

Article

Research on Microgrid Optimal Scheduling Based on the Salp Swarm Algorithm

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Abstract

To address uneven population distribution and premature convergence of the standard Salp Swarm Algorithm (SSA) in grid-connected microgrid scheduling, this study develops an Improved Salp Swarm Algorithm (ISSA). Sine chaotic mapping is used for population initialization. A distance-adaptive follower update is then employed, in which the weight is determined by the normalized distance between an individual and the current best solution, and an acceptance-based Lévy perturbation is applied to the best solution to enhance escape from local optima. The resulting ISSA is applied to a microgrid scheduling model that minimizes economic operation and environmental costs. Benchmark function and microgrid case studies are used to evaluate optimization accuracy, convergence behavior and scheduling feasibility.

Keywords: Salp Swarm Algorithm; chaotic map; levy flight; microgrid

1. Introduction

The energy crisis and environmental pollution problems are becoming increasingly severe, becoming the key factors restricting the sustainable development of the economy and society. How to enhance energy utilization efficiency, reduce reliance on traditional fossil fuels and address environmental pollution has long been an urgent issue that governments and research institutions around the world need to break through. As a new type of distributed energy organization, microgrids offer innovative technical paths to solve these problems. By integrating distributed generation units, energy storage systems and local loads, it forms a small-scale energy supply system that can be both grid-connected and independent, significantly enhancing the reliability and flexibility of energy supply [1]. Microgrids are regarded as an efficient platform for integrating intermittent renewable energy sources such as wind and solar power, effectively alleviating the volatility during their grid connection process and making it more convenient and safe for a high proportion of renewable energy to be integrated into the distribution network. Meanwhile, microgrids have achieved the integrated operation of distributed generation and loads, enhancing overall energy efficiency, reducing transmission losses and demonstrating significant potential in reducing pollutant emissions. They are gradually becoming an important component of the transformation of modern energy systems [2].

The core concept of microgrid optimal dispatching is to effectively allocate output and operation time among decentralized units to minimize environmental impact and

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operation costs while ensuring balanced power supply and complying with various constraints [3]. At present, the research of scholars at home and abroad on the optimal scheduling of microgrids mainly focuses on designing efficient solution methods. Li et al. [4] proposed an economic dispatch method for microgrids based on adaptive mutation particle swarm optimization, aiming to enhance the efficiency and economy of energy distribution. This method achieves reasonable scheduling of various energy sources within the microgrid through optimization algorithms to meet load demands and reduce operational costs. Nemati et al. [5] developed a method for optimizing unit commitment and economic dispatch in microgrids using genetic algorithms and mixed-integer linear programming, aiming to enhance the efficiency and reliability of energy management. This study provides effective decision support for the operation of microgrids, with the goal of reducing operational costs and meeting load demands. To address these issues, Yu et al. [6] proposed an improved ACO method for the economic dispatch of microgrids. The Harris Hawks Optimization (HHO) algorithm is characterized by a relatively simple framework, strong search capability and good robustness; however, its population diversity may decrease rapidly when solving complex optimization problems, which increases the risk of premature convergence and trapping in local optima. Yang et al. [7] improved the optimization performance of the Harris Hawks Optimization algorithm for microgrid scheduling by integrating an optimal point set mapping strategy with Gauss–Cauchy mutation perturbation. The sparrow search algorithm possesses favorable global exploration capability, but it may suffer from premature convergence and become trapped in local optima. To alleviate these limitations, Nguyen et al. [8] developed an enhanced sparrow search algorithm combining elite opposition-based learning with a firefly-inspired mutation mechanism for microgrid scheduling. The whale optimization algorithm is characterized by a simple structure and a small number of control parameters; however, its convergence speed and solution accuracy may deteriorate in complex optimization tasks, and it is also susceptible to local optima. Hao et al. [9] therefore introduced opposition-based learning, a nonlinear optimization mechanism, and Gaussian perturbation into the whale optimization framework for the optimal dispatch of grid-connected microgrids, with simulation results demonstrating improved optimization performance. Although the cuckoo search algorithm is straightforward and easy to implement, its stochastic search mechanism and parameter sensitivity can affect convergence stability, while its local exploitation capability remains relatively limited. Liu et al. [10] enhanced the grey wolf optimizer for microgrid scheduling by incorporating chaotic search, mutation operations and Lévy flight, and validated the effectiveness of the proposed approach through numerical experiments. The dung beetle optimization algorithm also shows competitive search capability and relatively fast convergence, but its performance may be restricted by insufficient population diversity and sensitivity to parameter configurations. Chang et al. [11] introduced a reverse learning strategy and adaptive distribution variation into the basic dung beetle algorithm, which solved the problems of poor population diversity and easy falling into local optimum in the microgrid optimization scheduling of the traditional dung beetle algorithm. The hybrid algorithm integrates the advantages of different algorithms, improving the solution quality and robustness. Zhang et al. [12] proposed an adaptive optimization scheduling method that integrates Deep Q-network (DQN) and particle swarm optimization algorithm. This method uses DQN to dynamically evaluate the operating status of the microgrid and accordingly adjusts the key parameters of the particle swarm optimization algorithm in real time, thereby achieving intelligent optimization of the scheduling strategy. Bektas et al. [13] combined genetic algorithms with simulated annealing algorithms to solve the problem of microgrid optimization management considering regional conditions and constraint factors. Furthermore, for expensive constrained multi-objective optimization problems, surrogate-assisted evolutionary algorithms provide an

effective way to reduce the computational burden while maintaining solution quality, as demonstrated by the hierarchical surrogate-assisted approach proposed by Tian et al. [14], which is of reference value for the large-scale multi-objective scheduling of microgrids. However, these traditional algorithms generally have problems such as population diversity, slow convergence speed and being prone to falling into local optima, and they usually need to be improved to enhance the solution efficiency.

The above research indicates that although intelligent optimization algorithms have achieved encouraging results in the scheduling problem of microgrids, there are still issues such as slow convergence speed and the tendency to become trapped in local optima. Moreover, they still face significant challenges in highly uncertain operating environments.

Against this background, the rapid development of data-driven and knowledge-guided learning methods has provided new ideas for coping with the highly uncertain operating environments of microgrids. Feng et al. [15] compared machine learning methods with a physical model and showed that data-driven approaches can effectively complement physical models when the underlying mechanisms are complex and difficult to describe explicitly. Knowledge-guided multimodal networks [16] and physics-informed deep spatiotemporal models [17] further demonstrate that embedding prior knowledge and multimodal information can markedly improve the accuracy of dynamic process prediction, which is instructive for constructing more accurate renewable output and load forecasting models in microgrid scheduling. In addition, as microgrids increasingly participate in distributed trading and grid-connected operation, information security and the trustworthiness of intelligent decision models have attracted growing attention. Blockchain-based privacy-preserving electricity trading in smart grids [18], the robustness of explainable models against backdoor attacks [19], and steganographic information protection in industrial systems [20] collectively highlight the need to consider security and reliability when intelligent scheduling algorithms are deployed in practical microgrids.

As a novel swarm intelligence algorithm, the Salp Swarm Algorithm (SSA) has the advantages of a simple principle and easy implementation, showing promising potential in the field of microgrid dispatch [21]. Davoudkhani et al. [22] investigated the optimal siting and sizing of renewable energy sources such as wind turbines and photovoltaic systems in distribution networks and proposed a multi-objective optimization method based on the Salp Swarm Algorithm to reduce network losses, improve voltage quality and lower the cost of renewable energy deployment. Sulaiman et al. [23] proposed an Improved Salp Swarm Algorithm to solve the optimal power flow problem with stochastic photovoltaic generation, with the objectives of minimizing network losses, operating cost and the combined cost–emission index; its superiority over other algorithms was verified on the IEEE 30-bus system. Saraswat et al. [24] proposed a memory-based Salp Swarm Algorithm for tuning a fractional-order PID controller, improving voltage and power regulation capability as well as operational resilience of a grid-connected microgrid with photovoltaic panels, wind turbines and batteries under renewable generation and load uncertainties as well as islanded operating conditions. However, SSA still suffers from limitations such as insufficient diversity in the initial population, an imbalance between global and local search capabilities, and a tendency to become trapped in local optima.

Related SSA studies have already explored weighted and multi-strategy modifications. Syed and Syed [25] proposed the Weighted Salp Swarm Algorithm (WSSA), which replaces the equal follower update with a weighted-distance position update derived from coefficient-vector weights. Chen et al. [26] developed SSA by combining dimension-by-dimension centroid opposition-based learning for the food source, a random factor in

follower updating. At the operator level, the present ISSA differs in that it uses Sine-chaotic initialization, calculates each follower weight directly from its normalized Euclidean distance to the current best solution and applies an acceptance-based Lévy perturbation to the current best candidate. Therefore, the contribution of this work is positioned as the specific coordination of these operators rather than the novelty of weighted updating or Lévy flight in isolation.

In summary, taking into account the engineering significance of microgrid optimal scheduling and the advantages of SSA, this paper proposes an Improved Salp Swarm Algorithm (ISSA) to solve the optimal scheduling problem of microgrids. The main contributions are summarized as follows:

- (1) To enhance the diversity of the initial population and avoid the clustering phenomenon caused by random initialization, a Sine chaotic map is employed to generate uniformly distributed initial individuals.
- (2) A distance-adaptive follower update mechanism is incorporated into SSA, where the normalized distance between each individual and the current best solution determines the follower weight. This mechanism is coordinated with an acceptance-based Lévy perturbation of the best solution to improve the balance between exploration and exploitation and reduce premature convergence.
- (3) Finally, the proposed algorithm is applied to a microgrid dispatch case study, and the effectiveness of the improved algorithm is verified.

The remainder of this paper is organized as follows: Section 2 introduces the SSA; Section 3 presents the ISSA and evaluates its performance using benchmark functions; Section 4 establishes an optimal scheduling model applicable to microgrids; Section 5 provides the experimental results and discussion; and the final section concludes the paper and presents future research directions.

2. Salp Swarm Algorithm

The SSA simulates the swarming and navigational behavior of salps during foraging in the ocean. A salp chain has a two-level hierarchical structure: leaders and followers. The leader is located at the front and guides the swarm in navigating the multidimensional search space toward the optimal solution of the optimization problem, i.e., the food source. The SSA starts from randomly initialized solutions and iteratively searches for the best fitness value of each salp by alternately exploring and exploiting the search space. The position update of the leader salp is determined based on its distance from the food source and is calculated using the following equation:

$$X_i^1 = \begin{cases} F_i + r_1((ub_i - lb_i) \times r_2 + lb_i), & r_3 \geq 0.5 \\ F_i - r_1((ub_i - lb_i) \times r_2 + lb_i), & r_3 < 0.5 \end{cases} \quad (1)$$

where X_i^1 denotes the leader position in the i -th dimension; F_i denotes the food source position in the i -th dimension; ub_i, lb_i denotes the upper and lower bounds of the i -th dimension; r_1, r_2, r_3 denotes a random number.

Parameter r_1 balances exploration and exploitation in the search space and is calculated as follows:

$$r_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (2)$$

where l denotes the current iteration number; L denotes the maximum number of iterations.

The position of the follower is updated according to Newton's laws of motion.

$$x_i^j = \frac{1}{2}at^2 + V_0t \quad (3)$$

where x_i^j denotes the position of the j -th follower in the i -th dimension; a denotes the acceleration, $a = \frac{V_{final}}{V_0}$; V_{final} and V_0 denote the final and initial velocities, respectively; t denotes time.

$$x_i^j = \frac{1}{2}(x_i^j + x_i^{j-1}) \quad (4)$$

where x_i^{j-1} denotes the position of the $(j-1)$ -th follower in the i -th dimension.

3. Improved Salp Swarm Algorithm

3.1. Sine Chaotic Initialization

To enhance the diversity of the initial population in the Salp Swarm Algorithm and avoid the issue that random initialization may cause individuals to cluster and distribute unevenly in the search space, a Sine chaotic map is employed to generate the initial individuals. This method leverages the inherent ergodicity and pseudo-randomness of chaotic systems to produce an initial population with a more uniform and broader spatial distribution, without introducing additional random bias. The specific procedure is as follows:

$$x_0 = rand(0,1) \quad (5)$$

$$x_{k+1} = \sin(\pi \cdot x_k) \quad (6)$$

$$X_i^j = lb_i + (ub_i - lb_i) \cdot x_k \quad (7)$$

The distribution of the population before and after the improvement is shown in Figure 1. As can be seen, using the Sine chaotic map to generate the initial population, on the one hand, increases population diversity, which helps the algorithm explore the solution space more thoroughly on a global scale and reduces the risk of being trapped in local optima; on the other hand, the more uniform distribution also provides a higher-quality starting point for subsequent iterative search, thereby improving the convergence accuracy and stability of the algorithm.

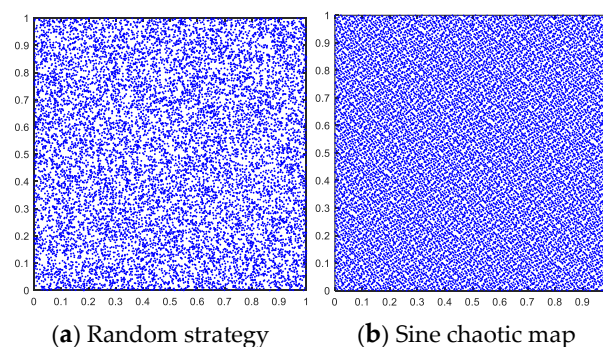


Figure 1. Comparison of the Two Initialization Methods.

3.2. Weighted Distance Position Update Strategy

Existing weighted SSA variants have shown that modifying the equal-weight follower update can improve search behavior [25]. Different from WSSA, which constructs

weights from coefficient vectors, the present method determines the follower weight directly from the normalized Euclidean distance between each individual and the current global best. When far from the best solution, a larger weight preserves more of the individual's own position to encourage exploration; when close to the best solution, a smaller weight increases dependence on the predecessor to strengthen exploitation. For the j -th follower ($j > 2$), its position in the i -th dimension is updated as:

$$X_i^j = \alpha_j \cdot X_i^j + (1 - \alpha_j) \cdot X_i^{j-1} \quad (8)$$

where the weighting coefficient α_j is adaptively determined by the Euclidean distance d_j between the individual and the global optimal solution F_i :

$$\alpha_j = \frac{2}{1 + e^{-\varepsilon \cdot d_j^{norm}}} - 1 \quad (9)$$

where $d_j^{norm} = d_j / d_{max}$ is the normalized distance (relative to the maximum distance in the current population), ε is an adjustment factor set to 5 based on experimental testing. When an individual is far from the optimal solution, α_j approaches 1, making it more inclined to retain its own position (enhancing global exploration); when an individual is close to the optimal solution, α_j approaches 0, then it relies more on the position of the previous individual (enhancing local exploitation). This strategy dynamically adjusts the weight of individual movement, thereby adaptively balancing exploration and exploitation during the iterative process, improving the convergence accuracy and stability of the algorithm.

3.3. Levy Flight Strategy

In the standard Salp Swarm Algorithm, the update of the leader's position depends solely on the current food source (global optimal solution) without any random perturbation mechanism. This causes the population to rapidly converge toward local optima in the later iterations, leading to a sharp decline in diversity and thus premature convergence. To alleviate this issue, a Levy flight disturbance [27] is introduced to improve the leader update strategy, and its mathematical formulation can be expressed as:

$$X_i^1 = X_i^1 + \text{Levy}(\theta) \odot (X_i^1 - F_i) \quad (10)$$

$$\text{Levy}(\theta) = 0.01 * \frac{\mu * \sigma}{|\gamma|^{\frac{1}{g}}} \quad (11)$$

$$\sigma = \left(\frac{\lambda(1+g) * \sin(\frac{\pi g}{2})}{\lambda * (\frac{1+g}{2}) * g * 2^{\frac{(g-1)}{2}}} \right)^{\frac{1}{g}} \quad (12)$$

where $\text{Levy}(\theta)$ is a random step-size vector following a heavy-tailed distribution, λ denotes the Gamma function, γ and μ are random variables obeying a normal distribution, g is a constant set to 1.5, and $\odot$ represents element-wise multiplication. By imposing Levy perturbations on the leader, the long-tailed step-length characteristic of "many short, fine-grained searches plus occasional long jumps" enables the leader to perform refined exploitation around the current optimal region while also having a certain

probability of escaping local optima to explore more distant regions of the search space. This effectively enhances population diversity and prevents premature convergence. Meanwhile, the pseudo-code of ISSA is shown as Algorithm 1.

Algorithm 1: Pseudocode of the ISSA

Input: Population size PS , maximum number of iterations L

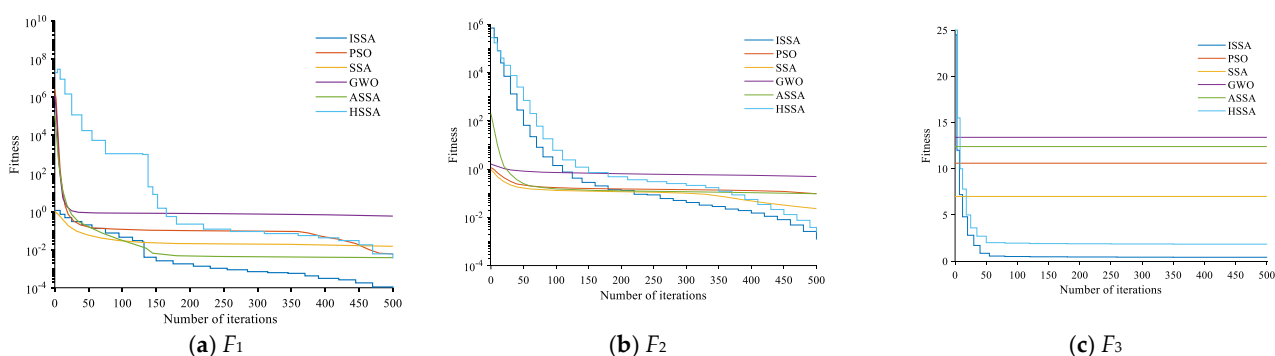
Output: Best solution F

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1: Initialize the population using the Sine chaotic map
2: Evaluate the fitness of all individuals and determine the current best solution  $F$ 
3: for  $l = 1$  to  $L$  do
4:     Update the leader position
5:     Update the position of the second follower
6:     for  $j = 3$  to  $PS$  do
7:         Calculate the distance between the  $j$ -th individual and the current best solution
8:         Calculate the normalized distance  $d_j^{norm}$ 
9:         Calculate the adaptive weight  $\alpha_j$  according to Equation (9)
10:        Update the position of the  $j$ -th follower
11:    end for
12:    Evaluate the fitness and update the current best solution  $F$ 
13:    Apply Lévy-flight perturbation to  $F$  to generate a candidate solution  $F_{new}$ 
14:    if  $f(F_{new}) < f(F)$  then
15:         $F = F_{new}$ 
16:    end if
17: end for
  
```

3.4. Function Tests

In this study, six benchmark test functions listed in Table 1 are employed to validate the effectiveness of the ISSA, and the obtained results are comparatively analyzed against those of SSA [21], PSO [28], GWO [29], ASSA [30] and HSSA [31]. For each test function, 30 independent runs are conducted, with a population size of 30 and a maximum iteration count of 500. The parameter settings of all algorithms are determined according to their respective reference literature. The optimization performance is comprehensively evaluated in terms of the Average value (AVE) and Standard Deviation (SD), so as to assess both the accuracy and robustness of the obtained solutions. The corresponding experimental results are presented in Table 2, and the convergence curves of the algorithms are shown in Figure 2.



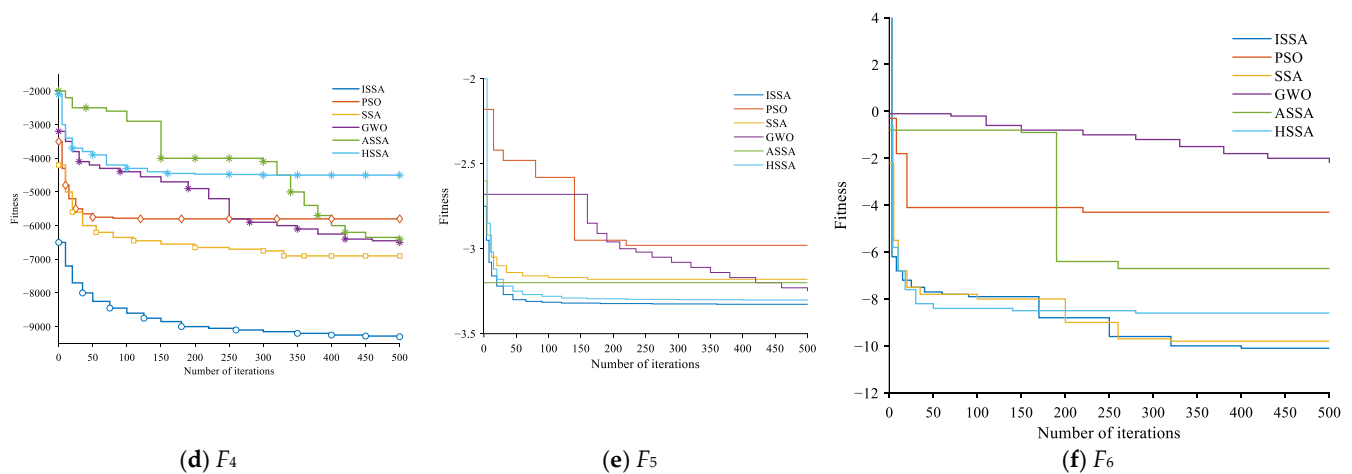


Figure 2. Convergence Curves of the Six Algorithms.

Table 1. Test Functions.

Functions	Variable Range	Fmin
$F_1(x) = \frac{\pi}{n} \left\{ 10 \sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 [1 + 10 \sin^2(\pi y_{i+1})] + (y_n - 1)^2 \right\} + \sum_{i=1}^n u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(x_i + a)^m & x_i < -a \end{cases}$	$[-50, 50]$	0
$F_2(x) = \sum_{i=1}^n ([x_i + 0.5]^2)$	$[-100, 100]$	0
$F_3 = \left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (x_i - a_{ij})^6} \right]$	$[-65, 65]$	0.99804
$F_4(x) = \sum_{i=1}^n -x_i \sin(\sqrt{ x_i })$	$[-500, 500]$	$-418.98n$
$F_5 = -\sum_{i=1}^4 c_i \exp(-\sum_{j=1}^6 a_{ij} (x_j - p_{ij})^2)$	$[0, 1]$	-3.32
$F_6 = -\sum_{i=1}^5 [(X - a_i)(X - a_i)^T + c_i]^{-1}$	$[0, 10]$	-10.1532

Table 2. Experimental Results.

Functions	ISSA	PSO	SSA	GWO	ASSA	HSSA
F_1 AVE	0.0072	0.4990	0.1423	0.7029	0.0203	0.2816
F_1 SD	0.0134	0.0404	0.0603	0.0239	0.0263	1.0078
F_2 AVE	0.0048	3.1887	1.0410	2.2078	0.8575	0.0199
F_2 SD	0.0016	0.2648	0.3911	0.1600	0.3971	0.0530
F_3 AVE	1.7536	9.7095	8.1555	12.6709	3.7725	3.3380
F_3 SD	0.9223	3.9343	5.2692	1.52×10^{13}	4.0132	3.4650
F_4 AVE	-8.12×10^3	-4.72×10^3	-7.23×10^3	-6.31×10^3	-5.88×10^3	-5.45×10^3
F_4 SD	411.1220	454.0656	645.1522	498.2322	854.3145	801.5845

F_5	AVE	-3.3000	-3.0583	-3.2084	-3.2007	-3.2637	-3.2990
	SD	0.0125	0.0906	0.0486	0.0061	0.0714	0.0472
F_6	AVE	-10.1475	-3.8314	-9.1202	-4.7394	-6.5635	-6.0150
	SD	0.0038	1.7684	1.3486	3.1464	3.5161	3.6196

The comparative experimental results in Table 2 show that ISSA outperforms other algorithms significantly on all six test functions. Firstly, in terms of Average value (AVE), ISSA achieves the lowest value on all test functions, especially on F_1 , F_2 and F_6 , demonstrating strong optimization capabilities and significant advantages in global search performance. Secondly, the Standard deviation (SD) indicator indicates that ISSA has stronger robustness; especially on F_1 and F_6 , its standard deviation is significantly lower than that of other algorithms, indicating higher stability in multiple runs. This is mainly attributed to the use of sinusoidal chaotic mapping to initialize the population, effectively avoiding premature clustering and enhancing population diversity. Additionally, by combining the update strategy based on weighted distance with the Levy flight perturbation mechanism, ISSA can achieve a good balance between global exploration and local exploitation, thereby further enhancing its search ability. The convergence curves shown in Figure 2 directly verify the above observations. Figure 3 presents the box plots of the results of 6 algorithms after running independently 30 times. The figure clearly shows that the results of ISSA are at the lowest position, further verifying its superior performance. Overall, ISSA converges faster and has stronger global search capabilities when solving complex optimization problems, laying a solid foundation for solving the optimal scheduling problem of microgrids.

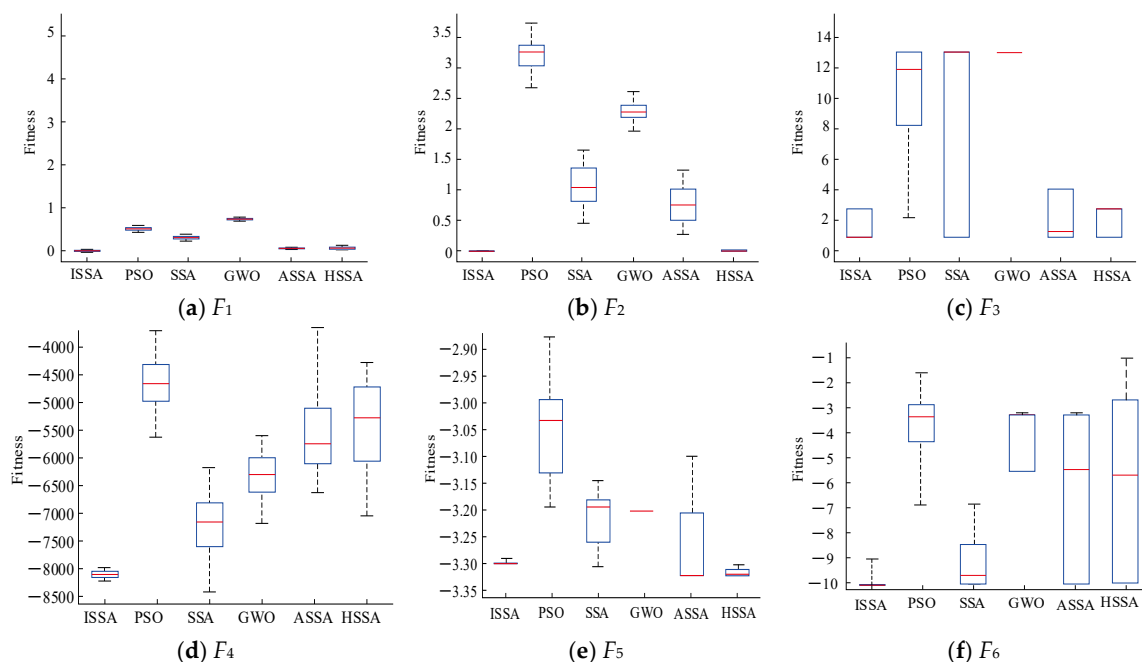


Figure 3. Six Algorithms Box Plots.

To further verify whether there are significant differences between the ISSA and other comparison algorithms, the Friedman test was conducted on the data in Table 2. The significance level was defined as 0.05. If the *p-value* is less than 0.05, it indicates that there is a significant difference between the ISSA and the comparison algorithms. Otherwise, there is no significant difference. The results are shown in Table 3. From Table 3, it can be seen that the *p-value* is 1.06×10^{-3} , indicating a significant difference between the algorithms. Additionally, Figure 4 presents a panel chart showing the average rankings of the

comparison algorithms. Through Figure 4, it can be intuitively observed that the ISSA has the highest average ranking (Combining all the results for testing, it was found that the average ranking of the results obtained by the ISSA was in the top 1.500.), verifying its superiority. In conclusion, by conducting the *Friedman* test on the optimized objective function values obtained from multiple independent runs of the algorithm, it can be determined that the ISSA and its comparison algorithms have significant differences statistically. This further validates the superiority of the ISSA.

Table 3. Results of *Friedman* Test Comparing ISSA with Other Algorithms.

Comparison Algorithm	Average Ranking	Chi-Square	<i>p</i> -Value	CD _α = 0.05	CD _α = 0.1
ISSA	1.500	20.381	1.06×10^{-3}	3.078	2.796
PSO	5.667				
GWO	5.000				
ASSA	2.833				
HSSA	3.100				
SSA	2.900				

Note: the average rank is calculated across the six benchmark functions (smaller is better). The critical difference is $CD = q_\alpha \sqrt{\frac{k(k+1)}{N}}$, where $k = 6$ algorithms and $N = 6$ benchmark functions. Thus, $CD_{0.05} = 3.078$ and $CD_{0.10} = 2.796$.

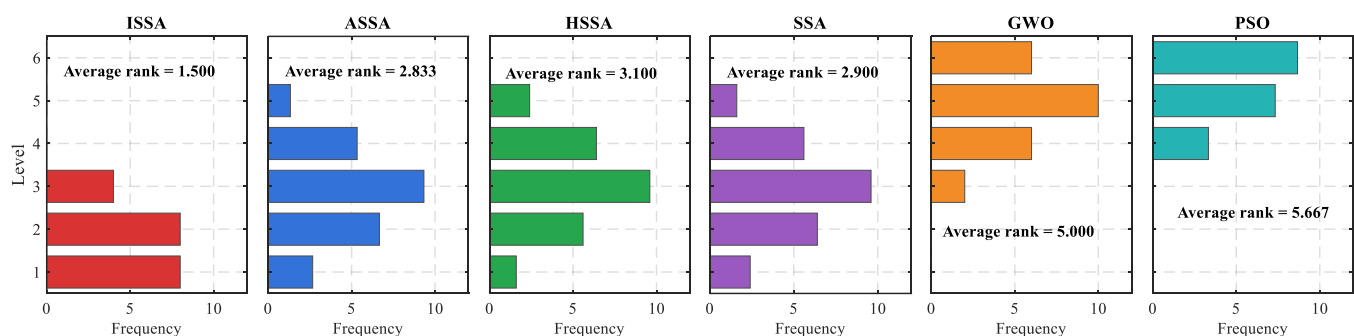


Figure 4. Average-rank panel chart of the compared algorithms.

3.5. Analysis of Strategy Effectiveness

To verify the effectiveness of each improvement strategy, we designed several variants of the ISSA. ISSA1 removes the Sine chaotic initial strategy; ISSA2 removes the weighted distance position update strategy; ISSA3 removes the Levy flight strategy. The evaluation indicators are the optimal value and variance. The experimental settings are the same as those in Section 3.4. The experimental results are shown in Table 4. The tests in Table 4 indicate that the proposed strategies contribute to the ISSA to some extent.

Table 4. Experimental Results of ISSA and Variant Algorithms.

Functions		ISSA1	ISSA2	ISSA3	ISSA
F_1	AVE	0.0094	0.0089	0.0085	0.0072
	SD	0.0210	0.0221	0.0183	0.0134
F_2	AVE	0.0068	0.0059	0.0062	0.0048
	SD	0.0024	0.0018	0.0019	0.0016
F_3	AVE	1.9326	1.9545	1.9247	1.7536
	SD	0.9954	0.9542	0.9622	0.9223
AVE		-8.06×10^3	-8.02×10^3	-8.07×10^3	-8.12×10^3

F_4	SD	415.5420	426.6542	432.6842	411.1220
F_5	AVE	−2.6542	−2.3252	−2.6245	−3.3000
	SD	0.8741	0.8665	0.8921	0.0125
F_6	AVE	−9.6527	−9.2546	−9.5580	−10.1475
	SD	0.0823	0.0952	0.0862	0.0038

From the results of the ISSA and its variant algorithms in Table 4, it can be seen that the ISSA outperforms its variant algorithms on all test functions. From the comparison of ISSA1 and ISSA, it can be observed that the introduced sinusoidal chaotic initial strategy helps to increase the diversity of the population, thereby improving the quality of the solution. From the comparison of ISSA2 and ISSA, it can be seen that the introduced weighted distance position update strategy well balances the global exploration and local exploitation capabilities of the algorithm. For the comparison of ISSA3 and ISSA, it can be seen that the introduction of the Levy flight strategy helps the algorithm escape from local optima. Notably, the numerical values of ISSA1 do not differ significantly from those of ISSA3 and ISSA, indicating that the introduction of the Levy flight strategy has a greater impact than simply introducing the sinusoidal chaotic initial strategy. In summary, these three improvement strategies contribute to the performance enhancement of the ISSA to some extent.

4. Optimal Scheduling in Microgrid

4.1. Mathematical Model of Microgrid

4.1.1. Photovoltaic Model

The output power of Photovoltaic (PV) cells is related to their output power under standard test conditions, as well as factors such as light intensity and operating temperature, as shown in Equation (13).

$$P_{PV} = P_m \frac{G}{G_{STC}} (1 + \varpi(Temp - Temp_r)) \quad (13)$$

where P_{PV} is the output power of the PV cell. P_m represents the maximum output power under standard conditions. G represents the intensity of light. G_{STC} represents the light intensity under standard conditions. ϖ is the temperature condition coefficient. $Temp$ represents the current temperature of the photovoltaic cell. $Temp_r$ is the reference temperature for photovoltaic cells.

4.1.2. Wind Turbine Model

Taking wind speed and other data as input, the output power of the Wind Turbine (WT) can be predicted based on the mathematical model, as shown in Equation (14) [32].

$$P_{WT} = \begin{cases} 0, v < v_{ci} \text{ or } v_{co} \leq v \\ P_n \frac{v - v_{ci}}{v_n - v_{ci}}, v_{ci} \leq v \leq v_n \\ P_n, v_n < v < v_{co} \end{cases} \quad (14)$$

where P_{WT} is the output power of the wind turbine. P_n is the rated power of the wind turbine. v_{ci} , v_n , v_{co} are the cut-in wind speed, rated wind speed and cut-out wind speed, respectively.

4.1.3. Micro Gas Turbine Model

The working efficiency of a Micro gas Turbine (MT) has a certain relationship with its output power. The function form of its efficiency varying with output power can be expressed by Equation (15). Meanwhile, the power generation cost of micro gas turbines is also related to their output power, and the relationship can be described by Equation (16).

$$Q_{MT}(k) = 0.0753\left(\frac{P_{MT}(k)}{65}\right)^3 - 0.3095\left(\frac{P_{MT}(k)}{65}\right)^2 + 0.4174\frac{P_{MT}(k)}{65} + 0.1068 \quad (15)$$

$$C'_{MT}(k) = \text{Cost} \frac{1}{\text{LHV}} \times \frac{P_{MT}(k)}{Q_{MT}(k)} \quad (16)$$

where $C'_{MT}(k)$, $P_{MT}(k)$, $Q_{MT}(k)$ are the fuel cost, output power and generation efficiency of the micro gas turbine at time k , respectively. LHV represents the low calorific value of natural gas. In this paper, LHV is taken as 9.7 kWh/m³ and $\text{Cost} = 3$.

4.1.4. Diesel Engine Model

The design of Diesel Engine (DE) them with features such as rapid start-up, stable operation, mature technology and easy maintenance. These characteristics keep them in an irreplaceable position in various application scenarios. The fuel cost of a diesel generator is also related to its output power and can be expressed by a quadratic function expression, as shown in Equation (17).

$$F_{DE} = H_1 P_{DE}^2 + H_2 P_{DE} + H_3 \quad (17)$$

where F_{DE} and P_{DE} are the fuel cost and output power of diesel generator, respectively. H_1, H_2, H_3 are the fuel cost coefficients of diesel generator sets. In this paper, $H_1 = 0.00011$, $H_2 = 0.1801$, $H_3 = 6$ are taken.

4.1.5. Battery Energy Storage System Model

Battery Energy Storage System (BESS) can provide more flexible power regulation, quickly respond to changes in grid load and meet the demands of microgrid systems for efficient and reliable energy storage. Therefore, the battery has become the preferred device in the microgrid energy storage system. The mathematical model of the battery in this paper is shown in Equation (18).

$$P_{SOC}(k) = \begin{cases} P_{SOC}(k-1) + \frac{1}{\chi^-} P_{BESS}(k), & P_{BESS}(k) \leq 0 \\ P_{SOC}(k-1) + \frac{1}{\chi^+} P_{BESS}(k), & P_{BESS}(k) > 0 \end{cases} \quad (18)$$

where $P_{SOC}(k)$ is the remaining capacity of the battery at time k . $P_{BESS}(k)$ represents the charging and discharging power of the battery at time k . where is positive for charging and negative for discharging. χ^+ and χ^- represent the charging and discharging efficiencies, respectively.

4.2. Objective Function

In this paper, the comprehensive cost is taken as the optimization objective, considering both the economic operation cost of the microgrid and the microgrid's environmental protection costs. So, the comprehensive cost expression of the microgrid is as follows:

$$C^* = \min(f'_1 + f'_2) \quad (19)$$

$$f'_1 = \sum_{k=1}^K (C_{FU}^*(k) + C_{OM}^*(k) + C_{GRID}^*(k) + C_{PUNISH}^*(k)) \quad (20)$$

$$C_{FU}^*(k) = \text{Cost} \frac{1}{LHV} \times \frac{P_{MT}(k)}{Q_{MT}(k)} + F_{DE}(k) \quad (21)$$

$$C_{OM}^*(k) = u_{WT}P_{WT}(k) + u_{PV}P_{PV}(k) + u_{DE}P_{DE}(k) + u_{MT}P_{MT}(k) + u_{BESS}P_{BESS}(k) \quad (22)$$

$$C_{GRID}^*(k) = C_{Buy}^*(k)P_{Buy}(k) - C_{Sell}^*(k)P_{Sell}(k) \quad (23)$$

$$C_{PUNISH}^*(k) = R_{punish}P_{loss}(k) + R'_{punish}P_{over}(k) \quad (24)$$

$$f'_2 = \sum_{k=1}^K \left(\sum_{n=1}^{n'} (C_n^* (\rho_{MT,n}P_{MT}(k) + \rho_{DE,n}P_{DE}(k) + \rho_{GRID,n}P_{GRID}(k))) \right) \quad (25)$$

where f'_1 is the operating cost of the microgrid. K is the number of scheduling periods of the microgrid, $K = 24$. C_{FU}^* is the fuel cost of the microgrid at time k , C_{OM}^* is the operation and maintenance cost of the microgrid at time k , and C_{GRID}^* is the electrical energy interaction cost between the microgrid and the main grid at time k . C_{PUNISH}^* is the penalty cost for the microgrid to exceed the limit at time k . u_{WT} , u_{PV} , u_{MT} , u_{DE} , u_{BESS} are the operation and maintenance coefficients of WT, PV, MT, DE and BESS, respectively. C_{Buy}^* and P_{Buy} represent the price and power at which the microgrid purchases electricity from the large grid at time k , respectively. C_{Sell}^* and P_{Sell} represent the price and power at which the microgrid sells electricity to the large grid at time k , respectively. R_{punish} and R'_{punish} are the penalty coefficients for load power-off and battery overload, respectively. $P_{loss}(k)$ is the power loss of the load at time k , and $P_{over}(k)$ is the excess capacity of the battery at time k . f'_2 represents the environmental protection cost of the microgrid, n represents the types of pollutants, and n' represents the types and quantities of pollutants, mainly including CO₂, SO₂ and NO_x. C_n^* represents the cost coefficient for treating the n -th type of pollutant, and ρ_{MT} , ρ_{DE} , ρ_{GRID} represent the emissions of the n -th type of pollutant generated during the operation of micro gas turbines, diesel generators and large power grids, respectively. C^* represents the comprehensive cost.

4.3. Constraint Conditions

To ensure the safe, stable and efficient operation of the microgrid system, all distributed power sources, energy storage devices and connection lines, certain constraints must be met. The specific constraints are as follows.

① Power balance constraint

$$P_{PV}(k) + P_{WT}(k) + P_{DE}(k) + P_{MT}(k) + P_{GRID}(k) + P_{BESS}(k) = P_{Load}(k) \quad (26)$$

where $P_{WT}(k)$ and $P_{PV}(k)$ are the scenery output at time k . $P_{DE}(k)$ represents the output of the diesel generator at time k . $P_{MT}(k)$ is the output of the micro gas turbine at time k . $P_{GRID}(k)$ represents the transaction power between the microgrid and the large grid at time k . A positive value indicates power purchase, and a negative value indicates power sale. $P_{BESS}(k)$ represents the charging and discharging power of the battery at time k , which is positive for charging and negative for discharging. $P_{Load}(k)$ is the load of the microgrid at time k .

② DE output constraint

$$P_{DE}^{\min} \leq P_{DE}(k) \leq P_{DE}^{\max} \quad (27)$$

$$|P_{DE}(k) - P_{DE}(k-1)| \leq r_{DE} \quad (28)$$

where $P_{DE}^{\min}$ is the minimum output power of DE. $P_{DE}^{\max}$ is the maximum output power of the DE. r_{DE} is the upper limit of the climbing power of the DE.

③ MT output constraint

$$P_{MT}^{\min} \leq P_{MT}(k) \leq P_{MT}^{\max} \quad (29)$$

$$|P_{MT}(k) - P_{MT}(k-1)| \leq r_{MT} \quad (30)$$

where $P_{MT}^{\min}$ is the minimum output power of MT; $P_{MT}^{\max}$ is the maximum output power of the MT. r_{MT} is the upper limit of the climbing power of the DE.

④ Power grid (GRID) output constraint

$$P_{GRID}^{\min} \leq P_{GRID}(k) \leq P_{GRID}^{\max} \quad (31)$$

where $P_{GRID}^{\min}$ and $P_{GRID}^{\max}$ are the minimum and maximum power traded between the microgrid and the large grid, respectively.

⑤ BESS output constraint

$$P_{BESS}^{\min} \leq P_{BESS}(k) \leq P_{BESS}^{\max} \quad (32)$$

$$SOC^{\min} \leq SOC(k) \leq SOC^{\max} \quad (33)$$

where $P_{BESS}^{\min}$ and $P_{BESS}^{\max}$ are the minimum and maximum values of the battery charging and discharging power, respectively. $SOC^{\min}$ and $SOC^{\max}$ represent the lower and upper limits of the battery's energy storage capacity, respectively.

5. Example Analysis

5.1. Example Parameters

This study considers a deterministic 24 h day-ahead scheduling case with PV, WT, DE, MT, GRID and BESS. Among them, the maximum capacity of BESS is 150 kWh, the minimum capacity is 5 kWh, the initial capacity is 50 kWh, the maximum output and input power are both 30 kW, the charge and discharge rate is 0.9, and the operation and maintenance cost is 0.026 USD/kW; The unit parameters are shown in Table 5, the pollutant emission coefficients and pollutant treatment costs are presented in Table 6, the selected time-of-use electricity price parameters are shown in Table 7, and the wind, solar and load power prediction curves of a typical day in a certain area are shown in Figure 5.

Table 5. Parameters of each distributed power generation unit.

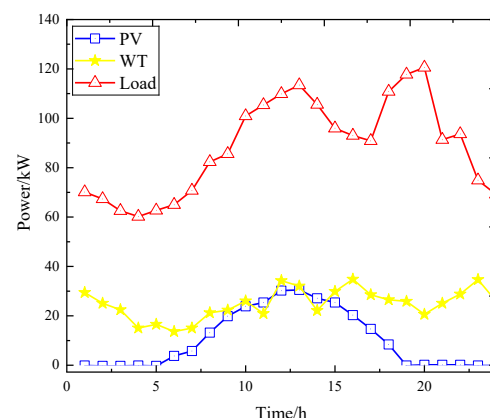
Type	Upper Power Limit	Lower Limit Power/kW	Maintenance Unit Price (USD/kW·h)	Upper Limit Climbing Power (kW/min)
PV	50	0	0	0
WT	100	0	0	0
MT	30	3	0.0293	1.5
DE	65	0	0.04	1.5
GRID	30	−30	0	0

Table 6. The cost of pollutant control and emission coefficient.

Types of Pollutants	Governance Cost (USD/Kg)	Pollutant Emission Coefficient (g/kW·h)		
		DE	GRID	MT
CO ₂	0.023	680	889	724
SO ₂	6	0.306	1.8	0.0036
NOX	8	10.09	1.6	0.2

Table 7. Time-of-use electricity price.

Type	Time Period	Purchase Price (USD/kW·h)	Sales Price (USD/kW·h)
Peak hours	10:00–15:00	0.78	0.54
	18:00–22:00		
Smooth period	08:00–09:00	0.62	0.53
	16:00–17:00		
Valley period	01:00–07:00	0.46	0.52
	23:00–24:00		

**Figure 5.** Typical daily wind, solar and load power prediction curves.

5.2. Analysis of Optimization Results

Based on the predicted data of day-before load, wind turbines and photovoltaic power in engineering practice, this paper uses GWO, HSSA, PSO, ASSA, SSA and ISSA to solve for the lowest economic operation cost, environmental protection cost and comprehensive cost, respectively, of the microgrid connection optimization dispatching model. The statistics in Table 8 show the optimal results of each algorithm for different targets. Figure 6 shows the convergence curves of the algorithm for different targets. Figure 7 shows the output of each distributed power source obtained by the ISSA under different objective functions.

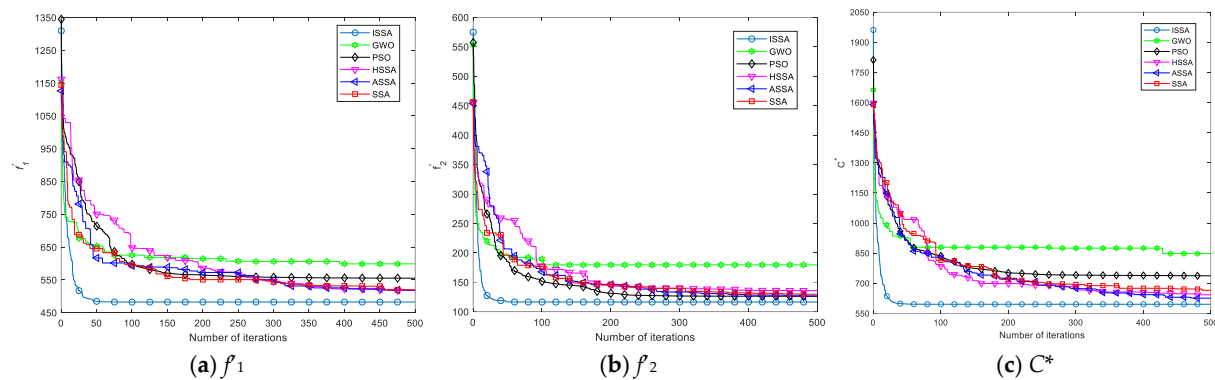


Figure 6. The iterative curves of each algorithm under different objective functions.

Table 8. Comparison of simulation results of six algorithms under different objective functions.

Objective Function	GWO	SSA	ASSA	HSSA	PSO	ISSA
f_1'	649.78	543.32	539.88	541.63	581.76	466.10
f_2'	198.45	139.56	138.22	138.96	140.23	113.12
C^*	848.23	682.88	678.10	680.59	721.99	579.22

As can be seen from Table 8, compared with the GWO, HSSA, PSO, ASSA and SSA, the optimization ability and stability of the ISSA have been significantly improved. No matter which target it is, the optimal cost of the ISSA is reduced by at least 15% or more. Figure 6 further visually verifies this point, demonstrating the superiority of the ISSA.

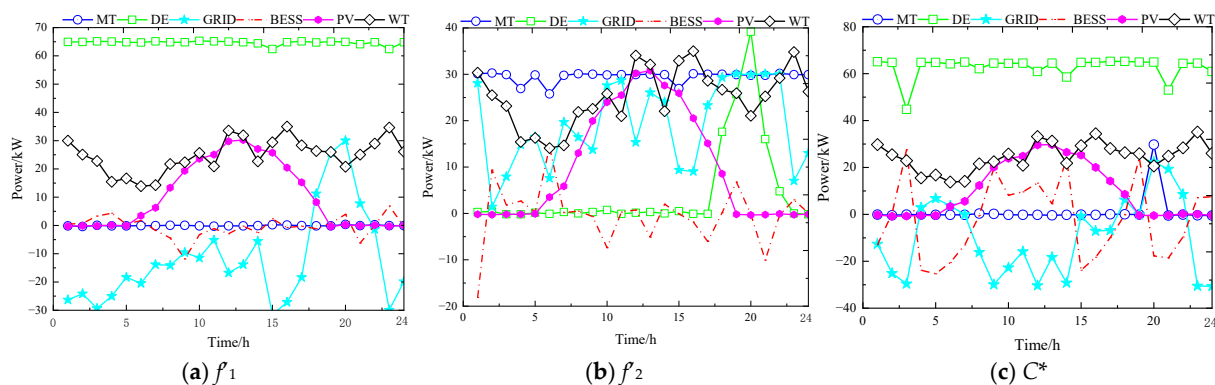


Figure 7. The optimal output situation of the ISSA on different objective functions.

As can be seen from Figure 7, for the same microgrid model, the optimal scheduling results obtained under different objective functions are different. Now, let us conduct a detailed analysis of them individually:

Figure 7 shows the optimal output of each distributed power source under different objective functions. As can be seen from Figure 7a, when the goal is to minimize the operating cost, DE operates at full capacity due to its power generation cost being lower than the power sales cost of the microgrid, while MT does not operate. Due to the operation and maintenance costs and capacity constraints, the output of storage batteries is relatively low. Therefore, it is necessary to maintain a stable power supply through alternating charging and discharging. During peak hours from 18:00 to 22:00, DE is unable to meet the surging power load, and the microgrid opts to purchase electricity from the large grid to ensure supply. During other periods, DE meets the load demand and sells the excess electricity to the main power grid.

As can be seen from Figure 7b, when the goal is to minimize environmental protection costs, MT operates at full capacity due to its environmental protection cost being lower than the power purchase cost of the microgrid. The environmental protection cost of DE is relatively high, so DE still needs to be started during peak hours to ensure power supply. Although the MT continues to operate, it still needs to purchase electricity from the large power grid, and the purchased electricity is affected by load demand and the condition of the battery.

As can be seen from Figure 7c, when the goal is to minimize the comprehensive cost, MT does not operate during the off-peak period, the battery ensures power supply through charging and discharging, and DE operates at full load for most of the time. When the purchase price is low, the microgrid selects to purchase electricity to charge the battery. During peak hours, DE and the battery supply power together to ensure the reliability of power supply.

In conclusion, the dispatching results of microgrids are influenced by the objective function and the economic and environmental costs of each distributed power source. Under different goals, the priority power supply varies. The ISSA performs exceptionally well in optimizing scheduling, enhancing the operational efficiency and benefits of microgrids.

The scope of the present validation is intentionally limited to the deterministic single-day scheduling problem considered above. An exactly equivalent MILP benchmark is not introduced because the original formulation contains nonlinear generation cost relationships and penalty-based constraint handling; constructing an MILP reference would require additional linearization and reformulation and would therefore no longer be strictly identical to the problem solved by ISSA. Accordingly, the present results are interpreted as comparative algorithmic evidence under the investigated model and operating condition, rather than as proof of global optimality or cross-day generalization.

6. Conclusions

To address the shortcomings of the conventional Salp Swarm Algorithm (SSA) in high-dimensional and complex optimization problems, such as slow convergence speed, insufficient population diversity and a tendency to become trapped in local optima, this paper proposes an Improved Salp Swarm Algorithm incorporating Sine chaotic map-based initialization, a weighted-distance position update strategy and Levy flight perturbation. Specifically, the Sine chaotic map is employed to generate an evenly distributed initial population, effectively alleviating the population clustering issue caused by random initialization and enhancing the initial diversity of the swarm. The weighted-distance position update strategy demonstrates superior performance in balancing global exploration and local exploitation, enabling the algorithm to adaptively adjust its step size during the search process. In addition, the Levy flight strategy introduces stochastic perturbations to individuals, thereby strengthening the algorithm's capability to escape local optima. The proposed algorithm is applied to the optimization of microgrid dispatch. Experimental results indicate that the improved algorithm significantly outperforms the comparative algorithms in terms of optimization accuracy, convergence speed and stability, which verifies its effectiveness and robustness in solving practical engineering optimization problems.

The conclusion of this study should be solved based on the deterministic 24 h scheduling environment considered in this paper. The results of the paper support the comparative search performance of ISSA in the studied microgrid model but do not prove its global optimality or statistical generalization ability under different operation days or uncertain renewable energy/load conditions. Long-term random testing, benchmark tests of

precise or approximate solvers, feasibility residual reports and more extensive reproducibility studies are still important extension directions for future work.

Future research will focus on the following aspects: first, investigating an adaptive parameter regulation mechanism so that the chaotic map parameters and Levy flight step size can be dynamically adjusted according to the search state, thereby improving adaptability to different problem characteristics; second, exploring hybridization of the proposed algorithm with other intelligent optimization methods, such as differential evolution and particle swarm optimization, to develop a more synergistic hybrid optimization framework; third, considering the uncertainties in practical microgrid systems, such as fluctuations in renewable energy output and random variations in load demand, robust optimization or interval optimization methods will be introduced to enhance the practical value of the algorithm in dynamic environments.

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