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Maximized Autonomous Economic Operation and Aggregated Equivalence for Microgrids with PVs and ESSs

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Abstract

With the rapid development of renewable energy, more microgrids integrating photovoltaics and energy storage systems (MGPEs) have been deployed. Frequent grid faults have consequently increased the likelihood of MGPEs operating in off-grid mode, highlighting the need to maximize their autonomous operation. This paper proposes an optimal day-ahead scheduling method, which aims to maximize autonomous economic operation and minimize dependence on the main grid. Based on the autonomous results, the internal resources of MGPEs are aggregated into an equivalent power unit (EPU) and an aggregated energy storage system (AESS). The aggregated demands and residual capabilities of these aggregated models are then quantified, thereby facilitating coordinated scheduling by the main grid. Compared with traditional cost-optimization approaches, this case study shows that the proposed method reduces the daily outage probability of MGPEs by at least 24.9%.

Keywords: microgrid with photovoltaic and energy storage systems (MGPE); autonomous economic operation (AEO); aggregated equivalence



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1. Introduction

With the increasing depletion of fossil resources and the growing emphasis on environmental sustainability, the transition of the energy structure toward low carbon has become inevitable [1,2]. Microgrids (MGs) are regarded as one of the essential technologies for the future development of the energy sector [3]. MGs can efficiently utilize distributed generators (DGs), energy storage systems (ESSs), and flexible loads to achieve localized power supply [4,5]. Microgrids with photovoltaics (PVs) and ESSs (MGPEs) have rapidly developed due to the increasing penetration of renewable energy.

An MGPE operates in two modes: on-grid and off-grid. In the event of a fault, an on-grid MGPE may be disconnected from the main grid and forced to operate in off-grid mode. Therefore, it is crucial for MGPEs to enhance their autonomous capabilities even during on-grid operation to reduce reliance on the main grid. This implies that MGPEs must be capable of maintaining power supply during off-grid operation. Consequently, optimal scheduling strategies that maximize autonomous operation are essential for MGPEs.

The optimal scheduling of MGs has been extensively studied in the current works. Most of these studies focus on proposing optimization models aimed at minimizing operational costs, primarily emphasizing the economic performance of MGs [6–14]. For example, Silva et al. [6] analyzed MG operating costs under time-of-use electricity pricing

and considered intentional islanding with potential load shedding. Both Gomes et al. [7] and Li and Xu [8] establish cost-optimal economic models for MG operation in both on-grid and off-grid modes. Both Nwulu and Xia [9] and Witharama et al. [10] incorporate demand response mechanisms into their optimal-dispatch model to further reduce MG operating costs. Sun et al. [11] propose a day-ahead economic dispatch strategy that maximizes the benefits for utilities and users. Silvente et al. [12] evaluate the economic advantages of selling surplus photovoltaic energy to the main grid and include the resulting revenue in the cost-benefit analysis. Hou et al. [13] propose a multi-objective economic dispatch approach that co-optimizes the operation of electric vehicles and transferable loads within the microgrid. Moreover, Aghajani and Ghadimi [14] present a multi-objective energy management framework that simultaneously minimizes electricity and environmental costs. However, these studies often overlook the priority of utilizing internal resources to enhance the self-sufficiency of MGs. This limitation increases the risks associated with unplanned islanding and undermines the security and reliability of MGs operation.

To address the risk of energy shortfall without relying on full-scale resilience modeling, several studies have incorporated uncertainty- or risk-based metrics into cost-oriented MG-scheduling frameworks. Cao et al. [15] propose a distributionally robust optimization model for MG energy management, which explicitly bounds the probability of energy shortfall under uncertain PV generation and load forecasts. Hou et al. [16] introduce a distributed model-predictive scheme for islanded MG that jointly accounts for battery degradation and cycle-life uncertainty, with aims to reduce the risk of premature capacity loss during extended islanding periods. Tan et al. [17] develop a two-stage robust optimization approach that exploits a data-driven uncertainty set to hedge against worst-case PV and electric-vehicle load deviations. Consequently, the above studies demonstrate that the cost-oriented MGs can incorporate probabilistic or risk-based metrics to assess internal resource adequacy. The present work addresses this gap while adhering to a primarily economic optimization framework.

MGs are increasingly required to aggregate internal resources to support flexible scheduling by the main grid. To address this requirement, models and methods for resource aggregation have been extensively studied. Zhao et al. [18] and Wu and Wang [19] aggregate diverse resources within MG to develop models of models for flexible resource clusters composed of equivalent generators and equivalent ESSs. Utkarsh et al. [20] aggregate DGs into a network-aware framework to achieve flexibility and optimal cost. Wen et al. [21] and Yi et al. [22] derive the feasible aggregation region of MG and equivalently aggregate flexible resources into a unified ESS representation. Moreover, He et al. [23] construct the flexibility model of MG, characterizing the flexibility boundaries that MG can provide to the main grid. However, these studies have not quantified the external demand and residual capacity of MGs following autonomous economic operation.

Given the above insights, the aim of this paper is primarily to maximize the utilization of internal resources to reduce external dependence in the event of faults and to aggregate resources to quantify the residual capabilities for the main grid. Compared to previous studies, the main contributions of this paper are summarized as follows:

1. Develop a sensitivity-based autonomous economic optimization for an MGPE to minimize electricity exchange while covering internal costs, concurrently lowering outage probability to secure supply reliability.
2. Establish aggregated equivalent models of the MGPE to reduce the scheduling complexity of scheduling and enhance the operational efficiency of the main grid.
3. Quantify both the physical and economic parameters of the aggregated models to provide valuable information for the main grid, enabling better resource management and improved energy utilization.

The paper is organized as follows. In Section 2, the autonomous economic operation of an MGPE is described. In Section 3, the proposed method is presented. In Section 4, a comprehensive case study analysis is provided. In Section 5, the case study results are discussed and interpreted. Finally, the paper is concluded in Section 6.

2. Autonomous Economic Operation (AEO)

The configuration of the MGPE is illustrated in Figure 1. The PVs and ESSs are connected to the AC bus via their respective power conversion devices. The MGPE is interconnected with the main grid via a Point of Common Coupling (PCC) [24].

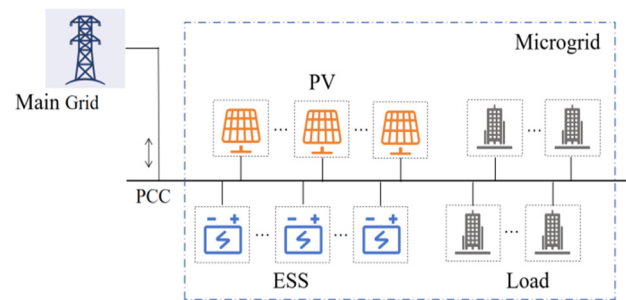


Figure 1. Schematic of the MGPE.

In autonomous economic operation, internal resources of the MGPE, such as PVs, ESSs, and flexible loads, are prioritized. The load demand is primarily met through self-consumption to reduce dependence on external resources, while surplus power is fed into the main grid. This approach aims to enhance the independence and reliability of the MGPE while the potential for economic operation of internal resources is explored to reduce operational costs.

Overall, the optimized operation provides a favorable guarantee for the security, reliability, and economic viability of the MGPE.

3. Methodology

3.1. Optimization Model

3.1.1. Objective Function

The optimization objective of the MGPE is formulated to prioritize the utilization of internal resources, aiming to achieve self-consumption, surplus power export, and economic operation. Dependence on the main grid is reduced and the economic operation of the MGPE is further optimized. Thus, the objective function in this study is established as follows:

Objective Function 1: Minimization of Electricity Deficit and Surplus

$$\min F_1 = \sum_{t=1}^T (|P_{buy,t}| + |P_{sell,t}|) \Delta T \quad (1)$$

where $P_{buy,t}$ and $P_{sell,t}$ is the power purchased from and sold to the main grid at t . T is the total number of time periods and ΔT is the duration of each time period.

Objective Function 2: Minimization of Internal Resource Cost

$$\min F_2 = \sum_{t=1}^T \left(\sum_{i=1}^{N_V} c_{v,i} P_{v,i,t} + \sum_{i=1}^{N_{ess}} c_{ess,i}^{dch} P_{ess,i,t}^{dch} + \sum_{i=1}^{N_{tl}} c_{tl,i,t} |\Delta P_{tl,i,t}| \right) \Delta T \quad (2)$$

where $c_{ess,i}^{dch}$, $c_{v,i}$, and $c_{tl,i,t}$ denote the discharge cost of the i th ESS, the generation cost of the i th PV, and the adjustment cost of the i th flexible load at t . $P_{v,i,t}$, $P_{ess,i,t}^{dch}$ and $\Delta P_{tl,i,t}$ represents

the generation power of the i th PV, the discharge power of the i th ESS, and the active power change in the i th flexible load at t . N_v , N_{ess} , and N_{tl} correspond to the total number of PVs, ESSs, and flexible loads.

To ensure the autonomy and minimize the costs of the MGPE, the aforementioned multiple objective functions are converted into a single objective function:

$$\min F = \omega F_1 + F_2 \quad (3)$$

where ω is the penalty factor, incorporated to ensure that the MGPE prioritizes the use of its internal resources for AEO.

3.1.2. Constraints

(a). Power Balance Constraint

$$P_{buy,t} + P_{sell,t} + \sum_{i=1}^{N_v} P_{v,i,t} + \sum_{i=1}^{N_{ess}} (P_{ess,i,t}^{dch} - P_{ess,i,t}^{ch}) = \sum_{i=1}^{N_{bl}} P_{bl,i,t} + \sum_{i=1}^{N_{tl}} P_{tl,i,t} \quad (4)$$

where $P_{ess,i,t}^{ch}$ represents the charging power of the i th ESS at t . $P_{bl,i,t}$ represents the active power of the i th fixed load at t . N_{bl} corresponds to the total number of fixed loads.

(b). ESS Operation Constraints

$$0 \leq P_{ess,i,t}^{ch} \leq z_{i,t} P_{ess,i,max}^{ch} \quad (5)$$

$$0 \leq P_{ess,i,t}^{dch} \leq (1 - z_{i,t}) P_{ess,i,max}^{dch} \quad (6)$$

where $P_{ess,i,max}^{ch}$ and $P_{ess,i,max}^{dch}$ represent the maximum charging and discharging power of the i th ESS, respectively. $z_{i,t}$ is a 0–1 binary variable; a value of 1 indicates that the i th ESS is charging at t , and a value of 0 indicates it is discharging.

The constraints for the state of charge (SOC) of the ESS are given by Equations (7) and (8).

$$S_{ess,i,t} = S_{ess,i,t-1} + \gamma_{ess,i}^{ch} \Delta T P_{ess,i,t}^{ch} / E_{ess,i} - \Delta T P_{ess,i,t}^{dch} / \gamma_{ess,i}^{dch} E_{ess,i} \quad (7)$$

$$S_{ess,i,min} \leq S_{ess,i,t} \leq S_{ess,i,max} \quad (8)$$

Within the scheduling period, the ESSs must satisfy the charge/discharge energy balance to ensure the sustainability of the dispatch strategy, as given by Equation (9).

$$S_{ess,i,0} = S_{ess,i,T} \quad (9)$$

where $S_{ess,i,t}$ denotes the SOC of the i th ESS at t . $S_{ess,i,min}$ and $S_{ess,i,max}$ is the minimum and maximum SOC limits of the i th ESS, respectively. $E_{ess,i}$ indicates the rated capacity of the i th ESS at t . $\gamma_{ess,i}^{ch}$ and $\gamma_{ess,i}^{dch}$ is the charging and discharging efficiencies of the i th ESS, respectively. $S_{ess,i,0}$ and $S_{ess,i,T}$ denote the initial SOC and end-of-period SOC of the i th ESS.

(c). Flexible Load Constraints

The flexible loads are subject to constraints including the upper and lower limits of load shifting, the ramp rate constraint, and the requirement that total energy consumption remains invariant over a scheduling period.

$$P_{tl,i,t} \triangleq P_{tl,i,t,base} + \Delta P_{tl,i,t} \quad (10)$$

$$\theta_{tl,i,t} P_{tl,i,t,min} \leq P_{tl,i,t} \leq \theta_{tl,i,t} P_{tl,i,t,max} \quad (11)$$

$$-\Delta P_{tl,i,t,d} \leq \Delta P_{tl,i,t} - \Delta P_{tl,i,t-1} \leq \Delta P_{tl,i,t,u} \quad (12)$$

$$\sum_{t=1}^T \Delta P_{tl,i,t} \Delta T = 0 \quad (13)$$

where $P_{tl,i,t,base}$ and $P_{tl,i,t}$ represent the i th baseline load and the i th load after shifting at t . $P_{tl,i,t,min}$ and $P_{tl,i,t,max}$ represent the minimum and maximum active power bounds of the i th load i after shifting at t , respectively. $\Delta P_{tl,i,t,u}$ and $\Delta P_{tl,i,t,d}$ represent the maximum upward and downward active power adjustments of the i th flexible load at t . $\theta_{tl,i,t}$ is a binary variable representing the shifting status of the i th flexible load at t , where 1 indicates that the load is being shifted.

3.2. Aggregation and Equivalence

Power flow constraints are typically neglected. Based on AEO dispatch results, the overall MGPE is characterized through net power output by an aggregated equivalent model consisting of an equivalent power unit (EPU) and an aggregated ESS (AESS). The aggregation of the MGPE is illustrated in Figure 2. On this basis, the residual regulation capability and surplus capability available for external interaction are further quantified, and the corresponding price coefficients are also calculated.

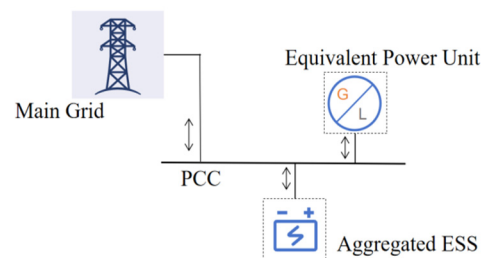


Figure 2. Aggregated Equivalence of the MGPE.

3.2.1. Residual Regulation Capability

When power deficits occur in the main grid, additional regulation power can be supplied by the MGPE, primarily through the discharge of the AESS. Thus, the residual regulation capability of the MGPE is quantified from the remaining capacity and discharge power of the AESS after AEO optimization.

The parameters of the AESS model are formulated as Equations (14)–(18).

$$P_{ess,max}^{B,ch} = \sum_{i=1}^{N_{ess}} P_{ess,i,max}^{ch} \quad (14)$$

$$P_{ess,max}^{B,dch} = \sum_{i=1}^{N_{ess}} P_{ess,i,max}^{dch} \quad (15)$$

$$E_{ess}^B = \sum_{i=1}^{N_{ess}} E_{ess,i} \quad (16)$$

$$S_{ess,min}^B = \frac{\sum_{i=1}^{N_{ess}} S_{ess,i,min} E_{ess,i}}{E_{ess}^B} \quad (17)$$

$$S_{ess,max}^B = \frac{\sum_{i=1}^{N_{ess}} S_{ess,i,max} E_{ess,i}}{E_{ess}^B} \quad (18)$$

where $P_{ess,max}^{B,ch}$ and $P_{ess,max}^{B,dch}$ represent the maximum charging and discharging power of the AESS. $S_{ess,min}^B$ and $S_{ess,max}^B$ denote the minimum and maximum SOC of the AESS. E_{ess}^B indicates the rated capacity of the AESS.

The residual regulation capability of the AESS is quantified by Equations (19)–(21).

$$P_{ess,t}^{res,ch} = \sum_{i=1}^{N_{ess}} (P_{ess,i,max}^{ch} - P_{ess,i,t}^{ch}) \quad (19)$$

$$P_{ess,t}^{res,dch} = \sum_{i=1}^{N_{ess}} (P_{ess,i,max}^{dch} - P_{ess,i,t}^{dch}) \quad (20)$$

$$S_{ess,t}^{res} = \frac{E_{ess,t}^B}{E_{ess}^B} = \frac{\sum_{i=1}^{N_{ess}} S_{ess,i,t} E_{ess,i}}{E_{ess}^B} \quad (21)$$

where $P_{ess,t}^{res,ch}$ and $P_{ess,t}^{res,dch}$ represent the residual regulation capability of the AESS in charging and discharging states at t . $E_{ess,t}^{res}$ indicates the remaining capacity of the AESS at t . $S_{ess,t}^{res}$ is the SOC of the AESS at t .

When the main grid requires regulation power from the MGPE, it prioritizes discharging the less-costly ESSs within the AESS to ensure economic efficiency. Thus, the segmented pricing of the residual regulation capability of the AESS ($c_{ess,1}^{dch} \leq c_{ess,2}^{dch} \leq \dots \leq c_{ess,N_{ess}}^{dch}$) is then determined.

$$c_{MG,t}^{tl} = \begin{cases} c_{ess,1}^{dch}, & 0 < E_{UG,t}^{tl} \leq E_{1,t} \\ c_{ess,2}^{dch}, & E_{1,t} < E_{UG,t}^{tl} \leq E_{2,t} \\ \vdots \\ c_{ess,i}^{dch}, & E_{i-1,t} < E_{UG,t}^{tl} \leq E_{i,t} \\ \vdots \\ c_{ess,N_{ess}}^{dch}, & E_{N_{ess}-1,t} < E_{UG,t}^{tl} \leq E_{N_{ess},t} \end{cases} \quad (22)$$

$$E_{i,t} = \sum_{j=1}^i S_{ess,j,t} E_{ess,j} \quad i = 1, 2, \dots, N_{ess} \quad (23)$$

where $c_{MG,t}^{tl}$ indicates the segmented regulation price of the MGPE to the main grid at t . $E_{UG,t}^{tl}$ represents the required regulation electricity of the main grid at t . $E_{i,t}$ indicates the cumulative remaining capacity of the first i ESS at t . Moreover, the constraints on maximum discharge power and minimum SOC must still be satisfied for the external regulation of each ESS.

Thus, the regulation revenue of the MGPE at t is calculated as the sum of the electricity prices of each segmented power.

$$R_t^{tl} = \sum_{j=1}^{i-1} c_{ess,j}^{dch} S_{ess,j,t} E_{ess,j} + c_{ess,i}^{dch} (E_{UG,t}^{tl} - E_{i-1,t}) \quad (24)$$

where R_t^{tl} represents the total regulation revenue of the MGPE to the main grid at t .

3.2.2. Residual Regulation Capability Residual Surplus Capability

After the MGPE maximizes its AEO, surplus power can be exchanged with the main grid. This surplus is mainly derived from the residual capacity of the EPU, particularly through excess PV generation. Thus, the residual surplus capability of the MGPE is quantified based on the remaining power of the EPU after AEO.

The EPU is composed of PVs and the total load, and its behavior is characterized by the net generation power and net load power.

$$P_{epu,t}^{B,G} = \sum_{i=1}^{N_v} P_{v,i,t} - \sum_{i=1}^{N_{bl}} P_{bl,i,t} - \sum_{i=1}^{N_{tl}} P_{tl,i,t} \geq 0 \quad (25)$$

$$P_{epu,t}^{B,G} = \sum_{i=1}^{N_{bl}} P_{bl,i,t} + \sum_{i=1}^{N_{tl}} P_{tl,i,t} - \sum_{i=1}^{N_v} P_{v,i,t} \geq 0 \quad (26)$$

where $P_{eq,t}^{B,G}$ and $P_{eq,t}^{B,L}$ represent the net generation power and net load power of the EPU at t .

The residual deficit or surplus electricity exchanged between the MGPE and the main grid is quantified by the net power measured at the PCC. Surplus electricity that arises from PV generation within the EPU after its autonomous demands has been fully satisfied.

$$S_{MG,t}^{nd} = P_{buy,t} \Delta T \quad (27)$$

$$S_{MG,t}^{sp} = P_{sell,t} \Delta T = \sum_{j=1}^{N_V} P_{v,j,t}^{res} \Delta T \quad (28)$$

where $S_{MG,t}^{nd}$ and $S_{MG,t}^{sp}$ denote the remaining demands and surplus electricity of the MGPE after AEO at t . $P_{v,j,t}^{res}$ indicates the surplus power of PV j at t .

When surplus power is drawn from the MGPE, priority is given to the less-costly PV generation within the EPU to achieve cost savings. Thus, the segmented pricing of the surplus power of the EPU ($c_{v,1} \leq c_{v,2} \leq \dots \leq c_{v,N_V}$) is then determined.

$$c_{MG,t}^{sp} = \begin{cases} c_{v,1}, & 0 < S_{UG,t}^{nd} \leq S_{1,t} \\ c_{v,2}, & S_{1,t} < S_{UG,t}^{nd} \leq S_{2,t} \\ \vdots & \\ c_{v,i}, & S_{i-1,t} < S_{UG,t}^{nd} \leq S_{i,t} \\ \vdots & \\ c_{v,N_V}, & S_{N_V-1,t} < S_{UG,t}^{nd} \leq S_{N_V,t} \end{cases} \quad (29)$$

$$S_{i,t} = \sum_{j=1}^i P_{v,j,t}^{res} \Delta T \quad i = 1, 2, \dots, N_V \quad (30)$$

where $c_{MG,t}^{sp}$ indicates the segmented surplus electricity price of the MGPE to the main grid at t . $S_{UG,t}^{nd}$ represents the electricity demand of the main grid at t . $S_{i,t}$ indicates the cumulative surplus electricity of the first i PV at t .

Thus, the surplus electricity revenue of the MGPE at t is calculated as the sum of the electricity prices of each segmented power.

$$R_t^{sp} = \sum_{j=1}^{i-1} c_{v,j} P_{v,j,t}^{res} \Delta T + c_{v,i} (S_{UG,t}^{nd} - S_{i-1,t}) \quad (31)$$

where R_t^{sp} represents the total surplus electricity revenue of the MGPE to the main grid at t . Equations (29) and (30) partition the main grid demand into successive segments, with the marginal cost of each segment determined by the ascending-ordered cost of surplus PV generation. Equation (31) calculates the total revenue received by the EPU from the main grid as the cumulative product of each segment quantity and its corresponding price.

3.3. Procedure

The procedure for Maximized Autonomous Economic Operation and Equivalent Aggregation of the MGPE is illustrated in Figure 3, and the pseudocode of the optimization scheduling is provided in Appendix A Algorithm A1.

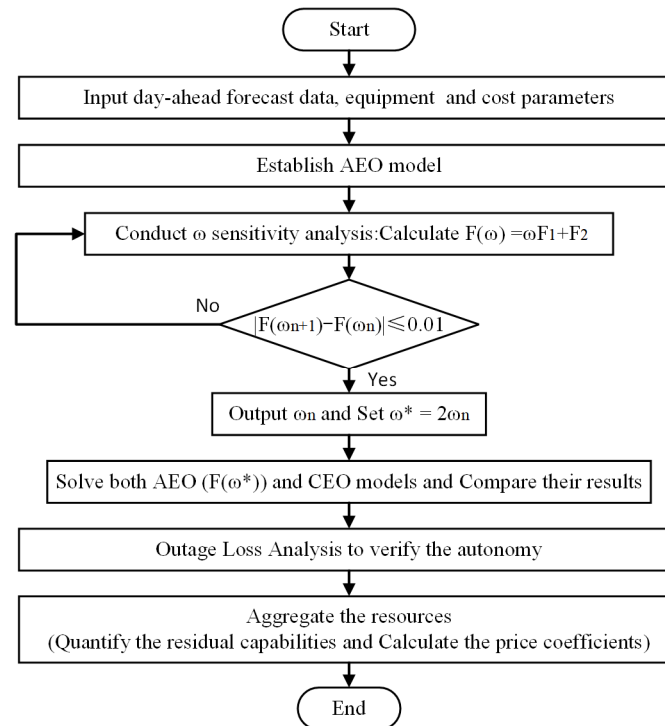


Figure 3. Flowchart of the AEO and aggregated equivalence.

1. **Data Input:** The input set is constructed by reading data of ESSs, PVs, loads, flexible loads, and cost parameters.
2. **Establish Modeling:** The AEO model is constructed using the optimization objective defined by Equations (1)–(3) together with the relevant constraints.
3. **ω Sensitivity Analysis:** the parameter ω is varied from 0 to 1 with a step size of 0.04. At each point, the MIQP is solved using CPLEX and YALMIP, and the F – ω curve is plotted. To maintain an adequate margin, the optimal weight ω^* is set to twice the knee-point value.
4. **Optimization:** Optimization with Fixed ω^* and Comparison between AEO and the minimized cost economic operation (CEO).
 - a. Substituting ω^* the MIQP is solved again to obtain the AEO scheduling result.
 - b. Using the same constraints but minimizing only the cost function ($F = \sum_{t=1}^T (c_{buy} P_{buy,t} + c_{sell} P_{sell,t} + \sum_{i=1}^{N_V} c_{v,i} P_{v,i,t} + \sum_{i=1}^{N_{ess}} c_{ess,i}^{dch} P_{ess,i,t}^{dch} + \sum_{i=1}^{N_{tl}} c_{tl,i,t} |\Delta P_{tl,i,t}|) \Delta T$), the CEO scheduling scheme is derived as a benchmark.
5. **Outage Loss Analysis:** the outage probability and outage losses under AEO and CEO scheduling are compared to quantify the autonomy benefits.
6. **Aggregated equivalence:** according to the AEO results, the internal resources are aggregated; the residual external capability and its corresponding price coefficient are then quantified.

4. Case Study Analysis

4.1. Model Verification

The proposed model is verified before the case-specific optimization results are presented.

(1) Internal consistency

All instances were solved using CPLEX and YALMIP, achieving an optimality gap of $\leq 1\%$ and an average runtime of 2.9 s. This confirms the robustness and applicability of the approach.

(2) Scalability and sensitivity

The MGPE model is tested by varying irradiance profiles and ESS capacities. The resulting grid-import energy decreases monotonically and converges asymptotically, demonstrating robustness to parameter perturbations and scalability.

(3) Data availability statement

24 h operational data from a fully instrumented microgrid and access to a real-time hardware-in-the-loop platform, are currently unavailable. Consequently, experimental validation on a physical system has not yet been conducted; such validation will be carried out once field data or platform access becomes available.

4.2. Basic Data

The experimental data in this section correspond to the standard input set read in Step 1 of Section 3.3. MGPE comprises PVs, ESSs, and daily loads, with flexible loads also considered. Specifically, it includes three PVs, three ESS units, and two types of flexible loads. The generation costs of the PVs are set at 0.16, 0.20, and 0.32 CNY/kWh. The adjustment costs of the flexible loads in different time periods are presented in Appendix A Table A1. The rated capacities of the ESS units are 600, 800, and 1000 kWh, and their discharge costs are set at 0.35, 0.65, and 0.75 CNY/kWh [25]. The charging and discharging efficiencies of each ESS are both specified at 95%. Other specific equipment parameters are detailed in Table 1. The cost of purchasing electricity from the main grid is determined to be 0.60 CNY/kWh, while the cost of selling electricity to the main grid is determined to be 0.20 CNY/kWh. The cost of power outage due to fault islanding is substantial [26]. The cost of power outage due to fault islanding is calculated as 3.00 CNY/kWh [27].

Table 1. Equipment Parameters of Each ESS.

ID	E_{ess}	$S_{ess,0}$	$S_{ess,min}$	$S_{ess,max}$	$P_{ess,max}^{ch}$	$P_{ess,max}^{dch}$
1	600	0.5	0.3	0.7	300	300
2	800	0.5	0.2	0.8	450	450
3	1000	0.5	0.1	0.9	500	500

Forecast data for total PV generation and load demand are used as inputs for optimization, as illustrated in Appendix A Figures A1 and A2. The predicted PV generation is obtained under three typical weather conditions: sunny, cloudy, and rainy, with corresponding total outputs of 6399 kWh, 5434 kWh, and 4758 kWh, respectively. The total load demand is 5700 kWh. Given that the forecasts span 24 h, the day-ahead optimization horizon is defined as $T = 24$ h with a temporal resolution of $\Delta t = 1$ h.

4.3. Dispatch Analysis

4.3.1. Sensitivity Analysis

A sensitivity analysis is performed under different weather conditions, as illustrated in Figure 4, whereby the impact of the penalty factor ω on Objective Functions 1 and 2 is

evaluated. The values of both objectives are observed to stabilize once ω , representing the maximum marginal cost of internal resources, exceeds 0.75.

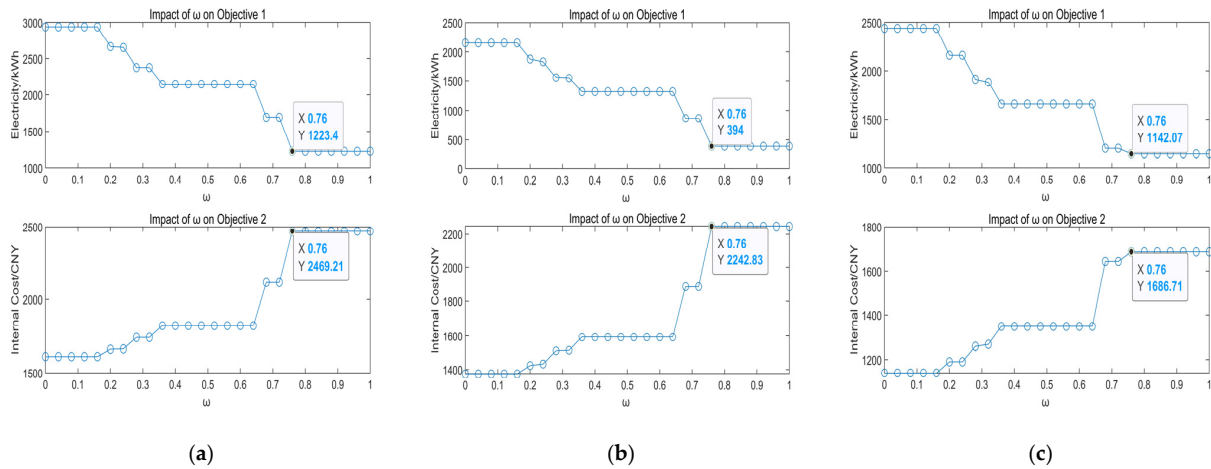


Figure 4. Sensitivity analysis of w under different weather conditions: (a) sunny, (b) cloudy, and (c) rainy. **Note:** The data in this figure are generated from Steps 2 and 3 in Section 3.3.

As a result, the penalty factor w should be set higher than this internal cost cap. In this study, ω is defined as twice the maximum internal resource cost in order to ensure a sufficient safety margin while maintaining computational simplicity. Therefore, $\omega^* = 1.50$ (i.e., 2×0.75) is selected as the penalty factor for the re-optimization in Step 4, and the corresponding results are shown in Figures 5 and 6.

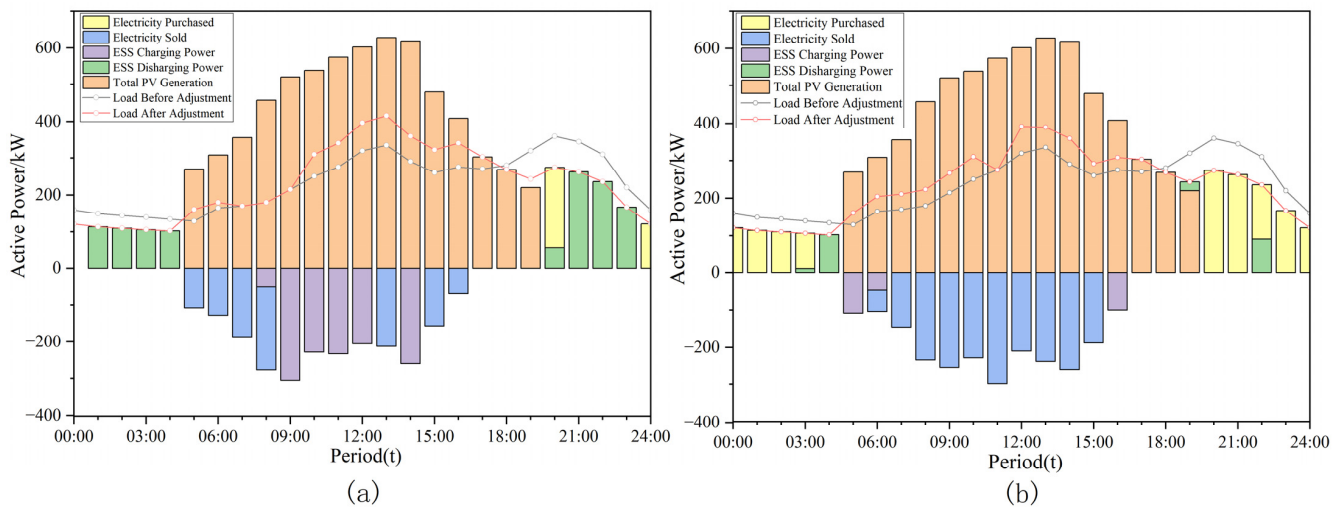


Figure 5. Day-ahead Scheduling Results of the MGPE under the Sunny Condition. (a) Results of AEO. (b) Results of CEO.

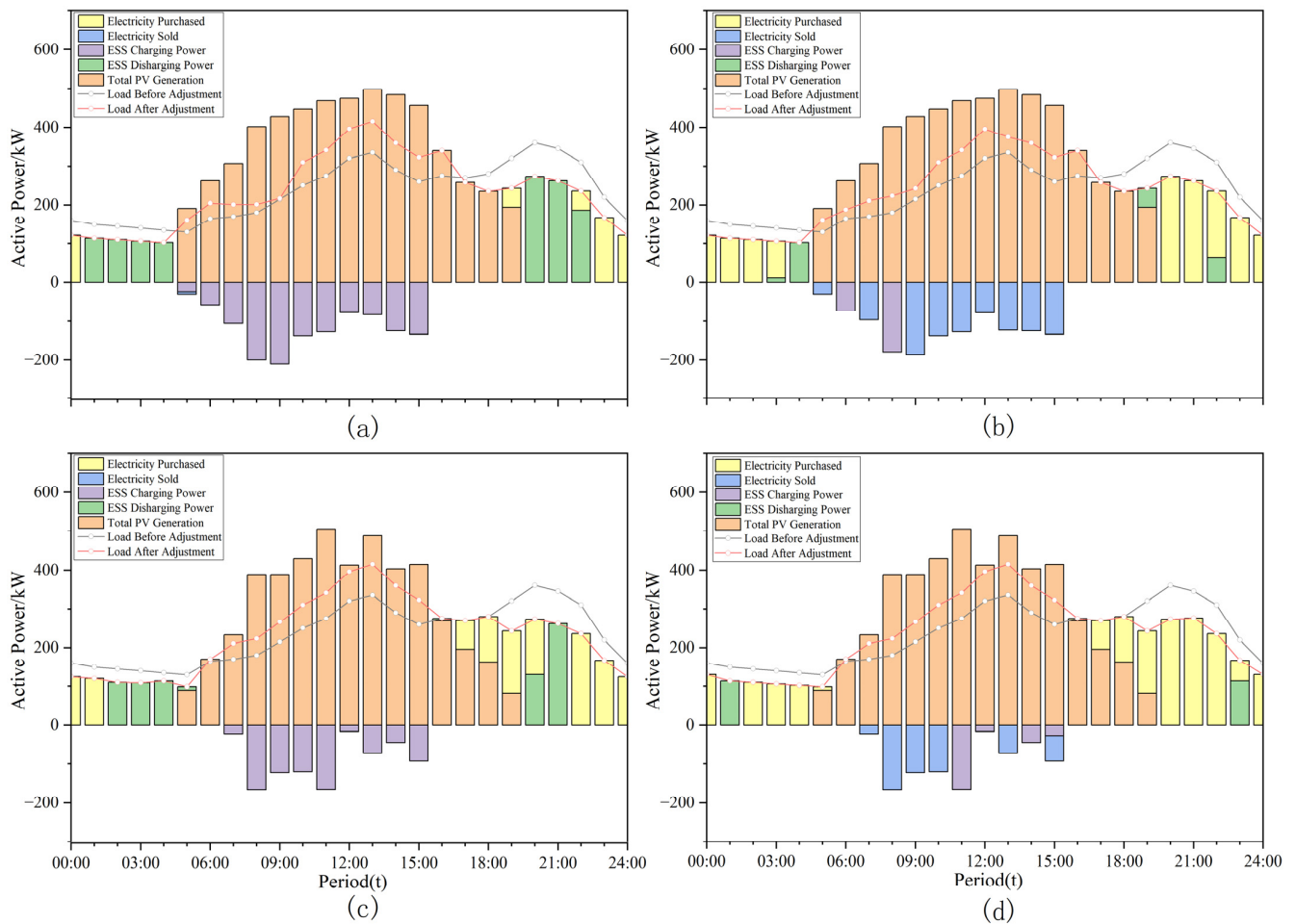


Figure 6. Day-ahead Scheduling Results of the MGPE. (a) Results of AEO under the Cloudy Condition. (b) Results of CEO under the Cloudy Condition. (c) Results of AEO under the Rainy Condition. (d) Results of CEO under the Cloudy Condition.

4.3.2. Optimized Scheduling

This section follows Step 4 in Section 3.3: the AEO scheduling scheme is re-solved with the selected ω^* obtained in Step 3, and the CEO scheduling scheme is also derived. These two schemes are then employed for subsequent comparisons of cost and regulation capability.

Case 1: Scheduling of the Sunny Day

Under the sunny condition, the total PV generation significantly exceeds the load demand. The day-ahead scheduling results obtained from the AEO and the CEO of the MGPE are presented in Figure 5.

The optimal results of the AEO under the Sunny Condition are depicted in Figure 5a. Between 01:00 and 04:00, PV generation is absent, and the internal ESSs are utilized to discharge preferentially to supply demand. By 05:00, the lower-cost ESSs (ESS 1 and ESS 2) are depleted to their minimum SOC. The power generation is concentrated between 05:00 and 19:00, when output is abundant and generation cost is low. During this period, demand is primarily satisfied by PVs, and the surplus is used to charge the ESSs. By 18:00, the ESSs are fully charged and charging is halted. Flexible loads tend to be shifted to this period to reduce reliance on grid exchange. Between 20:00 and 24:00, PV generation is again absent, and demand is met through the ESSs' discharge. However, since the ESSs are required to return to their initial SOC by the end of the 24 h horizon, part of the demand is supplied by electricity purchased from the external grid.

The optimal results of the CEO under the Sunny Condition are depicted in Figure 5b. Between 01:00 and 04:00, PV generation is absent. The purchase price of grid electricity is lower than the discharge costs of ESS 2 and ESS 3. Therefore, electricity is purchased from the grid, and ESS 1 is discharged to meet the load demand. In contrast, ESS 2 and ESS 3 remain inactive due to their higher discharge costs. By 05:00, only ESS 1 is depleted to its minimum SOC. From 05:00 to 19:00, abundant PVs are available. The surplus is utilized both to sell electricity to the grid and to charge ESS 1 to its maximum SOC. This strategy prepares the system for potential load deficits in subsequent hours. Between 20:00 and 23:00, no power is generated by the PVs. During this period, the load demand is supplied by ESS 1 and by electricity purchased from the main grid. During this period, ESS 1 is also discharged to return to its initial SOC.

Case 2–3: Scheduling of the Cloudy/Rainy Day

Compared with the sunny condition, the total PV generation is insufficient to meet the load demand under both cloudy and rainy conditions. The PV output under rainy conditions is significantly lower than that under cloudy conditions. The day-ahead scheduling results of the MGPE based on AEO and CEO for these two conditions are presented in Figure 6.

The optimal results of the AEO under cloudy and rainy conditions are illustrated in Figure 6a,c. Between 01:00 and 04:00, PV generation is absent. During this interval, demand is supplied by preferential ESS discharge, and flexible loads are predominantly shifted to this period. By 05:00, PV output remains low under rainy conditions, necessitating partial discharge from the ESSs. From 05:00 to 19:00, after meeting demand, a limited PV surplus is used to charge the ESSs. However, due to the overall shortage of PVs, power is no longer sold to the main grid. Since PV generation under the rainy condition is lower than that under the cloudy conditions, the charging level is correspondingly reduced. Between 20:00 and 24:00, demand continues to be met through ESSs' discharge. Nevertheless, constrained by SOC requirements and the PV generation deficit, additional electricity must be purchased from the grid, particularly under rainy conditions. Due to the lower charging amount in the earlier period, the available power from the ESSs is more limited under rainy conditions, leading to higher grid purchases compared with cloudy conditions.

The CEO results under cloudy and rainy conditions, presented in Figure 6b,d, confirm that the CEO closely follows the pattern observed under sunny conditions. When PV generation is absent, demand is supplied by electricity purchased from the grid and by discharge from the lower-cost ESSs. During PV generation periods, the surplus after meeting demand is utilized to charge the ESSs.

Motivated by time-of-use tariffs, the lower-cost type-1 loads are dispatched first until their common ceiling of 600 kWh is reached in all three weather scenarios, with any residual imbalance covered by type-2 loads. Consequently, the total adjustable energy amounts to 1120.8 kWh (type-2: 520.8 kWh) on sunny days, 1210.8 kWh (type-2: 610.8 kWh) on cloudy days, and 1111.6 kWh (type-2: 511.6 kWh) on rainy days. On sunny days, abundant PV surplus enables substantial battery charging between 09:00 and 15:00 followed by high-rate discharge during the evening peak (19:00–24:00), yielding a modest system imbalance. Under cloudy conditions, reduced PV surplus curtails battery charging and enlarges the evening discharge deficit, forcing a significant upward adjustment of type-2 loads. During rainy days, PV surplus is confined to 05:00–15:00, the overall imbalance is limited, and the requirement imposed by Equation (14) that upward and downward energy must balance within each cycle further constrains type-2 participation, resulting in a total adjustment slightly lower than that observed on cloudy days.

5. Case Study Improvements

5.1. Comparison of Outage Loss Performance

This section performs the 3 h islanding fault experiment in Step 5 using the AEO and CEO scheduling schemes obtained in Step 4. The outage cost and outage probability are compared to verify the autonomy benefits.

If a 3 h islanding fault occurs on the following day, the outage cost associated with CEO is significantly higher than that of AEO, as shown in Table 2, and the gap further widens with longer islanding durations. Although the day-ahead costs of AEO (CNY 2719.16, 2703.12, and 2637.18 under sunny, cloudy, and rainy conditions, respectively) are slightly higher than those of CEO (CNY 2420.21, 2404.17, and 2487.81), the fault scenarios reveal substantial differences. Specifically, under sunny conditions, the outage cost decreases to the maximum extent from CNY 2041.8 (CEO) to CNY 217.8 (AEO); under cloudy conditions, it decreases to the maximum extent from CNY 2119.8 to CNY 148.2; and under rainy conditions, it decreases to the maximum extent from CNY 957.6 to CNY 0.

Table 2. Costs of a Three-Hour Power outage (/CNY) under the Cloudy and Rainy Conditions.

Sunny			Cloudy			Rainy		
Time	AEO	CEO	Time	AEO	CEO	Time	AEO	CEO
1:00–3:00	0	957.6	1:00–3:00	0	957.6	1:00–3:00	0	649.8
2:00–4:00	0	615.6	2:00–4:00	0	615.6	2:00–4:00	0	957.6
3:00–5:00	0	285	3:00–5:00	0	285	3:00–5:00	0	653.4
						4:00–06:00	0	334.2
4:00–6:00 to 17:00–19:00	0	0	4:00–6:00 to 16:00–18:00	0	0	5:00–7:00 to 14:00–16:00	0	0
						15:00–17:00	222	240
						16:00–18:00	573	591
			17:00–19:00	147.6	0	17:00–19:00	573	1053.6
18:00–20:00	217.8	820.8	18:00–20:00	147.6	820.8	18:00–20:00	1171.8	1652.4
19:00–21:00	217.8	1607.4	19:00–21:00	147.6	1607.4	19:00–21:00	1607.4	2131.2
20:00–22:00	217.8	2041.8	20:00–22:00	148.2	2119.8	20:00–22:00	2314.2	2357.4
21:00–23:00	501.6	1722.6	21:00–23:00	649.8	1800.6	21:00–23:00	1667.6	1696.2
22:00–24:00	866.4	1300.8	22:00–24:00	1014.6	1378.8	22:00–24:00	1245.8	1259.4

The outage probabilities of AEO and CEO can be analyzed from Figures 5 and 6, as summarized in Table 3. The results further show that AEO also lowers the outage probability: from 33.3% to 8.33% under sunny conditions, from 33.3% to 12.5% under cloudy conditions, and from 41.6% to 33.3% under rainy conditions.

Table 3. Performance comparison of AEO vs. CEO under three weather conditions.

Conditions	Method	SSR	OP	RIP
sunny	CEO	66.7%	33.3%	-
	AEO	91.7%	8.33%	75.1%
cloudy	CEO	66.7%	33.3%	-
	AEO	87.5%	12.5%	62.5%
rainy	CEO	58.4%	41.6%	-
	AEO	66.7%	33.3%	24.9%

Note: The Supply Security Rate (SSR) is defined as $SSR = 100\% - OP$, where OP denotes the Outage Probability. The Relative Improvement Rate (RIP) is calculated as $(OP_{CEO} - OP_{AEO}) / OP_{CEO} \times 100\%$, and it indicates the relative reduction in outage probability achieved by AEO compared with CEO.

In summary, regardless of whether under sunny, cloudy, or rainy condition, the cost of AEO is always lower than that of CEO after a fault occurs. Moreover, the AEO can reduce

the probability of power outages, ensure the continuous supply of electricity, and enhance the power supply reliability of the MGPE.

5.2. Aggregation and Quantification

Once the autonomy has been verified in Steps 1–5, resources of the MGPE are aggregated, and its overall demands and residual capability are quantified. This enables flexible dispatch of the main grid. However, due to the unknown demand from the main grid, the relevant price coefficients cannot be calculated in this case study.

The demand/surplus capacity curve at the PCC is derived from Equations (27) and (28), as illustrated in Figure 7. Positive values indicate surplus exports from the MGPE to the main grid, whereas negative values represent the demand for grid imports on an hourly basis.

The charging and discharging power of the ESSs and their SOC are aggregated over a 24 h period. It aims to facilitate the utilization of the residual regulation capability of the MGPE by the main grid. This aggregation aims to quantify the residual charging and discharging power and the SOC of the AESS, as shown in Figure 8. Due to the different capacities of the internal ESSs, the SOC of the AESS cannot be simply summed. Instead, the SOC of each ESS must be calculated for each time period according to Equation (22).

The AESS is prioritized for discharging by the MGPE until renewable PV generation becomes available as depicted in Figure 8. Furthermore, PVs with lower generation costs are utilized by the MGPE for charging after meeting the load demands. It ensures that the AESS can discharge preferentially during subsequent PV shortages. The operational strategy reduces dependence on the main grid, thereby enhancing the autonomy and reliability of the MGPE. It also optimizes AEO by scheduling the charging and discharging of the AESS in a reasonable manner. If the residual regulation capability of the AESS after AEO is utilized by the main grid, the exchanged power must satisfy both the residual input/output limits and the SOC constraints of the AESS at each time step. By quantifying and reporting, flexible dispatch can be achieved by the main grid to effectively improve the resource consumption rate. Similarly, the results under cloudy and rainy conditions are aggregated and quantified, as presented in Appendix A Figure A3.

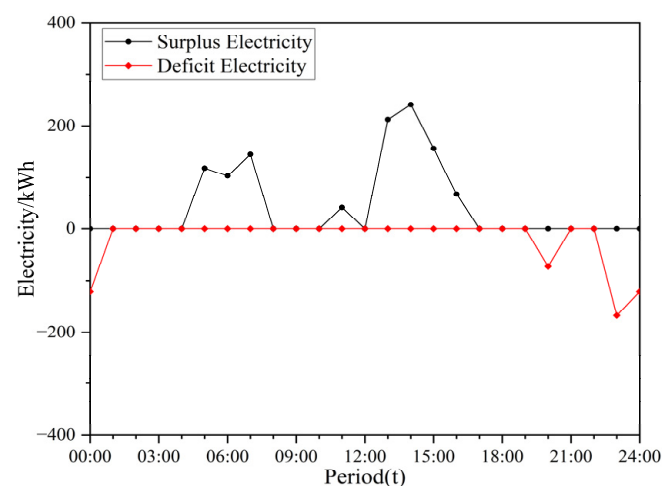


Figure 7. Demand and Residual Surplus Capability (under the sunny condition).

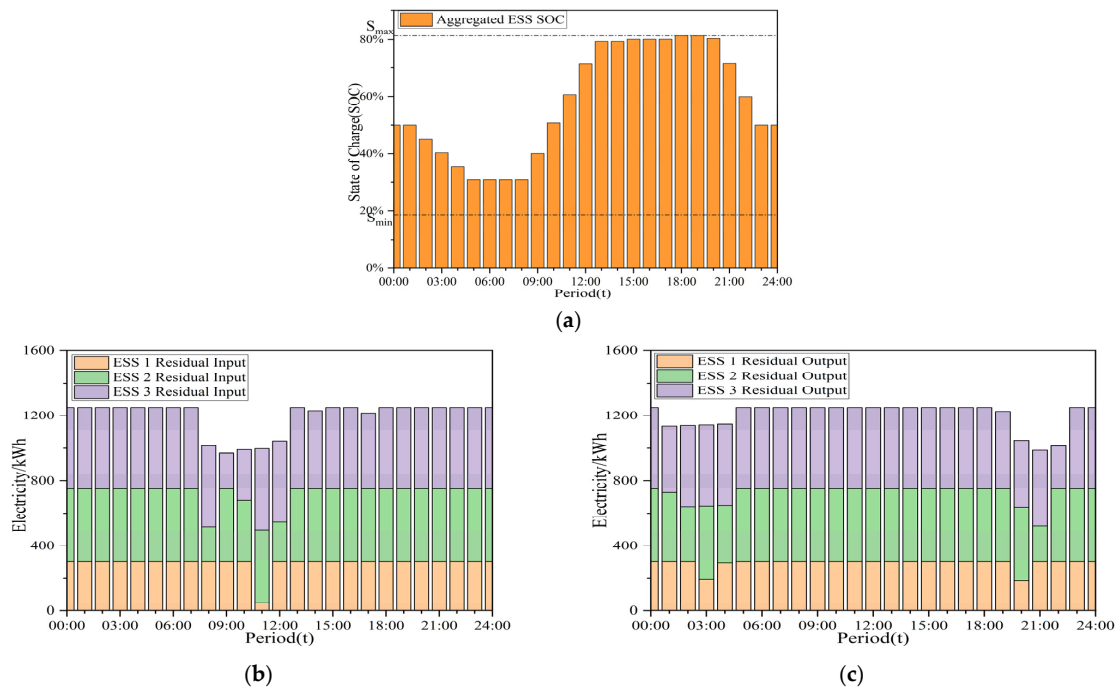


Figure 8. Residual Regulation Capability. (a) SOC of the AESS. (b) Residual output power of the AESS. (c) Residual input power of the AESS.

5.3. Further Experiments

5.3.1. Scalability

Scalability is examined by expanding the MGPE with two, six, and ten additional ESSs, each rated at 400 kWh and 200 kW charging/discharging limits. The discharge cost (0.30 CNY/kWh), SOC bounds, and round-trip efficiency of the baseline ESS 1 are applied to all supplementary units.

The impact of varying ESS capacities is illustrated in Figure 9. Under sunny conditions, abundant PV surplus is available. The additional ESS capacity stores this surplus and later discharges it during non-PV periods, thereby considerably reducing external energy imports compared with the baseline. However, once ESS capacities exceeds the PV-chargeable threshold, external demand stabilizes. The PV surplus cannot fully charge the enlarged fleet, and terminal SOC constraints force a net purchase from the grid. Under the cloudy condition, the reduced PV surplus limits additional charging. As a result, only a modest reduction in external demand is achieved, which saturates at the same threshold. During the rainy condition, no PV surplus is available even without additional ESSs.

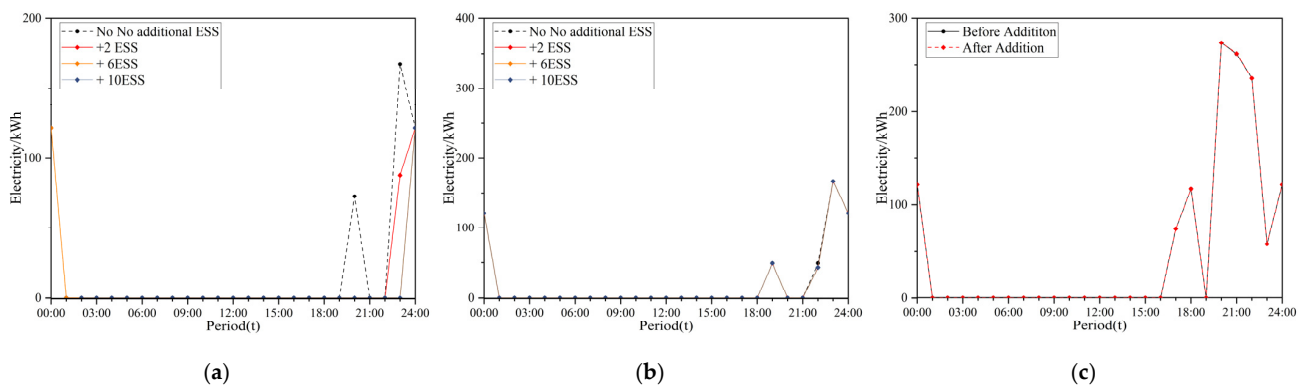


Figure 9. Impact of Varying ESS capacities on External Electricity Dependence under Different Weather Conditions: (a) sunny, (b) cloudy, and (c) rainy.

Consequently, further expansion of ESS capacity has little effect on external dependence.

5.3.2. Sensitivity Analysis of PV and ESS Capacity

Sensitivity analyses were conducted to examine the impact of varying PV conditions and ESS configurations on the penalty factor w . These analyses considered different weather scenarios and the addition of two, six, and ten ESSs, as described in Section 5.2 (see Appendix A Figure A4). Due to the limited PV surplus and the discharge cost hierarchy, PV generation first charges, and later discharges, the lowest-cost units. Because the added ESSs have lower discharge costs than the original units, w decreases as PV surplus shrinks and as the number of ESSs increases. Nevertheless, w always remains above the maximum discharge cost observed in the dispatch results.

This finding confirms that w must be set above the highest marginal cost of internal resources. For practical implementation, w is set to twice the observed maximum internal cost. This guarantees a sufficient safety margin without adding engineering complexity.

6. Conclusions

This study proposes a day-ahead scheduling framework for an MGPE that prioritizes autonomous operation while achieving internal economic optimality. Compared with traditional cost-oriented optimization, the framework reduces the daily outage probability by at least 24.9% while simultaneously lowering outage-related losses. A novel EPU–AEES dual aggregation structure is introduced to quantify the residual flexibility as closed-form cost coefficients of the MGPE, enabling direct dispatch by the main grid. Additionally, it provides a systematic method for setting the penalty factor threshold applicable to various weather conditions and ESS capacities. Due to the deterministic nature of the current model, forecast uncertainties are not yet considered. Future work will integrate stochastic optimization, conduct field data validation, and extend the approach to the cooperative operation of networked microgrids.

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

Appendix A

Algorithm A1: CPLEX-Based Maximized AEO for the MGPE with ω -Sensitivity

Input:

- Time horizon T, step ΔT
- Fixed load: $P_{bl,i,t}, i \in 1, \dots, N_{bl}$; flexible loads: $\Delta P_{tl,i,t,base}, P_{tl,i,t,max/min}, \Delta P_{tl,i,t,u/d}, i \in 1, \dots, N_{tl}$
- PV generation: $P_{v,i,t}, i \in 1, \dots, N_v$
- ESS parameters: $S_{ess,i,max/min}, S_{ess,i,0}, P_{ess,i,max/min}^{ch}, P_{ess,i,max/min}^{dch}, \eta_{ess,i}^{ch}, \eta_{ess,i}^{dch}, i \in 1, \dots, N_{ess}$
- Cost coefficients: $c_{v,i}, c_{ess,i}^{dch}, c_{l,i,t}$

Hyperparameters:

- Penalty factor set Ω (e.g., 0:0.04:1)
- Solver: IBM CPLEX via YALMIP (MIQP model, mipgap = 0.01, timelimit = 60 s)

Output:

- Optimal schedules: $P_{buy,t}, P_{sell,t}, P_{ess,i,t}^{ch}, P_{ess,i,t}^{dch}, S_{ess,i,t}, \Delta P_{tl,i,t}$
- F_1, F_2 , selected ω^*

1. Define Objective

1.1 Objective 1:

$$F_1 = \sum_{t=1}^T \left(|P_{buy,t}| + |P_{sell,t}| \right) \Delta T$$

1.2 Objective 2:

$$F_2 = \sum_{t=1}^T \left(\sum_{i=1}^{N_v} c_{v,i} P_{v,i,t} + \sum_{i=1}^{N_{ess}} c_{ess,i}^{dch} P_{ess,i,t}^{dch} + \sum_{i=1}^{N_{tl}} c_{l,i,t} |\Delta P_{tl,i,t}| \right) \Delta T$$

1.3 Total objective:

$$F(\omega) = \omega \cdot F_1 + F_2$$

2. Constraints

2.1 Power balance: grid exchange, PV generation, ESS charge/discharge must meet total load demand (fixed + flexible)

2.2 ESS operation: SOC dynamics, capacity limits, and mutually exclusive charge/discharge

2.3 Flexible load: shifting and ramp limits, total energy conservation $\sum \Delta P_{l,i,t} \Delta T = 0$

3. ω -Sensitivity Analysis

For each ω in Ω :

-Update objective $F(\omega)$

-Solve MIQP model with CPLEX

-CPLEX internally applies Branch-and-Bound for integer vars, Barrier/Simplex for QP relaxation

-Presolve, cut generation, heuristics are activated to improve efficiency

-Record $F(\omega)$, F_1 , and F_2

4. Select ω

4.1 Choose ω' based on trade-off between grid exchange and internal cost

4.2 Typically select ω' yielding minimal $F(\omega)$ under constraints

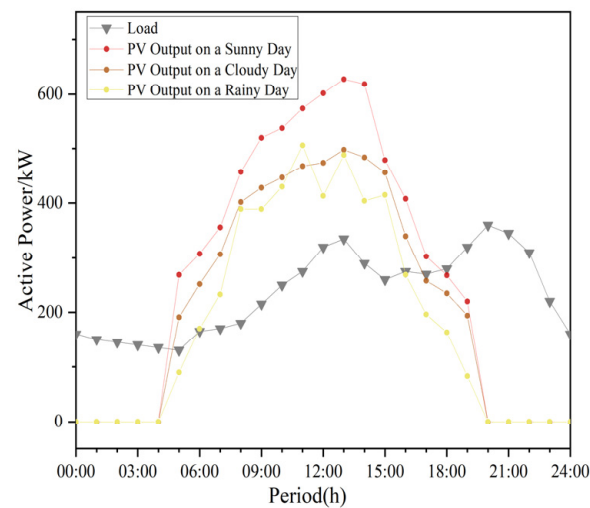
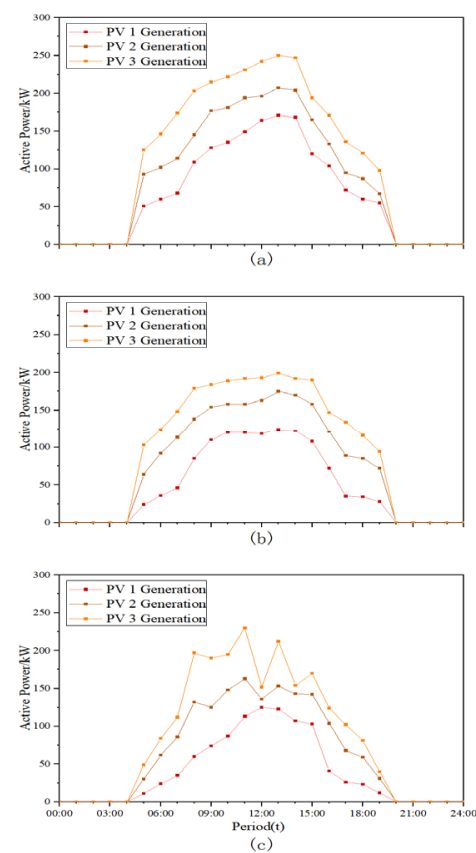
5. Final Scheduling

5.1 Fix $\omega = 2\omega'$, re-solve MIQP via CPLEX

5.2 Output dispatch

Table A1. Adjustment Cost of Flexible Loads in Different Time Periods.

Time Period	Flexible Load 1 Cost	Flexible Load 2 Cost
01:00–08:00; 19:00–24:00	0.18	0.28
12:00–14:00	0.25	0.35
09:00–11:00; 15:00–18:00	0.20	0.30

**Figure A1.** Total PV Generation and Load Forecasting Curve.**Figure A2.** PV Forecast under Three Weather Conditions: (a) sunny; (b) cloudy; (c) rainy.

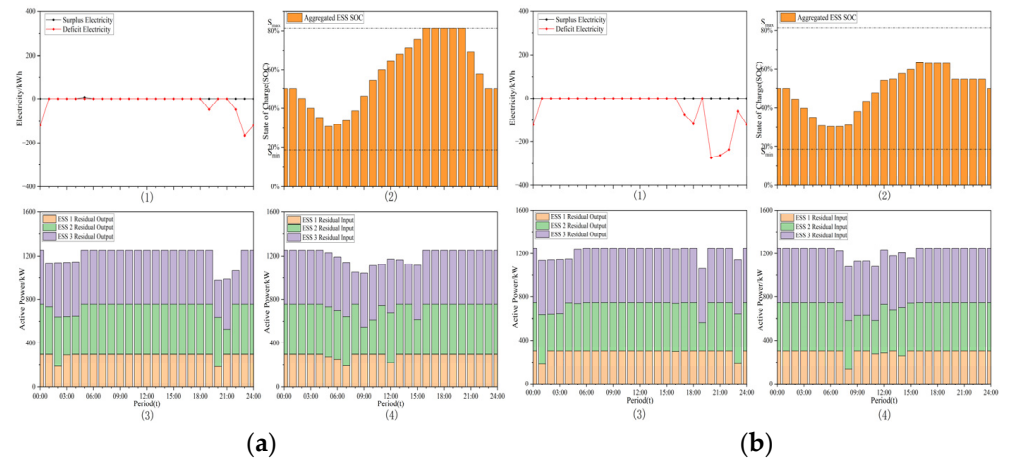
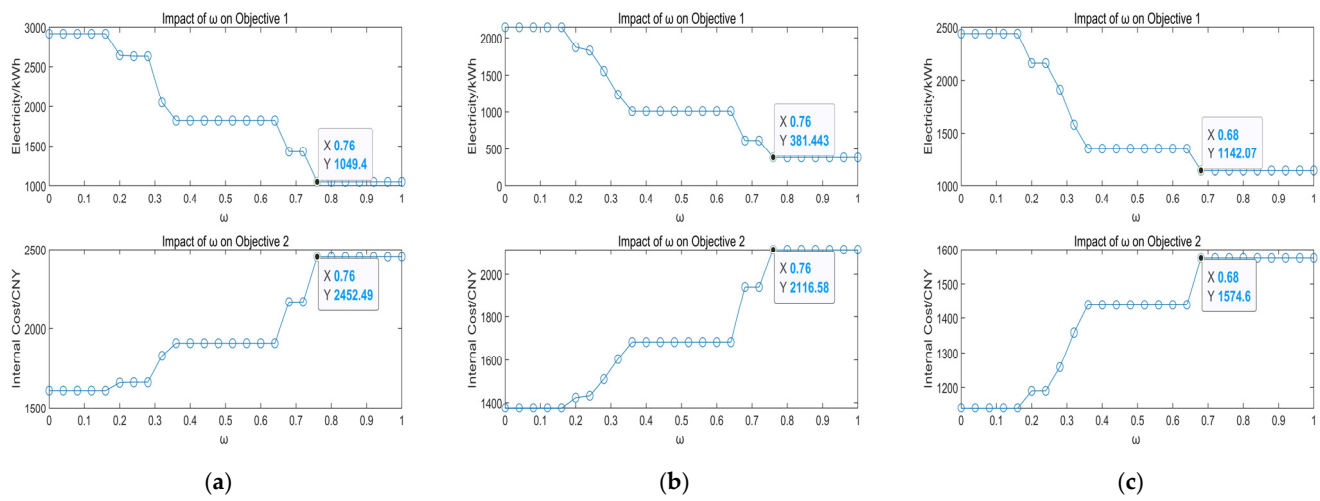
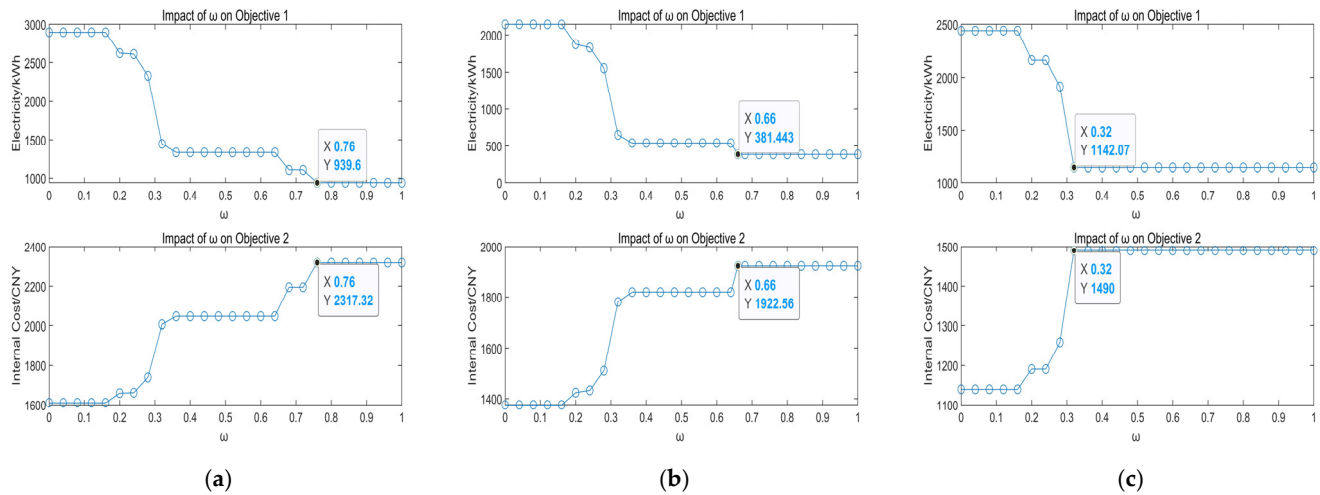


Figure A3. Aggregation and Quantification Results. (a) Results for Cloudy. (b) Results for Rainy.

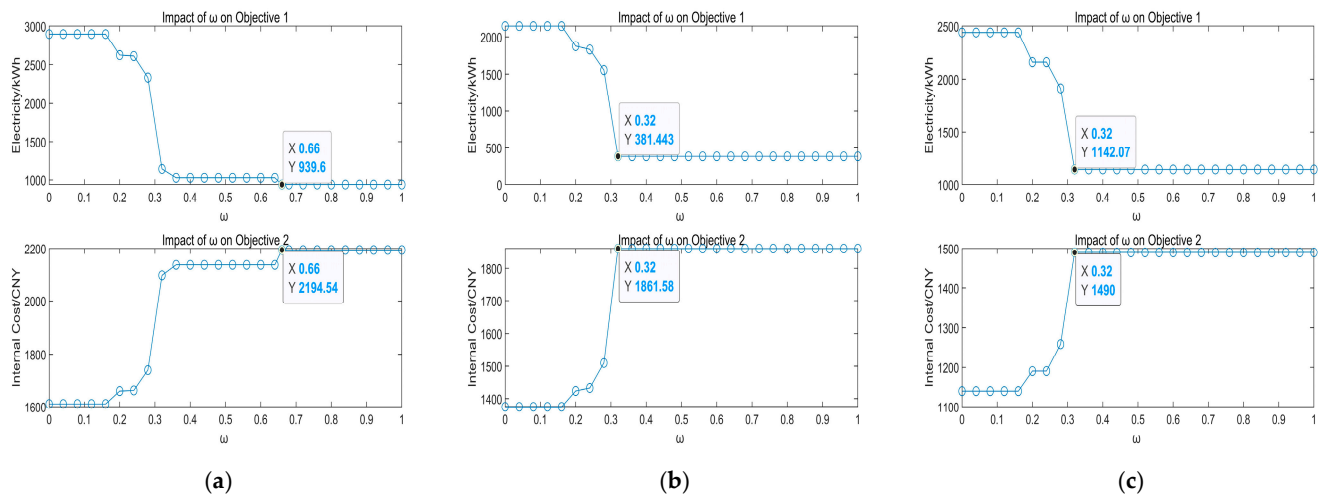


A4.1 ω -Sensitivity with +2 ESSs: (a) sunny, (b) cloudy, (c) rainy.



A4.2 ω -Sensitivity with +6 ESSs: (a) sunny, (b) cloudy, (c) rainy.

Figure A4. Cont.



A4.3 w -Sensitivity with +10 ESSs: (a) sunny, (b) cloudy, (c) rainy.

Figure A4. Sensitivity of w to Multi-Step ESS Additions (two, six, ten units) under Different Weather Conditions.

References

- Gielen, D.; Boshell, F.; Saygin, D.; Bazilian, M.D.; Wagner, N.; Gorini, R. The Role of Renewable Energy in the Global Energy Transformation. *Energy Strategy Rev.* **2019**, *24*, 38–50. [\[CrossRef\]](#)
- Kroposki, B.; Johnson, B.; Zhang, Y.C.; Gevorgian, V.; Denholm, P.; Hodge, B.-M.; Hannegan, B. Achieving a 100% Renewable Grid: Operating Electric Power Systems with Extremely High Levels of Variable Renewable Energy. *IEEE Power Energy Mag.* **2017**, *15*, 61–73. [\[CrossRef\]](#)
- Faisal, M.; Hannan, M.A.; Ker, P.J.; Begum, R.A.; Dong, Z.Y. Review of Energy Storage System Technologies in Microgrid Applications: Issues and Challenges. *IEEE Access* **2018**, *6*, 35143–35164. [\[CrossRef\]](#)
- Dawoud, S.M.; Lin, X.; Okba, M.I. Hybrid Renewable Microgrid Optimization Techniques A Review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2039–2052. [\[CrossRef\]](#)
- Muhtadi, A.; Pandit, D.; Nguyen, N.; Yu, D.C. Distributed Energy Resources Based Microgrid Review of Architecture, Control, and Reliability. *IEEE Trans. Ind. Appl.* **2021**, *57*, 2223–2235. [\[CrossRef\]](#)
- Silva, V.A.; Aoki, A.R.; Lambert-Torres, G. Optimal Day-Ahead Scheduling of Microgrids with Battery Energy Storage System. *Energies* **2020**, *13*, 5188. [\[CrossRef\]](#)
- Gomes, J.G.; Xu, H.J.; Yang, Q.; Zhao, C.Y. An Optimization Study on a Typical Renewable Microgrid Energy System with Energy Storage. *Energy* **2021**, *234*, 121210. [\[CrossRef\]](#)
- Li, Z.; Xu, Y. Optimal Coordinated Energy Dispatch of a Multi-Energy Microgrid in Grid-Connected and Islanded Modes. *Appl. Energy* **2018**, *210*, 974–986. [\[CrossRef\]](#)
- Nwulu, N.I.; Xia, X. Optimal Dispatch for a Microgrid Incorporating Renewables and demands Response. *Renew. Energy* **2017**, *101*, 16–28. [\[CrossRef\]](#)
- Witharama, W.M.N.; Bandara, K.M.D.P.; Azeez, M.I.; Logeeshan, V.; Wanigasekara, C. Advanced Genetic Algorithm for Optimal Microgrid Scheduling Considering Solar and Load Forecasting, Battery Degradation and demands Response Dynamics. *IEEE Access* **2024**, *12*, 123456–123470. [\[CrossRef\]](#)
- Sun, L.; Xu, Q.; Chen, X.; Fan, Y. Day-Ahead Economic Dispatch of Microgrid Based on Game Theory. *Energy Rep.* **2020**, *6*, 633–638. [\[CrossRef\]](#)
- Silvente, J.; Kopanos, G.M.; Pistikopoulos, E.N. A Rolling Horizon Optimization Framework for the Simultaneous Energy Supply and Demand Planning in Microgrids. *Appl. Energy* **2015**, *155*, 485–501. [\[CrossRef\]](#)
- Hou, H.; Xue, M.; Xu, Y.; Xiao, Z.; Deng, X.; Xu, T.; Liu, P.; Cui, R. Multi-Objective Economic Dispatch of a Microgrid Considering Electric Vehicle and Transferable Load. *Appl. Energy* **2020**, *262*, 114489. [\[CrossRef\]](#)
- Aghajani, G.; Ghadimi, N. Multi-Objective Energy Management in a Micro-Grid. *Energy Rep.* **2018**, *4*, 218–225. [\[CrossRef\]](#)
- Cao, Y.; Lu, D.; Zhang, Y.; Tang, Q.; Khodaei, A.; Zhang, H.; Han, Z. Optimal Energy Management for Multi-Microgrid under a Transactive Energy Framework with Distributionally Robust Optimization. *IEEE Trans. Smart Grid* **2022**, *13*, 599–612. [\[CrossRef\]](#)
- Nawaz, A.; Wu, J.; Ye, J.; Dong, Y.; Long, C. Distributed MPC-Based Energy Scheduling for Islanded Multi-Microgrid Considering Battery Degradation and Cyclic Life Deterioration. *Appl. Energy* **2023**, *329*, 120168. [\[CrossRef\]](#)
- Tan, B.; Chen, H.; Zheng, X. Two-Stage Robust Optimization Dispatch for Multiple Microgrids with Electric Vehicle Loads Based on a Novel Data-Driven Uncertainty Set. *Int. J. Electr. Power Energy Syst.* **2022**, *134*, 107359. [\[CrossRef\]](#)

18. Zhao, H.; Wang, B.; Wang, X.; Pan, Z.; Sun, H.; Liu, Z.; Guo, Q. Active Dynamic Aggregation Model for Distributed Integrated Energy System as Virtual Power Plant. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 831–840. [[CrossRef](#)]
19. Wang, S.; Wu, W. Aggregation Reference Model and Quantitative Metric System of Flexible Energy Resources. *Autom. Electr. Power Syst.* **2024**, *48*, 1–9. (In Chinese)
20. Utkarsh, K.; Ding, F.; Jin, X.; Blonsky, M.; Padullaparti, H.; Balamurugan, S.P. A Network-Aware Distributed Energy Resource Aggregation Framework for Flexible, Cost-Optimal, and Resilient Operation. *IEEE Trans. Smart Grid* **2021**, *13*, 1213–1224. [[CrossRef](#)]
21. Wen, Y.; Hu, Z.; You, S.; Duan, X. Aggregate Feasible Region of DERs: Exact Formulation and Approximate Models. *IEEE Trans. Smart Grid* **2022**, *13*, 4405–4423. [[CrossRef](#)]
22. Yi, Z.; Xu, Y.; Gu, W.; Yang, L.; Sun, H. Aggregate Operation Model for Numerous Small-Capacity Distributed Energy Resources Considering Uncertainty. *IEEE Trans. Smart Grid* **2021**, *12*, 4208–4224. [[CrossRef](#)]
23. He, G.; Huang, Y.; Huang, G.; Liu, X.; Li, P.; Zhang, Y. Assessment of Low-Carbon Flexibility in Self-Organized Virtual Power Plants Using Multi-Agent Reinforcement Learning. *Energies* **2024**, *17*, 3688. [[CrossRef](#)]
24. Yang, Z.; Wu, R.; Yang, J.; Long, K.; You, P. Economical Operation of Microgrid with Various Devices via Distributed Optimization. *IEEE Trans. Smart Grid* **2016**, *7*, 857–867. [[CrossRef](#)]
25. He, Y.; Chen, Y.; Liu, Y.; Liu, H.; Liu, D.; Sun, C. Analysis on Cost per kWh and Cost per mileage for energy storage technologies. *Adv. Technol. Electr. Eng. Energy* **2019**, *38*, 1–10. (In Chinese) [[CrossRef](#)]
26. Hamidieh, M.; Ghassemi, M. Microgrids and Resilience: A Review. *IEEE Access* **2022**, *10*, 106059–106080. [[CrossRef](#)]
27. Guangdong Provincial Development and Reform Commission. *Implementation Plan for High-Quality Development of Guangzhou Virtual Power Plant (2025)*; Guangdong Provincial Development and Reform Commission: Guangzhou, China, 2023.

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