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A Novel Heuristic Algorithm for Solving Non-convex Economic Load Dispatch Problem with Non-smooth Cost Function

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ABSTRACT

In this work, a novel heuristic algorithm is presented for solving economic load dispatch (ELD) problems in power systems. The implemented method is a hybrid method, called Hybrid Immune Genetic Algorithm (HIGA). ELD problems are complicated and nonlinear in nature with equality and inequality constraints. Two benchmark ELD problems of different characteristics were used to investigate the effectiveness of the proposed algorithm. The proposed methodology easily takes care of valve-point effects, prohibited operation zones (POZs), ramp-rate constraints and transmission losses. Comparing of the obtained numerical results with other available methods affirm the proficiency of proposed algorithm over other existing methods. It shows that the HIGA method has good convergence property. Furthermore, the generation costs of the HIGA approach are lower than other optimization algorithms reported in recent literature.
KEYWORDS: Economic load dispatch, Hybrid Immune Genetic Algorithm, prohibited operation zone, valve-point effect.

I. INTRODUCTION

The Economic Load Dispatch (ELD) problem is an important computational problem in the operation of power systems, where, the total required load is distributed among the generation units in operation. The objective of ELD problem is to minimizing total generation cost while satisfying load and operational constraints. Traditionally, fuel cost function of a generator is represented by single quadratic function. But a quadratic function is not able to show the practical behaviour of generator. For modeling of the practical cost function behaviour of a generator, a non-convex curve is used in literature. ELD problem is a non-convex and nonlinear optimization problem. Due to ELD complex and nonlinear characteristics, it is hard to solve the problem using classical optimization methods.

Many solution methods, based on stochastic search algorithms, have been proposed in literature for ELD problem. Biogeography-based optimization (BBO) algorithm to solve both convex and non-convex economic load dispatch (ELD) problems of thermal plants has been proposed in (Bhattacharya, A. and P. K. Chattopadhyay). Modified versions of particle swarm optimizer (PSO) algorithm have been applied to the economic power dispatch with valve-point effects in (Chen, C. H. and S. N. Yeh, 2006). Genetic algorithm and its improved versions also have been used to solve non-convex ELD problems (Amjady, N. and H. Nasiri-Rad, 2009; Chao-Lung, C., 2009; Chao-Lung, C., 2005; Chao-Lung, C. and et al., 2006). A modified tent-map-based chaotic PSO (TCPSO) is presented in (Zhang, T. and J.-d. Cai, 2009) to solve the economic load dispatch problem. Where, a dynamic inertial weight factor was incorporated with the modified hybrid TCPSO for improving the global and local search efficiency. Self-tuning hybrid differential evolution (self-tuning HDE) algorithm has been proposed in(Wang, S. K. and et al., 2007) for determining the optimal feasible solution of ELD problem. Nelder-Mead hybrid algorithm for solving constraint ELD problem is used in (Panigrahi, B. K. and V. R. Pandi, 2008), where, nelder-mead algorithm is implemented for improving the space exploring capability of bacterial foraging algorithm.

In this paper, a Hybrid Immune Genetic Algorithm (HIGA) is proposed to solve non-convex economic load dispatch (ELD) problems of power systems.

II. MATHEMATICAL FORMULATION OF ELD PROBLEM

The objective function of ELD problem is to minimize the total production cost over the operating horizon, which can be written as:

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

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where C_i is the production cost of unit i at time t, N is the number of dispatchable power generation units and P_i is the power output of i-th unit at time t. T is the total number of hours in the operating horizon. The production cost of generation unit considering valve-point effects is defined as:

$$C_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i(P_i^{min} - P_i))| \quad (2)$$

where a_i, b_i, c_i are the fuel cost coefficients of the i-th unit, e_i and f_i are the valve-point coefficients of the i-th unit. $P_i^{\min}$ is the minimum capacity limit of unit i.

The objective function of the ELD problem should be minimized subject to the following equality and inequality constraints:

1) Real power balance:

Hourly power balance considering network transmission losses is written as:

$$\sum_{i=1}^{N} P_i = P_D + P_{loss} \quad (3)$$

where $P_{loss}(t)$ and $P_D(t)$ are the total transmission loss and total load demand of the system at time t, respectively. In this paper, B−matrix coefficients method is used to calculate system loss as follows:

$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \quad (4)$$

2) Generation limits of units:

$$P_i^{min} \le P_i \le P_i^{max} \quad (5)$$

where $P_i^{\max}$ is the maximum power outputs of i-th unit.

3) Ramp up and ramp down constraints:

The output power change rate of the thermal unit must be in an acceptable range to avoid undue stresses on the boiler and combustion equipment. The ramp rate limits of generation units can be mathematically stated as follows:

$$P_i - P_{i,0} \le UR_i \quad (6)$$

$$P_{i,0} - P_i \le DR_i \quad (7)$$

where UR_i is the ramp up limit of the i-th generator (MW/hr) and DR_i is the ramp down limit of the i-th generator (MW/hr).

4) Prohibited Operation Zones limits (POZs):

Generating units may have certain restricted operation zone due to limitations of machine components or instability concerns. The allowable operation zones of generation unit can be defined as:

$$P_{it} \in \begin{cases} P_i^{min} \le P_i \le P_{i,1}^{l} \\ P_{i,j-1}^{u} \le P_i \le P_{i,j}^{l}, \\ P_{i,M_i}^{u} \le P_i \le P_i^{max} \end{cases} \quad j = 2,3,\ldots,M_i, \quad i = 1,\ldots,N \quad (8)$$

where $P_{i,j}^{l}$ and $P_{i,j}^{u}$ are the lower and upper limits of the jth prohibited zone of unit i, respectively. M_i is the number of prohibited operation zones of unit i.

III. HYBRID IMMUNE GENETIC ALGORITHM (HIGA)

The Immune Algorithm (IA) was first proposed by (J. Dreo and et al., 2003), it is inspired by the immune system of human's body. This system tried to identify the external particles trying to enter the body. The antibodies detect and remove them. The antibodies are randomly generated by immune system and those who better identify the external particles are colonized more and more (D. Floreano and C. Mattiussi, 2008). This concept has been used for solving the optimization problems. The objective functions and the constraints are assumed to be antigens while the solutions are the antibodies (L. C. Jain and et al., 2007). Like other heuristic algorithms, the Immune Algorithm is an iterative process which creates an initial set of solution and tries to improve its performance using three operators namely, affinity factor, hypermutation and clonal selection (A. Soroudi and et al., 2011). The affinity factor is a measure of strength of solutions in optimizing the

antigens (objective functions. and constraints). The hyper mutation operator acts as the mutation operator in GA (L.C. Jain and et al., 2007), but in IA, the probability of mutation is proportional to the inverse value of affinity factor of the solution. This means that if the affinity factor, i.e. AF_n, of a solution is low, it will be more mutated to explore the solution space and vice versa. In this paper, the crossover operator of GA is used to propagate the attributes of high quality solutions among others. This is done in "clonal selection". The clonal selection is an operator to give a chance of reproduction to each solution. This chance is proportional to the affinity factor of each solution. The affinity factor is calculated as follows:

$$AF = (TC_n)^{-1} \tag{9}$$

To do so, each antibody, is a vector containing the operating schedule of generating units. The steps of the algorithm are as follows:

- Step 1. Generate N initial random solutions.
- Step 2. Set iteration=1.
- Step 3. Calculate OF for each solution.
- Step 4. Sort the solutions based on their affinity factor obtained by (9).
- Step 5. Save the best N antibodies in the memory.
- Step 6. If the stopping criterion is met, go to step (13), else, continue.
- Step 7. Set the cloning counter, i.e. m = 1.
- Step 8. Select two antibodies of memory, i.e. X_p,X_q based on their affinity factors, using roulette wheel method.
- Step 9. Determine the cloning number, i.e. K_m, as follows:

$$k_m = round\left(\beta.N.\frac{AF_p + AF_q}{2\max(AF_n)}\right) \tag{10}$$

- Step 10. Clone the selected two antibodies Km times and generate 2Km new antibodies and save them.
- Step 11. Check if m < N, then increase cloning
- counter by one and go to step 9, else construct the new population of antibodies using the union of old and new antibodies, increase iteration by one and go to step 3.
- Step 12. End.

IV. CASE STUDIES AND NUMERICAL RESULTS

In this section, the proposed HIGA is applied on two test systems with different number of generating units. After a number of careful experimentation, following optimum values of HIGA parameters have finally been settled: N_P = 100; crossover probability = 0.6, mutation probability=0.2. The stopping criteria is defined as reaching to the maximum number of iterations (here 600 iterations) or when no significant changes observed in the objective function.

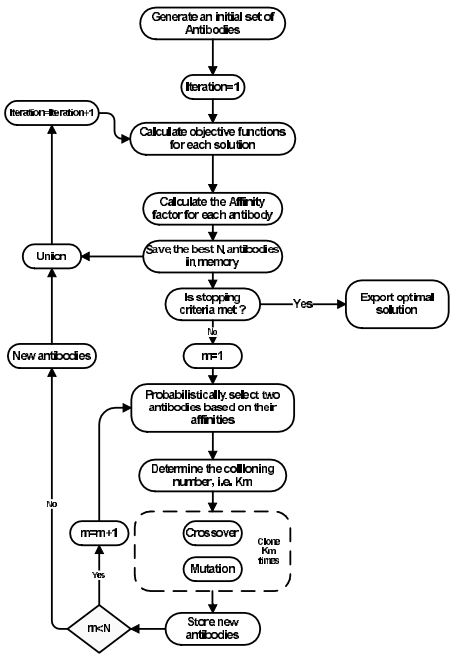

Fig. 1. The flowchart of the proposed HIGA algorithm

A. Case 1: 6-unit system

The first test system is a 6-unit system. System's total demand is 1263 MW. In this test system, the transmission losses, POZs and ramp-rate constraints are considered. The system data and loss coefficients can be found in (Cai, J. and et al., 2006).

Table 1 shows the obtained results for this system. These results are compared with the results of bacterial foraging optimization (BFO) (Panigrahi, B. K. and V. R. Pandi, 2008), PSO, GA and new PSO with local random search (NPSO-LRS) (Selvakumar, A. I. and K. Thanushkodi, 2007). It can be observed that the proposed algorithm's results are better than previously implemented similar methods.

Table 1: Comparison of simulation results for the 6-unit system

Unit	BFO	PSO	GA	NPSO-LRS	Proposed
1	449.46	447.5823	462.0444	446.96	**447.399**
2	172.88	172.8387	189.4456	173.3944	**173.241**
3	263.41	261.33	254.8535	262.3436	**263.382**
4	143.49	138.6812	127.4296	139.512	**138.98**
5	164.91	169.6781	151.5388	164.7089	**165.392**
6	81.252	74.8963	90.715	89.0162	**87.052**
Total Power	1275.402	1276.066	1276.04	1275.9351	**1275.446**
Total loss	12.402	13.0066	13.026	12.9351	**12.446**
Total Cost	15443.85	15450.14	15457.96	15450	**15443.1**

Table 2: Comparison of simulation results for case 2.

Unit	DE/BBO	QPSO	BBO	Proposed
1	110.7998	111.2	111.0465	110.906
2	110.7998	111.7	111.5915	110.804
3	97.3999	97.4	97.60077	97.4
4	179.7331	179.73	179.7095	179.733
5	87.9576	90.14	88.30605	87.828
6	140	140	139.9992	140
7	259.5997	259.6	259.6313	259.609
8	284.5997	284.8	284.7366	284.6
9	284.5997	284.84	284.7801	284.601
10	130	130	130.2484	130
11	168.7998	168.8	168.8461	168.8
12	94	168.8	168.8329	94
13	214.7598	214.76	214.7038	214.76
14	394.2794	304.53	304.5894	394.279
15	394.2794	394.28	394.2761	394.279
16	304.5196	394.28	394.2409	304.52
17	489.2794	489.28	489.2919	489.279
18	489.2794	489.28	489.4188	489.28
19	511.2794	511.28	511.2997	511.28
20	511.2794	511.28	511.3073	511.28
21	523.2794	523.28	523.417	523.279
22	523.2794	523.28	523.2795	523.28
23	523.2794	523.29	523.2793	523.279
24	523.2794	523.28	523.3225	523.279
25	523.2794	523.29	523.3661	523.279
26	523.2794	523.28	523.4362	523.279
27	10	10.01	10.05316	10
28	10	10.01	10.01135	10
29	10	10	10.00302	10
30	97	88.47	88.47754	97
31	190	190	189.9983	190
32	190	190	189.9881	190
33	190	190	189.9663	190
34	164.7998	164.91	164.8054	164.805
35	200	165.36	165.1267	200
36	200	167.19	165.7695	200
37	110	110	109.9059	110
38	110	107.01	109.9971	110
39	110	110	109.9695	110
40	511.2794	511.36	511.2794	511.279
TG	10500.0005	10500	10499.9086	10499.997
TC	121420.9	121448.21	121426.953	121416.937

B. Case 2: 40-unit system

This test case consists of 40 generating units with valve-point effects (Sinha, N. and et al., 2003). Total load demand of the system is 10500 MW. The obtained results by the proposed HIGA are presented in Table 2. In this table TG means total generation and TC represents total cost.

THE OBTAINED RESULTS ARE COMPARED WITH THE RESULTS OF HYBRID DE WITH THE RESULTS OF RECENTLY PUBLISHED WORKS, NAMELY, BIOGEOGRAPHY-BASED OPTIMIZATION (DE/BBO) ALGORITHM (BHATTACHARYA, A. AND P. K. CHATTOPADHYAY), QUANTUM-INSPIRED PSO (QPSO) (KE, M. AND ET AL.) AND BIOGEOGRAPHY-BASED OPTIMIZATION (BBO) ALGORITHM (BHATTACHARYA, A. AND P. K. CHATTOPADHYAY). THESE RESULTS IMPLY THE EFFICIENCY OF THE PROPOSED HIGA METHOD FOR DEALING WITH THE ELD PROBLEM.

V. CONCLUSION

This paper has employed HIGA Algorithm for solving the constrained economic load dispatch problem. Realistic operation constraints like as valve-point effect, prohibited operation zones, ramp-rate constraints and transmission losses are considered in this work. Two test cases with different characteristics are studied. For two ELD problems with valve-point effects, our method (HIGA algorithm) found solutions better than other methods in terms of cost and power loss. Based on the finding of the paper, it can be concluded that the proposed HIGA algorithm can be effectively used to solve constraint non convex ELD problems in power systems.

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