International Journal of Electrical and Computer Engineering (IJECE)
Vol. 6, No. 6, December 2016, pp. 2621~2628
ISSN: 2088-8708, DOI: 10.11591/ijece.v6i6.12152

A Modified ABC Algorithm for Solving Non-Convex Dynamic Economic Dispatch Problems

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Article Info

Article history:

Received Aug 12, 2016
Revised Nov 3, 2016
Accepted Nov 17, 2016

Keyword:

Dynamic economic dispatch
Modified artificial bee colony algorithm
Ramp rate limits
Valve-point effects

ABSTRACT

In this paper, a modified artificial bee colony (MABC) algorithm is presented to solve non-convex dynamic economic dispatch (DED) problems considering valve-point effects, the ramp rate limits and transmission losses. Artificial bee colony algorithm is a recent population-based optimization method which has been successfully used in many complex problems. A new mutation strategy inspired from the differential evolution (DE) is introduced in order to improve the exploitation process. The feasibility of the proposed method is validated on 5 and 10 units test system for a 24 h time interval. The results are compared with the results reported in the literature. It is shown that the optimum results can be obtained more economically and quickly using the proposed method in comparison with the earlier methods.

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1. INTRODUCTION

A power utility needs to ensure that the electrical power is generated with minimum cost. Hence, for economic operation of the system, the total demand must be appropriately shared among the generating units with an objective to minimize the total generation cost of the system. Dynamic economic dispatch (DED) is one of important problems in power system operation and control, which is used to determine the optimal schedule of generating outputs online so as to meet the load demand at the minimum operating cost under various system and operating constraints over the entire dispatch periods. DED is an extension of the conventional economic dispatch (ED) problem that takes into consideration the limits on the ramp rate of generating units to maintain the life of generation equipment [1-2].

Since the DED problem was introduced, several optimization techniques and procedures have been used for solving the DED problem with complex objective functions or constraints. There were a number of classical methods that have been applied to solve this problem such as gradient projection method, Lagrange relaxation, and linear programming [3-5]. Most of these methods are not applicable for non-smooth or non-convex cost functions. To overcome this problem, many stochastic optimization methods have been employed to solve the DED problem, such as genetic algorithm (GA) [6], simulated annealing (SA) [7], differential evolution (DE) [8], particle swarm optimization (PSO) [9], hybrid EP and SQP [10], deterministically guided PSO [11], artificial bee colony (ABC) algorithm [12], and imperialist competitive algorithm (ICA) [13]. Many of these techniques have proven their effectiveness in solving the DED problem without any or fewer restrictions on the shape of the cost function curves.

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. Motivated by the foraging behavior of honey bees, researchers have initially proposed artificial bee colony (ABC) algorithm for solving various optimization problems [14-15]. 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 [16-17].

This paper presents a novel optimization method based on modified artificial bee colony (MABC) algorithm applied to dynamic economic dispatch in a practical power system while considering some nonlinear characteristics of a generator such as valve-point effect, the ramp rate limits, and transmission losses. 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. DED Problem Formulation

The objective of DED problem is to find the optimal schedule of output powers of online generating units with predicted power demands over a certain period of time to meet the power demand at minimum operating cost.

The fuel cost function of the generating unit is expressed as a quadratic function of real power generation. The objective function of the DED problem is

$$\min F_T = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{i,t}(P_{i,t}) = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i\right) \quad \text{for } i = 1,2,\cdots,N;\ t = 1,2,\ldots,T \tag{1}$$

where $F_{i,t}$ is the fuel cost of unit i at time interval t in \$/hr, a_i, b_i, and c_i are the cost coefficients of generating unit i, $P_{i,t}$ is the real power output of generating unit i at time period t in MW, and N is the number of generators. T is the total number of hours in the operating horizon.

The valve-point effects are taken into consideration in the DED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoid component as follows [18]:

$$\min F_T = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{i,t}(P_{i,t}) = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i + \left|e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_{i,t}\right)\right)\right|\right) \tag{2}$$

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

The fuel cost is minimized subjected to the following constraints:

1) Active power balance equation

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{N} P_{i,t} = P_{D,t} + P_{L,t} \tag{3}$$

where $P_{D,t}$ and $P_{L,t}$ are the load demand and transmission loss in MW at time interval t, respectively. The transmission loss $P_{L,t}$ can be expressed by using $\boldsymbol{B}$ matrix technique and is defined by (4) as,

$$P_{L,t} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{n} B_{0i} P_{i,t} + B_{00} \tag{4}$$

where B_{ij}, B_{0i}, and B_{00} are coefficient of transmission loss.

2) Minimum and maximum power limits

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

$$P_{i,\min} \le P_{i,t} \le P_{i,\max} \tag{5}$$

where $P_{i,\,min}$ and $P_{i,\,max}$ are the minimum and maximum real power output of unit i in MW, respectively.

3) Ramp rate limits

The actual operating ranges of all online units are restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as (6) and (7), respectively.

$$P_{i,t} - P_{i,t-1} \le UR_i \tag{6}$$

$$P_{i,t-1} - P_{i,t} \le DR_i \tag{7}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the present and previous power outputs, respectively. UR_i and DR_i are the ramp-up and ramp-down limits of unit i (in units of MW/time period).

To consider the ramp rate limits and power output limits constraints at the same time, therefore, eqs. (5), (6) and (7) can be rewritten as follows:

$$\max\{P_{i,\min}, P_{i,t-1} - DR_i\} \le P_{i,t} \le \min\{P_{i,\max}, P_{i,t-1} + UR_i\} \tag{8}$$

2.2. 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 [14-15]. 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. 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:

a. Initialize.
b. REPEAT.
c. Place the employed bees on the food sources in the memory;
d. Place the onlooker bees on the food sources in the memory;
e. Send the scouts to the search area for discovering new food sources;
f. Memorize the best food source found so far.
g. 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 (9), and computes the nectar amount of this new food source as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{9}$$

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 $k \ne i$, 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:

$$p_i = \alpha \times \frac{fit_i}{\max(fit_i)} + \beta; \quad \alpha + \beta = 1 \tag{10}$$

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 (9). 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:

$$x_{ij} = x_{j\min} + \text{rand}(0,1) * \left(x_{j\max} - x_{j\min}\right) \tag{11}$$

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.

2.3. Modified Artificial Bee Colony (MABC) 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 [19-20]. 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:

$$v_i = x_a + F\left(x_b - x_c\right) \tag{12}$$

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 (13) as follows:

$$v_{ij} = x_{aj} + \varphi_{ij}\left(x_{ij} - x_{bj}\right) \tag{13}$$

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

Akay and Karaboga [16] proposed a modified artificial bee colony 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 [17]:

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{if } R_{ij} \le MR \\ x_{ij} \qquad \text{otherwise} \end{cases} \tag{14}$$

where R_{ij} is a uniformly distributed real random number within the range [0, 1]. The pseudo-code of the modified ABC 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 thesolution 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 (14) and evaluate its quality:
Select randomly $a \neq b \neq i$

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

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 (10) 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 (14) for the onlookerbee:
Select randomly $a \neq b \neq i$

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

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 (11)

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

end if
Memorize the best solution achieved so far
cycle = cycle+1
until (cycle = Maximum Cycle Number)

3. RESULTS AND ANALYSIS

The DED problem was solved using the MABC algorithm and its performance is compared with other methods reported in recent literature. The proposed technique has been applied to 5 and 10 unit test systems. The algorithm was implemented in MATLAB 7.1 on a Pentium IV personal Computer with 3.6

GHz speed processor and 2 GB RAM. For all cases, the dispatch horizon is selected as one day with 24 dispatch periods of each one hour.

Case 1: 5-unit system

The first test system is a 5-unit test system. The technical data of the units are taken from [21]. In this test system, valve-point effect, the ramp rate limits, and transmission losses are considered. The load demand for each time interval over the scheduling period is given in Table 1. The best results obtained through various methos and from the MABC method are shown in Table 2. It clear from the table that the proposed method produces much better results compared to recently reported different methods for solving DED problem. The best total production cost obtained using proposed method is $ 40122.2954 and the computation time taken by the algorithm is 43.718s. The optimum scheduling of generating units for 24 hours using proposed method is given in Table 3.

Table 1. Load Demand for 24 Hours (5-Unit System)

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

Table 2. Comparison of Results for 5-Unit System

Method	Production cost ($)	Computing time (s)
SA [7]	47356	351.98
DE [8]	43213	376
PSO [9]	50124	258.00
ABC [12]	44045.83	NA
MABC	40122.2954	43.718

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

Table 3. Best Scheduling of 5-Unit System Using MABC Method

Hour	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Cost ($)	Ploss (MW)
1	15.9000	74.6110	65.3926	113.9821	143.7123	1202.8966	3.5980
2	16.4689	75.2536	68.7360	125.2026	153.3943	1260.0539	4.0554
3	18.1862	80.6117	77.8790	140.3266	162.8244	1352.6344	4.8278
4	20.4935	86.0723	96.6599	160.3596	172.3869	1482.0066	5.9722
5	21.5864	89.1998	103.9743	166.6423	183.2109	1548.8321	6.6137
6	22.7800	97.1001	109.2865	187.4793	199.2541	1669.9284	7.8999
7	24.9083	96.9727	123.1182	193.9147	195.4027	1713.7105	8.3167
8	25.4661	99.4240	132.6351	196.6955	208.8397	1782.7959	9.0605
9	27.1946	104.6222	147.4868	210.9714	209.7943	1872.3901	10.0693
10	27.3792	105.0382	147.1780	222.1217	212.7978	1907.5325	10.5149
11	29.2308	107.9706	150.1629	227.9499	215.6908	1947.9061	11.0050
12	29.7396	109.8457	156.8215	230.4698	224.7371	1998.6549	11.6137
13	28.7616	107.6824	149.3106	218.7602	209.9832	1907.5458	10.4979
14	28.1167	105.6265	144.0928	208.6829	213.5594	1872.3991	10.0783
15	26.2046	100.9082	133.5592	201.4110	200.9790	1782.7041	9.0619
16	22.5439	92.9996	107.7045	176.5454	187.3638	1601.7711	7.1572
17	21.6900	89.5536	106.5160	169.8248	177.0206	1548.8295	6.6049
18	24.3860	96.5779	112.6824	188.8729	193.3567	1669.7625	7.8759
19	26.2384	101.0051	134.1256	196.7138	204.9696	1782.7391	9.0525
20	28.5897	105.6929	145.2721	28.6371	216.3205	1907.5198	10.5123
21	26.8848	102.5297	140.0851	206.3445	213.9508	1847.4105	9.7949
22	24.1782	95.8857	117.3797	182.3840	192.9371	1662.3964	7.7647
23	19.2625	86.7246	103.5288	151.9370	171.4194	1475.0242	5.8723
24	17.6299	72.5581	81.2373	138.5930	157.5374	1324.8510	4.5557

Total generation cost ($) = 40122.2954**;** Total power losses (MW) = 192.3756

Case 2: 10-unit system

The second test system is a 10-unit test system. In this case, generator capacity limits, ramp rate constraints, valve-point effects and transmission losses are considered. The data for this system can be found from [13], [21]. The load demand for each time interval over the scheduling period is given in Table 4. The best solution obtained through the proposed method is compared to those reported in the recent literature are shown in Table 5. The best total production cost obtained using proposed method is $ 1022205.6846 and the computation time taken by the algorithm is 45.61s. It clear from the table that the proposed method produces much better results compared to recently reported different methods for solving DED problem. The optimal dispatch of real power for the given scheduling horizon using MABC algorithm is given in Table 6.

Table 4. Load Demand for 24 Hours (10-Unit System)

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	1036	7	1702	13	2072	19	1776
2	1110	8	1776	14	1924	20	2072
3	1258	9	1924	15	1776	21	1924
4	1406	10	2072	16	1554	22	1628
5	1480	11	2146	17	1480	23	1332
6	1628	12	2220	18	1628	24	1184

Table 5. Comparison of Results for 10-Unit System

Method	Production cost ($)	Computing Time (s)
GA [12]	1052251	NA
PSO [12]	1048410	NA
ABC [12]	1043381	NA
ICA [13]	1040758.424	NA
MABC	1022205.6846	45.61

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

Table 6. Best Scheduling of 10-Unit System Using MABC Method

Hour	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	P7 (MW)	P8 (MW)	P9 (MW)	P10 (MW)
1	152.8696	135.0000	215.5641	60.0000	73.0000	160.0000	130.0000	47.0000	20.0000	55.0000
2	169.4802	135.0000	275.0999	60.0000	73.0000	160.0000	130.0000	47.0000	20.0000	55.0000
3	250.1791	141.0615	340.0000	60.0000	73.0000	160.0000	130.0000	47.0000	20.0000	55.0000
4	310.1379	194.5668	340.0000	60.0000	112.1634	160.0000	130.0000	47.0000	20.0000	55.0000
5	338.1778	219.5432	340.0000	60.0000	136.0085	160.0000	130.0000	47.0000	20.0000	55.0000
6	394.7858	270.1395	340.0000	60.0000	183.7220	160.0000	130.0000	47.0000	20.0000	55.0000
7	423.1917	295.6766	340.0000	60.0000	207.8462	160.0000	130.0000	47.0000	20.0000	55.0000
8	449.8081	315.7420	340.0000	60.0000	226.4674	160.0000	130.0000	59.0390	20.0000	55.0000
9	458.5437	405.8813	340.0000	116.4564	229.9376	160.0000	130.0000	57.0359	20.0000	55.0000
10	468.0060	407.8974	340.0000	205.4083	230.9734	160.0000	130.0000	93.9985	31.9882	55.0000
11	466.5000	455.708	340.0000	188.3701	221.3598	160.0000	130.0000	154.6791	28.5092	55.0000
12	469.9657	421.3228	340.0000	269.8678	232.3764	160.0000	130.0000	170.0000	24.6103	55.0000
13	468.0312	452.3119	340.0000	139.4186	224.7564	160.0000	130.0000	134.8804	20.0000	55.0000
14	469.6347	391.2385	340.0000	91.5604	241.0817	160.0000	130.0000	73.5287	20.0000	55.0000
15	449.4984	314.2598	340.0000	60.0000	228.0280	160.0000	130.0000	59.2178	20.0000	55.0000
16	366.4984	244.7241	340.0000	60.0000	159.7641	160.0000	130.0000	47.0000	20.0000	55.0000
17	338.2203	219.5821	340.0000	60.0000	135.9280	160.0000	130.0000	47.0000	20.0000	55.0000
18	394.8125	270.0284	340.0000	60.0000	183.8036	160.0000	130.0000	47.0000	20.0000	55.0000
19	449.1781	315.7060	340.0000	60.0000	227.0256	160.0000	130.0000	59.1384	20.0000	55.0000
20	467.6119	418.5122	340.0000	157.3762	235.5685	160.0000	130.0000	137.8902	20.0000	55.0000
21	465.9263	411.1727	340.0000	71.9382	235.4961	160.0000	130.0000	83.3707	20.0000	55.0000
22	394.8450	269.9871	340.0000	60.0000	183.8113	160.0000	130.0000	47.0000	20.0000	55.0000
23	282.2374	169.7011	340.0000	60.0000	88.4561	160.0000	130.0000	47.0000	20.0000	55.0000
24	207.8453	135.0000	312.5109	60.0000	73.0000	160.0000	130.0000	47.0000	20.0000	55.0000

Total generation cost ($) = 1022205.6846; Total power losses (MW) = 846.3426

4. CONCLUSION

In this paper, a modified ABC algorithm is proposed to solve the non-convex dynamic economic dispatch problem.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 effectiveness of the proposed method is illustrated by using a 5-unit and 10-unit test systems and compared with the results obtained from other method. It is evident from the comparison that the proposed technique provides better results than other methods in terms of minimum production cost and computation time.

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