International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 22 (2018) pp. 15672-15678
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Solution of Economic Power Dispatch with Cubic Cost Functions using Grasshopper Optimization Algorithm

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Abstract:

Economic Power Dispatch (EPD) is the main work in distributing the required energy load to the available generating units at low price. Although conventional EPD problem can be solved by mathematical techniques, nowadays modern power system introduces new model of power generating units which are non-convex in nature while considering cubic cost functions. In order to solve such non-convex EPD problem with Cubic Cost Functions (EPDCCF), a new approach based on Grasshopper Optimization Algorithm (GOA) is proposed in this article. To compute minimized fuel cost and to demonstrate the superiority of the proposed algorithm, three widely adopted test systems are employed and the simulation results are compared with the state-of-the-art algorithms.

1. INTRODUCTION

The present scenario of power system deals with the scarcity of energy resources, increasing power generation cost and environmental concerns which in turn necessitate optimal economic power dispatch. In reality power generators neither are at equal distances from load nor have similar fuel cost functions. Hence for providing cheaper power, load has to be distributed among various power generators in a way which results in lowest cost for generation.

The economic power dispatch problem assists the power generating unit to ensure optimal fuel cost for the decided load demand in the power system [1]. Traditionally, the cost function of the generating units is approximated as a quadratic function. A crucial issue in EPD studies is to determine the order and approximate the coefficients of the polynomial used to model the fuel cost function. A third order polynomial is realistic to model the operating cost. The conventional EPD problem gets more complex while the higher order cost functions replaces the traditional quadratic cost functions. This is because the higher order cost functions are proved to be more accurate and realistic form than quadratic cost functions [2-3].

A bibliographical survey of economic power dispatch with higher order cost function exposes that several numerical optimization techniques have been employed. The EPDCCF problem has been solved by algorithms such as Sequential Quadratic Programming (SQP) [4], Dynamic Programming (DP) [5], Evolutionary Programming (EP) [6], Improved Genetic Algorithm with Multiplier Updating (IGAMU) [7], Fast and Effective Algorithm [8], Genetic Algorithm (GA) [9], Particle Swarm Optimization (PSO) [9], Partition Approach Algorithm (PAA) [10], Parallel Population Repair Genetic Algorithm [11], Pattern Search (PS) [12], λ-logic [13], Equal Embedded Algorithm (EEA) [14], Firefly Algorithm (FA) [15], Teaching Learning Optimization algorithm (TLBO) [16] , Time Varying PSO with Gravitational Search Algorithm (TVPSOGSA) [17], PSO with Gravitational Search Algorithm (PSOGSA) [17] and Simulated Annealing (SA) [18] approach. Thus presently there is need to use more advanced heuristic methods for better results in these vital and complex cubic cost functions. Hence in this paper, we have proposed a novel nature inspired GOA method for solving EPDCCF problem.

2. PROBLEM FORMULATION

The EPDCCF considered deals with minimizing the total generating cost subject to satisfying the power balance and real power operating limits constraints. The fuel cost function of each unit can be expressed as in (1)

$$F_i(P_i) = \sum_{i=1}^{N} \left(a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i \right) \left(\frac{\$}{h} \right) \tag{1}$$

where $F_i(P_i)$ is the Fuel cost of the ith generator, P_i is Real power generation of unit i, a_i, b_i, c_i, d_i = Cost coefficients of generating unit i, N is the Number of generating units.

The EPDCCF is subjected to the following constraints:

2.1 Equality Constraint

The total generated power should be the same as the total load demand (P_D) plus the line loss (P_{LOSS}). Thus, the real power balance constraint can be modelled as in

$$\sum_{i=1}^{N} P_i = P_D + P_{LOSS} \text{ MW} \quad (2)$$

where P_i is total power generation of the system and P_D is total real power demand of the system.

P_{LOSS} is the transmission loss which is a function of active power generation of each generating unit for a given load demand.

$$P_{LOSS} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \quad (3)$$

where B_{ij} is the (i-j)th element of the symmetric loss coefficient matrix (B); B_{0i} is the ith element of the loss coefficient and B_{00} is the constant loss coefficient.

2.2 Inequality Constraint

The generator capacity constraint is represented by (4)

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

where $P_i^{\min}$ is minimum value of the real power allowed at generator i, $P_i^{\max}$ is maximum value of the real power allowed at generator i.

3. GRASSHOPPER OPTIMIZATION ALGORITHM

Grasshopper Optimization Algorithm (GOA) is a recent meta-heuristic optimization approach proposed by Seyedali Mirjalili in 2017 [19]. The GOA is an innovative approach imitating the social behavior of Grasshopper. The algorithm is stylized by the predating method adopted by a Grasshopper. The moving behavior of the insect varies at each stage. The mobility is slow in the nymph stage and abrupt in adult stage. The territory covered during adult stage is extensive than nymph stage during its prey search. The strategy disciplined by the grasshopper is concern with exploration and exploitation of the prey. In the exploration interval, the grasshopper finds the direction towards the prey and plan to fix the prey. The prey is exploited consecutively as and when the search agent is explored. The similar methodology is adopted in the formulation of GOA.

The industrial and various engineering optimization problems are solved [20-21] effectively by GOA method. The most deserving and approachable algorithm is GOA. The GOA is systemized by mimicking the swarming behavior of the grasshoppers. The population of grasshopper is considered for the science of searching during optimization. The grasshoppers initialize its motion to reach the target. In GOA the appropriate search agent is positioned and with certain computational limitation the best results is recognized by its various test sample. GOA has been adopted in this article to solve the EPDCCF problems.

Pseudo code for GOA

```
Initialize the swarm X_i (i=1, 2, 3 … n)
Initialize c_max, c_min and maximum number of iterations (L)
Calculate the fitness of each search agent
T = best search agent
while (l < Maximum number of iterations)
    Update $c = c_{\max} - l\frac{c_{\max} - c_{\min}}{L}$
    where c_max = maximum value, c_min = minimum value, l = current iteration,   L = maximum number of iterations
    for each search agent
        • Normalize the distances between grasshoppers
        • Update the position of the current search agent
            $X_i^d = c\left(\sum_{j=1, j\neq i}^{N} c\frac{ub_d - lb_d}{2} s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{di_j}\right) + \hat{T}_d$
          where $ub_d$ = the upper bound in the D_th dimension, $lb_d$ = the lower bound in the D^th dimension, $s(r) = f_i e^{\frac{-r}{l}} - e^{-r}, \hat{T}_d$ = the value of the D^th dimension in the target, c = a decreasing coefficient to shrink the comfort zone, repulsion zone and attraction zone.
        • Bring the current search agent back if it goes outside the boundaries
    end for
        Update T if there is a better solution
            l = l + 1
end while
        Return T
```

4. EXAMINATION ON TEST SYSTEMS AND DISCUSSION

The EPDCCF is executed with GOA algorithm to substantiate the achievability and effectiveness the proposed algorithm for non-linear optimization problems. The effectiveness of the proposed algorithm is verified by numerical simulation on lossless 5, 26 unit test system and 3 unit test system considering transmission loss. For all the test cases, the program is executed on Core i5, 2.65GHz PC with 4 GB RAM in Matlab 7.10 platform. The optimal fuel cost is obtained through adequate tests and it is further compared with various optimization algorithms.

4.1. 5 Unit System

The data to evaluate the fuel cost of 5 unit system are taken from [18].1800MW load demand is utilized to generate the result of EPDCCF problem using the proposed GOA method. The minimum fuel cost achieved is 18609.631($/h) and it is compared with (GA) [9], (PSO) [9], (FA) [15] and (SA) [18]. The cost fetched by GOA is best when compared to other methods and the detailed dispatch schedule is available in Table 1.

Table 1. Comparative dispatch results of 5 unit system for a demand of 1800MW

	GA [9]	PSO [9]	FA [15]	SA [18]	GOA
P_1	320.00	320.00	327.8004	320.00	320.00
P_2	343.74	343.70	341.9890	343.9873	343.6372
P_3	472.60	472.60	460.4127	473.9086	472.5366
P_4	320.00	320.00	327.8004	320.00	320.1787
P_5	343.74	343.70	341.9890	342.1032	343.639
F ($/h)	18611.07	18610.40	18610.00	18609.69	18609.631

4.2. 26 Unit System

The data for 26 unit generators with cubic cost coefficients, generator lower limits and upper limits are taken from [14]. The different load demands of 2400MW and 2200MW are considered to carry out the EPDCCF simulation. The result realised for the load demand 2400MW by GOA is compared with TLBO [16], EEA [14] and λ-logic [13] methods. The obtained fuel cost for the load demand 2200MW is compared with TLBO [16] as seen in Table 2. From the listed comparison results, it is observed that the proposed algorithm fetches the most optimal fuel cost for different power demands than recent optimization techniques.

Table 2. Comparison of EPDCCF results of 26 unit test system

P_i (MW)	Demands (MW)	
	2400	**2200**
P_1	2.4	2.4
P_2	2.4	2.4
P_3	2.4	2.4
P_4	2.4	2.4
P_5	2.4	2.4
P_6	4	4
P_7	4	4
P_8	4	4
P_9	4	4
P_{10}	76	33.718
P_{11}	76	31.0081
P_{12}	76	28.529
P_{13}	76	26.89
P_{14}	36.99	25
P_{15}	29.156	25
P_{16}	25	25
P_{17}	155	155
P_{18}	155	155
P_{19}	155	155
P_{20}	155	155
P_{21}	68.95	68.95
P_{22}	68.95	68.95
P_{23}	68.95	68.95
P_{24}	350	350
P_{25}	400	400
P_{26}	400	400
GOA	**32642.1689**	**29722.5197**
TLBO [16]	32642.24	29722.58
λ-logic [13]	32642.69	-
EEA [14]	32642.41	-

4.3. 3 Unit system considering transmission loss

In this test case, the input data of three generators considering transmission loss, upper and lower bounds are adopted from [16]. The two load demands for the simulation are 1200MW and 1400MW. Simulation of EPDCCF with GOA for a load demand of 1200MW is carried out and the obtained fuel cost is 5661.85$/h and the transmission loss is 41.51MW which is much less than the results reported by TLBO[16], TVPSOGSA [17], PSOGSA [17], PAA [10], EP[6], SQP[4] and SA[18]. Further for load demand of 1400MW, optimal cost realized by the proposed GOA is 6634.73$/h and the respective transmission loss is 41.67MW. For 1400MW load demand the obtained result of EPDCCF is least when compared to DP [5], PS [12], IGAMU [7], FA [15], SA [18] and TLBO [16] methods represented in Table 3, emphasizing GOA's better solution quality.

Table 3. Comparison of fuel cost for the 3 unit system considering transmission loss

	P_1	**P_2**	**P_3**	**F ($/h)**	**Loss (MW)**
P_D = 1200MW					
GOA	366.79	100.00	774.72	**5661.85**	**41.51**
TLBO [16]	365.67	100.00	777.63	5671.04	43.60
TVPSOGSA [17]	362.6257	100.00	781.0082	5671.066	43.63396
PSOGSA [17]	363.1447	100.00	780.4833	5671.067	43.62803
PAA [10]	362.2431	100.00	781.3953	5671.06	43.638
EP [6]	368.665	100.091	774.807	5671.066	42.8778
SQP [4]	500.00	109.4929	634.2312	5735.031	43.4270
SA [18]	342.8070	100.00	801.1004	5771.066	43.9074
P_D= 1400MW					
GOA	363.07	405.97	672.63	**6634.73**	**41.67**
TLBO [16]	362.830	100.000	1000.00	6639.13	62.83
FA [15]	362.7	100	1000	6638.8	62.7
IGAMU [7]	365.4085	100	997.3436	6639.18	62.7521
PS [12]	372.29	356	712	6639.01	40.29
DP [5]	360.200	406.400	676.8000	6642.26	43.4000
SA [18]	359.7034	406.5985	677.1375	6642.66	43.4344

4.4. Performance analysis

The convergence features of the successful fuel cost yielded in 100 iterations by proposed GOA for the chosen test cases are illustrated in Fig. 1, Fig. 2 and Fig. 3. In all test cases the ability of convergence are higher and it is qualitative when compared with other algorithm.

Each algorithm achieved its appreciable target by taking required number of trial, so randomness is an inherent property of these techniques. Hence the performance of stochastic search algorithms is evaluated by number of runs. Several runs with dissimilar initial habitats have been carried out to test the consistency of the GOA algorithm for 100 independent runs and the values are plotted as robustness characteristics in Fig. 4, Fig. 5 and Fig. 6.

From the results it is observed that GOA is robust as it has the success rate of 75, 72 and 74 for 5 unit, 26 unit and 3 unit test system respectively. Further, the solution iteration of each case is represented in the Table 4. The solution iteration for 5 unit, 26 unit and 3 unit test case is 15, 16 and 12 respectively; it shows the algorithm's quick converging ability. The Table 4 also lists the minimum, maximum and average cost values obtained over 100 independent trials.

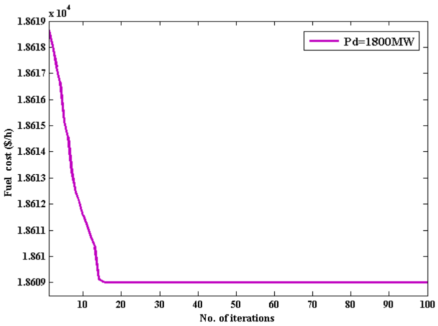

Fig. 1 Convergence characteristics of GOA for 5 unit system

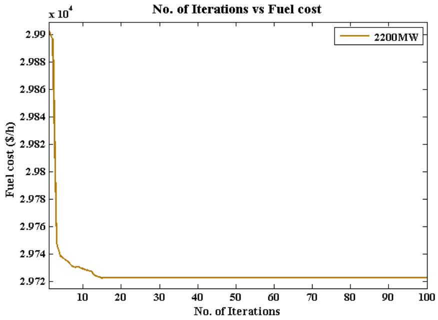

Fig. 2 Convergence characteristics of GOA for 26 unit system

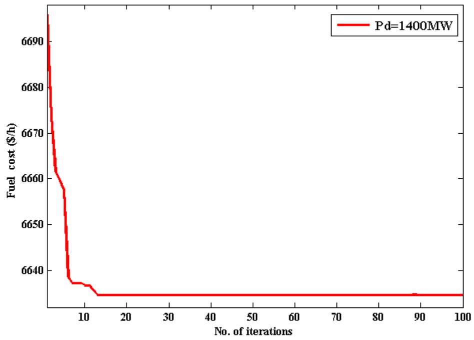

Fig. 3 Convergence characteristics of GOA for 3 unit system considering loss

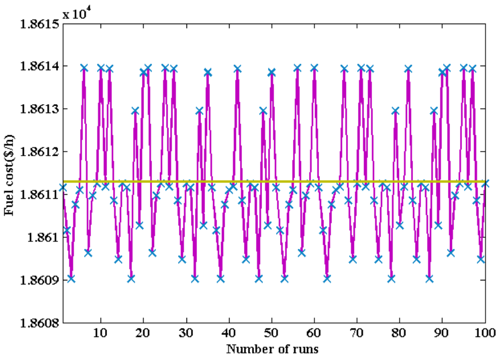

Fig. 4 Robustness characteristics of GOA for 5 unit system (P_D = 1800MW)

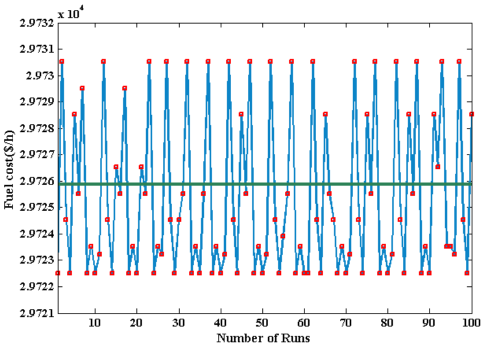

Fig. 5 Robustness characteristics of GOA for 26 unit system (P_D = 2200MW)

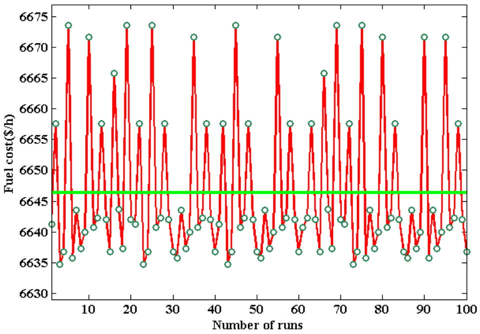

Fig. 6 Robustness characteristics of GOA for 3 unit system considering loss (P_D = 1400MW)

Table 4. Performance analysis of GOA for 3 different test systems

S. no		5 unit system	26 unit system	3 unit system
1.	Demand	1800MW	2200MW	1400 MW
2.	Solution iteration	15	16	12
3.	Minimum cost ($/h)	18609.631	29722.519	6634.73
4.	Maximum cost ($/h)	18613.95	29725.261	6673.57
5.	Average cost ($/h)	18611.31	27270.76	6646.33
6.	Success rate	75	72	74

5. CONCLUSION

The EPDCCF problem is solved using GOA algorithm with the inclusion of equality and inequality constraints for three different test cases involving cubic cost functions to find out the optimum fuel cost. The comparison of results for the test cases of three unit, five unit and twenty six unit system clearly shows that the proposed GOA method is indeed capable of obtaining reasonably higher quality solution for EPD problems considering higher order cost functions. Here, the solution process is independent of the fuel cost function of the generators and its convergence property is not affected by the inclusion of the equality and inequality constraints. Numerical result reveals that the GOA converges to more optimal and reliable solution than other stochastic search algorithms in the literature.

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