A MODIFIED PARTICLE SWARM OPTIMIZATION TO SOLVE THE ECONOMIC DISPATCH PROBLEM OF THERMAL GENERATORS OF A POWER SYSTEM

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Abstract: *The economic dispatch has the objective of generation allocation to the power generators in such a way that the total fuel cost is minimized while all operating constraints are satisfied. The schematic methods assume the cost curves of generators are linear but in case of modern generators this assumption makes inaccuracy in economic dispatch because of valve point loading effect, prohibited operating zone and ramp rate limits. By involving these three constraints the classical PSO unable to faces premature convergence.*

To handle the problem of premature convergence this paper presents an efficient approach for solving non-convex economic dispatch (NCED) problem using a modified particle swarm optimization (MPSO)combined with roulette wheel selection method. The proposed method applied to six unit system having nonconvex solution spaces, and better results are obtained when compare with previous approach.

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Key words*: Non-convex economic dispatch (NCED), premature convergence, prohibited operating zones (POZ), ramp rate limit, valve point loading effect, roulette wheel selection method.*

1. Introduction

Economic dispatch (ED) is one of the important optimization problems in power systems that have the objective of dividing the power demand among the online generators economically while satisfying various constraints [1][5]. Since the cost of the power generation is exorbitant, an optimum dispatch saves a considerable amount of money. Traditional algorithms like lambda iteration, base point participation factor, gradient method, and Newton method can solve the ED problems effectively if and only if the fuel-cost curves of the generating units are piece-wise linear and monotonically increasing [2].

Methods like dynamic programming [6], genetic algorithm [2], [4], [7], [8], evolutionary programming [3], [9]–[11], artificial intelligence [12], and particle swarm optimization [13]–[23] solve non-convex optimization problems efficiently and often achieve a fast and near global optimal solution. The PSO, first introduced by Kennedy and Eberhart [13] is a flexible, robust, population based algorithm with inherent parallelism. This method is increasingly gaining acceptance for solving economic dispatch [14]–[18] and a variety of power system problems [19]–[22], due to its simplicity, superior convergence characteristics and high solution quality. Recent research however has observed that classical PSO approach suffers from premature convergence, particularly for complex functions having multiple minima [16], [23].

A hybrid PSO is proposed [27] for OPF with emission constraint where inequality constraints are handled by a novel hybrid mechanism. Recently fuzzy adaptive PSO [28] has been applied for optimization in power spot price market [29]. Different techniques have been proposed to handle premature convergence in non-convex ED solution with stochastic search based evolutionary methods. In [8] an improved GA is proposed with multiplier updating to increase search efficiency and to handle constraints. The NCED problem was solved by integrating evolutionary programming, tabu search and quadratic programming [12]. ED with a dynamic space reduction technique is proposed in [15] to accelerate convergence. The concept of generating crazy agents was effectively applied in [16] to combat premature convergence in dynamic dispatch with valve point loading [18] combined a local search operator with PSO to enhance local exploration once the solution region is identified.

A novel parameter automation strategy called an self-organizing hierarchical PSO (SOH PSO) is applied in this paper for the NCED to address the problem of premature convergence. In this approach, the particle velocities are reinitialized whenever the population stagnates at local optima during the search. A relatively high value of the cognitive component results in excessive wandering of particles while a higher value of the social component causes premature convergence of particles [13]. Hence, time-varying acceleration coefficients (TVAC) [23] are employed to strike a proper balance between the cognitive and social component during the search. Integration of the

TVAC with SOH PSO for solving the practical economic dispatch problem has been found to avoid premature convergence during the early stages of the search and promote convergence towards the global optimum solution.

The Self-Organizing hierarchical particle swarm optimization still having some unsolved problems such as maximum number of iterations is adopted as the stopping criteria comparison with other strategies. To overcome the limitation of number of iterations in SOH PSO and Simple PSO, the modified particle swarm optimization with roulette wheel selection method was implemented and the average convergence time and number of iterations required for convergence in case of MPSO are lesser than Simple PSO and SOH PSO.

2. Non-convex economic dispatch

The basic ED becomes a non-convex optimization problem if the practical operating conditions are included.

A. Valve Point Loading Effects

The valve-point effects introduce ripples in the heat-rate curves and make the objective function discontinuous, non-convex and with multiple minima. For accurate modeling of valve point loading effects, a rectified sinusoidal function [2] is added in the cost function in this paper. The fuel input- power output cost function of the ith unit is given as:

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

Where, ai, bi, ci, ei and fi are the fuel-cost coefficients of ith generator. Pgi is generator active power output.

B. The Constraints

The above objective function is to be minimized subject to the following constraints

i) Power balance constraints

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

Where, PD is the load demand for the power system. The total transmission losses PL is a function of unit power outputs that can be expressed using B-coefficients as

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oj} P_i + B_{oo} \quad (3)$$

ii) Generator Capacity Constraints

$$P_i^{min} \le P_i \le \mathrm{P}_i^{max} \quad (4)$$

Where, Pi min and Pi max are the minimum and maximum power outputs of the ith unit.

C. Prohibited Operating Zone

References [2], [3], and [8] have shown the input-output performance curve for a typical thermal unit with many valve points. These valve points generate many prohibited zones. In practical operation, adjusting the generation output of a unit must avoid unit operation in the prohibited zones. The feasible operating zones of unit can be described as follows:

$$P_i \epsilon \begin{cases} P_i^{min} \le P_i \le P_{i1}^L \\ P_{ik-1}^U \le P_i \le P_{ik}^L \\ P_{izi}^U \le P_i \le P_i^{max} \end{cases} \quad (5)$$

Here zi are the number of prohibited zones in the ith generator curve, k is the index of prohibited zone of the ith generator, P_{ik}^{L} is the lower limit of the th prohibited zone, and P_{izi}^{U} is the lower limit of the th prohibited zone of the th generator.

D. Generator Ramp Rate Limits

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

$$Max\left(P_i^{min}, P_i^o - DR_i\right) \le P_i \le Min(P_i^{max}, P_i^o - UR_i) \quad (6)$$

Where P_i^{o} is the previous operating point of generator, $\mathrm{DR}_i$and $\mathrm{UR}_i$are the down and up ramp limits of the generator.

3. Overview of PSO

A. Simple PSO

Kennedy and Eberhart invented Particle Swarm Optimization (PSO) in 1995 [12]. The PSO can be best understood through an analogy of a swarm of birds in a field. Without any prior knowledge of the field, the birds move in random locations with random velocities looking for foods.

In PSO, particles change their positions (states) with time. Let ‘x’ and ‘v’ denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space respectively. The best previous position of the ith particle is recorded and represented as pbest. The index of the best particle among all the particles in the group is represented by the gbest. The modified velocity and position of each particle can be calculated as per following formulas:

$$v_{id}^{k+1} = C\begin{Bmatrix} w \times v_{id}^{k} + c_1 \times rand_1 \times (pbest_{id} - x_{id}) \\ +c_2 \times rand_2 (gbest_{gd} - x_{id}) \end{Bmatrix} \quad (7)$$

$$x_{id}^{k+1} = x_{id} + v_{id}^{k+1} \quad (8)$$

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 co-efficients, respectively, and $rand_1$, $rand_2$ are random numbers between 0 and 1. A larger inertia weight factor is used during initial exploration its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight (TVIW) was introduced in [24] as per which is w given by

$$w = (w_{max} - w_{min}) \times \frac{(iter_{max} - iter)}{iter_{max}} + w_{min} \quad (9)$$

Where, $iter_{max}$ is the maximum number of iteration. To improve the convergence of PSO algorithm, the constriction factor is also in use [22], [25].

$$C = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|} \quad (10)$$

B. SOH-PSO

In this novel PSO strategy the previous velocity term in (7) is made zero. With this modification the particles rapidly rush towards a local optimum solution and then stagnate because of the absence of momentum. To make this strategy effective, the velocity vector of a particle is reinitialized with a random velocity whenever it stagnates in the search space. When a particle stagnates, it's associated $pbest_{id}$ remains unchanged for a number of iterations. When more particles stagnate, the $gbest_{gd}$ also undergoes the same fate and the PSO algorithm converges prematurely to a local optima and v_{id}^{k} becomes zero. A necessary push to the PSO algorithm is imparted by reinitializing v_{id}^{k} by a random velocity term. The method works as follows [23]:

$$v_{id}^{k+1} = c_1 \times rand_1 \times (pbest_{id} - x_{id}) + c_2 \times rand_2 \times \left(gbest_{gd} - x_{id}\right) \quad (11)$$

The acceleration coefficients are expressed as [23]

$$c_1 = (c_{1f} - c_{1i}) \frac{iter}{iter_{max}} + c_{1i} \quad (12)$$

$$c_2 = (c_{2f} - c_{2i}) \frac{iter}{iter_{max}} + c_{2i} \quad (13)$$

If $v_{id} = 0$ and $rand_3 < 0.5$ then

$$v_{id} = rand_4 \times v_{dmax} \text{ else } v_{id} = -rand_5 \times v_{dmax} \quad (14)$$

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

C. Modified PSO

The classical PSO algorithm has been modified with a roulette selection operator [4] inspired from genetic algorithms [9]. In this paper, to solve NCED problems, this modified PSO (MPSO) technique has been proposed and explained. The feasibility of the proposed method has been demonstrated for a six generator system and compared with simple PSO and self-organizing hierarchical particle swarm optimization techniques in terms of solution quality and computation efficiency [15][16].

To ensure the selection probability of a particle is in inverse proportion to its original fitness, and the scaled fitness is non-negative, the following fitness scaling function has been used:

$$FS\big(f(x)\big) = \frac{a}{a + f(x) - GM} \quad (15)$$

Where, GM is the estimated extreme of the objective function, 'a' is a positive constant denotes the scaling degree; 'f(x)' is the original fitness of a particle.

Roulette wheel selection method has been adopted to randomly choose a particle. The selection of particle 'i' is computed by:

$$q[i] = \frac{FS(f(x[i]))}{\sum_{i=1}^{n} FS(f(x[i]))} \quad (16)$$

After calculating the value 'q[i]' for each particle as per equation (16), the mean value of 'q[i]' has been calculated as per following equation:

$$Mean(q) = \frac{\sum_{i=1}^{n} q[i]}{n} \quad (17)$$

Where, n is the size of population. i=1,2, ……n. Index 'i' is calculated as per following equation:

$$i = \frac{q[i]}{mean(q)} \quad (18)$$

That set of population, which gives maximum value of 'i' among total population size, is nothing but index. The position of particle 'i' is used to replace 'gbest' using following equation:

$$v_{id}^{k+1} = C\begin{Bmatrix} w \times v_{id}^{k} + c_1 \times rand_1 \times (pbest_{id} - x_{id}) \\ + c_2 \times rand_2 \times (gbest_{gd} - x_{id}) \end{Bmatrix} \quad (19)$$

$$x_{id}^{k+1} = x_{id} + v_{id}^{k+1} \quad (20)$$

4. Problem Formulation

To overcome the limitation of number of iterations in SOH PSO and Simple PSO, the modified particle swarm optimization with roulette wheel selection method was implemented and the average convergence time and number of iterations required for convergence in case of MPSO are lesser than Simple PSO and SOH PSO.

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 generating units, the th particle is represented as $P_{ij} = (P_{i1,} P_{i2}, P_{i3,} \dots \dots \dots \dots P_{iN})$.

Step 2) Defining the evaluation function: The merit of each individual particle in the swarm, is found using a fitness function called evaluation function.

The evaluation function f(pi) is defined to minimize the non-smooth cost function given by (1) for a given load demand while satisfying the constraints given by (2) and (4) as equation (15).
Roulette wheel selection method has been adopted to randomly choose a particle and evaluate particle 'i' to replace gbest value.

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 values of the particles. The best value among all the pbest values is identified as gbest.

Step 4) The update velocity and position are updated by using equations (19) and (20) and the particle are provided with a momentum by reinitializing the modulus of the velocity vector with a random velocity.

Step 5) If the evaluation of each individual is better than the previous Pbest, the current value is set to be Pbest. If the best Pbest is better than the Gbest, the valve is set to be Gbest.

Step 6) If the number of iterations reaches the maximum, then go to step 2 else go to next step.

Step 7) The individual that generates the latest gbest is the optimal generation power of each unit with the minimum total generation cost.

5. Numerical Results

The NCED problem was solved using the Modified PSO with Roulette wheel selection method and its performance is compared with Simple PSO and Self- organizing hierarchical PSO Algorithms. The proposed MPSO technique has been applied to six generator power systems (PS). The software program were written in MATLAB – 7.6 language and executed on 2.8GHz with 3GB RAM. The performance of each system has been judged out of 50 trails.

Six-Unit System: The system contains six thermal units, 26 buses, and 46 transmission lines [9]. The load demand is 1263MW. The characteristics of the six thermal units are given in Tables I and II.

Table I Cost Curves of Six Unit System

Unit	P_i^{min}	P_i^{max}	a_i	b_i	c_i
1	100	500	0.007	7	240
2	50	200	0.0095	10	200
3	80	300	0.0090	8.5	220
4	50	150	0.0090	11	200
5	50	200	0.0080	10.5	220
6	50	120	0.0075	12	190

Table II Ramp Rate and Prohibited Operating Zone Limits for Six Generator System

Unit	P_i^0	UR_i	DR_i	**Prohibited operating zone**
1	100	80	120	[210 240] [350 380]
2	50	50	90	[90 110] [140 160]
3	80	65	100	[150 170] [210 240]
4	50	50	90	[80 90] [110 120]
5	50	50	90	[90 110] [140 150]
6	50	50	90	[75 85] [100 105]

The parameter setting of proposed system. Population size = 100, Iterations = 2000, wmax = 0.95, wmin = 0.2, rand1 & rand2 = 0 to 1, C1 = 2.8, C2 = 1.3, Constriction factor = 0.729 (C), GM = 0, Constant a = 100.

The convergence behavior of the Modified PSO was tested for different cases having different dimensions and varying levels of complexity to study the effectiveness of the approach in handling premature convergence. The test system has six-generating units [9], a total load of 1263 MW; all the units have prohibited zones and ramp rate limit constraints and power losses have been calculated using B-matrix from reference paper [9]. The best reported cost is $15570.19/h after comparison of three different algorithms.

The best results of case system (Six generator system) for the three methods are tabulated in Table III.

The convergence characteristics of the six unit system is plotted in Figs. I, II and III for all three methods. (SPSO, SOH PSO, MPSO).

Table III Results of Six Unit System

Unit	SPSO (MW)	SOH SO (MW)	MPSO (MW)
1	362.987	375.529	395.620
2	200.000	195.533	196.345
3	292.540	292.955	291.857
4	145.522	150.000	149.473
5	200.000	188.685	181.385
6	120.000	119.940	110.318
Total Cost($)	15577.62	15573.23	15570.19
Time (sec)	9.2020	12.1272	9.5381

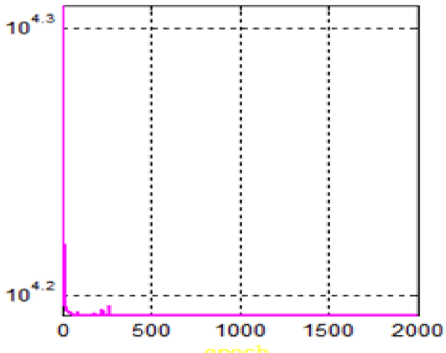

Fig. 1 Convergence characteristics of Simple PSO

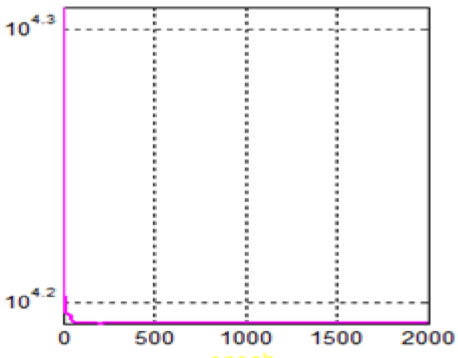

Fig. 2 Convergence characteristics of SOH PSO

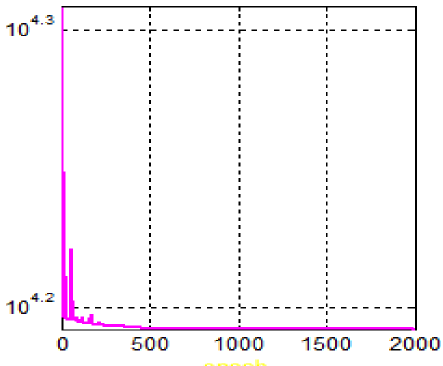

Fig. 3 Convergence characteristics of Modified PSO

Comparison of all three methods:

1) Convergence Characteristics:

The Figs. (1)(2) and (3) show the superior convergence characteristics of MPSO. After some iterations the simple PSO characteristics and SOH PSO show signs of premature convergence and settle to near global results.

2) Solution Quality:

Table 3 show that the minimum cost obtained by proposed system from comparison of other two methods.

3) Computational Efficiency:

Tables 3 present the best cost achieved by the different PSO algorithms for the six generator test case with constraint satisfaction. The costs achieved by MPSO are best and less than reported in other method.

6. Conclusion

A new technique that combines modified particle swarm optimization with roulette wheel selection algorithm to complex problem of non-convex economic dispatch. The formulated three different algorithms has been tested for six generating unit. The results obtained from Modified PSO method is compared with Simple PSO and SOH PSO methods.

The obtained results compared with Simple PSO and SOH PSO methods and the proposed approach provides an effective method to simplify the non-convex economic dispatch problems..

The test results clearly demonstrated that Modified PSO which is capable of achieving global solutions is simple, computationally efficient and has better and stable dynamic convergence characteristics, robustness and stability.

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