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Optimal Dispatch of Microgrids in Islanded and Grid-Connected Modes: A Mixed-Integer Linear Programming Approach for Cost Minimization and Renewable Energy Integration

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Abstract. The depletion of traditional fossil fuel energy and the increasingly apparent environmental pollution issues have made the development of clean and environmentally friendly new energy sources the optimal solution to address these severe problems. The proposal and application of the microgrid concept provide a new option for integrating various renewable energy sources. Microgrids can not only improve the utilization rate of renewable energy but also enhance the reliability of renewable energy power supply, reduce the use of traditional fossil fuels, and lower pollutant emissions. However, highly uncertain categories such as wind and solar power constitute the main part of renewable energy generation, and the load side also has certain uncertainties. Therefore, optimizing the operational logic of microgrids to ensure their safe, stable, economical, and efficient operation has become a significant issue. This paper studies the optimal dispatch of microgrids under both islanded and grid-connected scenarios. The research approach is as follows: 1. Analyze the operational characteristics of photovoltaic units, energy storage modules, and loads in microgrids, and establish corresponding mathematical models. The interaction between the microgrid and the main grid for electricity sales and purchases is also introduced. 2. Establish the constraints for the microgrid. 3. Set the minimum cost as the optimization objective for microgrid operation and establish the objective function. 4. Solve the model using mixed-integer linear programming.

Keywords: Microgrid, Integrated energy dispatching, Renewable energy, Mixed-integer programming

1. Introduction

With the rapid development of the global economy, the demand for fossil fuels continues to rise. However, fossil fuel reserves are limited and face increasingly severe depletion issues, exacerbating this contradiction. According to the International Energy Agency (IEA) report, at the current consumption rate, global oil reserves are expected to last only a few decades, and the situation for coal and natural gas resources is also not optimistic. The shadow of an energy crisis looms over the

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world, and its full outbreak could severely impact the global economy and social stability. In this context, vigorously developing and utilizing new energy sources to fill the energy gap and gradually replace traditional fossil fuels has become an urgent task in the global energy sector.

As a new type of power supply system, microgrids offer advantages such as diversified energy supply, high utilization of renewable energy, low environmental pollution, reduced feeder losses, convenient control, flexible operation modes, and high power supply reliability. However, compared to traditional centralized large power grid optimization models, microgrids, as a new type of power system network, have more complex optimization models. Optimizing the dispatch of microgrids requires considering factors such as economic costs of power generation, the combined benefits of distributed energy resources, and environmental benefits, all while ensuring energy supply-demand balance. Apart from Chapter 1, the main research content of this paper is as follows:

Chapter 3 summarizes the theoretical foundations required for this study. First, the relationship between light intensity and photovoltaic (PV) power generation is analyzed. Assuming that light intensity follows an approximate Beta distribution and combining the probability density function of light intensity with the photoelectric conversion efficiency of solar panels, the probability density function of PV power output is obtained. The battery energy storage unit within the microgrid are also described. Mathematical models for PV power generation, and loads in the microgrid are established, along with mathematical models for battery charging/discharging and energy interaction with the grid.

Chapter 4 establishes the constraints for microgrid operation, including power balance constraints, power limit constraints, ramp rate constraints, and tie-line transmission power constraints. The objective function is established with the goal of minimizing the operating cost of the microgrid.

Chapter 5 investigates the optimal dispatching of a microgrid system under both grid-connected and islanded operation modes. Additionally, in the grid-connected mode, a battery health penalty term is incorporated into the optimization model to account for battery degradation, ensuring a trade-off between cost efficiency and battery longevity

2. Literature review

Research on the economic dispatch of microgrids has been conducted from various perspectives, with major directions including: economic dispatch based on islanded and grid-connected operation modes; single-objective and multi-objective optimization dispatch; economic dispatch incorporating energy storage; optimization dispatch involving single or multiple types of distributed energy resources (DERs); and optimization dispatch considering different demand-side load responses. Additionally, there are studies focusing on improving algorithms for economic optimization dispatch.

Ikeyama et al. [1] investigate a microgrid system composed of photovoltaic (PV) generators, gas turbines, fuel cells, and energy storage devices. It establishes optimization dispatch models for both grid-connected and islanded operation modes. The objective function in islanded mode is to minimize the power generation cost while ensuring local load supply. In grid-connected mode, the goal is to maximize the economic benefits of the microgrid while maintaining local load supply. Cui et al.[2] studies the economic operation optimization of microgrids in both islanded and grid-connected modes, as well as the economic optimization considering operational mode switching. Wu et al. [3] constructs a mathematical model for the economic load distribution of microgrids with multiple distributed energy resources, considering reliability. The study takes into account multiple objectives, including microgrid operating costs, environmental factors, and reliability costs, and uses

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a quantum particle swarm optimization algorithm to solve the model, aiming to minimize the comprehensive cost of the microgrid. Dai et al. [4] optimizes the charging and discharging strategies of battery systems based on the predicted output of distributed energy resources and microgrid load forecasts. The goal is to maximize the use of surplus power from distributed energy resources to charge the batteries, thereby reducing the cost of charging from the main grid. Hao & Guo. [5] use real-world data on wind and solar resources, load, and microgrid operating costs to evaluate user benefits, environmental protection, and social benefits based on indicators such as operation and maintenance costs, unmet load, pollutant emissions, and capacity shortages. A fuzzy evaluation function is employed to simplify multiple objectives into a single objective, and a short-term economic optimization dispatch model for microgrids is proposed. Dong & Yu. [6] introduce a demand-side load response model to balance peak and valley load differences while constructing a distributed energy resource model for microgrids. An improved internal search method is used to establish the microgrid system model, achieving optimized dispatch. Since electric vehicles (EVs) possess dual characteristics of being both loads and distributed energy resources, they have significant potential in demand-side load response. From an economic operation perspective, the study investigates the charging and discharging behaviors of EVs, establishes a microgrid system model incorporating EVs, and proposes economic dispatch strategies for different operation modes, analyzed and discussed using intelligent algorithms.

By analyzing the development strategies and technological research on microgrids in various countries, it is evident that the goal is not to replace traditional power grids but to complement them, aiming for a future power system that is efficient, environmentally friendly, and reliable.

He et al. [7] established an economic dispatch model for microgrids considering demand response, prediction errors, and uncertainties at different dispatch stages. The study proposes a multi-time-scale optimization dispatch method based on light robust optimization and model predictive control, covering day-ahead and intra-day scheduling. Zhao &Wu. [8] applied blockchain technology to create a decentralized dispatch framework. Nodes in the framework can transmit data through a P2P energy blockchain network, and simulations demonstrate that this method reduces the cost of dispatching distributed energy resources. Liu et al. [9] proposes a resilient microgrid dispatch model that considers the significant uncertainty risks of renewable energy generation and load. Zhang. [10] introduces a continuous-time model that includes energy storage units, micro gas turbines, and energy interaction with the main grid.

Demand-side response has been proven to enhance the renewable energy integration capacity and economic operation of power systems, promoting efficient energy utilization. This is supported by numerous research findings: Luis et al. [11] propose an optimal load-shifting mathematical programming model for home energy management systems in smart grids. Case studies demonstrate its cost-saving potential for users, and the study provides a framework for smart grid analysis and future research directions. Hu et al. [12] present a complete distribution network load model incorporating equivalent capacitance and motors of varying sizes. Case comparisons validate its superior performance under transient conditions, with future research focusing on its generalization capabilities. M. Mirzadeh & A. Mertens. [13] study the modeling of microgrid components, distinguishing microgrids from similar network structures. It provides component modeling methods and examples, with future work aimed at constructing complete models and optimizing component selection and operation. Lan et al. [14] propose an active integrated load model incorporating distributed renewable energy, detailing its engineering requirements, structural design, and parameter calculation methods. Case studies confirm its ability to meet the modeling and simulation needs of large power grids. Liu et al.[15] introduce a convex optimization method for optimal power

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flow in integrated gas-electricity distribution systems, incorporating joint gas-electricity demand response. Case studies show that this method improves system economic operation and renewable energy integration capacity.

These studies collectively highlight the diverse approaches and advancements in microgrid economic dispatch, emphasizing the importance of integrating renewable energy, optimizing energy storage, and leveraging demand-side response to achieve efficient, reliable, and sustainable power systems.

3. Mathematical models of distributed energy resources and loads

3.1. Photovoltaic power generation

3.1.1. Basic logic of photovoltaic power generation

The principle of photovoltaic power generation is based on the photovoltaic effect at the semiconductor interface of solar panels, which directly converts light energy into electrical energy. The core component of a solar cell is a chip made of semiconductor devices with photovoltaic properties. When the PN junction of the semiconductor is exposed to sunlight, the energy of photons excites the semiconductor, causing electrons bound at low energy levels to absorb energy, transition to higher energy levels, and break free as free electrons.

These free electrons move randomly in all directions within the crystal, generating electron-hole pairs. Meanwhile, the remaining holes drift around the crystal. Due to the internal electric field of the semiconductor, free electrons accumulate in the N-type semiconductor region, while holes accumulate in the P-type semiconductor region. Over time, a large number of free electrons accumulate at the N-type junction, and a large number of holes accumulate at the P-type junction, creating an accumulation of opposite charges at the electrodes, thereby generating an electromotive force. This is known as the photovoltaic electromotive force.

3.1.2. Photovoltaic output characteristics

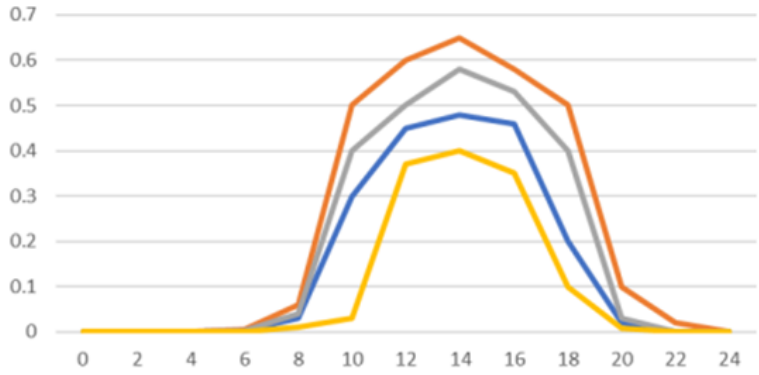


Figure 1. Typical daily output fitting curve for PV stations across Xinjiang

Blue line in Fig1 is spring; orange line is summer; gray line is autumn and yellow is winter. Figure 1 reveals that PV output is highest in summer when sunlight is abundant, followed by spring and autumn, and lowest in winter when daylight hours are shortest and sunlight intensity is weakest.

Due to the influence of natural factors such as geography, weather, and season, the light intensity and illuminated area received by PV cells can vary significantly, leading to high uncertainty in PV

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output. Research shows that when PV output is at a high level, the corresponding duration of sustained output is shorter. This phenomenon fully demonstrates the characteristics of PV output, including instability, strong randomness, and low energy density.

3.1.3. Photovoltaic modeling

Literature [16] points out that within a fixed short time period, the pattern of light intensity is similar to a Beta distribution. Therefore, the probability density function of light intensity can be expressed as:

$$f\left(r\right)=\frac{\tau(p+q)}{\tau(p)\tau(q)}\left(\frac{r}{r_{\max}}\right)^{p-1}\left(1-\frac{r}{r_{\max}}\right)^{q-1} \tag{1}$$

Here, r represents the actual light intensity during a unit time period, $r_{\max}$ is the maximum light intensity, and p and q are the shape parameters of the Beta function.

In addition to the influence of light intensity r, the magnitude of photovoltaic (PV) output is also constrained by the area of the PV module A and the photoelectric conversion efficiency α. The output power of the PV system can be expressed as:

$$P_{Mt}=\gamma A\alpha \tag{2}$$

From this, the probability density function of the PV power output can be further derived as follows:

$$f\left(r\right)=\frac{\tau(p+q)}{\tau(p)\tau(q)}\left(\frac{P_M}{R_M}\right)^{p-1}\left(1-\frac{P_M}{R_M}\right)^{q-1} \tag{3}$$

This modeling method accounts for the majority, but this article will use a more realistic modeling method, which is to import the radiation intensity measured by photovoltaic panels in the real world.

3.2. Battery energy storage module

3.2.1. Basic introduction to batteries

Energy storage devices are considered the core elements for ensuring the stable operation of microgrids. With their unique charging and discharging characteristics, energy storage components can effectively address the strong randomness and high volatility of distributed energy sources such as solar and wind turbines in microgrids. Energy storage systems not only significantly improve the reliability of microgrid power supply but also enable profitability by storing energy during low electricity price periods and releasing it during peak price periods.

Energy storage systems mainly include electromagnetic energy storage (e. g. , capacitor energy storage), electrochemical energy storage (represented by batteries), and physical energy storage (including flywheel energy storage, compressed air energy storage, pumped hydro storage, etc.). Among the various energy storage devices, batteries are the most widely used in microgrid systems due to their superior performance and cost-effectiveness.

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3.2.2. Battery modeling

Batteries have several key performance parameters, as follows:

Battery Capacity: This parameter measures the amount of electricity a battery can store, with the unit being A·h. Battery capacity is further divided into rated capacity and actual capacity. The rated capacity refers to the amount of electricity output when the battery is discharged at a specified current under 25°C conditions until the battery voltage drops below the specified voltage. The actual capacity is the product of the discharge current and discharge time. More precisely, it is the result of integrating the discharge current over time.

Cycle Life: When a battery undergoes a complete charge and discharge process, it is called one cycle. The cycle life of a battery refers to the number of cycles it can endure before its performance degrades to a specified capacity value.

The state of the battery at different times can be modeled by the following equation:

$$b_{sta,t} = b_{sta,t-1} + \eta_b b_t - \frac{1}{\eta_b} b_{dis,t} \; \forall t \tag{4}$$

where:

b_t is the charging amount of the battery at time t, $b_{dis,t}$ is the discharging amount of the battery at time t, $b_{sta,t}$ is the energy level of the battery at time t, η_b is the efficiency of the battery during charging and discharging.

4. Objective function and constraints

4.1. Objective function

When operating in islanded mode, the objective function is to maximize the load consumption power, i.e. :

$$\max \mathrm{F} = \max \quad \sum_{t=1}^{T} \left(\sum_i l_i x_{i,t} + \sum_j q_{j,t} + b_t - b_{dis,t} \right) \tag{5}$$

When operating in grid-connected mode, the objective function is to minimize costs, i.e. :

$$\min \mathrm{F} = \min \quad \sum_{t=1}^{T'} \left(\mathrm{C}_t^{grid} \right) \tag{6}$$

where:

$$\mathrm{C}_t^{grid} = P_t P_{grid,t} \tag{7}$$

C_t^{grid} is the cost of purchasing electricity from the grid at time t; P_t is the electricity price at time t; $P_{grid,t}$ is the amount of electricity purchased from the grid at time t.

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4.2. Constraints

4.2.1. Power balance constraint

$$\sum_i l_i x_{i,t} + \sum_j q_{j,t} + b_t - b_{dis,t} = P_{PV_t} + P_{grid,t}, \forall t \tag{8}$$

where:

l_i is the power consumption of shiftable loads per unit time; $x_{i,t}$ is a binary variable (0 or 1) representing the on/off state of shiftable loads; $q_{j,t}$ is a continuous variable representing the energy consumption of interruptible loads, which cannot exceed the maximum energy consumption $q_{\max,j,t}$; P_{PV_t} is the photovoltaic power generation at time t ;

$P_{grid,t}$ is the amount of electricity purchased from the grid, which is 0 in islanded mode.

4.2.2. Battery charging and discharging constraints

The battery can store energy during low electricity price periods and release stored energy during high price periods to achieve the optimization goal of cost reduction:

$$\min_{b,b_{dis}} \sum_{t=1}^{h} P_t \left(b_t - b_{dis,t}\right) \tag{9}$$

Battery Capacity Constraint:

$$0 \leq b_{\text{sta,t}} \leq s_{\max}, \forall t \tag{10}$$

Charging Rate Constraint:

$$0 \leq b_t \leq b_{\max}, \forall t \tag{11}$$

Discharging Rate Constraint:

$$0 \leq b_{dis,t} \leq b_{dis,\max}, \forall t \tag{12}$$

Energy Storage Property Constraint:

$$b_{sta,t-24} \geq b_{sta,t}, \quad \forall \text{ t} \tag{13}$$

where:

$b_{sta,t}$ is the state of charge of the battery; η_b is the charging and discharging efficiency; $s_{\max}$ is the upper limit of the battery capacity; $b_{\max}$, $b_{dis,\max}$ are the maximum charging and discharging rates of the battery, respectively;

The energy storage property constraint requires that the battery cannot be used as a power source but as a tool for peak shaving and valley filling. Therefore, it is stipulated that the battery's energy level should not decrease over a 24-hour period.

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4.2.3. Energy storage health

Since the lifespan of energy storage is strongly correlated with the number of charge-discharge cycles, constraints for energy storage health are considered. Binary variables αt and βt are used to segment the state of charge (SOC) management:

$\alpha_t = 1$ ： SOC $> 80\%$

$\beta_t = 1$ ： SOC $> 20\%$

The SOC must satisfy the following constraints:

$$\begin{aligned} S_t &\geq (0.\ 5\alpha_t + 0.\ 25\beta_t) \times S_{\max}\ \forall t \in [0, T-1] \\ S_t &\leq (0.\ 5\alpha_t + 0.\ 25\beta_t + 0.\ 25) \times S_{\max}\ \forall t \in [0, T-1] \end{aligned} \tag{14}$$

Charging and discharging states are represented by binary variables γ_t and δ_t :

Charging state： $\gamma_t \in \{0,1\}$

Discharging state: $\delta_t \in \{0,1\}$

Only charging or discharging can occur at the same time:

$$\gamma_t + \delta_t \leq 1\ \forall t \in [0, T-1] \tag{15}$$

The relationship between charging/discharging power and SOC is as follows:

The Big-M method is used to ensure logical consistency between charging/discharging states and rates:

Charging Rate Constraints:

$$\begin{aligned} P_t &= (1 - 0.\ 4\alpha_t - 0.\ 2\beta_t) \times b_{\max}\ \forall t \in [0, T-1] \\ P_{\text{dis},t} &= (0.\ 4 + 0.\ 4\alpha_t + 0.\ 2\beta_t) \times b_{\max}\ \forall t \in [0, T-1] \end{aligned} \tag{16}$$

Discharging Rate Constraints:

$$\begin{aligned} P_{\text{dist}} &\leq M\delta_t\ \forall t \in [0, T-1] \\ P_{\text{dist}} &\leq P_{\text{dist}}^{\max}\ \forall t \in [0, T-1] \\ P_{\text{dist}} &\geq P_{\text{dist}}^{\max} - M(1 - \delta_t)\ \forall t \in [0, T-1] \end{aligned} \tag{17}$$

where M is a large constant (e.g. , M=50).

Additionally, a penalty coefficient CF is added to the total optimization objective to account for changes in the energy storage's SOC:

$$\max \mathrm{F} = \max \quad \sum_{t=1}^{T} \mathrm{C}_t^{grid} + CF(b_t - b_{dis,t}) \tag{18}$$

4.2.4. Shiftable load constraints

User Demand Constraints:

$$\sum_{t=1}^{H} R_{i,t} x_{i,t} = T_i,\ \forall i \tag{19}$$

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where:

$R_{i,t}$ is a 24-bit array of decision variables representing user-preferred electricity usage times;

T_i is the required operating time of the load.

4.2.5. Interruptible load constraints

Temperature Constraints:

$$T_{\min,j,t} \leq T_{\text{int},j,t} \leq T_{\max,j,t},\ \forall(j,t) \tag{20}$$

Energy Consumption Constraints:

$$0 \leq q_{j,t} \leq q_{\max,j,t},\ \forall(j,t) \tag{21}$$

Thermal Inertia Constraint Equation:

$$C_j\left(T_{\text{int},j,t} - T_{\text{int},j,t-1}\right) = \eta_j q_{j,t-1} + K_j\left(T_{\text{ext},j,t-1} - T_{\text{int},j,t-1}\right),\ \forall(j,t) \tag{22}$$

where:

$T_{\text{int},j,t}$ is the indoor temperature, bounded by the user-defined minimum $T_{\min,j,t}$ and maximum $T_{\max,j,t}$; $q_{j,t}$ cannot exceed the maximum energy consumption $q_{\max,j,t}$; C_j K_j are constants in the thermal inertia equation; η_j is the efficiency of the device's electrical-to-thermal conversion; $T_{\text{ext},j,t}$ is the external temperature.

5. Case study analysis

5.1. Islanded operation case study

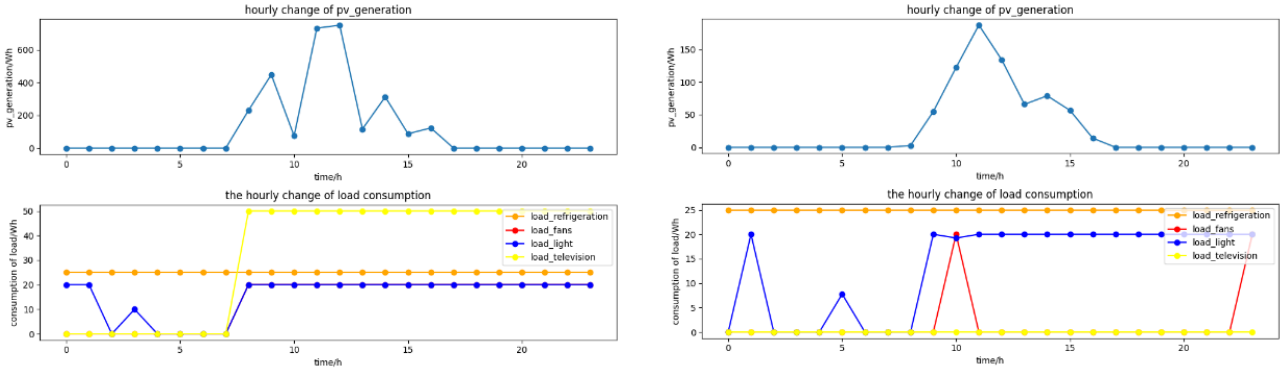
Consider the following source-storage-load configuration in table 1:

Table 1. Source-storage-load configuration

Equipment	Power（W）	Operating Time	Remarks
Refrigerator	25	24h uninterrupted operation	Uninterrupted
Fan	20	At least 6 hours per day	Discrete load
Lighting	20	At least 7 hours per day	Continuous load
TV	50	Can operate after meeting the above loads	Continuous Interruptible load
PV Power	1kW*0. 5	-	
Battery	500W	-	Initial daily energy > 250Wh

Based on typical measured data from the laboratory for sunny and cloudy days, the optimal dispatch scenario is shown in the figure 2:

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(a) sunny (b)cloudy

Figure 2. The optimal dispatch scenario

It can be observed that on sunny days, photovoltaic (PV) generation reaches about 800W between 11 am and 1 pm, while on cloudy days, the highest output occurs at 11 am, around 200W, which is only a quarter of that on sunny days. The total daily generation on cloudy days is significantly lower than on sunny days. Correspondingly, the most noticeable observation is that the low-priority load, such as the television, operates immediately after the period without PV generation (before 7 am) and continues until the end of the day on sunny days, while it remains off throughout the day on cloudy days. In both scenarios, the refrigerator load operates normally, indicating that the microgrid meets the demand for uninterrupted loads such as vaccine storage and fire protection systems. The continuous lighting load operates at full capacity after the night ends and even runs for a considerable period during the night to consume excess PV energy. On cloudy days, the lighting load level fluctuates several times to ensure sufficient power is reserved. Due to the discrete nature of the fan load (a fixed load with only on/off states), it is almost fully operational throughout the day on sunny days but barely operates on cloudy days. The optimization algorithm intelligently schedules the operation time and load levels of different loads based on the day's PV generation, effectively meeting the requirements of various loads in the microgrid.

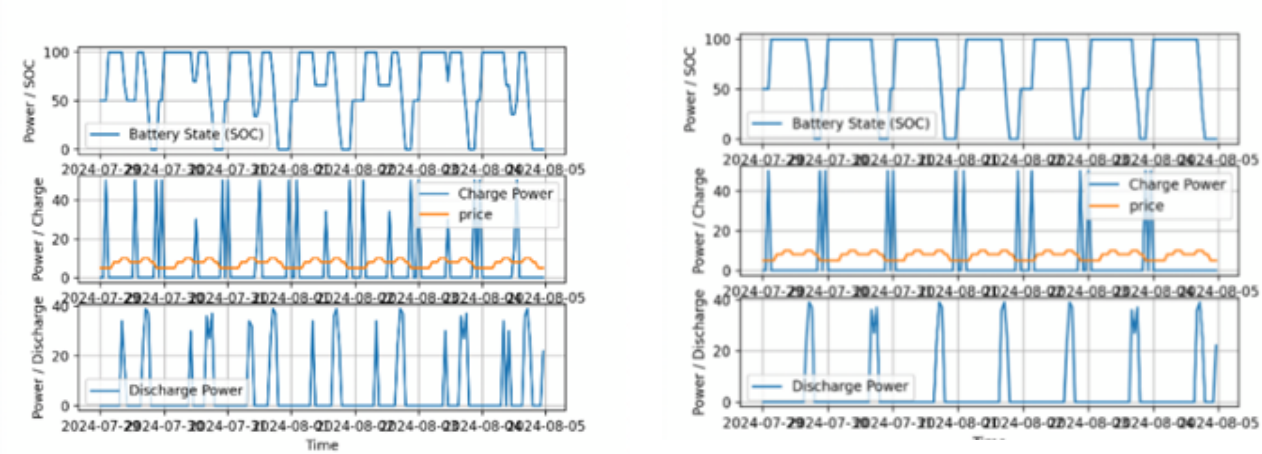
5.2. Grid-connected operation case study

The source-storage-load configuration is the same as in the islanded case, except the energy storage is modified to 50W/200kWh.

From Fig 3 we can find:

When CF is set to 0 (i. e. , without considering the health state of the battery), the dispatch results are as shown in the figure below. It can be observed that the battery's state of charge changes frequently, with electricity purchased from the grid during medium-price periods to prioritize supplying additional television loads.

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(a) CF = 0 (b) CF = 0.2

Figure 3. Dispatch results of different CF

When CF is set to 0.2, introducing the battery's health state (i.e. the absolute value of battery power flow) into the optimization objective through CF, it can be seen that the battery's charging and discharging behaviors are reduced. The system chooses to forgo supplying additional loads and only charges the battery during low-price periods to achieve both economic optimization and battery health management requirements.

6. Conclusion

This study investigated the optimal dispatch of microgrids in both islanded and grid-connected modes, addressing the challenges posed by the inherent uncertainties of renewable energy generation and load demand. By establishing mathematical models for photovoltaic (PV) power generation, battery energy storage, and various load types, the research formulated a mixed-integer linear programming (MILP) framework to minimize operational costs while ensuring power balance and system stability. The case studies demonstrated the effectiveness of the proposed approach: in islanded mode, the algorithm efficiently allocated energy resources based on PV output, prioritizing critical loads, while in grid-connected mode, the introduction of a battery health penalty factor (CF) balanced economic dispatch with battery longevity. The findings highlight the potential of microgrids to enhance renewable energy utilization, reduce reliance on fossil fuels, and improve power supply reliability. Future research could extend this work by incorporating additional renewable sources, multi-timescale optimization, and advanced machine learning techniques for real-time adaptive dispatch. Overall, this study contributes to the advancement of sustainable and resilient microgrid operation strategies.

Declaration of interests

The author has nothing to disclose.

Authorship

Bo Chang: Conceptualization, Methodology, Data collection, Data analysis, Validation, Investigation, Writing, Review & editing, Visualization, Project administration, Funding acquisition.

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