Economic Dispatch Optimization for Microgrid Based on Fireworks Algorithm with Momentum

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Abstract. As an efficient organization form of distributed energy resources with high permeability, microgrid (MG) is recognized as a promising technology with the promotion of various clean renewable sources. Due to uncertainties of renewable sources and load demands, optimizing the dispatch of controllable units in microgrid to reduce economic cost has become a critical issue. In this paper, an economic dispatch optimization model for microgrid including distributed generation and storage is established with the considering of inherent links between intervals, which aims to minimize the economic and environmental costs. In order to solve the optimization problem, a novel swarm intelligence algorithm called fireworks algorithm with momentum (FWAM) is also proposed. In the algorithm, the momentum mechanism is introduced into the mutation strategy, and the generation of the guiding spark is modified with the historical information to improve the searching capability. Finally, in order to verify the rationality and effectiveness of the proposed model and algorithm, a microgrid system is simulated with open data. The simulation results demonstrate FWAM lowers the economic cost of the microgrid system more effectively compared with other swarm intelligence algorithms such as GFWA and CMA-ES.

Keywords: Fireworks algorithm · Swarm intelligence · Microgrid · Smart grid · Economic dispatch

1 Introduction

Facing the increasing environment protection needs, clean energy with remarkable renewable and environment-friendly characteristics, such as photovoltaic (PV) power and wind power (WP), is gradually replacing the traditional thermal power which has harmful environmental effects. In the relevant case study, the global renewable energy consumption has already accounted for 15% of global energy consumption in 2020 and will further increase to 27% in 2050 [15]. However, due to the randomness of natural conditions, renewable clean energy usually shows significant intermittent and irregularity. Directly injecting the renewable

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power into the utility grid will lead to the power mismatching and seriously affect the power quality [1]. The technique of energy decentralization like microgrid can effectively alleviate the problem by maintaining a stable power demand and supply ratio.

Microgrid is a system concept including multiple coordinated loads and distributed energy resources (DER), operating as a controllable structure to the utility grid with well defined electrical boundaries [14]. In addition, the microgrid is also equipped with necessary control device which can manage the power output of the controllable unit to maintain the power balance and control interaction with the utility grid under the grid-tied mode, so as to downscale the fluctuation and boost the overall economic benefits of grid and users [16]. On the basis of meeting the above requirements, making a reasonable day ahead dispatch schedule to minimize the economic cost is of great significance in the microgrid and smart grid.

Due to the complex form of objective functions of the microgrid economic dispatch optimization, various swarm intelligence algorithms are introduced to solve the optimization problem, which have already achieved notable success on some real-world problems like spam detection [12], multiple targets search [17] and multi-objective optimization [3,8,18]. Fireworks algorithm (FWA) is a novel swarm intelligence algorithm proposed by Tan et al. in 2010 [13]. FWA has a double-layer structure, one layer is the global coordination between the populations represented by fireworks, and the other one is the independent search of each firework. This hierarchical structure ensures that FWA can adapt to a variety of optimization problems with different characteristics. In recent years, some variants of fireworks algorithms such as guided FWA (GFWA [7]) and loser-out tournament FWA (LoTFWA [5]) further enhance the search ability of FWA. The superiority of the those variants on the optimization of multi-modal test functions prove that FWA has great potential in real-world optimization problems like multi-objective.

Based on the comprehensive consideration of the power characteristics and constraints of renewable energy and energy storage, a dynamic economic dispatch optimization model for the microgrid is built with the goal of minimizing the overall costs and simulated with the open datasets in this paper. This work also improves the mutation operator of FWA by introducing momentum mechanism and the resulting algorithm is called FWA with momentum (FWAM). In GFWA, the guidance vector (GV) is determined by the difference between the centroids of two certain groups of sparks in the current population, and a guidance spark (GS) are generated accordingly as the elite individual. Meanwhile, FWAM additionally introduces its own historical information when calculating the guiding vector to reduce the randomness of guidance spark generation. Simulation result shows that FWAM exhibits more powerful exploration and exploitation ability than previous FWA variants and other swarm intelligence algorithms like CMA-ES.

The remaining chapters of this paper is organized as follows. Section 2 introduces the essential background information and related works. Section 3 describes our proposed dispatch model in detail. Section 4 explains and analyzes

FWAM and its improved mutation operator. Then Sect. 5 presents the simulation results to show the performance of FWAM on the dispatch problem. And Sect. 6 gives the conclusion.

2 Related Works

2.1 Economic Dispatch Optimization for Microgrid

Microgrid economic dispatch can be roughly divided into static dispatch and dynamic dispatch. The static dispatch strategy obtains the optimal value of the objective function for each time interval, and adds the results together to obtain the global optimal. The static strategy ignores the inherent links between intervals, and thus cannot meet the actual requirements. In addition, some studies also simplify the architecture, constraint and objective function of the microgrid system. Peng et al. built an economic dispatch model for microgrid under the island mode without the state of charge constraints of the energy storage [9]. Ding et al. proposed a similar dispatch model with the goal of minimizing operating cost of distributed generation system, but ignore the environmental cost [2]. Recently, some studies try to simulate a more realistic microgrid system model, and put forward more meaningful and useful dispatch strategies on this basis, which leads to a sharp increase in the complexity of the microgrid dispatch optimization, and a variety of swarm intelligence algorithms are introduced to solve the problems. Tan et al. proposed a hybrid non-dominated sorting genetic algorithm (NSGA) and adopted it on the multi-objective dispatch optimization for microgrid [11]. Lezama et al. optimized bidding in local energy market with particle swarm algorithm (PSO) [4].

This paper describes the constraints of each DER and the objective function of the entire system in detail, and establishes the links between intervals. In order to solving the optimization problem, a novel FWA is proposed and introduced.

2.2 Guided Fireworks Algorithm

FWA conducts explosion and selection iteratively to search the global optimum. In the explosion operation, each firework would generate several sparks in a hypersphere centered on itself, where the radius of hypersphere is called explosion amplitude. Then, firework of next iteration would be selected from the candidate pool formed by firework and its sparks. Variants like adaptive FWA (AFWA [6]) and dynamic search FWA (dynFWA [16]) improve the explosion operator by adjusting the explosion amplitude adaptively in each iteration. LoTFWA and Fireworks Algorithm based on search space partition (FWASSP [8]) attempted to design a more efficient collaboration mechanism.

GFWA introduced a landscape information utilization-based elite steategy [6]. In GFWA, the firework and its sparks are sorted according to their fitness after the explosion operation in each iteration. Then, the guiding vector (GV) is calculated as the difference between the centroids of the top $\sigma\lambda_i$ sparks and the bottom $\sigma\lambda_i$ sparks, where σ is a super parameter to control the size of the two subsets. By adding the GV to the firework, a elite individual named guiding spark (GS) is generated. And GS will be selected together with other individuals in the candidate pool to select new firework. The experimental result shows this novel mutation operator can enhance the convergence speed and the local search ability significantly.

3 Dynamic Economic Dispatch Optimization Model for Microgrid

A dynamic economic dispatch optimization model for microgrid under the grid-tied mode is established in this paper. The microgrid system is mainly consist of the distribution energy resources and the load, where the distribution energy resources include photovoltaic (PV) system, wind turbine (WT), micro turbine(MT) and energy storage (ES) devices. And there is also a control device to control the power output of the DER and the interaction with the utility grid. The power generated by DER gives the priority to meeting the load demand, and the excess energy will be transmitted to ES and the utility grid according to the electricity price. Figure 1 illustrates the structure of the entire microgrid system.

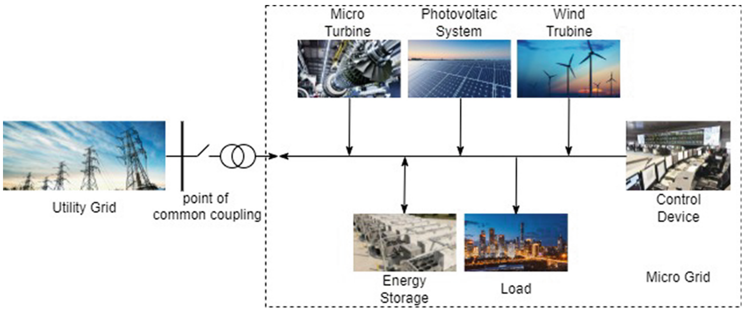


Fig. 1. The structure of the microgrid system.

The dynamic economic dispatch optimization model is usually regarded as a dynamic system. Taking the state of charge (SoC) of the ES as the system state variable, the model can be described as the following dynamic equation:

$$SoC_{t+1} = SoC_t + \sum_{i=1}^{N} P_t^{(i)} + P_{g,t}, \quad t = 0, 1, ..., T-1, \tag{1}$$

where N is the number of DER, and P_g is the power interaction with the utility grid. The dispatch in this paper is a day-ahead hourly scheduling, thus T is set as 24.

3.1 Objective Function of the Dispatch Model

The main objective of the dispatch is maximizing the utilization of renewable resources to reduce the pollution emissions, while minimizing the economic cost of the entire system. The objective function is expressed as the following:

$$\min f = f_{eco} + f_{env}, \tag{2}$$

$$f_{eco} = \sum_{t=0}^{T-1} \left(\sum_{i=1}^{N_W} C_W(P_{W,t}^{(i)}) + \sum_{i=1}^{N_P} C_P(P_{P,t}^{(i)}) + \sum_{i=1}^{N_M} C_M(P_{M,t}^{(i)}) + \sum_{i=1}^{N_S} C_S(P_{S,t}^{(i)}) + C_G(P_{G,t}) \right), \tag{3}$$

$$f_{env} = \sum_{t=0}^{T-1} \left(\sum_{i=1}^{N_M} E_M(P_{M,t}^{(i)}) + E_G(P_{G,t}) \right), \tag{4}$$

where f_{eco} and f_{env} are functions of the economic cost and environmental cost. C_W, C_P, C_M and C_S are the operation cost of WT, PV, MT and ES. N and P represent the number and power of the corresponding units. C_G is the transaction cost with utility grid. E_M and E_G represent the environmental compensation expense of MT and grid. Detailed definitions of the cost function above are introduced as follows.

Cost Function of Wind Turbine. Wind power is one of the main clear energy resources with the well established technology at present, which could lower the pollution emissions effectively. The maintenance cost of the wind turbines can be abstracted as a linear relation with the active output:

$$C_W = \alpha_W P_W, \tag{5}$$

where α_W is the coefficient of the maintenance cost of WT.

Cost Function of Photovoltaic System. Photovoltaic power is also a important clean alternative energy, and it has a more extensive application scenarios compared with the wind power. The maintenance cost of photovoltaic system can also be expressed as a linear relation:

$$C_P = \alpha_P P_P, \tag{6}$$

where α_P is the coefficient of the maintenance cost of PV.

Cost Function of Micro Turbine. Due to the stable and controllable power output, the micro turbine can relieve the short-term power shortage and stabilize the fluctuation of voltage and frequency caused by the randomness of clean energy. The operation cost of micro turbine mainly includes the maintenance cost and the fuel cost, which are defined as the followings:

$$C_M = C_{mt} + C_f, \tag{7}$$

$$C_{mt} = \alpha_M P_M, \tag{8}$$

$$C_f = \alpha_f P_M^2 + \beta_f P_M + \gamma_f, \tag{9}$$

where α_M, α_f, β_f and γ_f are parameters determined by the type of the micro turbine.

Cost Function of Energy Storage. ES can be charged and discharged according to the electricity price and power surplus, so as to effectively mitigate the negative impact of fluctuation of the load and reduce the operation cost of microgrid system. The maintenance cost of ES are usually expressed as a linear relation with the power of charging and discharging:

$$C_S = \alpha_S |P_S|, \tag{10}$$

where α_S is the coefficient of the maintenance cost of ES, and P_S represents the charging power of discharging power of ES. For convenience, the charging power is set to negative, and the discharging power is set to positive.

Cost Function of Energy Transaction. Under the grid-tied mode, the microgrid system can establish the energy transaction between the utility grid. If the power of DER cannot meet the load demand, the microgrid can purchase energy from the utility grid. If there is a power surplus, the excess energy can be transmitted to ES or sell to the utility grid according to the real-time electricity price. Thus, the cost of energy transaction can be expressed as the following:

$$C_G = \begin{cases} p_b P_G, & P_G \geq 0 \\ p_s P_G, & P_G < 0, \end{cases} \tag{11}$$

where p_b and p_s are the purchase price and the selling price respectively, and P_G is the interactive power. The interactive power P_G is set to negative when the microgrid purchase the electricity form the utility grid, otherwise it is set to positive.

Environmental Cost. Thermal power generation like micro turbine usually emits certain polluting gases, among which sulfide and nitride have a relatively strong negative impact on the environment. This would require certain environmental compensation for the pollution prevention and control. It's worth noting that thermal power also account for a significant portion in the utility grid today. Thus, when purchasing the electricity from the utility grid, the microgrid system still need paying the environmental compensation. The environmental compensation expense of MT can be abstracted as the following:

$$E_M = \alpha_n \beta_n^M P_M + \alpha_s \beta_s^M P_M, \tag{12}$$

where α_n and α_s are the compensation expense of nitride and sulfide. β_n^M and β_s^M are emission parameters of nitride and sulfide. And the compensation expense of the utility grid is similar as the MT:

$$E_G = \begin{cases} \alpha_n \beta_n^G P_G + \alpha_S \beta_s^G P_G, & P_G > 0 \\ 0, & P_G \leq 0, \end{cases} \tag{13}$$

where β_n^G and β_s^G are emission parameters of nitride and sulfide of the utility grid.

3.2 Constraints of the Dispatch Model

For the stability and safety of microgrid operation, it is necessary to enforce certain constraints on each unit in the microgrid. The constraints can be divided into equality constraint and the inequality constraints in this paper, where the equality constraint describe the power balance. And the inequality constraints are mainly the power constraints of the distributed generation and storage. Detailed constraints are listed as follows.

The Power Balance of the Microgrid System. There must be a balance between the power supply and demand in each time interval:

$$P_L(t) = P_W(t) + P_P(t) + P_M(t) + P_E(t) + P_G(t), \tag{14}$$

where P_L represents the power of all loads int the microgrid system.

The Constraints of Distributed Generations.

$$P_W^{min} \leq P_W(t) \leq P_W^{max}, \tag{15}$$

$$P_P^{min} \leq P_P(t) \leq P_P^{max}, \tag{16}$$

$$P_M^{min} \leq P_M(t) \leq P_M^{max}, \tag{17}$$

$$P_M(t) - P_M(t-1) \leq R_{up}, \tag{18}$$

$$P_M(t) - P_M(t-1) \geq R_{down}, \tag{19}$$

where P_W^{min}, P_P^{min}, P_M^{min}, P_W^{max}, P_P^{max} and P_M^{max} are the minimum and the maximum of active output power of WT, PV and MT respectively. R_{up} and R_{down} are limitations of the ramp rate of MT.

The Constraints of Energy Storage. Both the capacity and power of ES need to be limited, where the capacity is usually described by the state of charge SoC, that is the ratio of the residual capacity to the rated capacity:

$$SoC = \frac{Q_0 - \int_0^t I(t)dt}{Q_m}, \tag{20}$$

where Q_0 is the initial capacity of ES, and Q_m is the rated capacity of ES. Then, the main constraints of ES can be given as follows:

$$\begin{cases} SoC(t+1) = SoC(t) + \eta_{in} P_S(t)/Q_m \\ P_{min}^{in} \leq P_S(t) \leq P_{max}^{in} \\ SoC_{min} \leq SoC(t) \leq SoC_{max} \end{cases}, P_S(t)<0, \tag{21}$$

$$\begin{cases} SoC(t+1) = SoC(t) + \eta_{out} P_S(t)/Q_m \\ P_{min}^{out} \leq P_S(t) \leq P_{max}^{out} \\ SoC_{min} \leq SoC(t) \leq SoC_{max} \end{cases}, P_S(t) \geq 0. \tag{22}$$

where η_{in} and η_{out} are the charging and discharging efficiency of ES. P_{min}^{in}, P_{max}^{in}, P_{min}^{out} and P_{max}^{out} are limitations of charging and discharging power. SoC_{min} and SoC_{max} are limitations of SoC.

4 Fireworks Algorithm with Momentum

4.1 Principle

GFWA improves the local search ability of fireworks algorithm by further utilizing the information of population and landscape. In GFWA, the guiding vector (GV) can be seem as an estimator of the gradient of the objective function, especially when the explosion amplitude is short. Thus, a GV with the accurate direction and length could generate a guiding spark (GS) on a promising position, which is more likely to be selected as the firework of the population in the next iteration.

For reducing the randomness, GFWA calculate the GV by the centroids of the top and bottom sparks instead of the best and worst spark. The technique could extract the common qualities of the top sparks (the bottom sparks), and cancels out the random noise on the irrelevant directions. However, there are still several weaknesses in the technique: (1) When the firework locates in a local/global optimum area, the explosion amplitude is usually shortened dramatically, which means that the length of GV would also be too short to generate a GS on the promising position. And the effect of the elite strategy would be weakened. (2) The stability of the guiding spark mechanism is sensitive to the change of super parameter σ. If the guiding mutation ratio σ is too large, some moderate sparks would be selected to calculate the centroid, and this would lead to the vague of common qualities of the top sparks/bottom sparks. While if σ is too small, the random noise could not be cancelled out.

To solve the problems above, FWAM introduces a momentum mechanism to generate GS with the historical information. Specifically, in each iteration, the calculation of GV is not only determined by the difference in the current iteration, but also the GV in the previous iteration:

$$\Delta_{i,t} = \frac{1}{\sigma\lambda_i}\left(\sum_{j=1}^{\sigma\lambda_i} \mathbf{s_{ij,t}} - \sum_{\mathbf{j=\lambda_i-\sigma\lambda_i+1}}^{\lambda_i} \mathbf{s_{ij,t}}\right), \tag{23}$$

$$\mathbf{v}_{i,t} = \gamma \mathbf{v}_{i,t-1} + \eta \Delta_{i,t}, \tag{24}$$

where $\mathbf{v_t}$ is defined as the GV in FWAM, and $\mathbf{v_{t-1}}$ can be seem as a momentum term. γ is a momentum parameter to control the ratio of current difference Δ_t and the historical information, and a larger γ means that GV would sotre more historical information in the current GV. Compared with GFWA, a obvious advantage is that even if the random noise in the difference between the top and bottom sparks affects GV's estimation of gradient, GV could still be corrected and compensated by the historical information. Thus, when the firework locates near the optimum, this improved GV could also has a promising direction. Another important advantage is that the momentum mechanism can lengthen the GV on the relevant direction, which would accelerate the convergence of the firework. Algorithm 1 gives the description of FWAM. The next subsection will give analysis of this mechanism in detail.

Algorithm 1. Framework of Fireworks Algorithm with Momentum

Input: Firework num μ, spark num λ, mutation ratio σ, momentum params γ, η
Output: Optimal solution
  Initialize μ fireworks randomly within the feasible region Ω
  while termination condition not satisfied **do**
    for $Fireworks_i$ in $Fireworks$ **do**
      Explosion:
      Generate λ_i spark randomly around $Fireworks_i$ within amplitude A_i
      Mutation:
      Sort sparks according to their fitness in ascending order
      Calculate guiding vector $\mathbf{v}_{i,t} = \gamma \mathbf{v}_{i,t-1} + \eta \frac{1}{\sigma\lambda_i}(\sum_{j=1}^{\sigma\lambda_i} \mathbf{s_{ij,t}} - \sum_{\mathbf{j=\lambda_i-\sigma\lambda_i+1}}^{\lambda_\mathbf{i}} \mathbf{s_{ij,t}})$
      Generate guiding spark $G_{i,t} = \mathbf{v}_{i,t} + Firework_{i,t}$
      Selection:
      Evaluate $Firework_i$ and all sparks' fitness
      Select the best candidate as the $Firework_i$ of the next iteration
      Adjust A_i adaptively
    end for
  end while

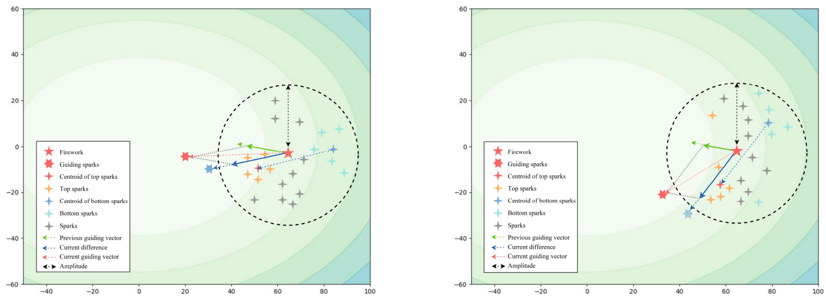
4.2 Analysis

Considering the relation between the previous GV (momentum term) $\mathbf{v_{t-1}}$ and current difference Δ_t, the effect of momentum mechanism can be analyzed in the following two possible situations.

If current difference Δ_t has a direction consistent with $\mathbf{v_{t-1}}$ (see Fig. 2(a)), the projection of $\mathbf{v_{t-1}}$ on Δ_t would be relatively large and current GV $\mathbf{v_t}$ would be lengthened on the relevant direction. Actually, the momentum mechanism can be regarded as a weighted average method, and thus the lengthening effect would be more significant if the direction of Δ_t always keeps consistent with the historical GV in recent iterations. Due to the characteristic of adaptive strategy in FWA, there is always the same change trend of amplitudes on different dimensions, and this would lead to premature convergence on some key dimensions. As a result, FWA might underperform when the global optimum locates on the boundaries of feasible region. While the momentum mechanism can help the GS keep sufficient distance separation with the firework even when the population locates near the optimum or boundaries, which ensure the guiding spark can still make sense in this situation.

If the direction of current difference Δ_t has a obvious divergence with the promising direction (see Fig. 2(b)), GV in GFWA tends to have a large oscillation on the irrelevant direction and the GS is likely not going to seek a better position, which means that GS would not be selected as the firework. While $\mathbf{v_{t-1}}$ represents the accumulation of historical GV information in FWAM, and thus there is a higher probability for GV to approach the relevant direction. As the sum of $\mathbf{v_{t-1}}$ and Δ_t, components of GV on the irrelevant direction in FWAM would be shortened and the GS would be closer to the optimum. From another point of view, Δ_t also has a significant effect on $\mathbf{v_t}$, and such a "compromise" strategy ensure that the GS in FWAM still can lead the population to get rid of the local optimum.

In summary, by introducing the momentum mechanism, the variance of GV in FWAM can be reduced effectively and the GV would be more aggressive when it approach the promising direction, which could accelerate the convergence of the algorithm and enhance the tolerance of the selection of parameter σ.



(a) (b)

Fig. 2. Illustration of two possible situations of FWAM in the search process.

5 Case Study

For verifying the rationality and effectiveness of the proposed dispatch model and the improved algorithm, this paper simulates a dispatch optimization model under the grid-tied mode as the definition in Sect. 3 , and conducts the FWAM on the model to get a day-ahead dispatch schedule for each controllable components. Detailed description are given as the followings.

5.1 Simulation Settings

The distributed generations in the system consist of 4 micro turbines, 100 wind turbines, 20 PV arrays (each PV array has 40 PV panels) and 2 energy storage systems. The detailed parameters of each DER units above are listed in Table 1 and Table 2. Loads is mainly composed of 3 office buildings and 10 personal residential houses. And the real-world power profiles of WT, PV and loads are selected form the open datasets available in PES ISS website [10]. Time-of-use (TOU) price of the electricity transaction with utility grid is shown as Table 3.

In order to fully verify the reliability of the proposed algorithm, the power profiles from 1 June to 30 June are chosen to conduct the simulation 30 times repeatedly with a maximum evaluation number of 100000. Some FWA variants, such as GFWA and FWA based on search space partition (FWASSP), and other swarm intelligence algorithm like CMA-ES and PSO are selected as the baseline.

Table 1. Parameters of distributed generations in the microgrid system.

DG	Minimum Output (kW)	Maximum Output (kW)	Minimum Ramp Rate (kW/h)	Maximum Ramp Rate (kW/h)	Maintenance Parameters (CNY/(kW·h))
WT	0	50.0	–	–	0.12
PV	0	80.0	–	–	0.02
MT1	0	35.0	−15.0	15.0	0.03
MT2	0	35.0	−15.0	15.0	0.02
MT3	0	35.0	−15.0	15.0	0.04
MT4	0	35.0	−15.0	15.0	0.01

Table 2. Parameters of distributed storage systems in the microgrid system.

DS	rated Capacity (kW·h)	Minimum SoC (%)	Maximum SoC (%)	Maximum Discharing Power (kW)	Maximum Charging Power (kW)	Maintenance Parameters (CNY/(kW·h))
ES1	30.0	0.1	0.9	10.0	−5.0	0
ES2	30.0	0.1	0.9	10.0	−5.0	0

Table 3. Time-of-use price of electricity transaction.

Period	Time	Purchase price (CNY)	Sell price (CNY)
Peak	11:00–15:00, 19:00–21:00	0.83	0.65
Peace	8:00–10:00, 16:00–18:00, 22:00–23:00	0.49	0.38
Valley	0:00–7:00	0.17	0.13

5.2 Encoding of Solutions

The object of the dispatch is reducing the overall cost of the microgrid system by adjust the active output of the controllable DER and the transaction with the utility grid. Thus, the solutions in this paper is 144-dimensional, which consists of the scheduled hourly active output of 4 MT and 2 ES in the next day. And the transaction with the utility grid can be determined according to the constraint of power balance.

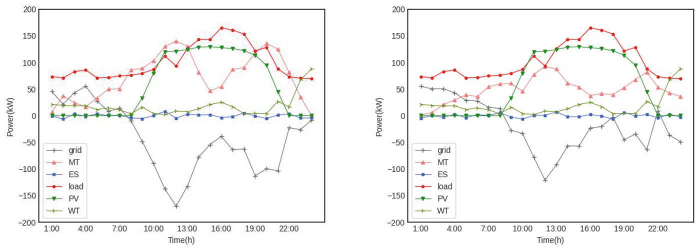
5.3 Cost Analysis

The simulation results are shown as Table 4. Momentum parameters γ and η are set as 0.9 and 0.6 by grid search. The results indicate that the average rank of mean cost of FWAM is 1.57, which is the best compared with other baseline algorithms. And the standard deviation of FWAM also indicates that the momentum mechanism improve the stability of the algorithm.

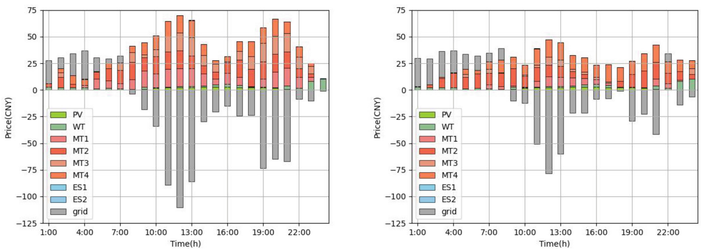
Table 4. Comparing FWAM with baseline algorithms on the simulation datasets.

Day	FWAM		GFWA		FWASSP		PSO		CMA-ES	
	mean	std	mean	std	mean	std	mean	std	mean	std
1	**3.41e+02**	3.46e+00	3.84e+02	1.56e+01	4.29e+02	9.67e+00	4.21e+02	1.48e+01	3.87e+02	1.26e+00
2	**1.44e+02**	9.01e+00	1.66e+02	1.05e+01	2.14e+02	1.90e+01	1.74e+02	3.76e+00	1.50e+02	7.07e+00
3	**−2.16e+02**	3.26e+00	−2.08e+02	7.35e+00	−1.75e+02	7.60e+00	−1.68e+02	1.64e+01	−2.12e+02	2.22e+01
4	5.32e+02	1.04e+01	5.46e+02	8.43e+00	5.64e+02	2.81e+01	5.64e+02	1.34e+01	**5.28e+02**	3.81e+00
5	**2.27e+02**	6.36e+00	2.53e+02	1.23e+01	3.05e+02	2.49e+01	3.18e+02	9.54e+00	2.52e+02	6.19e+00
6	**5.05e+02**	8.79e+00	5.14e+02	8.76e+00	5.62e+02	1.69e+01	5.85e+02	5.64e+00	5.07e+02	1.09e+01
7	2.60e+02	6.17e+00	2.61e+02	5.02e+00	3.40e+02	3.25e+01	3.30e+02	1.28e+01	**2.56e+02**	5.20e+00
8	**4.80e+02**	3.44e+00	5.01e+02	1.32e+01	5.16e+02	2.02e+01	5.28e+02	2.50e+01	4.88e+02	1.30e+01
9	6.17e+02	8.51e+00	6.23e+02	1.03e+01	6.43e+02	1.61e+01	6.64e+02	1.65e+01	**6.16e+02**	6.03e+00
10	3.95e+02	7.38e+00	**3.93e+02**	4.15e+00	4.63e+02	3.56e+01	4.37e+02	1.37e+01	4.03e+02	1.42e+01
11	8.21e+02	1.90e+00	8.24e+02	7.87e+00	8.29e+02	7.31e+00	8.34e+02	1.63e+01	**8.08e+02**	1.14e+01
12	**−4.88e+01**	5.32e+00	−4.75e+01	6.38e+00	3.15e+01	3.29e+01	1.01e+00	1.47e+01	−4.45e+01	6.59e+00
13	6.49e+02	6.63e+00	6.58e+02	5.34e+00	6.89e+02	1.46e+01	6.86e+02	7.86e+00	**6.37e+02**	1.60e+00
14	**6.04e+02**	9.69e+00	6.15e+02	7.59e+00	6.60e+02	2.64e+01	6.45e+02	1.16e+01	6.15e+02	1.85e+00
15	4.30e+02	7.84e+00	4.35e+02	1.43e+01	4.59e+02	2.39e+01	4.87e+02	1.61e+01	**4.26e+02**	8.33e+00
16	7.32e+02	4.94e+00	7.49e+02	5.81e+00	7.82e+02	5.53e+00	7.58e+02	1.21e+01	**7.26e+02**	1.00e+01
17	**6.66e+02**	8.11e+00	6.81e+02	1.15e+01	7.03e+02	1.36e+01	7.14e+02	1.68e+01	6.68e+02	5.36e+00
18	**3.43e+02**	3.90e+00	3.67e+02	9.25e+00	4.00e+02	3.20e+01	4.10e+02	2.06e+01	3.61e+02	1.06e+01
19	**2.89e+02**	3.90e+00	3.15e+02	9.42e+00	3.71e+02	1.59e+01	3.78e+02	2.10e+01	2.91e+02	5.56e+00
20	3.97e+02	5.04e+00	3.98e+02	7.06e+00	4.46e+02	8.13e+00	4.59e+02	4.91e+00	**3.85e+02**	4.31e+00
21	−6.97e+02	2.06e+00	−6.95e+02	9.17e+00	−6.39e+02	2.95e+01	−6.30e+02	1.35e+01	**−7.02e+02**	5.31e+00
22	**−1.09e+02**	9.29e+00	−1.03e+02	1.12e+01	−6.35e+01	1.70e+01	−4.20e+01	1.40e+00	−1.04e+02	7.32e+00
23	−3.72e+02	3.18e+00	**−3.76e+02**	1.61e+01	−2.60e+02	1.80e+01	−3.13e+02	1.95e+01	−3.69e+02	8.32e+00
24	−6.45e+01	1.59e+00	**−6.70e+01**	1.34e+01	−7.80e+00	1.47e+01	−9.13e+00	1.42e+01	−5.97e+01	1.48e+01
25	3.99e+02	4.44e+00	3.94e+02	1.08e+01	4.75e+02	9.55e+00	4.68e+02	9.14e+00	**3.93e+02**	1.43e+01
26	4.33e+02	5.54e+00	4.54e+02	1.59e+01	4.77e+02	2.03e+01	4.92e+02	1.09e+01	**4.30e+02**	9.49e+00
27	**4.37e+02**	6.53e+00	4.49e+02	5.98e+00	5.08e+02	1.07e+01	4.82e+02	2.02e+01	4.40e+02	3.83e+00
28	8.51e+02	2.24e+00	8.54e+02	6.15e+00	8.67e+02	3.05e+01	8.71e+02	9.58e+00	**8.35e+02**	3.06e+00
29	8.18e+02	5.48e+00	8.21e+02	9.71e+00	8.39e+02	1.68e+01	8.44e+02	1.32e+01	**8.11e+02**	5.27e+00
30	**3.04e+02**	9.95e+00	3.16e+02	1.14e+01	3.63e+02	1.71e+01	3.50e+02	1.80e+01	3.20e+02	6.14e+00
AR	1.57	1.83	2.67	2.83	4.47	4.33	4.53	3.73	1.77	2.27

Here, we take the simulation of 1 June as the case to analyze the internal logic of the dispatch schedule. The scheduled output of each component is shown as the Fig. 3. During 1:00–8:00, the output of PV and WT is in a relatively low range and cannot meet the load demand. Owing to that the cost of electricity transaction is lower than the MT's in this time, purchasing electricity from the utility grid accounts for a large proportion in the power supply. As the growth of load demand and electricity price, the output of MT increases gradually during 9:00–13:00. And If there is power supply surplus, the microgrid system would sell the extra power to the utility grid. When the clean energy covers the most power demands in the daytime, the power of MT would decrease accordingly to reduce the pollution emission. The output schedule during 16:00–24:00 follows the same logic as the daytime. ES generally tends to store the energy while the load demand in a low range, and discharges during the peak time to reduce the power fluctuation of the system. Compared with the dispatch schedule obtained by GFWA during 13:00–19:00 and 23:00–24:00, FWAM can response to the changes and adjust the output of the controllable units more timely. Besides, although there is a differences of parameters between MTs, the cost of each MT is still maintained at a relatively same level under the dispatch of FWAM, which means that FWAM could find a better solution to balance the output of different MTs.



(a) Power curve of FWAM (b) Power curve of GFWA



(c) Cost composition of FWAM (d) Cost composition of GFWA

Fig. 3. Power curve and overall cost of 1 June obtained by FWAM and GFWA.

6 Conclusion

This paper establishes an economic dispatch optimization model for microgrid system with the objective of minimizing the economic cost and environment cost, and proposes an improved GFWA with the momentum mechanism to improve the search ability and mitigate the instability caused by the randomness of guiding spark generation. The simulation results indicate that FWAM is competitive against other swarm intelligence algorithms on the grid application. There are plenty of application scenarios for FWA, and we expect this work could be a inspiration for more application researches of FWA on the real-world problems.

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