

Article

The Study of Scheduling Optimization for Multi-Microgrid Systems Based on an Improved Differential Algorithm

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Abstract: As traditional power grids are unable to meet growing demand, extensive research on multi-microgrid scheduling has begun to address the issues present in conventional power grids. However, existing studies on the scheduling of grid-connected multi-microgrids still lack sufficient focus on system demand-side and interaction-side aspects. At the same time, the uncertainties of renewable energy and demand-side responses further complicate this research. To address this, this paper proposes an operational scheduling strategy based on an improved differential evolution algorithm, aiming to incorporate power interactions between microgrids, demand-side responses, and the uncertainties of renewable energy, thus enhancing the operational reliability and economic efficiency of multi-microgrid systems. The research in this paper is divided into the following steps: (1) constructing a multi-microgrid model primarily based on renewable energy; (2) formulating an optimization model with the objective of minimizing economic costs while ensuring stable system operation and solving it; (3) proposing an improved differential evolution algorithm for optimizing system scheduling; (4) testing and validating the improved differential algorithm; and (5) designing an operational strategy that accounts for the uncertainties of renewable energy and load demand. Through the application of real-world cases, the feasibility and effectiveness of the operational scheduling strategy based on the improved differential evolution algorithm are verified.



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Keywords: power interaction between multiple microgrids; renewable energy; improved differential evolution algorithm; operational scheduling strategy

1. Introduction

With societal progress, the demand for electricity and the quality of power supply have continued to increase, making it difficult for traditional power grids to meet current needs. To address this challenge, research into new power networks has gradually emerged, and microgrids have become a popular focus of study [1–3]. A microgrid is a small-scale power system that integrates distributed energy sources (such as photovoltaic and wind power), energy storage devices, and demand-side loads. Compared with traditional power grids, microgrids not only improve the utilization of renewable energy but also significantly reduce the consumption of fossil fuels, playing a crucial role in environmental protection [4,5].

Currently, research on the grid connection of single microgrid systems is relatively mature, primarily focusing on optimizing the uncertainty of new energy output [6–8]. The authors of reference [6] proposed an optimization scheme based on two-stage stochastic scheduling, which comprehensively considers the uncertainties of distributed photovoltaic and wind power generation, as well as demand response. This scheme addresses uncertainty issues through probabilistic distribution sampling and is suitable for the optimization of single multi-energy systems. In addition, reference [7] provides a literature review on

the unit commitment problem in power systems, summarizes solutions for the uncertainty of renewable energy, reviews various optimization techniques, and highlights the current gaps in research. The authors of reference [8] used the Monte Carlo method to model uncertain power sources and proposed an optimal operation mode by combining meta-heuristic algorithms to constrain variables. Furthermore, reference [9] proposed a two-stage energy management strategy that optimizes the next day's output source operation mode in the first stage, while the second stage manages load control, predicts influencing factors, and develops an optimal operation strategy to address the uncertainties of renewable energy and loads. In addition, reference [10] proposes a distributed gradient algorithm for solving the economic dispatch problem, taking into account energy storage systems (ESS), distributed energy sources, variable fuel prices, and multiple uncertainties. The feasibility of the algorithm is verified through a case study model. The authors of reference [11] introduce an improved particle swarm optimization algorithm, which dynamically adjusts the individual and social learning relationships of particles by incorporating nonlinear cognitive and social cooperation. Additionally, a Levy flight strategy is included to enhance randomness. The algorithm controls the variable output power and ramp rates of generating units, and its feasibility is validated through practical case models. Due to the limited capacity of individual microgrids, it is difficult to significantly improve the power quality of large power systems. Therefore, research has gradually shifted to the interconnected scheduling of multiple microgrids to enhance the overall system's stability and operational efficiency [12,13]. In a multi-microgrid system, each microgrid operates independently but remains closely interconnected through point-to-point connections or power lines, reducing reliance on the main grid [14–16].

Current research on multi-microgrid grid connections mainly focuses on structural models and scheduling optimization. The authors of reference [17] proposed a coordinated optimal scheduling model for multi-microgrids and introduced a real-time optimal control strategy based on storage coordination, greatly improving the absorption rate of renewable energy. In addition, reference [18] studied the multi-objective scheduling of a combined heat and power microgrid, constructing an optimization model aimed at minimizing operational and environmental costs, which was solved using a hybrid gravity search algorithm and a random forest regression algorithm. Furthermore, reference [19] proposed a microgrid scheduling method that considers traditional generators, wind energy, solar energy, batteries, and electric vehicles. This method used a hybrid DE-HS algorithm to optimize the system's total cost and investment, enhancing the stability of the microgrid. In addition, reference [20] proposed a multi-microgrid energy storage sharing model, which reduced the system's daily storage and operational costs through a two-layer optimization scheme and a non-dominated sorting equilibrium optimization algorithm.

This study addresses the scheduling and total operational cost optimization of multi-microgrid grid-connected systems by proposing an optimization method based on an improved differential evolution algorithm. The main contributions of this research include:

- (1) Developing a renewable energy multi-microgrid model with photovoltaic and wind power as the primary sources, taking into account system operational stability, costs, power interactions between microgrids and the main grid, and demand-side response.
- (2) Proposing an improved algorithm that combines chaotic mapping with the differential evolution algorithm. This algorithm enhances global search capability, avoids local optima, and improves the efficiency of the solution space search for complex problems.
- (3) Designing a new scheduling strategy for multi-microgrid grid connections based on the improved algorithm. This strategy reduces operational costs while achieving peak shaving and valley filling, ensuring stable system operation.

The content of this study is organized as follows:

1. Introduction: This section introduces the background of the article, the current state of research, and the main contributions of this study.

2. Model Construction for Multi-Microgrid Integration: This section constructs models for each unit within the microgrid, including the optimization objective model, constraints for state variables and condition variables, and scheduling operation strategies.

3. Improved Differential Evolution Algorithm: This section describes how the differential algorithm is improved and tests the algorithm using multiple benchmark functions to verify its feasibility.

4. Case Validation: This section validates the algorithm through case studies to determine the operating states of each unit within the microgrid system.

5. Conclusion: This section summarizes the overall research findings.

6. Outlook: This section summarizes the limitations of this study and proposes solutions for future research.

2. Construction of the Multi-Microgrid Grid-Connected Model

2.1. Overview of Multi-Microgrid Grid Connections

In traditional radial microgrid structures, microgrids are connected to the main grid only through a bus. However, in the multi-microgrid grid-connected model studied in this paper, each microgrid operates independently and is connected to the main grid through a bus. Figure 1 illustrates the multi-microgrid grid-connected system structure adopted in this research, which consists of three independent microgrids. The grid connection modes for multi-microgrids can be broadly categorized into distributed and centralized grid connections. Considering economic benefits and the stability of the power supply, this paper adopts the centralized grid connection. The advantage of centralized grid connection lies in its ability to provide stable power, allow flexible regulation, and improve economic efficiency. Energy losses in transmission lines and conversion losses are not considered in this study.

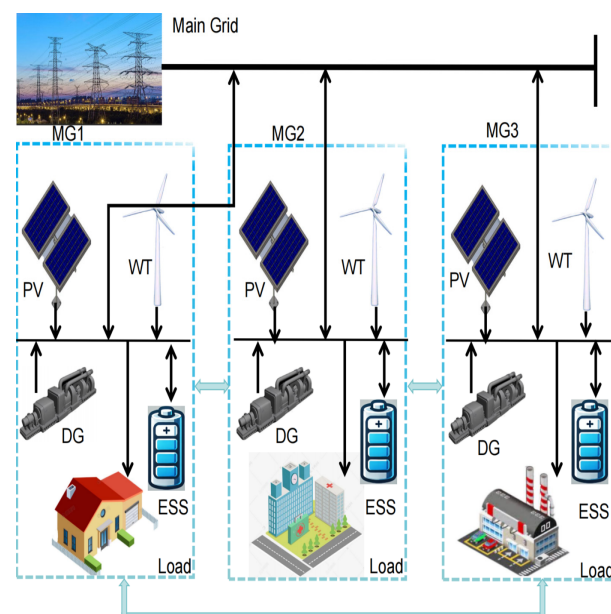


Figure 1. Structure Model of the Multi-Microgrid Grid-Connected System.

As shown in Figure 1, the system is composed of three independent microgrids: MG1, MG2, and MG3. The photovoltaic generation equipment, wind power generation equipment, diesel generators, and energy storage devices in each microgrid are modeled using the same equivalent models. However, in practical microgrid construction, due to various influencing factors, some microgrids may not be equipped with a complete set of renewable energy devices. Therefore, it is assumed that MG1 primarily uses photovoltaic generation, MG2 relies on wind power generation, and MG3 is equipped with both photovoltaic

and wind power generation devices. Additionally, MG1, MG2, and MG3 all have diesel generators as backup power sources.

2.2. Objective Function Optimization

In a multi-microgrid grid-connected system, the objective function for each independent microgrid is the total operating cost C_{MG} . This study aims to develop a scheduling strategy through operational optimization to minimize the total operating cost of the system. The total system cost is composed of the operating costs of multiple independent microgrids, denoted as $C_{MG,i}$. The operating cost of each independent microgrid includes equipment investment costs, operating and maintenance costs $C_{MG,i.1}$, fuel costs $C_{MG,i.2}$, interaction costs with the main grid $C_{MG,i.3}$, and environmental management costs $C_{MG,i.4}$. The specific related formulas are as follows:

$$\min = \sum_{i=1}^{N_{MG}} C_{MG,i} \quad (1)$$

$$C_{MG,i} = C_{MG,i.1} + C_{MG,i.2} + C_{MG,i.3} + C_{MG,i.4} \quad (2)$$

$$\left\{ \begin{array}{l} C_{MG,i.1} = f(T) * \sum_{j=1}^{N_0} \frac{(C_{MG,i.cost1,j} + C_{MG,i.cost2,j})}{n * T} \\ f(T) = \left(1 - \frac{2}{n}\right)^T \\ C_{MG,i.cost2,j} = K_{MG,i(t)}^{PV} * P_{MG,i(t)}^{PV} + K_{MG,i(t)}^{WT} * P_{MG,i(t)}^{WT} + K_{MG,i(t)}^{DG} * P_{MG,i(t)}^{DG} + K_{MG,i(t)}^{ESS} * P_{MG,i(t)}^{ESS} \end{array} \right. \quad (3)$$

$$C_{MG,i.2} = \sum_{k=1}^{N_1} \left(a_{MG,i.k} + b_{MG,i.k.DG} * P_{MG,i.k.n}^{DG} + c_{MG,i.k} * P_{MG,i.k.a(t)}^{DG} \right) \quad (4)$$

$$C_{MG,i.3} = d_{MG,i.buy,1(t)} * P_{MG,i.buy,1(t)} - d_{MG,i.sell,1(t)} * P_{MG,i.sell,1(t)} \quad (5)$$

$$C_{MG,i.4} = \sum_{i=1}^N \sum_{j=1}^3 l_{MG,i,j} \lambda_j P_{MG,i.k.a(t)} \quad (6)$$

where N_{MG} represents the number of independent microgrids, $f(T)$ is the equipment depreciation loss factor, n is the equipment's lifespan, and T is the time the equipment has been in operation (in years). Variable N_0 denotes the number of devices in the microgrid system, Variable $C_{MG,i.cost1,j}$ indicates the investment cost of the microgrid system's equipment, and $C_{MG,i.cost2,j}$ represents the operation and maintenance costs of the equipment. $K_{MG,i(t)}^{PV}$, $K_{MG,i(t)}^{WT}$, $K_{MG,i(t)}^{DG}$, and $K_{MG,i(t)}^{ESS}$ denote the operation and maintenance cost coefficients for photovoltaic, wind, and diesel generators, as well as energy storage devices, respectively, at time period t . $P_{MG,i(t)}^{PV}$, $P_{MG,i(t)}^{WT}$, $P_{MG,i(t)}^{DG}$, and $P_{MG,i(t)}^{ESS}$ represent the power output of photovoltaic, wind, and diesel generators, as well as energy storage devices, at time period t , respectively. $a_{MG,i.k}$, $b_{MG,i.k.DG}$, and $c_{MG,i.k}$ are the fuel cost coefficients for the k -th diesel generator in microgrid system i . $P_{MG,i.k.n}^{DG}$ and $P_{MG,i.k.a(t)}^{DG}$ represent the rated power of the k -th diesel generator in microgrid system i and its actual output power at time period t , respectively. $d_{MG,i.buy,1(t)}$ and $d_{MG,i.sell,1(t)}$ indicate the amount of electricity purchased from and sold to the main grid during time period t , while the corresponding prices for purchasing and selling electricity are also indicated for that time period. Additionally, the purchase and sale quantities between microgrids during time period t are represented as well. N denotes the number of diesel generators in the microgrid, j indicates the type of pollutant generated, $l_{MG,i,j}$ represents the amount of the j -th pollutant emitted by the diesel generator in microgrid i , and λ_j is the cost associated with treating one unit of the corresponding pollutant.

2.3. Construction of the Microgrid Model

In a multi-microgrid system, distributed energy devices include both clean energy sources and traditional diesel generators. Due to the uncertainty in the output power of renewable energy devices, it is crucial to establish an appropriate output model based on the actual operating conditions of the equipment.

2.3.1. Output Power of Photovoltaic Devices

In sunny, flat areas, photovoltaic solar panels are typically installed, as these devices can efficiently utilize solar energy. Due to the material characteristics of solar panels, their output power is influenced by both irradiance and temperature [21]. The specific output power model can be expressed by Equation (7):

$$P_{PV}(t) = P_{pv0} \frac{G}{G_0} [1 + k(T_C - T_0)] \quad (7)$$

where $P_{PV}(t)$ represents the output power of the photovoltaic device, P_{pv0} is the rated output power of the photovoltaic device, G is the irradiance, G_0 is the maximum irradiance that the photovoltaic panel can produce under maximum solar radiation, k is the temperature coefficient, k is the actual operating temperature, and T_0 is the specified reference temperature.

2.3.2. Wind Power Generation

Wind power generation equipment is typically installed in areas with abundant wind resources, such as coastal regions, to harness wind energy for power generation. One characteristic of wind power devices is that their initial investment costs are relatively high, and the output power of the equipment is significantly affected by wind speed [22]. The specific output power model for wind power generation is shown in Equation (8):

$$P_{WT}(t) = \begin{cases} 0 & 0 \leq V \leq V_a \\ P_{WTO} * \frac{V - V_a}{V_b - V_a} & V_a \leq V \leq V_b \\ P_{WTO} & V_b \leq V \leq V_c \\ 0 & V_c \leq V \end{cases} \quad (8)$$

where $P_{WT}(t)$ represents the output power of the wind power generation device, P_{WTO} is the rated output power of the wind turbine, V is the actual wind speed, V_a is the wind speed at which the wind power generation output reaches its minimum power, V_b is the wind speed at which the rated power can be produced, and V_c is the critical wind speed at which the turbine can output its rated power. Beyond this wind speed, the turbine ceases operation to prevent irreparable damage.

2.3.3. Energy Storage System Model Construction

Due to the presence of numerous renewable energy devices within the microgrid system, which share the common characteristic of unstable output power, the output can fluctuate significantly due to various factors such as temperature, irradiance, and wind speed. The output power of new energy equipment may be curtailed or abandoned due to insufficient grid load or improper scheduling, resulting in some electricity not being effectively utilized. The main reasons are as follows: (1) fluctuations in electricity demand, (2) insufficient grid access capacity, (3) scheduling issues, and (4) deficiencies in market mechanisms. This curtailment not only leads to a waste of resources but also affects the economic benefits of renewable energy. These fluctuations can sometimes result in excessive power generation and, at other times, insufficient power, leading to significant impacts on power quality. To mitigate the effects of renewable energy devices on power quality, improve energy utilization, and reduce energy losses, energy storage systems (ESSs) must be installed in the system [23]. The operating characteristics and

power balance relationships of the energy storage devices can be specifically described by Equations (9)–(12):

$$S_{oc}(t) = S_{oc}(t-1) + Q_c^{ESS}(t) * \eta_c - Q_d^{ESS}(t) * \eta_d \quad (9)$$

$$30\% * S_{OC.max} \leq Q_c^{ESS}(t) \leq S_{OC.max} \quad (10)$$

$$30\% * S_{OC.max} \leq Q_d^{ESS}(t) \leq S_{OC.max} \quad (11)$$

In the above equations, Equation (9) represents the current state of the energy storage device, where $Q_c^{ESS}(t)$ denotes the energy in a charging state, $Q_d^{ESS}(t)$ denotes the energy in a discharging state, η_c and η_d represent the efficiencies during the charging and discharging processes, respectively, and $S_{OC.max}$ indicates the maximum capacity of the energy storage device.

2.3.4. Diesel Generator Model Construction

In a microgrid system, renewable energy generation devices are included; however, due to their unstable output power, they may affect the operation of the main grid. To ensure stable output power for the entire microgrid system, traditional diesel generators are typically configured as backups to balance power output fluctuations [24]. The diesel generator model can be specifically described by Equation (12):

$$C_{DG}(p) = a + b * P_{DG.n} + c * P_{DG.a}^2 \quad (12)$$

In the above equation, $C_{DG}(p)$ represents the fuel cost of the generator, $P_{DG.n}$ denotes the rated power of the generator, and $P_{DG.a}$ represents the actual output power of the generator. The coefficients a , b , and c are the fuel cost coefficients.

2.4. Construction of Microgrid System Constraints

2.4.1. Load Balance Constraint

At any time period, the total load within the entire system must satisfy the load balance constraint. In each microgrid system, the power load of all devices at any given time must be balanced. The constraint can be expressed by the following equation:

$$P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_{ESS}(t) + P_{buy}(t) = P_{load}(t) + P_{sell}(t) \quad (13)$$

2.4.2. Distributed Energy Constraints

The output power of distributed energy sources is influenced by their own operational characteristics. The specific constraint equations are as follows:

$$P_{PV.min} \leq P_{pv}(t) \leq P_{pv.max} \quad (14)$$

$$P_{WT.min} \leq P_{WT}(t) \leq P_{WT.max} \quad (15)$$

$$P_{DG.min} \leq P_{DG}(t) \leq P_{DG.max} \quad (16)$$

2.4.3. Energy Storage Constraints

The charging and discharging of energy storage devices are subject to a specific power range and cannot exceed the prescribed upper and lower limits. Additionally, during operation, the charging and discharging processes are mutually exclusive, meaning the energy storage system cannot perform both functions simultaneously. In other words, the energy storage system can only be in either a charging or discharging state at any given

time, but not both. This operational constraint is crucial to ensure the safety of the energy storage devices and the overall stability of the system.

$$\begin{cases} S_{soc,min} \leq S_{soc}(t) \leq S_{soc,max} \\ P_c^{min} \leq P_c(t) \leq P_c^{max} \\ P_d^{min} \leq P_d(t) \leq P_d^{max} \end{cases} \quad (17)$$

In the above constraints, $S_{soc,min}$ represents the minimum energy storage of the energy storage device and $S_{soc,max}$ represents the maximum output energy of the energy storage device. P_c^{min} and P_d^{min} represent the minimum charging power and the minimum discharging power, respectively. P_c^{max} and P_d^{max} represent the maximum charging power and the maximum discharging power.

2.4.4. Power Trading Constraints Between the Microgrid and Main Grid

This study involves multiple independent microgrid systems, where the power purchasing and selling activities of each microgrid are conducted independently. Under the condition of interconnected multi-microgrid systems, it is essential to consider the trading capacity limits between each microgrid and the main grid. These capacity limits are crucial to maintaining the operational stability of the system. The specific constraint equations are as follows:

$$\begin{cases} P_{buy.MG}^{min} \leq P_{buy.MG}(T) \leq P_{buy.MG}^{max} \\ P_{sell.MG}^{min} \leq P_{sell.MG}(T) \leq P_{sell.MG}^{max} \end{cases} \quad (18)$$

In these equations, $P_{buy.MG}^{min}$ and $P_{sell.MG}^{min}$ represent the minimum power purchase and minimum power sale amounts for the microgrid system, respectively. Similarly, $P_{buy.MG}^{max}$ and $P_{sell.MG}^{max}$ represent the maximum power purchase and maximum power sale amounts for the microgrid system, respectively.

In a microgrid system, the output of wind and photovoltaic power generation is random, while diesel generators play a crucial role in maintaining stable power output. Energy storage devices effectively manage energy and reduce system fluctuations. Therefore, in multiple independently operating microgrids, it is essential to properly manage load demand and ensure the stable operation of renewable energy devices to meet power demand. Establishing appropriate microgrid models and constraint conditions plays an important role in optimizing the objective function.

2.5. System Operation Strategy

In the process of optimizing system operations, the harmonious interaction between the main grid and microgrids plays a critical role, with the core focus on maintaining the stable operation of the entire system. At the same time, efficient use of energy resources is key to enhancing the system's economic benefits. This not only strengthens the linkage between microgrids and the main grid but also fosters further cooperation and mutual benefits. The steps of the system operation strategy are shown in Figure 2:

Step 1: Set the relevant parameters for each device in the multi-microgrid system and establish the microgrid and load models.

Step 2: Based on changes in load data, divide the power consumption periods into peak, normal, and off-peak stages.

Step 3: Optimize the multi-microgrid system using the IDE algorithm. In this process, fully utilize renewable energy devices to maximize the advantages of renewable energy. Due to the uncertainty in renewable energy output, any power shortfall is supplemented by the main grid, diesel generators, and energy storage devices. When there is a surplus of renewable energy, the excess power is first stored in the energy storage devices. If the storage is full, the remaining power is sold to the main grid to reduce operating costs.

Step 4: When the IDE algorithm outputs the optimal results and reaches the maximum number of iterations, output the interaction results between each microgrid and the main grid, as well as the operating costs.

Step 5: If the IDE algorithm has not yet reached the maximum number of iterations, continue optimizing the microgrid system until the maximum number of iterations is achieved.

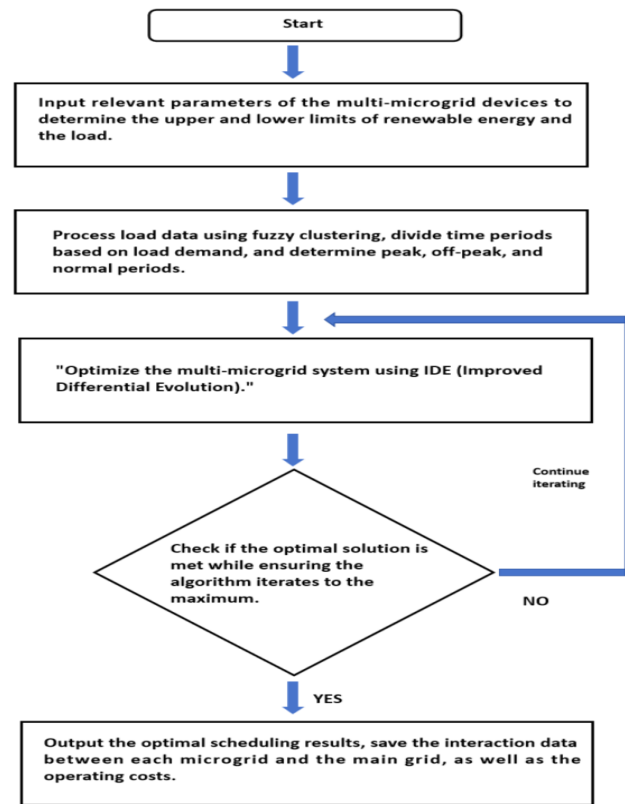


Figure 2. Operational Strategy Diagram.

3. Improved Differential Evolution Algorithm

3.1. Steps of the Improved Differential Evolution Algorithm

Similar to other multi-objective optimization algorithms, the Differential Evolution (DE) algorithm faces challenges such as getting trapped in local optima, a limited search range, and slow convergence when dealing with multi-objective optimization tasks. To enhance the performance of the DE algorithm, we optimized its traditional control parameters and introduced an external archive set (AR) to improve the algorithm's superiority and reliability [25]. By ensuring sample diversity, the algorithm can obtain a broader search space and faster convergence in the initial phase, while improving the accuracy of convergence in later stages. This effectively avoids the trap of local optima. The specific steps of the improved differential evolution algorithm are as follows:

Step 1: Population Initialization.

Initialize the population to ensure that the population is randomly distributed while uniformly covering the entire search space.

$$X_{ij} = X_j^{\min} + \text{rand}(0, 1) + \text{rand} * (X_j^{\max} - X_j^{\min}) \quad (19)$$

In Equation (19), X_{ij} represents the position of the particle, where j is a positive integer within the range $(0, \text{dim})$ and dim is the dimensionality of the particle. i represents the i -th particle in the population.

Step 2: Generating the External Archive Set (A_{RO}).

In multi-objective optimization problems, conflicts may exist between objective functions, which can lead to non-uniqueness in optimization solutions, forming a set of optimal solutions known as the Pareto optimal set [26]. During each iteration of the algorithm, the best positions obtained from the current iteration are compared with the best positions

from the initial population, and the non-dominated individuals are stored in the external archive set, A_{RO} . The specific expression for this is as follows:

$$A_{RO} = \{x_j | x_j \prec x_k, j, k \in [1, Np]\} \quad (20)$$

In Equation (20), parameter x_j and parameter x_k represent the j -th and k -th individuals in the population, respectively. Inequality $x_j \prec x_k$ indicates that individual x_j dominates individual x_k , while Np represents the population size. The initial population is brought into the subsequent iterations and is iterated together with the later populations for selection and refinement.

Step 3: Mutation Operation.

In the improved differential evolution algorithm, a mutation operation is performed on each individual in the original population to generate new mutated individuals, thereby enhancing the diversity of the population [27,28]. In this improvement, we optimized the mutation factor, and the specific mutation operation formula is as follows:

$$V_i(G+1) = w_G * X_{G_{best}} + c * F_{G,i} * (x_{Gr_1} - x_{Gr_2} + x_{Gr_1} - x_{Gr_3}) \quad (21)$$

$$w_G = w_{\max} - (w_{\max} - w_{\min}) * \frac{G}{G_{\max}} \quad (22)$$

$$F_{G,i} = \max(F_{G,1}, F_{G,2}) \quad (23)$$

$$F_{G,1} = F_{\max} * \left(\frac{\Delta f_{G,i}}{\lambda_{\text{con}} + \Delta f_{G,i}} \right) \quad (24)$$

$$F_{G,2} = F_{\max} * (1 - e^{-\Delta f_{G,i}}) \quad (25)$$

$$\Delta f_{G,i} = |f(X_{G,i}) - f(X_{G,best})| \quad (26)$$

In Formulas (22)–(26), $V_i(G+1)$ represents the velocity expression after iteration to generation $G+1$, while w_G is the weight expression for particles in generation G , primarily adjusting the influence of the best position of the particle on its velocity. $X_{G,best}$ represents the best particle position in the population at generation G , and $w_{\max}$ and $w_{\min}$ denote the maximum and minimum weight factors, respectively. $G_{\max}$ represents the maximum number of iterations. c is a constant weight factor, ranging between [1,2]. $F_{G,i}$ represents the scaling factor of particle i at generation G , and $x_{Gr_1}, x_{Gr_2}, x_{Gr_3}$ are three different randomly selected particles that undergo mutation at generation G . $F_{\max}$ is a given parameter, and λ_{con} is the shrinkage factor of the fitness function. $f_{(X_{G,i})}$ represents the current fitness of the i -th particle at the G -th iteration. $f_{(X_{G,best})}$ represents the fitness of the best particle at the G -th iteration.

Step 4: Crossover Operation.

To improve population diversity, a probabilistic crossover operation is performed between each individual in the population and the mutated individuals, forming new trial individuals. The expression is as follows:

$$U_i(G) = \begin{cases} V_{G,i} & \text{rand}(0,1) < C_R \text{ or } i = j \\ x_{G,i} & \text{others} \end{cases} \quad (27)$$

$$C_R = C_{R_{\max}} - (C_{R_{\max}} - C_{R_{\min}}) * \left(\frac{G}{G_{\max}} \right)^2 \quad (28)$$

In Formulas (27) and (28), $U_i(G)$ represents the trial individual at generation G for particle i , $V_{G,i}$ represents the velocity of particle i at generation G , and $x_{G,i}$ represents the position of particle i at generation G . C_R is the crossover factor, while $C_{R_{\max}}$ and $C_{R_{\min}}$ denote the upper and lower bounds of the crossover factor, which are constants.

Step 5: Selection Operator.

Calculate the objective function values of both the current individual particle and the trial individual particle. Compare the dominance relationship between their objective functions. If the trial individual particle dominates the current individual particle, the trial individual particle is retained for the next iteration. If neither particle dominates the other, one of them is randomly selected to enter the next iteration. The specific selection formula is as follows:

$$X_i(G+1) = \begin{cases} U_i(G) & U_i(G) \prec x_i \parallel [U_i(G) \not\prec x_i \&\&rand(0,1) > 0.5] \\ X_i(G) & \text{others} \end{cases} \quad (29)$$

In the above equation: $\parallel$ and $\&\&$ represent the logical “or” and “and” operations, respectively. $U_i(G) \not\prec x_i$ indicates non-dominance between individuals.

Step 6: Update the External Archive. Merge the initial external archive A_{R0} and the offspring population $x(G+1)$. Compare the objective function values of the merged population and store the non-dominated solutions in the external archive to achieve archive updating. The specific expression is as follows:

$$A_{RO} = \{x_j | x_j \prec x_k, j, k \in [1, Np + dim], j \neq k\} \quad (30)$$

Repeat steps three to six until the maximum number of iterations is reached. At this point, the individuals stored in the external archive A_{RO} represent the optimal solution set of the improved differential evolution algorithm. The detailed flowchart of the algorithm is shown in Figure 3:

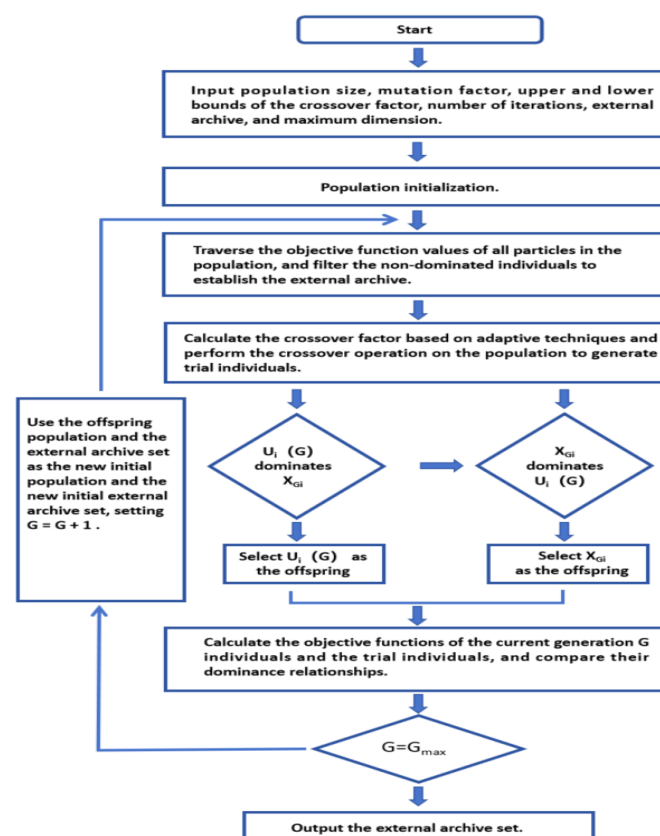


Figure 3. Flowchart of the Improved Differential Evolution Algorithm.

3.2. Performance Verification of the IDE Algorithm

To verify the performance of the improved differential evolution algorithm, six classic test functions were selected for testing. Table 1 presents the relevant information for these six test functions. Additionally, similar intelligent algorithms were chosen for comparison, including Particle Swarm Optimization (PSO), the traditional Differential Evolution (DE)

algorithm, Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and Artificial Bee Colony (ABC) algorithms.

Table 1. Relevant Information of Test Functions.

Function	Name	Type	Bounds	Optimum
$f_{(x)} = \sum_{i=1}^n x_i^2$	Sphere Function	Unimodal Functions	[−5.12, 5.12]	0
$f_{(x)} = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	Schwefel 2.22 Function	Unimodal Functions	[−10, 10]	0
$f_{(x)} = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^n x_i^2}\right)$	Ackley Function	Multimodal Functions	[−32, 32]	0
$f_{(x)} = 1 + \frac{1}{4000}\sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right)$	Griewank Function	Multimodal Functions	[−600, 600]	0
$f_2(x) = \left(1 + \frac{9}{n-1}\sum_{i=2}^n x_i\right) \left[1 - \sqrt{\frac{x_1}{g(x)}}\right]$ $f_1(x) = x_1$	ZDT1	Constraint Optimization Problem Test Functions	(0, 1)	0
$f_2(x) = \left(1 + \frac{9}{n-1}\sum_{i=2}^n x_i\right) \left[1 - \left(\frac{f_1(x)}{g(x)}\right)^2\right]$ $f_1(x) = x_1$	ZDT2	Constraint Optimization Problem Test Functions	(0, 1)	0

Table 2 lists the relevant parameters for each algorithm, setting the maximum number of iterations for the population at 1000 and the number of particles in the population at 50. Each standard function was tested 20 times. The test results were evaluated from three perspectives: optimal value, average value, and standard deviation, with the specific results presented in Table 3.

Table 2. Parameters of the PSO, ACO, GWO, ABC, DE, and IDE Algorithms.

Algorithm	Parameters
PSO	$c1 = 1.490, c2 = 1.490; wmax = 0.90, wmin = 0.10$
ACO	$\alpha = 1; \beta = 2; \rho = 0.5;$
GWO	$C = \text{rand}(0, 1) \times 2, A = \text{rand}(0, 1) \times 2a - a,$
ABC	$OBN = 25; SR = 0.1;$
DE	$F = 0.5; CR = 0.9;$
IDE	See Section 3.1 for specific parameters

Table 3. Comparative Analysis of Results from Intelligent Algorithms.

Name	Stats	Algorithm					
		PSO	ACO	GWO	ABC	DE	IDE
Sphere	MIN	5.832594158×10^0	4.926541638×10^0	5.25167942×10^0	5.301451646×10^0	6.014300616×10^0	0.000000015×10^0
	AVG	2.479520294×10^1	2.325640351×10^1	2.371273654×10^1	2.392057931×10^1	3.021351948×10^1	0.000000007×10^0
	STD	1.157536974×10^1	1.1024910744×10^1	1.129751351×10^1	1.13047371×10^1	1.295429678×10^1	0.000000010×10^0
Schwefel 2.22	MIN	5.268132616×10^3	3.125612445×10^2	4.161421517×10^1	5.756429607×10^1	6.264412415×10^2	0.000000035×10^0
	AVG	2.651583834×10^2	2.420034173×10^1	5.216623567×10^1	7.732110651×10^2	3.712619215×10^3	0.000000051×10^0
	STD	5.953215552×10^3	4.124147946×10^1	2.733651681×10^2	3.754613546×10^2	6.439418971×10^3	0.000000007×10^0
Ackley	MIN	2.513235486×10^1	2.723113741×10^1	1.995468138×10^1	2.640414134×10^1	3.156413546×10^1	0.000000015×10^0
	AVG	2.875421561×10^1	1.943418715×10^1	2.616841811×10^1	2.841348635×10^1	3.014431824×10^1	0.000000021×10^0
	STD	1.135974194×10^0	1.461861968×10^0	$8.463184181 \times 10^{-1}$	$5.466865148 \times 10^{-1}$	2.468643548×10^1	0.000000001×10^0
Griewank	MIN	$4.514861348 \times 10^{-2}$	$2.451641842 \times 10^{-2}$	$7.464167182 \times 10^{-2}$	$5.413321842 \times 10^{-1}$	$6.054218421 \times 10^{-1}$	0.000000030×10^0
	AVG	$1.448182174 \times 10^{-1}$	$2.513248612 \times 10^{-1}$	1.054318641×10^0	$4.461302384 \times 10^{-1}$	$7.046432842 \times 10^{-2}$	0.000000057×10^0
	STD	$6.451812118 \times 10^{-2}$	$3.564381282 \times 10^{-2}$	$4.465384154 \times 10^{-1}$	$6.451384128 \times 10^{-2}$	$3.351384208 \times 10^{-2}$	0.000000071×10^0
ZDT1	MIN	$1.462152965 \times 10^{-2}$	$7.894289717 \times 10^{-3}$	$5.054168541 \times 10^{-3}$	$9.219129174 \times 10^{-5}$	$6.719636915 \times 10^{-3}$	0.000000011×10^0
	AVG	$3.471981891 \times 10^{-2}$	$4.484148412 \times 10^{-3}$	$4.543484218 \times 10^{-3}$	$7.450640641 \times 10^{-4}$	$5.695415489 \times 10^{-3}$	0.000000005×10^0
	STD	$2.141842185 \times 10^{-2}$	$2.645187421 \times 10^{-2}$	$1.044128512 \times 10^{-3}$	$7.546414718 \times 10^{-3}$	$3.415451548 \times 10^{-2}$	0.000000054×10^0
ZDT2	MIN	$2.431006518 \times 10^{-3}$	$7.916515245 \times 10^{-5}$	$6.854184218 \times 10^{-7}$	$4.652154205 \times 10^{-3}$	$3.192489549 \times 10^{-4}$	0.000000041×10^0
	AVG	$1.832191891 \times 10^{-2}$	$1.456125642 \times 10^{-4}$	$7.413584116 \times 10^{-6}$	$1.568997617 \times 10^{-2}$	$6.631245185 \times 10^{-5}$	0.000000054×10^0
	STD	$8.589612561 \times 10^{-3}$	$6.984154784 \times 10^{-5}$	$5.544749129 \times 10^{-6}$	$3.611874185 \times 10^{-2}$	$3.451211818 \times 10^{-4}$	0.000000017×10^0

The Sphere and Schwefel 2.22 functions are unimodal test functions. From Table 3, it is evident that the IDE algorithm shows a significant advantage in optimization performance compared to the other algorithms. The other centralized optimization algorithms have relatively similar values in terms of average, standard deviation, and optimal value, whereas the IDE algorithm demonstrates a stronger local search capability.

The Griewank and Ackley functions are multimodal test functions. The results in Table 3 indicate that the IDE algorithm performs exceptionally well in optimization, with its average value and standard deviation still superior to those of other centralized algorithms. This suggests that the IDE algorithm has a clear advantage in global search capabilities and in escaping local optima.

ZDT1 and ZDT2 are multi-objective test functions. From Table 3, it can be seen that the IDE algorithm has a significant advantage in searching the Pareto front. Moreover, the IDE algorithm also exhibits higher computational efficiency and a faster convergence speed compared to other intelligent algorithms.

4. Simulation Analysis of a Real Case

4.1. Data Case Introduction

The data for this study are sourced from electricity data in Jiangsu Province, China, selecting two representative days for simulation analysis within a year. Jiangsu Province has a subtropical monsoon climate characterized by hot and rainy summers with strong sunlight and distinct monsoon patterns, where temperatures generally range from 25 to 35 degrees Celsius. In contrast, winters are dry and cold, often featuring clear weather, with temperatures typically between 0 and 10 degrees Celsius. Relevant data on wind speed, temperature, and solar radiation intensity can be found in Figures 4–6. Figure 7 illustrates the variations in load data over 24 h on a summer day and a winter day.

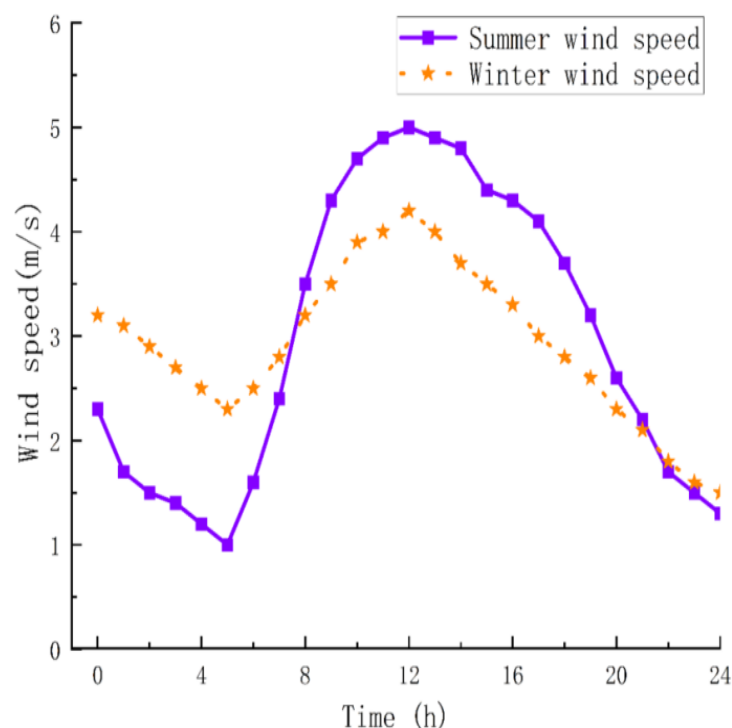


Figure 4. Typical Summer and Winter Daily Wind Speed.

The various energy-related data for the microgrid system are detailed in Table 4. Additionally, Table 5 presents information on the pollutants generated by the microgrid and the associated costs for their treatment. The time-of-use electricity pricing for purchasing and selling electricity in the microgrid is provided in Table 6.

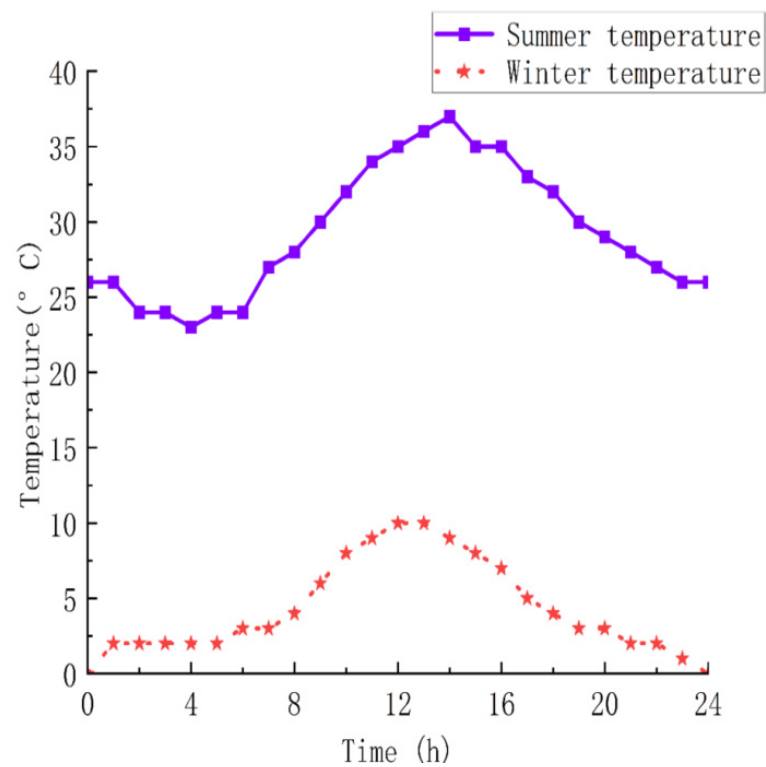


Figure 5. Typical Summer and Winter Daily Temperature.

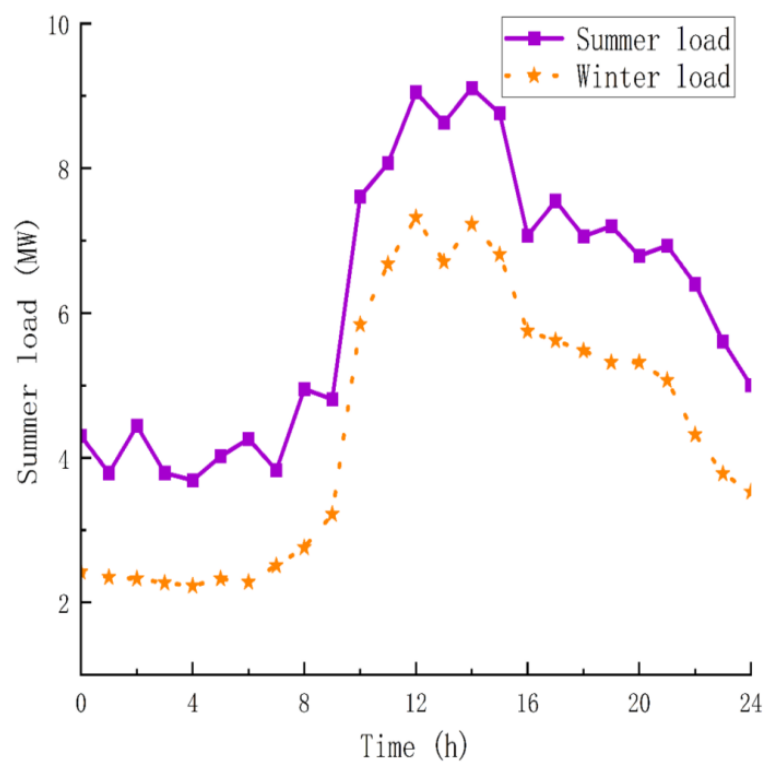


Figure 6. Typical Summer and Winter Daily Solar Radiation Intensity.

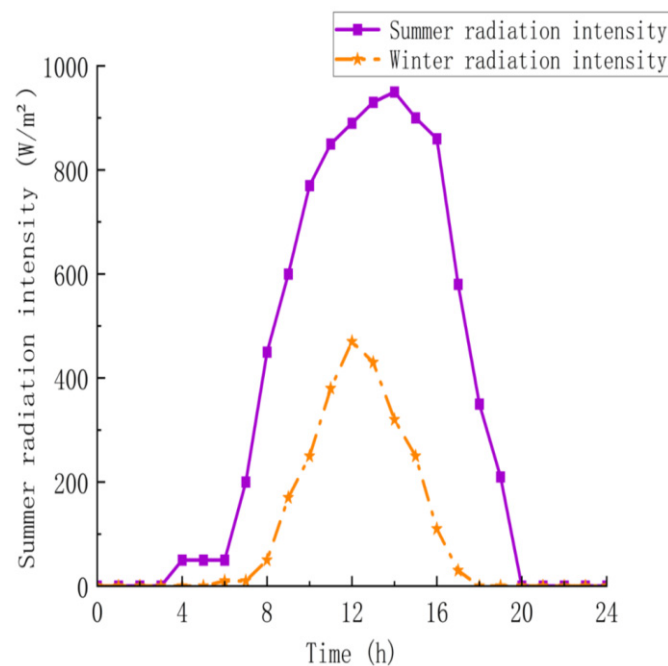


Figure 7. 24-Hour Load Profile for Summer and Winter Seasons.

Table 4. Parameters of Various Power Sources in the Microgrid System.

PV		WT		DG	
Rated Power (MW)	2	Rated Power (MW)	0.6	Rated Power (MW)	10
Rated Illuminance (kW/m ²)	1	Cut-in Wind Speed (m/s)	1	a-Fuel Cost Coefficient (CNY/kWh)	0.8
Rated Temperature (°C)	25	Rated Wind Speed (m/s)	4	b-Fuel Cost Coefficient (CNY/kWh)	0.6
		Critical Wind Speed (m/s)	8	c-Fuel Cost Coefficient (CNY/kWh)	0.5

Table 5. Pollutant Emission Parameters and Treatment Costs.

Pollutant Type	Pollutant Type	Pollutant Type
CO ₂	0.2	724
SO ₂	5	0.002
NO _x	6	6.3

Table 6. Time-of-Use Electricity Purchase and Sale Prices for the Microgrid.

Time Period	Purchase Price (CNY/kWh)	Purchase Price (CNY/kWh)
Peak Hours (08:00–12:00, 17:00–21:00)	0.8	0.45
Mid-Peak Hours (12:00–17:00, 21:00–24:00)	0.4	0.30
Off-Peak Hours (00:00–08:00)	0.3	0.18

In the simulation, it is assumed that under the same solar radiation, the output power of the photovoltaic panels is not affected by the installation location. Similarly, it is assumed that the output power of wind energy equipment does not vary based on the installation site under the same wind speed conditions.

4.2. Simulation Analysis

Based on the operating strategy introduced in Section 2.5, this study applies the Improved Differential Evolution (IDE) algorithm to the operational simulation of microgrids. The goal is to ensure stable output power from renewable energy devices while reducing the consumption of fossil fuels, thereby lowering operating costs.

Figure 8 illustrates the output power of various microgrid devices at a specific moment during the summer. Specifically, Figure 8a shows the output power of Microgrid 1 and Figure 8b presents the output power of Microgrid 2. Figure 8c displays the output power of Microgrid 3.

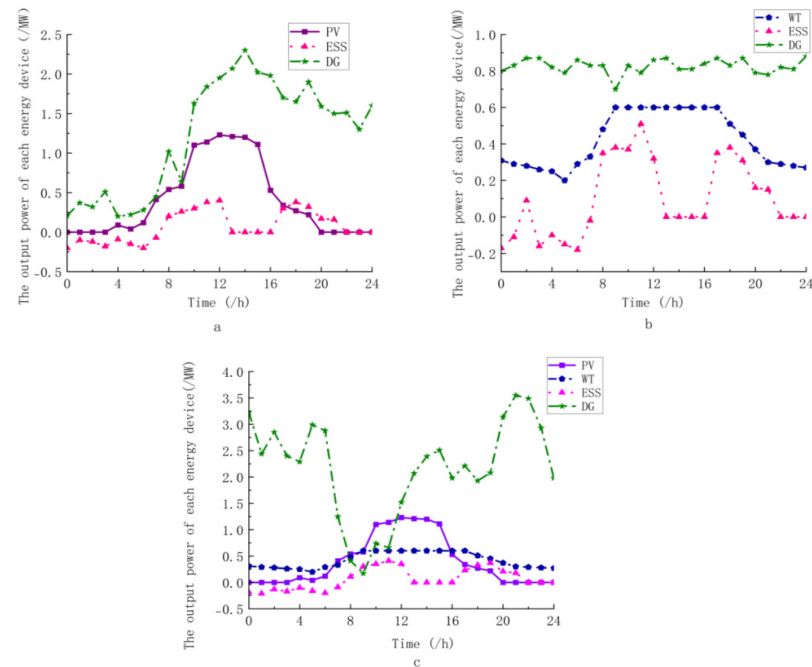


Figure 8. Output Power of Each Device in the Microgrid at a Specific Moment During Summer.

Figure 9 presents the output power of various microgrid devices at a specific moment during the winter, where Figure 9a represents the output power of Microgrid 1, Figure 9b shows the output power of Microgrid 2, and Figure 9c illustrates the output power of Microgrid 3.

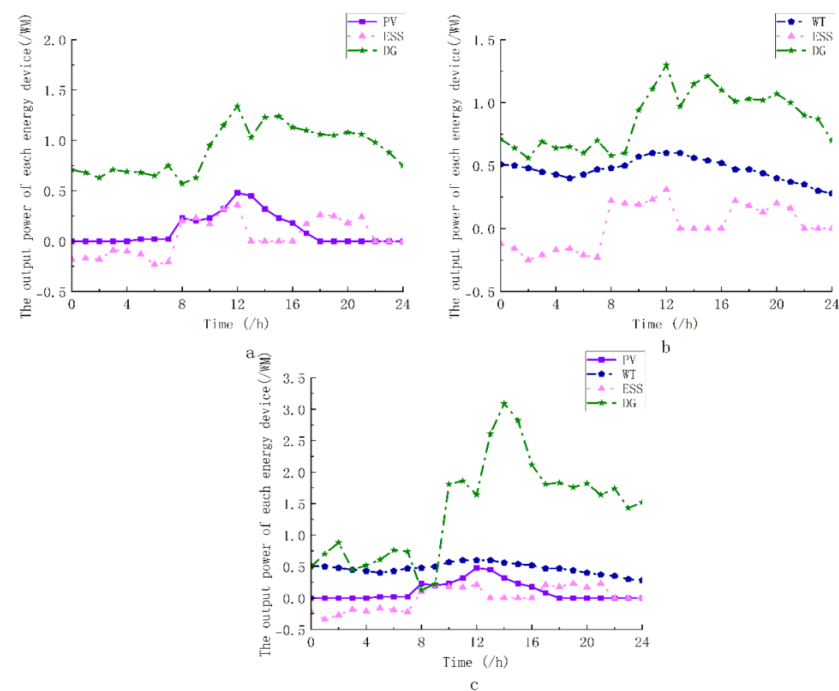


Figure 9. Output Power of Each Device in the Microgrid at a Specific Moment During Winter.

Additionally, Figure 10 depicts the interactions between each microgrid system and the main power grid. Figure 10a represents the interactions of each microgrid system with the main grid on a summer day. Figure 10b displays the interactions of each microgrid system with the main grid on a winter day.

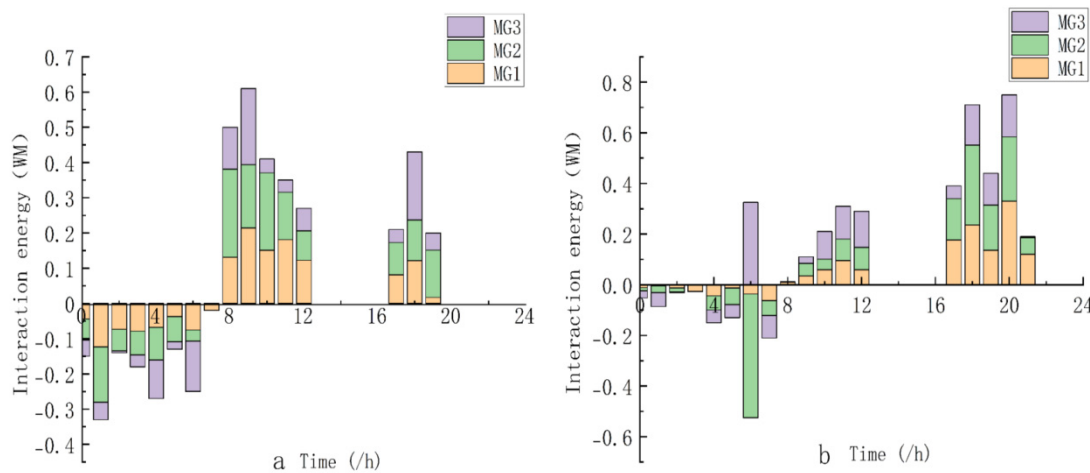


Figure 10. Schematic Diagram of Energy Interactions Between the Microgrid and the Main Grid for a Day in Summer and Winter.

These figures will assist in analyzing the operational performance of the microgrid under different seasonal conditions and its interaction with the main power grid.

Figures 8 and 9 illustrate the power output variations of different energy devices in the microgrid systems over a 24 h period during specific summer and winter days. The operating strategy of the system aims to maximize the utilization of clean energy to minimize the use of fossil fuels. Figure 10 shows the electrical energy exchanges between the microgrid systems and the main grid. Given the considerations for economic benefits—such as electricity prices, fuel costs, and environmental policy constraints—we opted not to increase the output power of diesel generators but instead balanced supply and demand through energy exchange.

Figure 10 provides detailed insights into the energy interactions during a summer day and a winter day. Specifically, the energy exchanges in summer primarily occur between 00:00–12:00 and 17:00–19:00, while in winter, they occur between 00:00–12:00 and 17:00–21:00.

During the summer from 00:00 to 07:00, the three independent microgrids purchased 1470 kW from the main grid while selling 2980 kW back. Specifically, Microgrid 1 (MG1) sold 519.8 kW, Microgrid 2 (MG2) purchased 541.3 kW, and Microgrid 3 (MG3) purchased 408.9 kW.

In the 08:00–12:00 and 17:00–19:00 time periods, the sales were as follows: MG1 sold 1101.9 kW, MG2 sold 1209.8 kW, and MG3 sold 751.2 kW.

During the winter from 00:00 to 07:00, the three independent microgrids purchased a total of 886 kW from the main grid, with MG1 purchasing 211.2 kW, MG2 purchasing 722.58 kW, and MG3 purchasing 47.78 kW.

In the 08:00–12:00 and 17:00–21:00 time periods, the total amount of electricity sold by the three independent microgrids to the main grid reached 3412 kW, where MG1 sold 1257.95 kW, MG2 sold 1241 kW, and MG3 sold 913.05 kW.

These data indicate that the microgrid system adjusts its energy interactions with the main grid flexibly across different seasons and time periods, thereby maximizing economic benefits and effectively reducing reliance on fossil fuels.

Tables 7 and 8 provide detailed quantitative information on the output power of energy devices across the three independent microgrid systems during summer and winter, respectively, supporting the analysis presented above.

Table 7. Output Power Data for Each Device in Summer.

Time (/h)	MG1				MG2		MG3			
	PV/W/M	ESS/W/M	DG/W/M	WT/W/M	ESS/W/M	DG/W/M	PV/W/M	WT/W/M	ESS/W/M	DG/W/M
00:00	0.00	−0.20	0.21	0.31	−0.17	0.80	0.00	0.31	−0.19	3.23
01:00	0.00	−0.10	0.37	0.29	−0.11	0.83	0.00	0.29	−0.21	2.44
02:00	0.00	−0.12	0.32	0.28	0.09	0.87	0.00	0.28	−0.13	2.85
03:00	0.00	−0.18	0.51	0.26	−0.16	0.87	0.00	0.26	−0.17	2.40
04:00	0.09	−0.09	0.20	0.25	−0.10	0.82	0.09	0.25	−0.10	2.29
05:00	0.04	−0.15	0.22	0.20	−0.15	0.79	0.04	0.20	−0.16	2.99
06:00	0.12	−0.20	0.28	0.29	−0.18	0.86	0.12	0.29	−0.20	2.88
0700	0.41	−0.07	0.45	0.33	−0.02	0.83	0.41	0.33	−0.09	1.25
08:00	0.54	0.20	1.02	0.48	0.35	0.83	0.54	0.48	0.11	0.41
09:00	0.58	0.26	0.64	0.60	0.38	0.70	0.58	0.60	0.30	0.17
10:00	1.10	0.30	1.63	0.60	0.37	0.83	1.10	0.60	0.35	0.74
11:00	1.14	0.38	1.84	0.60	0.51	0.79	1.14	0.60	0.41	0.66
12:00	1.23	0.40	1.95	0.60	0.32	0.86	1.23	0.60	0.35	1.52
13:00	1.21	0.00	2.07	0.60	0.00	0.87	1.21	0.60	0.00	2.07
14:00	1.20	0.00	2.30	0.60	0.00	0.81	1.20	0.60	0.00	2.39
15:00	1.11	0.00	2.02	0.60	0.00	0.81	1.11	0.60	0.00	2.51
16:00	0.53	0.00	1.98	0.60	0.00	0.84	0.53	0.60	0.00	1.98
17:00	0.34	0.30	1.70	0.60	0.35	0.87	0.34	0.60	0.23	2.21
18:00	0.27	0.38	1.65	0.51	0.38	0.83	0.27	0.51	0.33	1.93
19:00	0.22	0.32	1.90	0.45	0.31	0.87	0.22	0.45	0.37	2.08
20:00	0.00	0.17	1.59	0.37	0.16	0.79	0.00	0.37	0.21	3.14
21:00	0.00	0.16	1.50	0.30	0.15	0.78	0.00	0.30	0.18	3.55
22:00	0.00	0.00	1.51	0.29	0.00	0.82	0.00	0.29	0.00	3.49
23:00	0.00	0.00	1.30	0.28	0.00	0.81	0.00	0.28	0.00	2.93
24:00	0.00	0.00	1.60	0.27	0.00	0.88	0.00	0.27	0.00	1.98

Table 8. Output Power Data for Each Device in Winter.

Time (/h)	MG1				MG2		MG3			
	PV/W/M	ESS/W/M	DG/W/M	WT/W/M	ESS/W/M	DG/W/M	PV/W/M	WT/W/M	ESS/W/M	DG/W/M
00:00	0	−0.18	0.71	0.51	−0.12	0.71	0	0.51	−0.22	0.50
01:00	0	−0.17	0.68	0.50	−0.16	0.64	0	0.50	−0.34	0.70
02:00	0	−0.18	0.63	0.48	−0.25	0.56	0	0.48	−0.27	0.88
03:00	0	−0.09	0.71	0.45	−0.21	0.69	0	0.45	−0.18	0.45
04:00	0	−0.10	0.69	0.43	−0.17	0.64	0	0.43	−0.21	0.52
05:00	0.02	−0.13	0.68	0.40	−0.16	0.65	0.02	0.40	−0.16	0.61
06:00	0.02	−0.23	0.65	0.43	−0.21	0.60	0.02	0.43	−0.19	0.76
0700	0.02	−0.21	0.75	0.47	−0.23	0.70	0.02	0.47	−0.22	0.74
08:00	0.23	0.20	0.57	0.48	0.22	0.58	0.23	0.48	0.10	0.13
09:00	0.20	0.23	0.63	0.50	0.20	0.60	0.20	0.50	0.20	0.22
10:00	0.23	0.17	0.95	0.57	0.19	0.94	0.23	0.57	0.18	1.81
11:00	0.32	0.32	1.15	0.60	0.23	1.11	0.32	0.60	0.17	1.86
12:00	0.48	0.36	1.34	0.60	0.31	1.30	0.48	0.60	0.21	1.64
13:00	0.45	0.00	1.03	0.60	0.00	0.97	0.45	0.60	0.00	2.61
14:00	0.32	0.00	1.23	0.56	0.00	1.15	0.32	0.56	0.00	3.09
15:00	0.23	0.00	1.24	0.54	0.00	1.21	0.23	0.54	0.00	2.82
16:00	0.18	0.00	1.13	0.52	0.00	1.10	0.18	0.52	0.00	2.12
17:00	0.08	0.17	1.10	0.47	0.22	1.01	0.08	0.47	0.21	1.81
18:00	0.00	0.26	1.06	0.47	0.18	1.03	0.00	0.47	0.18	1.83
19:00	0.00	0.25	1.05	0.44	0.13	1.02	0.00	0.44	0.23	1.76
20:00	0.00	0.18	1.08	0.40	0.20	1.07	0.00	0.40	0.17	1.82
21:00	0.00	0.24	1.06	0.37	0.16	1.00	0.00	0.37	0.23	1.64
22:00	0.00	0.00	0.98	0.35	0.00	0.90	0.00	0.35	0.00	1.74
23:00	0.00	0.00	0.88	0.30	0.00	0.87	0.00	0.30	0.00	1.43
24:00	0.00	0.00	0.75	0.28	0.00	0.70	0.00	0.28	0.00	1.52

Figure 11 illustrates the optimization results under summer and winter conditions, with subfigures a and b displaying the optimal convergence curves of various algorithms. The data indicate that the IDE algorithm exhibits the fastest convergence speed and the highest convergence accuracy, demonstrating superior performance in the optimization process compared to the other algorithms. In contrast, the other algorithms show relatively similar results in terms of convergence speed and accuracy, failing to achieve the effectiveness of the IDE algorithm. These findings further validate the superiority and reliability of the improved differential evolution algorithm in multi-objective optimization scenarios.

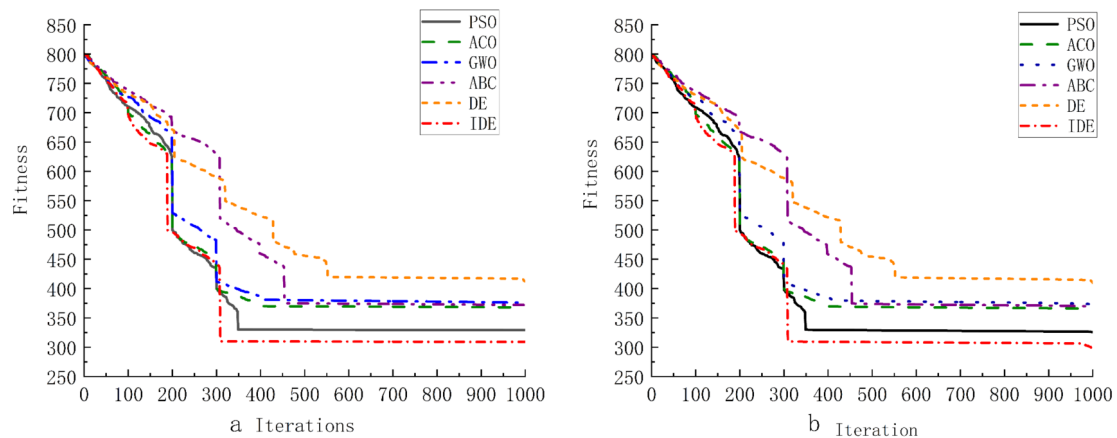


Figure 11. Optimization Iteration Charts of Different Algorithms Under Summer and Winter Conditions.

Table 9 presents the economic costs after optimizing the system using the IDE algorithm, and the economic costs of each microgrid are also reflected in Table 9.

Table 9. Economic Costs After System Optimization Using the IDE Algorithm.

	WG1/(CNY)	WG2/(CNY)	WG3/(CNY)
Summer system operating cost	18,359.65	16,864.72	33,543.59
Winter system operating cost	13,511.59	15,385.26	24,375.19

5. Conclusions

This study focuses on minimizing system operating costs as the optimization objective and conducts a practical case study on the operational scheduling of multi-microgrid systems, assessing the economic reliability of grid-connected multi-microgrid systems. The main conclusions are as follows:

1. **Optimization Objective Construction:** This research establishes an optimization model aimed at minimizing system operating costs, clearly defining the corresponding objective function. The model comprehensively considers the operational status of various generation devices, load demands, and energy exchange scenarios, facilitating effective resource allocation.

2. **Adoption of an Improved IDE Algorithm:** To enhance the optimization results of the multi-microgrid system, an Improved Differential Evolution (IDE) algorithm is employed for in-depth optimization. This algorithm improves its search capability and convergence speed by introducing an external archive set and optimizing control parameters.

3. **Validation of Optimization Performance:** A series of performance tests demonstrate the significant advantages of the IDE algorithm in optimization capability. Empirical results indicate that under the premise of ensuring stable system operation, the IDE algorithm effectively improves the economic performance of multi-microgrid systems. The system can flexibly adjust energy exchanges with the main grid during different seasons

and time periods, maximizing the reduction of reliance on fossil fuels and enhancing economic benefits.

In summary, the research findings provide a practical and effective solution for the economic scheduling of multi-microgrid systems, laying a foundation for future related research.

6. Outlook

This study conducted a comparative analysis of the rationality and economic efficiency of multi-microgrid grid-connected operation and scheduling optimization. It also verified the feasibility of the improved algorithm by comparing various intelligent algorithms with the IDE algorithm. However, there are still some shortcomings to this paper:

1. The construction of the multi-microgrid equipment model is relatively idealized, lacking in-depth analysis of the impact of photovoltaic and wind power in real environments. Additionally, the transmission power losses of various new energy devices have not been thoroughly studied. Future model development could enhance research on the impact of real environments on equipment.

2. In maintaining system stability, this study only considered demand coverage, without addressing the issue of grid frequency coverage. Future research could incorporate frequency coverage into the analysis.

3. Distributed microgrids present a highly complex issue. This study did not explore the grid connection locations of distributed photovoltaics and wind turbines, nor did it analyze multi-scenario energy. Future research could delve deeper into these aspects.

4. This study does not consider the scheduling between microgrids, focusing solely on the interaction between the microgrid and the main grid. Future research could incorporate energy interactions between microgrids.

Author Contributions: Conceptualization, A.D.; methodology, A.D.; software, A.D.; validation, A.D.; formal analysis, A.D.; investigation, S.-K.L.; resources, data curation, A.D.; writing—original draft preparation, A.D.; writing—review and editing, A.D. and S.-K.L.; visualization, A.D. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ufa, R.A.; Malkova, Y.Y.; Rudnik, V.E.; Andreev, M.V.; Borisov, V.A. A review on distributed generation impacts on electric power system. *Int. J. Hydrogen Energy* **2022**, *47*, 20347–20361. [\[CrossRef\]](#)
2. Marnay, C.; Aki, H.; Hirose, K.; Kwasinski, A.; Ogura, S.; Shinji, T. Japan's pivot to resilience: How two microgrids fared after the 2011 earthquake. *IEEE Power Energy Mag.* **2015**, *13*, 44–57. [\[CrossRef\]](#)
3. Wang, Z.; Dong, L.; Shi, M.; Qiao, J.; Jia, H.; Mu, Y.; Pu, T. Market power modeling and restraint of aggregated prosumers in peer-to-peer energy trading: A game theoretic approach. *Appl. Energy* **2023**, *348*, 121550. [\[CrossRef\]](#)
4. Mason, K.; Duggan, J.; Howley, E. A multi-objective neural network trained with differential evolution for dynamic economic emission dispatch. *Int. J. Electr. Power Energy Syst.* **2018**, *100*, 201–221. [\[CrossRef\]](#)
5. Li, Z.; Wu, L.; Xu, Y. Risk-averse coordinated operation of a multi-energy microgrid considering voltage/var control and thermal flow: An adaptive stochastic approach. *IEEE Trans. Smart Grid* **2021**, *12*, 3914–3927. [\[CrossRef\]](#)
6. Li, M.; Mei, W.; Zhang, L.; Bai, B.; Zhao, C.; Cai, L. Research on multi-energy microgrid scheduling optimization model based on renewable energy uncertainty. *Power Syst. Technol.* **2019**, *43*, 1260–1270. (In Chinese)
7. Abdou, I.; Tkiouat, M. Unit Commitment Problem in Electrical Power System: A Literature Review. *Int. J. Electr. Comput. Eng. (IJECE)* **2018**, *8*, 1357–1372. [\[CrossRef\]](#)
8. Valizadeh, M.; Kouhzadipour, A.H.M.; Sarvenoe, A.K.; Gowtham, N.; Kareem, M. Optimum management of microgrid generation containing distributed generation sources and energy storage devices by considering uncertainties. *Comput. Electr. Eng.* **2024**, *118*, 109469. [\[CrossRef\]](#)
9. Hassaballah, E.G.; Keshta, H.E.; Abdel-Latif, K.M.; Ali, A.A. A novel strategy for real-time optimal scheduling of grid-tied microgrid considering load management and uncertainties. *Energy* **2024**, *299*, 131419. [\[CrossRef\]](#)

10. Chen, C.; Li, Y.; Qiu, W.; Liu, C.; Zhang, Q.; Li, Z. Cooperative-gamebased day-ahead scheduling of local integrated energy systems with shared energy storage. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1994–2011. [\[CrossRef\]](#)
11. Kubicek, K.; Cech, M.; Strelec, M. A Robust Distributed Algorithm for Solving the Economic Dispatch Problem with the Penetration of Renewables and Battery Systems. *Appl. Sci.* **2024**, *14*, 1991. [\[CrossRef\]](#)
12. Fu, C.; Zhang, S.; Chao, K.-H. Energy Management of a Power System for Economic Load Dispatch Using the Artificial Intelligent Algorithm. *Electronics* **2020**, *9*, 108. [\[CrossRef\]](#)
13. Li, L.-L.; Ji, B.-X.; Liu, G.-C.; Yuan, J.-P.; Tseng, S.-W.; Lim, M.K.; Tseng, M.-L. Grid-connected multi-microgrid system operational scheduling optimization: A hierarchical improved marine predators algorithm. *Energy* **2024**, *294*, 130905. [\[CrossRef\]](#)
14. Meng, X.; Wang, Y.; Shao, B.; Mao, X.; Wang, Q. Distributed cooperative control for global power sharing management of interconnected microgrids in flexible multi-terminal DC connection scheme. *Electr. Power Syst. Res.* **2024**, *237*, 110969. [\[CrossRef\]](#)
15. Ma, Y.; Zhang, M.; Yang, H.; Wang, X.; Xu, J.; Hu, X. Decentralized and coordinated scheduling model of interconnected multi-microgrid based on virtual energy storage. *Electr. Power Energy Syst.* **2023**, *148*, 108990. [\[CrossRef\]](#)
16. Shi, R.; Gao, Y.; Zhang, J.; Jia, L.; Lee, K.Y. A planning method for energy storage capacity of highway self-consistent multi-microgrid system considering carbon trading. *J. Energy Storage* **2024**, *100*, 113616. [\[CrossRef\]](#)
17. Wu, N.; Xu, J.; Linghu, J.; Huang, J. Real-time optimal control and dispatching strategy of multi-microgrid energy based on storage collaborative. *Electr. Power Energy Syst.* **2024**, *160*, 110063. [\[CrossRef\]](#)
18. ShahzadNazira, M.; Almasoudi, F.M.; Abdallac, A.N.; Zhua, C.; Alatawi, K.S.S. Multi-objective optimal dispatching of combined cooling, heating and power using hybrid gravitational search algorithm and random forest regression: Towards the microgrid orientation. *Energy Rep.* **2023**, *9*, 1926–1936.
19. Reddy, S.S.; Park, J.Y.; Jung, C.M. Optimal operation of microgrid using hybrid differential evolution and harmony search algorithm. *Front Energy* **2016**, *10*, 355–362. [\[CrossRef\]](#)
20. Dai, B.; Wang, H.; Li, B.; Li, C.; Tan, Z. Capacity model and optimal scheduling strategy of multi-microgrid based on shared energy storage. *Energy* **2024**, *306*, 132472. [\[CrossRef\]](#)
21. Wang, Y.; Wu, M.; Guo, X.; Zhang, C.; Zhou, Y. Multi-strategy reference vector guided evolutionary algorithm and its application in multi-objective optimal scheduling of microgrid systems containing electric vehicles. *J. Energy Storage* **2024**, *95*, 112500. [\[CrossRef\]](#)
22. Lei, Y.; Ali, M.; Khan, I.A.; Yinling, W.; Mostafa, A. Presenting a model for decentralized operation based on the internet of things in a system multiple microgrids. *Energy* **2024**, *293*, 130637. [\[CrossRef\]](#)
23. Álvarez-Arroyo, C.; Vergine, S.; de la Nietac, A.S.; Alvarado-Barrios, L.; D'Amicod, G. Optimising microgrid energy management: Leveraging flexible storage systems and full integration of renewable energy sources. *Renew. Energy* **2024**, *229*, 120701. [\[CrossRef\]](#)
24. Zhang, Y.; Yan, S.; Li, B.; Liu, D.; Ye, J.; Liu, L. Multi-Scenario Off-Grid Microgrid Optimization Design Based on HOMER. *Acta Energetica Solaris Sin.* **2024**, *254*, 0812312.
25. Wang, X.; Wang, X.; Qin, B. Improved multi-objective differential evolution algorithm and its application in the capacity configuration of urban rail photovoltaic hybrid energy storage systems. *J. Energy Storage* **2024**, *98*, 113155. [\[CrossRef\]](#)
26. Yan, Q.; Li, W.; Wang, J.; Ma, L.; Zhao, J. Heating Furnace Scheduling Method Based on Improved Differential Evolution Algorithm. *Chin. J. Eng.* **2021**, *43*, 422432.
27. Muhsen, D.H.; Nabil, M.; Haider, H.T.; Khati, T. A novel method for sizing of standalone photovoltaic system using multi-objective differential evolution algorithm and hybrid multi-criteria decision making methods. *Energy* **2019**, *174*, 1158–1175. [\[CrossRef\]](#)
28. Yu, X.; Lu, Y. Reinforcement learning-based multi-objective differential evolution for wind farm layout optimization. *Energy* **2023**, *284*, 129300. [\[CrossRef\]](#)

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