A NEW APPROACH FOR DYNAMIC ECONOMIC DISPATCH USING HYBRID MODIFIED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

This article presents a novel optimization approach to constrained dynamic economic dispatch (DED) problems using the hybrid particle swarm optimization (HPSO) technique. The proposed methodology easily takes care of different constraints like transmission losses, ramp rate limits and also uses for non-smooth cost functions. To illustrate its efficiency and effectiveness, the developed HPSO approach is tested with different number of generating units and comparisons are performed with other approaches under consideration.

1. INTRODUCTION

The dynamic economic dispatch (DED) is an extension of the traditional economic dispatch problem used to determine the schedule of real-time control of power system operation so as to meet the load demand at the minimum operating cost under various system and operational constraints. DED procedure follows the dynamic connection by handling the ramp rate limits of generating units and by modifying the steady state cost to include the extra fuel consumption. The DED problem is not only the most accurate formulation of the economic dispatch problem (EDP).

Most of the literature addresses DED problem with convex cost function [1-2]. However, in reality, large steam turbines have steam admission valves, which contribute non Convexity in the fuel cost function [3]. Accurate modeling of the DED problem will be improved when the valve point loadings in the generating units are taken into account. Previous efforts on solving DED problem have employed various mathematical programming methods and optimization techniques. Conventional method like Lagrangian relaxation [1], gradient projection method [2] and dynamic programming etc, when used to solve DED problem suffer from myopia for non-linear, discontinuous search space, leading them to a less desirable performance and these methods often use approximations to limit complexity.

Recently, stochastic optimization techniques such as Genetic algorithm (GA) [4-5], evolutionary programming (EP) [6-7], simulated annealing (SA) [8-9] and particle swarm optimization (PSO) [10-12] have been given much attention by many researches due to their ability to seek for the near global optimal solution. However, all the previous work mentioned above neglected the non-smooth characteristic of generator, which actually exist in the real power system.

This paper presents a novel optimization method based on hybrid particle swarm optimization (HPSO) algorithm applied to dynamic economic dispatch in a practical power system while considering some nonlinear characteristics of a generator such as ramp rate limits, generators constraints, power loss and non-smooth cost function. The proposed methodology emerges as a robust optimization technique for solving the DED problem for different size power system.

2. DED PROBLEM FORMULATION

The objective of the DED is to schedule the outputs economically over a certain period of time under various system and operational constraints. The conventional DED problem minimizes the following incremental cost function associated to dispatchable units.

$$M_{in} F = \sum_{t=1}^{T} \sum_{i=1}^{N} F_{it}(P_{it}) \quad \$ \qquad (1)$$

Where F is the total operating cost over the whole dispatch period, T is the no. of intervals in the scheduled horizon, N is the no. of generating units and $F_{it}(P_{it})$ is the fuel cost in terms of its real power output P_{it} at time't'. Taking into valve-point effects, the fuel cost of the i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form is given by

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + C_i + \left| e_i \sin\left(f_i\left(P_{i,\min} - P_{it}\right)\right)\right| \quad \$/h \qquad (2)$$

Where a_i, b_i, c_i are cost coefficients and e_i, f_i are constants from the valve point effect of the i^{th} generating unit, subject to the following equality and inequality constraints.

a. Real power balance

$$\sum_{t=1}^{N} P_{it} - P_{Dt} - P_{Lt} = 0 \qquad (3)$$

Where t = 1, 2 …T, is the total power demand at time t and P_{Lt} is the transmission power loss at i^{th} interval in MW.

b. Real power operating limits

$$P_{t\min} \le P_{it} \le P_{t\max} \qquad (4)$$

Where $P_{t\min}$ and $P_{t\max}$ are respectively the minimum and maximum real power output of i^{th} generator in MW.

c. Generating unit ramp rate limits

$$P_{it} - P_i(t-1) \le UR_i, \qquad i = 1, 2, 3, ..., N \qquad (5)$$

$$P_i(t-1) - P_{it} \le DRi, \qquad i = 1,2,3,....,N \qquad (6)$$

Where UR_i and DR_i are the ramp-up and ramp- down limits of i^{th} unit in MW. So the constraint given by Eq. (5) is modified as follows:

$$\max\left(P_{i\min}, P_i(t-1) - DR_i\right) \le \min\left(P_{i\max}, P_i(t-1) + UR_i\right) \qquad (7)$$

3. OVERVIEW OF PSO

The particle swarm optimization method conducts its search using a population of particles, corresponding to individuals. It starts with a random initialization of a population of individuals in the search space and works on the social behavior of the particles in the swarm, like birds flocking, fish schooling and the swarm theory. Therefore, it finds the global optimum by simply adjusting the trajectory of each individual towards its own best location and towards the best particle of the swarm at each generation of evolution. The position and the velocity of the i^{th} particle in the d dimensional search space can be represented as $X_i = [x_{i1}, x_{i2}, ..., x_{id}]^T$ and $V_i = [v_{i1}, v_{i2}, ..., v_{id}]^T$. Each particle has its own best position (Pbest) $P_i(t) = [p_{i1}(t), p_{i2}(t), ..., p_{id}(t)]^T$ corresponding to the personal best objective value obtained so far at generation 't' . The global best particle (Gbest) is denoted by $P_g(t) = [p_{g1}(t), p_{g2}(t), ..., p_{gd}(t)]^T$. The new velocity of each particle is calculated as follows:

$$v_{IJ}(t+1) = \omega v_{ij}(t) + c_1 r_1\left(p_{ij}(t) - x_{ij}(t)\right) + c_2 r_2\left(p_{gi}(t) - x_{ij}(t)\right) \qquad \forall j = 1,2,........d \qquad (8)$$

Where c_1 and c_2 are constants of acceleration coefficients corresponding to cognitive and social behavior, ω is the inertia factor , n is the population size , r_1 and r_2 are two independent random numbers. Thus, the position of each particle at each generation is updated according to the following equation:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$
$$i = 1,2,.......,n \text{ and } j=1,2,\ldots\ldots,d \qquad (9)$$

4. MODIFIED PSO :

In the conventional PSO method, the inertia weight is made constant for all the particles in a single generation, but the most important parameter that moves the current position towards the optimum position is the inertia weight ω. In modified PSO, the particle position is adjusted such that the highly fitted particle (best particle) moves slowly when compared to the lowly fitted particle. This can be achieved by selecting different ω values for each particle according to their rank, between $\omega_{\min}$ and $\omega_{\max}$ as in the following form:

$$\omega_i = \omega_{\max} + \frac{(\omega_{\max} - \omega_{\min}) * Rank_i}{Total\,Population} \qquad (10)$$

So, from Eq. (9), shows that the best particle takes first rank, and the inertia weight for that particle is set to minimum value while for the lowest particle takes the maximum inertia weight, which particle move a high velocity. The velocity of each particle is updated using Eq. (15), and if updated velocity goes beyond maximum velocity $V_{\max}$, than it is limited to $V_{\max}$

$$\begin{aligned} v_{ij}(t+1) = \omega_i v_{ij}(t) + c_1 r_1 (p_{ij}(t) - x_{ij}(t)) \\ + c_2 r_2 (p_{gi}(t) - x_{ij}(t)) \end{aligned} \qquad (11)$$

$$v_{ij}(t+1) = sign(v_{ij}(t+1)) * \min(|v_{ij}(t+1)|, \quad V_{j\max}) \qquad (12)$$

$$j = 1,2,......,d \qquad and \quad i = 1,2,......,n$$

The new particle position is obtained by using Eq. (17), and if any particle position beyond the rang e specified, it is limited to its boundary using Eq. (18),

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$
$$j = 1,2,......,d; \qquad i = 1,2,.......n \qquad (13)$$

$$x_{ij}(t+1) = \min(x_{ij}(t+1), \quad range_{j\max})$$
$$x_{ij}(t+1) = \max(x_{ij}(t+1), \quad range_{j\min}) \qquad (14)$$

The concept of re-initialization is introduced in the proposed HPSO method after a specific number of generations if there is no improvement in the convergence of the algorithm. At the end of the method the specific generation is re-initialized with new randomly generated individuals. The number of new individuals is selected from '*k*' least individuals of the original population, where '*k*' is the percentage of total population to be changed. This re-initialization of population is performed after checking the change in the 'Fbest' value in each and every specific generation.

5. SEQUENTIAL QUADRATIC PROGRAMMING (SQP):

Sequential quadratic programming (SQP) [13] is widely used to solve practical optimization problems. It outperforms every other nonlinear programming method in terms of efficiency, accuracy and percentage of successful solutions. The method closely mimics Newton's method for constrained optimization just as is done for unconstrained optimization. At each major iteration, an approximation is made of the Hessian of the Lagrange function using Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton updating method. This is then used to generate a quadratic programming subproblem whose solution is used to form a search direction for a line search procedure.
As the objective function to be minimized is nonconvex, SQP requires a local minimum for an initial solution. In this paper, SQP is used as a local optimizer for fine-tunning the better region explored by AIS. Here, the formulation of SQP subroutine is taken from [15].
For each iteration, a QP is solved to obtain the search direction which is used to update the control variables. QP problem can be described as follows

Minimize the following

$$\nabla F_T(\mathrm{P}_k)^{\mathrm{T}} d_k + \frac{1}{2} d_k^{\mathrm{T}} \mathrm{H}_K d_k$$

subject to

$$g_i(P_k) + [\nabla g(P_k)]^{\mathrm{T}} d_k = 0$$
$$i = 1,...., m_e$$
$$g_i(P_k) + [\nabla g(P_k)]^{\mathrm{T}} d_k \le 0$$
$$i = m_e + 1,..., m$$

where

H_k the Hessian matrix of the Lagrangian function at the k th iteration

d_k the search direction at the k th iteration

P_k the real power vector at the k th iteration

$g(\mathrm{P}_k)$ constraints from (3) to (4)

m_e number of equality constraints

6. m number of constraints

$$L(\mathrm{P},\lambda) = F_{\mathrm{T}}(\mathrm{P}) + g(\mathrm{P})^{\mathrm{T}}\lambda$$

where λ is the vector of Lagrangian multiplier.

H_k is calculated using quasi-Newton formula given by,

$$\mathrm{H}_{k+1} = \mathrm{H}_k + \frac{q_k q_k^{\mathrm{T}}}{q_k^{\mathrm{T}} S_k} - \frac{\mathrm{H}_k^{\mathrm{T}} S_k^{\mathrm{T}} S_k \mathrm{H}_k}{S_k^{\mathrm{T}} \mathrm{H}_k S_k}$$

where

$$S_k = \mathrm{P}_{k+1} - \mathrm{P}_k$$

$$q_k = \nabla L(\mathrm{P}_{k+1}, \lambda_{k+1}) - \nabla L(\mathrm{P}_k, \lambda_{k+1})$$

For each iteration of the QP sub-problem the direction d_k is calculated using the objective function. The solution obtained forms a new iterate given by,

$$\mathrm{P}_{k+1} = \mathrm{P}_k + \alpha_k d_k$$

The step length value α_k is determined to produce a considerable reduction in an augmented Lagrangian merit function as follows

$$L_{\mathrm{A}}(\mathrm{P},\lambda,\rho) = F_{\mathrm{T}}(\mathrm{P}) - \lambda^{\mathrm{T}} g(\mathrm{P}) + \frac{\rho}{2} g(\mathrm{P})^{\mathrm{T}} g(\mathrm{P})$$

where ρ is a nonnegative scalar. The procedure is repeated until the value of S_k has reached some tolerance value.

6. HPSO ALGORITHM

6.1) Initialize number of population of particles dimension d with random position velocities and get the input parameters such as range [min, max] for each variable, c1, c2 and iteration counter. Set iteration counter = 0.

6.2) Increment iteration counter by one.

6.3) Find out the fitness function of all particles in the population and update the objective function.

6.4) If stopping criterion is reached than go to step (5.9). Otherwise continue.

6.5) Evaluate the inertia factor according to Eq. (10).

6.6) Update the velocity given in Eq. (11) and correct it using Eq. (12).

6.7) Update the position of each particle using Eq. (13) and if the new position goes out of range, set it to boundary value using Eq. (14).

6.8) For every 5 generations, the {Fbest, new value} is compared with the {Fbest, old value}. If there is no change, then use the re-initialization concept and go to step (5.3).

6.9) Output the Gbest particle and its objective value.

6.10) solve the DED problem using the SQP method with the selected solution obtained from PSO.

7. SIMULATION RESULTS

The five unit system with non-smooth fuel cost function is used to demonstrate the performance of the proposed HPSO. We have used the same system data as done by Panigrahi et al. [8]. The load demand of the system is taken over 24 hour. The result of the proposed method is given in Table 1. The earlier reported result for the cost is 47356 $. For the present simulation, the cost is found to be 44568 $.

8. CONCLUSIONS

The paper has employed the HPSO algorithm on constrained of dynamic economic dispatch problem. The proposed approach has produced comparable to or better than those generated by other algorithms, and the solution has superior quality and good convergence characteristics.

from this limited comparative study, it can be concluded that the HPSO can be effectively used to solve non-smooth as well as smooth constrained economic load dispatch problems. In the future, the work will can be made to incorporate more realistic constraints to the problem and the large size problems will be solved by the proposed methodology.

Table1: Result for five unit system with 24 h load demand

No. of hours	Load demand	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G4} (MW)	P_{G5} (MW)
1	410	12.3675	104.4735	108.9301	38.4012	140.3918
2	435	42.4708	95.9732	113.6381	40.1022	138.6778
3	475	72.0578	96.6296	121.2753	43.9813	139.7721
4	530	45.0234	97.9622	116.7643	75.0224	179.8301
5	558	19.7435	105.2582	115.7942	89.9066	197.7502
6	608	41.9471	103.3492	116.6698	96.8961	215.1322
7	626	11.9462	89.4341	116.7647	171.8153	221.9615
8	654	23.6745	85.3441	117.9742	210.0113	228.9501
9	690	47.4359	98.0986	117.7644	208.0518	231.5196
10	704	64.1105	99.5385	116.6747	209.1853	229.5385
11	720	43.0118	101.5421	142.6332	210.1692	230.1596
12	740	39.7598	97.3598	164.9799	207.5818	229.3214
13	704	42.6758	96.5389	143.9599	208.9857	228.3597
14	690	48.6036	96.7388	118.7045	208.9947	220.6617
15	654	19.6033	95.3773	110.7656	200.6448	201.9233
16	580	11.1709	87.4059	112.8548	206.2245	191.5503
17	558	11.1801	97.6698	97.4321	207.5764	178.4851
18	608	23.5582	99.5398	113.6849	209.8158	156.1376
19	654	21.0434	100.5196	114.6753	211.1986	188.1579
20	704	49.4497	105.3416	114.4284	210.6318	196.1342
21	680	34,4159	103.6783	116.0614	210.8963	213.9615
22	605	11.7202	90.5406	108.5995	198.7053	215.0352
23	527	10.0035	62.1432	92.0095	160.9033	223.2762
24	463	10.0205	39.6943	83.0064	135.9715	225.6296

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