Optimal Dynamic Economic Dispatch Including Renewable Energy Source using Artificial Bee Colony Algorithm

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Abstract— **Power utilities strive for optimal economic operation of their electric networks while considering the challenges of escalating fuel costs and increasing demand for electricity. The dynamic economic dispatch (DED) occupies a prominent place in a power system's operation and control. It aims to determine the optimal power outputs of on-line generating units in order to meet the load demand subject to satisfying various operational constraints over finite dispatch periods. Similar to most real-world complex engineering optimization problems, the nonlinear and nonconvex characteristics are more prevalent in the DED problem. Therefore, obtaining a truly optimal solution presents a challenge. In this paper, the artificial bee colony (ABC) algorithm – a recently introduced population-based technique – is utilized to solve the DED problem. Integrating a renewable-energy source and analyzing its impact is considered as well. A sample test system with a dispatch period of 24-hour is designated to validate the outcomes. The promising results prove that the ABC algorithm has a great potential to be applied in different electric power system optimization areas.**

Keywords-component; Artificial Bee Colony (ABC) Algorithm; Dynamic Economic Dispatch (DED) Problem; Renewable Energy Sources.

I. INTRODUCTION

The ultimate goal of power plants is to meet the required load demand with the lowest operating costs possible while taking into consideration practical equality and inequality constraints algorithms. Optimal operation of electric power system networks is a challenging real-world engineering problem. Indeed, the optimal operation of these networks is the result of multiple optimization problems that interact with each other sufficiently and efficiently. Those – linked – optimization problems are the unit commitment, optimal power flow, and economic dispatch scheduling.

The dynamic economic dispatch (DED) occupies a prominent place in a power system's operation and control. The goal of DED is to determine the optimal power outputs of on-line generating units in order to meet the load demand subject to satisfying various operational constraints over finite dispatch periods. In practice, there are static economic dispatch (SED) and DED problems. The latter considers additional practical constraints such as upper and lower bounds on the units' ramping-rates. In reality, units will not respond to steep or instantaneous load variations. Early research works responding to this aspect were published in the 1970s [1, 2]. Most of the early methods proposed to solve the DED problem used deterministic techniques such as non-linear programming (NLP) [3], dynamic programming (DP) [4], and variational techniques based on Lagrange multipliers [5].

Optimization based on swarm intelligence, known as meta-heuristic algorithms, gained popularity in solving complex and real-world optimization problems years ago. Because the performance of most of the meta-heuristic methods are independent of the initial solutions and are derivative-free, they overcome the main limitations of deterministic optimization methods, e.g., getting trapped in local extrema and divergence situations. An example of the recently introduced meta-heuristic methods is the artificial bee colony (ABC) algorithm. It is a population-based technique proposed late in 2005 [6], and inspired by the intelligent foraging behaviour of the honeybee swarm. The DED problem was one of the real-world optimization problems that has benefited from the development of the meta-heuristic algorithms. Based on the genetic algorithm (GA), the authors in [7] and [8] suggested a GA-based method to solve the DED problem. The particle swarm optimization (PSO) method is also utilized in [9] and [10] to solve the DED problem. An evolutionary programming (EP) technique in [11] and [12] is adopted to solve the DED problem. Simulating annealing method (SA), quantum evolutionary algorithm (QEA), and Tabu search approach (TS) have been also designated to solve the DED problem in [13], [14], and [15], respectively.

Although renewable sources, e.g., wind, tidal, and photovoltaic, are environmentally-friendly practices, the intermittent nature of the renewable sources choices degrades their applicability as dispatchable options [16]. Despite that, according to the Global Wind Energy Council (GWEC) [17], the installed capacity of wind power farms in Canada is increasing exponentially, as Fig. 1indicates.

In this paper, the ABC algorithm is proposed to solve the DED problem. In addition, the ABC algorithm is utilized to verify the efficiency of a previously introduced – by the same authors – constrained search-tactic [18] in solving high dimensional dynamic problems. An attempt to integrate a

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renewable resource and analyze its impact is considered. A sample system with a 24-hour dispatch period is adopted to validate the proposed algorithm competence.

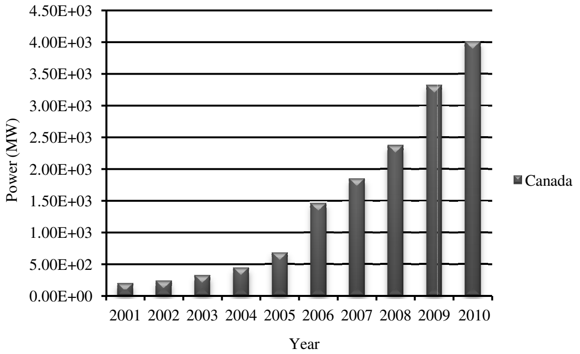

Figure 1. Total installed capacity of wind power in Canada.

This paper is organized as follows: Section II offers the mathematical formulations of the DED problem. Section III presents a brief description of the ABC optimization algorithm. Computational results and comparative study are demonstrated in sections IV. Section V contains the conclusion.

II. Mathematical Formulations

A. Objective Function

Since the objective function of the DED problem is to minimize the operating fuel's costs of committed generating units to meet the load demand, subject to equality and inequality constraints over a predetermined dispatch period, the result's practical usefulness will be degraded if the units' valve-point effects are neglected. Consequently, there are two models to represent the units' valve-point effects in the literature [19]. The first represents the units' valve-point effects in terms of prohibited operating zones which are included as inequality constraints. The second form represents the units' valve-point effects as a rectified sinusoid term which is superimposed on the approximate quadratic fuel cost function. The general mathematical form of the DED problem is as follows:

$$\boldsymbol{F} = min \sum_{t=1}^{T} \sum_{i=1}^{N} f_i \left(P_i^t\right)$$

$$f_i(P_i) = a_i + b_i P_i + c_i {P_i}^2 + \left| d_i \times sin\left(g_i \times \left(P_{i,min} - P_i\right)\right)\right| \quad (1)$$

where, f_i (P_i) is the fuel cost function of i^{th} generator; P_i^t is the output power of i^{th} generator at a time t, $\forall$ $i \in \{1, 2, \ldots, N\}$ and $\forall$ $t \in \{1, 2, \ldots, T\}$; a_i, b_i, c_i, d_i, and g_i are the i^{th} generator's coefficients, and $P_{i\,min}$ is the minimum limit of i^{th} generator.

B. Equality Constraints

It is impractical to neglect the system's transmission losses so the B-coefficient formula is commonly used to express it. Thus, the real power balance equation representing equality constraints of the problem considered is as follows:

$$\sum_{t=1}^{T} \sum_{i=1}^{N} P_i^t = \sum_{t=1}^{T} P_D^t + P_L^t \quad (2)$$

Integration of a renewable source (RS) modifies the equality constraints function [16] to be as follows:

$$\sum_{t=1}^{T} \sum_{i=1}^{N} P_i^t = \sum_{t=1}^{T} \left(P_D^t + P_L^t - \sum_{RS=1}^{M} \mu_{RS}\, P_{RS}^t \right) \quad (3)$$

where, $P_D{}^t$ and $P_L{}^t$ are the load demand and system's loss at a time t respectively. The multiplier μ_{RS} is set to a permissible amount of active power injected by RS, $P_{RS}{}^t$ is the forecasted real power from RS at time t $\forall$ $RS \in \{1, 2, \ldots, M\}$. In this paper, μ_{RS} is set to one.

The system's active power loss can be calculated using George's loss expression [20] as follows:

$$\sum_{t=1}^{T} P_L^t = \sum_{t=1}^{T} \sum_{j=1}^{N} \sum_{i=1}^{N} P_i^t B_{ij} P_j^t \quad (4)$$

where, B_{ij} is the ij^{th} element of the loss coefficient square matrix.

C. Inequality Constraints

The inequality constraints of the DED problem are the units' ramp-rate limits, i.e., upper rate (UR_i) and down rate (DR_i), are considered as follows:

$$\begin{aligned} P_i^t - P_i^{t-1} &\le UR_i \\ P_i^{t-1} - P_i^t &\le DR_i \end{aligned} \quad (5)$$

Additional inequality constraints are the minimum and maximum power output of each unit:

$$P_{i,min} \le P_i \le P_{i,max} \quad (6)$$

Therefore, to incorporate the constraints of units' ramp-rate limits (5) in the real power output limit constraints (6), the modified units' real power outputs are evaluated [21] as follows:

$$\begin{aligned} P_{i,min}^t &= max\left(P_{i,min}, P_i^{t-1} - DR_i\right) \\ P_{i,max}^t &= min\left(P_{i,max}, P_i^{t-1} + UR_i\right) \end{aligned} \quad (7)$$

The following inequality constraints describe the case when units have prohibited operating zones [9] defined by:

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

where, $P^{\,l}{}_{i,1}$ is the lower limit of the first prohibited zone of the i^{th} generator; $P^{\,u}{}_{i,j\text{-}1}$ is the upper limit of the (j-1)th prohibited zone of the i^{th} generator; $P^{\,u}{}_{i,ni}$ is the upper limit of the n^{th} prohibited zone of the i^{th} generator; n_i is the number of prohibited zones in the i^{th} generator.

III. Artificial Bee Colony Algorithm

Inspired by the intelligent foraging behaviour of honeybee swarms, the ABC algorithm was introduced [6] and [22]. The colony of artificial bees consists of three groups: employed, onlookers, and scout bees. The employed bees (E_b) randomly search for food-source positions (solutions.) By dancing they share information (communicate) about that food source, such as nectar amounts (solutions qualities), with the onlooker bees (O_b) waiting in the dance area at the hive. The duration of a dance is proportional to the nectar's content (fitness value) of the food source being exploited by the employed bee. Onlooker bees watch various dances before choosing a food-source position, according to the probability proportional to the quality of that food source. Consequently, a good food-source position attracts more bees than a bad one. Onlookers and scout bees, once they discover a new food-source position, may change their status to become employed bees. When the food-source position has been visited (tested) fully, the employed bee associated with it abandons it and may once more become a scout or onlooker bee.

It is clear that the ABC algorithm has the following control parameters: 1) the *CS* that consists of employed bees (E_b) plus onlooker bees (O_b), 2) the *limit* value, which is the number of trials for a food-source position to be abandoned, and 3) the maximum cycle number (*MCN*.) Although the ABC algorithm has three parameters to be tuned, once the *CS* parameter has been determined by the practitioner, the *limit* value can be calculated easily as half of the *CS* multiplied by the problem's dimension. Therefore, technically speaking, the ABC algorithm has only two parameters to be adjusted: *CS* and the *MCN* values. Updating these two parameters towards the most effective values has a higher likelihood of success than in other competing meta-heuristic methods. The pseudo-code of the ABC algorithm is as follows:

1. Initialize the population.
2. Modify positions.
3. Apply selection criterion.
4. ***Repeat*** (cycle.)
5. Allow the employed bees to share the food information with onlooker bees.
6. Allow the onlooker bees to choose the best food source based on the probability calculation.
7. Apply selection criterion.
8. Check for an abundant solution, and (if exists) initiate a new food-source position. Otherwise, follow the next step.
9. Retain best solution so far.
10. ***Until*** stopping rule.

IV. Results and Discussion

The five units system is selected to verify the validity of the proposed algorithm. The acceptable violation of equality constraints is adjusted to be $\leq 10^{-4}$. The control parameters of selected techniques are tuned after trial-and-error experiments. The proposed search-tactic is implemented in C, and executed on an Intel® core™ 2 duo PC with 2.66-GHz speed and 4GB RAM. The results are obtained after carrying out 30 independent runs for each system, and are compared with those obtained using other well-known algorithms. It is important to mention that the constraints of the DED are handled using the penalty factor method. The performance of the ABC algorithm without and with the integration of the constrained search-tactic reported in [18] is analyzed as well. Two test cases are examined, and the results are compared with those of other well-known methods. The integration of a renewable energy source is considered in the second test case. Details of test cases are highlighted in the following sub-sections.

A. Case 1

The aim of this system is to operate its five generating units economically to meet the 24-hour load demand subject to satisfying various equality and inequality constraints. Table I records the five units' coefficients and characteristics. This system's constraints are the transmission losses using George's loss expression, units' bound limits, and unit's ramp-rate limits. The operating fuel cost's function superimposes the unit's prohibited operating zones by a rectify sinusoid term. The system's load demand and *B*-loss coefficient matrix are reported in Table II and Table III respectively. The ABC algorithm is designated to solve this system with, and without the integration of the constrained search-tactic reported in [18].

TABLE I. GENERATING UNITS' COEFFICIENTS AND CHARACTERISTICS FOR THE 5-UNIT SYSTEM.

Units	1	2	3	4	5
P^0 (MW)	50.7118	40.9004	100.0930	116.8943	161.0431
P_{min} (MW)	10.0000	20.0000	30.0000	40.0000	50.0000
P_{max} (MW)	75.0000	125.0000	175.0000	250.0000	300.0000
a ($)	25.0000	60.0000	100.0000	120.0000	40.0000
b ($/MW)	2.0000	1.8000	2.1000	2.0000	1.8000
c ($/MW^2)	0.0080	0.0030	0.00120	0.0010	0.0015
d ($)	100.000	140.0000	160.0000	180.0000	200.0000
UR (MW/h)	30.0000	30.0000	40.0000	50.0000	50.0000
DR (MW/h)	30.0000	30.0000	40.0000	50.0000	50.0000

TABLE II. LOAD DEMAND FOR THE 5-UNIT SYSTEM.

Hour (h)	P_D (MW)	Hour (h)	P_D (MW)
1	410	13	704
2	435	14	690
3	475	15	654
4	530	16	580
5	558	17	558
6	608	18	608
7	626	19	654
8	654	20	704
9	690	21	680
10	704	22	605
11	720	23	527
12	740	24	463

TABLE III. *B*-LOSS COEFFICIENTS' MATRIX FOR THE 5-UNIT SYSTEM.

i \ *j*	1	2	3	4	5
1	0.000049	0.000014	0.000015	0.000015	0.000020
2	0.000014	0.000045	0.000016	0.000020	0.000018
3	0.000015	0.000016	0.000039	0.000010	0.000012
4	0.000015	0.000020	0.000010	0.000040	0.000014
5	0.000020	0.000018	0.000012	0.000014	0.000035

After trail-and-error experiments, the ABC parameters: *CS*, *limit*, and *MCN* were tuned as 300, 18×10^3, and 30×10^3 respectively. Utilizing the constrained search-tactic [18] will alter the main objective function for the first 3×10^3 (φ) iterations.

As presented in Table IV, the integration of the constrained search-tactic [18] enhanced the ABC algorithm's performance resulting in a significant reduction (4.41%) in the operating fuel's cost. The cost saving ($2,254.60 daily) is shown in Fig. 2. An average 21% reduction in the required CPU time was obtained as well. The load demand curve, each committed unit's output power, and the total system's input power are exemplified in Fig. 3. The optimal dispatched power for this system guaranteed that the system's constraints were satisfied during the 24-hour dispatch period, as shown in Table V and Fig. 3. In other words, the output power of each unit in every time interval was consistent with the output power of adjacent units. The ABC algorithm's performance for this system is in Fig. 4.

TABLE IV. COMPARISON OF RESULTS OF THE PROPOSED ABC ALGORITHM FOR CASE 1; MAX: MAXIMUM; AVG.: AVERAGE; MIN: MINIMUM; STD.DEV.: STANDARD DEVIATION.

Method	Max. ($)	Avg. ($)	Min. ($)	Std.Dev.	CPU (s)
ABC	51,868.90	51,462.82	51,102.80	229.191	280.440
ABC*	50,195.90	49,814.28	**48,848.20**	288.168	221.520

* With the integration of the constrained search-tactic offered in [18].

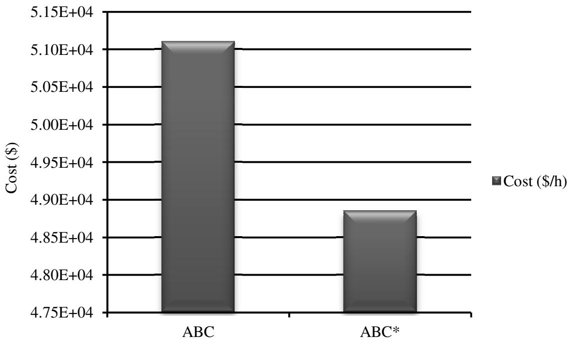

Figure 2. Operating fuel costs for case 1 due to ABC algorithm with and without the integration of the constrained search-tactic.

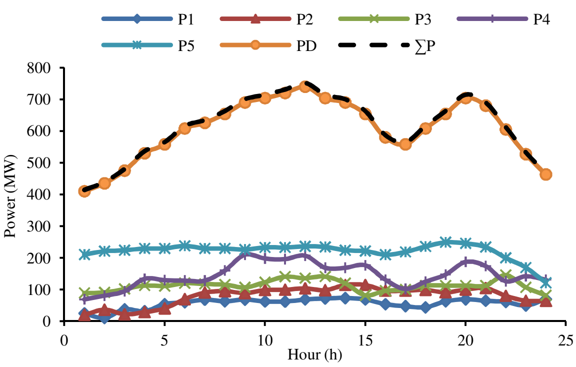

Figure 3. Optimal units' dispatch schedule, load demand curve, and total power supply for case 1.

TABLE V. OPTIMAL DISPATCH POWER FOR CASE 1 USING ABC ALGORITHM WITH THE INTEGRATION OF THE CONSTRAINED SEARCH-TACTIC.

Time (h)	Units' optimal output power and total power supply, both in (MW)					
	P_1	P_2	P_3	P_4	P_5	$\sum P$
1	24.90640	20.44230	89.00000	69.00000	210.33820	413.68690
2	10.12730	36.44830	90.92960	80.64500	221.00020	439.15040
3	37.63000	22.00010	101.70000	94.48800	224.03600	479.85410
4	31.17770	28.85390	112.65200	133.75600	229.52000	535.95960
5	53.67679	40.35030	111.01879	130.01300	229.52000	564.57888
6	59.46100	70.00000	120.16420	128.20410	237.96910	615.79840
7	68.10929	90.79000	117.64000	128.21195	229.52000	634.27124
8	62.99900	95.05200	115.43330	160.03000	229.52000	663.03430
9	68.00000	89.09100	106.90000	210.00000	226.16150	700.15250
10	62.15450	98.54000	123.00350	198.01000	232.78100	714.48900
11	61.80400	99.54000	140.59600	195.87000	233.08070	730.89070
12	68.58800	103.76350	135.92940	206.97000	236.30170	751.55260
13	72.12000	98.00810	141.00000	168.87110	234.38000	714.37920
14	73.03300	114.53950	120.01190	168.60430	223.87860	700.06730
15	68.43499	114.54150	82.20120	176.48584	221.58730	663.25083
16	53.50430	96.40200	96.12900	131.11160	210.00000	587.14690
17	47.31110	96.45100	100.02000	102.10090	218.77329	564.65629
18	43.57430	98.89896	112.67330	124.91000	235.81870	615.87526
19	62.43000	91.54000	112.66000	147.31700	249.14970	663.09670
20	68.80430	100.02940	112.67330	187.32000	245.72590	714.55290
21	64.42430	104.60303	112.67310	174.06160	234.05680	689.81883
22	60.60000	80.30000	145.66000	126.01700	200.00000	612.57700
23	49.38430	65.02312	107.03100	142.02000	169.30200	532.76042
24	69.36430	64.35970	81.67300	131.06820	121.00143	467.46663
Total operating fuel cost ($)			**48,848.20**			
Total system's power loss (%)			1.300			

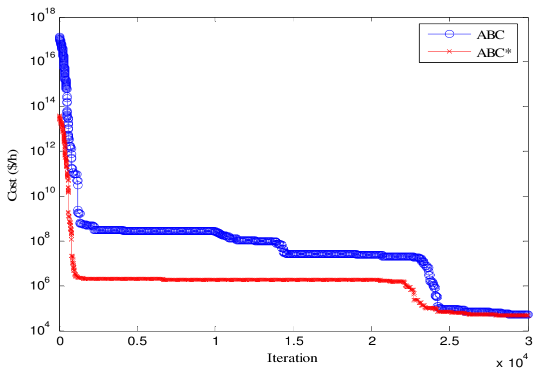

Figure 4. The ABC algorithm's performance for case 1.

B. Case 2

In this test case, the impact of integrating renewable energy resources is examined on the five units system used previously. A wind-power farm is designated to share a 10% of the system's load demand. In addition, the ABC algorithm's parameters are tuned as in case 1. The ABC algorithm with the utilization of that designated tactic [18] is employed in this test case.

As shown in Table VI, and with respect to Table V, the integration of RS decreased the operating fuel cost and the system's transmission losses. The 10% contribution of a RS led to 2.71% reduction in the fuel cost for this system with regard to non-RS integration scenario. The total system's loss is decreased by 20.15% due to the 10% sharing of RS practice. The average CPU time required to attain a solution in this case was approximately 200.000 seconds, which was less than that of the previous test case.

TABLE VI. OPTIMAL DISPATCH POWER FOR CASE 2 USING ABC ALGORITHM WITH THE INTEGRATION OF THE CONSTRAINED SEARCH-TACTIC.

Time (h)	Units' optimal output power and total power supply, both in (MW)					
	P_1	P_2	P_3	P_4	P_5	$\sum P$
1	53.00000	35.00000	80.00000	78.00000	125.80800	371.80800
2	39.65957	64.10482	71.87489	65.53363	153.57705	394.74996
3	49.28233	75.67546	92.35823	76.70595	137.27795	431.29992
4	36.48119	52.14938	105.57053	126.68860	160.80950	481.69920
5	64.99354	56.50897	93.86012	127.53065	164.55193	507.44521
6	57.86589	73.92488	99.40114	163.08726	159.18274	553.46191
7	40.10564	89.02398	121.97463	130.52654	188.38893	570.01972
8	56.10172	106.55467	108.33142	136.19100	188.71398	595.89279
9	74.25326	97.08604	134.72116	108.27100	214.76170	629.09316
10	70.18770	83.05224	114.33486	155.00623	219.45800	642.03903
11	73.72856	88.30782	126.53435	154.95246	213.25231	656.77550
12	69.25282	86.51000	133.90429	159.17164	226.43400	675.27275
13	72.22919	87.69308	131.92719	125.81428	224.34800	642.01174
14	72.99018	76.38711	142.32171	132.32986	204.96343	628.99229
15	74.89765	101.73754	136.14901	121.46363	161.53230	595.78013
16	65.13230	82.07555	103.00153	131.25100	146.19226	527.65264
17	74.94059	63.48749	90.45637	133.72639	144.83885	507.44969
18	73.54776	54.90115	112.07866	119.61939	193.29377	553.44073
19	74.95189	67.99570	105.63626	145.87981	201.39886	595.86252
20	74.33483	92.85957	145.63517	118.09636	211.04199	641.96792
21	58.96502	87.17871	111.22778	122.22385	240.37016	619.96552
22	65.75197	69.17475	84.66006	140.12104	191.06119	550.76901
23	71.44790	45.01166	99.43192	121.81690	141.23045	478.93883
24	42.89456	43.22525	88.81553	104.58387	140.75652	420.27573
Total operating fuel cost ($)			**47,522.60**			
Total system's power loss (%)			1.155			

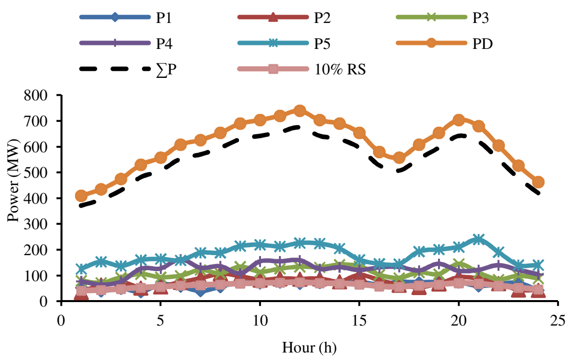

Figure 5. Optimal units' dispatch schedule, load demand curve, and total power supply for case 2.

The improvement in the operating fuel cost is demonstrated in Fig. 6. Clearly, significant daily cost saving of $1,325.60 is the result of the 10% RS's sharing with respect to case 1.

C. Comparative Study

The result of the proposed ABC* algorithm was compared with those obtained by hybrid harmony search (HHS) [23] and adaptive particle swarm optimization (APSO) [24]. Although both HHS and APSO methods attained "less" operating fuel costs than that of the ABC* algorithm, they disregarded the P^0 scheduling values, and relaxed the accepted value for violating the equality constraints. Moreover, the outcomes of the APSO approach claimed in [24] violated the units' ramp-rate constraints of unit-1 at hours 4, 14, and 19; unit-3 at hour 13; unit-4 at hour 6; unit-5 at hour 18. The dispatch schedule with a high power output mismatch degraded the practicality of the attainable solutions by these methods. Clearly, as shown in Fig. 7, the dispatch schedule of on-line units in every time interval was more consistent using the ABC* algorithm than the compared methods. The proposed ABC* algorithm provided the least absolute value of violating the system's equality constraints and, therefore, represented the minimum total system's power loss.

Although relaxing the equality constraints' violation plays a significant role (in addition to other factors such as the utilized algorithm and PC's features) in achieving a faster solution, the offered ABC* algorithm outperformed that of HHS method with respect to the CPU time requirement (~28%) as seen in Table VII.

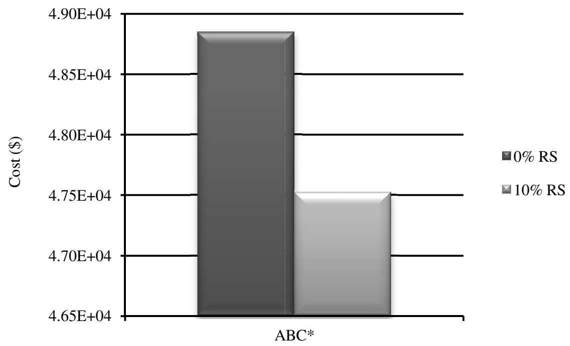

Figure 6. Operating fuel cost reduction due to the 10% RS contribution obtained by the ABC algorithm with the integration of the constrained search-tactic.

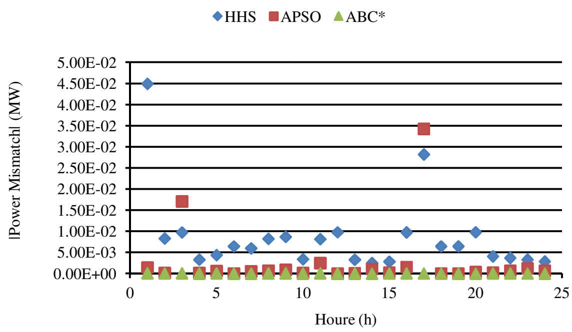

Figure 7. Violation of equality constraints due to different algorithms for case 1.

TABLE VII. COMPARISON OF RESULTS FOR CASE 1.

Time (h)	HHS [23] $\lvert P_{mismatch}\rvert$ (MW)	HHS [23] P_{loss} (MW)	APSO [24] $\lvert P_{mismatch}\rvert$ (MW)	APSO [24] P_{loss} (MW)	Proposed ABC* $\lvert P_{mismatch}\rvert$ (MW)	Proposed ABC* P_{loss} (MW)
1	0.04497	3.98993	0.00149	3.68599	0.00009	3.68681
2	0.00833	4.44333	0.00016	4.05636	0.00003	4.15043
3	0.00976	5.36546	0.01713	4.79507	0.00008	4.85418
4	0.00331	6.35801	0.00016	5.90654	0.00002	5.95962
5	0.00438	6.84172	0.00065	6.68515	0.00009	6.57897
6	0.00647	7.95917	0.00006	7.88534	0.00001	7.79841
7	0.00601	8.45969	0.00055	8.44065	0.00002	8.27126
8	0.00825	9.25765	0.00068	9.18548	0.00005	9.03425
9	0.00870	10.19960	0.00090	10.17370	0.00010	10.15240
10	0.00340	10.55940	0.00020	10.55940	0.00000	10.48900
11	0.00820	11.04460	0.00250	10.93730	0.00010	10.89080
12	0.00980	11.71960	0.00000	11.45470	0.00000	11.55260
13	0.00330	10.55940	0.00010	10.48940	0.00000	10.37920
14	0.00250	10.16830	0.00110	10.16810	0.00000	10.06730
15	0.00285	9.08335	0.00023	9.23697	0.00005	9.25088
16	0.00979	7.20059	0.00157	7.22987	0.00010	7.14700
17	0.02824	6.68326	0.03427	6.87957	0.00006	6.65635
18	0.00647	7.95057	0.00005	7.93155	0.00004	7.87530
19	0.00648	9.25758	0.00002	9.21798	0.00001	9.09669
20	0.00980	10.65710	0.00040	10.59840	0.00000	10.55290
21	0.00409	9.90149	0.00027	9.89417	0.00009	9.81892
22	0.00373	7.87063	0.00068	7.87302	0.00007	7.57693
23	0.00331	6.15349	0.00127	5.91707	0.00003	5.76039
24	0.00288	4.97762	0.00069	4.69031	0.00002	4.46665
$\sum P_{loss}$ (MW)		196.6615		193.8921		192.0672
Total operating fuel cost ($)		44677.30		43154.90		48,848.20
CPU (s)		--		308.400		221.520

* With the integration of the constrained search-tactic offered in [18].

V. CONCLUSION

This paper has employed the ABC algorithm with the constrained search-tactic previously offered by the same authors in solving the DED problem. Different test cases as well as a comparative analysis verified the effectiveness of the proposed algorithm. An attempt of integrating renewable energy source and analyzing its impact on the objective function has been addressed in this paper. A fraction contribution of RS led to a significant reduction in the operating fuel cost. From the promising outcomes, the ABC method has a potential to be applied in the dynamic economic and emission dispatch problems in future publications.

REFERENCES

[1] T.E. Bechert and H.G. Kwatny, "On the Optimal Dynamic Dispatch of Real Power," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-91, no. 3, pp. 889-898, 1972.

[2] T.E. Bechert and Nanming Chen, "Area Automatic Generation Control by Multi-Pass Dynamic Programming," *Power Apparatus and Systems, IEEE Transactions on,* vol. 96, no. 5, pp. 1460-1469, 1977.

[3] P.P.J. van den Bosch, "Optimal Dynamic Dispatch Owing to Spinning-Reserve and Power-Rate Limits," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-104, no. 12, pp. 3395-3401, 1985.

[4] D.W. Ross and Sungkook Kim, "Dynamic Economic Dispatch of Generation," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-99, no. 6, pp. 2060-2068, 1980.

[5] W.G. Wood, "Spinning Reserve Constrained Static and Dynamic Economic Dispatch," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-101, no. 2, pp. 381-388, 1982.

[6] D. Karaboga, "An Idea based on Honey Bee Swarm for Numerical Optimization," Erciyes University, Engineering Faculty, Computer Engineering Department., Tech. Rep. TR06, pp. 1-10, 2005.

[7] W. Ongsakul and J. Tippayachai, "Parallel Micro Genetic Algorithm Based on Merit Order Loading Solutions for Constrained Dynamic Economic Dispatch," *Electr. Power Syst. Res.,* vol. 61, no. 2, pp. 77-88, 2002.

[8] F. Li, R. Morgan and D. Williams, "Towards More Cost Saving Under Stricter Ramping Rate Constraints of Dynamic Economic Dispatch Problems-a Genetic Based Approach," *Genetic Algorithms in Engineering Systems: Innovations and Applications, 1997. GALESIA 97. Second International Conference on (Conf. Publ. no. 446),* pp. 221-225, 1997.

[9] Zwe-Lee Gaing, "Constrained Dynamic Economic Dispatch Solution using Particle Swarm Optimization," *Power Engineering Society General Meeting, 2004. IEEE,* pp. 153-158, 2004.

[10] Bo Zhao, Chuangxin Guo and Yijia Cao, "Dynamic Economic Dispatch in Electricity Market using Particle Swarm Optimization Algorithm," *Intelligent Control and Automation, 2004. WCICA 2004. Fifth World Congress on,* vol. 6, pp. 5050-5054, 2004.

[11] K. Shailti Swamp and A. Natarajan, "Constrained Optimization using Evolutionary Programming for Dynamic Economic Dispatch," *Intelligent Sensing and Information Processing, 2005. Proceedings of 2005 International Conference on,* pp. 314-319, 2005.

[12] A.M.A.A. Joned, I. Musirin and Titik Khawa Abdul Rahman, "Solving Dynamic Economic Dispatch using Evolutionary Programming," *Power and Energy Conference, 2006. PECon '06. IEEE International,* pp. 144-149, 2006.

[13] C.K. Panigrahi, P.K. Chattopadhyay, R.N. Chakrabarti and M. Basu, "Simulated Annealing Technique for Dynamic Economic Dispatch," *Electric Power Components and Systems,* vol. 34, no. 5, pp. 577-587, 2006.

[14] G.S.S. Babu, D.B. Das and C. Patvardhan, "Dynamic Economic Dispatch Solution using an Enhanced Real-Quantum Evolutionary Algorithm," *Power System Technology and IEEE Power India Conference, 2008. POWERCON 2008. Joint International Conference on,* pp. 1-6, 2008.

[15] S. Pothiya, I. Ngamroo and W. Kongprawechnon, "Application of Multiple Tabu Search Algorithm to Solve Dynamic Economic Dispatch Considering Generator Constraints," *Energy Conversion and Management,* vol. 49, no. 4, pp. 506-516, 2008.

[16] I.A. Farhat and M.E. El-Hawary, "Dynamic Adaptive Bacterial Foraging Algorithm for Optimum Economic Dispatch with Valve-Point Effects and Wind Power," *Generation, Transmission & Distribution, IET,* vol. 4, no. 9, pp. 989-999, 2010.

[17] Global Wind Energy Council (GWEC), vol. 2011, no.010/15, 2011.

[18] F. S. Abu-Mouti and M. E. El-Hawary, "Novel Constrained Search-Tactic for Optimal Dynamic Economic Dispatch Via Modern Meta-Heuristic Optimization Algorithms," *IEEE Electrical Power & Energy Conference (EPEC),* pp. 170-175, 2011.

[19] T.A.A. Victoire and A.E. Jeyakumar, "Reserve Constrained Dynamic Dispatch of Units with Valve-Point Effects," *Power Systems, IEEE Transactions on,* vol. 20, no. 3, pp. 1273-1282, 2005.

[20] M.E. El-Hawary, Electrical Power Systems: Design and Analysis, New York: Wiley, 1995.

[21] T.A.A. Victoire and A.E. Jeyakumar, "A Modified Hybrid EP–SQP Approach for Dynamic Dispatch with Valve-Point Effect," *International Journal of Electrical Power & Energy Systems,* vol. 27, no. 8, pp. 594-601, 2005.

[22] D. Karaboga and B. Basturk, "Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems," *Foundations of Fuzzy Logic and Soft Computing,* pp. 789-798, 2007.

[23] M. Fesanghary and M.M. Ardehali, "A Novel Meta-Heuristic Optimization Methodology for Solving various Types of Economic Dispatch Problem," *Energy,* vol. 34, no. 6, pp. 757-766, 2009.

[24] B. K. Panigrahi, V. Ravikumar Pandi, and Sanjoy Das, "Adaptive particle swarm optimization approach for static and dynamic economic load dispatch," *Energy Conversion and Management*, vol. 49, no. 6, pp. 1407-1415, 2008.