Hybrid Particle Swarm Optimization for Economic Load Dispatch

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Abstract— Economic Dispatch is an important optimization task in power system. It is the process of allocating generation among the committed units such that the constraints imposed are satisfied and the energy requirements are minimized. More just, the soft computing method has received supplementary concentration and was used in a quantity of successful and sensible applications. Here, an attempt has been made to find out the minimum cost by using Particle Swarm Optimization (PSO) Algorithm using the data of three generating units. In this work, data has been taken such as the loss coefficients with the maxim power limit and cost function. A non-convex method for ELD problem using PSO is applied to find out the minimum cost for different power demand. When the results are compared with the traditional technique, PSO seems to give a better result with better convergence characteristic. All the methods are executed on MATLAB. The effectiveness and feasibility of the proposed method were demonstrated by three generating unit's case study. The experiment showed encouraging results, suggesting that the proposed approach of computation is capable of efficiently determining higher quality solutions addressing economic dispatch problems

I. INTRODUCTION

In the present scenario, the study focuses on small thermal power generating system where main concern is continuous and reliable power generation to meet the increasing demand with optimum generation schedule of the generators. With the Increase in power demand and fuel cost, the generation cost is higher which ultimately affects the user community. So the other aim of optimization of power generation and distributionis to minimize the overall generation cost and power loss in transmission lines.

The economic dispatch (ED) aims at determining the optimalscheduling of thermal generating units so as to minimize the fuel cost while satisfying several operational and power system network constraints. The generator fuel cost functions are invariably nonlinear and also exhibit discontinuities due to prohibited operating zones (POZs). In addition, the valve point loading effect causes non convex characteristic with multiple minima in the generator fuel cost functions and thus imposes challenges of obtaining the global optima for high dimensional ED problems. Thus, ED is a highly nonlinear, complex combinatorial, non-convex, and multi constraint optimization problem with continuous decision variables. The classical mathematical methods like gradient, Lagrange relaxation methods, and so forth, except dynamicprogramming, are not suitable for such complex optimizationproblems. The modern met heuristic search techniques such asparticle swarm optimization (PSO), genetic algorithms (GAs), biogeography-based optimization (BBO), differential evolution (DE), ant colony optimization (ACO), artificial bee colony (ABC), and hybrid swarm intelligent based harmonysearch algorithm (HHS) have shown potential to solve suchcomplex ED problems due to their ability to obtain global ornear global solution but are computationally demanding especially for modern power systems which are large andcomplex.

The PSO has several advantages over other met heuristic techniques in terms of simplicity, convergence speed, and robustness. It provides convergence to the global or near global optima, irrespective of the shape or discontinuities of the cost function. The potential of PSO to handle non-smooth and non-convex ELD problem was demonstrated. However, the performance of the PSO greatly depends on its parameters and it often suffers from the problems such as being trapped in local optima due to premature convergence, lack of efficient mechanism to treat the constraints, and loss of diversity and performance in optimization process. PSO is a population-based optimization technique in which the movement of the particles is governed by the two stochastic acceleration coefficients, that is, cognitive and social components and the inertia component. In order to enhance the exploration and exploitation capabilities of PSO, the components affecting velocity of particles should be properly managed and controlled.

II. PROBLEM FORMULATION

The generator cost function is usually considered as quadratic, when valve-point loading effects are neglected. The large turbine generators usually have a number of fuel admission valves which are operated in sequence to meet out increased generation. The opening of a valve the throttling losses rapidly and thus the incremental heat rate rises suddenly. This valve-point loading effect introduces ripples in the heat-rate curves which introduces non-convexity in the generator fuel cost function as shown in Figure 1. The effect of valve-point loading effects can be modeled as sinusoidal function in the cost function. Therefore, the increases Advances in Electrical Engineering 3 objective function for the non-convex ED problem may be stated as

$$\text{Minimize } F(P_{Gi}) = \sum_{i=1}^{N_G} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) + \left|e_i \sin\left(f_i \left(P_{Gi\min} - P_{Gi}\right)\right)\right|$$

where ai, bi, and ci are the cost coefficients of the ith generator,ei and fi are the valve-point effect coefficients,PGi is the real power output of the ith generator, and NG is the number of generating units in the system.

Subject to the following constraints:

(1) Power Balance Constraint

The total power generationof all generators must be equal to the sum of total power demand plus the network power loss. The network power losscan be evaluated using B-coefficient loss formula. Therefore, the generator power balance

$$\sum_{i=1}^{N_G} P_i = PD + \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_G} P_{Gi} B_{i0} + B_{00},$$

equation may be stated as follows:

where Bij is the transmission loss coefficient i =1, 2, . . . , $NG$and j = 1, 2, . . . , NG, Bi0 is the ith element of the loss coefficient vector. B00 is the loss coefficient constant.

(2) Generator Constraint.

For stable operation, power output of each generator is restricted within its minimum and maximum limits. Thegenerator power limits are expressed as follows:

(3) Prohibited Operating Zones.

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}.$$

Prohibited operating zones lead to discontinuities in the input output relation of generators. Prohibited zones divide the operating region between minimum and maximum generationlimits into disjoint convex sub regions. The generation limitsfor the ith unit with j number of prohibited zones can be expressed as follows:

where superscripts L and U stand for the lower and upper limitof prohibited operating zones of

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi,1}^{L},$$

$$P_{Gi,j-1}^{U} \le P_{Gi} \le P_{Gi,j}^{L},$$

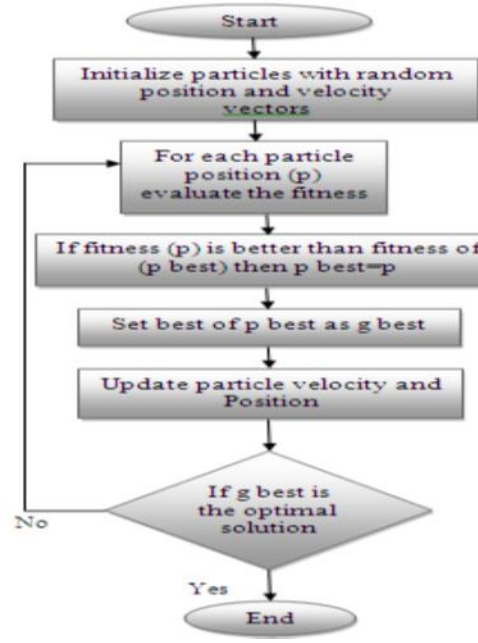
$$P_{Gi,N_{PZi}}^{U} \le P_{Gi} \le P_{Gi}^{\max};$$

$$i \in \{1, 2, \ldots, N_{GPZ}\}, \quad j \in \{2, 3, \ldots, N_{PZi}\}$$

generators. $NGPZ$ and NPZidenote the total number of generators with prohibited zonesand the total number of prohibited zones for the ith generator, respectively.

III. HYBRID PSO-ACO APROACH

PSO is a population-based heuristic search algorithm thatemulates the movement of swarm in finding best solution ofan optimization problem. In PSO, the particles make parallelsearches for optima in the search space by updating theirvelocity and position dynamically. In every iteration, the PSOkeeps track of two updated values – one is the '*pbest*' or the best value (fitness) achieved so far by a given particle whilethe other is the '*gbest*' i.e. the best value attained so far by the population. ACO is another swarm based method for finding optimum solution by following the strategy of movement ofan ant colony towards the source of food through the shortest path. Though each ant finds a new solution, better solutions are yielded by exchanging information with other ants throughthe '*pheromone'* trail. Thus, analogous to an ant, the ACO algorithm constructively builds or improves a solution to an optimization problem by moving through nodes (or states) ofa neighborhood graph. Though PSO is good for ELDproblems for its flexibility, robustness and fast convergence, it sometimes give unsatisfactory result due to large accumulation of particles at '*gbest*' position. ACO, on theother hand, known for its good downhill behaviour near the global optimal region, imparts better balance between localand global search when combined with PSO in the hybrid PSO-ACO algorithm.



IV. METHODOLOGY

Non-convex economic dispatch formulation

The practical NCED problem with generator nonlinearities such as valve point loading effects, prohibited operating zones and ramp rate limits, are solved in this Paper using PSO based approaches.

4.1.1 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 is added in the cost function in this Paper. The fuel input-power output cost function of i^{th} unit is given as

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

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:

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

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

For a given total real load P_D the system loss P_L 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 are in use. The latter is adopted in this Paper as per which transmission losses are expressed as

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

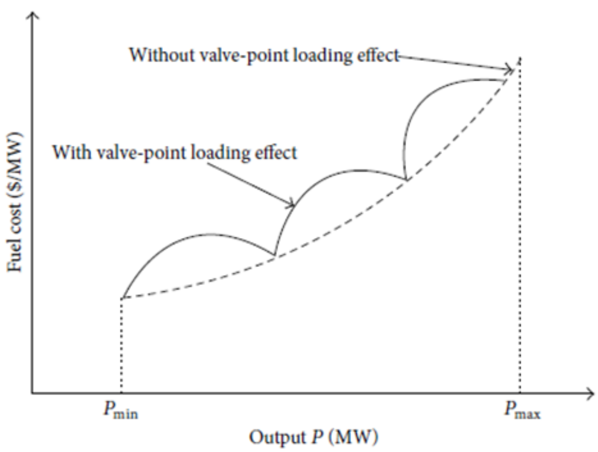


FIGURE 1: Fuel cost function with and without valve-point loading effect.

4.1.2 New Crazy PSO

To handle the problem of premature convergence in PSO, the concept of craziness was introduced. The idea was to randomize the velocities of some of the particles, referred to as "crazy particles", selected by applying a certain probability. The probability of craziness ρ_{cr} is defined as a function of inertia weight,

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

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

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

If the PSO algorithm tends to saturate in the beginning 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 performance of the PSO improves significantly with time varying inertia weight, constriction factor and crazy particles; however, the effectiveness and suitability of a PSO algorithm depends on type of function to be optimized .

4.1.3 Time-Varying Acceleration Coefficients (TVAC)

The time-varying inertia weight (TVIW) can locate good solution 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.

In TVAC, this is achieved by changing the acceleration coefficients c_1 and c_2 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

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

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

The velocity is

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

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

V. RESULT AND ANALYSIS

5.1 The PSO algorithm with crazy particles for practical non convex ED problem is tested on The first system has 3-generating units has a total load of 850 MW, and cost function includes the valve-point effects in addition to the constraints

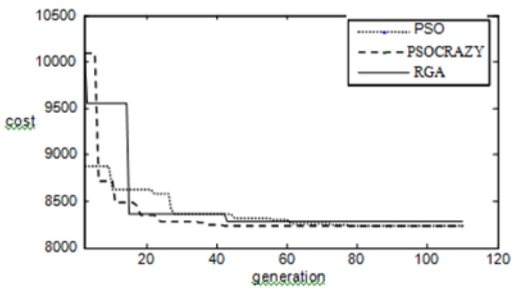


Fig. 5.1. Comparison of convergence characteristics (3-unit system)

Table 5.1.
Comparison of different PSO methods for three-unit system (50 trials)

S.no	Method	Minimum cost($/h)	Maximum cost($/h)	Average cost($/h)
1	PSO	8234.0718	8421.5231	8330.8512
2	New PSO-crazy	8234.0717	8382.0081	8279.1650
3	RGA	8234.0725	8432.1571	8337.0334

5.2 Computational Efficiency
It can be seen from Table 5.2 that the PSO with crazy particles is computationally quite efficient as the cpu time required is almost comparable to the PSO method but the results are much superior. Table 5.2

The global minimum cost reported for the three-unit system without considering losses is $8234.07These Tables show that all three strategies achieve global minimum solution for the 3-unit systems, but New PSO_crazy performs better for the six-unit system which is more complex. The previous reported best cost is $15,450.00. The New PSO_crazy approach achieves $ 15,449.3394 which is lesser.

Table 5.2. Generator output for least cost (three unit system; 50 trials)

Unit power output	PSO	New PSO_crazy	RGA
P1(MW)	400.000	400.000	400.000
P2(MW)	300.2667	300.2668	300.2653
P3(MW)	149.7333	149.7332	149.7347
Total power output(MW)	850	850	850
Total generation cost($/h)	8234.0718	8234.0717	8234.0725

Table 5.3 Comparison of different PSO strategies for three unit system (50 trials)

Population size	PSO variant	Min cost($/h)	Max cost($/h)	Average cost($/h)
50	PSO	8234.1480	8508.4103	8362.9334
	PSO_TVAC	8234.0719	8424.7031	8277.9354
	NEW PSO_CRAZY	8236.7055	8499.7296	8373.6601
	NEW PSO	8242.0734	8668.1003	8378.3502

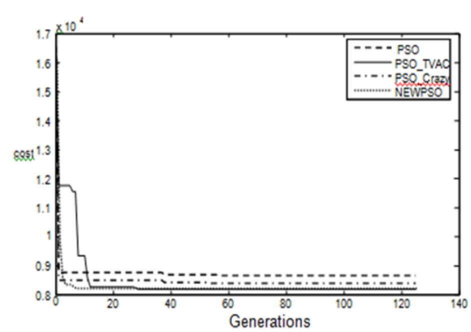


Fig 5.2 Convergence characteristics of different PSO strategies (3-unit system)

Table 5.4 Best results of PSO strategies for three unit system including loss (50 trials)

Unit power output	PSO	PSO_TVAC	
P1(MW)	400.050	400.604	399.885
P2(MW)	324.125	324.572	326.376
P3(MW)	150.402	149.462	149.740
Total Load (MW)	850	850	850
Total loss (MW)	24.577	24.638	26.389
Total generation cost($/h)	8454.501	8440.901	8631.737
CPU time (seconds)	0.0900	0.0914	0.1080

CONCLUSION

The non-convex economic problem of power dispatch is solved using PSO strategy. These results are compared with the results available in literature for 3-generator system and it is found that results are significantly improved by the proposed algorithm. Tuning of various parameters of PSO is important and it is found that the values of parameters in this paper are perfect for the improvement of results. The results demonstrate that PSO out performs other methods, particularly for non-convex cases, in terms of solution quality, dynamic convergence, computational efficiency, robustness and stability. The proposed algorithm can be applied to other non-convex, and non-smooth cost function having different constraints like prohibited operating zones, ramp rates and multi-fuel options. The proposed algorithm can also be applied to other power system optimization problems like dynamic economic dispatch and reactive power dispatch.

The New PSO_crazy strategy is proposed for solving the complex problem of nonconvex economic power dispatch with multiple minima. The performance of this method is compared with RGA and PSO

The PSO_TVAC outperforms other methods particularly for problems with multiple local minima. It has been clearly demonstrated that PSO_TVAC is capable of achieving global solutions.

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