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Hierarchical Energy Management of DC Microgrid with Photovoltaic Power Generation and Energy Storage for 5G Base Station

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Abstract: For 5G base stations equipped with multiple energy sources, such as energy storage systems (ESSs) and photovoltaic (PV) power generation, energy management is crucial, directly influencing the operational cost. Hence, aiming at increasing the utilization rate of PV power generation and improving the lifetime of the battery, thereby reducing the operating cost of the base station, a hierarchical energy management strategy based on the improved dung beetle optimization (IDBO) algorithm is proposed in this paper. The first control layer provides bus voltage control to each power module. In the second control layer, a dynamic balance control strategy calculates the power of the ESSs using the proportional–integral (PI) controller and distributes power based on the state of charge (SOC) and virtual resistance. The third control layer uses the IDBO algorithm to solve the DC microgrid’s optimization model in order to achieve the minimum daily operational cost goal. Simulation results demonstrate that the proposed IDBO algorithm reduces the daily cost in both scenarios by about 14.64% and 9.49% compared to the baseline method. Finally, the feasibility and effectiveness of the proposed hierarchical energy management strategy are verified through experimental results.

Keywords: DC microgrid; photovoltaic power generation and energy storage; dung beetle optimization algorithm; dynamic power balance control strategy; energy management



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1. Introduction

Due to the increasing environmental issues caused by conventional fast-depleting energy sources such as coal, power from distributed energy generating sources, especially solar energy, has emerged as a viable alternative [1]. As 5G base stations proliferate, the cost associated with the power supply system (operating cost) for these stations has emerged as a hindrance to the progress of 5G technology. Therefore, power generation from alternate energy sources has been increasingly considered in 5G base stations, as it can help reduce operating costs and promote sustainable development. To cope with the intermittency of alternate energy sources and ensure uninterrupted power to base stations, energy storage systems (ESSs) are integrated at base station locations [2,3]. Effective energy management is crucial especially due to the diverse nature of energy sources at the base stations, which can be considered a DC microgrid. Many experts and scholars have studied the energy management strategies for DC microgrids integrated with alternate energy sources [4,5].

Effective energy management strategies enable reliable and efficient power supply in DC microgrids. Thus, energy management and autonomous control strategies are the focus of research in energy management strategies [6–8]. Given the challenges of intermittent PV power generation, load fluctuation, and the economy of microgrid systems, it is necessary to realize the control of multiple objectives, i.e., increasing the life of ESS devices [9], maximizing the utilization of new-energy power generation, stabilizing bus voltage in

a certain range [10], and minimizing the economic cost of microgrid operation [11]. In general, the control hierarchy is divided into three layers. The first layer is responsible for bus voltage stability [12]. The second layer manages bus voltage correction and power compensation to enhance system stability [13]. Lastly, the third control layer focuses on minimizing cost, extending the energy storage system lifespan, or optimizing system efficiency [14–16].

In [17], a multilevel energy management approach is proposed for the real-time scheduling of a DC microgrid with multiple slack terminals. The secondary control is implemented for bus voltage restoration and power equalization compensation to improve the system power quality and control accuracy. Then, economic dispatch is introduced at the third level to generate a power reference for the second level. However, the effect of battery virtual resistance loss on battery lifetime is not considered in the multi-storage power allocation. To improve the battery lifetime, a publication in the literature [18] proposed an energy management strategy based on model predictive control to trade-off between the energy loss and charge state consistency of an energy storage system, effectively reducing the energy loss and improving battery lifetime. However, the authors only considered the virtual resistance of the battery and neglected the influence of the DC/DC virtual resistance on the charge state consistency of the energy storage system. A further work in the literature [19] introduced a multilevel energy management framework for DC microgrids with multiple energy storage systems, employing a particle swarm-based intelligent algorithm at the third layer to achieve the lowest daily operating cost of DC microgrids by optimizing the settings of virtual battery model parameters. However, in [19], only theoretical analysis without experimental verification was conducted for the first and second control layers, and the algorithms used were prone to local optimization and slow convergence. In this regard, [20,21] discussed the flocking algorithm and annealing variational particle swarm optimization algorithm, respectively. These algorithms effectively solved scheduling problems in microgrids and improved optimization performances by increasing the scheduling convergence accuracy, stability, and speed. However, refs. [20,21] only performed optimal scheduling and did not perform overall microgrid control analysis.

Considering the findings and shortcomings in the literature, a hierarchical energy management strategy based on the IDBO optimization algorithm is proposed for energy management at 5G base stations. This strategy can effectively improve the economic efficiency of the DC microgrids integrated with PV power generation and ESSs, the utilization rate of PV power generation, and the service life of batteries. The main contributions of this paper are as follows: (1) at the second control layer, a dynamic power balance control strategy improves the utilization of PV power generation and enhances the battery life by distributing the power according to the state of charge (SOC) of the ESS and the virtual resistance; (2) an optimization model of the DC microgrid is solved using the IDBO algorithm to achieve the lowest daily operating cost.

This paper is organized as follows: Section 2 explains the DC microgrid with PV and ESS topology and control hierarchy. Section 3 introduces the control details of the first and second layers. Day-ahead energy management is provided with the IDBO algorithm for economic optimization in Section 4. Section 5 presents the simulation results of day-ahead energy management. Section 6 details the experimental results of the first and second control layers. Section 7 presents the conclusion of the paper.

2. DC Microgrid with PV and ESS Topology and Control Hierarchy

A DC microgrid consists of a combination of distributed power sources, loads, and storage units. This paper explores the integration of PV power generation and ESS into the DC microgrid to supply the required energy to a 5G base station. The loads in the 5G base station are all DC in nature, and the microgrid can have single or multiple energy storage units. Figure 1 shows the under-investigation architecture of the DC microgrid topology and the associated control hierarchy.

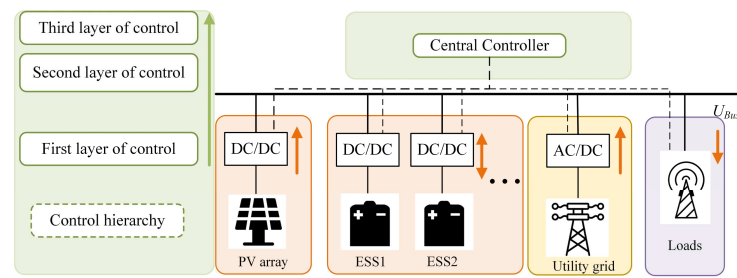


Figure 1. Topology of the DC microgrid.

A detailed view of the hierarchical control structure is shown in Figure 2. The goal of the first control layer is to maintain the stability of the DC bus voltage, U_{Bus} . In this paper, the stabilization of U_{Bus} is achieved through autonomous control by PV modules and grid-associated AC/DC converters. Subsequently, the ESS is controlled as a current source and does not participate in the U_{Bus} regulation, reducing the complexity of the control system and enhancing the reliability and scalability of the system. The goal of the second control layer is to improve the service life of the ESS unit and enhance the utilization of energy from the PV source.

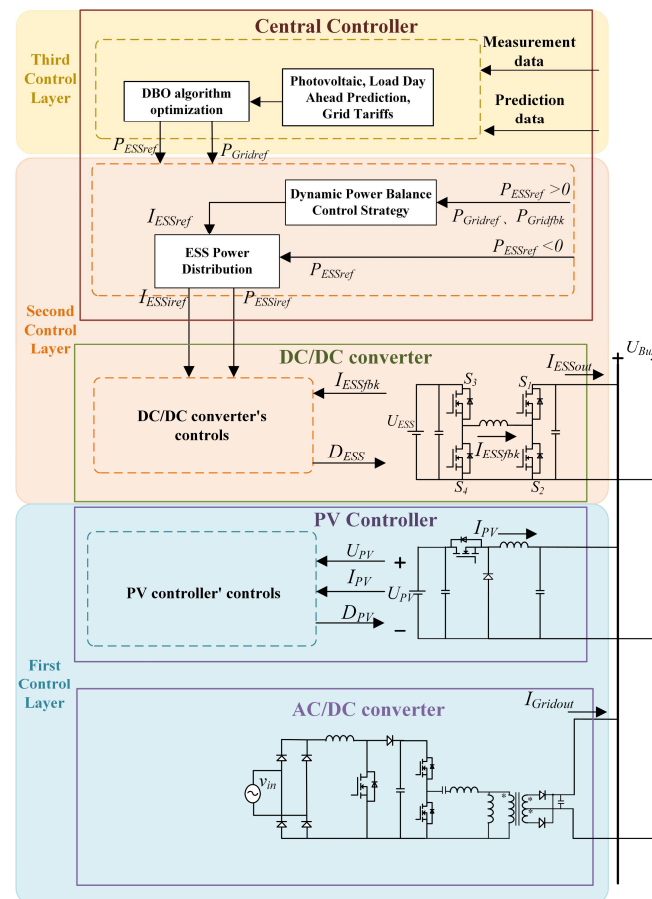


Figure 2. Hierarchical control structure diagram.

The predicted power is processed and allocated through a central controller in this paper. A dynamic power balance control strategy is adapted to optimally regulate the real-time grid power during the discharging of the ESS to reduce power deviations and increase the utilization of PV power generation. The ESS parameters, namely state of charge (SOC) and virtual resistance, are monitored for power allocation during charging to improve the service life of the battery units. In the third layer of control, day-ahead

energy management is performed, where power is predicted a day ahead using the IDBO algorithm to reduce the operating cost of 5G base stations. The economic operation goal is achieved through PV power forecasting, load forecasting, and finding optimal scheduling considering different constraints and daily cost minimization goals.

3. First and Second Control Layers

3.1. First Control Layer

3.1.1. Control of ESS

The energy supply system of the 5G base station has a stable bus voltage, U_{Bus} , while the battery voltage varies widely. To address this, ESS is interfaced with the U_{Bus} through a four-switch buck–boost converter [22]. This converter can rapidly charge and discharge the ESS to address the load and PV power fluctuations. The control of the ESS-interfaced DC/DC converter is illustrated in Figure 3.

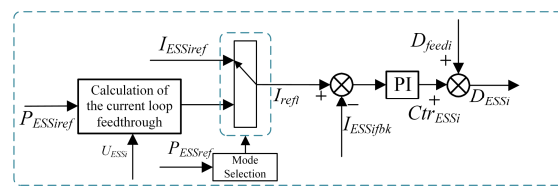


Figure 3. DC/DC converter's controls associated with ESS.

The DC/DC converter's control calculates the current reference based on the ESS's power reference P_{ESSref} , as follows:

$$I_{refi} = \begin{cases} \frac{(P_{ESSiref}/U_{ESSi})}{D_3} & P_{ESSref} < 0 \\ \frac{I_{ESSiref}}{D_3} & P_{ESSref} > 0 \end{cases} \quad (1)$$

where P_{ESSref} represents the charging power reference of the ESS, $P_{ESSiref}$ indicates the charging power reference of the i th ESS, which is generated based on (5), U_{ESSi} symbolizes the battery terminal voltage of the i th ESS, $I_{ESSiref}$ denotes the discharging current reference of the i th ESS, which is generated based on (6), and D_3 defines the duty cycle of the three tubes of the DC/DC converters. When P_{ESSref} is greater than zero, the ESS is discharging and charging otherwise. The central controller communicates the operating power reference or current reference to the ESS's converter. The PI controller acts on the error between the reference current and sensed current as

$$Ctr_{ESSi} = k_p(I_{refi} - I_{ESSifbk}) + k_i \int (I_{refi} - I_{ESSifbk})dt \quad (2)$$

where Ctr_{ESSi} is the PI controller's output, k_p and k_i represent the proportional and integral parameters, $I_{ESSifbk}$ denotes the current through the inductor of the ESS's converter, and I_{refi} indicates the reference current.

3.1.2. Photovoltaic Unit Control

PV power is a commonly used renewable energy source at 5G base stations. The PV controller uses the maximum power point tracking (MPPT) method to extract maximum power from the PV system [23]. This method helps maximize the use of available solar energy. Suppose the power generated by the PV system exceeds the base station and energy storage system (ESS) requirements. In that case, the PV controller transitions out of maximum power point tracking (MPPT) mode. This is performed to avoid overcharging of the ESS or over-voltage conditions at the DC bus. In this scenario, the controller switches to constant-voltage mode to ensure the stability of U_{Bus} . The controller for the PV-associated converter is shown in Figure 4.

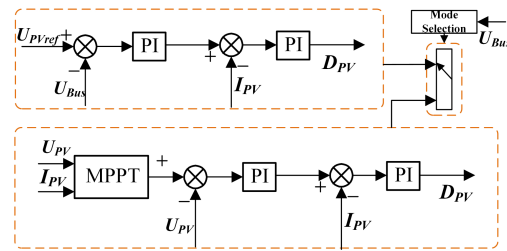


Figure 4. PV converter's controller.

The PV controller performs mode selection by sensing the bus voltage, U_{Bus} . When U_{Bus} crosses a predefined threshold value, the PV controller enters the constant-voltage mode, after which the PV bus voltage is regulated at U_{PVref} .

3.1.3. Grid-Interfaced AC/DC Converter Control

The DC microgrid and AC grid are connected through an AC/DC converter [24]. The front-end of the converter is a single-phase full-bridge rectifier (microgrid side), while the back-end power conversion adopts a two-stage structure. The first stage of the back-end converter uses a boost topology, which is controlled to operate in continuous conduction mode (CCM), ensuring a power factor of more than 95%. The second stage is a DC/DC converter, which is realized using a half-bridge LLC resonance topology. During normal operation, the AC/DC converter is used to maintain the stability of U_{Bus} .

3.2. Second Control Layer

3.2.1. Dynamic Power Balance Control Strategy

Although the amount of power generated from a PV system during the day can be predicted, it is affected by various factors, such as partial shading and temperature, and the output power can fluctuate. To ensure that the PV controller operates in the MPPT mode and improves PV utilization, a dynamic power balance strategy is employed. Based on this strategy, the discharge power of the ESS is reduced when there is surplus PV power to maintain the power balance in the system. If the increased PV power exceeds the load power, the ESS is charged to save excess power.

In this case, the input to the PI controller is the difference between the reference grid power and measured power and outputs I_{ESSref} as follows:

$$I_{ESSref} = k_p(P_{Gridref} - P_{Gridfbk}) + k_i \int (P_{Gridref} - P_{Gridfbk})dt \quad (3)$$

where I_{ESSref} denotes the reference current to the ESS, $P_{Gridref}$ represents the optimal power reference generated from the day-ahead energy management, and $P_{Gridfbk}$ indicates the actual power drawn from the grid.

3.2.2. ESS Power Distribution

Many experts and scholars have studied the energy distribution of energy storage systems from various perspectives [25]. To ensure the longevity of ESSs and stability of the system, it is essential to consider SOC consistency and energy loss when multiple ESSs are connected to the DC microgrid. Therefore, the central controller aims to achieve SOC equalization among the ESSs in the early stage of power allocation. Once the SOC equalization is achieved, the objective is to reduce the energy loss in the energy storage units.

The SOC distribution in the early stages is achieved as

$$SOC_{all} = \sum_{i=1}^n SOC_i \quad (4)$$

$$P_{ESSiref} = P_{ESSref}(SOC_i/SOC_{all}) \quad (5)$$

$$I_{ESSiref} = I_{ESSref}(SOC_i/SOC_{all}) \quad (6)$$

where SOC_{all} represents the total remaining capacity of the ESSs, SOC_i denotes the remaining capacity of i th ESS, and P_{ESSref} indicates the optimal power reference for the ESSs generated from the day-ahead energy management.

After performing SOC equalization among the ESSs, power allocation is adjusted to account for the differences in virtual resistances of the ESSs, which otherwise can cause unequal energy losses among the storage units. The allocation is performed based on the virtual resistance of the ESS, R_{vi} , as [26]

$$R_{vall} = \sum_{i=1}^n R_{vi} \quad (7)$$

$$P_{ESSiref} = \left(\frac{P_{ESSref}}{\sum_{i=1}^n \left(\frac{R_{vall}}{R_{vi}} \right)} \right) \frac{R_{vall}}{R_{vi}} \quad (8)$$

$$I_{ESSiref} = \left(\frac{I_{ESSref}}{\sum_{i=1}^n \left(\frac{R_{vall}}{R_{vi}} \right)} \right) \frac{R_{vall}}{R_{vi}} \quad (9)$$

where R_{vall} represents the virtual resistance of the ESSs, and R_{vi} indicates the virtual resistance of the i th ESS and is given as below.

$$R_{vi} = \left(\frac{U_{outi}}{U_{bi}\eta_{DC/DC}} \right)^2 r_b \quad (10)$$

where U_{outi} represents the output voltage of the DC/DC converter connected to the ESS, U_{bi} denotes the terminal voltage of the battery in the ESS, $\eta_{DC/DC}$ indicates the operating efficiency of the ESS's DC/DC converter, and r_b symbolizes a virtual resistance of the battery in the ESS, which can be obtained from the battery management system (BMS) of the ESS.

4. Day-Ahead Energy Management

Energy management can be divided into three stages, namely (i) prediction, (ii) optimization, and (iii) control. As the name indicates, energy management is performed the day before, where both prediction and optimization stages take place. A visual representation of the overall energy management process is depicted in Figure 5.

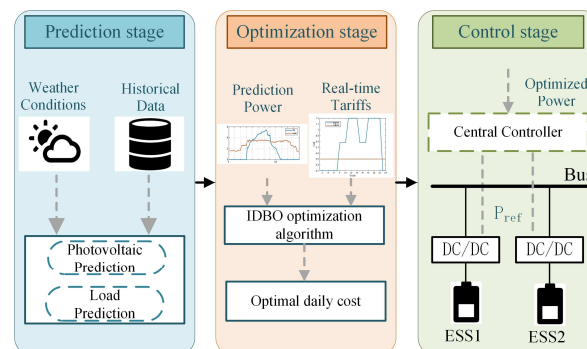


Figure 5. Energy management flowchart.

During the prediction stage, the forecasted power from the PV system and the estimated load power are transferred to the optimization stage. Advanced machine learning models, such as neural networks and deep learning prediction methods, are utilized to predict the generated PV power [27,28] and 5G base station load [29] based on historical

data and meteorological conditions. Due to the limited scope of this paper, the algorithms are not discussed in detail here.

The optimization stage plays a crucial role in energy management, where the IDBO algorithm performs economic optimization. Once optimization is completed, the optimal power of each component is communicated to the central controller. Subsequently, the central controller processes optimal power information and issues commands to the DC/DC converter to minimize the daily operating costs for the following day.

4.1. Modeling of Energy Storage Devices

The main role of the energy storage device is to absorb excess power from PV power generation, realize peak shaving and valley filling, and maintain stable system operation. Charging and discharging operations are carried out based on the load power and distributed power changes. The main consideration is the battery's remaining capacity and power constraints during the charging and discharging operations, and its model is expressed as [30]

$$SOC(t) \begin{cases} SOC(t-1) + \eta_{ch} P_{BAT} \\ SOC(t-1) + \eta_{dis} P_{BAT} \end{cases} \quad (11)$$

where SOC denotes the present charging state of the energy storage unit, and P_{BAT} indicates the charge/discharge power of the battery, where it is considered positive during discharging and negative while charging. In addition, η_{ch} and η_{dis} represent the charging and discharging efficiencies of the ESS, respectively.

4.2. Economic Optimization Model

4.2.1. Objective Function

The power generated by PV system in the DC microgrid is prioritized to maximize its utilization, and minimizing the daily operating cost of the system is considered as an optimization objective. The mathematical formulation is given as follows:

$$C = \min \left(\sum_i^{24} (C_{grid_i} + C_{BESS_i} + C_{PV_i}) \right) \quad (12)$$

where C_{grid_i} is the cost of energy exchanged between the microgrid and the grid. Moreover, C_{BESS_i} and C_{PV_i} are the operation and maintenance costs associated with the ESS and PV system, respectively. The mathematical expression of C_{grid_i} is given as follows:

$$C_{grid_i} = \begin{cases} C_{grid_{i-1}} + Buy_i P_i & P_i > 0 \\ C_{grid_{i-1}} + Sell_i P_i & P_i < 0 \end{cases} \quad (13)$$

where Buy_i , $Sell_i$, and P_i are the buying tariff, selling tariff, and grid power at the i th moment, respectively. C_{BESS_i} and C_{PV_i} can be mathematically expressed as follows:

$$C_{BESS_i} = C_{BESS_{i-1}} + K_{BESS} |P_{BESS_i}| \quad (14)$$

$$C_{PV_i} = C_{PV_{i-1}} + K_{PV} |P_{PV_i}| \quad (15)$$

where K_{BESS} and K_{PV} are the maintenance coefficients of the ESS and PV system, respectively.

4.2.2. Constraints

The power balance constraints of the considered microgrid should be satisfied:

$$P_i + P_{BESS_i} + P_{PV_i} - P_{Load_i} = 0. \quad (16)$$

where P_{BESS_i} represents the ESS power whose charging is considered as negative and discharging as positive, P_{PV_i} denotes the PV power, and P_{Load_i} indicates the load power at i th moment.

The PV module's output power should be less than the maximum output power with the following constraint:

$$0 \leq P_{PV_i} \leq P_{PV_MAX_i} \quad (17)$$

where $P_{PV_MAX_i}$ is the real-time maximum PV power. The charging and discharging powers and ESS capacity during its charging and discharging should satisfy the following constraints:

$$P_{BESS_min} \leq P_{BESS_i} \leq P_{BESS_max} \quad (18)$$

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (19)$$

P_{BESS_min} and P_{BESS_max} are the power limits of the ESS, SOC_{min} denotes the minimum state of charge of the ESS, and SOC_{max} indicates the maximum state of charge of the ESS.

To ensure stable grid-interfaced AC/DC converter operations, the following power constraints need to be satisfied:

$$0 \leq P_i \leq P_{max} \quad (20)$$

where P_{max} is the upper limit of the AC/DC converter.

4.3. IDBO Algorithm

The dung beetle optimization (DBO) algorithm produces accurate results and has a fast convergence rate when solving a single-objective optimization problem [31]. The DBO algorithm models dung beetle behaviors, such as rolling, dancing, foraging, stealing, and breeding. It is described in detail in Appendix A. In this paper, DBO-based optimization is adapted.

4.3.1. Introduction of the Levy Flight Strategy

The algorithm treats the scenario where the population converges to a local optimum as analogous to the global scenario converging to a local optimum. To avoid premature convergence to a locally optimal solution during the iterative process, the DBO algorithm introduces the Levy flight strategy to update the position of the optimal solution of the population [32]. The formula to update the position is expressed as follows:

$$x_i^{t+1} = x_i^t + \alpha \text{Levy}(\beta)(x_{gbest}^t - x_i^t) \quad (21)$$

where x_{gbest}^t represents the global optimal solution at moment t . As the iterations progress, the particles gradually converge to the optimal position. However, in the later stages, there is a potential risk that the Levy flight strategy could lead the particles away from the optimal solution. To address this issue, the α coefficient is introduced, and its value decreases as the iterations progress. In the pre-iteration period, the Levy flight strategy aids in global search and improves the local search capabilities in the subsequent stages.

Levy (β) is a randomized search path, which is given by:

$$\text{Levy}(\beta) = \frac{u}{|v|^{1/\beta}} \quad (22)$$

where u and v satisfy the normal distribution $u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2)$

$$\sigma_v = 1 \quad (23)$$

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta) \sin(\frac{\beta\pi}{2})}{\Gamma[\frac{(1+\beta)}{2}] \beta 2^{\frac{\beta-1}{2}}} \right\}^{\frac{1}{\beta}} \quad (24)$$

where β is taken as 1.5 [33].

4.3.2. Variant Operations

In the later stages of the algorithm iteration, the particles tend to cluster around the optimal position as the iteration approaches its conclusion. However, if this position happens to be a local optimum, the algorithm may fail to find the global optima as it keeps searching for the optimal value near the local optima. To overcome this, a variant perturbation operation is employed to enhance the diversity of the particles by interfering with them when the iteration is close to 90%. This facilitates the particles in escaping from the local optima, allowing them to persist in searching for the global optima.

Therefore, a mutation perturbation operation is added to the optimal individual in the DBO algorithm. The Gaussian operator is utilized to perturb the optimal individual [34], enabling the algorithm to break free from the local optimal solution and expand the search range, which is formulated as follows:

$$x_{\text{best}}^{t+1} = x_{\text{best}}^t (0.5 + N(0, 1) \text{Gaussian}(0, 1)) \quad (25)$$

where $N(0, 1)$ is a random number between 0 and 1; and $\text{Gaussian}(0, 1)$ is a Gaussian normal distribution. As it constitutes a mutation perturbation of the optimal individual, it is not possible to ascertain if the individual after the perturbation is better than the individual before the perturbation. To ensure that the local optimum is found, a greedy rule is added, and the fitness value is calculated after the perturbation to determine whether to update the optimal individual. The mathematical formulation is given as

$$x_{\text{gbest}}^{t+1} = \begin{cases} x_{\text{best}}^t & f(x_{\text{best}}^t) > f(x_{\text{best}}^{t+1}) \\ x_{\text{best}}^{t+1} & f(x_{\text{best}}^t) < f(x_{\text{best}}^{t+1}) \end{cases} \quad (26)$$

4.4. IDBO Algorithm Solution

The flowchart of the IDBO algorithm is shown in Figure 6.

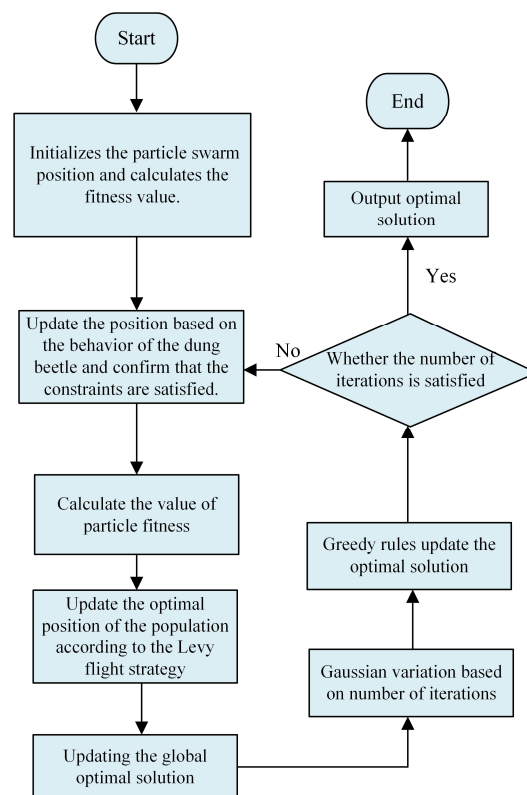


Figure 6. Flowchart of IDBO algorithm.

The algorithm is executed using the following steps:

1. Initialize the particle swarm position and calculate the fitness value;
2. Adjust the position according to the dung beetle's behavior and verify if the constraints are met;
3. Calculate the particle fitness value, revise the optimal position of the population using the Levy flight strategy, and update the optimal solution;
4. Update the optimal solution by performing the Gaussian variation and greedy rule operations;
5. Determine whether the number of iterations is satisfied. If satisfied, output the optimal 24 h power and daily cost values for each device. If the number of iterations is not satisfied, continue to perform the operations numbered from 2 to 5.

5. Simulation Results and Discussions

5.1. Parameters of the Algorithm

Numerical simulation is conducted in the MATLAB/Simulink environment to investigate the optimal power settings of modules under different PV installed capacities and loads. The algorithm is applied to solve the optimization problem using data from two distinct days at a base station in Wuhan, China. The selected days represent different weather conditions, with one being sunny and the other cloudy, and the time scale for the analysis is set at 15 min. The DBO and IDBO algorithms are compared with the particle swarm optimization (PSO) algorithm [35] and adaptive mutant particle swarm optimization (AMPSO) algorithm [36]. Each algorithm has a uniform population size of 100 and a maximum of 300 iterations. In IDBO and DBO algorithms, 20% of the dung beetles are assigned to ball rolling, 25% to breeding, and 25% to stealing. In both cases, the battery capacity is 25 kWh, and the initial SOC value of the ESS is set to 0.5.

The PV and load data used in the simulations for a typical sunny day are shown in Figure 7, whereas the corresponding data for a typical cloudy day are illustrated in Figure 8.

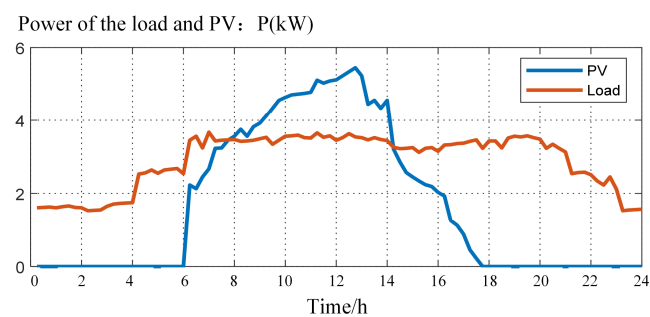


Figure 7. Load profile and PV power output on a sunny day.

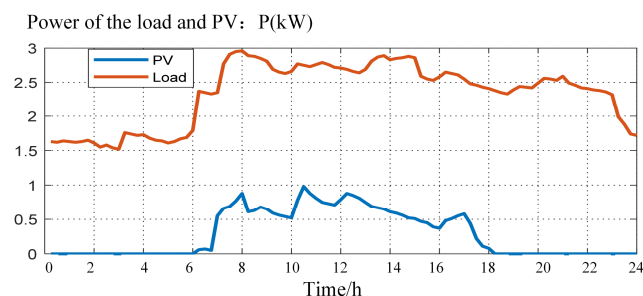


Figure 8. Load profile and PV output power on a cloudy day.

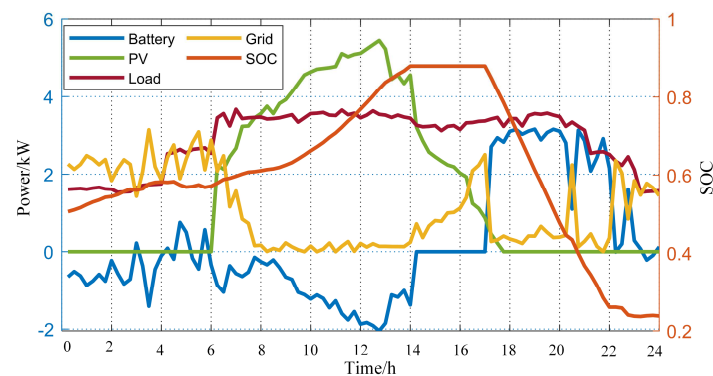
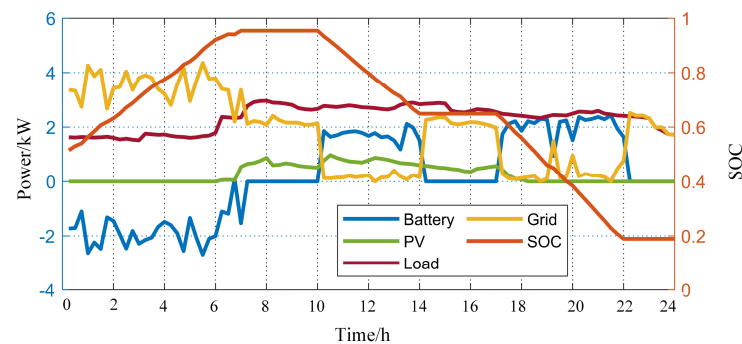
The 24 h electricity price data for the local grid of the base station are shown in Table 1.

Table 1. Purchase price of electricity for 24 h.

Times	Tariff [CNY(kWh) ^{−1}]
10:00–14:00, 17:00–22:00	1.2
7:00–10:00, 14:00–17:00	0.78
22:00–7:00	0.3

5.2. Comparative Analysis of Results

The DBO algorithm, IDBO algorithm, PSO algorithm, and AMPSO algorithm are individually simulated to calculate the optimal power of each device for 24 h under different scenarios. Scenario 1 takes the data in Figure 7 as input, and the power allocation calculated for 24 h through the IDBO algorithm is shown in Figure 9; Scenario 2 takes the data in Figure 8 as input, and the power allocation calculation for 24 h by the IDBO algorithm is shown in Figure 10.

**Figure 9.** Optimized scheduling results for Scenario 1.**Figure 10.** Optimized scheduling results for Scenario 2.

The following inferences can be drawn from the simulation results of the above two scenarios:

Scenario 1: To ensure that the ESSs have enough capacity to absorb the excess power generated by the PV system, they are charged and discharged when the grid electricity price is low during the 22:00–7:00 h period. As a result, the SOC is at the optimal value. During the 8:00–14:00 h period, power generated from the PV system is greater than the load power. Hence, the ESSs are charged to ensure the effective utilization of PV power. During the 17:00–22:00 h period, ESSs are discharged when the grid electricity price is high.

Scenario 2: Charge the ESSs between 22:00 and 7:00 h when the grid's electricity prices are low. Perform charging or not charging and discharging the ESSs either during the 7:00–10:00 h period or the 14:00–17:00 h period when the grid tariff is flat. Discharge the ESSs between 10:00–14:00 h or 17:00–22:00 h when the grid electricity price is high.

Differences in PV power generation result in different battery scheduling, which can be seen by the SOC curves in Figures 9 and 10. When the PV-generated power exceeds the

load power, the batteries can absorb the excess power through scheduling, further reducing the daily operating cost of the microgrid. The optimal fitness values of each algorithm for scenarios 1 and 2 are shown in Figures 11 and 12. The optimal fitness value is the daily cost of the base station during optimal operation. It can be seen from the figures that the IDBO algorithm can quickly find the optimal fitness value, and it is better than the DBO algorithm in terms of optimization speed and optimization results. Also, the IDBO algorithm is better than other algorithms in terms of optimization results.

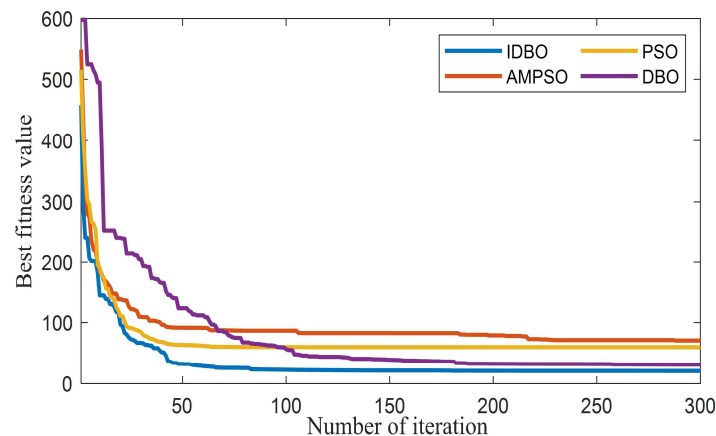


Figure 11. Best fitness values for each algorithm in Scenario 1.

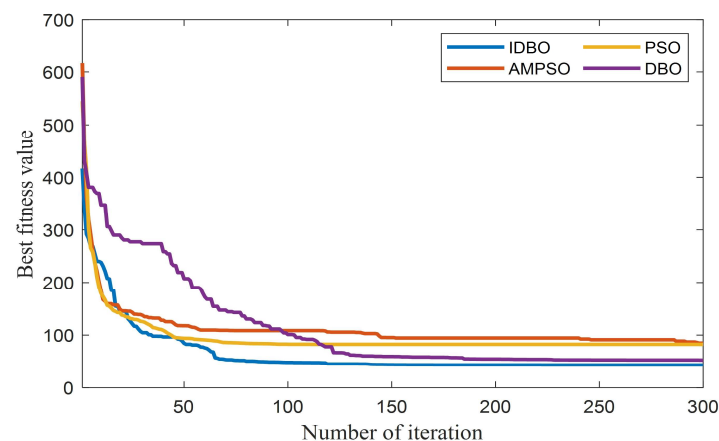


Figure 12. Best fitness values for each algorithm in Scenario 2.

Scenario 1: The optimal daily costs of the DC microgrids obtained using PSO, AMPSO, DBO, and IDBO algorithms are CNY 51.3, CNY 58.4, CNY 31.1, and CNY 20.1, respectively. Through the proposed IDBO algorithm, the optimization reduces the cost of power supply by 14.64% compared to the baseline method [37].

Scenario 2: The optimal daily costs of the DC microgrids obtained using PSO, AMPSO, DBO, and IDBO algorithms are CNY 88.1, CNY 95.4, CNY 55.5, and CNY 49.0, respectively. Through the proposed IDBO algorithm, the optimization reduces the cost of power supply by 9.49% compared to the baseline method.

In both cases, the power generated by the PV system is effectively utilized, adhering to the power balance constraints and resulting in daily costs of 14.64% and 9.49%, respectively. The IDBO algorithm demonstrates its effectiveness in reducing the operating costs of base stations, thereby confirming the effectiveness of the third control layer. Increased utilization of photovoltaic power generation and reduced daily operating costs promote the sustainability of 5G base stations.

5.3. Algorithm Comparisons

To further verify the superior performance of the IDBO algorithm over the other algorithms, this section compares it with the PSO, the genetic algorithm (GA) [38], and the DBO algorithm. To integrate all the algorithms on the same platform, the population size and maximum number of generations of all the algorithms are set to 100 and 300, respectively.

Comparisons shown in Table 2 are conducted using Scenario 1. The minimum electricity cost of the algorithms is CNY 17.29, obtained by the IDBO algorithm, whereas the DBO algorithm exhibits the highest deviation. A Wilcoxon test is also conducted for statistical comparison purposes, where P less than 0.05 indicates the statistical significance of the IDBO algorithm [39]. It is observed that the IDBO has higher statistical significance than all other algorithms, as shown in Table 3. Therefore, it can be concluded that the IDBO algorithm has demonstrated superior performance to the other optimization algorithms.

Table 2. Statistical comparison of algorithms for 31 runs.

Cost Function (C)	Min	Max	Average	STD
IDBO	17.29	32.06	23.84	3.23
DBO	20.92	100.71	33.75	20.9
PSO	37.98	108.62	65.44	17.23
GA	25.87	50.27	37.25	11.18

Table 3. Wilcoxon test for comparing algorithms.

Algorithms	IDBO vs. DBO	IDBO vs. PSO	IDBO vs. GA
P	0.0062	1.17×10^{-6}	0.00028
Significant IDBO	Yes	Yes	Yes

6. Experimental Results and Analysis

The experimental platform of the DC microgrid with photovoltaic power generation and energy storage is developed as shown in Figure 13, where the central controller and controllers for the DC/DC converter are implemented in a Texas Instruments-made TMS320F28335. The communication between the central controller and the DC/DC converter is implemented through the CAN protocol. In contrast, the communication between the DC/DC converter and the battery is through the RS485 protocol.

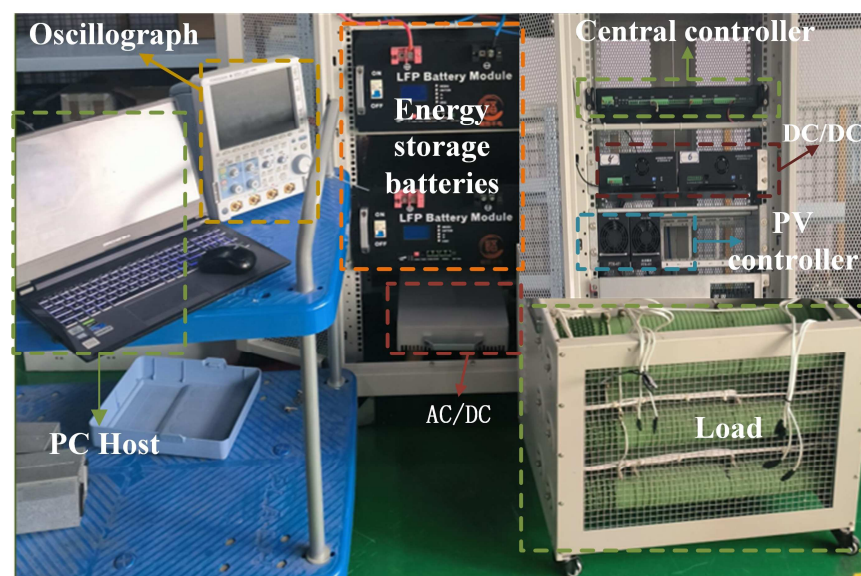


Figure 13. Experimental platform of DC microgrid.

6.1. Experiments on Power Dynamic Balance Control Strategy

When ESSs are discharging, as shown in Figure 14a, some loads are disconnected at t_1 . To maintain system stability, the ESS transitions from discharge to charge mode, while the photovoltaic controller can continue to operate in the MPPT mode after 2 s. As shown in Figure 14b, photovoltaic power generation gradually increases at t_2 , causing a corresponding decrease in the discharge power of the energy storage system. By t_3 , the ESS transitions from discharge to charge mode again, while the photovoltaic controller works in MPPT mode. The above-discussed experimental results verify the effectiveness of the dynamic power balance control strategy while improving the utilization rate of PV power generation.

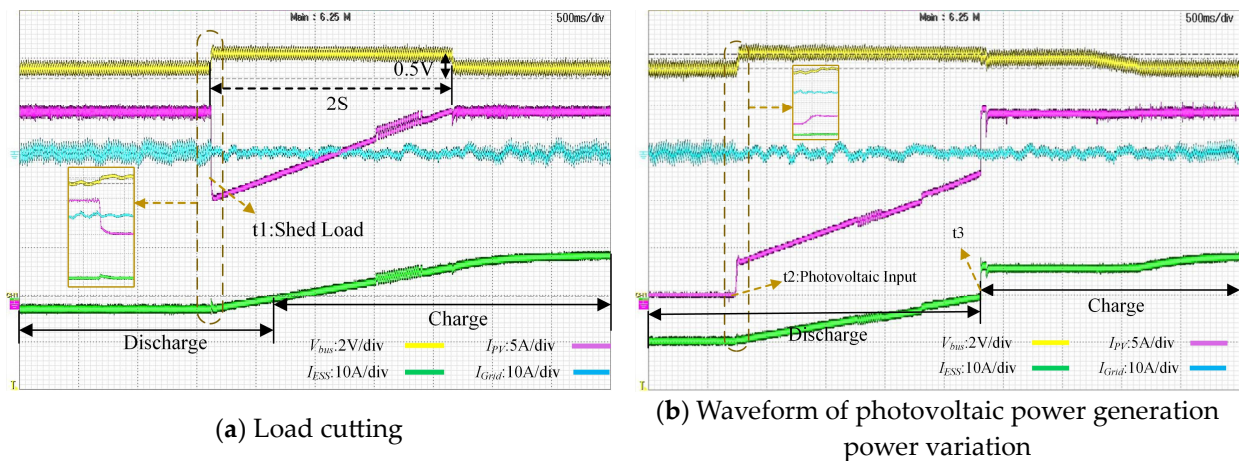


Figure 14. Experimental waveforms confirming the power dynamic balance control strategy.

6.2. Twenty-Four-Hour Experiments

To verify the feasibility and reliability of the first and second layers of control of the DC microgrid, a 24 h experiment during the 00:00–24:00 h period is conducted. Figure 15 shows the control strategy, in which the load power is 1.8 kW, the installed capacity of PV is 2 kW, the ESSs have two storage batteries with a capacity of 10.8 kWh, and the maximum grid power is 3 kW. The initial SOC for energy storage batteries is set at 30%. The AC/DC converter outputs at a voltage level of 53.5 V. The computer communicates with the central controller via a serial port to monitor the whole system. The sampling time of the monitoring processes is five minutes. Figure 16a shows the 24 h power variation of the grid, energy storage system, and PV system. Figure 16b shows the variations in the bus voltage during the 24 h period. Figure 16c shows the variation in the SOC of the battery measured over 24 h.

It can be seen from Figure 16a that between 0:00–8:00 h, the charging operation of the energy storage system happens, and bus voltage is regulated by AC/DC converter to maintain stability. During the 8:00–10:00 h period, the energy storage system is discharging; with an increase in the P_{PV} , the ESS discharge power decreases. At 10:00, the P_{PV} exceeds the load demand. Between 10:00 and 11:00, ESS is used to absorb excess PV power, which ensures the effective utilization of PV power. Between 12:00 and 16:00 h, the PV power gradually reduces, and ESS begins to discharge to maintain the stable operation of the system. Figure 16b shows that the bus voltage fluctuates between 52.4 V and 54.0 V, which is suitable for reliable load operations. From Figure 16c, it can be seen that the SOC of the battery is always balanced. The overall system stability is good, as observed from the continuous experiments conducted for 24 h, which verifies the feasibility and effectiveness of the first and second layers of control.

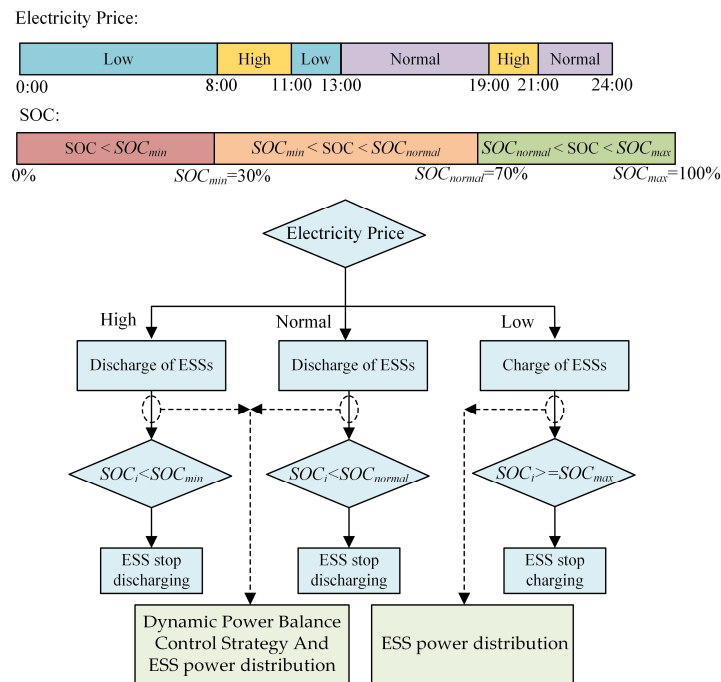


Figure 15. Twenty-four-hour experimental control strategy.

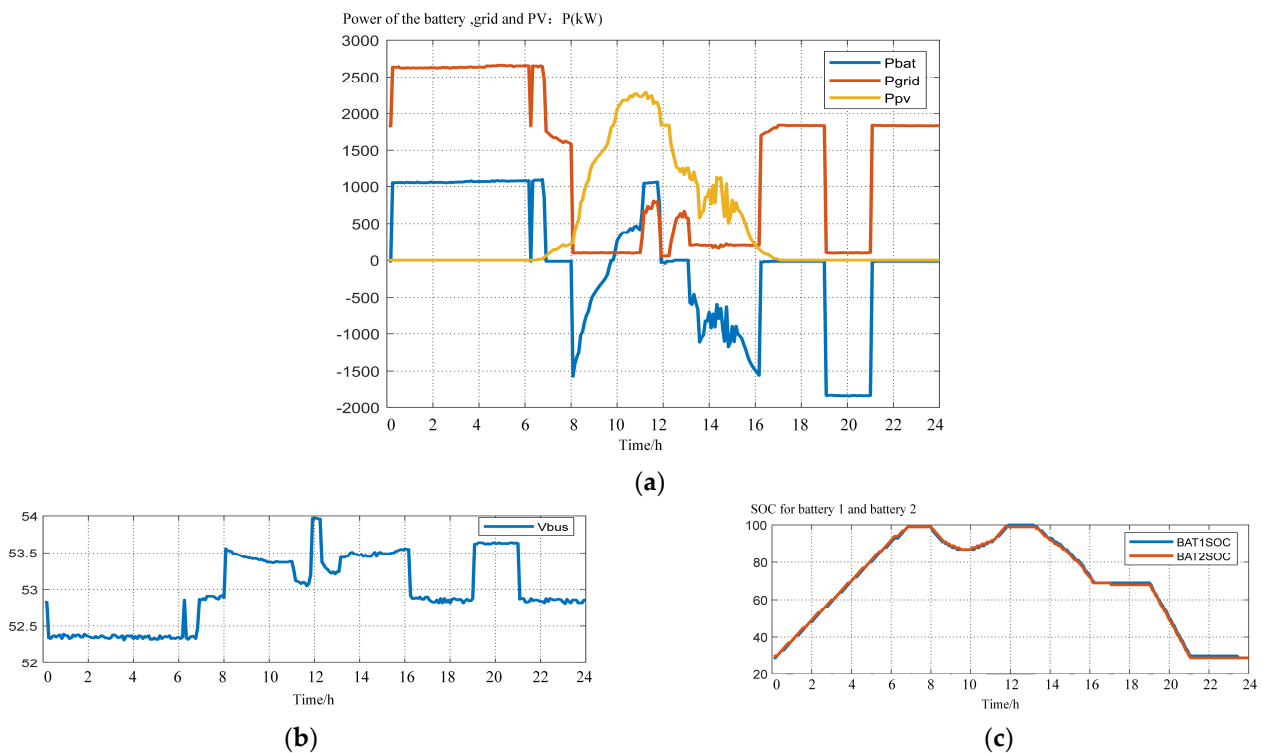


Figure 16. Experimental results of power deviations: (a) change in powers for a 24 h period; (b) change in bus voltage during a 24 h period; (c) change in SOC during a 24 h period.

7. Conclusions

Creating a scheduling model for the DC microgrid involves designing a single-objective optimization framework. This model focuses on determining the optimal values for grid output, storage system output, and photovoltaic output over 24 time periods. The goal is to minimize the daily operation cost of a 5G base station, which is the primary

objective function for optimization. The model is solved using the DBO, IDBO, PSO, and AMPSO algorithms. Simulation and experimental results show that:

1. The IDBO algorithm is capable of optimizing faster and better than PSO, AMPSO, and DBO algorithms. In two different scenarios, it is shown that the use of the IDBO algorithm reduces the daily operating cost of the base station by 14.64% and 9.49%, proving the effectiveness of the third layer of control. This promotes sustainable economic development;

Through the constructed DC microgrid experimental platform, continuous 24 h experiments were conducted, and the experimental results show that:

2. The DC microgrid operates stably for 24 h, and the SOC of the two batteries are always in equilibrium, which verifies the feasibility and effectiveness of the first and second control layers;
3. The power fluctuations from the PV source are stabilized by implementing a dynamic power balancing control strategy. When the PV power generated is more than what is consumed by the load, the excess energy is stored in an ESS, thereby improving the overall efficiency of PV power generation.

This energy management strategy is applicable to small microgrid systems. In the near future, complex stand-alone microgrid systems such as those containing wind power, photovoltaic power, and energy storage systems, among others, will need to be studied for stability and environmental assessment. More new-energy generation systems are connected to the base station's power supply system to promote the sustainable development of 5G base stations.

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Appendix A

The principle of the dung beetle optimization algorithm is as follows:

Line classified dung beetles into four populations for ball rolling behavior, reproductive behavior, foraging behavior, and stealing behavior. In dung beetles, ball rolling behavior was classified into obstructed and unobstructed modes.

In the absence of obstacles, the dung beetle will use the sun to navigate as it rolls the ball, and its position is updated as shown in Equation (A1):

$$x_i^{t+1} = x_i^t + \alpha k x_i^{t-1} + b |x_i^t - x_{\text{worst}}^t| \quad (\text{A1})$$

When there is an obstacle, the dung beetle cannot continue to move forward; it will readjust itself by dancing to gain direction, using the tangent function to simulate the dung beetle's dancing behavior. After regaining its direction, it will continue to move forward and its position is updated as shown in Equation (A2):

$$x_i^{t+1} = x_i^t + \tan(\theta) |x_i^t - x_i^{t-1}| \quad (\text{A2})$$

where t denotes the current number of iterations, x_i^t denotes the position of the i th dung beetle in the population at the t th iteration. $\alpha = 1$ denotes no bias, and $\alpha = -1$ denotes a deviation from the original direction. $k \in (0, 0.2)$ denotes the coefficient of deflection, which is generally taken as 0.1, and b represents the factor of variation of light intensity, which is a constant of (0, 1) and is generally taken as 0.3. x_{worst}^t denotes the worst position in the current population. θ is a $[0, \pi]$ random number within the population.

In the breeding behavior of dung beetles, only for female dung beetles, determining the boundary conditions of the particles and making dynamic adjustments to the particles can be well optimized to solve the local optimum problem. The formulas are shown in (A3) and (A4):

$$\begin{cases} Lb^* = \begin{cases} x_{\text{gbest}}^t(1-R) & x_{\text{gbest}}^t(1-R) > Lb \\ Lb & x_{\text{gbest}}^t(1-R) < Lb \end{cases} \\ Ub^* = \begin{cases} x_{\text{gbest}}^t(1+R) & x_{\text{gbest}}^t(1+R) < Ub \\ Ub & x_{\text{gbest}}^t(1+R) > Ub \end{cases} \end{cases} \quad (\text{A3})$$

$$x_i^{t+1} = x_{\text{gbest}}^t + b_1(x_i^t - Lb^*) + b_2(x_i^t - Ub^*) \quad (\text{A4})$$

where $R = (T - t)/T$. T is the maximum number of iterations, and the Lb and Ub are the lower and upper bounds of the particles. x_{gbest}^t is the global optimal position of the current population, and b_1 and b_2 are random numbers within (0, 1).

In dung beetles, foraging behavior is only for small dung beetles; the equations are shown in (A5) and (A6):

$$\begin{cases} Lb^l = \begin{cases} x_{\text{lbest}}^t(1-R) & x_{\text{lbest}}^t(1-R) > Lb \\ Lb & x_{\text{lbest}}^t(1-R) < Lb \end{cases} \\ Ub^l = \begin{cases} x_{\text{lbest}}^t(1+R) & x_{\text{lbest}}^t(1+R) < Ub \\ Ub & x_{\text{lbest}}^t(1+R) > Ub \end{cases} \end{cases} \quad (\text{A5})$$

$$x_i^{t+1} = x_i^t + C_1(x_i^t - Lb^l) + C_2(x_i^t - Ub^l) \quad (\text{A6})$$

where C_1 is a random number obeying a normal distribution and C_2 is a (0, 1) random number.

In the case of dung beetles, stealing behavior is only for stealing dung beetles; the equation is shown in (A7):

$$x_i^{t+1} = x_{\text{lbest}}^t + Sg(|x_i^t - x_{\text{gbest}}^t| + |x_i^t - x_{\text{lbest}}^t|) \quad (\text{A7})$$

where g is a random number obeying a normal distribution and S is a random number within (0, 1).

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