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Multiobjective Environment/Economic Power Dispatch Using Evolutionary Multiobjective Optimization

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ABSTRACT Environmental/economic dispatch (EED) problems play a salient role in the power system, which can be defined as a complex constrained optimization problem. Many different methods have been introduced to handle EED problems and got some inspiring positive results in the research. In this paper, a new multiobjective global best artificial bee colony (ABC) algorithm is proposed to tackle multiobjective EED problems. To manipulate this problem effectively, we propose a global best ABC algorithm to generate the new individual to speed up the convergence of the proposed algorithm. Afterwards, a crowding distance assignment approach is employed to evolve the population. Finally, a straightforward constraint checking procedure is used to tackle those different constraints of EED problems. Experimental results can conclude that MOGABC can provide best solutions in solving multiobjective EED problems.

INDEX TERMS Environmental/economic dispatch, multiobjective algorithm, artificial bee colony.

I. INTRODUCTION

Electrical power systems are the complex problems in engineering since the characterize of their nonlinear and computationally challenging circumstances [1]. Traditional economic dispatch problems are often employed to compute the optimal aggregate for power products to reduce the fuel cost under different constraints. However, those problems cannot be considered alone because of the rising public consciousness of the protection created by the fossil fuel. To deal with the environmental/economic dispatch problems, different multiobjective decomposition methods [2]–[8] have been proposed to optimize it. However, because of the constraints with the features of non-linear and nonconvex, these methods are incurring difficult problems to gain the optimal solutions for multiobjective environmental/economic dispatch problems. Although some exact methods are fast and convergence, the shortcoming of those algorithms is the character of piecewise linear cost approximation. In fact, the most direct approach is to convert the multiobjective optimization problem to some single objective optimization problems based on the multiobjective evolutionary algorithms. However, these multiobjective evolutionary algorithms still suffer from low optimization efficiency and premature convergence [9]–[20]. Therefore, future research works are still necessary to develop novel multiobjective evolutionary algorithms for analyzing multiobjective environmental/economic dispatch problems.

Recently, artificial bee colony has been proposed to solve many difficult optimization problems in different fields such as, constraint optimization problem, machine learning, and bioinformatics. Artificial bee colony algorithm (ABC) [21], [22] is a swarm intelligence algorithm contained three various species of bees. The first and second bee are employed and onlooker bees. The last bee is scout bees. For the employed bees, they are mainly used to exploit the nectar sources and have a share in their knowledge with onlookers. After that, onlooker bees can discover the new food source based on the probability values. Then, a new solution is generated as one of the most stable solutions for scout bees. Compared with other evolutionary algorithms, this algorithm involves fewer parameters and has a simple structure.

In this paper, we propose a multi-objective global best artificial bee colony algorithm to slove multi-objective environmental/economic dispatch problems. Firstly, we introduce a global best artificial bee colony algorithm to generate the new individual to make the algorithm convergence faster. The proposed new updated strategy can produce the new candidate solution around the best solutions. A new constraint method is applied to dispose of the power balance equality constraints of the environmental/economic dispatch problem for avoiding the unfeasible solutions. To demonstrate the benefits of our algorithm MOGABC, we compare our proposed algorithm with other well-known multiobjective algorithms for different instances. From the results, we can conclude that MOGABC is a very effective method.

II. ENVIRONMENT/ECONOMIC POWER DISPATCH PROBLEM

In this section, we introduce the environment/economic power dispatch optimization problem with two different conflicting objective functions under some constraints.

A. OBJECTIVE FUNCTION

For a power system with N generators, its entire fuel cost ($\$/h$) $H(\overrightarrow{X}_G)$ represents the curve approximated which is defined as follows:

$$H(X_G) = \sum_{i=1}^{N} a_i + b_i H_{X_i} + c_i H_{X_i}^2; \tag{1}$$

where a_i, b_i and c_i are the fuel-cost coefficients of the ith unit. $H(X_G)$ is the function of generator i.

The total emission $I(\overrightarrow{X}_G)$ (tons per hour) of atmospheric pollutants caused by the fossil-fueled thermal units are summarized as follows:

$$I(X_G) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i X_{G_i} + \gamma_i X_{G_i}^2) + \zeta_i exp(\lambda_i X_{G_i}); \tag{2}$$

where α_i, β_i, γ_i, ζ_i and λ_i are the coefficients of the ith generator.

B. CONSTRAINTS OF EED PROBLEM

Power balance constraints are proposed based on the law of equilibrium, which can be defined as follows:

$$\sum_{i=1}^{N} x_i^t = x_D^t + x_L^t; \tag{3}$$

where x_D^t and x_L^t is the total demand and transmission loss at the t time interval, and x_L^t is measured by B matrix loss method, which is described as follows:

$$X_D^t = \sum_{i=1}^{N}\sum_{j=1}^{N} X_i^t B_{ij} X_j^t + \sum_{j=1}^{N} B_{0j} X_i^t + B_{00}; \tag{4}$$

where B_{ij} is the ij-th element of the loss coefficients.

Generation capacity constraints are described by the inequality limitations, which can be described as follows:

$$X_i^{min} \leq X_i^t \leq X_i^{max} \tag{5}$$

where X_i^{min} and X_i^{max} are the minimized and maximum boundaries of the i-th generating unit.

C. MULTI-OBJECTIVE OBJECTIVE FUNCTION

Under two objective functions and several constraints, multi-objective environment/economic power dispatch optimization problems are described as follows:

$$FE = \min[H(\overrightarrow{X}_G), I(\overrightarrow{X}_G)]; \tag{6}$$

$$\begin{cases} \sum_{i=1}^{N} x_i^t = x_D^t + x_L^t \\ X_i^{min} \leq X_i^t \leq X_i^{max}, \quad i = 1, 2, \cdots, N \end{cases} \tag{7}$$

III. ARTIFICIAL BEE COLONY ALGORITHM

In this algorithm, the model of the ABC algorithm consists of three groups of bees: employed bees, onlooker bees, and scout bees. Employed bees are responsible for exploiting the nectar sources explored before, sharing their information with onlookers within the hive. After that, the onlooker bees go to food source in order to exploit by considering the information shared by employed foragers. An employed bee becomes a scout if the food source is abandoned, and then starts to search a new food source randomly. Also half of the population is employed bees and the other half of the population is onlooker bees in the basic ABC. 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. At the beginning of the algorithm, it generates the population with randomly generated food solutions. The newly generated population contains the SN individuals with D dimensions. $X_i = \{x_{i1}, x_{i2}, \cdots, x_{iD}\}$ denotes a food source in the standard ABC algorithm. The parameter SN is the size of the population which is identical to the number of those different kinds of bees. The population is generated as follows:

$$x_{ij} = x_{j,min} + (x_{j,max} - x_{j,min}) \times r \tag{8}$$

where $i \in \{1, 2, \cdots, SN\}$ is the index of the population and $j \in \{1, 2, \cdots, D\}$ is the index of the dimension, r is a real number between 0 and 1. $x_{j,min}$ and $x_{j,max}$ is the minimize and maximize boundaries for the j-th dimension respectively.

After initialization, an employed bee produces a modification on position x_{ij} in its memory depending on the local information and evaluates the profitability of the nectar amount of the new food source v_{ij}. If the employed bee finds better nectar source, it memorizes the new nectar source to use it instead of the old one. Then each employed bee x_{ij} generates a new food source v_{ij} in the neighborhood of its present position as follows:

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

Where $k = int(rand * (SN - 1)) + 1$ is an integer number from 1 to SN, $\varphi_{ij} = (rand - 0.5) \times 2$ is a uniformly real random number within the range [-1,1], $k \in \{1, 2, \cdots, SN\}$ is a randomly chosen index which satisfies $k \neq i$. After obtaining the new solution, the algorithm will calculate the population and compare with the previous solutions. If the new individual is better than the previous individual, the new individual will be replaced by the previous individual. Otherwise, if the fitness of the new individual is worse than the previous individual, the previous individual will be kept. If the produced individual is out of the boundaries, it will be moved to the neighborhood of the boundaries.

After finishing the employed bees stage, the next stage is the onlooker bee stage. For the onlooker bees, they can obtain the information from the employ bee stage based on the probability value as follows:

$$p_i = \frac{fitness_i}{\sum_{i=1}^{N} fitness_i} \tag{10}$$

Where $fitness_i$ is the objective function value of the ith-food source. The probability value is used to produce the new food source for the onlooker bees. After that, we can compare the new food source with the previous individual. If the results obtained are better than the earlier solutions, the new results can be retained.

Finally, the algorithm will check each food source whether it is to be dropped. A parameter "limit" is defined to show which individual should be abandoned. After that, we will transform the employed bee into scout bee by a random method by using the equ. (8).

IV. OUR APPROACH: MOGABC

In this section, we will introduce the proposed MOGABC algorithm. The motivation of this algorithm is to design a multi-objective optimization, which can balance the exploration and exploitation capability for attainting better solutions for the Pareto-optimal front. First, a global best artificial bee colony algorithm will be proposed to balance the exploration and exploitation capability. Then, the MOGABC will be designed to solve the EED problem.

A. GLOBAL BEST ARTIFICIAL BEE COLONY

In ABC, employed bees are responsible for exploiting the nectar sources explored before and giving information to the waiting bee in the hive about the quality of the food source sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. The algorithm has a good exploitation for global optimization. However, it is slow at exploration of the optimal solution. In order to achieve better results on these optimization functions, a global artificial bee colony is proposed to solve this problem.

In the standard ABC algorithm, the algorithm generates the new individual v_{ij} by the neighborhood of its current position:

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}); \tag{11}$$

Inspired by the differential evolution, in this section, we propose a global best artificial bee colony algorithm. We know that differential evolution is an evolutionary Algorithm first introduced by Storn and Price [23]. 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 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. Different kinds of strategies of DE have been proposed based on the target vector selected, the number of difference vectors used. The following is a mutation strategy frequently used in the literature:
DE/Best/1

$$v_i = x_{best} + F \times (x_a - x_b); \tag{12}$$

where a and b are different random integer indices from $\{1, 2, \cdots, SN\}$. F is the scaling factor.

Based on the "DE/Best/1" mutation strategy in differential evolution, a novel global best search strategy is introduced as follows:

$$v_{ij} = \begin{cases} x_{best,j} + \varphi_{ij}(x_{ij} - x_{kj}) & if \quad rand_j[0, 1] < 0.5; \\ x_{best,j}; \end{cases} \tag{13}$$

Based on the new proposed search strategy, the offspring solutions are generated using the information of the best individual in the current population which can improve the convergence speed of the algorithm.

After that, we present the new proposed MOGABC in Algorithm 1. The MOGABC is a easy framework. Furthermore, this proposed method can balance the lack of the exploration of the ABC algorithm.

B. GLOBAL BEST SOLUTION IN MOGABC

The global best solution is the best solution of a population. When solving a single objective problem, it is completely determined once a new population is established. However, for the multi-objective problem, the conflicting nature of multiple objective makes the choice of a single optimum solution difficult. In order to handle this problem, we use an external archive to store the non-dominated solutions found. Then, the concept of crowing distance is proposed in [22] to choose the global best solution from the archive based on the diversity of the non-dominate solution.

C. BEST COMPROMISE SOLUTION

Inspired by the reference [11], a decision marker's judgment is applied. For each objective function, DM contains

Algorithm 1 Algorithm Description of MOGABC

```
1. Set the iteration for the whole algorithm gen = 0;and
a population of SN is generated.
2. The parameter "limit".
3. Calculated the Objective function of each individual
X based on the environmental/economic dispatch (EED)
problems.
4. Find the non-dominated solutions and store in a new
vector Ar_0.
5. Select the global best food source best for each bee
from the archive.
while the terminate criteria is not met do
    for i = 1 -> SN do
        select randomly k != i;
        for j = 1 -> D do
            if rand(0, 1) <= 0.5 then
                v_{i,j} = x_{best,j} + φ_{ij}(x_{ij} - x_{kj})
            else
                v_{i,j} = x_{best,j};
    Use the archive Ar_{gen+1} to store the non-dominated
    solutions.
    i = 1; t = 0;
    while t < SN do
        if rand(0, 1) < prob_i then
            t = t + 1;
            select randomly k != i;
            for j = 1 -> D do
                if rand(0, 1) <= 0.5 then
                    v_{i,j} = x_{best,j} + φ_{ij}(x_{ij} - x_{kj});
                else
                    v_{i,j} = x_{best,j};
        i = i + 1;
        if i == SN + 1 then
            i = 1;
    Use the archive Ar_{gen+1} to maintain the
    non-dominated solutions.
if max(trial_i > limit) then
    x_{i,j} = x_{j,min} + (x_{j,max} - x_{j,min}) × r
Output the Pareto front based on the archive Ar_{gen+1}.
```

fuzzy or imprecise objects. Following [4] and [11], for each objective f_i, a membership function u_i is a rigorously monatomic decreasing function which can be described as follows:

$$u_i = \begin{cases} = 1 & if \quad f_i \leq f_i^{min}; \\ = \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & if \quad f_i^{min} < f_i < f_i^{max}; \\ = 0 & if \quad f_i \geq f_i^{max}; \end{cases} \tag{14}$$

where f_i^{max} and f_i^{min} are the maximum and minimum values of each objective solution in all non-dominated solutions respectively. After that, the sum of the membership function values for those two objective functions in our multi-objective optimization problem is computed as follows:

$$u^q = \frac{\sum_{i=1}^{N_{obj}} u_i^q}{\sum_{k=1}^{N_s} \sum_{i=1}^{N_{obj}} u_i^k} \tag{15}$$

The best compromise solution is the maximum value of u^q.

D. MOGABC FOR EED PROBLEM

In our paper, we propose MOGABC for solving multi-objective environment/economic power dispatch optimization problems including IEEE 30-bus six-generator test system [6], [12] which consists of 41 transmission lines in the power system. The data is from [24] and [25]. Table 1 summarizes the parameter of this system. The transmission loss of B-coefficients can be found in [24] and [25]. The load demand used in this system is 283.4MW. Equations (16)–(18) are given at the bottom of this page.

In the first stage, the population is initialized by creating all solutions of power outputs. For the algorithm, all individuals are generated within the feasible boundary for the real power output as follows:

$$P_{G_i} = P_{i,min} + (P_{i,max} - P_{i,min}) \times rand(0, 1); \tag{19}$$

Since the proposed MOGABC algorithm is introduced for solving multiobjective environmental/economic dispatch (EED) optimization problems, a constraint handling scheme should be considered to address the constrained in multiobjective environmental/economic dispatch optimization problems. A straightforward constraint checking procedure is used to tackle these constraints, called the rejecting strategy [18]. The step of the rejecting strategy can be described in Algorithm 2.

In this algorithm, if $|Dif|$ is higher than the parameter ε, X_i will be changed for its kth dimension until the constraints is satisfied. In [18], the value of ε sets 10^{-10}.

$$B = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.001 & 0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix} \tag{16}$$

$$B_0 = \begin{bmatrix} -0.0107 & 0.0060 & -0.0017 & 0.0009 & 0.0002 & 0.0030 \end{bmatrix} \tag{17}$$

$$B_{00} = \begin{bmatrix} 9.8573E - 4 \end{bmatrix} \tag{18}$$

TABLE 1. Generator cost and emission coefficients of IEEE test system.

	a	b	c	α	β	γ	ζ	λ
G_1	10	200	100	4.091	-5.554	6.49	2.00E-04	2.857
G_2	10	150	120	2.543	-6.047	5.638	5.00E-04	3.333
G_3	20	180	40	4.258	-5.094	4.586	1.00E-06	8
G_4	10	100	60	5.326	-3.55	3.38	2.00E-03	2
G_5	20	180	40	4.258	-5.094	4.586	1.00E-06	8
G_6	10	150	100	6.131	-5.555	5.151	1.00E-05	6.667

Algorithm 2 Method for Modifying the Unfeasible Solution

1. X_i is the current food source. P_D^{min} and P_D^{max} are the minimum and the maximum limits of generation capacity. P_D is the total demand. B is the loss coefficients.
2. Calculate the difference value between the sum of X_i and $P_D + P_L$ by
$Dif = P_D + P_L - \sum_i X_i$;
3. Select a number $k \in \{1, 2, \cdots, n\}$.

while $|Dif| > \varepsilon$ **do**
  $x_{i,k} \leftarrow x_{i,k} + Dif$;
  if $x_{i,k} < P_G^{min}$ **then**
    $x_{i,k} \leftarrow P_G^{min}$
  if $x_{i,k} > P_G^{max}$ **then**
    $x_{i,k} \leftarrow P_G^{max}$
  $Dif = P_D + P_L - \sum_i X_i$;
  $k = mod(k, n) + 1$;

V. EXPERIMENTAL RESULTS

In our paper, to demonstrate the effectiveness of the multi-objective global best artificial bee colony algorithm, two different cases are applied. These cases can be described as follows:

The first case: an IEEE 30-bus six-generator test system without the loss is considered in this case. This environmental/economic dispatch (EED) problems constraints include two different constraints. The first one is the generation capacity constraint, and the other is the power balance constraints without transmission loss.

The second case: The transmission losses are also considered in the first instance.

We develop our algorithm MOGABC using the Matlab-7 language. In the simulate runs, the population size and the capacity of the archive are fixed at 50 and 50, respectively. The maximum number of fitness function evaluations is set to 10,000 and the value of the limit is 100. The algorithm parameters are selected after conducting many experiments in the wide range to obtain the best fuel cost value and the best emission value.

A. BEST EXPERIMENTAL RESULTS

For this experiment, the curial goal is to measure the performance of our proposed MOGABC, which explores the points of the Pareto front in the first case. Table 2 shows the points of the Pareto front for two objective functions in multiobjective environmental/economic dispatch (EED) optimization problems [12].

TABLE 2. The results for 5-unit test system.

Hour	Best cost	Best emission
1	0.1095	0.4058
2	0.2997	0.4592
3	0.5245	0.538
4	1.016	0.383
5	0.5247	0.537
6	0.3596	0.5101
Fuel Cost	600.112	638.26
Emission	0.22214	0.194203

For the first case, we compare our proposed algorithm MOGABC with other different multiobjective algorithms including MODE/PSO [18], LP [6], MOSST [26], NSGA [11], NPGA [10], SPEA [12], NSGA-II [13], and FCPSO [27]. The experimental results are summarized in Table 3 and Table 4. As depicted, they can conclude that the saving with the LP and MOSST approaches are about 5 to 6 \$/hr in the fuel cost. The experimental results show that our multiobjective algorithm MOGABC has the effectiveness and potential ability to solve multi-objective environmental/economic dispatch problems. Compared with other algorithms, MOGABC can provide less fuel cost and emission by evaluating 10000 fitness function evaluations to find the Pareto front. In practical, The MODE/PSO takes the same fitness function evaluations with the MOGABC. Therefore, we can summarize that our proposed multi-objective method MOGABC can find better solutions for those multi-objective environmental/economic dispatch (EED) problems. After that, The membership functions are employed to check each element in the whole solutions. By using this function, the best compromise solution can be found by the maximum value of membership functions. The compromise solutions including NSGA, NPGA, SPEA, and FCPSO are summarized in Table 5. Figure 1 shows the Pareto front. From this Figure, we can find that those optimal solutions have a well-distributed.

TABLE 3. Compared our proposed algorithm MOGABC with nine multiobjective algorithms for cost in case 1.

Algorithm	MOGABC	MO-DE/PSO	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	FCPSO
P_{G_1}	**0.1099**	0.1078	0.15	0.1125	0.1567	0.108	0.1062	0.1059	0.107
P_{G_2}	**0.2999**	0.304	0.3	0.302	0.287	0.3284	0.2897	0.3177	0.2897
P_{G_3}	**0.5242**	0.5237	0.55	0.302	0.4671	0.5386	0.5289	0.5216	0.525
P_{G_4}	**1.0159**	1.0147	1.05	1.0208	1.0467	1.0067	1.0025	1.0146	1.015
P_{G_5}	**0.5241**	0.5223	0.46	0.5311	0.5037	0.4949	0.5402	0.5159	0.53
P_{G_6}	**0.3598**	0.3616	0.35	0.3625	0.3729	0.3574	0.3664	0.3583	0.3673
Fuel Cost	**600.1114**	600.115	606.314	605.889	600.572	600.259	600.15	600.155	600.132
Emission	**0.22211**	0.22201	0.2233	0.2222	0.22282	0.22116	0.22151	0.22188	0.22226

TABLE 4. Compared our proposed algorithm MOGABC with nine multiobjective algorithms for emission in case 1.

Algorithm	MOGABC	MO-DE/PSO	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	FCPSO
P_{G_1}	0.4059	0.4061	0.4	**0.4095**	0.4394	0.4002	0.4116	0.4074	0.4097
P_{G_2}	0.459	0.4581	0.45	**0.4626**	0.4511	0.4474	0.4532	0.4577	0.455
P_{G_3}	0.538	0.5408	0.55	**0.5426**	0.5105	0.5166	0.5329	0.5389	0.5363
P_{G_4}	0.3831	0.3822	0.4	**0.3884**	0.3871	0.3688	0.3832	0.3837	0.3842
P_{G_5}	0.5379	0.5376	0.55	**0.5427**	0.5553	0.5751	0.5383	0.5352	0.5348
P_{G_6}	0.5101	0.5091	0.5	**0.5152**	0.4905	0.5259	0.5148	0.511	0.514
Fuel Cost	0.194203	0.194203	0.194227	**0.194182**	0.194356	0.194327	0.19421	0.194204	0.194207
Emission	638.253	638.27	639.6	**644.112**	639.209	639.18	638.507	638.249	638.358

TABLE 5. The compromise solution for case 1.

Algorithm	MOGABC	NSGA	NPGA	SPEA	FCPSO
P_{G_1}	**0.24**	0.2571	0.2696	0.2785	0.3193
P_{G_2}	**0.3628**	0.3774	0.3673	0.3764	0.3934
P_{G_3}	**0.5425**	0.5381	0.5594	0.53	0.5359
P_{G_4}	**0.7172**	0.6872	0.6496	0.6931	0.5921
P_{G_5}	**0.5416**	0.5404	0.5396	0.5406	0.5457
P_{G_6}	**0.4299**	0.4337	0.4486	0.4153	0.447
Fuel Cost	**608.1665**	610.067	612.127	610.254	619.998
Emission	**0.202**	0.2006	0.19941	0.20055	0.19715

TABLE 6. The evolution metric SP for Case 2.

Algorithm	MOGABC	MO-DE/PSO	CMOPSO	SMOPSO	TV-MOPSO
Best	**0.0018**	0.0051	0.0125	0.0057	0.0108
Worst	**0.0039**	0.0146	0.026	0.0433	0.0663
Median	**0.0028**	0.006	0.0145	0.0083	0.0199
Average	**0.0028**	0.0074	0.0169	0.0156	0.0281
Std.	**0.000533**	0.0028	0.0046	0.0132	0.0174

B. ANALYSES OF MULTI-OBJECTIVE PERFORMANCE

Four well-known multi-objective algorithms including the multi-objective differential evolution and particle swarm optimization (MODE/PSO) [18], multi-objective particle swarm optimization (CMOPSO) [28], multi-objective particle swarm optimization with sigma method (SMOPSO) [29] and time variant multi-objective particle swarm optimization (TV-MOPSO) [30] are applied in this paper as the compared algorithm. In this case, we use the second case as the test instance by spacing metric measure mechanism. For the spacing metric, ‘‘zero’’ indicates all members of the Pareto front, which has the equally spaced. Table 6 summarizes the experimental results between MOGBAC and MODE/PSO [18], CMOPSO [28], SMOPSO [29], TV-MOPSO [30] regarding spacing metric. This table summarizes that MOGABC could succeed in finding the best solution for the

TABLE 7. Statistical results of the normalized distance metric for Case 2.

Algorithm	MOGABC	MO-DE/PSO	CMOPSO	SMOPSO	TV-MOPSO
Best	0.8939	0.9046	0.8972	0.9435	0.9625
Worst	**0.8854**	0.8682	0.8224	0.7959	0.7875
Median	**0.8894**	0.8771	0.8677	0.8576	0.8468
Average	**0.8897**	0.8798	0.8644	0.8634	0.8589
Std.	**0.0029**	0.0096	0.0247	0.0546	0.0601

TABLE 8. Best solutions for cost with five algorithms for case 2.

Algorithm	MOGABC	MO-DE/PSO	CMOPSO	SMOPSO	TV-MOPSO
P_{G_1}	**0.1219**	0.122	0.1155	0.1217	0.1482
P_{G_2}	**0.2871**	0.2843	0.2764	0.2933	0.3062
P_{G_3}	**0.5831**	0.5857	0.5809	0.5707	0.5798
P_{G_4}	**0.9927**	0.9962	0.9858	0.9959	1.0005
P_{G_5}	**0.5236**	0.5149	0.5342	0.5268	0.4529
P_{G_6}	**0.3511**	0.3566	0.3669	0.3514	0.3725
Fuel Cost	**605.9761**	606.0073	606.0472	605.9909	606.4028
Emission	**0.220681**	0.22089	0.220468	0.220692	0.21977
loss	**0.025565**	0.02555	0.0256	0.02597	0.02604

TABLE 9. Best solutions for emission with five algorithms for case 2.

Algorithm	MOGABC	MO-DE/PSO	CMOPSO	SMOPSO	TV-MOPSO
P_{G_1}	**0.4101**	0.4118	0.4067	0.398	0.3926
P_{G_2}	**0.4636**	0.4616	0.4666	0.4783	0.4724
P_{G_3}	**0.5446**	0.5435	0.5447	0.5498	0.5484
P_{G_4}	**0.3912**	0.3922	0.3917	0.3629	0.4133
P_{G_5}	**0.5448**	0.5454	0.5417	0.5518	0.5503
P_{G_6}	**0.5151**	0.5148	0.5177	0.5282	0.4909
Fuel Cost	**646.0909**	646.0243	645.9985	648.5035	642.7938
Emission	**0.194179**	0.194179	0.194182	0.19425	0.194267
loss	**0.03527**	0.03535	0.03517	0.03495	0.33922

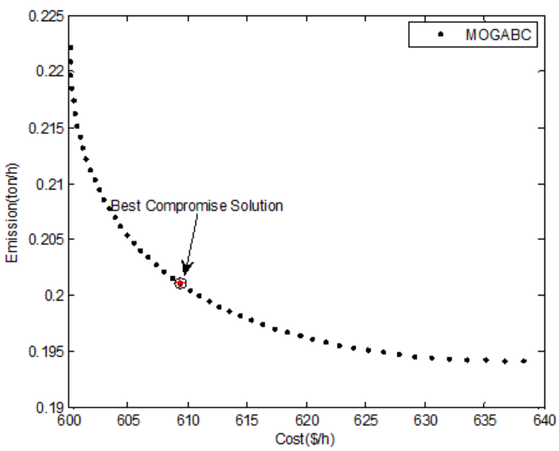

FIGURE 1. Pareto front obtained by MOGABC for case 1.

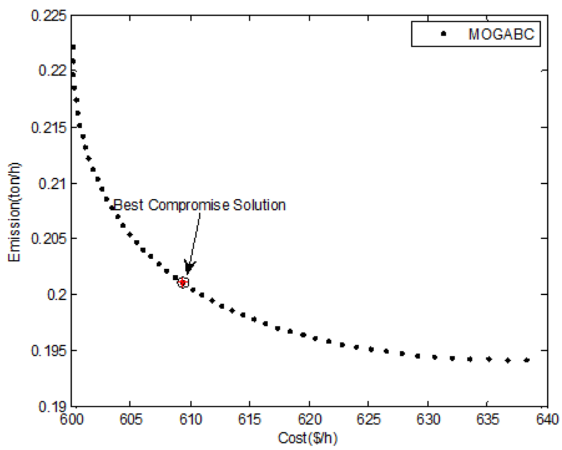

FIGURE 2. Pareto front obtained by MOGABC for case 2.

compared methods. Figure 2 shows the obtained Pareto front produced by MOGABC [31].

In this section, we will measure the performance of the Pareto-optimal solutions. The measure estimates the normalized distance between two extreme solutions including the best cost solution and the best emission solution. Table 7 shows the experimental result of the standardized distance metric. From Table 7, TV-MOPSO can provide the best solution for this case; however, the MOGABC can obtain the better average, median, worst values concerning the Pareto-optimal solutions. Also, the best fuel cost and emission for these five algorithms are summarized in Table 8 and Table 9. It can conclude that the MOGABC can find the smallest emission and cost values.

Finally, we can conclude that MOGABC performs better than other multiobjective evolutionary algorithms for multiobjective environmental/economic dispatch (EED) optimization problems.

VI. CONCLUSION

This paper demonstrates the application of multi-objective global best artificial bee colony algorithm in multi-objective environmental/economic dispatch (EED) problems with constraints. To improve the convergence of standard artificial bee colony algorithm, a new global best artificial bee colony is proposed. After that, the new search method can be proposed to modify the original search method by finding the neighborhood solution of the best solution. Moreover, some constraint handling methods are combined into the multi-objective algorithm that makes the algorithm more effective for the multiobjective environmental/economic dispatch (EED) problems with constraints. Experimental results suggest that the proposed algorithms perform better than the recent state-of-the-art. In the future, we will apply the MOGABC to solve some other multi-objective power system optimization problems.

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