

Non-convex Dynamic Economic Power Dispatch Problems Solution Using Hybrid Immune-Genetic Algorithm

Behnam Mohammadi-Ivatloo, Abbas Rabiee, Alireza Soroudi

Abstract—The objective of dynamic economic dispatch (DED) problem is to determine the generation schedule of the committed generation units, which minimizes the total operating cost over a dispatch period, while satisfying a set of constraints. The effect of valve-points and prohibited operating zones (POZs) in the generating units' cost functions makes the DED a highly non-linear and non-convex optimization problem with multiple local minima. Considering the ramp-rate limits and transmission losses, makes the DED problem even more complicated. Hence, proposing an effective solution method for this optimization problem is of great interest. This paper presents a novel heuristic algorithm to solve DED problem of generating units, by employing hybrid immune genetic algorithm (IGA). To illustrate the effectiveness of the proposed approach, four test systems consisting different number of generating units are studied. The valve-point effects, POZs and ramp-rate constraints along with transmission losses are also considered in simulation cases. The results obtained through the proposed method are compared with those reported in the literature. These results substantiate the applicability of the proposed method for solving the constrained DED problem with non-smooth cost functions.

Index Terms—Dynamic economic dispatch , immune-genetic algorithm , Prohibited operation zone (POZ) , valve-point effect

I. INTRODUCTION

Generally, the economic dispatch of power system can be categorized into static economic dispatch (SED) and dynamic economic dispatch (DED). The SED optimizes the system objective function (total fuel cost in general) in specified time and does not take into account the fundamental relation of system between the different operating times. The DED takes into account the connection of different operating times by considering ramp rate constraints. The DED is one of the important optimization problems used in power systems to obtain the optimal operation schedule of the committed units over the entire dispatch period. Considering the dynamic constraints like ramp rate limits makes the DED problem more complicated. One way to simplify the solution of DED is to consider it as a sequential SED problems [1] and force the ramp rates between the sequential hours. It is shown that this method would lead into being trapped in a local optimal solution [2]. Generators are modeled using input-output curves in most of the power system operation studies.

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Traditionally an approximate quadratic function used to model the generator input-output curves [1], [3]. This would result in an inaccurate dispatch. Because 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) [4], [5].

Obtaining the global optimum or better local optimum for non-convex DED problems is a great challenge. Application of the classical methods such as Lagrangian relaxation approach [6] and dynamic programming [7] are restricted [8]. In recent years, Maclaurin Series approximation has been applied to model the valve-point effects [9]–[11] but it has been shown that this method leads to non-optimal solution. Optimization methods based on artificial intelligence has shown better performance in solving the DED problem with capability of modeling more realistic objective function and constraints. In [12], Hybrid evolutionary programming and sequential quadratic programming (SQP) method has been proposed to solve non-convex DED problem. Chiou [13] proposed variable scaling hybrid differential evolution (VSHDE) method for solution of large scale DED problems. Time-varying acceleration coefficients IPSO (TVAC-IPSO) is implemented in [14] for solution of non-convex DED problem considering different constraints. Differential evolution algorithm has received a great deal of attention in solving DED problems [15]–[21]. Other stochastic search methods have been applied to solve DED problems in the past decade. These include genetic algorithm [22], quantum genetic algorithm [23], artificial immune system method [24], artificial bee colony algorithm [8], particle swarm optimization [25]–[28], multiple tabu search algorithm [29], enhanced cross-entropy method [30], Simulated annealing algorithm [31]. Multiobjective teaching-learning-based optimization (TLBO) has been employed in [32] to solve the dynamic economic emission dispatch problem. Self-adaptive modified firefly algorithm is presented in [33] for solution of reserve constrained dynamic economic dispatch, where three types of the system spinning reserve requirements are considered.

Hybrid methods are found to be more effective in solving complex optimization problems such as DED problem. Hybridization of SQP algorithm with one of the heuristic algorithms (for instance: artificial immune systems, EP, seeker optimization algorithm (SOA) and PSO) are widely used in literature for solution of DED problem [12], [34]–[37]. Hybrid swarm intelligence based harmony search algorithm has been proposed in [4] for solution of non-convex DED problems. Hybrid Hopfield neural network (HNN) and quadratic programming (QP) is also implemented for solution of DED problems in [38], [39].

In this paper, a hybrid immune-genetic algorithm (IGA)

is proposed to solve non-convex dynamic economic dispatch problem with constraints. More details of the proposed algorithm are provided in Section III. Wind power generation is the fastest growing renewable energy resources in the world [40]. The effect of the wind power generation is also considered in simulations using the methods proposed in [41], [42].

The remainder of the paper is organized as follows: Section II gives the mathematical formulation of the DED problem considering POZs, ramp-rate limits, valve-point effects and transmission losses. Section III describes the proposed IGA algorithm. Section IV presents four application cases and gives the corresponding comparison results with the most recent applied methods. Conclusions are finally given in Section VI.

II. DYNAMIC ECONOMIC DISPATCH PROBLEM FORMULATION

The objective function of DED problem is to minimize the total production cost over the operating horizon, expressed as:

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

where C_{it} is the production cost of unit i at time t , N is the number of dispatchable power generation units and P_{it} 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:

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

where a_i , b_i and 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 . It should be noted that the added sinusoidal term in the production cost function reflects the effect of valve-points. The DED problem will be non-convex and non-differentiable considering valve-point effects [43]. 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:

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

where $P_{loss}(t)$ and $P_D(t)$ 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 can be calculated using the results of load flow problem [37] or Kron's loss formula known as B -matrix coefficients [38]. In this work, B -matrix coefficients method is used to calculate system loss as follows:

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

2) Generation limits of units:

$$P_i^{min} \leq P_{it} \leq P_i^{max} \quad (5)$$

- 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 [44]. The ramp rate limits of generation units can be mathematically stated as follows:

$$P_{it} - P_{it-1} \leq UR_i \quad (6)$$

$$P_{it-1} - P_{it} \leq DR_i \quad (7)$$

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). Considering ramp rate limits of unit, generator capacity limit (5) can be rewritten as follows:

$$\max(P_i^{min}, P_{it-1} - DR_i) \leq P_{it} \quad (8)$$

$$P_{it} \leq \min(P_i^{max}, P_{it-1} + UR_i)$$

It should be mentioned that the constraints (5)- (7) are replaced with the new compact form presented in (8).

III. HYBRID IMMUNE- GENETIC ALGORITHM

One of the most recent heuristic algorithms is immune algorithm (IA). The applications of this algorithm have been reported in the literature in various fields such as DG planning [45] and voltage control [46]. In this work the best characteristics of IA is hybridized with Genetic algorithm in order to find a better solution in a non-convex solution space of the DED problem. The concept of IA is based on the reaction of immune system of human body to external particles entering into it. Actually even it does not know them initially but it tries to identify them and find a solution to remove them. The external particles are called antigens and the response of the immune system would be the antibodies. The antibodies should be match with the unknown antigens. This inspires the engineers to use it for solving optimization problem. In this regard, the objective function and its associated constraints form the antigens and the solution which optimize them are called the antibodies. The human body initially produces some antibodies and measures how similar they are to the stranger antigens. This measure is called affinity factor. The affinity factor (ξ_n) indicates the measure of applicability of antibodies to antigens [47]. The affinity factor is defined as:

$$\xi_n = \frac{1}{TC_n} \quad (9)$$

Each antibody, is defined as a vector containing the operating hourly schedule for committed units. The steps of the proposed algorithm are described as follows [47]:

- Step 1. Initialize the N initial solutions randomly.
- Step 2. Set $iteration = 1$.
- Step 3. Evaluate each solution by solving (1).
- Step 4. Solve (9) and find the best solutions.
- Step 5. Store the best N antibodies in the memory.
- Step 6. If the stopping criterion is met, go to End, else, continue.
- Step 7. Set $m = 1$.
- Step 8. Select two antibodies X_1, X_2 according to their affinity factors (calculated in Step. 4).

Step 9. Determine the cloning number, i.e. K_m , and the mutation probability, i.e. ς_m , as follows [47] :

$$K_m = \text{round}(\beta \times N \times \frac{\xi_1 + \xi_2}{2\text{max}(\xi_n)}) \quad (10)$$

$$\varsigma_m = \varsigma^{\text{max}} \times \frac{2\text{max}(\xi_n)}{\xi_1 + \xi_2} \quad (11)$$

Where, *round* is a function which gives the nearest integer value, β is a control parameter, ς^{max} is the maximum mutation probability.

Step 10. Clone the two selected antibodies (in Step. 8) K_m times and store them.

Step 11. Check if $m < N$, then $m = m + 1$ and go to step 9, else add the new population to old one, $\text{iteration} = \text{iteration} + 1$ and go to step 3.

Step 12. End.

The flowchart of the proposed algorithm is depicted in Fig.1.

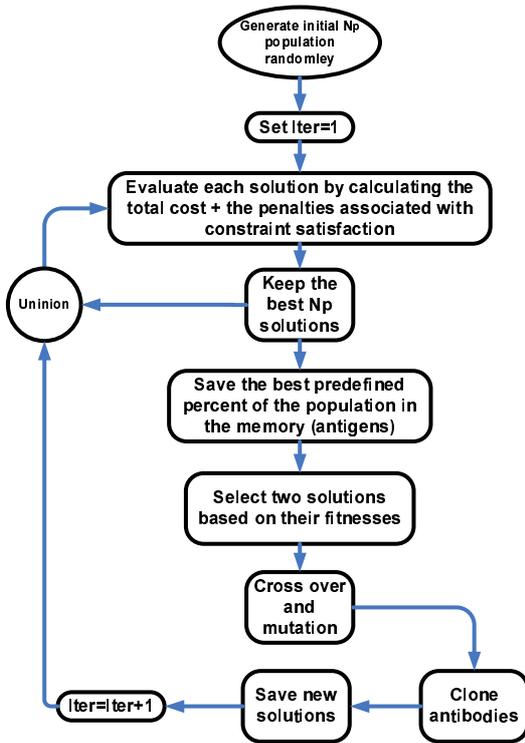


Fig. 1. The flowchart of the proposed hybrid Immune-GA

IV. CASE STUDIES AND NUMERICAL RESULTS

In this section, the proposed IGA is applied on four test systems with different number of generating units. The proposed algorithm is implemented in MATLAB 7 programming language and executed on a Pentium IV, 3-GHz, 2-GB RAM processor. For all cases, The dispatch horizon is selected as one day with 24 dispatch periods of each one hour. The hourly load profile for all cases are presented in Table. I. The IGA parameters are assumed are as follows: N is 100, β is 30%, ς^{max} is 5%. 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.

TABLE I
HOURLY LOAD PROFILE FOR CASE STUDY SYSTEMS.

Hour	Case 1	Case 2&3	Case 4
1	410	1036	3108
2	435	1110	3330
3	475	1258	3774
4	530	1406	4218
5	558	1480	4440
6	608	1628	4884
7	626	1702	5106
8	654	1776	5328
9	690	1924	5772
10	704	2072	6216
11	720	2146	6438
12	740	2220	6660
13	704	2072	6216
14	690	1924	5772
15	654	1776	5328
16	580	1554	4662
17	558	1480	4440
18	608	1628	4884
19	654	1776	5328
20	704	2072	6216
21	680	1924	5772
22	605	1628	4884
23	527	1332	3996
24	463	1184	3552

A. Case 1: Five unit system

The first test system is a 5-unit test system. The data for this system is provided in [31]. The B -matrix coefficients of this system are given in [48]. 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 II shows the obtained results for this system.

TABLE II
OPTIMAL SOLUTION OF 5-UNIT USING IGA ALGORITHM (CASE 1)

Hour	P_1	P_2	P_3	P_4	P_5	Cost(\$)	Loss(MW)
1	10.00	20.00	30.00	124.47	229.52	1226.59	3.99
2	10.00	20.00	54.87	124.91	229.52	1409.12	4.30
3	10.00	27.58	87.91	124.91	229.52	1540.32	4.92
4	10.06	57.58	113.81	125.02	229.52	1639.52	6.00
5	10.00	87.58	112.67	124.91	229.52	1615.30	6.68
6	10.00	98.54	112.67	165.22	229.52	1853.47	7.95
7	10.00	98.50	86.82	209.82	229.52	1852.70	8.65
8	12.71	98.54	112.67	209.82	229.52	1797.26	9.26
9	42.71	105.03	112.92	209.88	229.66	2012.79	10.20
10	64.01	98.54	112.67	209.82	229.52	1996.60	10.56
11	75.00	103.83	112.74	209.96	229.52	2038.13	11.05
12	75.00	98.54	138.64	209.82	229.52	2190.02	11.52
13	64.01	98.54	112.67	209.82	229.52	1996.60	10.56
14	49.62	98.54	112.67	209.82	229.52	1977.66	10.17
15	35.89	98.54	112.67	186.50	229.52	2010.65	9.13
16	10.00	98.54	112.67	136.50	229.52	1682.80	7.23
17	10.00	87.93	112.56	124.91	229.29	1615.81	6.68
18	10.00	98.54	112.67	165.22	229.52	1853.48	7.95
19	12.71	98.54	112.67	209.82	229.52	1797.23	9.26
20	42.71	98.54	133.91	209.82	229.52	2123.66	10.49
21	39.35	98.54	112.67	209.82	229.52	1944.60	9.90
22	10.00	98.54	112.67	162.14	229.52	1843.52	7.87
23	10.00	98.54	112.67	124.91	186.79	1677.55	5.91
24	10.00	98.52	94.39	124.91	139.76	1430.01	4.57
Total						43125.365	194.804

These results are compared with Adaptive particle swarm optimization (APSO) algorithm [25], Simulated annealing (SA) algorithm [31], artificial immune system (AIS) [24], Maclaurin series based Lagrangian method (MSL) [10], Genetic Algorithm (GA) [8], Particle Swarm optimization (PSO) [8], Artificial Bee Colony (ABC) algorithm [8], Time-varying acceleration coefficients IPSO (TVAC-IPSO) [14] and GA [8] in Table III. The maximum iteration number is selected to be 1500. The convergence characteristic of the proposed algorithm is depicted in Fig. 2. By investigating the results presented in Table III, it is observed that the obtained results outperform the existing

methods.

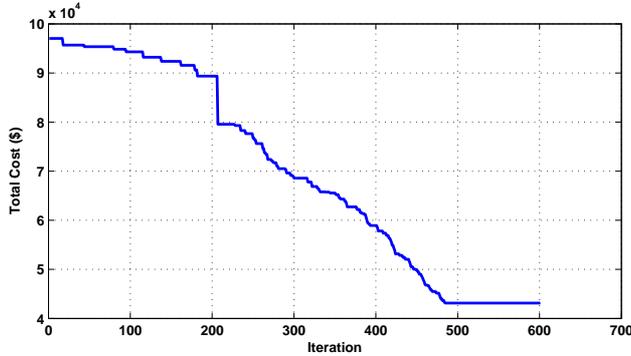


Fig. 2. Convergence characteristics of the IGA algorithm for 5-unit test system

TABLE III
COST AND COMPUTATION TIME COMPARISON OF OPTIMIZATION RESULTS IN CASE 1

Method	Minimum (\$)	Average (\$)	Maximum (\$)	Computation time (min)
SA [31]	47356	NA	NA	5.86
APSO [25]	44678	NA	NA	NA
AIS [24]	44385.43	44758.8363	45553.7707	4
PSO [8]	44253.24	45657.06	46402.52	3.5506
ABC [8]	44045.83	44064.73	44218.64	3.2901
TVAC-IPSO [14]	43136.56	43185.664	43302.233	1.1
MSL [24]	49216.81	NA	NA	0.024
GA [8]	44862.42	44921.76	45893.95	3.3242
Proposed	43125.365	43162.243	43259.352	1.65

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

B. 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 can be found in [48]. Table IV shows the obtained results for 10-unit system without considering transmission losses.

The obtained optimal results are compared with results of previously developed algorithms such as differential evolution (DE) [17], hybrid EP and SQP [12], Hybrid PSO-SQP [37], deterministically guided PSO (DGPSON) [26], modified hybrid EP-SQP (MHEP-SQP) [35], improved PSO (IPSO) [27], Hybrid DE (HDE) [18], Improved DE (IDE) [19], artificial bee colony algorithm (ABC) [8], modified differential evolution (MDE) [20], covariance matrix adapted evolution strategy (CMAES) [49], artificial immune system (AIS) [24], hybrid swarm intelligence based harmony search algorithm (HHS) [4], improved chaotic particle swarm optimization algorithm (ICPSO) [28], hybrid artificial immune systems and sequential quadratic programming (AIS-SQP) [34], hybrid SOA-SQP algorithm [36], chaotic sequence based differential evolution algorithm (CS-DE) [15], chaotic differential evolution (CDE) method [21], adaptive hybrid differential evolution algorithm (AHDE) [50], and enhanced cross-entropy method (ECE) [30] in Table V.

The maximum iteration number is selected to be 2000. The convergence characteristic of the proposed algorithm is depicted in Fig. 3. It is evidently observed that the obtained results with IGA algorithm is less than those of reported in literature.

TABLE V
COST AND COMPUTATION TIME COMPARISON OF OPTIMIZATION RESULTS IN CASE 2

Method	Minimum (\$)	Average (\$)	Maximum (\$)	Computation time (min)
DE [17]	1019786.000	NA	NA	11.25
EP-SQP [12]	1031746.000	1035748.000	NA	20.51
PSO-SQP [37]	1027334.000	1028546.000	1033986.000	16.37
DGPSON [26]	1028835.000	1030183.000	NA	15.39
MHEP-SQP [35]	1028924.000	1031179.000	NA	21.23
IPSO [27]	1023807.000	1026863.000	NA	0.06
HDE [18]	1031077.000	NA	NA	NA
IDE [19]	1026269.000	NA	NA	NA
ABC [8]	1021576.000	1022686.000	1024316.000	2.6029
MDE [20]	1031612.000	1033630.000	NA	12.50
CMAES [49]	1023740.000	1026307.000	1032939.000	0.63
AIS [24]	1021980.000	1023156.000	1024973.000	19.01
HHS [4]	1019091.000	NA	NA	12.233
ICPSO [28]	1019072.000	1020027.000	NA	0.467
AIS-SQP [34]	1029900.000	NA	NA	NA
SOA-SQP [36]	1021460.010	NA	NA	NA
CS-DE [15]	1023432.000	1026475.000	1027634.000	0.24
CDE [21]	1019123.000	1020870.000	1023115.000	0.32
AHDE [50]	1020082.000	1022474.000	NA	NA
ECE [30]	1022271.579	1023334.930	NA	NA
Proposed	1018473.380	1019328.460	1022283.542	3.53

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

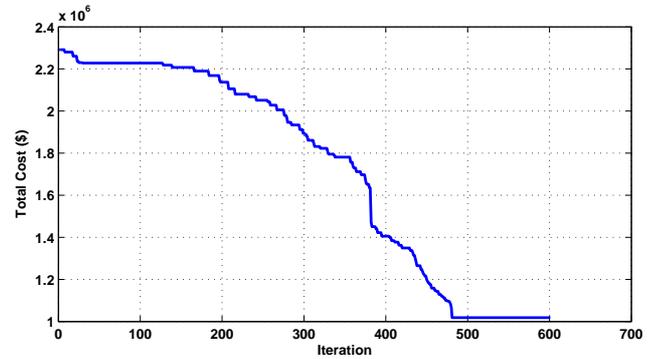


Fig. 3. Convergence characteristics of the IGA algorithm for 10-unit test system

C. 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 in per unit in 100 MW base can be found in [31]. The proposed algorithm applied to ten-unit test case with taking into account the transmission losses. The corresponding generation dispatch is presented in Table VI.

The obtained optimal results are compared with the results of Evolutionary Programming (EP) [35], hybrid EP-SQP (EP-SQP) [35], modified hybrid EP-SQP (MHEP-SQP) [35], GA [8], PSO [8], improved PSO (IPSO) [27], enhanced cross-entropy method (ECE) [30] and artificial immune system (AIS) [24] in Table VII.

TABLE VII
COST AND COMPUTATION TIME COMPARISON OF OPTIMIZATION RESULTS IN CASE 3

Method	Minimum (\$)	Average (\$)	Maximum (\$)	Computation time (min)
EP [35]	1054685	1057323	NA	47.23
EP-SQP [35]	1052668	1053771	NA	27.53
MHEP-SQP [35]	1050054	1052349	NA	24.33
GA [8]	1052251	1058041	1062511	3.4456
PSO [8]	1048410	1052092	1057170	4.0933
IPSO [27]	1046275	1048145	NA	NA
ECE [30]	1043989.154	1044470.0849	NA	NA
ABC [8]	1043381	1044963	1046805	3.4083
AIS [24]	1045715	1047050	1048431	23.22
Proposed	1041087.802	1042980.147	1044926.653	3.8

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

TABLE IV
OPTIMAL 24-HOUR SCHEDULE OF 10-UNIT TEST SYSTEM NEGLECTING TRANSMISSION LOSSES (CASE 2)

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost (\$)
1	150.00	135.00	193.43	60.00	122.87	123.12	129.59	47.00	20.00	55.00	28240.69
2	226.66	135.00	190.96	60.00	122.88	122.90	129.60	47.00	20.00	55.00	29830.09
3	303.25	142.27	185.25	60.00	172.86	142.79	129.59	47.00	20.00	55.00	33342.17
4	379.87	222.27	197.08	60.00	172.74	122.45	129.59	47.00	20.00	55.00	36291.06
5	379.87	222.27	185.19	60.00	222.60	158.48	129.59	47.00	20.00	55.00	37986.53
6	456.49	302.27	260.14	62.37	172.73	122.41	129.59	47.00	20.00	55.00	41423.26
7	379.87	309.53	303.50	112.37	222.63	122.51	129.59	47.00	20.00	55.00	42802.50
8	456.50	316.80	297.96	120.42	172.73	160.00	129.59	47.00	20.00	55.00	44600.31
9	456.50	396.80	305.55	130.96	222.60	160.00	129.59	47.00	20.00	55.00	47875.33
10	456.50	460.00	302.04	180.96	222.60	160.00	129.59	55.31	50.00	55.00	51946.10
11	456.50	460.00	326.04	230.96	222.60	160.00	129.59	85.31	20.00	55.00	53612.65
12	456.50	460.00	339.31	241.25	243.00	160.00	129.63	85.31	50.00	55.00	55663.56
13	456.50	396.80	310.38	235.82	222.60	160.00	129.59	85.31	20.00	55.00	51402.52
14	456.50	396.80	299.79	185.82	172.73	122.45	129.59	85.31	20.00	55.00	47799.73
15	379.87	396.75	287.02	177.13	122.87	122.45	129.59	85.31	20.00	55.00	44601.80
16	303.25	316.75	321.50	127.13	73.00	122.46	129.60	85.31	20.00	55.00	39939.73
17	226.60	309.53	288.30	120.38	122.86	122.43	129.59	85.31	20.00	55.00	37974.15
18	303.25	314.06	305.08	120.42	172.74	122.54	129.60	85.31	20.00	55.00	41275.92
19	379.86	394.06	296.58	120.42	172.73	122.45	129.59	85.31	20.00	55.00	44391.27
20	456.50	460.00	340.00	170.42	222.60	132.58	129.60	85.31	20.00	55.00	51860.44
21	456.50	389.54	322.55	120.42	222.63	122.45	129.60	85.31	20.00	55.00	47914.43
22	379.79	309.54	283.19	70.42	172.73	122.44	129.59	85.31	20.00	55.00	41282.78
23	303.25	229.54	203.19	60.00	123.00	123.12	129.59	85.31	20.00	55.00	34953.61
24	226.63	222.27	189.58	60.00	73.00	122.62	129.60	85.31	20.00	55.00	31462.75
Total											1018473.380

TABLE VI
OPTIMAL 24-HOUR SCHEDULE OF 10-UNIT TEST SYSTEM CONSIDERING TRANSMISSION LOSSES (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	150.00	135.00	202.22	60.00	122.90	126.41	129.60	47.00	20.00	55.00	28608.59	12.14
2	226.64	137.46	197.57	60.00	123.04	127.11	129.59	47.00	20.00	55.00	30274.05	13.41
3	303.25	142.27	186.03	60.00	172.74	160.00	130.00	47.00	20.00	55.00	33733.61	18.28
4	379.87	222.27	221.95	60.00	172.73	122.45	130.00	47.00	20.00	55.00	36999.72	25.28
5	379.89	225.96	208.31	60.00	222.73	160.00	129.59	47.00	20.00	55.00	38851.32	28.48
6	456.48	305.96	288.31	66.04	172.73	122.45	129.59	47.00	20.00	55.00	41956.89	35.56
7	379.87	309.53	303.99	116.04	222.73	122.69	129.59	77.00	20.00	55.00	43797.56	34.45
8	456.50	310.44	297.23	166.04	172.73	160.00	129.59	47.00	20.00	55.00	45589.58	38.52
9	456.50	390.44	300.32	180.83	222.73	160.00	129.59	55.31	20.96	55.00	49250.32	47.68
10	456.50	460.00	316.57	191.31	222.60	160.00	129.59	85.31	50.96	55.00	53264.45	55.84
11	456.59	460.00	340.00	241.31	223.67	160.00	129.59	85.32	52.06	55.00	55019.27	57.54
12	456.51	460.00	340.00	241.25	242.03	160.00	129.59	115.32	80.00	55.00	57657.18	59.70
13	456.50	396.80	325.96	241.25	222.71	160.00	129.59	85.32	50.00	55.00	52780.38	51.12
14	456.50	396.80	297.36	233.52	172.71	122.45	129.59	85.31	20.00	55.00	48916.02	45.23
15	379.87	396.63	310.10	183.52	123.00	131.26	130.00	85.31	20.00	55.00	45556.45	38.69
16	303.25	316.63	297.22	178.90	73.00	122.45	129.59	85.31	20.00	55.00	40409.72	27.34
17	226.63	309.53	301.11	128.90	123.00	127.02	129.59	85.31	20.00	55.00	38667.14	26.09
18	299.87	309.53	297.26	166.11	172.73	122.44	129.59	85.31	20.00	55.00	42115.73	29.85
19	379.87	389.53	297.40	163.32	172.72	122.44	129.59	85.31	20.00	55.00	45638.91	39.18
20	456.50	460.00	327.71	180.83	222.72	160.00	129.59	85.31	50.00	55.00	53187.96	55.66
21	456.50	389.53	318.18	170.42	222.63	122.48	129.60	85.31	20.00	55.00	49130.96	45.64
22	379.86	309.53	264.80	120.42	172.63	122.44	129.59	85.31	20.00	55.00	42092.45	31.57
23	303.25	229.53	213.62	70.42	123.00	122.45	129.59	85.31	20.00	55.00	35608.19	20.17
24	226.65	222.27	198.48	62.82	73.00	126.61	130.00	85.31	20.00	55.00	31981.37	16.14
Total											1041087.802	853.53

TABLE VIII
COST COMPARISON OF OPTIMIZATION RESULTS FOR 30-UNIT TEST SYSTEM (CASE 4)

Method	Minimum (\$)	Average (\$)	Maximum (\$)
EP [12]	3164531	3,200,171	NA
EP-SQP [12]	3159204	3,169,093	NA
MEP-SQP [35]	3151445	3,157,438	NA
IPSO [27]	3090570	3,090,570	NA
ICPSO [28]	3064497	3,071,588	NA
HS [4]	3143253.84	NA	NA
HHS [4]	3057313.39	NA	NA
DGPSO [26]	3148992	3,154,438	NA
CE [30]	3086109.595	3,088,869.8572	NA
ECE [30]	3084649.032	3,087,847.1893	NA
Proposed	3055435.068	3058126.233	3066754.92

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

D. Case 4: Thirty unit system

This case is a 30-unit test system which is obtained by tripling the ten-unit system of Case 2. The load demand is given in Table I. The obtained results for this case are compared with results reported in literature in Table VIII. The compared methods include evolutionary programming (EP) [12], hybrid EP and SQP (EP-SQP) [12], modified hybrid EP and SQP (MEP-SQP) [35], improved PSO (IPSO) [27], Improved chaotic particle swarm optimization algorithm (ICPSO) [28], harmony search algorithm (HS) [4], hybrid swarm intelligence based harmony search algorithm (HHS) [4], deterministically guided PSO (DG-PSO) [26], cross-entropy method (CE) [30] and enhanced cross-entropy method (ECE) [30].

E. Effect of wind power generation

In order to investigate the ability of the proposed approach for solving the DED problem in the presence of wind power generation, and its superiority to the existing methods, two additional studies conducted on the 5-unit test system. In the first study (i.e. Case 5), a wind farm with the capacity, equals

to fixed fraction of the system's load demand is considered, in order to compare the obtained results with the results presented in [41]. In the second study (Case 6), forecasted output power of the wind farm considered. In this case, up-spinning reserves (USR) and down-spinning reserves (DSR) are also included in

the DED model, through the following equations.

$$USR_t = \sum_{i=1}^N RU_{it} \geq LSR_t + WP_t \times u \quad (12)$$

$$RU_{it} = \min(P_i^{max} - P_{it}, UR_i) \quad (13)$$

where, USR_t indicates the required total USR at time t . RU_{it} is the supplied USR by unit i . LSR_t and WP_t are the required spinning reserve and forecasted wind power, respectively. u is the percentage of wind generation contributing to the USR.

$$DSR_t = \sum_{i=1}^N RD_{it} \geq (WP^{max} - WP_t) \times d \quad (14)$$

$$RD_{it} = \min(P_{it} - P_i^{min}, DR_i) \quad (15)$$

where, RD_{it} is the supplied DSR by unit i . d is the percentage of wind generation contributing to the DSR and WP^{max} represents the maximum power capacity of wind turbines. It should be noted that the real power balance constraint equation (3) should be modified considering wind power generation as follows:

$$\sum_{i=1}^N P_{it} + WP_t = P_D(t) + P_{loss}(t) \quad (16)$$

In the following two cases, the USR and DSR requirement are considered as a simple fraction of the total wind power generation, i.e. ($u\% = 20$) and ($d\% = 40$). Also, the LSR_t is assumed to be a fraction of 10% the corresponding hourly load (i.e. $LSR_t = 0.1 \times P_D(t)$).

1) *Case 5*: Similar to [41], in this case it assumed that the wind power capacity of wind farm in each hour is a fraction of the system load demand in that hour. Specifically, it is assumed that the wind generation capacity in each hour equals to 10% of that hour's active power demand. Also, valve point effects, ramp-rate limits and transmission losses are considered, without considering USR and DSR constraints. Table IX gives the obtained results by the HIGA algorithm. The obtained thermal power generation cost, and transmission losses are \$40,096.41 and 155.129 MW, respectively. The obtained total power loss is 1.064% of the system total load demand. These results are compared with the results presented in [41], i.e. the total cost of \$47,522.60, and total transmission loss of 1.155% (i.e. 168.36 4MW). This comparison indicates that the proposed IGA approach obtains a solution with lower cost and less transmission losses.

2) *Case 6*: The forecasted power output of the wind farm with 70MW capacity, is presented in Fig. 4. In this case, USR and DSR constraints along with valve-points effect, transmission losses and ramp-rate constraints are considered. The system reserve requirement (LSR) is supposed to be 10% of the total system load at each hour. Table X gives the obtained results by the proposed HIGA approach. The overall cost of thermal power generation, and transmission losses are obtained equal to \$40,403.957 and 165.957 MW (1.138% of the system total load), respectively. Due to the uncertain nature of wind power generation, the USR and DSR are employed to ensure the reliability of the system in the presence of wind farms. Consequently, the total cost in Case 6 is higher than that in Case 5, where the wind power generation effects in the USR and

TABLE IX
OPTIMAL SOLUTION OF 5-UNIT TEST SYSTEM CONSIDERING WIND POWER GENERATION (CASE 5)

Hour	P_1	P_2	P_3	P_4	P_5	Loss(MW)	Cost(\$)
1	10.00	67.41	30.00	124.91	139.76	3.08	1243.78
2	10.00	90.36	30.00	124.88	139.76	3.50	1208.42
3	10.00	88.19	68.61	124.89	139.76	3.95	1459.43
4	10.00	98.54	108.61	124.91	139.76	4.82	1385.43
5	40.00	90.16	112.65	124.90	139.73	5.23	1564.16
6	70.00	106.07	112.69	124.92	139.76	6.24	1647.05
7	75.00	98.77	112.69	143.79	139.76	6.61	1745.24
8	75.00	98.54	112.67	124.91	184.73	7.25	1887.48
9	63.54	98.54	112.67	124.91	229.52	8.18	1798.19
10	75.00	99.99	112.69	124.91	229.52	8.51	1807.71
11	75.00	114.82	112.69	124.91	229.52	8.94	1920.66
12	75.00	98.54	112.67	159.65	229.52	9.38	2048.04
13	75.00	99.98	112.71	124.91	229.52	8.51	1807.72
14	63.53	98.54	112.67	124.91	229.52	8.18	1798.20
15	75.00	98.54	112.67	124.91	184.73	7.25	1887.48
16	51.78	98.54	112.67	124.91	139.76	5.66	1572.97
17	45.00	85.09	112.66	124.91	139.76	5.22	1595.50
18	75.00	100.90	112.84	124.93	139.76	6.23	1605.10
19	75.00	98.54	112.67	124.91	184.73	7.25	1887.48
20	75.00	99.98	112.71	124.91	229.52	8.51	1807.72
21	54.31	98.54	112.68	124.91	229.52	7.95	1788.96
22	33.30	98.54	112.67	124.91	181.31	6.23	1801.51
23	10.00	98.54	112.67	118.08	139.76	4.75	1400.17
24	10.00	89.89	112.66	68.08	139.76	3.69	1428.00
Total						155.129	40096.41

DSR constraints are not considered. By comparing the obtained optimal values for fuel costs in Cases 1, 5 and 6, it is concluded that contribution of wind power generation in the DED problem considerably reduces the fuel cost and transmission losses.

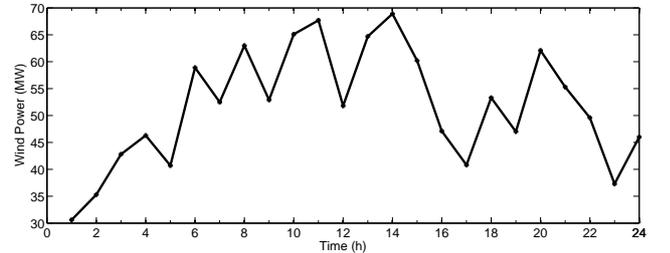


Fig. 4. Forecasted wind power profile for the study period.

V. DISCUSSION OF THE RESULTS

The results are compared in terms of minimum cost, mean cost, and maximum cost over 100 runs with the results of other reported algorithms in six case studies. The results of the aforementioned methods that presented in Tables III, V, VII, VIII, have been directly quoted from their corresponding references. Observing the results obtained from the proposed methodology, the following re-marks are made:

- The minimum and maximum solutions of the proposed method are close to each other, which indicates stability of the results of the IGA.
- The proposed algorithm always gives the minimum cost less than the other methods.
- It is observed that the proposed method performance is better for large scale cases too, and the proposed method can be used for scheduling of practical large power systems. The computational burden of the algorithm is not high.
- By comparing the obtained results, with and without considering wind power generations, it is evidently observed

TABLE X
OPTIMAL SOLUTION OF 5-UNIT TEST SYSTEM CONSIDERING WIND POWER
GENERATION AND RESERVE CONSTRAINTS (CASE 6)

Hour	P_1	P_2	P_3	P_4	P_5	Loss(MW)	Cost(\$)
1	10.00	20.00	30.00	93.35	229.52	3.47	1320.22
2	10.00	20.00	30.00	124.90	218.56	3.77	1272.42
3	10.00	20.00	30.00	147.10	229.52	4.42	1406.81
4	12.64	20.00	30.00	197.10	229.52	5.56	1490.72
5	10.00	20.00	54.12	209.82	229.52	6.16	1602.97
6	10.00	20.00	86.45	209.82	229.52	6.68	1683.66
7	10.00	20.00	111.30	209.82	229.52	7.14	1615.74
8	10.00	36.54	112.67	209.82	229.52	7.55	1729.23
9	27.24	66.54	112.67	209.82	229.52	8.69	1946.52
10	10.00	87.13	111.27	209.82	229.52	8.84	1819.97
11	10.95	98.56	112.67	209.82	229.52	9.22	1786.17
12	40.00	106.32	112.69	209.83	229.52	10.16	2009.07
13	10.00	86.13	112.67	209.82	229.52	8.84	1817.43
14	10.00	67.44	112.65	209.82	229.52	8.33	1841.16
15	11.94	37.44	112.67	209.83	229.52	7.61	1747.52
16	10.00	20.00	112.67	166.80	229.52	6.10	1688.39
17	24.51	20.00	112.67	136.19	229.52	5.70	1601.22
18	10.00	22.94	112.67	186.19	229.52	6.62	1714.17
19	10.00	52.94	112.68	209.82	229.52	7.95	1812.71
20	15.83	82.94	112.67	209.82	229.52	8.88	1862.33
21	28.11	52.94	112.67	209.82	229.52	8.35	1923.34
22	10.00	22.94	112.67	186.91	229.52	6.64	1712.76
23	31.86	20.00	76.65	136.91	229.52	5.24	1720.33
24	10.00	20.00	36.65	124.91	229.52	4.07	1279.12
Total						165.96	40403.96

that the fuel cost of thermal power generation cost and transmission losses are reduced in the presence of wind power generation. Besides, considering USR and DSR constraints in order to compensate the errors in forecasting the scheduled wind farms' output power, increases the fuel costs and transmission losses, in comparison with the case of neglecting reserve constraints.

- The computation time of the proposed algorithm is acceptable for DED problem solution. It is worth to mention that the DED problem is solved offline and solution time of several minutes is acceptable. However if the network's power flow constraints are also considered, the problem would become a DED-OPF. The non-convexity of this problem can be dealt with semi-definite programming (SDP) optimization to construct the dual of an equivalent form of the problem. For real time applications of DED-OPF problem, the method presented in [51] can be helpful.

VI. CONCLUSION

A heuristic optimization method called immune genetic algorithm (IGA) is developed for determination of optimal solution for dynamic economic dispatch (DED) problem. The practical operational constraint of generators like ramp-rate limits and valve-point effects along with transmission loss constraints are considered in the analysis. The feasibility and efficiency of the proposed method was demonstrated on five, ten, and thirty-unit test systems. The numerical results have been compared with the recently reported approaches. Besides, due to the recent trends toward utilization of wind power generation, applicability of the proposed IGA approach to solve DED with wind power generation constraints, is investigated. The numerical results reveal that the dispatch solution obtained by the proposed IGA approach, leads to a less operating cost than those found by other methods, which shows the capability of the algorithm to determine the global or near global solutions for DED problem.

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