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Application of New Hybrid Particle Swarm Optimization and Gravitational Search Algorithm for Non Convex Economic Load Dispatch Problem

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Abstract

The Gravitational Search Algorithm (GSA) is a novel optimization method based on the law of gravity and mass interactions. It has good ability to search for the global optimum, but its searching speed is really slow in the last iterations. So the hybridization of Particle Swarm Optimization (PSO) and GSA can resolve the aforementioned problem. In this paper, a modified PSO, which the movement of particles is also based on getting away from individual worst solution other than going toward the best ones, is combined with GSA, named (PSOGSA) and is applied on ELD problem. A 6 unit case study considering transmission loss, prohibited zones and ramp rate limits and also a 40 unit system with valve point loading effect has been used to show the feasibility of the method. The results show fast and great convergence compared to the many other previously applied methods.

Keywords: *Economic Load Dispatch, Gravitational search, particle swarm optimization, Valve point loading, Optimization*

1. Introduction

Economic load dispatch (ELD) is one of the most important tasks in electric power system generation. ELD is the fundamental issue during unit commitment process. Over the years, various methods has been applied on ELD problem, considering various constraints that make the problem more real such as transmission loss, valve point loading effect, generator prohibited zones, ramp rate limits, etc. In the most basic type of ELD, Conventional linear methods such as lambda iteration method, gradient method and the Newton method [1] were used ,assuming that the incremental costs of the generators are monotonically increasing functions. But when the aforementioned nonlinearities are being taken into account, this assumption become infeasible[2]. In the past decade, several non-linear heuristic computational algorithm techniques such as Genetic Algorithm (GA) [3, 4], Tabu Search (TS)[5], Differential Evolution (DE)[6], simulated annealing(SA) [7], Hopfield neural network [8], particle swarm optimization(PSO)[9,30], Incremental artificial bee colony with local search **(**IABC)[10], ESO[11]**,** DEC-SQP[12, 13], ST-HDE[14], HPSOM[15], SOHPSO[16], TM[17], improved GA[18], TSA[19], GAAPI[20] etc. have been used to solve nonlinear, non-convex ELD problems each having advantages and disadvantages compared together in giving better quality solutions, less Execution time, minimum function evaluation numbers etc.

Particle swarm optimization[21, 22] was a popular heuristic algorithm that had been applied on many optimization problems over the years including ELD problem. Although it was very simple but the global optimum solution was not comparable to the later methods. On the other hand a recently introduced method called gravitational search algorithm (GSA)[23] had also been applied on ELD, giving better and more quality solutions but suffering from long execution time, specially for last iterations. So it seemed beneficial to apply a hybrid method to ELD problem which exploit both fast convergence and high quality optimum solutions from two mentioned methods. So in this paper a hybrid PSOGSA algorithm is applied on ELD problem. In this modified algorithm the PSO is modified in such way that the movement of particles is also based on the getting away from individual and global worst solution other than going toward the best ones. Also the algorithm constants have a small decreasing variation after each iteration of the algorithm. This modified PSO is combined with gravitational search algorithm to solve its slow Execution time in the last iterations, making the hybrid PSOGSA algorithm. To our knowledge this method has not been applied to ELD problems yet. The case studies considered in this work, are a 6 generating unit with prohibited operating zones, transmission loss, ramp rate limits and also a 40 unit system with valve point loading effect which greatly challenge the modified method.

2. Economic load dispatch problem

2.1 ELD objective function

ELD can be formulated as an optimization problem with the goal of minimizing the total power system generation cost, as follows:

$$\min \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

Where N is number of generator units, P_i is the power output of each unit and F_i is the production cost of the ith unit given as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

However, valve-point loadings cause ripples in the heat rate curves. To take this effect into account, sinusoidal functions are usually added to the quadratic cost functions as Eq. (3). Figure 1 depicts the effect of valve point loadings on the cost function characteristic:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin(f_i(P_i^{\min} - P_i)) \right| \tag{3}$$

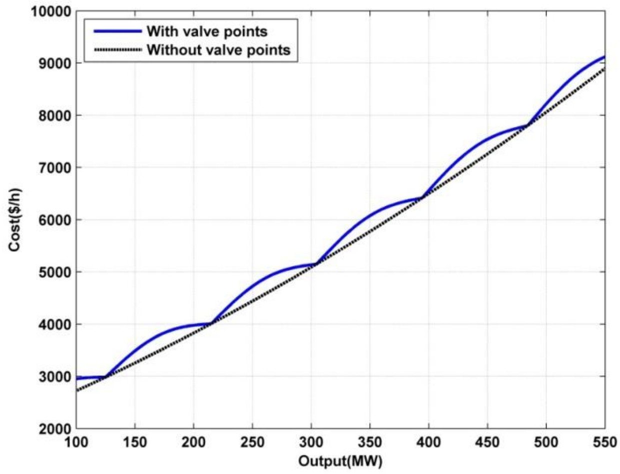

Figure 1. Cost function characteristics with and without valve-points effect.

2.2 Constraints:

ELD objective function is to be minimized subject to the following constraints:

2.2.1 Real power operating limits:

Each unit has generation range, described as:

$$P_i^{\min} \le P_i \le P_i^{\max} \quad i = 1, \ldots, N \tag{4}$$

2.2.2 Real power balance constraint

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{5}$$

Where, the total transmission network losses, PL can be expressed using B-coefficients matrix as follows:

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \tag{6}$$

Where B is loss coefficient matrix, B0i is linear term constant and B00 is transmission line system constant.

2.2.3 Ramp rate limit constraints:

For each unit, output is limited by time dependent ramp rates at each hour and the generation may increase or decrease with corresponding upper and downward ramp rate limits as mentioned below:

$$\begin{aligned} &P_i - P_i^0 \le UR_i \quad i = 1, \ldots, N \\ &P_i^0 - P_i \le DR_i \quad i = 1, \ldots, N \end{aligned} \tag{7}$$

where UR_i is the ramp up limit of the ith generator (MW/h) and DR_i is the ramp down limit of the ith generator (MW/h) and P_i^0 is the previous output power of unit i. New formulation of generator capacity limits is obtained when considering ramp rate limits and can be expressed as:

$$\max(P_i^{\min}, P_i^o - DR_i) \le P_i \le \min(P_i^{\max}, P_i^o + UR_i) \\ P_i \in AZ_i, \quad i = 1,..., N \tag{8}$$

2.2.4 Generators' prohibited operating zones:

Prohibited zones divide the operating region into disjoint sub regions. The generation limits for units with prohibited zones are:

$$AZ_i = \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^l \\ P_{i,m-1}^u \le P_i \le P_{i,m}^l & m = 2,3,..., M_i, i = 1,..., N \\ P_{i,M_i}^u \le P_i \le P_i^{\max} \end{cases} \tag{9}$$

Where $P_{i,m}^l$ and $P_{i,m}^u$ are the lower and upper limits of the *Mth* POZ of unit i, respectively. M_i is the number of POZs of unit i.

3. Hybrid PSOGSA

3.1 Standard PSO

PSO is a robust optimization technique based on swarm intelligence, introduced by Kennedy and Eberhart in 1995[21, 22], which implements the simulation of social behavior. Where each member is seen as a particle and each particle is a potential solution to the problem. Each particle at iteration k with position vector $x_i^k = (x_{i1}^k, x_{i2}^k, ..., x_{iN}^k)$ and velocity vector $v_i^k = (v_{i1}^k, v_{i2}^k, ..., v_{iN}^k)$ gives a solution. The best solution achieved by ith particle in iteration k is defined as $P_{best_i}^k = (P_{best_{i1}}^k, P_{best_{i2}}^k, ..., P_{best_{iN}}^k)$ and the best $P_{best_i}^k$ among all particles is considered as $g_{best_i}^k$. A particle approaches to better position with using its current velocity, previous experience, and the experience of other particles. In the modified PSO each particle also tries to get away from the worst position experienced by itself. So the whole formulations for updating velocity and position in each iteration is given below:

$$v_{in}^{k+1} = \omega \times v_{in}^k + C_1 \times r_1^n \times (P_{best_{in}}^k - x_{in}^k) + \\ C_2 \times r_2^n \times (g_{best}^k - x_{in}^k) + C_3 \times r_3^n \times (x_{in}^k - P_{worst_{in}}^k) \tag{10}$$

$$x_{in}^{k+1} = x_{in}^k + v_{in}^{k+1} \tag{11}$$

Moreover, a new dynamic inertia weight was incorporated with PSO, which takes advantage of the self adaptation inertia weight idea. With dynamic acceleration and weight coefficients, great exploration and exploitation happen in the first iterations of the algorithm, and the final iterations respectively, resulting better and faster solutions. The dynamic acceleration and weight coefficients consist of:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k} \times k \tag{12}$$

$$C_1 = C_{1i} + \frac{C_{1f} - C_{1i}}{k} \times k$$
$$C_2 = C_{2i} + \frac{C_{2f} - C_{2i}}{k} \times k \qquad (13)$$
$$C_3 = C_{3i} + \frac{C_{3f} - C_{3i}}{k} \times k$$

Where C_{1i}, C_{2i}, C_{3i} are the initial and C_{1f}, C_{2f}, C_{3f} are the final values of dynamic acceleration factors. Also $\omega_{\min}$ and $\omega_{\max}$ are the initial and final inertia weights.

3.2 Gravitational search algorithm

The Gravitational Search Algorithm[24] is a swarm-based and also an memory-less optimization algorithm based on the law of gravity. In GSA, agents are considered as objects and their performance which will be calculated by using a fitness function expressed by their masses. In a system with N masses the positions are defined as follow:

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^n)$$
$$For\ i = 1, 2, 3, ...N \qquad (14)$$

At the specific iteration (k), the force acting on i^{th} mass from j^{th} mass is defined as follow:

$$F_{ij}^d(k) = G(t)\frac{M_{pi}(k) \times M_{aj}(k)}{R_{ij}(k) + \varepsilon}(x_j^d(k) - x_i^d(k)) \qquad (15)$$

Where M_i and M_j are the masses related to the i^{th} and j^{th} agent, respectively. $G(k)$ is the gravitational constant at time/iteration (k), ε is a small constant, and $R_{ij}(k)$ is the Euclidian distance between i^{th} and j^{th} agents. The form of $G(k)$ is as follows:

$$G(k) = G_0 e^{\frac{-ak}{T}} \qquad (16)$$

Where t and T are current and total iterations of the algorithm, respectively. G_0 and α are GSA controlling constants. Total force that acts on the i^{th} agent in d^{th} dimension is calculated as follow:

$$F_i^d(k) = \sum_{i=1\, j \neq i}^{N} rand_j F_{ij}^d(k) \qquad (17)$$

Where, $rand_j$ is a random number in the interval [0, 1].

Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by mass of inertia:

$$a_i^d(k) = \frac{F_i^d(k)}{M_i(k)} \qquad (18)$$

$$V_i^d(k+1) = rand \times v_i^d(k) + a_i^d(k) \tag{19}$$

When acceleration and velocity of each mass are calculated, the new position of the masses could be considered as follow:

$$x_i^d(k+1) = x_i^d(k) + v_i^d(k+1) \tag{20}$$

New positions mean new masses. The gravitational and inertial masses are updated by the following equations:

$$m_i(k) = \frac{fit_i(k) - worst(k)}{best(k) - worst(k)} \tag{21}$$

$$M_i(k) = \frac{m_i(k)}{\sum_{j=1}^{N} m_j(k)} \tag{22}$$

Where $fit_i(k)$ represents the fitness value of the i^{th} agent at iteration k and $worst(k)$ and $best(k)$ are defined as follow For a minimization problem:

$$best(k) = \min\{\ fit_i(k)\} \tag{23}$$

$$worst(k) = \max\{\ fit_i(k)\} \tag{24}$$

3.3 Hybrid PSOGSA

The basic idea of PSOGSA is to combine the ability for social thinking (gbest) in PSO with the local search capability of Gravitational search algorithm(GSA)[25].

In PSOGA, all agents are randomly initialized first. After initialization, the gravitational force, gravitational constant, and resultant forces among agents are calculated using (15), (16) and (17) respectively. Then the accelerations of particles are defined as (18). The best solution so far should be updated after each iteration. After calculating the accelerations and updating the best solution, the velocities of all agents can be calculated using the following equation:

$$\begin{aligned} v_{in}^{k+1} &= \omega \times v_{in}^{k} + C_1 \times r_1^n \times a_i^d(t) + \\ & C_2 \times r_2^n \times (g_{best}^k - x_{in}^k) + C_3 \times r_3^n \times (x_{in}^k - P_{worst_{in}}^k)\ (25) \end{aligned} \tag{25}$$

Where, $a_i^d(k)$ is the acceleration of agent i at iteration k. Finally the agent positions are updated using (11).

4. Numerical results

4.1 Case study 1:

A six unit system is has been used as the first case study. Transmission loss, ramp rate limits and generator prohibited zones are considered in this case study. Fuel cost and prohibited zone data were obtained from[7] and also are given in tables 1 and 2 respectively:

Table1. Fuel cost data for case study 1

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a ($/MW^2)	b ($/MW)	c ($)
1	100	500	0.0070	7.0	240
2	50	200	0.0095	10.0	200
3	80	300	0.0090	8.5	220
4	50	150	0.0090	11.0	200
5	50	200	0.0080	10.5	220
6	50	120	0.0075	12	190

Table 2. Ramp rate limits and POZs for case study I

Unit	P_i^0 (MW)	UR$_i$ (MW/h)	DR$_i$ (MW/h)	Prohibited Zone 1	Prohibited Zone 2
1	440	80	120	[210-240]	[350-380]
2	170	50	90	[90-110]	[140-160]
3	200	65	100	[150-170]	[210-240]
4	150	50	90	[80-90]	[110-120]
5	190	50	90	[90-110]	[140-150]
6	150	50	90	[75-85]	[100-105]

The B loss coefficient matrix is given below:

$$[B]=0.001*\begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 1.0 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 1.0 & 0.0 & 2.4 & -0.6 & -0.8 \\ -0.5 & -0.6 & -1.0 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix}$$

$$[B_0]=0.001*\begin{bmatrix} -0.3908 & -0.1297 & 0.7047 & 0.0591 & 0.2161 & -0.6635 \end{bmatrix} \quad [B_{00}]=0.0056$$

The algorithm has been run for 10 times with the parameters set to: $nPop = 30$, $\alpha = 20$, $G_0 = 1$, $k = 50$, $C_{1i} = 2.5$, $C_{1f} = 0.5$, $C_{2i} = C_{3i} = 0.5$, $C_{2f} = C_{3f} = 2.5$, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.5$. The initial values of acceleration and mass are also set to 0 for each particle. Table 3 shows the optimum results and also a comparison with other methods in literature. Figure2 also depicts the convergence characteristics for case study I.

Table 3. Results comparison for case study I with 1263 MW total demand.

Generator No	1(MW)	2(MW)	3(MW)	4(MW)	5(MW)	6(MW)	$\sum P_i$ (MW)	P_{loss}(MW)	F_{total} ($/h)
PSOGSA	440.57	179.84	261.38	132.0	171.0	90.82	1275.60	12.72	15444
IPSO[26]	440.57	179.83	261.37	131.91	170.98	90.82	1275.50	12.548	15444.1
GAAPI[20]	447.12	173.41	264.11	138.31	166.02	87.00	1275.97	12.98	15449.7
DE[27]	447.74	173.41	263.41	139.08	165.36	86.94	1275.95	12.96	15449.7
GA[9]	474.80	178.63	262.20	134.28	151.90	74.18	1276.03	13.02	15459.0
PSO[9]	447.49	173.32	263.47	139.05	165.47	87.12	1276.01	12.95	15450
TSA[19]	449.36	182.25	254.29	143.45	161.96	86.01	1277.34	14.34	15451.63
SA[7]	478.12	163.02	261.71	125.76	153.70	93.79	1276.13	13.13	15461.10

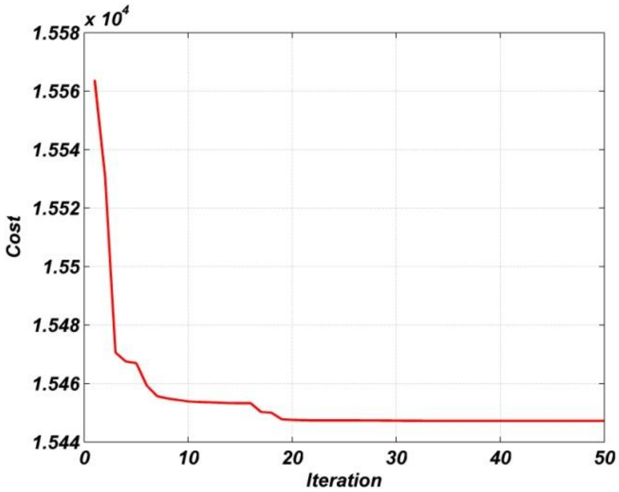

Figure 2. Convergence behavior of PSOGSA for a load demand of 1263 MW (Case study I).

It can be apparently seen that although the algorithm has been set to run for 50 iterations, but the convergence happened in about 20 ones.

4.2 Case study II:

The second case study is a 40 unit system considering valve point loading effect. This system has more local minima than the previous one and takes the algorithm into the real challenge. The system data for this case study is taken from [28]. The algorithm has been run for 10 times with the parameters similar to the previous case study but with $nPop = 60$ and $k = 200$ Table 4 and 5 show the best results and also a comparison with other previously applied methods, respectively. Convergence characteristics is also given for case study II in Fig.3 :

Table 5. Best results for case study II with total 10500 MW load demand

Gen. No	Best	Gen. No	Best
1(MW)	110.82	22(MW)	523.27
2(MW)	110.82	23(MW)	523.28
3(MW)	97.40	24(MW)	523.28
4(MW)	179.73	25(MW)	523.28
5(MW)	87.97	26(MW)	523.28
6(MW)	139.99	27(MW)	10
7(MW)	259.60	28(MW)	10
8(MW)	284.61	29(MW)	10.05
9(MW)	284.62	30(MW)	96.94
10(MW)	130	31(MW)	190
11(MW)	168.80	32(MW)	190
12(MW)	94.06	33(MW)	190
13(MW)	214.76	34(MW)	164.79
14(MW)	394.24	35(MW)	200
15(MW)	394.25	36(MW)	199.94
16(MW)	304.53	37(MW)	199.95
17(MW)	489.25	38(MW)	110

Gen. No	Best	Gen. No	Best
18(MW)	489.27	39(MW)	109.99
19(MW)	511.27	40(MW)	511.25
20(MW)	511.29	$\sum P_i$ (MW)	10500
21(MW)	523.27	F_{total} (\$/h)	121424.75

Table 6. Results comparison for Test case II with 10500 MW total demand.

Method	Best cost (\$/h)
NAPSO[28]	121491.0662
PSO[9]	124875.8523
IABC[10]	121491.2751
IABC-LS[10]	121488.7636
DEC-SQP[12, 13]	122174.16
ST-HDE[14]	121,698.51
HPSOM[15]	122,112.40
SOHPSO[16]	121,501.14
TM[29]	122,477.78
ESO[11]	122,122.16
Improved GA[18]	121,915.93
PSOGSA	121424.75

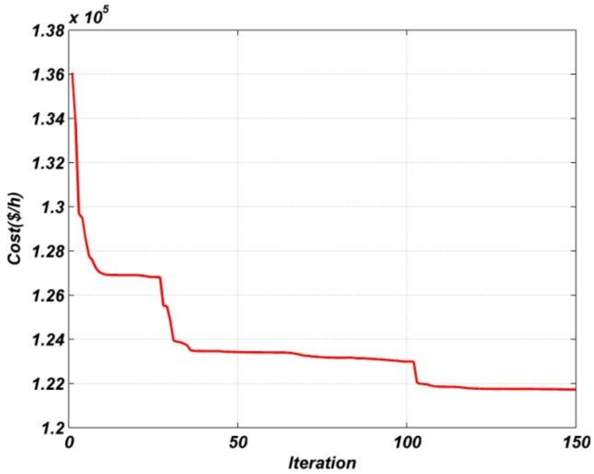

Fig. 3. Convergence behavior of PSOGSA for a load demand of 10500MW (Case study II).

5. Discussion

Although PSOGSA results are close to other previously applied methods specially close to more recent applied ones, but the execution time is much lower than others. For example in test case I, for IABC-LS[10], cpu time value of 0.018 s have been reported for the load demand of 1263 MW, while these value for PSOGSA was about 0.01. However, unfortunately the execution time may not directly and exactly comparable among the methods due to various computers and programming languages used.

6. Conclusion

In this paper, a hybrid PSOGSA algorithm has been applied on ELD problem. For the PSO a more effective method has been used for the movement of particles, considering the worst solutions of every individual and also the global solution. Also the PSO factors have been exchanged with dynamic ones, which get a small change after each iteration. The hybridization of the modified PSO with GSA solved the slow speed of GSA algorithm on the final iterations, well. Two case studies including a 6 unit systems considering transmission loss, ramp rate limits and prohibited zones and also a 40 unit system with valve point loading and multiple local minima have been used to show the feasibility of the method. The results show fast convergence and better solutions compared to other methods in literature.

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