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Solving Economic Dispatch Problem with Valve-Point Effect using a Modified ABC Algorithm

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ABSTRACT

This paper presents a new approach for solving economic dispatch (ED) problem with valve-point effect using a modified artificial bee colony (MABC) algorithm. Artificial bee colony algorithm is a recent population-based optimization method which has been successfully used in many complex problems. This paper proposes a novel best mechanism algorithm based on a modified ABC algorithm, in which a new mutation strategy inspired from the differential evolution (DE) is introduced in order to improve the exploitation process. To demonstrate the effectiveness of the proposed method, the numerical studies have been performed for two different sample systems. The results of the proposed method are compared with other techniques reported in recent literature. The results clearly show that the proposed MABC algorithm outperforms other state-of-the-art algorithms in solving ED problem with the valve-point effect.

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1. INTRODUCTION

Economic dispatch (ED) is an important optimization task in power system operation for allocating generation among the committed units. The objective of the ED problem is to determine the amount of real power contributed by online thermal generators satisfying load demand at any time subject to all unit and system equality and inequality constraints so as the total generation cost is minimized. Therefore, it is very important to solve the problem as quickly and precisely as possible. Several classical optimization techniques such as lambda iteration method, gradient method, Newton's method, linear programming, interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution. In reality, however, the input-output characteristics of generating units are non-convex due to valve-point loadings and multi-fuel effects, etc. Also there are various practical limitations in operation and control such as ramp rate limits and prohibited operating zones, etc. Therefore, the practical ED problem is represented as a non-convex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming (DP) method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the past few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed for ED problem such as genetic algorithm (GA) [3]-[5], improved tabu search (TS) [6], simulated annealing (SA) [7], neural network (NN) [8]-[10], evolutionary programming (EP) [11]-[13], biogeography-based optimization (BBO) [14], particle swarm optimization (PSO) [15]-[17], and differential evolution (DE) [18], [19].

Swarm intelligence has become a research interest to different domain of researchers in recent years. These algorithms simulate the food foraging behavior of a flock of birds or swarm of bees. Particle swarm optimization (PSO) and its variants have been introduced for solving numerical optimization problems and successfully applied to solve many real world problems [20]. PSO algorithm is a population based stochastic optimization technique and suitable for optimizing non linear multi modal error function. Motivated by the foraging behavior of honeybees, researchers have [21], [22] initially proposed artificial bee colony (ABC) algorithm for solving various optimization problems. Artificial bee colony (ABC) algorithm is a relatively new member of swarm intelligence. ABC tries to model natural behavior of real honey bees in food foraging. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. Despite the simplicity and the superiority of ABC algorithm, recent studies reported that it suffers from a poor exploitation process and a slow convergence rate. To overcome these pitfalls, some research papers have introduced modifications to the classical ABC algorithm in order to improve its performance and tackle more complex real-world problems [23], [24].

This paper proposes a new approach for ED problems with non-smooth cost functions due to valve-point effects using a modified ABC algorithm. Although ABC algorithm has several prominent advantages, it may get trapped in a local optimum when handling heavily constrained optimization problems with multiple local optima. In order to improve the exploitation process, this paper proposes a novel best mechanism algorithm based on a modified ABC algorithm, in which a new mutation strategy inspired from the differential evolution (DE) is introduced. The proposed method is tested for two different systems and the results are compared with other methods reported in recent literature in order to demonstrate its performance.

2. RESEARCH METHOD

2.1. Economic dispatch problem

The objective of an ED problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i\right) \tag{1}$$

Where F_T is total fuel cost of generation in the system (\$/hr), a_i, b_i, and c_i are the cost coefficient of the i th generator, P_i is the power generated by the i th unit and n is the number of generators.

The cost is minimized subjected to the following constraints:
Power balance constraint,

$$P_{i,\min} \le P_i \le P_{i,\max} \text{ for } i = 1,2,\cdots,n \tag{2}$$

Generation capacity constraint,

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \tag{3}$$

Where $P_{i,\,min}$ and $P_{i,\,max}$ are the minimum and maximum power output of the i th unit, respectively. P_D is the total load demand and P_{Loss} is total transmission losses. The transmission losses P_{Loss} can be calculated by using B matrix technique and is defined by (4) as,

$$P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{4}$$

Where B_{ij} , B_{0i} and B_{00} are transmission loss coefficients.

2.2. The ED problem considering valve-point effect

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [16]. The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators. These "valve-point effect" are illustrated in Figure 1.

The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear. The valve-point effects are taken into consideration in the ED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoid component as follows:

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_i \right) \right) \right| \right) \tag{5}$$

Where F_T is total fuel cost of generation in ($/hr) including valve point loading, e_i, f_i are fuel cost coefficients of the i th generating unit reflecting valve-point effects.

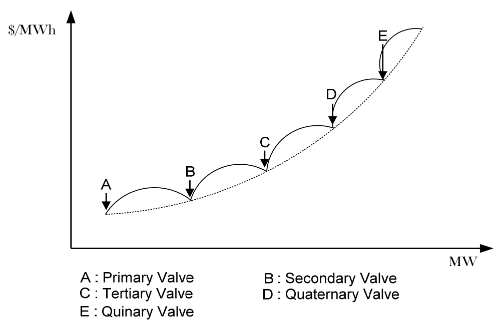

Figure 1. Valve-point effect

2.3. Artificial bee colony (ABC) algorithm

Artificial bee colony is one of the most recently defined algorithms by Karaboga in 2005, motivated by the intelligent behavior of honey bees [21], [22]. In the ABC system, artificial bees fly around in the search space, and some (employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. Some (scouts) fly and choose the food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one [22]. Thus, the ABC system combines local search methods, carried out by employed and onlooker bees, with global search methods, managed by onlookers and scouts, attempting to balance exploration and exploitation process.

In the ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlooker bees, and scout bees. The main steps of the ABC algorithm are described as follows:

1. Initialize.
2. REPEAT.
   (a) Place the employed bees on the food sources in the memory;
   (b) Place the onlooker bees on the food sources in the memory;
   (c) Send the scouts to the search area for discovering new food sources;
   (d) Memorize the best food source found so far.
3. UNTIL (requirements are met).

In the ABC algorithm, each cycle of the search consists of three steps: moving the employed and onlooker bees onto the food sources, calculating their nectar amounts respectively, and then determining the scout bees and moving them randomly onto the possible food source. Here, a food source stands for a potential solution of the problem to be optimized. The ABC algorithm is an iterative algorithm, starting by associating all employed bees with randomly generated food solutions. The initial population of solutions is filled with SN number of randomly generated D dimensions. Let $X_i = \{x_{i1}, x_{i2}, \ldots, x_{iD}\}$ represent the ith food source in the population, SN is the number of food source equal to the number of the employed bees and onlooker bees. D is the number of optimization parameters. Each employed bee x_{ij} generates a new food source v_{ij} in the neighborhood of its currently associated food source by (6), and computes the nectar amount of this new food source as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{6}$$

Where $\varphi_{ij} = (\text{rand} - 0.5)\times 2$ is a uniformly distributed real random number within the range [-1, 1], $i \in \{1, 2, \ldots, SN\}$, $k = \text{int}(\text{rand} * SN) + 1$ and $k \neq i$, and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. The new solution v_i will be accepted as a new basic solution, if the objective fitness of v_i is smaller than the fitness of x_i, otherwise x_i would be obtained.

When all employed bees finish this process, an onlooker bee can obtain the information of the food sources from all employed bees and choose a food source according to the probability value associated with the food source, using the following expression:

$$p_i = \alpha \times \frac{fit_i}{\max(fit_i)} + \beta; \quad \alpha + \beta = 1 \tag{7}$$

Where fit_i is the fitness value of the solution i evaluated by its employed bee. Obviously, when the maximum value of the food source decreases, the probability with the preferred source of an onlooker bee decreases proportionally. Then the onlooker bee produces a new source according to (6). The new source will be evaluated and compared with the primary food solution, and it will be accepted if it has a better nectar amount than the primary food solution.

After all onlookers have finished this process, sources are checked to determine whether they are to be abandoned. If the food source does not improve after a determined number of the trails "limit", the food source is abandoned. Its employed bee will become a scout and then will search for a food source randomly as follows:

$$x_{ij} = x_{j\min} + \text{rand}(0,1) * \left(x_{j\max} - x_{j\min}\right) \tag{8}$$

Where $x_{j\,min}$ and $x_{j\,max}$ are lower and upper bounds for the dimension j respectively.

After the new source is produced, another iteration of the ABC algorithm will begin. The whole process repeats again till the termination condition is met.

2.4. Modified ABC algorithm

Following this spirit, a modified ABC algorithm inspired from differential evolution (DE) to optimize the objective function of the ED problems. Differential evolution is an evolutionary algorithm first introduced by Storn and Price [25], [26]. Similar to other evolutionary algorithms, particularly genetic algorithm, DE uses some evolutionary operators like selection recombination and mutation operators. Different from genetic algorithm, DE uses distance and direction information from the current population to guide the search process. The crucial idea behind DE is a scheme for producing trial vectors according to the manipulation of target vector and difference vector. If the trail vector yields a lower fitness than a predetermined population member, the newly trail vector will be accepted and be compared in the following generation. Currently, there are several variants of DE. The particular variant used throughout this investigation is the DE/rand/1 scheme. The differential mutation strategy is described by the following equation:

$$v_i = x_a + F\left(x_b - x_c\right) \tag{9}$$

Where $a, b, c \in SN$ are randomly chosen and mutually different and also different from the current index *i*. $F \in (0,1)$ is constant called scaling factor which controls amplification of the differential variation of $x_{bj} - x_{cj}$.

Based on DE and the property of ABC algorithm, we modify the search solution described by (10) as follows:

$$v_{ij} = x_{aj} + \varphi_{ij}\left(x_{ij} - x_{bj}\right) \tag{10}$$

The new search method can generate the new candidate solutions only around the random solutions of the previous iteration.

Akay and Karaboga [23] proposed a modified artificial bee colony (ABC) algorithm by controlling the frequency of perturbation. Inspired by this algorithm, we also use a control parameter, i.e., modification rate (MR). In order to produce a candidate food position v_{ij} from the current memorized x_{ij}, improved ABC algorithm uses the following expression:

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{ if } & R_{ij} \le MR \\ x_{ij} & \text{otherwise} \end{cases} \tag{11}$$

Where R_{ij} is a uniformly distributed real random number within the range [0, 1]. The pseudo-code of the MABC algorithm is given below:

Initialize the population of solutions x_{ij}, $i = 1...SN$; $j = 1...D$, $trial_i = 0$; $trial_i$ is the non-improvement number of the solution x_i, used for abandonment

Evaluate the population

cycle = 1

repeat

{--- Produce a new food source population for employed bee ---}

for $i = 1$ to SN **do**

Produce a new food source v_i for the employed bee of the food source x_i by using (11) and evaluate its quality:

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{if } & R_{ij} \le MR \\ x_{ij} & \text{otherwise} \end{cases}$$

Apply a greedy selection process between v_i and x_i and select the better one. If solution x_i does not improve $trial_i = trial_i + 1$, otherwise $trial_i = 0$

end for

Calculate the probability values p_i by (7) for the solutions using fitness values:

$$p_i = \alpha \times \frac{fit_i}{\max(fit_i)} + \beta; \quad \alpha + \beta = 1$$

{--- Produce a new food source population for onlooker bee ---}

$t = 0$, $i = 1$

repeat

if random < p_i **then**

Produce a new v_{ij} food source by (11) for the onlooker bee:

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{if } & R_{ij} \le MR \\ x_{ij} & \text{otherwise} \end{cases}$$

Apply a greedy selection process between v_i and x_i and select the better one. If solution x_i does not improve $trial_i = trial_i + 1$, otherwise $trial_i = 0$

$t = t + 1$

end if

until ($t = SN$)

{--- Determine scout bee ---}

if max ($trial_i$) > limit **then**

Replace x_i with a new randomly produced solution by (8)

$$x_{ij} = x_{j\min} + \text{rand}(0,1) * \left(x_{j\max} - x_{j\min}\right)$$

end if

Memorize the best solution achieved so far

cycle = cycle+1

until (cycle = Maximum Cycle Number)

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3. RESULTS AND ANALYSIS

In order to demonstrate the performance of the proposed method, it is tested with 2 system tests with 6 and 13 thermal units are used to test the proposed approach for solving the ED problem. The first case consists of 6 generating units with valve-point effects considering transmission losses. The second test system consists of 13 generating units with valve-point effects and transmission losses are neglected.

Test Case 1: 6-unit system

The first system consists of 6 generating units with valve point effects. The total load demand on the system is 1263 MW. The parameters of all thermal units are presented in Table 1 [15], followed by *B*-loss coefficient.

The obtained results for the 6-unit system using the proposed method are given in Table 2 and the results are compared with other methods reported in literature, including GA, PSO and IDP [27], NPSO and NPSO-LRS [17]. It can be observed that MABC algorithm can get total generation cost of 15,438 ($/hr) and power losses of 11.9069 (MW), which is the best solution among all the methods. Note that the outputs of the generators are all within the generator's permissible output limit.

Table 1. Generating units capacity and coefficients (6-units)

Unit	$P_{i,\min}$ (MW)	$P_{i,\max}$ (MW)	a	b	c	e	f
1	100	500	0.0070	7.0	240	300	0.035
2	50	200	0.0095	10.0	200	200	0.042
3	80	300	0.0090	8.5	220	200	0.042
4	50	150	0.0090	11.0	200	150	0.063
5	50	200	0.0080	10.5	220	150	0.063
6	50	120	0.0075	12.0	190	150	0.063

$$B_{ij}=\begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i}=1.0e^{-3}*\left[-0.3908\ \ -0.1297\ \ 0.7047\ \ 0.0591\ \ 0.2161\ \ -0.6635\right]$$

$$B_{00}=0.0056$$

Table 2. Comparison of the best results of each methods (P_D = 1263 MW)

Unit Output	GA [27]	PSO [27]	IDP [27]	NPSO [17]	NPSO-LRS [17]	**MABC**
P1 (MW)	474.8066	447.4970	450.9555	447.4734	446.9600	449.8393
P2 (MW)	178.6363	173.3221	173.0184	173.1012	173.3944	173.3804
P3 (MW)	262.2089	263.0594	263.6370	262.6804	262.3436	257.0373
P4 (MW)	134.2826	139.0594	138.0655	139.4156	139.5120	142.3461
P5 (MW)	151.9039	165.4761	164.9937	165.3002	164.7089	161.7242
P6 (MW)	74.1812	87.1280	85.3094	87.9761	89.0162	90.5797
Total power output (MW)	1276.03	1276.01	1275.98	1275.95	1275.94	1274.91
Total generation cost ($/hr)	15,459	15,450	15,450	15,450	15,450	**15,438**
Power losses (MW)	13.0217	12.9584	12.9794	12.9470	12.9361	**11.9069**

Test Case 2: 13-unit system

The second system consists of 13 generating units and the input data of 13-generator system are given in Table 3 [13]. In this sample system consisting of thirteen generators with valve-point loading effects and have a total load demands of 1800 MW and 2520 MW, respectively.

The best fuel cost result obtained from proposed method and other optimization algorithms are compared in Table 4 and Table 5 for load demands of 1800 MW and 2520 MW, respectively. In Table 4, generation outputs and corresponding cost obtained by the proposed method are compared with those of DEC-SQP, NN-EPSO, and EP-EPSO [28]. The MABC algorithm provides a better solution (total generation cost of 17777.1232 $/hr) than other methods while satisfying the system constraints. In Table 5, generation outputs and corresponding cost obtained by the proposed method are compared with those of GA-SA, EP-

SQP, and PSO-SQP [28]. The MABC algorithm provides a better solution (total generation cost of 24208.8330 $/hr) than other methods while satisfying the system constraints. We have also observed that the solutions using MABC algorithm always are satisfied with the equality and inequality constraints.

Table 3. Generating units capacity and coefficients (13-units)

Unit	$P_{i,\ min}$ (MW)	$P_{i,\ max}$ (MW)	a	b	c	e	f
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Table 4. Comparison of the best results of each methods (P_D = 1800 MW)

Unit power output	DEC-SQP [28]	NN-EPSO [28]	EP-EPSO [28]	**MABC**
P1 (MW)	526.1823	490.0000	505.4731	584.1153
P2 (MW)	252.1857	189.0000	254.1686	187.2947
P3 (MW)	257.9200	214.0000	253.8022	176.9922
P4 (MW)	78.2586	160.0000	99.8350	180.0000
P5 (MW)	84.4892	90.0000	99.3296	89.4176
P6 (MW)	89.6198	120.0000	99.3035	81.7422
P7 (MW)	88.0880	103.0000	99.7772	86.6977
P8 (MW)	101.1571	88.0000	99.0317	85.5267
P9 (MW)	132.0983	104.0000	99.2788	85.0988
P10 (MW)	40.0007	13.0000	40.0000	57.0983
P11 (MW)	40.0000	58.0000	40.0000	52.6708
P12 (MW)	55.0000	66.0000	55.0000	65.5906
P13 (MW)	55.0000	55.0000	55.0000	67.7552
Total power output (MW)	1800	1800	1800	1800
Total generation cost ($/h)	17938.9521	18442.5931	17932.4766	**17777.1232**

Table 5. Comparison of the best results of each methods (P_D = 2520 MW)

Unit power output	GA-SA [28]	EP-SQP [28]	PSO-SQP [28]	**MABC**
P1 (MW)	628.23	628.3136	628.3205	628.2814
P2 (MW)	299.22	299.0524	299.0524	360.0000
P3 (MW)	299.17	299.0474	298.9681	311.5206
P4 (MW)	159.12	159.6399	159.4680	153.5888
P5 (MW)	159.95	159.6560	159.1429	152.6347
P6 (MW)	158.85	158.4831	159.2724	159.9050
P7 (MW)	157.26	159.6749	159.5371	143.5473
P8 (MW)	159.93	159.7265	158.8522	106.3185
P9 (MW)	159.86	159.6653	159.7845	159.7066
P10 (MW)	110.78	114.0334	110.9618	102.2707
P11 (MW)	75.00	75.0000	75.0000	74.6333
P12 (MW)	60.00	60.0000	60.0000	112.5930
P13 (MW)	92.62	87.5884	91.6401	55.0000
Total power output (MW)	2520	2520	2520	2520
Total generation cost ($/h)	24275.71	24266.44	24261.05	**24208.8330**

4. CONCLUSION

This paper proposes a new approach for solving the non-smooth ED problem with valve-point effect using a modified ABC algorithm. The proposed MABC algorithm employs a new mutation strategy inspired from the differential evolution (DE) to enhance the performance of the conventional ABC algorithm. The differential mutation is devised to improve the global searching capability and to enhance the capability of escaping from a local minimum. The feasibility of the proposed method for solving the ED problem is demonstrated using six units and thirteen units test systems. The comparison of the results with other methods reported in the literature shows the superiority of the proposed method and its potential for solving non-smooth ED problems in a power system operation.

Although the proposed MABC algorithm had been successfully applied to the ED problem with valve-point effect, the practical ED problem should consider multiple fuels as well as prohibited operating zones. This remains a challenge for future work.

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