Imperialist Competition Algorithm for Solving Non-convex Dynamic Economic Power Dispatch

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Abstract

Dynamic economic dispatch (DED) aims to schedule the committed generating units' output active power economically over a certain period of time, satisfying operating constraints and load demand in each interval. Valve-point effect, the ramp rate limits, prohibited operation zones (POZs), and transmission losses make the DED a complicated, non-linear constrained problem. Hence, in this paper, imperialist competition algorithm (ICA) is proposed to solve such complicated problem. The feasibility of the proposed method is validated on five and ten units test system for a 24 hour time interval. The results obtained by the ICA are compared with other techniques of the literature. These results substantiate the applicability of the proposed method for solving the constrained DED with non-smooth cost functions. Besides, to examine the applicability of the proposed ICA on large power systems, a test case with 54 units is studied. The results confirm the suitability of the ICA for large-scale DED problem.

Keywords: Dynamic economic dispatch, Imperialist competition algorithm, Prohibited operation zone, Valve-point effect, Ramp-rate limits, Optimization

1. Introduction

The power utility needs to ensure that the electrical power is generated with minimum cost. Hence, for economic operation of the system, the total demand must be appropriately shared among the generating units with an objective to minimize the total generation cost of the system. Thus, economic dispatch (ED) is one of the important problems of power system operation and control. Traditional ED problem, attempts to minimize the cost of

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supplying energy subject to constraints on static behaviour of the generating units. It is assumed that the amount of power to be supplied by a given set of committed units is constant for a given interval of time. However, to avoid shortening of the life of their equipment, plant operators, try to keep thermal gradients inside the turbine within safe limits. This mechanical constraint is usually translated into a limit on the rate of increase of the electrical output. Such ramp-rate constraints lead to the construction of dynamic economic dispatch (DED) problem, which is an extension of conventional ED problem.

DED refers to the problem of determining minimum cost of dispatch of generators for a given horizon of time, taking into consideration the constraints imposed on system operation by the generator ramp-rate limitations. To solve DED problem, generators are modeled using input-output curves in most of the power system operation studies. Traditionally an approximate quadratic function used to model the generator input-output curves [1, 2]. But, the generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions; and thus the natural input-output curve is non-linear and non-smooth due to the effect of multiple steam admission valves (known as valve-points effect) [3, 4]. Besides, generating units may have certain prohibited operation zones (POZs) due to limitations of machine components or instability concerns. Hence, considering the effect of valve-points and POZs in generators' cost function, makes the DED a non-convex optimization problem.

Lots of optimization methods including classical and heuristic algorithms were applied to solve DED problem. Due to non-convexity of the DED problem, application of classical methods like Lagrangian relaxation [5] and dynamic programming [6] are restricted. In recent years, Maclaurin series approximation has been applied to model the valve-point effects [7–9] but it has been shown that this method leads to non-optimal solution.

More recent works have been around artificial intelligence (AI) methods, such as artificial neural networks (ANN), simulated annealing (SA), genetic algorithms (GA), differential evolution (DE), particle swarm optimization (PSO), evolutionary programming (EP), tabu search (TS), and hybrid methods. Optimization methods based on AI have shown better performance in solving the DED problem with capability of modeling more realistic objective functions and constraints. In [10] hybrid EP and sequential quadratic programming (SQP) method has been proposed to solve non-convex DED problem. Chiou [11] proposed a variable scaling hybrid differential evolution (VSHDE) method for large scale

DED problems. DE algorithms have received attention in solving DED problems [12–18]. Other heuristic search methods have been applied to solve DED problems in the past decade. These include GA [1], quantum GA (QGA) [19], artificial immune system method [20], artificial bee colony algorithm (ABC) [21], PSO [16, 17, 22, 23], multiple TS (MTS) algorithm [24], enhanced cross-entropy method [25], and SA algorithm [26]. Hybrid methods such as hybrid artificial immune systems and SQP [27], hybrid EP and SQP method [10, 23], hybrid swarm intelligence based harmony search algorithm [3], hybrid seeker optimization algorithm (SOA) and SQP [28], hybrid Hopfield neural network (HNN) and quadratic programming (QP) [29, 30], adaptive hybrid DE algorithm [31], hybrid PSO and SQP [32], and artificial immune system (AIS) [33] are found to be effective in solving complex optimization problems such as DED problem.

In this paper, an imperialist competition algorithm (ICA) is proposed to solve constrained non-convex DED problems. ICA is recently proposed by Atashpaz-Gargari and Lucas [34]. This algorithm is inspired by the imperialistic competition. Application of ICA to benchmark and large scale DED test cases show that ICA is capable to find better results comparing with other heuristic algorithms. The rest of the paper is organized as follows:

In Section 2 the mathematical formulation of the DED problem is given, considering POZs, ramp-rate limits, valve-point effects and transmission losses. Section 3 proposes the ICA and describes its implementation on DED problems. Section 4 is devoted to case studies and numerical results. In this section, four application cases are studied, and the corresponding comparisons with the recently applied methods are presented. Conclusions are finally outlined in Section 5.

2. Dynamic Economic Dispatch Problem Formulation

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

$$\min\ TC = \sum_{t=1}^{T} \sum_{i=1}^{N} C_{it}(P_{it}) \tag{1}$$

where C_{it} (in \$/hr) is the production cost of unit i at time t, N is the number of dispatchable power generation units and P_{it} (in MW) is the power output of ith unit at time t.

T is the total number of hours in the operating horizon. The production cost of a generation unit considering valve-point effects is defined as:

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

where a_i, b_i and c_i are the fuel cost coefficients of the ith unit, e_i and f_i are the valve-point coefficients of the ith unit. The units of the above coefficients are $(\$/MW^2hr)$, (\$/MWh), (\$/hr), (\$/hr) and $(1/MW)$, respectively . P_i^{min} (in MW) is the minimum capacity limit of unit i. The added sinusoidal term in the production cost function reflects the effect of valve-points. The DED problem is non-convex and non-differentiable considering valve-point effects [35].

The objective function of the DED problem (1) should be minimized subject to the following constraints:

1. Real power balance

   Hourly power balance considering network transmission losses is written as:

$$\sum_{i=1}^{N} P_{it} = P_D(t) + P_{loss}(t) \quad t = 1, 2, \ldots, T \tag{3}$$

   where $P_{loss}(t)$ and $P_D(t)$ (both in MW) are total transmission loss and total load demand of the system at time t, respectively. System loss is a function of units power production and the topology of the network which can be calculated using the results of load flow problem [32] or Kron's loss formula known as $B-$ matrix coefficients [29]. In this work, $B-$ matrix coefficients method is used to calculate system loss, as follows:

$$P_{loss}(t) = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{it} B_{ij} P_{jt} + \sum_{i=1}^{N} B_{i0} P_{it} + B_{00} \quad t = 1, 2, \ldots, T \tag{4}$$

2. Generation limits of units:

$$P_i^{min} \leq P_{it} \leq P_i^{max} \qquad i = 1, \ldots, N, \; t = 1, 2, \ldots, T \tag{5}$$

   where P_i^{max} (in MW) is the maximum power outputs of ith 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 equipments [36]. The ramp rate limits of generation units are stated as follows:

$$P_{it} - P_{it-1} \leq UR_i \qquad i = 1, \ldots, N, \; t = 1, 2, \ldots, T \tag{6}$$

$$P_{it-1} - P_{it} \leq DR_i \qquad i = 1, \ldots, N, \; t = 1, 2, \ldots, T \tag{7}$$

where UR_i is the ramp up limit of the ith generator (MW/hr) and DR_i is the ramp down limit of the ith generator (MW/hr). Considering ramp rate limits of unit, generator capacity limit (5) can be rewritten as follows:

$$\begin{aligned} \max(P_i^{min}, P_{it-1} - DR_i) \leq P_{it} \leq \min(P_i^{max}, P_{it-1} + UR_i) \\ i = 1, \ldots, N, \;\; t = 1, 2, \ldots, T \end{aligned} \tag{8}$$

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:

$$P_{it} \in \begin{cases} P_i^{min} \leq P_{it} \leq P_{i,1}^l \\ P_{i,j-1}^u \leq P_{it} \leq P_{i,j}^l \;\; j = 2, 3, \ldots, M_i \;\; i = 1, \ldots, N \;\; t = 1, 2, \ldots, T \\ P_{i,M_i}^u \leq P_{it} \leq P_i^{max} \end{cases} \tag{9}$$

   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.

3. Imperialist Competition Algorithm

The ICA was first proposed in [34]. It is inspired by the imperialistic competition. It starts with an initial population called colonies. The colonies are then categorized into two groups namely, imperialists (best solutions) and colonies (rest of the solutions). The imperialists try to absorb more colonies to their empire. The colonies will change according to the policies of imperialists. The colonies may take the place of their imperialist if they become stronger than it (propose a better solution). This algorithm has been successfully applied to PSS design [37] and data clustering [38] and unit commitment [39]. The flowchart of proposed algorithm which is the same as [34] for solving the DED problem is depicted in Fig.1. The imperialist competition algorithm is very strong in pattern recognition. This aspect is used in this paper to find the optimal generating schedule of thermal units over a given period. The objective function (OF) is defined as summation of total cost (1)) and penalties for constraint violations.

$$
\begin{aligned}
OF_c = &\sum_{t=1}^{T}\sum_{i=1}^{N} C_{it}(P_{itc}) + \beta_1 \sum_{t=1}^{T}[\sum_{i=1}^{N}(P_{itc}) - P_D(t) + P_{loss}(t)]^2 \\
&+\beta_2 \sum_{t=1}^{T}\sum_{i=1}^{N}|P_{itc} - P_{it}^{lim}| + \beta_3 \sum_{t=1}^{T}\sum_{i=1}^{N}|P_{itc} - P_{it}^{pozlim}|
\end{aligned}
\tag{10}
$$

where β_1, β_2 and β_3 are penalty parameters. P_{itc} refers to power production of unit i at time t in colony c. P_{it}^{lim} and P_{it}^{pozlim} are constraint violation indicator and defined as follows.

$$
P_{it}^{lim} = \begin{cases}
\max(P_i^{min}, P_{it-1} - DR_i) & if\ P_{it} \leq \max(P_i^{min}, P_{it-1} - DR_i) \\
\min(P_i^{max}, P_{it-1} + UR_i) & if\ P_{it} \geq \min(P_i^{max}, P_{it-1} + UR_i) \\
P_{it} & \text{otherwise}
\end{cases}
\tag{11}
$$

$$
P_{it}^{pozlim} = \begin{cases}
P_i^{min} & if\ P_{it} \leq P_i^{min} \\
P_{i,1}^{l} & if\ P_{it} \geq P_{i,1}^{l} \\
P_{i,j-1}^{u} & if\ P_{it} \leq P_{i,j-1}^{u} \\
P_{i,j}^{l} & if\ P_{it} \geq P_{i,j}^{l} \\
P_{i,M_i}^{u} & if\ P_{it} \leq P_{i,M_i}^{u} \\
P_i^{max} & if\ P_{it} \geq P_i^{max} \\
P_{it}\ , & \text{otherwise}
\end{cases}
\tag{12}
$$

The steps of the proposed ICA for minimization problems are described as follows:

Step 1. An initial set of colonies with the size of N_c should be created.

Step 2. The objective function is calculated for each colony using (2) and the power of each colony is set as follows:

$$CP_c = \frac{1}{OF_c}, c = 1 : N_c \tag{13}$$

Step 3. The N_{imp} strongest colonies are kept as the imperialists and the power of each imperialist i.e. IP_i, is set as follows:

$$IP_i = \frac{1}{OF_i}, i = 1 : N_{imp} \tag{14}$$

Step 4. Assign the colonies to each imperialist according to calculated IP_i. This means the number of colonies owned by each imperialist is proportional to its power, i.e. IP_i. $\frac{IP_i}{\sum_{j=1}^{N_{imp}} IP_j} \times (N_c - N_{imp})$

Step 5. The colonies are moved toward their imperialist using crossover and mutation operators.

Step 6. Exchange the position of a colony and the imperialist if it is stronger ($CP_c > IP_i$). If there are several colonies better than th imperialist then the imperialist will be replaced by the best of them.

Step 7. Compute the empire's power, i.e. EP_i for all empires as follows:

$$EP_i = w_1 \times IP_i + w_2 \times \sum_{c \in E_i} CP_c \tag{15}$$

where w_1 and w_2 are weighting factors which are selected in a way that the algorithm will not be trapped into a local Minima. For this reason, the value of w_1 is selected as a number about 10 to 20% and $w_2 = 1 - w_1$.

Step 8. Pick the weakest colony and give it to one of the best empires (select the destination empire probabilistically based on its power (EP_i)).

Step 9. Eliminate the empires that have no colony.

Step 10. If more than one empire remained then go to Step. 5

Step 11. End.

It should be noted that the N_c and N_{imp} are given constants and are determined by the expert who uses the algorithm. Typically 10 to 20% of N_c would be a good choice for N_{imp}. The steps of the algorithm is shown in Fig.1.

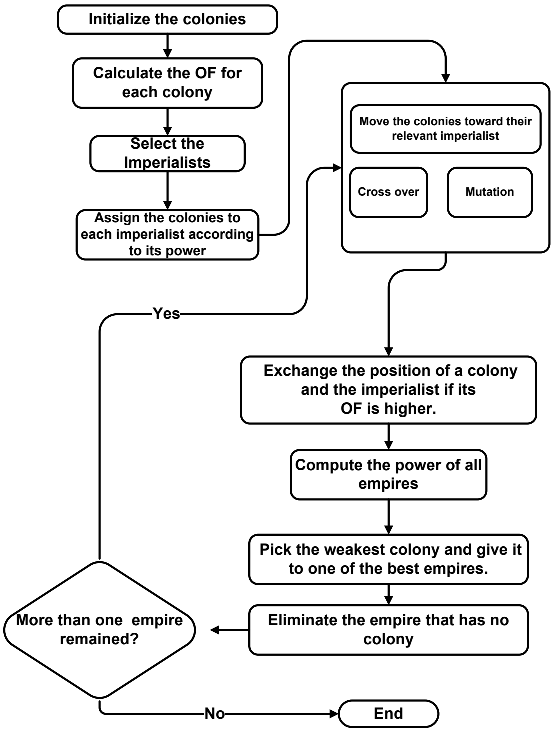

Figure 1: The flowchart of the proposed algorithm

The operating schedule of each country (for all operating periods) is binary coded as described in Fig.2. There is a column for each generating unit and for each time period, there is a row containing the binary values. The generation value in time t of unit i is calculated as follows: suppose that the row t in the column corresponding to unit i is $vec =$ [string of binary values]. $P_{it} = (P_i^{max} - P_i^{min}) * [vec' * [2^{n-1}, n = N : 1]]/2^N + P_i^{min}$. where N is the number of generating units. The binary coding of each country (which may become an imperialist or not) can be helpful in easily using the crossover and mutation operators of GA.

4. Case Studies and Numerical Results

In this section, the proposed ICA is applied to four test systems with different number of generating units. By computational experiments, the following parameters are found suitable as follows: $N_c = 100$; crossover probability = 0.6, mutation probability=0.2, $w_1 = 0.15, w_2 = 0.75$ For all cases, The dispatch horizon is selected as one day with 24 dispatch periods where each period is assumed to be one hour. In this paper he stopping criteria is

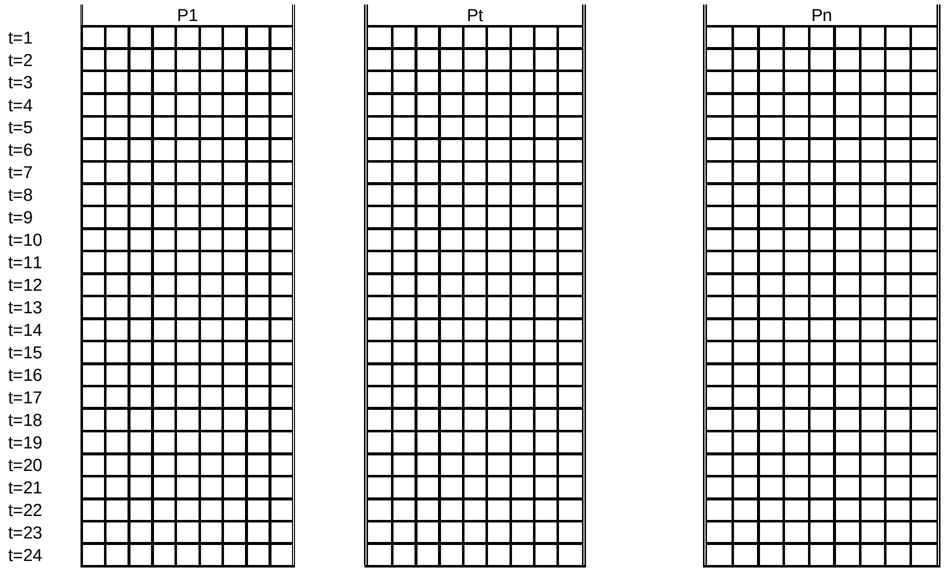

Figure 2: The binary coding of each country

defined as reaching to the maximum number of iterations (200 iterations for cases 1-3 and 800 iterations for case 4) . Stopping criteria also can be defined when no significant changes (for example 10^{-6}) observed in the objective function. All the programs are developed using MATLAB 7.1 on a Pentium IV personal computer with 3.6 GHz speed processor and 2 GB RAM.

4.1. Case 1: Five unit system

The first test system is a 5-unit test system. The data for this system is provided in [26]. In this test system, transmission losses and ramp rate constraints are considered. The hourly load profile for this case is presented in last column of Table 1.

The DED problem of 5-unit system is solved using the proposed algorithm. The valve-point effects, transmission losses, ramp rate constraints and generation limits are considered in this system. The prohibited operating zones are not considered in this test case for the sake of comparison of results with those reported in literature using different methods. Table 1 shows the obtained results for this system.

These results are compared with several methods presented in recent literature in terms of minimum cost, mean cost, and maximum cost over 100 runs in Table 2. The maximum iteration number is selected to be 200. The convergence characteristic of the proposed algorithm is depicted in Fig. 3.

By investigating the results presented in Table 2, it can be observed that the obtained results outperform the other cited methods for 5-unit test case.

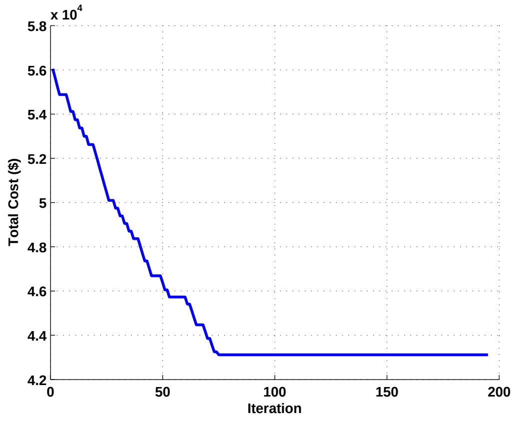

Figure 3: Convergence characteristics of the ICA algorithm for 5-unit test system

Table 1: Optimal solution of 5-unit using proposed algorithm.

Hour	$P_1\,(MW)$	$P_2\,(MW)$	$P_3\,(MW)$	$P_4\,(MW)$	$P_5\,(MW)$	Cost($)	$\sum_{i=1}^{5} P_i\,(MW)$	P_D (MW)
1	10	20	30	124.485	229.504	1226.587	413.989	410
2	19.078	20	30	140.846	229.52	1418.346	439.444	435
3	10	20	30	190.846	229.519	1493.566	480.365	475
4	10	20	67.023	209.816	229.52	1662.802	536.359	530
5	10	20	95.511	209.816	229.515	1667.456	564.842	558
6	13.949	50	112.675	209.816	229.52	1826.62	615.96	608
7	10	72.451	112.673	209.816	229.52	1840.605	634.46	626
8	12.709	98.54	112.674	209.815	229.52	1797.229	663.258	654
9	42.709	102.78	115.353	209.817	229.52	2013.697	700.179	690
10	64.03	98.54	112.671	209.799	229.519	1996.68	714.559	704
11	75	98.791	117.878	209.816	229.52	2039.988	731.005	720
12	75	124.71	112.674	209.816	229.521	2180.027	751.721	740
13	64.012	98.54	112.673	209.816	229.52	1996.599	714.561	704
14	49.62	98.54	112.673	209.816	229.519	1977.667	700.168	690
15	35.892	98.54	112.673	186.5	229.52	2010.648	663.125	654
16	10	98.54	112.674	136.5	229.52	1682.8	587.234	580
17	10	87.586	112.672	124.905	229.519	1615.305	564.682	558
18	10	98.54	112.674	165.218	229.52	1853.472	615.952	608
19	12.709	98.54	112.674	209.816	229.52	1797.224	663.259	654
20	42.709	119.939	112.674	209.816	229.52	2115.511	714.658	704
21	39.353	98.54	112.674	209.816	229.52	1944.597	689.903	680
22	10	98.541	110.204	164.619	229.52	1860.868	612.884	605
23	10.001	98.54	70.204	124.908	229.52	1643.076	533.173	527
24	10	73.366	30.204	124.908	229.519	1455.677	467.997	463
Total						43117.047	14773.737	

Table 2: Comparison of optimization results for 5-unit test system (case 1).

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Number of trial runs
SA [26]	47356	NA	NA	NA
APSO [22]	44678	NA	NA	NA
AIS [20]	44385.43	44758.8363	45553.7707	30
GA [21]	44862.42	44921.76	45893.95	30
PSO [21]	44253.24	45657.06	46402.52	30
ABC [21]	44045.83	44064.73	44218.64	30
MSL [20]	49216.81	NA	NA	NA
Proposed (ICA)	**43117.055**	**43144.472**	**43209.533**	100

NA denotes that the value was not available in the literature.

4.2. Case 2: Ten unit system without transmission loss

The second test system is ten-unit test system. In this case, generators capacity limits, ramp rate constraint and valve-point effects are considered. The transmission losses are ignored in this case for sake of comparison. The data for this system is adapted from [26]. The hourly load profile for this case is presented in last column of Table 3.

Table 3 shows the obtained results for 10-unit system without considering transmission losses. The minimum cost, mean cost, and maximum cost of obtained optimal results are compared with results of previously developed algorithms such as differential evolution (DE) [14], hybrid EP and SQP [10], Hybrid PSO-SQP [32], deterministically guided PSO (DGPSO) [23], modified hybrid EP-SQP (MHEP-SQP) [40], improved PSO (IPSO) [16], Hybrid DE (HDE) [41], Improved DE (IDE) [15], artificial bee colony algorithm (ABC) [21], modified differential evolution (MDE) [17], covariance matrix adapted evolution strategy (CMAES) [42], artificial immune system (AIS) [20], hybrid swarm intelligence based harmony search algorithm (HHS) [3], improved chaotic particle swarm optimization algorithm (ICPSO) [43], hybrid artificial immune systems and sequential quadratic programming (AIS-SQP) [27], hybrid SOA-SQP algorithm [28], chaotic sequence based differential evolution algorithm (CS-DE) [12], chaotic differential evolution (CDE) method [18], adaptive hybrid differential evolution algorithm (AHDE) [31], and enhanced cross-entropy method (ECE) [25] in Table 4. The maximum iteration number and number of trails are selected to be 200 and 100, respectively. The convergence characteristic of the proposed algorithm is depicted in Fig. 4. It can be observed that the obtained results with ICA algorithm is less than those of reported in literature.

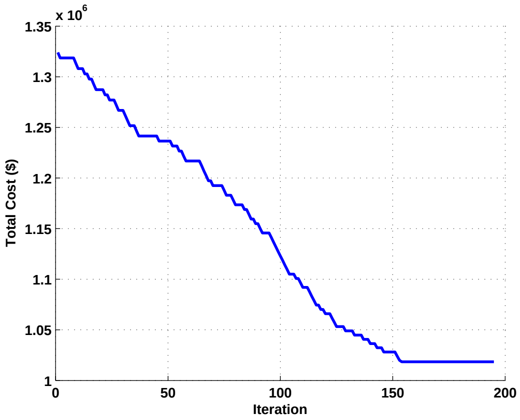

Figure 4: Convergence characteristics of the ICA algorithm for 10-unit test system

Table 3: Optimal 24-hour schedule of ten-unit test system (case 2).

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost($)	P_D
1	150	135	194.065	60	122.88	122.46	129.594	47	20	55	28238.754	1036
2	226.624	135	191.461	60	122.867	122.457	129.591	47	20	55	29828.077	1110
3	303.249	142.266	185.208	60	172.733	142.546	129.997	47	20	55	33347.045	1258
4	379.874	222.266	196.603	60	172.733	122.526	129.997	47	20	55	36296.715	1406
5	379.868	222.266	183.675	60	222.6	160	129.59	47	20	55	37991.334	1480
6	455.434	302.266	263.674	60	172.601	122.434	129.59	47	20	55	41387.159	1628
7	379.898	309.534	305.892	110	222.601	122.481	129.594	47	20	55	42844.529	1702
8	456.497	316.799	297.946	120.418	172.747	160	129.593	47	20	55	44600.484	1776
9	456.497	396.799	303.71	132.802	222.6	160	129.59	47	20.002	55	47885.318	1924
10	456.497	460	297.781	182.802	233.328	160	129.59	47	50.002	55	51887.342	2072
11	456.491	460	300.462	232.802	222.598	159.999	129.59	77	52.057	55	53788.277	2146
12	456.498	460	318.192	282.802	222.6	160	129.594	85.312	50.002	55	55605.118	2220
13	456.497	396.8	307.935	238.264	222.6	160	129.59	85.312	20.002	55	51357.359	2072
14	456.446	396.799	297.407	188.264	172.733	122.45	129.59	85.312	20	55	47818.061	1924
15	379.872	393.192	297.301	170.448	122.863	122.421	129.59	85.312	20	55	44649.659	1776
16	303.251	313.192	331.753	120.449	73	122.451	129.592	85.312	20	55	39816.706	1554
17	226.624	309.533	295.168	113.568	122.755	122.449	129.59	85.312	20	55	37983.869	1480
18	303.248	315.523	303.703	120.416	172.751	122.456	129.59	85.312	20	55	41294.355	1628
19	379.872	395.523	295.242	120.341	172.671	122.448	129.59	85.312	20	55	44374.06	1776
20	456.512	460	340	170.341	222.671	132.571	129.592	85.312	20	55	51862.515	2072
21	456.497	389.533	322.67	120.342	222.604	122.45	129.591	85.312	20	55	47915.54	1924
22	379.85	309.533	283.231	70.342	172.707	122.435	129.59	85.312	20	55	41280.418	1628
23	303.249	229.533	203.235	60	122.867	123.214	129.59	85.312	20	55	34952.455	1332
24	226.639	222.267	189.711	60	73	122.481	129.591	85.312	20	55	31462.345	1184
Total											1018467.494	

Table 4: Comparison of optimization results for case 2.

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
DE [14]	1019786.000	NA	NA
EP-SQP [10]	1031746.000	1035748.000	NA
PSO-SQP [32]	1027334.000	1028546.000	1033986.000
DGPSO [23]	1028835.000	1030183.000	NA
MHEP-SQP [40]	1028924.000	1031179.000	NA
IPSO [16]	1023807.000	1026863.000	NA
HDE [41]	1031077.000	NA	NA
IDE [15]	1026269.000	NA	NA
ABC [21]	1021576.000	1022686.000	1024316.000
MDE [17]	1031612.000	1033630.000	NA
CMAES [42]	1023740.000	1026307.000	1032939.000
AIS [20]	1021980.000	1023156.000	1024973.000
HHS [3]	1019091.000	NA	NA
ICPSO [43]	1019072.000	1020027.000	NA
AIS-SQP [27]	1029900.000	NA	NA
SOA-SQP [28]	1021460.010	NA	NA
CS-DE [12]	1023432.000	1026475.000	1027634.000
CDE [18]	1019123.000	1020870.000	1023115.000
AHDE [31]	1020082.000	1022474.000	NA
ECE [25]	1022271.579	1023334.930	NA
Proposed (ICA)	**1018467.49**	**1019291.358**	**1021795.773**

NA denotes that the value was not available in the literature.

4.3. Case 3: Ten unit system with transmission loss

The data for this case is similar to Case 2. In this case, the transmission losses also considered. The $B-$ matrix coefficients of this system can be found in [26] which is given in perunit (100 MW base). The proposed algorithm applied to ten-unit test case with taking into account the transmission losses. The corresponding generation dispatch is presented in Table 5. The minimum cost, mean cost, and maximum cost of obtained optimal results over 100 runs are compared with the results of Evolutionary Programming (EP) [40], hybrid EP-SQP (EP-SQP) [40], modified hybrid EP-SQP (MHEP-SQP) [40], Genetic Algorithm (GA) [21], Particle Swarm Optimization (PSO) [21], improved PSO (IPSO) [16], enhanced cross-entropy method (ECE) [25], artificial bee colony algorithm (ABC) [21] and artificial immune system (AIS) [20] in Table 6.

The convergence characteristic of the proposed algorithm is depicted in Fig. 5.

4.4. Case 4: 54 unit system

In this case, a 54-unit test system is employed. The data of this system is adopted from [44]. The Valve-point effects and POZs are considered here. Hence this is a large non-

Table 5: Optimal 24-hour schedule of ten-unit test system (case 3).

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost($)	Loss (MW)
1	150	135	206.166	60	122.87	122.499	129.602	47	20	55	28592.287	12.137
2	226.624	135	204.767	60	122.867	122.463	129.592	47	20	55	30218.122	13.313
3	303.249	142.272	186.402	60	172.758	160	129.591	47	20	55	33728.388	18.272
4	379.87	222.267	222.291	60	172.754	122.466	129.613	47	20	55	36993.096	25.261
5	379.873	222.27	211.933	60	222.61	160	129.59	47	20	55	38788.438	28.276
6	456.496	302.27	290.073	67.72	172.718	122.449	129.59	47	20	55	42039.292	35.316
7	379.879	309.534	331.883	117.72	222.718	124.031	129.936	47	20	55	43737.143	35.701
8	456.497	314.872	328.142	130.832	172.732	160	129.591	47	20	55	45776.26	38.666
9	456.497	394.872	297.293	180.832	222.597	160	129.59	55.313	20	55	49108.729	47.994
10	456.5	460	307.325	230.832	222.605	160	129.59	85.313	20	55	53074.979	55.165
11	456.498	460	340	241.936	222.6	160	129.958	115.313	20	55	55072.649	55.305
12	456.497	460	340	264.671	243	160	129.591	120	50	55	57430.259	58.759
13	456.511	396.8	340	250.839	222.73	160	129.949	90	20	55	52887.564	49.829
14	456.499	396.799	297.406	233.434	172.736	122.45	129.591	85.312	20	55	48916.081	45.227
15	379.873	396.557	318.492	183.434	122.87	123.333	129.598	85.312	20	55	45517.715	38.469
16	303.248	316.557	296.785	179.396	73	122.45	129.591	85.312	20	55	40406.888	27.339
17	226.624	309.533	305.063	129.396	122.882	122.649	129.597	85.312	20	55	38655.592	26.056
18	303.249	316.799	333.065	120.416	172.733	122.453	129.591	85.312	20	55	42178.909	30.618
19	379.872	396.799	322.806	130.766	172.733	122.753	129.591	85.312	20	55	45537.406	39.632
20	456.497	460	340	180.766	222.599	160	129.591	101.423	20	55	53346.47	53.876
21	456.497	389.548	340	130.766	222.602	140.445	129.591	85.311	20	55	49313.097	45.760
22	379.873	309.548	304.15	80.884	172.754	122.45	129.591	85.313	20	55	42008.685	31.563
23	303.249	229.548	224.15	60	122.866	122.45	129.591	85.312	20	55	35495.677	20.166
24	226.625	222.267	205.669	60	73	122.626	129.591	85.319	20	55	31934.698	16.097
Total											1040758.424	848.797

Table 6: Comparison of optimization results for case 3.

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
EP [40]	1054685	1057323	NA
EP-SQP [40]	1052668	1053771	NA
MHEP-SQP [40]	1050054	1052349	NA
GA [21]	1052251	1058041	1062511
PSO [21]	1048410	1052092	1057170
IPSO [16]	1046275	1048145	NA
ECE [25]	1043989.154	1044470.0849	NA
ABC [21]	1043381	1044963	1046805
AIS [20]	1045715	1047050	1048431
Proposed (ICA)	**1040758.424**	**1041664.622**	**1043173.551**

NA denotes that the value was not available in the literature.

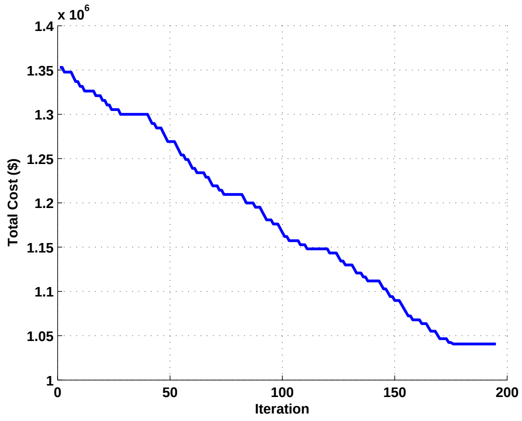

Figure 5: Convergence characteristics of the ICA algorithm for 10-unit test system with loss

convex test case. The results obtained using the ICA are presented in Table A.1 for the load demand which is also given in Table A.1. Beside the ICA, two different algorithms (GA [1] and PSO [45]) are used for optimal dispatch of this system. For GA algorithm, mutation and selection rates are 0.2 and 0.5, respectively. For PSO algorithm cognitive and social parameters are equal to 1 and 2.5 , respectively. The maximum iteration number for PSO and GA are same as ICA. The obtained results over 25 trial runs are compared in Table 7. The minimum cost obtained using ICA is 1807081.174 $/day, whereas for the case of GA and PSO algorithms the minimum costs are 1834373.494 $/day and 1832121.861 $/day, respectively. With assumption that the daily load profile is same as studied day during the entire year, it means that using ICA will result in 9,139,850.75 $ annual saving comparing to PSO and 9,961,696.80 $ annual saving comparing to GA. It should be mentioned that in a practical power system the daily load profile is changing and DED problem should be solved for each day separately and the numbers are provided just for illustration of the economic effect of better solution. It is observed that the performance of the proposed method is better for large scale test cases too, and the proposed method can be used for scheduling of practical large power systems. The Convergence characteristics of the ICA algorithm compared with PSO and GA for this case are given in Fig. 6. The maximum iteration number for this case is selected to be 800.

Table 7: Comparison of optimization results for case 4.

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
GA	1834373.494	1839422.714	1850775.804
PSO	1832121.861	1835851.611	1845937.037
Proposed (ICA)	**1807081.174**	**1809664.219**	**1811388.285**

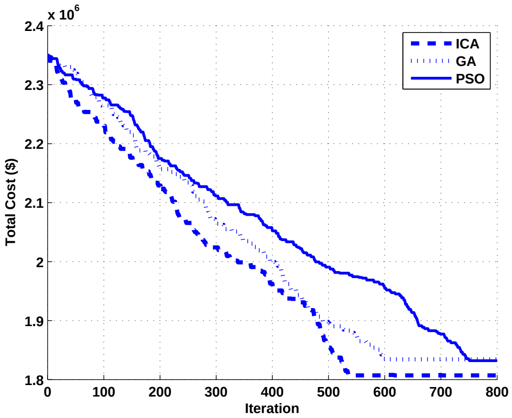

Figure 6: Convergence characteristics of the ICA algorithm compared with PSO and GA for case 4

5. Conclusion

In this paper, the Imperialist Competition Algorithm (ICA) approach has been applied to solve the DED problem of generating units considering the valve-point effects, prohibited operation zones (POZs), ramp rate limits and transmission losses. The effectiveness of the proposed algorithm has been examined by comprehensive studies on DED problems of different dimensions and complexities. At the first, the ICA is tested on five and ten units test system for a 24 hour time interval. The results justify the applicability of the proposed method for solving the constrained DED with non-smooth cost functions. Also the proposed algorithm is implemented on a 54 units test system and the ICA is compared with two well-known heuristic algorithm, i.e. GA and PSO. Numerical experiments on 4 test systems show that the proposed method can obtain better quality solution with higher precision and convergence property, so it provides a new and efficient approach to solve large-scale constrained DED problem.

Appendix A.

Optimal 24-hour schedule of 54-unit test system is provided in Table A.1.

Table A.1: Optimal 24-hour schedule of 54-unit test system (case 4).

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
P_1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_2	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_3	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_5	212.2	249.6	212.2	287	212.2	100	100	212.2	287	287	212.2	174.8	287	137.4	100	100	100	100	100	174.8	287	137.4	249.6	249.6
P_6	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
P_7	50	85	91.538	85	85	85	85	91.554	100	92.138	85	85	65	85	85	85	35	85	56.719	85	85	98.6	65	35
P_8	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_9	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_{10}	100	100	100	120	249.6	145	249.6	249.6	120	120	100	249.6	120	249.6	120	270	120	100	120	249.6	249.6	287	174.8	100
P_{11}	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350	350
P_{12}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{13}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{14}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{15}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{16}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{17}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{18}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{19}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{20}	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250
P_{21}	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250
P_{22}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{23}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{24}	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
P_{25}	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200	200
P_{26}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{27}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{28}	349.333	399.199	399.199	399.199	399.199	399.199	399.199	349.333	399.199	420	399.199	399.199	399.199	399.199	399.199	399.199	399.199	399.199	399.199	399.199	399.199	399.199	349.333	249.6
P_{29}	273.364	292.819	300	300	276.015	300	300	300	300	300	300	300	300	297.17	287.97	264.346	261.789	295.417	293.54	270.119	300	300	300	278.342
P_{30}	36.609	40	70	70	37.237	40	40	70	80	70	40	40	40	70	40	34.474	33.868	40	40	35.841	70	70	40	37.788
P_{31}	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
P_{32}	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_{33}	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
P_{34}	39.577	56.106	91.538	90	50	90	90	91.554	100	92.138	90	68.414	70	90	90	50	29.743	58.313	56.719	90	90	98.6	70	40
P_{35}	50	90	91.538	90	50	90	90	91.554	100	92.138	90	90	70	90	90	50	29.743	58.313	90	90	90	98.6	70	40
P_{36}	300	300	300	150	150	150	300	300	300	300	300	300	300	150	150	150	150	150	150	300	150	300	300	150
P_{37}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{38}	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
P_{39}	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
P_{40}	100	100	100	100	100	100	100	100	249.6	174.8	100	100	100	100	100	100	100	100	100	100	100	174.8	100	100
P_{41}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{42}	20	20	20	20	20	20	20	20	26.734	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
P_{43}	100	100	100	100	100	100	249.6	300	300	300	249.6	100	100	100	100	100	100	100	249.6	300	300	300	300	300
P_{44}	100	100	100	100	100	249.6	300	300	300	300	300	249.6	100	100	100	100	100	100	100	249.6	300	300	300	300
P_{45}	100	100	100	100	174.8	300	300	300	300	300	249.6	100	100	100	100	100	100	100	249.6	300	300	300	300	300
P_{46}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{47}	60	60	91.538	73.446	60	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	60	60	60	29.743	60	60	60	71.169	98.6	71.328	40
P_{48}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{49}	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
P_{50}	25	25	25	25	25	25	25	25	26.734	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25
P_{51}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{52}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{53}	39.577	56.106	91.538	73.446	41.829	69.015	80.2	91.554	100	92.138	79.262	68.414	76.523	59.803	51.986	31.915	29.743	58.313	56.719	36.82	71.169	98.6	71.328	43.806
P_{54}	25	25	25	25	25	25	25	25	26.734	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25
Load (MW)	3900	4300	4800	4500	4100	4600	5200	5500	5800	5600	5100	4700	4600	4300	4000	3800	3500	4000	4300	4700	5200	5700	5100	4300
Cost ($/h)	61229.265	68706.276	78654.861	72839.349	64468.602	74364.815	85298.934	91201.079	97671.104	93399.176	83265.125	75799.456	74533.399	68798.421	63529.631	59428.216	54010.349	63478.427	68510.324	75384.953	85204.075	95168.903	83328.531	68807.903
Total Cost ($)	1807081.174																							

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