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PARTICLE SWARM OPTIMIZATION FOR ECONOMIC LOAD DISPATCH CONSIDE-RING VALVE POINT LOADING EFFECT

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ABSTRACT - A simple and efficient algorithm is proposed for solving the economic dispatch problem of power systems with valve point discontinuities employing a particle swarm optimization-based approach. Evolutionary methods such as GA and PSO are known to perform better than conventional gradient-based optimization methods for nonconvex optimization problems. The performance of the proposed method has been compared with Real-coded genetic algorithm (RGA) results for validation. The effectiveness of the algorithm has been tested on a test system having three generating units.

***Index Terms* - ELD, PSO, Valve Point Loading Effect.**

1. INTRODUCTION

ECONOMIC dispatch is one of the main functions of the modern energy management system. It is formulated as an optimization problem with the objective of minimizing the total fuel cost while satisfying the specified constraints. Conventionally, input-output characteristics of generators, known as cost functions, are approximated using quadratic or piecewise quadratic functions, assuming that the incremental cost curves of generators are monotonically increasing [1]. However, in practice, this assumption is not valid because the cost functions exhibit higher order non-linearities and discontinuities due to valve point loading effects in units fired by fossil fuels [2]. Approaches, which avoid approximation of cost function and still do not require large computational time, are required for satisfactory handling of non convex optimization problems. A solution method, which does not directly rely on the incremental cost function, but performs a direct search, is required. The methods that qualify for solving such problems are dynamic programming [3], genetic algorithm [4- 6], evolutionary programming [7,8] and particle swarm optimization [9].etc. Although, these heuristic methods do not always guarantee global best solutions, they are often found to achieve a fast and near global optimum solution. Genetic algorithms [10] are effective search tools based on the mechanics of natural selection and survival of the fittest found in natural genetics.

They merge solution evaluation with randomized structured exchange of information between various solutions to obtain optimality. GAs are robust tools as no restriction is imposed on search space during the process of evaluation. The driving force behind these algorithms is their ability to exploit historical information from previous solutions to improve the performance of future solutions. GAs maintain a population of solutions throughout evaluation, therefore they are not limited by initial single point guesses. The PSO is a flexible, robust population based stochastic search/optimization algorithm with inherent parallelism [11]. Unlike conventional techniques, PSO can handle non-differentiable objective functions easily. This method is less likely to get trapped in local minima unlike GA. In a PSO, the search for optimal solution is conducted using a population of particles, each of which represents a possible solution to the optimization problem. Particles fly around in a multi dimensional search space by adjusting its trajectory towards its own previous best and the best of its neighbors. The PSO technique is capable of generating high quality solutions with stable convergence characteristics. It is increasingly gaining acceptance for solving various power system problems. The paper presents a PSO based approach for solving the ELD problem with non smooth cost functions.

2. ECONOMIC DISPATCH WITH VALUE POINT EFFECT

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

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

function. Therefore, the increases Advances in Electrical Engineering 3 objective function for the non-convex ED problem may be stated as

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

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

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

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

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

where a_i, b_i, and c_i are the cost coefficients of the ith generator,e_i and f_i are the valve-point effect coefficients,$P_{Gi}$is the real power output of the ith generator, and N_G 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 equation may be stated as follows:

where B_{ij} is the transmission loss coefficient i =1, 2, . . . , $NG$and j = 1, 2, . . . , NG, B_{i0} is the ith element of the loss coefficient vector. B_{00} 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*.

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

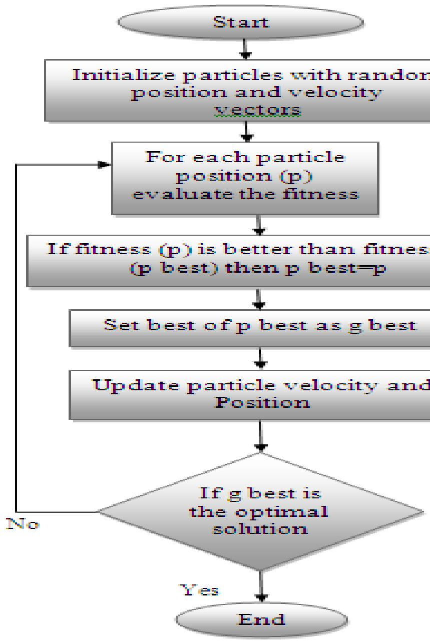
where superscripts L and U stand for the lower and upper limitof prohibited operating zones of generators. $NGPZ$ and NPZi denote the total number of generators with prohibited zonesand the total number of prohibited zones for the ith generator, respectively.

3. 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 thebest value (fitness) achieved so far by a given particle while the 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

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

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, itsometimes give unsatisfactory result due to largeaccumulation 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 hybridPSO-ACO algorithm.



4. 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

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

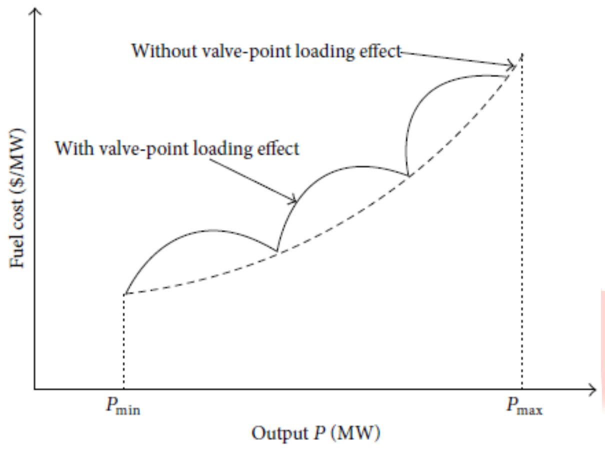


FIGURE 1: Fuel cost function with and without valve-point loading effect.

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.

5. 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

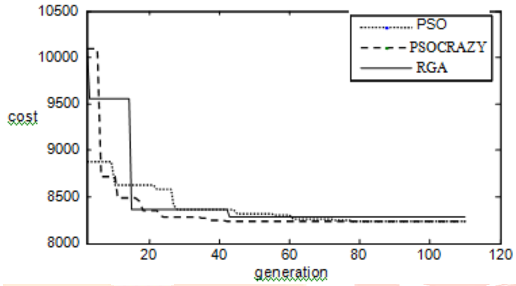


Fig. 5.1. Comparison of convergence characteristics (3-unit system)

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

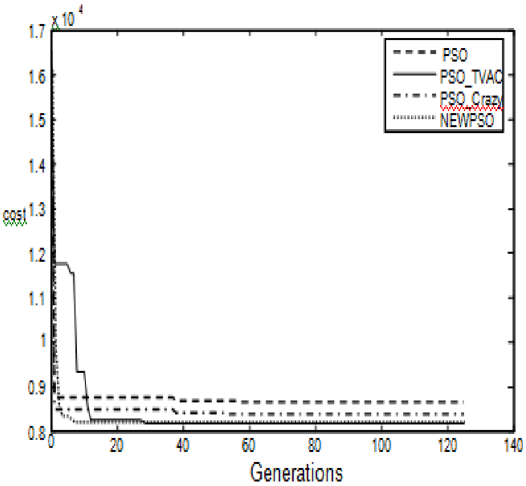


Fig 5.2 Convergence characteristics of different PSO strategies (3-unit system)

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

Unit power output	PSO	PSO_TVAC	NEW PSO_CRAZY
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

6.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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