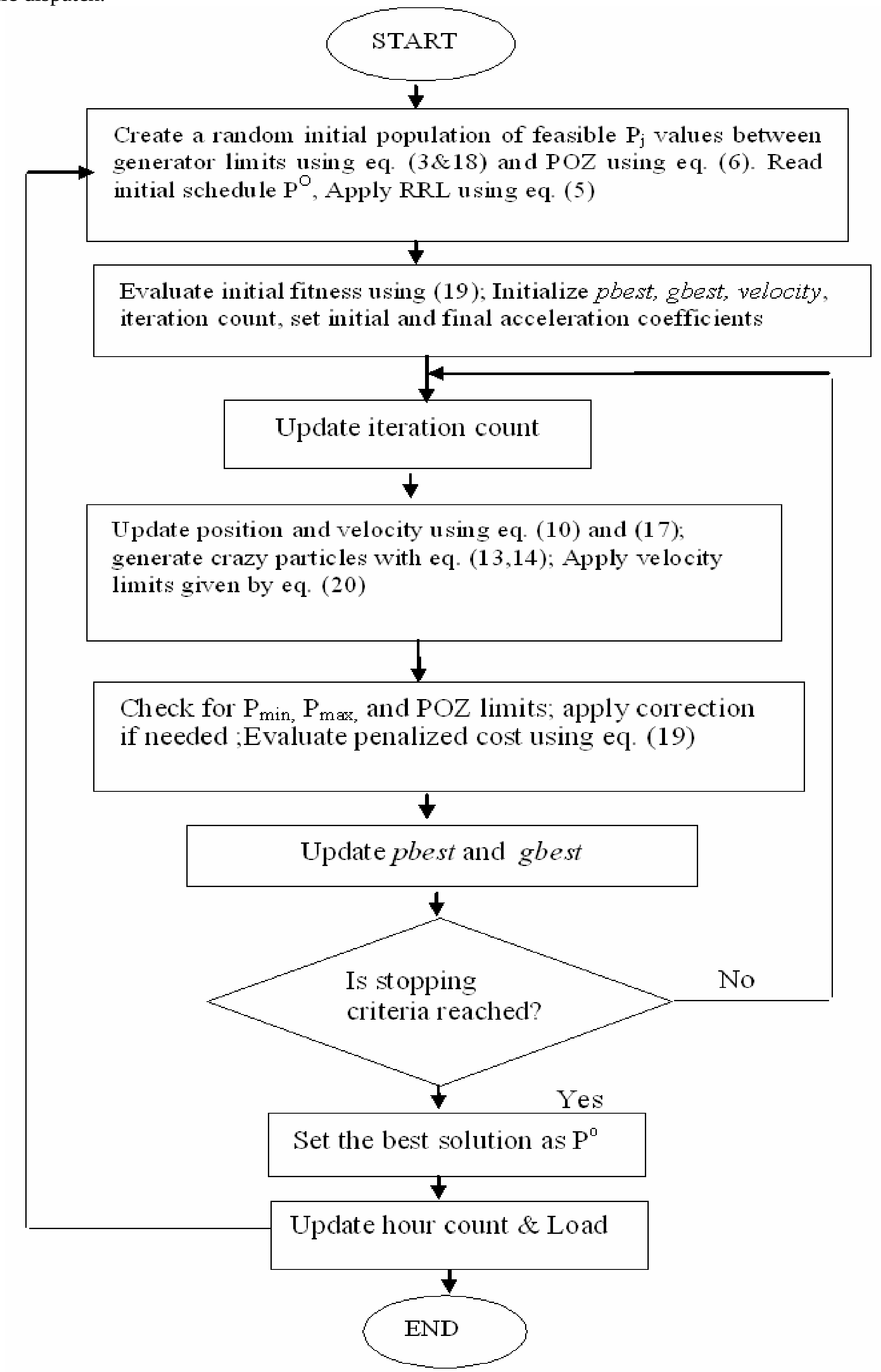

Figure 1. Flowchart of Nonconvex Dynamic Economic Dispatch (NCDED) using IPSO method

Test Case I: The above system with RRL and POZ but without VPL and losses
Test Case II: The above system with RRL, POZ and losses but without VPL
Test Case III: The above system with RRL, POZ and VPL but without losses
Test Case IV: The dynamic 24-hour scheduling with POZ and RRL
Test Case V: The dynamic 24-hour scheduling with POZ, VPL and RRL

For Test Case II the IPSO results are compared and validated with previously published results (Bhattacharya et al, 2010). The IPSO has achieved better results than those reported in literature (Bhattacharya et al, 2010).The Performance of IPSO is also compared with classical PSO (CPSO) method in terms of convergence behavior, solution quality, consistency and computational efficiency and it was observed that IPSO outperforms CPSO. The superiority of IPSO over CPSO in more pronounced for complex Test Cases II (with loss) and III (with VPL).

5.2 Parameter set-up

The number of iterations used is 100, *w* is varied from 0.9 to 0.4 using (9), constriction factor is also reduced from 0.73 to 0.64 similar to the inertial weight w (for, $4.1 \leq \varphi \leq 4.2$ in eq. 12) as search proceeds. These values The value of $c_1 = c_2 = 2.0$ is found to be most suitable for CPSO. Population size was set at 100 for all the five test cases.

5.3 Effect of cognitive and social coefficients

To evaluate the role of TVAC in solving complex DED problem, the values of c_{1f} and c_{2i} were varied between 0.1 and 0.5 and it was noticed that the best results were obtained when both were fixed at 0.2. Then the value of c_{1i} was increased from 1.8 to 2.5 and c_{2f} was reduced from 2.5 to 1.8, while c_{1f} and c_{2i} were kept fixed at 0.2. The initial value of cognitive parameter c_{1i} and final value of global parameter c_{2f} were targeted for study because c_{1i} controls the initial roaming of the swarm and c_{2f} facilitates global convergence in the final stage of the search. The final and initial values of c_1 and c_2 are to be selected by the user. The upper and lower limits for these values are normally 2.5 and 0.1. To show the effect of this variation results were computed and tabulated in Table 1 for different parameter settings. The optimal values are found to be problem dependant. However, for every parameter setting the global minimum value is achieved, only the consistency of achieving the minima is different for different settings.

Table 1 shows the results of this variation on the minimum, maximum, average costs and their standard deviation (S.D) out of 50 different trials for Test Case I. Best results were obtained when c_{1i}=2.5, c_{1f}=0.2, c_{2i}=0.2 and c_{2f}=2.2.

5.4 Effect of population size

The study carried out in this paper found that population size should be optimum for achieving global best results. Too large or a very small population may not be capable of searching a minimum, particularly in complex multimodal problems.

The population size is a very important issue in stochastic search methods. Too large a population makes an algorithm slow and computationally inefficient, while a very small population may not be capable of searching a minimum, particularly in complex problems. The optimum population size is found to be related to the problem dimension. Table 2 lists the performance of Test Case I for a population of 10, 20, 40, 60, 80 and 100. It can be seen that with increase in population, there is a steady improvement in minimum value, average value and S.D.

5.5 Convergence Characteristics

The convergence behavior of the CPSO and IPSO was compared employing the same evaluation function, same initial population and velocity for same number of iterations. The results for one trial are shown in Figure. 2. It can be seen that the IPSO exhibits superior convergence characteristics, i.e. saturation does not occur in the initial iterations.

5.6 Solution Quality

The dynamic convergence behavior of the IPSO and CPSO was also studied by calculating the mean and standard deviation of each individual in the swarm after each iteration. The mean value μ and standard deviation σ are defined as:

$$\mu = \frac{\sum_{i=1}^{PS} f(P_i)}{PS} \tag{21}$$

$$\sigma = \sqrt{\frac{1}{PS}\sum_{i=1}^{PS}}\left(f(P_i)-\mu\right)^2 \tag{22}$$

PS is the population size here and $f(P_i)$ is the evaluation function defined in (18). Figure 3 and Figure 4 plot and compare the standard deviation and mean of IPSO and PSO for Test Case I. The IPSO method clearly establishes its superiority over the classical PSO (CPSO) and produces better dynamic convergence, because the mean cost and the standard deviation of the swarm reduce continuously. The CPSO shows premature convergence and does not achieve minima for the complex 3-unit test case with RRL, POZ.

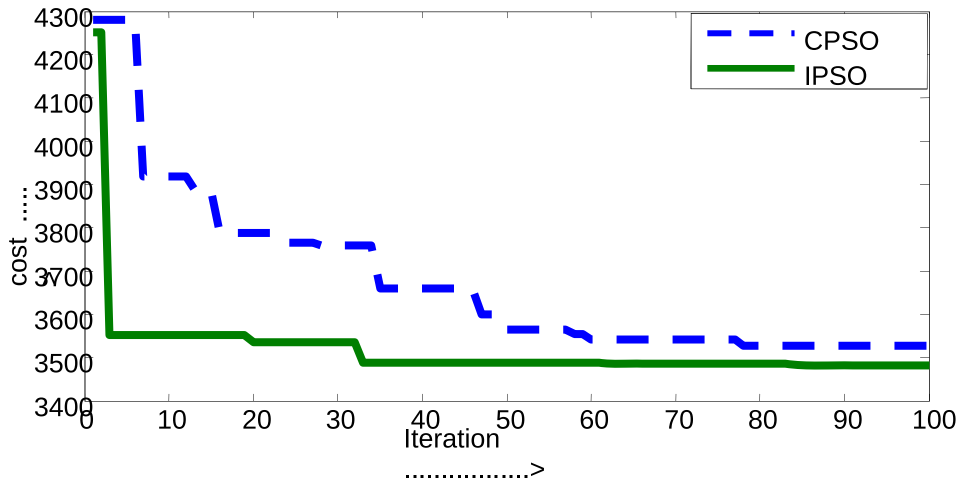

Figure 2. Comparison convergence characteristics

Table 1. Effect of acceleration coefficients on performance of IPSO (Test Case I; 50 trials)

S.No.	c_{1i}	c_{1f}	c_{2i}	c_{2f}	Minimum Cost($/h)	Max cost($/h)	Average cost($/h)	S.D#.
1		0.2	0.2	2.5	3.4829e+003	3.5155e+003	3.4892e+003	4.4985
2	**2.5**	**0.2**	**0.2**	**2.2**	**3.4829e+003**	**3.4834e+003**	**3.4887e+003**	**0.7362**
3		0.2	0.2	1.9	3.4829e+003	3.5156e+003	3.4890e+003	5.0013
4		0.2	0.2	1.8	3.4829e+003	3.5177e+003	3.4892e+003	6.1077
5		0.2	0.2	2.5	3.4829e+003	3.5130e+003	3.4904e+003	5.9825
6	2.2	0.2	0.2	2.2	3.4829e+003	3.5227e+003	3.4902e+003	6.4204
7		0.2	0.2	1.9	3.4830e+003	3.5112e+003	3.4883e+003	4.3430
8		0.2	0.2	1.8	3.4829e+003	3.5136e+003	3.4887e+003	4.8034
9		0.2	0.2	2.5	3.4829e+003	3.5161e+003	3.4892e+003	5.0779
10	2	0.2	0.2	2.2	3.4829e+003	3.5222e+003	3.4892e+003	5.0828
11		0.2	0.2	1.9	3.4829e+003	3.5137e+003	3.4894e+003	5.6721
12		0.2	0.2	1.8	3.4829e+003	3.5220e+003	3.4907e+003	6.5701
13		0.2	0.2	2.5	3.4829e+003	3.5093e+003	3.4892e+003	4.9600
14	1.8	0.2	0.2	2.2	3.4829e+003	3.5216e+003	3.4904e+003	6.4442
15		0.2	0.2	1.9	3.4830e+003	3.5046e+003	3.4877e+003	3.3622
16		0.2	0.2	1.8	3.4829e+003	3.5195e+003	3.4896e+003	5.8175

Standard Deviation

Table 2. Effect of population size on performance of IPSO (Test Case I; 50 trials)

Population Size	Minimum Cost($/h)	Mean Cost($/h)	Maximum Cost($/h)	S.D.	cpu time (50 trials)
10	3.4830e+003	3.4924e+003	3.5219e+003	6.4093	1.368170
20	3.4830e+003	3.4915e+003	3.5160e+003	6.2054	2.040088
40	3.4830e+003	3.4909e+003	3.5252e+003	6.0338	2.785883
60	3.4831e+003	3.4887e+003	3.5175e+003	4.3751	3.791913
80	3.4829e+003	3.4848e+003	3.4949e+003	2.0369	5.625992
100	**3.4829e+003**	**3.4834e+003**	**3.4887e+003**	**0.7362**	**7.472024**

5.7 Comparison of best results

It can be seen from Table 3 and Table 4 that the proposed IPSO achieves very good results as compared to the classical PSO. Table 3 presents the results for Test case I for different loads. The CPSO and IPSO achieve comparable results for this case with IPSO showing slight superiority. Both methods satisfy the constraints imposed by ramp rate limits (RRL), prohibited operating zones (POZ), power balance constraint and unit operating limits.

From Table 4 it can be seen that though the solution given by (Bhattacharya et al, 2010) is minimum, it is violating the ramp rate limits. On the other hand, IPSO satisfies all constraints without violations. As per the data given in Appendix section P^o= [215, 72, 98,] down ramp rate DR_i= [95 78 64] and P_{min}= [50, 5, 15]. Due to ramp rate limits (RRL)the unit operating limits get modified as per eq. (5) and now unit $P_{min(modified)}$= [120, 5, 34]. The solution given by (Bhattacharya et al, 2010) has P_3=15 which is infeasible as the lower limit for unit three becomes 34 due to RRL.

Table 5 gives the results of Test Case III (with VPL) for different loads. The cost function is plotted for generating unit 1 and 2 and shown in Figure 5(a) and Figure 5(b). In Figure 5(a) the cost curves with VPL effects are compared with quadratic cost curves for both units. The cost function becomes rippled due to VPL and discontinuous due to prohibited operating zones. In Figure 5(b) the effect of ramp rate limits (RRL) on the cost curves can be seen. The Pmin and Pmax limits get modified due to RRL. The resulting cost function is nonconvex and hence very difficult to optimize. Similar characteristics can also be drawn for P3 using the data (P_{min}, P_{max}, POZ and cost coefficients) in the Appendix. Due to space shortage and to show the characteristics clearly, only two generator cost characteristics have been shown here.

For this complex non-convex system, the IPSO searches the global minimum value very effectively, where as the CPSO is not able to achieve the global best value due to the inclusion of valve point loading (VPL) effects. Thus, the superiority of the IPSO over CPSO is more prominent for complex cases.

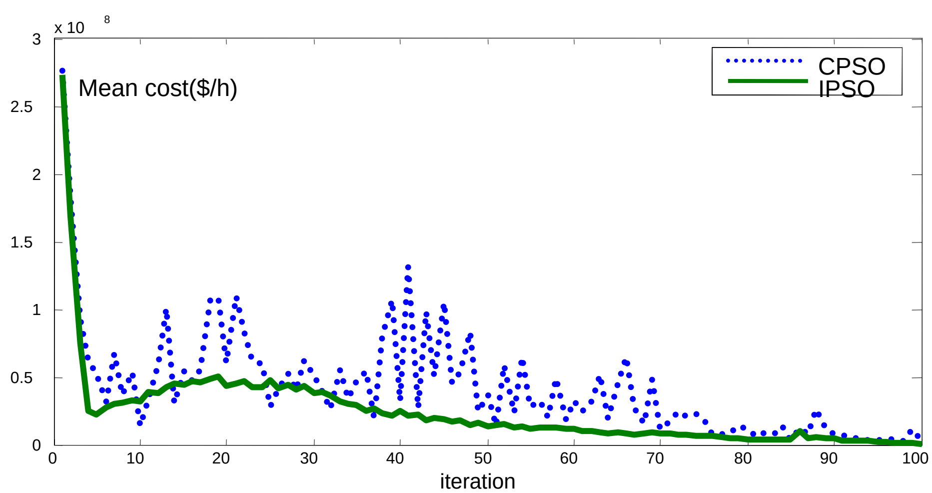

Figure 3. Variation of mean value of the swarm for CPSO and IPSO

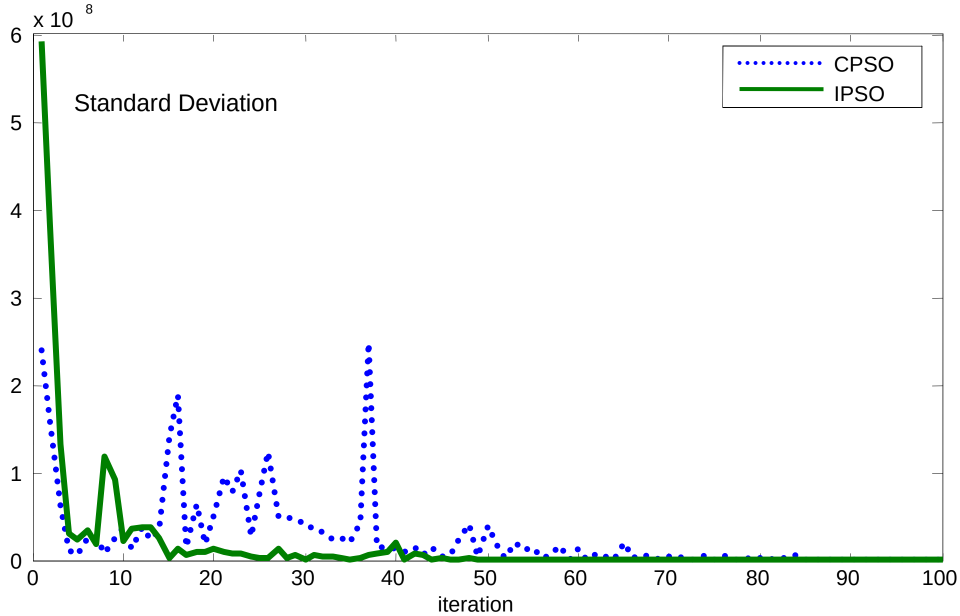

Figure 4. Variation of standard deviation of the swarm for CPSO and IPSO

Table 3. Comparison of best results of Test Case I for different loads

Units (MW)	Load Demand					
	300 MW		400 MW		470 MW	
	CPSO	IPSO	CPSO	IPSO	CPSO	IPSO
P1	183.3945	183.9845	215.6883	221.8246	250.0000	250.0001
P2	45.8225	45.5391	91.7337	78.1754	120.0000	119.9999
P3	70.7830	70.4764	100.0000	100.0000	100.0000	100.0000
Cost($/h)	3482.8701	3482.8674	4561.9250	4561.4979	5345.7735	5345.7707
violation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4 Comparison of best results for Test Case II (with loss)

Output(MW)	IPSO	CPSO	DE/BBO[14]	APSO[18]	GA[19]	TPNN[20]
P1	200.5714	219.3163	207.637	200.528	194.26	165
P2	78.2694	60.0000	87.2833	78.2776	50	113.45
P3	34.0000	34.0000	15.0000*	33.9918*	79.62	34
Total power	312.8408	313.3163	309.9203	312.7974	323.88	312.45
loss	12.8409	13.3164	9.9204	12.8364	24.011	12.45
Violation	-0.0001	-0.0001	-0.0001	-0.039	0.131	0.000
cost ($/h)	**3634.7690**	3639.6686	3619.7565	3634.3127	3737.20	3652.6000
Time (sec)	0.2057	0.2068	0.015	-	-	

*** Solution violating ramp rate limits**

Table 5. Best results of Test Case III (with VPL) for different loads

Units	Load Demand					
	300 MW		400 MW		470 MW	
	CPSO	IPSO	CPSO	IPSO	CPSO	IPSO
P1	184.5313	188.2885	244.7938	250.0000	250.0000	250.0000
P2	48.4691	44.7115	88.2060	50.0000	120.2319	121.8858
P3	67.0000	67.0000	67.0000	99.9999	99.7683	98.1141
Cost	3518.0378	**3499.8842**	4645.2900	**4634.3549**	5444.1727	**5430.0706**
Violation	0.0004	0.0001	0.0002	0.0001	0.0002	0.0000

5.8 *Robustness*

The performance of heuristic search based optimization algorithms is judged through many trials with different initial populations to compare the robustness/consistency of IPSO with CPSO. The lowest cost for each of the 50 different trials has been plotted in Figure 6 for the complex Test Case III. It can be seen that IPSO method produces lowest cost most consistently as compared to the CPSO.

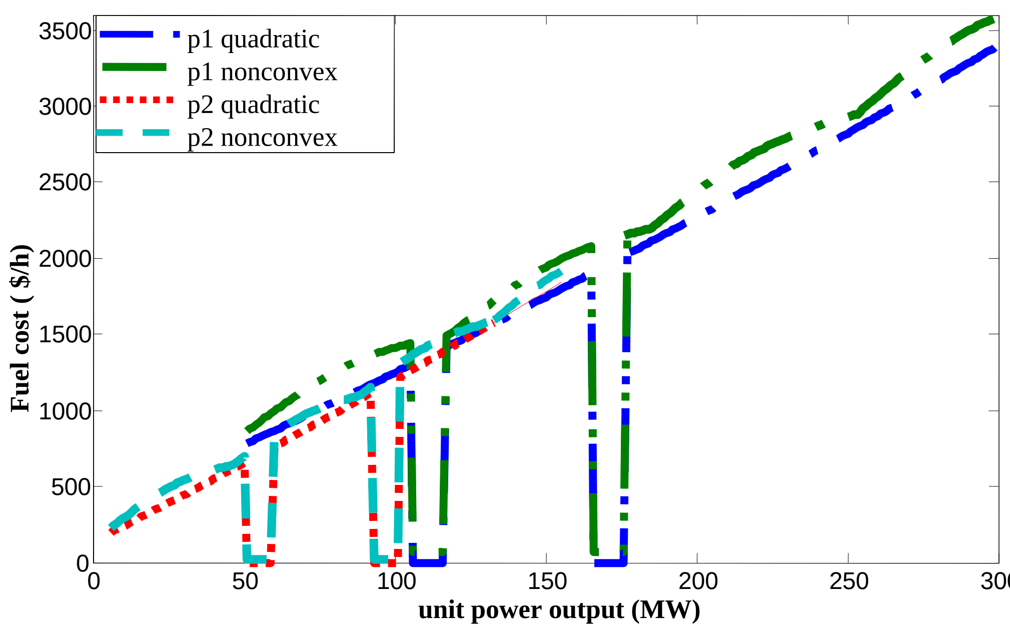

Figure 5 (a). Cost curves of generating units with and without valve point loading effects

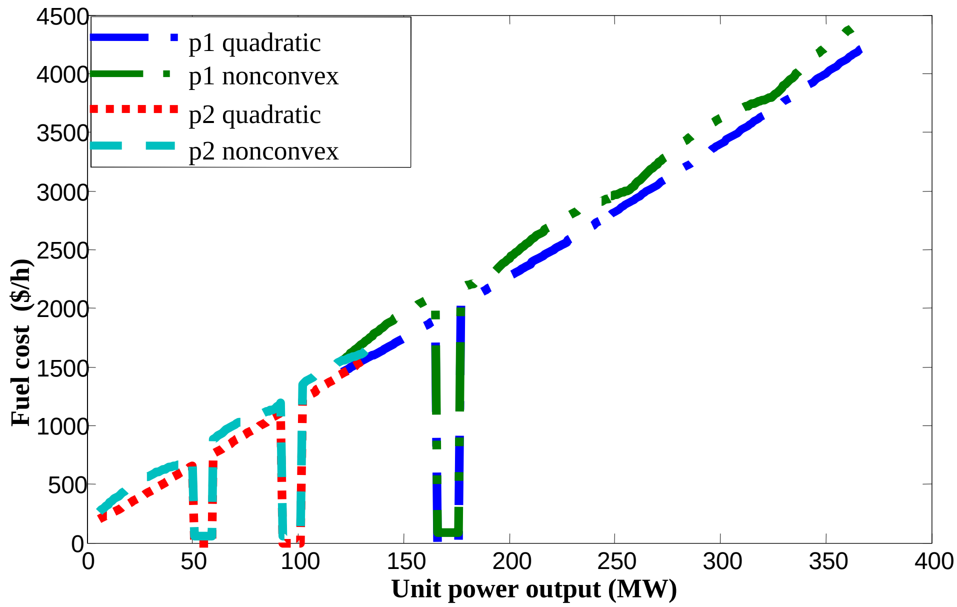

Figure 5 (b). Effect of ramp rate limits on cost curves of units with/without VPL effects

5.9 Solution of Nonconvex Dynamic Economic Dispatch (NCDED)

So far static dispatch results were computed for different loads and varying constraints, considering the ramp rate limits and prohibited operating zones mentioned in data Tables in the Appendix Section for one/next hour only. In NCDED the solution for the first hour is the initial solution for the next hour and optimal dispatches are computed on hourly basis for 24-hour period, for a given load. The losses have been neglected here but POZ and VPL are considered. The optimal solutions for Test Case IV for 24-hours are listed in Table 6. The optimal solutions for NCDED of Test Case V with VPL are listed in Table 7. Cpu time/trial has been shown for all test cases in Table 8.

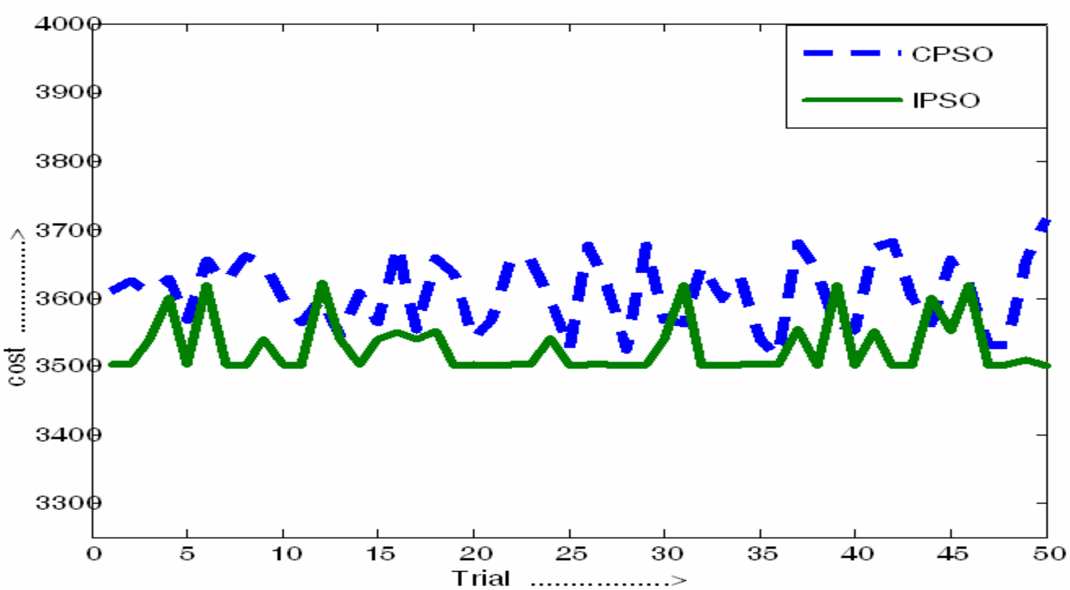

Figure 6. Comparison of best results of CPSO and IPSO (Case III)

Table 6 Results of optimal dynamic dispatch using IPSO (Test case IV))

Hour	Load(MW)	P1(MW)	P2(MW)	P3(MW)	Cost ($/h)	Violation
1	300	183.9845	45.5391	70.4764	3482.8674	0.0001
2	315	189.7884	49.9763	75.2352	3642.2181	0.0001
3	330	197.3877	50.0000	82.6123	3802.6432	0.0001
4	336	195.3137	60.0000	80.6863	3866.8395	0.0001
5	342	198.5733	60.0000	83.4267	3931.2267	0.0001
6	352	202.6541	61.9055	87.4403	4038.9542	0.0001
7	361	206.4414	64.2721	90.2862	4136.2532	0.0002
8	380	213.4426	70.7636	95.7937	4342.6653	0.0000
9	392	218.4550	73.8838	99.6611	4473.7493	0.0001
10	405	224.7052	80.2947	100.0000	4616.5297	0.0001
11	445	242.9999	102.0000	100.0000	5061.9563	0.0001
12	470	250.0000	119.9999	100.0000	5345.7707	0.0001
13	400	223.7784	77.8661	98.3556	4561.6153	0.0001
14	382	213.5666	71.5456	96.8878	4364.4719	0.0001
15	370	209.5917	66.9317	93.4766]	4233.8547	0.0000
16	364	207.0180	65.7036	91.2782	4168.7511	0.0002
17	355	203.7440	63.1887	88.0672	4071.3522	0.0000
18	345	200.3401	60.0000	84.6598	3963.4960	0.0001
19	339	196.5646	60.0000	82.4353	3899.0099	0.0000
20	325	195.1397	50.0000	79.8602	3749.0297	0.0001
21	320	192.1366	50.0000	77.8634	3695.5536	0.0001
22	316	189.8123	50.0000	76.1877	3652.8744	0.0001
23	310	187.4466	48.5125	74.0409	3589.0058	0.0001
24	300	183.8532	45.3336	70.8131	3482.8684	0.0000

Table 7 Results of optimal dynamic dispatch using IPSO (Test case V)

Hour	Load(MW)	P1(MW)	P2(MW)	P3(MW)	Cost ($/h)	violation
1	300	187.5215	45.4785	67.0000	3499.9827	0.0000
2	315	229.1125	5.0000	80.8874	3671.7802	0.0001
3	330	202.4080	46.8879	80.7041	3804.5780	0.0000
4	336	240.4247	46.8879	48.6874	3904.6568	0.0000
5	342	213.7202	46.8883	81.3913	3944.2733	0.0001
6	352	187.0157	88.7758	76.2085	4070.2219	0.0000
7	361	228.60671	50.0000	82.3932	4171.2388	0.0001
8	380	201.9022	88.7758	89.3219	4376.5764	0.0001
9	392	243.4930	91.1328	57.3742	4508.9031	0.0000
10	405	216.7885	138.7965	49.4149	4668.0087	0.0001
11	445	225.4112	140.4746	79.1141	5131.1313	0.0000
12	470	223.2955	150.0000	96.7044	5384.8987	0.0001
13	400	196.5910	113.8879	89.5211	4606.5498	0.0000
14	382	237.2292	77.7708	67.0000	4418.3082	0.0001
15	370	210.5247	88.7758	70.6995	4276.2967	0.0000
16	364	183.8202	102.0000	78.1798	4225.0135	0.0000
17	355	157.1157	107.7758	90.1084	4139.2634	0.0001
18	345	198.7067	71.6637	74.6296	4014.9798	0.0001
19	339	240.2977	46.8879	51.8143	3937.2702	0.0001
20	325	213.5932	88.7758	22.6309	3811.2918	0.0001
21	320	186.8887	86.0543	47.0570	3752.6818	0.0000
22	316	228.4797	8.0543	79.4659	3673.5408	0.0001
23	310	201.7752	48.2247	60.0000	3645.6840	0.0001
24	300	177.0000	46.8879	76.1121	3508.8980	0.0000

Table 8 CPU time for the different test cases

TEST CASE	Test case I	Test case II	Test case III	Test case IV	Test case V
cpu time/trial	0.1412	0.2057	0.1562	3.4129	3.7613

6. Conclusions

An improved PSO based strategy is proposed in this paper for solving the nonconvex dynamic economic dispatch (NCDED problem. The proposed IPSO strategy is found to improve the performance of PSO and to handle the problem of premature convergence found in CPSO very effectively by i)generating crazy particles whose velocities are reinitialized with a certain probability ii) employing iterative variation of cognitive and social parameters. The superiority of IPSO becomes more evident for more complex systems having multiple minima. This method outperforms CPSO in terms of solution quality, computational efficiency, dynamic convergence, robustness and stability. The proposed IPSO approach is tested on five different test cases having different levels of complexities and constraints. The results are compared with previously published results and found to be superior or/and comparable. The IPSO is capable of handling all the complex constraints imposed by ramp rate limits, valve point loading effects and prohibited operating zones very effectively.

Nomenclature

P_i Power output of the i^{th} generating unit
$F_i(P_i)$ Fuel cost function of the i^{th} generating unit
$P_i^{\min}$, $P_i^{\max}$ Minimum and maximum generation limits on i^{th} unit
N Number of generating units
P_D Total real power demand
P_L Total real power loss
DR_i Down ramp rate limit
UR_i Up ramp rate limit
x_{id} position of d^{th}dimension of the i^{th} particle
v_{id} velocity of d^{th}dimension of the i^{th} particle

Appendix

Table A1. Cost coefficients and unit operating limits

unit	$P_{\min}$	$P_{\max}$	a_i($/M$W^2$)	b_i($/MW)	c_i($)	e_i	f_i
1	50	250	0.00525	8.663	328.13	125	0.046
2	5	150	0.00609	10.04	136.91	75	0.075
3	15	100	0.00592	9.76	59.16	50	0.098

Table A2. Ramp rate limits and prohibited operating zones

unit	P_i^0	UR_i(MW/h)	DR_i(MW/h)	Prohibited zone (MW)
1	215	55.0	97.0	[105,117] [165, 177]
2	72.0	55.0	78.0	[50 ,60] [92, 102]
3	98.0	45.0	64.0	[25 ,32] [60,67]

Table A3. B-loss coefficients of three unit systems

Bij	0.000136	0.0000175	0.000184
	0.0000175	0.000154	0.000283
	0.000184	0.000283	0.00165

Acknowledgement

The authors sincerely acknowledge the financial support provided by UGC under major research project entitled Power System Optimization and Security Assessment Using Soft Computing Techniques, vide F No.34-399/2008 (SR) dated, 24th December 2008. The authors also thank the Director, M.I.T.S. Gwalior for providing facilities for carrying out this work. The third author acknowledges UGC research award for post doctoral work sanctioned by UGC, New Delhi vide letter no. F-30-120(SC)/2009 (SA-II).

References

Bhattacharya A. and Chattopadhyay P.K., 2010.Hybrid differential evolution with biogeography- based optimization for solution of economic load dispatch. *IEEE Transactions on Power System*, Vol. 25, No.4, pp. 1955 – 1964.

Chaturvedi K. T., Pandit M. and Srivastava L., 2008. Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch. *IEEE. Transactions on Power System*, Vol. 23, No. 3, pp. 1079-1087

Chen P.H. and Chang H.C., 1995. Large scale economic dispatch approach by genetic algorithm. *IEEE Transactions on Power Systems*, Vol. 10, No.4, pp. 1919-1926,.

Chiou J. P., 2009. A variable scaling hybrid differential evolution for solving large-scale power dispatch problems. *IET Generation, Transmission Distribution*, Vol. 3, No. 2, pp. 154-163.

Damousis Ioannis G., Bakirtzis Anastasios G. and Dokopolous Petros S., 2003. Network constrained economic dispatch using real-coded genetic algorithms. *IEEE Transactions on Power System*, Vol. 18, No. 1, pp. 198-205.

Kennedy J. and Eberhart R., 1995.Particle swarm optimization. in *Proc. IEEE Conf. on Neural Networks (ICNN'95)*, Vol. IV, Perth, Australia, pp.1942-1948.

Naresh R., Dubey J. and Sharma J.D., 2004. Two-phase neural network based frame work for modelling of constrained economic load dispatch. *IEE proceedings Generation, Transmission and Distribution*, Vol. 151, No. 3, pp. 373 -380.

Orero S. O.and Irving M.R., 1996. Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach. *IEE proceedings, Generation, Transmission and Distribution*, Vol. 143, No. 6

Panigrahi B. K., Pandi V. R., and Das S., 2008. Adaptive particle swarm optimization approach for static and dynamic economic load dispatch. *Energy Conversion and Management*, Vol. 49, No. 6, pp. 1407–1415.

Park J. B. Jeong Y.W, Shin J.R.and Lee K.Y., 2007. An improved particle swarm optimization for nonconvex economic dispatch problems, *IEEE. Transactions on Power system*, Vol. 25, No. 1, pp.156-166.

Park J. B., Jeong Y.W. and Shin J.R., 2010. An improved particle swarm optimization for nonconvex economic dispatch problems. *IEEE Transactions on Power System*, Vol. 25, No. 1, pp.156-166.

Ratnaweera A., Halgamuge S.K. and Watson H.C., 2004 Self-organizing hierarchical Particle swarm optimizer with time-varying acceleration coefficients, *IEEE Transactions on Evolutionary Computation*, Vol. 8, No. 3, pp.240-255

Selvakumar A. I. and Thanushkodi K., 2007. A new particle swarm optimization solution to nonconvex economic dispatch problems. *IEEE. Transactions on Power System*, Vol. 22, No. 1, pp.42-51.

Shi Y. and Eberhart R.C., 1999. Empirical study of particle swarm optimization, *Proc. of IEEE Int. Congress on Evolutionary Computation*, Vol. 3, pp. 101-106.

Shoults R.R., 1986. A dynamic programming based method for developing dispatch curves when incremental heat rate curves are non-monotonically increasing. *IEEE Transactions on Power System*, Vol. 1, pp.10-16.

Sinha N., Chakrabarti R. and Chattopadhyay P.K., 2003. Evolutionary programming techniques for economic load dispatch", IEEE Transactions on Evolutionary Computation, Vol. 7, No. 1, pp. 83-94.

Victoire T.A.A. and Jeyakumar A.E., 2005. Reserve constrained dynamic dispatch of units with valve point effects. *IEEE Transactions on Power System*, Vol. 20, No. 3, pp. 1273-1282.

Walter D.C. and Sheble G. B., 1993. Genetic algorithm solution of economic load dispatch with valve point loading. *IEEE Transactions on Power System*, Vol. 8, pp.1325-1332.

Wang and Shahidehpour S.M., 1993. Effects of ramp-rate limits on unit commitment and economic dispatch. *IEEE Transactions on Power System*, Vol. 8, No. 3, pp.1341-1350

Wood A.J. and Wollenberg B.F., 1984. *Power Generation Operation and Control*, New York: Wiley.

Biographical notes

Rajkumari Batham obtained her B.E. degree in Electrical Engineering from M.I.T.S., Gwalior, (India) in 2008 and is presently persuing M.Tech in Industrial systems and Drives from M.I.T.S., Gwalior.

Kalpana Jain obtained her M.E. degree in Electrical Engineering from Madhav Institute of Technology & Science Gwalior (India) in 2010. She is currently working as Project Fellow in the department of Electrical Engineering, M.I.T.S., Gwalior (India). Her areas of interest are Power System Security Analysis, Optimization and soft computing/evolutionary methods.

Manjaree Pandit obtained her M.Tech degree in Electrical Engineering from Maulana Azad College of Technology, Bhopal, (India) in 1989 and Ph.D. degree from Jiwaji University Gwalior (India) in 2001. She is currently working as Professor in Department of Electrical Engineering, M.I.T.S., Gwalior, (India). Her areas of interest are Power System Security Analysis, Optimization using soft computing/ evolutionary methods, ANN and Fuzzy neural applications to Power System.

Received June 2011
Accepted June 2011
Final acceptance in revised form June 2011