Multi-objective Bacterial Colony Optimization Based on Multi-subsystem for Environmental Economic Dispatching

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Abstract. When addressing the multi-objective optimization, bacterial colony optimization algorithms are easy to fall into local optimum, which leads to the insufficient diversity and convergence. To overcome this drawback, in this study, a new multi-objective bacterial colony optimization based on multi-subsystems, abbreviated as MOBCOMSS, is proposed. The MOBCOMSS uses a hierarchical clustering approach to adapt the colony into multiple sub-colony systems based on evolutionary state. Each subsystem in the colony searches and stores information independently. Then, the diversity and convergent information from subsystems are returned to the elite archive for the whole colony. Besides, information suitable for the development of diverse subsystems is extracted from the elite archive for adaptive updating to eventually balance global and local search and achieve problem adaptation. Finally, the proposed MOBCOMSS is compared with 4 popular algorithms in the environmental economic dispatch of power systems (EED) on the standard IEEE 30-bus test system. The results demonstrate that MOBCOMSS can find optimal solutions with better convergence and diversity than other comparison algorithms in solving the EED problem with lower computational consumption, showing good feasibility and effectiveness.

Keywords: Multi-objective optimization · Environmental economic dispatching · Bacterial colony optimization · Multi-subsystem

1 Introduction

Environmental/Economic Dispatch (EED) has become an important optimization problem in power system operation with the increasing concern for environmental pollution. According to EED, economic maintenance and pollutant emissions are both kept as low as possible while satisfying all equality and inequality constraints [1]. Nonetheless, minimizing total emissions and economic maintenance costs are inherently contradictory, and they cannot be addressed just using traditional single-objective optimization techniques simply due to their multiple nonlinear constraints. Therefore, it is necessary

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to transform EED problem into a multi-objective optimization problem (MOP) while handling multiple equality and inequality constraints.

MOP means two or more contradictory goals are optimized concurrently. Moreover, these objective functions always contradict each other. Numerous evolutionary algorithms have been used to solve the multi-objective EED problem successfully, attracting the interest of many scholars [1, 2]. Many optimization algorithms based on bacteria were proposed in recent years, where the prominent examples are bacterial foraging algorithm (BFO) [3], bacterial colony optimization (BCO) [4], slime mould algorithm (SAM) [5]. On the one hand, most bacterial algorithms could be highly efficient in solving single-objective optimization problems for its global search ability [5, 6].On the other hand, bacterial optimization algorithms showed adaptive behavior of intelligent emergence facing high computational consumption and inefficient utilization of prior knowledge in multi-objective optimization problems [3, 7]. For EED problem, Panigrahi et al. [8] applied a fuzzy method for BFO to solve the EED problem. Tan et al. [9] proposed a discrete BFO that used the health classification method to control the reproduction and elimination opportunities on EED problem.

Simulation results show the effectiveness of above algorithms. However, these multi-objective BFO algorithms are based on a complex three-layer nested computing structure, effective calculations are at the cost of sacrificing a large amount of computing power. In addition, the capability to balance global search and local search is still needed to enhance for multi-objective BFO algorithms. The disequilibrium leads to local Pareto or even stops convergence prematurely. The BCO further proposed a life cycle model instead of the three-layer nested structure that enhances computing effectiveness. However, BCO is updated and iterated with the guidance of individual bacteria which leads to trapping into local optimal easily.

Given the above considerations, a new multi-objective bacterial colony optimization based on multi-subsystems, abbreviated as MOBCOMSS, is developed in this paper. The MOBCOMSS newly proposed to consider not only the behavior in the evolutionary structure but also multi-subsystems search strategy for enhancing the diversity of population and avoiding trapping in local Pareto front.

2 Background

2.1 Environmental/economic Power Dispatch (EED)

EED is to find a dispatching scheme that solves for the optimal value of both objective functions (fuel cost and pollution emissions) while satisfying the power supply-demand balance and unit capacity constraints. The EED is a non-linear and high-dimensional optimization problem that must also satisfy both equation and inequality constraints, making it difficult to find a globally optimum solution using traditional gradient-based optimization methods.

In this paper, the IEEE 6 machine 30-bus standard system is chosen for verifying the performance of MOBCOMSS, More detailed parameters can check [9].

2.2 Bacterial Colony Optimization (BCO)

Bacterial Colony Optimization (BCO)is a new evolutionary algorithm proposed by Niu et al. [4] that simulates bacterial life-cycle behaviors in the swarm intelligence way. The main improvement in BCO is the way to forage that bacterium usually towards nutrients by exchanging information between individuals instead of random walks. More information about BCO can refer to [4, 6].

3 Multi-objective Bacterial Colony Optimization Based on Multi-subsystems

From previous multi-objective optimization algorithms based on bacteria, it seems that there are generally problems such as insufficient population diversity and poor convergence, which in turn lead to failure to obtain a good Pareto front [3, 9]. In order to enable populations to preserve and extract information with diversity and convergence, this paper proposes a multi-subsystem search strategy with adaptive colony behaviors. For a specific algorithmic framework see Fig. 1 and Algorithm 1.

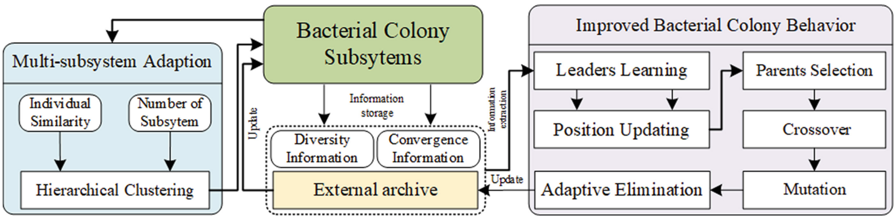

Fig. 1. The overall framework of MOBCOMSS.

3.1 Multi-subsystems Search Strategy

The main idea of bacterial colony optimization is to first initialize the colony $X_i = [x_{i_1}, x_{i_2}, \ldots, x_{i_n}]^T$, $i = 1, 2, 3, \ldots, m$, and perform random foraging behavior. The whole population is updated through continuous iteration with each bacterium updating its position through group communication [4]. Traditional bacterial colony optimization algorithms typically set a global optimum individual and drives the entire population towards found global optimum [6, 9]. The global optimum oriented search allows the algorithm to converge more quickly than a random search. Nevertheless, a single global optimum is not necessarily effective in multi-objective optimization problems. Multi-objective optimization is often not optimal for all objectives due to conflicts between objectives, which drives us to explore how to obtain the information that drives the evolution of the entire population.

Inspired by the biological swarm phenomenon of system-subsystem-individual system, we explored the influence of multiple subsystems in a bacterial colony system and devised a multi-subsystem search strategy. As shown in the Algorithm 1 on lines 3–10, the similarity of the population is calculated firstly with the metric that can be used as positional similarity, convergent similarity relative to the origin, and diversity similarity. The whole population is sliced by means of hierarchical clustering to obtained multiple sub-colony systems, each of which includes multiple bacteria.

Multiple bacterial colony subsystems operate independently and an external archive of a central information hub is designed to store the optimality search information. For multi-objective optimization problems, diversity and convergence information is stored in the external archive. During independent optimization searches, subsystems extract information from the central information hub that is appropriate for the development of that subsystem and proceeds to the next step of the adaptive optimization process until a specified number of iterations.

Algorithm 1. Overview of MOBCOMSS

```
Input: npop; MaxFEs; learning rate α; Genetic Parameters
Initialization: Pop (Population)
while Fes ≤ MaxFEs do
    Calculate the individual similarity with crowding distance and position;
    Hierarchical Clustering;
    Store non-dominated solutions to EA (External archive);
    for each subsystem ∈ Pop do
        for each bacterium ∈ subsystem do
            Position updating using Eq.(1)
        end
    end
    Parents selection;
    Crossover;
    Mutation;
    if meet elimination condition then
        Adaptive Elimination;
    else
        Continue;
    end
    Update the elite archive
end
Output: EA (External archive)
```

3.2 Improved Bacterial Colony Behaviors

The previous bacterial colony optimization had a high reliance on individual optimum and single global optimum, which did not satisfy the requirements for diversity and convergence in multi-objective optimization. To enhance the ability to improve the diversity of the population and accelerate the convergence of the algorithm, a new updating method is proposed as shown in Eq. (1).

$$x_i^t = w \cdot x_i^{t-1} + C_i \cdot \left\{ r_1 \cdot \left(x_c - x_i^{t-1} \right) + r_1 \cdot \left(x_d - x_i^{t-1} \right) \right\} \tag{1}$$

where w is the initial weight, C_i represents the chemotaxis steps and the x_c and x_d are convergent leaders and diversity leaders suit for each of subsystem. As shown in lines 11–13, in order to further enhance population diversity, the proposed algorithm introduces operations such as selection, crossover and mutation in genetic algorithms instead of the traditional replication operations of colony optimization. Furthermore, to avoid the population falling into a local optimum, an adaptive elimination strategy is proposed, see lines 14–18. Adaptive elimination refers to the fact that if the current convergent optimum stored in the central information hub does not change for a long time which means that the whole algorithm is not further improved. If the convergence information remains unchanged for a long time, as shown in Eq. (2), the probability of elimination of the population is increased as the number of iterations increases.

$$Ped^t = Ped^{t-1} + 0.1, \text{ if } x_d \text{ not changed} \tag{2}$$

A timer is put up in the adaptive elimination adjustment to keep track of the time it takes for the convergence to stagnate. Whenever the counter hits a predetermined value, the likelihood of elimination rises in lockstep with the growth in the counter. Similarly, the eliminated bacteria are replaced to some new position.

4 Simulation Analysis

4.1 Experimental Setup

In this paper, MOBCOMSS is applied to the EED optimization problem and the energy consumption parameters, emission parameters and loss factors of the generating units are referred to the relevant literature [9]. In this paper, MOPSOCD [10], MMOPSO [11], NSGAII [12], PESAII [13] are selected as comparative algorithms. The simulation analysis is carried out for the two cases of considering network losses and not considering network losses respectively. All experiments are carried out on a PC with Intel Core i-5 10210U @1.60 GHz and 16 GB memory, windows 11 system and Matlab 2020b. Among all comparison algorithms, the population size is set to 100 and the maximal number of fitness evaluations (FEs) is set at 10000. All the experimental results are obtained after 30 independent runs. In the experiments, the Hypervolume (HV) [14] and Spread [15] metric are used to evaluate the optimization performance of the algorithm, and the reference point for HV is set as $[1.1,1.1,\ldots,1.1]^d$.

4.2 Results and Analysis

Table 1 gives the best solutions for economic cost in case 1 and case 2 obtained by diverse algorithms. The proposed MOBCOMSS and the MMOPSO get the minimum value of economic cost is 605.9984 (\$/h), significantly better than other algorithms. As shown in Table 1, The proposed MOBCOMSS gets the minimum value of economic cost is 605.9984 (\$/h) while other algorithms getting results above it, which means the MOBCOMSS is much better than other algorithms. Table 2 gives the best solutions for environmental emission in case 1 and case 2 by selected algorithms. From Table 2, the minimum value of case 1 emissions obtained by the proposed MOBCOMSS is 0.194180 (t/h), while the minimum values of that obtained by MOPSOCD, MMOPSO, NSGAII, PESAII are higher than that of MOBCOMSS. Table 2 shows that MOBCOMSS, MMOPSO and NSGAII reach 0.194179 simultaneously in case 2. However, the proposed algorithm outperforms other algorithms in terms of emission at higher precision.

Table 1. Best solutions for cost ($/h) in case 1/2. (30 trials).

Methods	Case	P_1	P_2	P_3	P_4	P_5	P_6	Cost	Emission
MOBCOMSS	C1	**0.121165**	**0.286481**	**0.583648**	**0.992943**	**0.523379**	**0.351946**	**605.9984**	0.220724
	C2	**0.120808**	**0.286384**	**0.583565**	**0.992423**	**0.524187**	**0.352195**	**605.9984**	0.220702
MOPSOCD	C1	0.114755	0.288016	0.590255	0.988176	0.525345	0.352914	606.0074	0.220654
	C2	0.118497	0.288106	0.582691	0.988334	0.526146	0.35583	606.0028	0.22043
MMOPSO	C1	0.121026	0.286232	0.584042	0.992663	0.523847	0.351736	**605.9984**	0.220722
	C2	0.121004	0.286407	0.583672	0.9929	0.523653	0.351926	**605.9984**	0.220729
NSGAII	C1	0.121191	0.283844	0.58349	0.994651	0.526673	0.349685	606.0002	0.220925
	C2	0.121343	0.284665	0.583159	0.992522	0.525649	0.352203	605.9989	0.220723
PESAII	C1	0.125551	0.288536	0.583595	0.988879	0.523704	0.349215	606.0034	0.22031
	C2	0.122422	0.286405	0.584904	0.991566	0.51855	0.355684	606.0016	0.220542

Table 2. Best solutions for emission (ton/h) in case 1/2. (30 trials).

Methods	Case	P_1	P_2	P_3	P_4	P_5	P_6	Cost	Emission
MOBCOMSS	C1	**0.411291**	**0.465579**	**0.543524**	**0.390158**	**0.54634**	**0.512457**	646.2336	**0.19418**
	C2	**0.410987**	**0.461506**	**0.543599**	**0.391264**	**0.546415**	**0.51553**	646.0564	**0.194179**
MOPSOCD	C1	0.404013	0.466756	0.546965	0.392052	0.540709	0.518472	645.8045	0.194184
	C2	0.410904	0.466762	0.537149	0.395849	0.54337	0.515441	645.9386	0.194183
MMOPSO	C1	0.413928	0.464214	0.546861	0.391304	0.53896	0.514232	646.3356	0.194181
	C2	0.410271	0.464083	0.545808	0.388842	0.546933	0.513304	646.2185	**0.194179**
NSGAII	C1	0.412433	0.462986	0.543986	0.392253	0.546065	0.511635	646.0202	0.19418
	C2	0.411563	0.461548	0.546942	0.389859	0.545276	0.514091	646.1526	**0.194179**
PESAII	C1	0.409714	0.45389	0.555662	0.388831	0.548949	0.511831	645.6954	0.194193
	C2	0.413379	0.459561	0.553073	0.389989	0.539954	0.513335	646.16	0.194185

To demonstrate further the distribution of solutions on the obtained Pareto front, Fig. 2 displays the graphical results produced by the MOBCOMSS algorithm and other four algorithms for case 1 and case 2. At the same time, the hypervolume HV and Spread are applied to measure the performance of algorithm. As shown in Fig. 2, the Pareto front obtained by MMOPSO on case 1/2, MOPSOCD on case 1, NSGAII on case 1 and PESAII on case 1/2 can be seen to be unevenly distributed, with vacant Pareto fronts. In addition, the Pareto front of MOPSOCD on case 2, NSGAII on case 2 and PESAII on case 1/2 have overlapping solutions. In contrast, the pareto fronts obtained by the proposed MOBCOMSS on case 1 and case 2 are smoother and more uniform, with a wider distribution and no overlapping solutions.

From Table 3, the proposed MOBCOMSS is able to achieve the highest HV value compared to the other algorithms in Case 1 and Case 2, respectively, and Table 4 shows that the lowest Spread value can be achieved for the diversity metric, which proves the effectiveness of the proposed algorithm in improving diversity as well as convergence.

Table 3. Statistical results of the metrics HV for Case 1/2 (30 trials).

HV	Case	Best	Worst	Median	Average	STD
MOBCOMSS	C1	0.128396	0.128356	0.128387	**0.128385**	8.03E-06
	C2	0.128394	0.128355	0.12839	**0.128387**	8.38E-06
MOPSOCD	C1	0.128371	0.128327	0.128354	0.128352	1.16E-05
	C2	0.12837	0.128296	0.128351	0.128347	2.01E-05
MMOPSO	C1	0.128391	0.128366	0.128387	0.128384	7.65E-06
	C2	0.128394	0.128372	0.128388	0.128387	5.25E-06
NSGAII	C1	0.128385	0.128366	0.128379	0.128378	5.38E-06
	C2	0.128386	0.12837	0.128379	0.128378	4.34E-06
PESAII	C1	0.128348	0.128157	0.128311	0.128306	4.14E-05
	C2	0.128352	0.128169	0.128304	0.128292	5.07E-05

Table 4. Statistical results of the metrics Spread for Case 1/2 (30 trials).

HV	Case	Best	Worst	Median	Average	STD
MOBCOMSS	C1	0.555919	0.665939	0.627925	**0.620376**	3.03E-02
	C2	0.548758	0.670397	0.619972	**0.621405**	3.07E-02
MOPSOCD	C1	0.607426	0.757483	0.694027	0.69153	3.63E-02
	C2	0.597029	0.776177	0.684779	0.682769	0.045266
MMOPSO	C1	0.548858	0.714839	0.652339	0.651771	4.77E-02
	C2	0.515596	0.750139	0.652181	0.650466	0.049113
NSGAII	C1	0.568894	0.792423	0.689091	0.694539	5.33E-02
	C2	0.632373	0.840626	0.705666	0.712683	0.044622
PESAII	C1	0.887064	1.133629	0.997456	0.987289	5.25E-02
	C2	0.744185	1.169833	0.927624	0.940232	0.079911

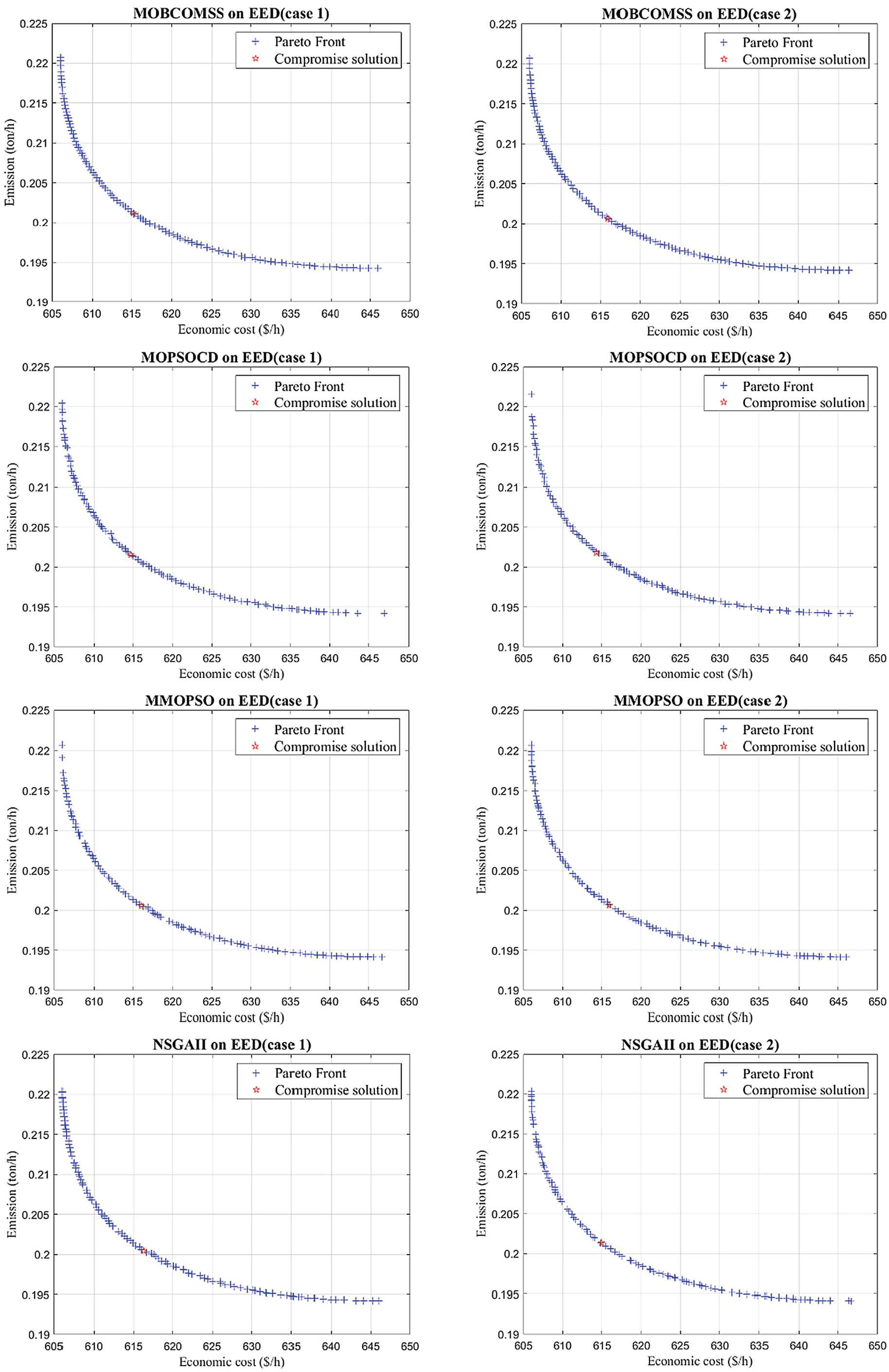

Fig. 2. Pareto solutions produced by five methods for case1 and case2

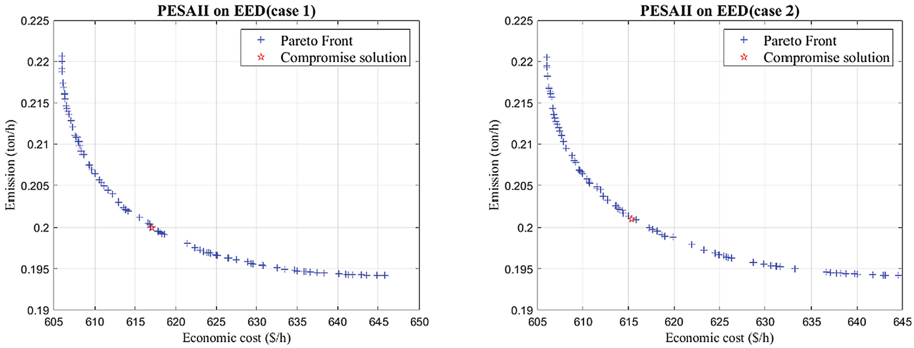

Fig. 2. continued

5 Conclusion

In this paper, a novel multi-objective bacterial colony optimization based on multi-subsystem (MOBCOMSS) is proposed and used to solve the EED problem. The MOBCOMSS proposed a multi-subsystem search strategy, which enhances the population diversity and multi-objective optimization adaptability during algorithm execution process. Furthermore, the MOBCOMSS proposed an adaptive pattern of bacterial colony behavior to accelerate the convergence of the algorithm and avoid falling into local optimum. Finally, the simulation is validated in two cases considering transport losses and not. The simulation results show that the proposed MOBCOMSS has good performance and the Pareto frontier obtained with limited computational power is uniformly distributed.

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References

1. Qu, B.Y., Zhu, Y.S., Jiao, Y.C., Wu, M.Y., Suganthan, P.N., Liang, J.J.: A survey on multi-objective evolutionary algorithms for the solution of the environmental/economic dispatch problems. **38**, 1–11 (2017)
2. Goudarzi, A., Li, Y., Xiang, J.: A hybrid non-linear time-varying double-weighted particle swarm optimization for solving non-convex combined environmental economic dispatch problem. Appl. Soft Comput. **86**, 105894 (2019)
3. Niu, B., Liu, Q., Wang, Z., Tan, L., Li, L.: Multi-objective bacterial colony optimization algorithm for integrated container terminal scheduling problem. Nat. Comput. **20**(1), 89–104 (2021)

4. Niu, B., Hong, W.: Bacterial colony optimization. Disc. Dyn. Nat. Soc. 2012 (2012)
5. Li, S., Chen, H., Wang, M., Heidari, A.A., Mirjalili, S.: Slime mould algorithm: a new method for stochastic optimization. Futur. Gener. Comput. Syst. **111**, 300–323 (2020)
6. Wang, H., Niu, B., Tan, L.: Bacterial colony algorithm with adaptive attribute learning strategy for feature selection in classification of customers for personalized recommendation. Neurocomputing (2020)
7. Yi, D., Huang, S., Fu, H., He, J.: Multi-objective bacterial foraging optimization algorithm based on parallel cell entropy for aluminum electrolysis production process. IEEE Trans. Ind. Electron. **63**, 2488–2500 (2015)
8. Panigrahi, B.K., Pandi, V.R., Das, S., Das, S.: Multiobjective fuzzy dominance based bacterial foraging algorithm to solve economic emission dispatch problem. Energy **35**, 4761–4770 (2010)
9. Tan, L., Wang, H., Yang, C., Niu, B.: A multi-objective optimization method based on discrete bacterial algorithm for environmental/economic power dispatch. Nat. Comput. **16**, 549–565 (2017)
10. Dai, D., Fang, Y., Rui, L., Liu, Z., Wei, L.: Performance analysis and multi-objective optimization of a Stirling engine based on MOPSOCD. Int. J. Therm. Sci. **124**, 399–406 (2018)
11. Liu, R., Liu, J., Li, Y., Liu, J.: A random dynamic grouping based weight optimization framework for large-scale multi-objective optimization problems. Swarm Evol. Comput. **55**, 100684 (2020)
12. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**, 182–197 (2002)
13. Jain, A., Lalwani, S., Lalwani, M.: A comparative analysis of MOPSO, NSGA-II, SPEA2 and PESA2 for multi-objective optimal power flow. In: International Conference on Power, Energy and Environment: Towards Smart Technology (Year)
14. Leng, R., Ouyang, A., Liu, Y., Yuan, L., Wu, Z.: A multi-objective particle swarm optimization based on grid distance. Int. J. Patt. Recogn. Artif. Intell. **34** (2019)
15. Soheyl, K.: Bahman, naderi, saman, khalilpourazary: multi-objective stochastic fractal search: a powerful algorithm for solving complex multi-objective optimization problems. Soft. Comput. **24**, 3037–3066 (2020)