

Article

Cooperative Game Enabled Low-Carbon Energy Dispatching of Multi-Regional Integrated Energy Systems Considering Carbon Market

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Abstract: With the growing global environmental concerns and the push for carbon neutrality, rural multi-regional integrated energy systems (IESs) face challenges related to low energy efficiency, high carbon emissions, and the transition to cleaner energy sources. This paper proposes a cooperative game-based low-carbon economic dispatch strategy for rural IESs, integrating carbon trading mechanisms. A novel multi-regional IESs architecture is developed to exploit the synergy between photovoltaic (PV) and biomass energy systems. The proposed model described the anaerobic fermentation heat loads, incorporates variable-temperature fermentation, and employs a Nash bargaining model solved via the Alternating Direction Method of Multipliers (ADMM) to optimize cooperation while preserving stakeholder privacy. Simulation results show that the proposed strategy reduces total operating costs by 16.9% and carbon emissions by 7.5%, validating its effectiveness in enhancing efficiency and sustainability in rural energy systems.

Keywords: rural integrated energy systems; cooperative game; carbon trading; Nash bargaining; ADMM



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1. Introduction

In light of escalating global environmental challenges, rural regions, which account for a substantial share of carbon emissions, must urgently revamp their energy consumption practices [1,2]. At present, rural energy largely depends on fossil fuels. While this reliance fulfills immediate needs, it significantly contributes to environmental degradation and pollution [3–5]. The increasing deployment of distributed photovoltaic (PV) systems and the availability of biomass resources present an opportunity to integrate renewable energy sources. This integration can enhance energy efficiency, curb carbon emissions, and alleviate dependence on fossil fuels, thereby promoting environmental sustainability and meeting growing rural energy demands [6–8].

To address these challenges, researchers worldwide have extensively studied the low-carbon operational optimization of integrated energy systems (IESs) under carbon trading mechanisms. For instance, Ref. [9] investigated the optimal scheduling of electricity–gas systems integrating Power-to-Gas (P2G) technology with carbon trading, achieving significant reductions in both carbon emissions and operational costs. Ref. [10] proposed a dynamic optimal energy flow approach for integrated electricity and gas systems in continuous space, achieving low-carbon economic performance through improved energy system efficiency and carbon emission reductions. The study in [11] developed a multi-energy system scheduling model under real-time electricity pricing and carbon trading

mechanisms, enabling the dynamic optimization of carbon emissions. Similarly, Ref. [12] proposed a multi-objective optimization scheduling model for IESs using the Information Gap Decision Theory (IGDT) approach, optimizing uncertain operational strategies under hierarchical carbon trading mechanisms. Ref. [13] introduced a multi-timescale security evaluation and regulation framework for integrated electricity and heating systems, effectively improving carbon reduction efficiency and operational reliability under market-based contexts. Ref. [14] introduced blockchain-enabled carbon and energy trading for network-constrained coal mines with uncertainties, significantly improving carbon emission reductions under market-based contexts. Additionally, Ref. [15] analyzed the impact of electric vehicle charging patterns on IESs and proposed a multi-energy coupling low-carbon economic optimization approach that balances carbon reduction and cost-effectiveness.

While most existing studies focus on industrial parks, limited efforts have been made to validate carbon trading mechanisms in rural energy systems. This paper addresses this gap by analyzing the effects of carbon trading mechanisms on reducing carbon emissions in rural multi-regional energy systems, leveraging carbon quotas and trading frameworks.

In rural IESs research, biomass energy utilization is a key enabler of clean energy substitution on the source side. For example, Ref. [16] proposed a two-stage stochastic energy scheduling model for multi-energy rural microgrids with irrigation systems and biomass fermentation, achieving effective energy use and low-carbon operation. In [17], a distributed robust operation method was developed for rural IESs in the context of broiler farming, optimizing both energy supply reliability and economic performance. The study in [18] designed a renewable heat-driven poly-generation system utilizing advanced absorption cycles to enhance the efficiency of biomass energy usage in rural communities. Ref. [19] introduced an optimized scheduling method for inter-regional wind–biomass–hydrogen IESs, significantly improving energy synergy utilization. In [20], a robust energy management method based on scenario prediction was proposed to optimize the low-carbon operation of rural IESs in greenhouse environments. Furthermore, Ref. [21] presented a multi-timescale scheduling model for micro-energy grids based on biomass waste energy conversion, effectively addressing the carbon reduction impact of multi-energy demand response.

This paper builds upon these studies by integrating processes such as anaerobic fermentation, energy conversion, and combined heat and power (CHP). The complementarity of photovoltaic and biomass energy is examined with a focus on reducing reliance on energy storage while minimizing carbon emissions and operational costs in rural systems through optimized scheduling strategies.

Rural areas often consist of multiple energy systems managed by distinct stakeholders. However, existing research has largely overlooked the challenges of collaborative operation among these systems. Nash bargaining offers an effective framework for addressing cooperative game problems among multiple systems, balancing overall benefits and revenue distribution among subsystems [22]. For instance, Ref. [23] applied a non-cooperative game theory approach to optimize energy trading strategies in distribution systems, enhancing trading efficiency for distributed energy resources. In [24], a Nash bargaining model was utilized to achieve the joint optimization of capacity and operation in IESs, enhancing system-level synergies. Similarly, Ref. [25] proposed a Nash bargaining framework to study energy sharing between microgrids and energy storage systems, improving resource allocation and operational efficiency. The work in [26] employed a bi-level Stackelberg–Nash game theory to optimize low-carbon scheduling in park-level IES, enhancing carbon control performance. Moreover, Ref. [27] introduced an asymmetric Nash bargaining framework to design cooperative energy and backup trading strategies among multiple IESs, optimizing

energy complementarity and reliability. Incorporating cooperative game theory into rural multi-regional IESs can enable collaborative operation across regions, reduce overall system costs, and improve the economic performance of individual regions.

Existing studies primarily focus on the synergy and complementarity among different energy sources within rural regions, often neglecting collaborative operation among energy systems across different regions. To address this limitation, this paper proposes a collaborative low-carbon economic scheduling strategy for rural multi-regional energy systems. First, the source–load characteristics of different agricultural regions are analyzed to establish a novel rural multi-regional IESs under joint operation. The synergy and complementarity mechanisms among these multi-regional energy systems are then thoroughly examined. Subsequently, the precise modeling of material flows, energy dynamics, and carbon emissions is conducted, considering biomass material pretreatment, thermal assistance for biogas generation, and fermenter heat transfer processes. Finally, a joint optimization model for multi-regional IESs operation is established based on Nash bargaining theory. The Alternating Direction Method of Multipliers (ADMM) is utilized to solve the Nash game for multi-energy systems, demonstrating the effectiveness of the proposed approach.

2. Overview of the Rural IESs Structure

The rural multi-regional IESs structure is illustrated in Figure 1. The system primarily comprises fisheries, agriculture, and livestock farming with each agricultural region functioning as a microgrid capable of independent operation through interactions with the upper-level distribution grid. Each microgrid mainly consists of energy supply equipment, energy conversion equipment, and energy storage equipment.

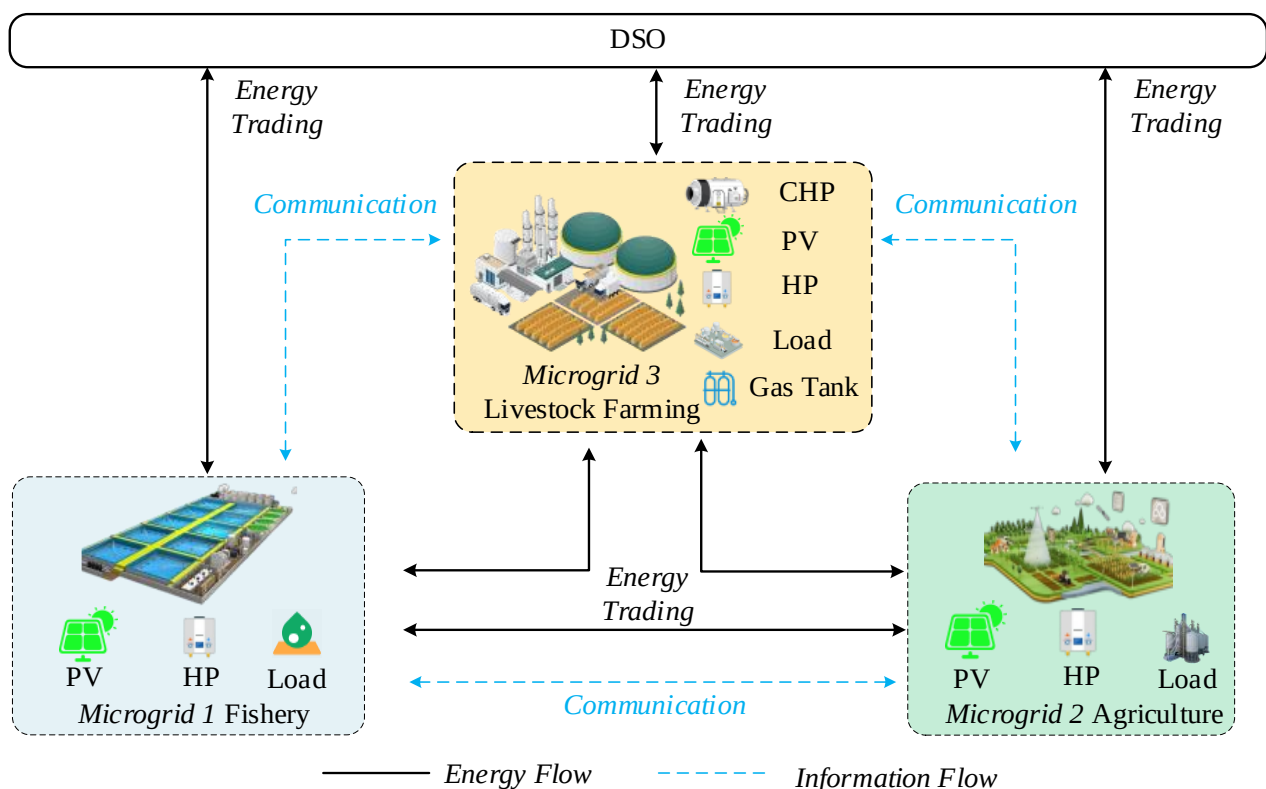


Figure 1. Structure of the rural multi-area integrated energy system.

The electrical energy in the system originates from rural renewable energy generation systems, including PV systems, biogas power generation, and interactions with the upper-level grid. This energy primarily supports heat pumps (HPs) and the system's internal electrical loads. The thermal energy of the system is mainly derived from waste heat recovery devices of biogas generators and heat pumps, which primarily supply the system's internal thermal loads.

For different types of agricultural regions, the energy and load profiles vary, resulting in distinct source–load characteristics. The fishery region, with minimal self-load and substantial distributed photovoltaic (PV) capacity, exhibits source characteristics capable of supplying surplus energy to other agricultural regions. The livestock farming region's biogas system not only consumes energy for fermentation heating but also generates electricity through biogas combustion, exhibiting source–load characteristics. This region can both supply electricity to other agricultural regions and absorb surplus energy from other microgrids. The agriculture region, with a higher load and smaller scale of renewable energy, displays load characteristics, primarily consuming energy supplied by other microgrids.

In most agricultural regions, PV generation is the primary renewable energy source. However, due to the uncertainties and intermittency associated with PV generation, and the flexible operational schedule of biomass power generation, interconnecting various agricultural regions through the power grid forms a complementary PV–biogas coupled system. Excess PV generation can be transmitted through the power grid to heat pumps, converting electricity into heat to raise the temperature for anaerobic digestion, thereby promoting biogas production. This approach effectively enhances the system's internal energy conversion flexibility. Additionally, gas storage tanks enable the power control of biogas generation equipment, achieving efficient coupling and complementary operation between PV generation, biogas production, and biogas power generation.

3. Problem Formulation

This section defines the optimization problem for low-carbon dispatch in rural multi-regional IESs. The objective is to minimize operating costs and carbon emissions while maintaining energy balance. Key components, including biogas production, energy storage, and photovoltaics, are modeled with their constraints. Carbon trading mechanisms and regional energy variability are also considered. The following subsections outline the system models and cost function.

3.1. Biogas Production and Storage Model

3.1.1. Anaerobic Digestion Gas Production Model

The biogas yield is influenced by various factors, such as feedstock input, fermentation temperature, and external environmental temperature [28]. Given the relatively large scale of livestock farming within the ecological agricultural IESs, it is assumed that the daily production of biomass feedstock is constant. This assumption is made based on the actual situation at the research site. In order to maintain the stability of the feed, farm enterprises usually do not use all the manure for anaerobic fermentation at one time but maintain a relatively stable feed rate. In this article, in order to facilitate research and calculation, the feed rate is fixed to a constant value. The anaerobic digestion gas production model is formulated as follows.

$$\mu_{st}^d = \begin{cases} \alpha_{11}e^{\alpha_{12}T_t^{\text{dig}}}, & T_0 \leq T_t^{\text{dig}} < T_1 \\ \alpha_{21}T_t^{\text{dig}} - \alpha_{22}, & T_1 \leq T_t^{\text{dig}} \leq T_2 \end{cases} \quad (1)$$

$$K^{\text{bio}} = \beta_{11}e^{\beta_{12}S_0} + \beta_{13} \quad (2)$$

$$G_{st}^{AD} = \frac{B_0 S_0 V_{AD}}{24 t_{HRT}} \left(1 - \frac{K^{bio}}{t_{HRT} \mu_{st}^d - 1 + K^{bio}} \right) \quad (3)$$

where μ_{st}^d denotes the maximum growth rate of microorganisms under mesophilic and thermophilic fermentation conditions. K^{bio} is the kinetic parameter of the anaerobic fermentation tank. α_{11} , α_{12} , α_{21} , α_{22} , β_{11} , β_{12} , and β_{13} represent coefficients associated with microorganism proliferation. T_0 , T_1 , and T_2 are temperature thresholds corresponding to different microorganism types. G_{st}^{AD} reflects the temperature-dependent microorganism population and its activity, influencing the hourly biogas production rate. S_0 indicates the concentration of volatile solids in the substrate. B_0 represents the methane production potential of microorganisms. V_{AD} is the volume of the anaerobic digester. t_{HRT} is the hydraulic retention time of the fermentation liquid. and T_t^{dig} denotes the fermentation temperature at time t .

3.1.2. Gas Storage Tank Model

The mathematical formulation of the gas storage tank is given as follows [29].

$$G_t^{gs} = G_{t-1}^{gs} \eta_h^{los} + G_t^{gs,in} \eta_h^{in} - \frac{G_t^{gs,out}}{\eta_h^{out}} \quad (4)$$

where G_t^{gs} represents the amount of biogas in the gas storage tank during time period t . $G_t^{gs,in}$ and $G_t^{gs,out}$ denote the inflow and outflow rates of biogas in the gas storage tank during time period t , respectively. η_h^{los} represents the self-consumption rate of the gas storage tank. η_h^{in} and η_h^{out} denote the conversion efficiencies during biogas inflow and outflow processes, respectively.

3.1.3. Anaerobic Digestion Heat Model

Before the material enters the anaerobic digestion device, it needs to be heated to the fermentation temperature. The required heat is modeled as follows.

$$H_t^{base} = c_{bio} M_{bio} (T_t^{dig} - T_t^{mas}) (1 - \eta_H) \quad (5)$$

where H_t^{base} represents the heat consumed for material pretreatment during time period t . c_{bio} denotes the specific heat capacity of the material. T_t^{mas} is the temperature of the material entering the digester, which is approximately equal to the ambient temperature. T_t^{dig} is the anaerobic digestion temperature. M_{bio} represents the mass of the material. η_H is the heat exchange efficiency.

When the fermentation temperature changes, the total heat change model for the material inside the digester is expressed as follows.

$$H_t^{flc} = c_{bio} M_{sum}^{bio} (T_{t+1}^{dig} - T_t^{dig}) \quad (6)$$

where M_{sum}^{bio} represents the total mass of material inside the digester. H_t^{flc} denotes the heat required to account for the temperature changes of the material. Due to the large volume of the digester and the fact that the thickness of each layer of the walls is much smaller than the diameter of the tank, the heat transfer processes at the top and bottom of the tank can be simplified as typical one-dimensional steady-state heat conduction problems [30]. The volume of the digester is significantly larger than the wall thickness, and heat transfer primarily occurs in the radial direction. Therefore, approximating the process as one-dimensional conduction effectively simplifies the analysis while maintaining computational efficiency. According to Ref. [30], similar assumptions have been successfully

applied in heat transfer analysis for comparable equipment, providing sufficient accuracy to describe the overall heat transfer process. The sidewalls can be abstracted as a multi-layer cylindrical wall heat transfer problem. The heat loss from the digester body consists of three components: the top, the walls, and the bottom of the tank. The heat transfer model for the digester is expressed as

$$H_t^{\text{los}} = H_t + H_m + H_b = \sum K_i S_i (T_t^{\text{dig}} - T_t^{\text{air}}) \quad (7)$$

$$T_t^{\text{min}} \leq T_t^{\text{dig}} \leq T_t^{\text{max}} \quad (8)$$

where K_i refers to the comprehensive heat transfer coefficient for the top, walls, and bottom of the tank. It is determined by the heat transfer coefficient between the inner surface of the digester and the external environment as well as the thermal conductivity of the tank walls. S_i denotes the heat transfer surface area of each component. T_t^{air} represents the temperature of the external environment at each component. H_t^{los} is the total heat loss from the digester to the external environment during time period t . H_t refers to the heat loss through the top of the tank to the external environment. H_m represents the heat loss through the walls of the tank to the external environment. H_b denotes the heat loss through the bottom of the tank to the external environment. T_t^{max} and T_t^{min} are the upper and lower limits of fermentation temperature, respectively.

3.2. Energy Units

3.2.1. PV Model

The model for distributed PV generation equipment is as follows:

$$P_t^{\text{PV}} = \begin{cases} P_{\text{max}}^{\text{PV}} \frac{I_t^{\text{D}}}{I_{\text{test}}^{\text{PV}}}, & I_t^{\text{D}} \leq I_{\text{test}}^{\text{PV}} \\ P_{\text{max}}^{\text{PV}}, & I_t^{\text{D}} > I_{\text{test}}^{\text{PV}} \end{cases} \quad (9)$$

where P_t^{PV} represents the active power output of the PV system during time period t . I_t^{D} denotes the solar radiation intensity reaching the ground during time period t . $I_{\text{test}}^{\text{PV}}$ refers to the solar radiation intensity under standard test conditions when the PV system outputs electrical power. $P_{\text{max}}^{\text{PV}}$ represents the maximum power of the PV system.

3.2.2. Biogas Generator Unit

The biogas power generation model is as follows:

$$P_t^{\text{BG}} = L_{\text{HV}} G_t^{\text{BG}} \eta_{\text{BG}} \quad (10)$$

where P_t^{BG} represents the power output of the biogas generator. L_{HV} denotes the lower heating value of biogas, which is set to 23.86 MJ/m³. G_t^{BG} represents the volume of biogas consumed by the gas engine. η_{BG} is the electric-to-thermal conversion efficiency of the biogas generator, which is set to 35%.

The waste heat recovery device model is as follows:

$$H_t^{\text{HR}} = P_t^{\text{BG}} \eta_{\text{R}} \quad (11)$$

where H_t^{HR} represents the heat recovery rate. η_{R} denotes the heat recovery efficiency, which is set to 28%.

3.2.3. Air Source Heat Pump

The relationship between the heating power and electric power of the air source heat pump is expressed as

$$H_t^{\text{HP}} = \eta_{\text{HP}} P_t^{\text{HP}} \quad (12)$$

where H_t^{HP} represents the heating power produced by the heat pump during time period t . P_t^{HP} denotes the electric power consumed by the heat pump during time period t . η_{HP} is the operational efficiency of the heat pump.

3.2.4. Min–Max Constraint

$$\begin{cases} P_x^{\min} \leq P_{x,t} \leq P_x^{\max} \\ P_x^{\text{down}} \leq P_{x,t} - P_{x,t-1} \leq P_x^{\text{up}} \end{cases} \quad (13)$$

where $P_{x,t}$ represents the power output of device x at time t . $P_x^{\max}$ and $P_x^{\min}$ are the upper and lower limits of the power output of device x , respectively. P_x^{up} and P_x^{down} are the upper and lower limits of the ramping rate of device x , respectively.

3.3. Cost Function

This study focuses on optimizing the operation of rural integrated energy systems to minimize operating costs and carbon emissions while maintaining energy balance. The research is based on a real-world agricultural enterprise that has already installed photovoltaic systems and biomass facilities with the associated capital costs fully accounted for. As a result, the study specifically targets the operational phase, aiming to improve the efficiency of existing infrastructure. Investment and capital cost considerations, while critical for system design and planning, are beyond the scope of this work. Future research could expand on this framework to incorporate long-term planning and infrastructure development. The cost function of rural IES microgrids is given as follows [31].

$$C_i^{\text{MG}} = C_i^{\text{buy}} + C_i^{\text{sys}} + C_i^{\text{CO2}} - C_i^{\text{sell}} + C_i^{\text{trans}} + C_i^{\text{P2P}} \quad (14)$$

where C_i^{MG} represents the total operating cost of the i th microgrid. C_i^{buy} denotes the system's energy purchase cost. C_i^{sys} is the system's operation and maintenance cost. C_i^{CO2} represents the carbon emission cost. C_i^{sell} denotes the profit from selling electricity to the external grid. C_i^{trans} is the electricity transmission cost between microgrids. C_i^{P2P} represents the electricity trading cost between microgrids.

The system's electricity purchasing cost refers to the cost incurred for purchasing electricity from the upper-level grid.

$$C_i^{\text{buy}} = \sum_{t=1}^T c_{i,t}^{\text{grid,e}} P_{i,t}^{\text{grid}} \quad (15)$$

where $c_{i,t}^{\text{grid,e}}$ is the power purchase price.

The system operation and maintenance cost refers to the cost associated with the operation and maintenance of the equipment in the system:

$$C_i^{\text{sys}} = \sum_{t=1}^T \sum_{x \in V} c_{sd,x} P_{i,x,t} \quad (16)$$

where $c_{sd,x}$ represents the unit operation and maintenance cost of device x . $P_{i,x,t}$ denotes the power output of device x . V is the set of devices, $V = \{\text{PV}, \text{CHP}, \text{GS}, \text{HP}\}$ where

PV represents photovoltaic systems, CHP represents combined heat and power units, GS represents gas storage tanks, and HP represents heat pumps.

The profit from selling electricity to the external grid is the revenue generated from selling surplus electricity from each microgrid to the upper-level grid:

$$C_i^{\text{sell}} = \sum_{t=1}^T c_{i,t}^e P_{i,t}^e \quad (17)$$

where $c_{i,t}^e$ is the energy purchase price from the upper-level grid and $P_{i,t}^e$ is the trading quantity.

The electricity transmission between microgrids requires the payment of a network usage fee. The electricity transmission cost is

$$C_i^{\text{tran}} = \sum_{t=1}^T \sum_{\substack{i,j \in J \\ i \neq j}} a_e P_{ij,t}^{\text{P2P}} \quad (18)$$

where a_e represents the transmission price per unit of electricity. J is the set of microgrids. $P_{ij,t}^{\text{P2P}}$ denotes the transaction electricity quantity between microgrid i and microgrid j during time period t . $P_{ij,t}^{\text{P2P}} > 0$ represents the electricity purchased by microgrid i from microgrid j . $P_{ij,t}^{\text{P2P}} < 0$ represents the electricity sold by microgrid i to microgrid j .

The energy trading cost between the microgrids is as follows.

$$C_i^{\text{P2P}} = \sum_{t=1}^T \sum_{\substack{i,j \in J \\ i \neq j}} r_{ij,t}^{\text{P2P}} P_{ij,t}^{\text{P2P}} \quad (19)$$

where $r_{ij,t}^{\text{P2P}}$ is the P2P energy trading price.

3.4. Carbon Trading

In this study, carbon trading does not occur directly between microgrids. Instead, it serves as an external mechanism to incentivize cleaner energy usage within each microgrid. By enabling microgrids to offset emissions via purchased quotas, carbon trading promotes the adoption of renewable energy and improves the overall energy structure.

Under the carbon trading mechanism, carbon emissions are treated as a tradable commodity. If the system's actual carbon emissions are less than the initial carbon emission quota, the excess quotas can be sold in the carbon trading market to generate profit. Conversely, if emissions exceed the quota, additional carbon quotas must be purchased. This paper adopts the free allocation method widely implemented in China and provides the system with carbon emission quotas based on the baseline method [32]. The model for the initial carbon quota is

$$\begin{cases} E_C = E_{EP} + E_{GT} \\ E_{EP} = \alpha \sum_{t=1}^T P_t^{\text{grid}} \\ E_{GT} = \beta \sum_{t=1}^T (\beta_{e,h} P_t^{\text{BG}} + H_t^{\text{HR}}) \end{cases} \quad (20)$$

where E_C , E_{EP} , and E_{GT} represent the carbon quotas for the IESs, the upper-level grid thermal power generation units, and the biogas power generation units, respectively. α denotes the carbon quota per unit of electricity generation. P_t^{grid} represents the electricity purchase

quantity during time period t . β denotes the carbon quota per unit of heat generation. $\beta_{e,h}$ is the electricity-to-heat power conversion parameter. T is the scheduling period.

The actual carbon emissions include the carbon emissions from coal-fired power generation units purchased from the upper-level grid, the carbon emissions from biogas power generation units, and the carbon emissions during the biogas production process. The specific model is

$$\begin{cases} E_{C,P} = E_{EP,P} + E_{CT,P} \\ E_{EP,P} = \sum_{t=1}^T (a_1 + b_1 P_t^{\text{grid}} + c_1 P_t^{\text{grid}^2}) \\ E_{GT,P} = \sum_{t=1}^T (a_2 + b_2 P_t^{\text{BG}} + c_2 P_t^{\text{BG}^2}) \end{cases} \quad (21)$$

where $E_{C,P}$ represents the actual carbon emissions of the IESs. $E_{EP,P}$ denotes the actual carbon emissions from electricity purchased from the upper-level grid. $E_{CT,P}$ represents the actual carbon emissions from the biogas power generation unit. a_1, b_1, c_1 are the calculated generation parameters for the coal-fired power generation units from the upper-level grid. a_2, b_2 , and c_2 are the calculated parameters for the biogas power generation units. The total traded carbon emission and carbon emission cost are given as

$$E_{C,t} = E_{C,P} - E_C \quad (22)$$

$$C^{\text{CO}_2} = \sigma_C E_{C,t} \quad (23)$$

where $E_{C,t}$ is the total traded carbon emission and σ_C is the emission penalty cost.

3.5. Power Balance

The energy exchange and power balance of all the microgrids are as follows.

$$P_{i,t}^{\text{grid}} + P_{i,t}^{\text{PV}} + P_{i,t}^{\text{BG}} = P_{i,t}^{\text{HP}} + P_{i,t}^{\text{load}} + P_{i,t}^e \quad (24)$$

$$H_{i,t}^{\text{HR}} + H_{i,t}^{\text{HP}} = H_{i,t}^{\text{los}} + H_{i,t}^{\text{base}} + H_{i,t}^{\text{flc}} \quad (25)$$

$$G_{i,t}^{\text{AD}} + G_{i,t}^{\text{gs,out}} = G_{i,t}^{\text{BG}} + G_{i,t}^{\text{gs,in}} \quad (26)$$

$$\begin{cases} \sum_{i \in J} P_{i,t}^{\text{P2P}} = 0, \forall t \\ \sum_{i \in J} u_{i,t}^{\text{P2P}} = 0, \forall t \end{cases} \quad (27)$$

where $P_{i,t}^{\text{load}}$ is the power demand and $P_{i,t}^{\text{P2P}}$ is the total trading quantity. $u_{i,t}^{\text{P2P}}$ represents the total energy trading cost of the microgrid i at t hour

4. Methodology

This section presents a cooperative game-based framework for low-carbon dispatch in rural multi-regional IESs. The methodology combines a Nash bargaining model, carbon trading mechanisms, and a distributed optimization approach using the Alternating Direction Method of Multipliers (ADMM). This integration enables dynamic energy trading, fair profit distribution, and adaptive operation while preserving stakeholder privacy. The following subsections detail the cooperative game formulation, problem reformulation, and ADMM-based solution.

4.1. Cooperative Game Model

4.1.1. Nash Bargaining Model

In this study, each microgrid aims to reduce its own costs and maximize its own benefits through cooperation. To achieve this, a cooperative game model needs to be introduced. This paper establishes a cooperative game model based on Nash bargaining for multi-regional energy systems. After achieving the maximization of collective benefits for all participants, the cooperative profits are then distributed among the multiple participants [33]. The standard Nash bargaining model is shown in Equation (28), where the solution that maximizes the Nash product is the equilibrium solution to the Nash bargaining game.

$$\begin{cases} \max & \prod_{i \in J} (U_i - U_i^0) \\ \text{s.t.} & U_i \geq U_i^0 \end{cases} \quad (28)$$

where U_i represents the benefit of the negotiation agent. U_i^0 denotes the benefit of the participant before cooperation, i.e., the negotiation breakdown point. The Nash bargaining model in Equation (28) is a multivariable coupled non-convex nonlinear problem. Therefore, the above model is decomposed into two subproblems—the system's overall cost minimization subproblem and the profit distribution subproblem, which are solved sequentially.

4.1.2. Model Reformulation

The total system cost is the sum of the energy costs of each microgrid. The multi-microgrid electricity cooperation and sharing model based on the Nash bargaining theory is formulated as follows:

$$\begin{cases} \min \prod_{i \in J} [C_i^{\text{MG}}(P_{i,t}^{\text{P2P}})] \\ \text{s.t.} (1)-(27) \end{cases} \quad (29)$$

The interaction power between the microgrids in the system, denoted as $P_{ij,t}^{\text{P2P}}$ and $P_{ji,t}^{\text{P2P}}$, are treated as coupling variables, and they are constrained by the condition $P_{ij,t}^{\text{P2P}} + P_{ji,t}^{\text{P2P}} = 0$. This means that electricity sharing between microgrids only occurs when the expected electricity trading volume between the microgrids is consistent.

4.1.3. Profit Allocation Reformulation

The optimal interaction power obtained from the system's overall cost minimization subproblem is substituted into the profit distribution subproblem. The multi-microgrid profit distribution model based on the Nash bargaining model in Equation (28) is formulated as follows:

$$\begin{cases} \max \prod_{i \in J} (C_i^0 - C_i^{\text{MG}} + C_i^{\text{P2P}}) \\ \text{s.t.} (19), (27) \\ C_i^0 - C_i^{\text{MG}} + C_i^{\text{P2P}} > 0 \end{cases} \quad (30)$$

where C_i^0 represents the cost of microgrid i before participating in electricity sharing. Since the natural logarithm is a strictly monotonically increasing convex function, by taking the logarithm of Equation (30), the problem of maximizing the objective function can be transformed into a problem of minimizing the objective function, which is easier to solve as follows.

$$\max \prod_{i \in J} (-\ln(C_i^0 - C_i^{\text{MG}} + C_i^{\text{P2P}})) \quad (31)$$

4.2. ADMM-Based Energy Trading Algorithm

To effectively address the challenges of economic low-carbon operation and low energy utilization efficiency in rural incorporating biomass energy, this paper proposes a

Alternating Direction Method of Multipliers (ADMM)-based energy trading algorithm. This strategy employs distributed optimization to achieve cost minimization and balance decision making among multiple stakeholders while protecting the privacy of each microgrid. The following algorithm introduces an augmented Lagrangian function to decompose the system's overall cost minimization problem into subproblems, which are iteratively solved to dynamically adjust power transactions and optimize the operational benefits of the microgrids. The specific steps are as follows:

(1) Establish the augmented Lagrangian function for the system's overall cost minimization subproblem.

$$L_i^{P1} = C_i^{\text{MG}} + \sum_{j \in J} \sum_{t=1}^T \lambda_{ij}^{P1} (P_{ij,t}^{P2P} + P_{ji,t}^{P2P}) + \frac{\rho_j^{P1}}{2} \|P_{ij,t}^{P2P} + P_{ji,t}^{P2P}\|_2^2 \quad (32)$$

where L_i^{P1} is the form of the augmented Lagrangian function. λ_{ij}^{P1} is the Lagrange multiplier. ρ_j^{P1} is the penalty parameter, which is set as 1×10^{-4} .

(2) Each microgrid updates its own transaction power strategy through local computation. Microgrids only exchange transaction power information with each other. Let k represent the iteration count. In each iteration, the following steps are executed:

Microgrid i updates its decision through Equation (33):

$$P_{ij,t}^{P2P}(k+1) = \operatorname{argmin} L_i^{P1}(\lambda_{ij}^{P1}(k), P_{ij,t}^{P2P}(k), P_{ji,t}^{P2P}(k)) \quad (33)$$

The other microgrid j receives the updated decision information to update its own decision:

$$P_{ji,t}^{P2P}(k+1) = \operatorname{argmin} L_j^{P1}(\lambda_{ji}^{P1}(k), P_{ij,t}^{P2P}(k+1), P_{ji,t}^{P2P}(k)) \quad (34)$$

Repeat the calculation of Equations (33) and (34) until each microgrid updates its transaction power strategy during the current iteration.

(3) After one iteration, update the Lagrange multiplier according to the following rule:

$$\lambda_{ij}^{P1}(k+1) = \lambda_{ij}^{P1}(k) + \rho_i^{P1} (P_{ij,t}^{P2P} + P_{ji,t}^{P2P}) \quad (35)$$

(4) Update the iteration count: $k = k + 1$.

(5) Check the convergence of the algorithm:

$$\sum_{j \in J} \sum_{t=1}^T \|P_{ij,t}^{P2P}(k+1) - P_{ij,t}^{P2P}(k)\|_2 \leq \delta_1 \quad (36)$$

where δ_1 is the convergence tolerance of the algorithm. If Equation (36) is satisfied, the iteration stops. Otherwise, return to step (2) and enter the next iteration until the convergence condition is met or the maximum iteration count is reached. The detailed procedure of the algorithm is shown as follows. The revenue distribution subproblem can also be solved by ADMM distributedly. The steps are as above in the Figure 2 and will not be repeated here.

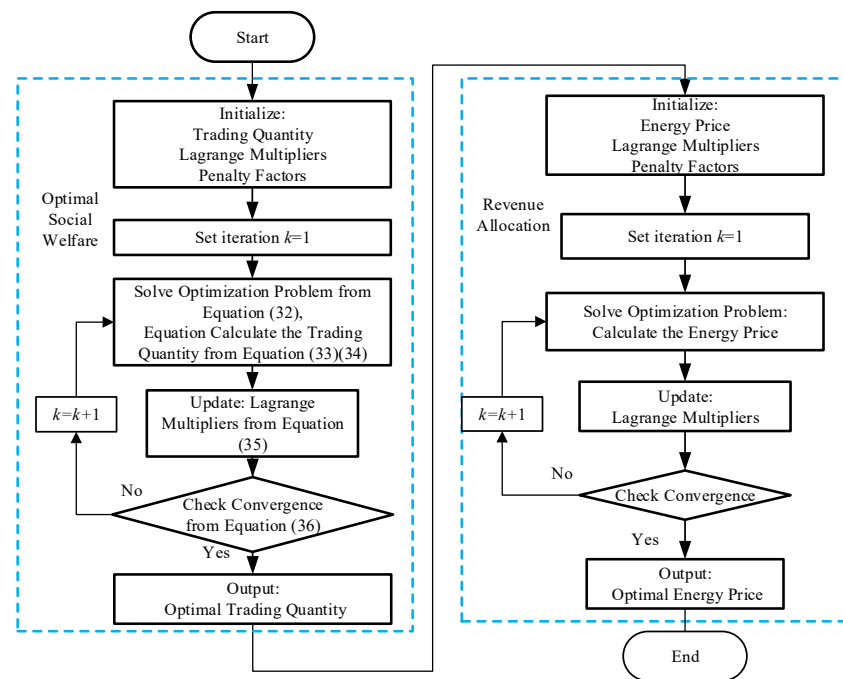


Figure 2. The proposed ADMM-based energy trading algorithm.

5. Case Studies and Results

In this paper, we take a real farm enterprise, which is configured with only photovoltaic and biomass clean energy sources, and consider the problem of sharing and interacting electrical energy among three micro-integrated energy systems (IESs). A farm IES is constructed, consisting of three microgrids (Microgrid 1 for fisheries, Microgrid 2 for crop cultivation, and Microgrid 3 for livestock farming). Four typical days in spring, summer, autumn, and winter are selected for the analysis. The load profiles for typical days in different seasons for the three microgrids are shown in Appendix A. Simulations are conducted on an Intel I7-9700K CPU with 16 GB of memory. The simulation program is developed in MATLAB R2023b and solved using the Gurobi 11.0.1 solver. The value of δ_1 is 0.01.

To verify the effectiveness of the proposed strategy, a comparison is made between the joint operation method presented in this paper and the traditional operation method. In the traditional operation mode, the energy systems in each region operate independently with no electricity interaction. Four scenarios are set based on whether the carbon trading mechanism is considered, as shown in Table 1.

Table 1. Scenario settings.

Scenarios	Cooperative Game	Carbon Emission Trading
1	×	×
2	×	✓
3	✓	×
4	✓	✓

5.1. Energy Trading Result

The energy interaction results between the microgrids are shown in Figure 3. From 10:00 to 17:00 each day, the load of Microgrid 1 is small, and after meeting its own load, the photovoltaic generation still has surplus. During this time, the transaction electricity prices between Microgrid 1 and Microgrids 2 and 3 are higher than the selling price to the upper-level grid but lower than the purchasing price from the upper-level grid.

Therefore, Microgrid 1 transmits energy to Microgrids 2 and 3, which not only increases its own revenue but also reduces the purchasing cost for Microgrids 2 and 3. From 17:00 to 22:00, the purchasing price peaks, and photovoltaic generation is unavailable. Microgrid 3 generates electricity by burning biogas from its storage tank, with the excess energy being transmitted to Microgrids 1 and 2, which cannot generate electricity at night. During this time, the transaction prices between the three microgrids are all between the purchasing and selling prices of the upper-level grid. Therefore, Microgrid 3 significantly reduces its operational cost by selling electricity to other microgrids, while Microgrids 1 and 2 can also reduce their purchasing costs.

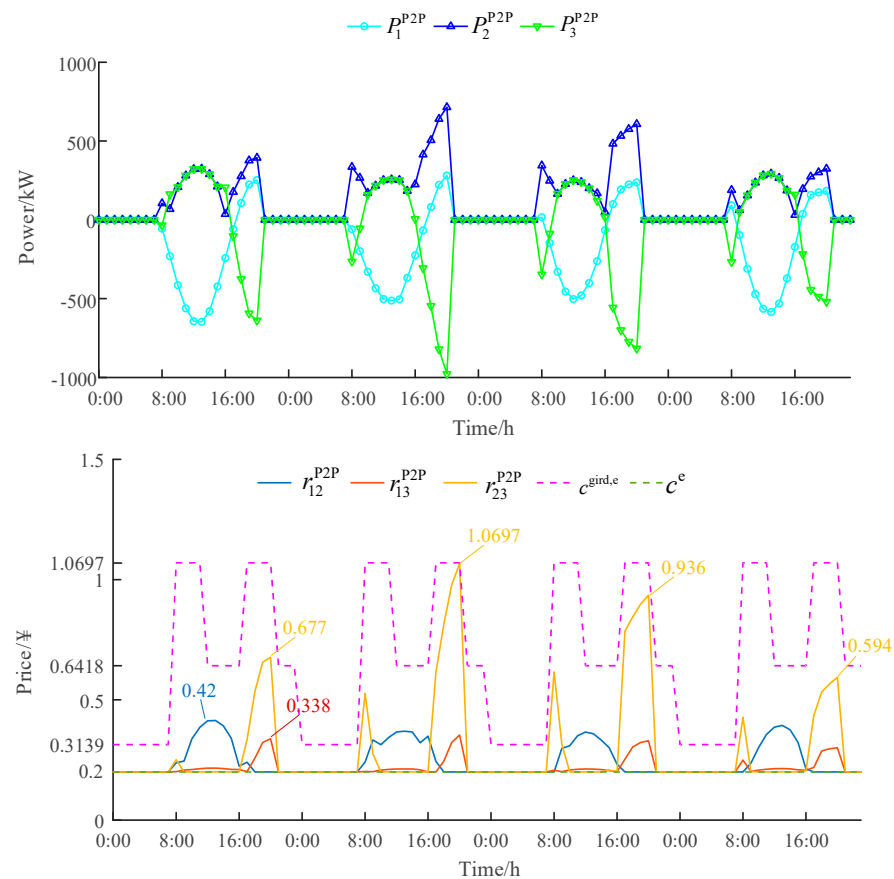


Figure 3. Optimization results of inter-microgrid power interactions and trading tariffs.

Taking Microgrid 3 as an example, Figure 4 shows the internal energy optimization results of Microgrid 3 for different typical days. From 00:00 to 08:00 and 22:00 to 24:00, the purchasing electricity price is at a low point, and the microgrid prefers to purchase electricity from the upper-level grid. From 08:00 to 17:00, the photovoltaic generation of Microgrids 1 and 2 exceeds their load, so Microgrid 3's surplus photovoltaic energy is sold to the upper-level grid. During this time, the transaction electricity price between Microgrid 3 and Microgrid 1 is relatively low, so Microgrid 3 buys some electricity from Microgrid 1. From 17:00 to 22:00, both the microgrid transaction price and the purchasing price are high. Microgrid 3's biogas power generation unit mainly operates during this time with excess energy transmitted to Microgrids 1 and 2. Throughout the entire operation cycle, the heat pump operates mainly from 00:00 to 17:00 and 22:00 to 24:00, primarily because these periods correspond to the low electricity price and high photovoltaic generation phases, which help reduce operating costs and improve photovoltaic consumption. From 17:00 to 22:00, the biogas heating unit generates heat for the heating load and fermentation temperature rise.

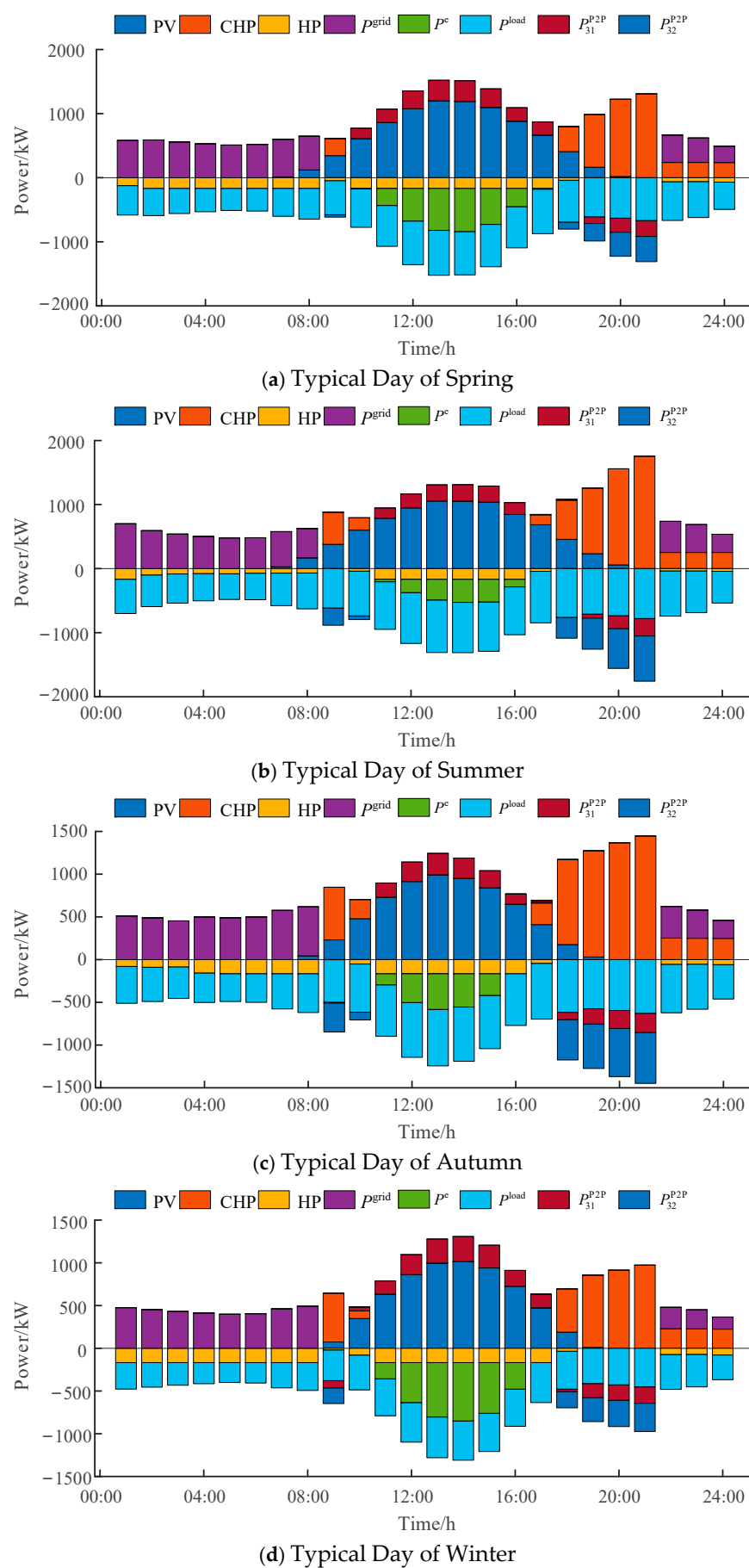


Figure 4. Results of power optimization within Microgrid 3.

5.2. Impact of Carbon Emissions

Table 2 shows the carbon emissions under four different operation scenarios. According to the calculations, under distributed operation, the carbon emissions only decrease by 0.3% after introducing the carbon trading mechanism. This is because under distributed operation, the scheduling space is limited due to the internal equipment constraints of each microgrid. However, under combined operation, carbon emissions decrease by 4.3% after introducing the carbon trading mechanism. Compared to distributed operation, the carbon emissions under the combined operation mode are reduced by 7.5%. This indicates that adopting the combined operation mode can help each microgrid reduce electricity purchases, thereby lowering carbon emissions. Additionally, combined operation increases the resource scheduling space of the entire energy system, and when paired with the carbon trading mechanism, it can effectively reduce carbon emissions.

Table 2. Carbon emissions from microgrids under different scenarios.

Scenario	Microgrid 1 Carbon Emission (kg)	Microgrid 2 Carbon Emission (kg)	Microgrid 3 Carbon Emission (kg)	Total Carbon Emission (kg)
1	2737.1	7484.77	13,682.60	23,904.47
2	2737.08	7484.77	13,611.65	23,833.5
3	2008.03	4819.24	16,279.94	23,107.22
4	2008.03	4783.83	15,316.17	22,108.05

5.3. Comparison of Operation Strategy

Table 3 shows the total cost under four different operation scenarios. Compared to Scenario 1, the total system operating cost in Scenario 3 decreases by 16.9%, with each microgrid's operating cost reducing by approximately 1000 yuan, and Microgrid 3 also achieving a small profit. Compared to Scenario 2, when considering the carbon trading mechanism, the total system operating cost in Scenario 4 decreases by 32.0%, which is a significantly higher reduction than the case without considering the carbon trading mechanism. The main reason for this is that after considering the carbon trading mechanism, the overall operating cost increases significantly, while the combined operation mode reduces the purchase of electricity from the upper-level grid by each microgrid, thus lowering carbon emission costs.

Table 3. Operational costs in different scenarios.

Scenario	Microgrid 1 Cost (¥)	Microgrid 2 Cost (¥)	Microgrid 3 Cost (¥)	Total Cost (¥)
1	3484.43	16,729.31	736.75	20,950.49
2	4168.70	18,600.51	8402.73	31,171.94
3	2315.72	15,526.19	−431.21	17,410.7
4	1291.98	14,505.06	5398.03	21,195.07

6. Conclusions

To address the issues of economic low-carbon operation and low energy utilization efficiency in rural integrated energy systems (IESs) that incorporate biomass energy, this paper proposes a combined operation strategy for rural multi-energy systems, achieving a balanced decision-making process for multiple stakeholders. The ADMM (Alternating Direction Method of Multipliers) is used for distributed solving.

Key contributions of this work include the following:

(1) Under the combined operation mode, energy interactions between regions are more flexible, and the operating costs of each microgrid are effectively reduced. This approach significantly increases the local consumption rate of renewable energy and improves the overall energy utilization efficiency.

(2) ADMM exhibits good convergence and convergence accuracy, ensuring fair and reasonable benefit distribution among all stakeholders. During the solving process, only limited information is exchanged, effectively protecting the privacy of each stakeholder.

(3) The carbon trading mechanism and the electricity exchange mechanism between microgrids encourage the utilization of renewable energy, reduce electricity purchases from the upper-level grid, and effectively lower carbon emissions during the operation of the microgrids, achieving low-carbon operation.

This study provides a cooperative game-based optimization framework for rural integrated energy systems focusing on photovoltaic and biomass resources. Future research could explore (1) incorporating additional renewable energy sources, such as wind power, to adapt the model to regions with diverse energy profiles; (2) addressing uncertainties in energy supply and demand using stochastic or robust optimization methods; and (3) analyzing the impact of advanced carbon trading mechanisms, such as dynamic or hierarchical systems, to further enhance economic and environmental performance.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: Author Peiran Liang was employed by China Energy Engineering Group ShanXi Electric Power Engineering Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

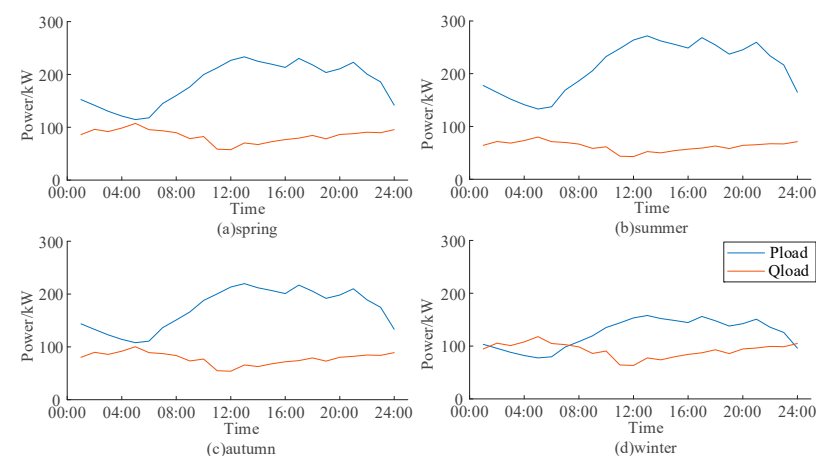


Figure A1. Load profiles of electricity and heat in Microgrid 1.

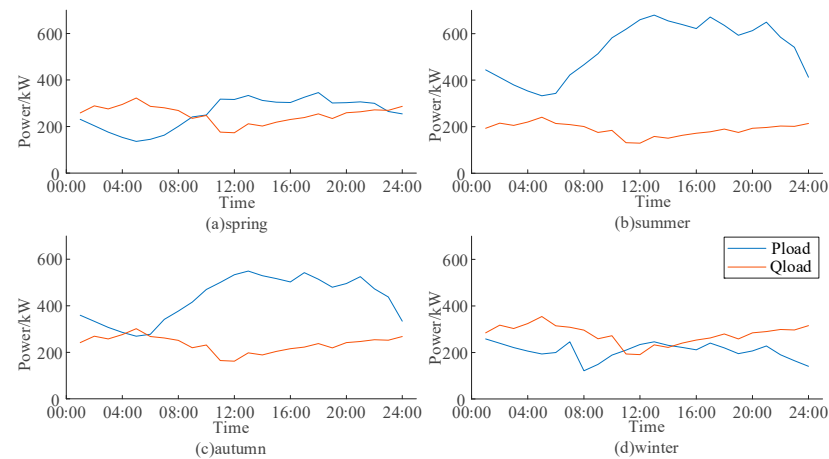


Figure A2. Load profiles of electricity and heat in Microgrid 2.

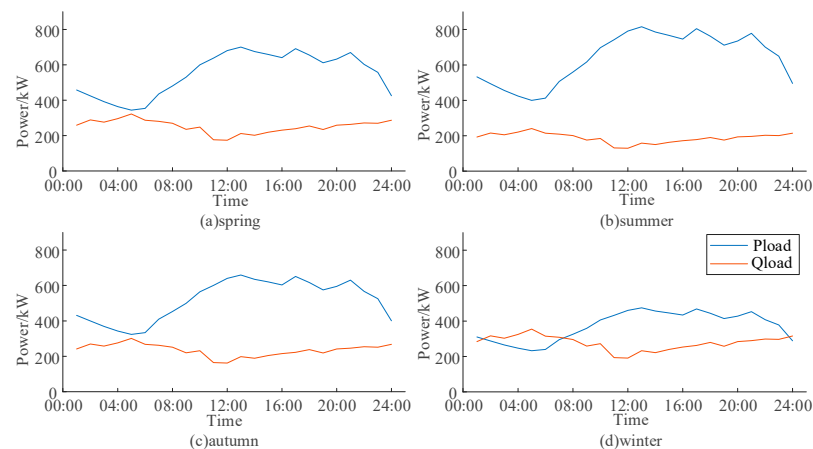


Figure A3. Load profiles of electricity and heat in Microgrid 3.

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