Optimal Operation of Multi-energy Microgrids: A Hybrid Methodology Using Stochastic Programming and Generalized Nash Bargaining

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***Abstract*—With the increasing penetration of distributed energy resources (DERs) in the power system, the microgrid (MG) as a relatively independent system has been widely used and developed. The MG can smooth the output fluctuation of renewables through the interaction of the main grid, renewables, loads, and energy storage systems, which is conducive to friendly access and local consumption of renewables. The interconnection of adjacent MGs to form a MG cluster system can effectively improve the reliability, economy, and low carbon of the system. In order to optimize the operation of the whole MG alliance and distribute the benefits reasonably among MGs, based on stochastic programming and generalized Nash bargaining (GNB) theory, an optimal cooperative operation model of the multi-agent multi-energy MG system considering uncertainty and carbon trading is proposed in this paper. First, carbon capture systems (CCSs) and power-to-gas (P2G) devices are integrated into traditional combined heat and power (CHP) units. Second, using statistical programming to deal with uncertainty, the optimal operation model of the MG alliance is established. The model is decomposed into two subproblems: the social welfare maximization subproblem and the energy trading payment bargaining subproblem. Finally, to protect the privacy of each agent, two algorithms for solving the subproblems are proposed based on the alternating direction method of multipliers (ADMM). The asymmetric bargaining quantifying contributions is employed to achieve fair distribution of benefits. The effectiveness, superiority, and scalability of the proposed model is verified through case studies.**

***Index Terms*—Alternating direction method of multipliers, carbon capture systems, microgrids, Nash bargaining, renewables, statistical programming.**

I. Introduction

A. Research Motivation

WITH the high attention of the world to energy conservation, emission reduction, and climate issues, renewable energy generation has been attached great importance. It is imperative to build energy systems with renewables as the main body. The grid-connection and absorption of the high penetration of renewables has become an important issue of scientific research. As an important supplement to traditional forms of power generation, renewable generation such as photovoltaic (PV) and wind generation has problems such as low energy density and resource constraints. As a relatively independent system, the multi-energy microgrid (MG) has distributed energy resources (DERs) and other devices. The multi-energy MG has the characteristics of flexible operation and high reliability, which are conducive to the friendly access and effective local consumption of renewables. Furthermore, the multi-energy MG can improve the efficiency and cleanliness of terminal energy consumption, and is an important means to achieve the low-carbon and sustainable development of energy.

However, due to limitations in the current measurement and control technology, the energy storage level and power supply capacity of the multi-energy MG are limited, resulting in the operation of the MG still showing low inertia and weak anti-disturbance ability. Therefore, it is necessary to form a multi-energy MG system [1]–[3] by interconnecting several geographically adjacent MGs in a local distribution area. The autonomous management of each MG and the mutual aid between MGs realize the coordination and complementarity of power generation resources, and improve the consumption rate of renewables. MGs also make the power system obtain better stability and reliability, and improve the energy utilization efficiency. Peer-to-peer (P2P) energy trading between multi-energy MGs can effectively enhance the economy of MG, and reduce carbon emissions [4]. However, because each MG belongs to different stakeholders, the interest interaction among multiple MGs and the complex coupling of multi-energy flow make the traditional scheduling method of a single MG difficult to apply to the scheduling of MGs.

Uncertainty is ubiquitous in the power system, and we should deal with it seriously. Because the uncertainties of loads and the output of renewables such as PV and wind generation can greatly affect the control and decision-making of power systems, we must consider these uncertainties in the operation and planning of multi-energy MGs in order to make our results more reasonable and close to the actual situation.

Therefore, it is necessary to study the optimal operation and reasonable benefit distribution of the multi-energy MG alliance considering uncertainty, which has important theoretical and practical significance.

B. Literature Review

Generally speaking, there are two kinds of energy management methods for MGs: centralized and distributed methods. In the centralized energy management method, the dispatch center collects the global information and completes the processing of massive data to issue instructions. The fault of the dispatch center will cause the whole system to break down. With the expansion of the system scale, higher requirements are put forward for communication and computing power, and there are information barriers between stakeholders. The centralized mode (point-to-multipoint) may lead to problems such as excessive communication burden and privacy exposure. In contrast, distributed optimization iteratively solves the whole problem by splitting the whole problem into several coupled subproblems, and each agent solves its own subproblem independently and exchanges limited information through local communication. This can well protect the privacy of participants, reduce computing and communication costs, avoid the huge impact of the failure of the dispatch center on the whole, and have better flexibility, scalability and reliability. Reference [5] proposed a approach based on consensus to solve the distributed optimization of the operating cost of MGs. In [6], a distributed algorithm without initialization was presented, and an event triggering mechanism is introduced to realize day-ahead and real-time collaborative energy management of multi-agent integrated energy systems. Reference [7] adopted a distributed hierarchical scheme for the energy management of MGs.

Compared with the above methods, the alternating direction method of multipliers (ADMM) has been widely used because of its flexibility, good convergence, and simple framework. The ADMM is very suitable for large-scale distributed computing. Instead of the centralized calculation of MG information, each MG solves its own objective function, and then updates and iterates the multiplier. The ADMM-based method satisfies the minimum operating cost of each MG and achieves the energy balance of the entire system. At the same time, the ADMM also protects the privacy of the agent. The ADMM based on consensus variables was used to realize the optimal dispatch solution to the integrated community energy system in [8]. Reference [9] proposed an ADMM-based decentralized energy management approach with the past information from distributed energy resources (DERs). Reference [10] established robust scheduling of MGs, but it fails to ensure the reasonable distribution of benefits among MGs. The main methods of benefit distribution include the Shapley method and Nash bargaining [11], but the computational efficiency is low when Shapley is used to solve the problems with many participants. Many models such as [10] resolved the benefit distribution among MGs by centralized methods, which violate the privacy of the agent; many references such as [11] did not consider the uncertainties of renewables and loads, the emission reduction potential, and the improvement of renewable consumption rates.

From the above statement, it can be seen that despite certain research achievements on the optimal operation of MGs, the following problems still exist: 1) the benefit of the MG alliance has not been reasonably distributed, 2) the privacy of each agent has not been well protected, 3) the uncertainty has not been well considered, and 4) the potential of the emission reduction and the improvement of renewable consumption rates have not been well paid attention to.

C. Contributions

In order to fill the gaps mentioned in Section I-B, this paper addresses the optimal operation problem of multi-energy MGs based on stochastic programming and generalized Nash bargaining (GNB). Specifically, the main contributions of this paper are as follows.

1) Carbon capture systems (CCSs) and power-to-gas (P2G) devices are integrated into combined heat and power (CHP) units to reduce CO_2 emissions and enhance energy efficiency.
2) An optimal operation model of multi-energy MGs is proposed based on stochastic programming and GNB.
3) Two ADMM-based algorithms are proposed to protect the privacy of each MG, and benefits are distributed fairly based on asymmetric bargaining.
4) The superiority and effectiveness of the proposed model and algorithms are verified by case studies.

D. Organization of this Paper

The rest of the paper is organized as follows. Section II elaborates the energy sharing framework and model of multi-energy MGs. In Section III, we propose the optimal operation and benefit distribution methodologies. Section IV validates the proposed model and methods. Section V concludes the paper, and gives the future work.

II. The Energy Sharing Framework and Model of Multi-energy MGs

A. The Energy Sharing Framework of Multi-energy MGs

The energy sharing framework of networked multi-energy MGs is shown in Fig. 1 (taking the interconnection of three MGs as an example), where the structure of each multi-energy MG is shown in Fig. 2. The main equipment of the multi-energy MG includes CHP with CCSs and P2G [12], PV panels, wind turbines (WTs), gas boilers (GBs), and battery energy storage systems (BESSs). In a system of interconnected MGs, each MG can not only trade electricity with the main grid, but also interact with its interconnected MGs, that is, each MG can be considered a user who can sell power to or buy power from other MGs.

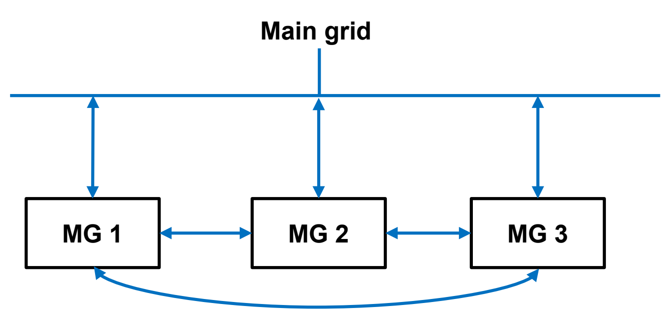


Fig. 1. Energy sharing framework of MGs.

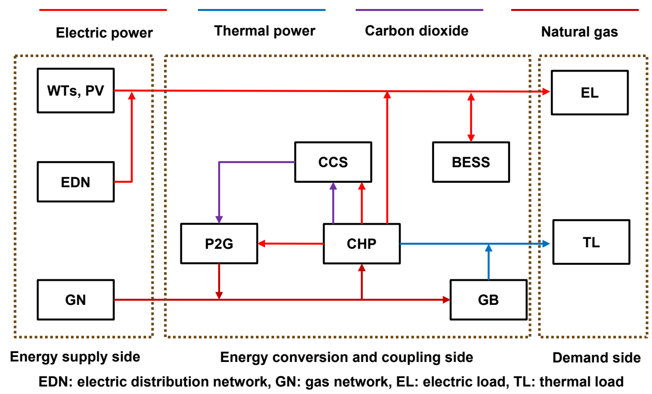


Fig. 2. Schematic diagram of the MG.

B. The Mathematical Models of the Main Equipment of the MG

1) The CHP With CCSs and P2G Devices: The electric power $P^{\mathrm{EP}}_{i,s,t}$ generated by the i-th CHP with CCSs and P2G devices in scenario s is given by

$$P^{\mathrm{EP}}_{i,s,t} = P^{\mathrm{EG}}_{i,s,t} + P^{\mathrm{CCS}}_{i,s,t} + P^{\mathrm{P2G}}_{i,s,t}, \quad \forall s, \forall t, \tag{1}$$

where $P^{\mathrm{EG}}_{i,s,t}$ is the electric power supplying the grid at time t in scenarios s. $P^{\mathrm{CCS}}_{i,s,t}$ is the electric power consumed by CCS at time t in scenarios s, and $P^{\mathrm{P2G}}_{i,s,t}$ is the electric power consumed by P2G at time t in scenarios s.

The relationships between the gas power $P^{\mathrm{gas}}_{i,s,t}$ from P2G, $P^{\mathrm{P2G}}_{i,s,t}$, the amount of CO_2 $C^{\mathrm{CCS}}_{i,s,t}$ required by P2G, and $P^{\mathrm{CCS}}_{i,s,t}$ are given by the following three formulas:

$$P^{\mathrm{gas}}_{i,s,t} = \alpha P^{\mathrm{P2G}}_{i,s,t}, \quad \forall s, \forall t, \tag{2}$$

$$C^{\mathrm{CCS}}_{i,s,t} = \beta P^{\mathrm{P2G}}_{i,s,t}, \quad \forall s, \forall t, \tag{3}$$

$$P^{\mathrm{CCS}}_{i,s,t} = \xi C^{\mathrm{CCS}}_{i,s,t}, \quad \forall s, \forall t, \tag{4}$$

where α, β, and ξ represent the conversion efficiency of $P^{\mathrm{P2G}}_{i,s,t}$ to $P^{\mathrm{gas}}_{i,s,t}$, the coefficient for calculating the amount of CO_2, and the corresponding coefficient between $C^{\mathrm{CCS}}_{i,s,t}$ and $P^{\mathrm{CCS}}_{i,s,t}$, respectively.

The electric power supplying the grid should meet the following constraint:

$$\begin{aligned} \max\Big\{ & P^{\mathrm{EG}}_{i,\min} - \mu_{i,1} P^{\mathrm{HP}}_{i,s,t}, \mu_{i,m}\left(P^{\mathrm{HP}}_{i,s,t} - P^{\mathrm{HP0}}_{i}\right) \\ & - P^{\mathrm{P2G}}_{i,\max} - P^{\mathrm{CCS}}_{i,\max} \Big\} \le P^{\mathrm{EG}}_{i,s,t} \\ \le\; & P^{\mathrm{EG}}_{i,\max} - \mu_{i,2} P^{\mathrm{HP}}_{i,s,t} - P^{\mathrm{P2G}}_{i,\min} - P^{\mathrm{CCS}}_{i,\min}, \quad \forall s, \forall t, \end{aligned} \tag{5}$$

where $\mu_{i,1}$ and $\mu_{i,2}$ are the conversion coefficients corresponding to the minimum and maximum power output, respectively. $\mu_{i,m}$ is the linear supply slope of thermal power and electric power. P^{HP0}_{i} is the thermal power corresponding to the minimum electric power.

The coupling relationship of $P^{\mathrm{EG}}_{i,s,t}$, the thermal power $P^{\mathrm{HP}}_{i,s,t}$ by the i-th CHP, and $P^{\mathrm{gas}}_{i,s,t}$ is expressed by

$$\begin{aligned} \max\Big\{ & \frac{\alpha}{1+\xi\beta}\Big[\left(P^{\mathrm{EP}}_{i,\min} - \mu_{i,1} P^{\mathrm{HP}}_{i,s,t} - P^{\mathrm{EG}}_{i,s,t}\right), \\ & \mu_{i,m}\left(P^{\mathrm{HP}}_{i,s,t} - P^{\mathrm{HP0}}_{i}\right) - P^{\mathrm{EG}}_{i,s,t}\Big]\Big\} \le P^{\mathrm{gas}}_{i,s,t} \\ \le\; & \frac{\alpha}{1+\xi\beta}\left(P^{\mathrm{EP}}_{i,\max} - \mu_{i,2} P^{\mathrm{HP}}_{i,s,t} - P^{\mathrm{EG}}_{i,t}\right), \quad \forall s, \forall t, . \end{aligned} \tag{6}$$

The number of CO_2 emissions of the CHP is expressed as

$$\begin{aligned} E^{\mathrm{co_2}}_{i,s,t} =\; & a_{\mathrm{co_2}}\left(P^{\mathrm{EP}}_{i,s,t} + \mu_{i,1} P^{\mathrm{HP}}_{i,s,t}\right) + b_{\mathrm{co_2}}\big(P^{\mathrm{EP}}_{i,s,t} \\ & + \mu_{i,1} P^{\mathrm{HP}}_{i,s,t}\big)^2 + c_{\mathrm{co_2}} - C^{\mathrm{CCS}}_{i,s,t}, \quad \forall s, \forall t, \end{aligned} \tag{7}$$

where $a_{\mathrm{co_2}}$, $b_{\mathrm{co_2}}$, and $c_{\mathrm{co_2}}$ are emission coefficients.

2) GB: The thermal power $P^{\mathrm{HGB}}_{i,s,t}$ generated by the GB is shown as follows:

$$P^{\mathrm{HGB}}_{i,s,t} = \eta^{\mathrm{GB}}_{i} P^{\mathrm{GGB}}_{i,s,t} = \eta^{\mathrm{GB}}_{i} V^{\mathrm{GB}}_{i,s,t} q, \quad \forall i, \forall s, \forall t, \tag{8}$$

where η^{GB}_{i} is the heat efficiency of the GB. $P^{\mathrm{GGB}}_{i,s,t}$ and $V^{\mathrm{GB}}_{i,s,t}$ are the volume and energy of the consumed gas, respectively. q is the calorific value of gas.

3) BESS: The BESS model is formulated as follows:

$$\begin{aligned} E^{\mathrm{BESS}}_{i,s,t} =\; & (1-\delta) E^{\mathrm{BESS}}_{i,s,t-1} + \eta^{\mathrm{BESS+}} P^{\mathrm{BESS+}}_{i,s,t} \\ & - \frac{P^{\mathrm{BESS-}}_{i,s,t}}{\eta^{\mathrm{BESS-}}}, \quad \forall i, \forall s, \forall t, \end{aligned} \tag{9}$$

$$0 \le P^{\mathrm{BESS-}}_{i,s,t} \le B^{\mathrm{BESS-}}_{i,s,t} \eta^{\mathrm{BESS-}} P^{\mathrm{BESS}}_{i,\max}, \quad \forall i, \forall s, \forall t, \tag{10}$$

$$0 \le P^{\mathrm{BESS+}}_{i,s,t} \le \left(1 - B^{\mathrm{BESS-}}_{i,s,t}\right) \frac{P^{\mathrm{BESS}}_{i,\max}}{\eta^{\mathrm{BESS+}}}, \forall i, \forall s, \forall t, \tag{11}$$

$$SoC_{i,\min} \le SoC_{i,s,t} \le SoC_{i,\max}, \quad \forall i, \forall s, \forall t, \tag{12}$$

$$SoC_{i,1} = SoC_{i,T}, \quad \forall i, \forall s, \forall t, \tag{13}$$

where $E^{\mathrm{BESS}}_{j,s,t}$ is the stored energy. δ is the self-discharging rate. $\eta^{\mathrm{BESS-}}$, $\eta^{\mathrm{BESS+}}$, $P^{\mathrm{BESS+}}_{i,s,t}$, and $P^{\mathrm{BESS-}}_{i,s,t}$ are the discharging, charging efficiency, charging, and discharging power, respectively. SoC represents the state of charge of the BESS. 1 and T indicate the start time period and end time period of the scheduling cycle, respectively.

C. Cost Models

The operation cost C^{MG}_{i} of the i-th MG in the system of interconnected MGs is represented as follows:

$$\begin{aligned} C^{\mathrm{MG}}_{i} = & \sum_{s=1}^{|\mathcal{S}|} p_s \Big(C^{\mathrm{CHP}}_{i,s} + C^{\mathrm{imp}}_{i,s} - C^{\mathrm{exp}}_{i,s} + C^{\mathrm{BESS}}_{i,s} \\ & + C^{\mathrm{emi}}_{i,s} + C^{\mathrm{DR}}_{i,s} + C^{\mathrm{tran}}_{i,s} - C^{\mathrm{P2P}}_{i,s} \Big), \quad \forall i, \end{aligned} \tag{14}$$

$$C^{\mathrm{tran}}_{i,s} = \sum_{j=1, j\ne i}^{|\mathcal{M}|} \sum_{t=1}^{T} \rho_e P^{\mathrm{P2P}}_{i-j,s,t}, \quad \forall i, \forall s, \tag{15}$$

$$C^{\mathrm{P2P}}_{i,s} = \sum_{j=1, j\ne i}^{|\mathcal{M}|} \sum_{t=1}^{T} \pi^{\mathrm{P2P}}_{i-j,t} P^{\mathrm{P2P}}_{i-j,s,t}, \quad \forall i, \forall s, \tag{16}$$

$C^{\mathrm{CHP}}_{i,s}$, $C^{\mathrm{imp}}_{i,s}$, $C^{\mathrm{BESS}}_{i,s}$, $C^{\mathrm{emi}}_{i,s}$, $C^{\mathrm{DR}}_{i,s}$, $C^{\mathrm{tran}}_{i,s}$, $C^{\mathrm{exp}}_{i,s}$, and $C^{\mathrm{P2P}}_{i,s}$ are the CHP operation, purchasing electricity and gas, BESS aging, carbon trading, demand response (DR), electricity transmission cost, revenue from selling electricity, and electricity sharing revenue, respectively. p_s is the probability of scenario s, and $|\mathcal{S}|$ is the number of scenarios. ρ_e is the network crossing cost per unit. $|\mathcal{M}|$ is the number of MGs. $P^{\mathrm{P2P}}_{i-j,s,t}$ denotes the amount of electrical energy traded between MG i and MG j during time period t in scenario s. $\pi_{i-j,t}$ stands for the unit price of electrical energy traded between between MG i and MG j during time period t.

D. Constraints

The electric power balance constraints are written as

$$\begin{aligned} &P^{\mathrm{EG}}_{i,s,t}+P^{\mathrm{CCS}}_{i,s,t}+P^{\mathrm{P2G}}_{i,s,t}+P^{\mathrm{PV}}_{i,s,t}+P^{\mathrm{WTs}}_{i,s,t}\\ &+P^{\mathrm{BESS-}}_{i,s,t}+P^{\mathrm{imp}}_{i,s,t}=P^{\mathrm{EL}}_{i,s,t}+P^{\mathrm{P2P}}_{i-j,s,t}\\ &+P^{\mathrm{BESS+}}_{i,s,t}+P^{\mathrm{exp}}_{i,s,t},\quad \forall s,\forall t, \end{aligned} \tag{17}$$

where $P^{\mathrm{EL}}_{i,s,t}$ is the actual electric load after DR.

Thermal and gas balance constraints are formalized as

$$P^{\mathrm{HP}}_{i,s,t}+P^{\mathrm{HGB}}_{i,s,t}=P^{\mathrm{HL}}_{i,s,t},\quad \forall i,\forall s,\forall t, \tag{18}$$

$$V^{\mathrm{GB}}_{i,s,t}+V^{\mathrm{CHP}}_{i,s,t}-V^{\mathrm{P2G}}_{i,s,t}=V^{\mathrm{imp}}_{i,s,t},\quad \forall s,\forall t, \tag{19}$$

where $P^{\mathrm{HL}}_{i,s,t}$ is the actual thermal load after DR.

The power transmission between MGs should meet the capacity limit:

$$P^{\mathrm{P2P}}_{i-j,\min}\le P^{\mathrm{P2P}}_{i-j,s,t}\le P^{\mathrm{P2P}}_{i-j,\max},\quad \forall i,\forall j, i\ne j, \tag{20}$$

where $P^{\mathrm{P2P}}_{i-j,\min}$ and $P^{\mathrm{P2P}}_{i-j,\max}$ are the upper and lower limits of the exchanged electric power between MG i and MG j, respectively.

The sum of the interactive electric power between all MGs and the sum of the transaction cost between all MGs should both be zero:

$$\sum_{j=1,j\ne i}^{|\mathcal{M}|}\sum_{i=1}^{|\mathcal{M}|}P^{\mathrm{P2P}}_{i-j,s,t}=0, \tag{21}$$

$$\sum_{j=1,j\ne i}^{|\mathcal{M}|}\sum_{i=1}^{|\mathcal{M}|}\pi^{\mathrm{P2P}}_{i-j,t}P^{\mathrm{P2P}}_{i-j,s,t}=0. \tag{22}$$

E. Optimal Operation of an MG Without Joining the Alliance

When there is no alliance between MGs, that is, there is no energy exchange between MGs, the operation cost C^{mg0}_i of the i-th MG can be represented as follows:

$$\begin{aligned} C^{\mathrm{mg0}}_i=&\sum_{s=1}^{|\mathcal{S}|}p_s\Big(C^{\mathrm{CHP}}_{i,s}+C^{\mathrm{imp}}_{i,s}-C^{\mathrm{exp}}_{i,s}\\ &+C^{\mathrm{BESS}}_{i,s}+C^{\mathrm{emi}}_{i,s}+C^{\mathrm{DR}}_{i,s}\Big),\quad \forall i. \end{aligned} \tag{23}$$

The electric power balance constraints in this mode are rewritten as

$$\begin{aligned} &P^{\mathrm{EG}}_{i,s,t}+P^{\mathrm{CCS}}_{i,s,t}+P^{\mathrm{P2G}}_{i,s,t}+P^{\mathrm{PV}}_{i,s,t}+P^{\mathrm{WTs}}_{i,s,t}+P^{\mathrm{BESS-}}_{i,s,t}\\ &+P^{\mathrm{imp}}_{i,s,t}=P^{\mathrm{EL}}_{i,s,t}+P^{\mathrm{BESS+}}_{i,s,t}+P^{\mathrm{exp}}_{i,s,t},\quad \forall s,\forall t. \end{aligned} \tag{24}$$

Therefore, the optimization problem of a single MG i without joining the alliance can be formulated as follows:

$$\begin{aligned} \min\quad & C^{\mathrm{mg0}}_i\\ \text{s.t.}\quad & (1)\text{–}(13),\ (18)\text{–}(19),\ (23)\text{–}(24). \end{aligned} \tag{25}$$

F. Optimal Operation of the Alliance of MGs

As described in Section II-A to Section II-D, the MG system studied in this paper is composed of several interconnected MGs, and there is power exchange and information interaction between MGs. The optimization objective is to minimize the overall operating cost of MGs. Therefore, the optimization problem of the whole alliance can be formalized as follows:

$$\begin{aligned} \min\quad & \sum_{i=1}^{|\mathcal{M}|}C^{\mathrm{MG}}_i\\ \text{s.t.}\quad & (1)\text{–}(22). \end{aligned} \tag{26}$$

III. Proposed Optimal Operation and Benefit Distribution Methodologies

This paper assumes that each MG belongs to different stakeholders and is an independent and rational individual. If each MG reaches a direct transaction agreement through bargaining and the income of each MG is improved, then MGs will cooperate to conduct direct electrical energy transactions. Compared with the independent operation of each MG, the part of the total operating cost reduction during the interconnected operation of MGs is the emerging benefits of the system. Although the cooperative operation of MGs can optimize the overall economy of the alliance, how to allocate these benefits reasonably to each MG is a very worthwhile problem. Game theory handles the problem of how to make reasonable decisions for agents according to their own ability and information when there is interest correlation or conflict among multiple decision-making agents. Each MG is a participant with reciprocal cooperative relationships with other MGs. A cost lower than the cost of operating independently is realized through the distribution of emerging benefits, and thus a binding agreement is reached between MGs, which meets the requirements of the cooperative game. In order to ensure the stability of the cooperative relationship between MGs and the reasonable distribution of benefits, this paper adopts the GNB model to determine the optimal operation strategy of each MG and balance the interests of all parties. The GNB, a kind of asymmetric cooperative game, is an effective means to study multi-agent optimization. Therefore, it is often used to solve multi-agent complex optimization problems to obtain negotiated solutions, and its transformation models have typical distributed characteristics, which is conducive to solving them with distributed algorithms. Different from the common Nash bargaining (CNB) model, the GNB model pays more attention to the reasonable distribution of benefits among participants.

A. GNB Model

In this paper, the multi-energy MG operation model built in Section II is incorporated into the framework of GNB. The framework optimizes the overall performance of the alliance while pursuing the minimization of the operating cost of each MG itself. The GNB model can be expressed as follows:

$$\begin{aligned}\max \quad & \prod_{i=1}^{|\mathcal{M}|}\left[-C_i^{\mathrm{mg}}+C_i^{\mathrm{P2P}}-\left(-C_i^{\mathrm{mg0}*}\right)\right]^{\lambda_i} \\ \text{s.t.} \quad & -C_i^{\mathrm{mg}*}+C_i^{\mathrm{P2P}} \geq -C_i^{\mathrm{mg0}*}, \\ & (1)\text{–}(22).\end{aligned} \tag{27}$$

where $C_i^{\mathrm{mg}}=C_i^{\mathrm{CHP}}+C_i^{\mathrm{imp}}-C_i^{\mathrm{exp}}+C_i^{\mathrm{BESS}}+C_i^{\mathrm{emi}}+C_i^{\mathrm{DR}}+C_i^{\mathrm{tran}}$, and $C_i^{\mathrm{mg0}*}$ is the optimal operation point when MG i does not participate in the alliance, i.e. the optimal solution to Problem (25). $C_i^{\mathrm{mg0}*}$ is also called the breaking point. λ_i is the contribution coefficient, which can be calculated by the following equations:

$$\lambda_i=\mathrm{e}^{E_i^{+}/E_{\max}^{+}}-\mathrm{e}^{-E_i^{-}/E_{\max}^{-}}, \tag{28}$$

$$E_i^{+}=\sum_{j=1,j\neq i}^{|\mathcal{M}|}\sum_{t=1}^{T}\max\left\{0,P_{i-j,t}^{\mathrm{P2P}}\right\}, \tag{29}$$

$$E_i^{-}=-\sum_{j=1,j\neq i}^{|\mathcal{M}|}\sum_{t=1}^{T}\min\left\{0,P_{i-j,t}^{\mathrm{P2P}}\right\}, \tag{30}$$

$$E_{\max}^{+}=\max\left\{E_i^{+}\right\}, \tag{31}$$

$$E_{\max}^{-}=\max\left\{E_i^{-}\right\}. \tag{32}$$

The solution to Problem (27) is called the Nash bargaining solution (NBS) [13], which enables all participants to obtain Pareto optimal benefits. The NBS has many excellent properties. Specifically, the NBS satisfies the following axioms.

1) *Individual rationality:* the NBS should enhance the utilities, i.e. benefits, of all MGs participating in the MG alliance compared with the benefits when they do not participate in the alliance; otherwise, they would not cooperate.
2) *Pareto optimality:* an MG (player) cannot find other solutions that can increase the utility of the MG without worsening the utilities of other MGs.
3) *Invariance to affine transformations:* the NBS is invariant if the utility function are scaled by an affine transformation.
4) *Independence of irrelevant alternatives:* if the bargaining solution is found on a subset of the feasible set, then the solution does not vary by expanding the subset within the feasible set.

Since the GNB model takes into account the different market powers of different agents, it no longer has the axiom of *symmetry* that the CNB model has.

Problem (27) is essentially an intractable non-convex nonlinear problem, which is difficult to resolve directly. By proof by contradiction and the properties of the logarithmic function, we can prove that Problem (27) can be equivalently converted into two easy subproblems: *the social welfare maximization (MG alliance benefit maximization) subproblem* and *the energy trading payment bargaining subproblem*.

B. Social Welfare Maximization Subproblem

The social welfare maximization subproblem can be expressed as:

$$\begin{aligned}\max \quad & \sum_{i=1}^{|\mathcal{M}|}\left(-C_i^{\mathrm{mg}}\right) \\ \text{s.t.} \quad & (1)\text{–}(22).\end{aligned} \tag{33}$$

Based on Problem (26) and (22), we can easily prove that Problem (26) and Problem (33) are equivalent.

C. Energy Trading Payment Bargaining Subproblem

The energy trading payment bargaining subproblem is shown as follows:

$$\begin{aligned}\max \quad & \sum_{i=1}^{|\mathcal{M}|}\lambda_i\ln\left[-C_i^{\mathrm{mg}*}+C_i^{\mathrm{P2P}}-\left(-C_i^{\mathrm{mg0}*}\right)\right] \\ \text{s.t.} \quad & -C_i^{\mathrm{mg}*}+C_i^{\mathrm{P2P}} \geq -C_i^{\mathrm{mg0}*}, \forall i \\ & (16),\end{aligned} \tag{34}$$

where $C_i^{\mathrm{mg}*}$ is the optimal value of Problem (33).

D. Solution Methods Based on the ADMM

Problems (33) and (34) have the characteristics of distributed optimization problems, so they can be solved by distributed optimization algorithms. In this paper, in order to protect the privacy of each entity participating in the bargaining, the ADMM is used to solve the two subproblems. Moreover, the ADMM has the advantages of good convergence, simplicity, and strong robustness. The optimal solution to Problem (27) can be obtained by solving the two subproblems.

E. Solution Algorithm for the Social Welfare Maximization Subproblem

For the convenience of expression, let

$$P_{i-j,t}^{\mathrm{P2P}}=\sum_{s=1}^{|\mathcal{S}|}p_sP_{i-j,s,t}^{\mathrm{P2P}}, \tag{35}$$

$$P_{j-i,t}^{\mathrm{P2P}}=\sum_{s=1}^{|\mathcal{S}|}p_sP_{j-i,s,t}^{\mathrm{P2P}}, \tag{36}$$

where $P_{i-j,t}^{\mathrm{P2P}}$ and $P_{j-i,t}^{\mathrm{P2P}}$ represent the expected amount of electricity that MG i expects to trade with MG j and the expected amount of electricity that MG j expects to trade with MG i, respectively. When $P_{i-j,t}^{\mathrm{P2P}}=P_{j-i,t}^{\mathrm{P2P}}$, it indicates that there is an electricity transaction consensus between MG i and MG j. The solution method of Problem (33) based on the ADMM is shown in Algorithm 1*.

*To save space, Algorithms 1 and 2 omit the steps of the 0-th iteration.

Algorithm 1 Solution method of Problem (33) based on the ADMM

1: Set the maximum number of iterations $k_{\max}^{\mathrm{P1}}$, convergence accuracy ϵ^{P1}, penalty factor ρ_i^{P1}, number of initial iterations $k^{\mathrm{P1}} = 0$, initial values of $P_{i-j,t}^{\mathrm{P2P}} = P_{j-i,t}^{\mathrm{P2P}} = 0$, Lagrange multiplier $\lambda_{i-j,t}^{\mathrm{P1}}$.

2: Construct the augmented Lagrange function of Problem (33) for MG i, i.e.

$$\begin{aligned} L_i^{\mathrm{P1}} = C_i^{\mathrm{mg}} + \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \lambda_{i-j,t}^{\mathrm{P1}} \left(P_{i-j,t}^{\mathrm{P2P}} - P_{j-i,t}^{\mathrm{P2P}}\right) \\ + \frac{\rho_i^{\mathrm{P1}}}{2} \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \left\| P_{i-j,t}^{\mathrm{P2P}} - P_{j-i,t}^{\mathrm{P2P}} \right\|_2^2 \end{aligned} \quad (37)$$

3: **while** $\sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \left\| P_{i-j,t}^{\mathrm{P2P},k} - P_{j-i,t}^{\mathrm{P2P},k} \right\|_2^2 \leq \epsilon^{\mathrm{P1}}$ or $k > k_{\max}^{\mathrm{P1}}$ has not been satisfied **do**

4: Solve the following problems:

$$\begin{aligned} \min \quad & L_i^{\mathrm{P1}} \\ \text{s.t.} \quad & (1)\text{–}(22). \end{aligned} \quad (38)$$

$$\begin{aligned} \min \quad & L_j^{\mathrm{P1}} \\ \text{s.t.} \quad & (1)\text{–}(22). \end{aligned} \quad (39)$$

to obtain $P_{i-j,t}^{\mathrm{P2P},k+1}$ and $P_{j-i,t}^{\mathrm{P2P},k+1}$.

5: Update Lagrange multipliers $\lambda_{i-j,t}^{\mathrm{P1},k+1} = \lambda_{i-j,t}^{\mathrm{P1},k} + \rho_i^{\mathrm{P1}} \left(P_{i-j,t}^{\mathrm{P2P},k+1} - P_{j-i,t}^{\mathrm{P2P},k+1}\right)$.

6: Update the number of iterations $k^{\mathrm{P1}} = k^{\mathrm{P1}} + 1$.

7: **end while**

F. Solution Algorithm for the Energy Trading Payment Bargaining Subproblem

Through Algorithm 1, we can obtain the optimal expected transaction electricity between MGs, namely $P_{i-j,t}^{\mathrm{P2P}\,*}$. Hence, Problem (34) can be further rewritten as

$$\begin{aligned} \max \quad & \sum_{i=1}^{|\mathcal{M}|} \lambda_i \ln\left[-C_i^{\mathrm{mg}*} + C_i^{\mathrm{P2P}} - \left(-C_i^{\mathrm{mg0}*}\right)\right] \\ \text{s.t.} \quad & -C_i^{\mathrm{mg}*} + C_i^{\mathrm{P2P}} \geq -C_i^{\mathrm{mg0}*}, \forall i \\ & C_i^{\mathrm{P2P}} = \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \pi_{i-j,t}^{\mathrm{P2P}} P_{i-j,t}^{\mathrm{P2P}\,*}, \quad \forall i, \end{aligned} \quad (40)$$

Let $\pi_{i-j,t}^{\mathrm{P2P}}$ represent the transaction electricity price expected by MG i, and $\pi_{j-i,t}^{\mathrm{P2P}}$ represent the transaction electricity price expected by MG j. $\pi_{i-j,t}^{\mathrm{P2P}} = \pi_{j-i,t}^{\mathrm{P2P}}$ indicates that there is an electricity price transaction consensus between MG i and MG j. Following the idea of Algorithm 1, one can obtain the solution method of Problem (34), i.e. Algorithm 2.

Algorithm 2 Solution method of Problem (34) based on the ADMM

1: Set the maximum number of iterations $k_{\max}^{\mathrm{P2}}$, convergence accuracy ϵ^{P2}, penalty factor ρ_i^{P2}, number of initial iterations $k^{\mathrm{P2}} = 0$, initial values of $\pi_{i-j,t}^{\mathrm{P2P}} = \pi_{j-i,t}^{\mathrm{P2P}} = 0$, Lagrange multiplier $\lambda_{i-j,t}^{\mathrm{P2}}$.

2: Calculate the contribution coefficient λ_i of MG i as per (28)–(32).

3: Construct the augmented Lagrange function of Problem (40) for MG i, i.e.

$$\begin{aligned} L_i^{\mathrm{P2}} = & -\lambda_i \ln\left[-C_i^{\mathrm{mg}*} + C_i^{\mathrm{P2P}} - \left(-C_i^{\mathrm{mg0}*}\right)\right] \\ & + \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \lambda_{i-j,t}^{\mathrm{P2}} \left(\pi_{i-j,t}^{\mathrm{P2P}} - \pi_{j-i,t}^{\mathrm{P2P}}\right) \\ & + \frac{\rho_i^{\mathrm{P2}}}{2} \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \left\| \pi_{i-j,t}^{\mathrm{P2P}} - \pi_{j-i,t}^{\mathrm{P2P}} \right\|_2^2 \end{aligned} \quad (41)$$

4: **while** $\sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \left\| \pi_{i-j,t}^{\mathrm{P2P},k} - \pi_{j-i,t}^{\mathrm{P2P},k} \right\|_2^2 \leq \epsilon^{\mathrm{P2}}$ or $k^{\mathrm{P2}} > k_{\max}^{\mathrm{P2}}$ has not been satisfied **do**

5: Solve the following problems:

$$\begin{aligned} \min \quad & L_i^{\mathrm{P2}} \\ \text{s.t.} \quad & -C_i^{\mathrm{mg}*} + C_i^{\mathrm{P2P}} \geq -C_i^{\mathrm{mg0}*}, \\ & C_i^{\mathrm{P2P}} = \sum_{j=1,j\neq i}^{|\mathcal{M}|} \sum_{t=1}^{T} \pi_{i-j,t}^{\mathrm{P2P}} P_{i-j,t}^{\mathrm{P2P}\,*}, \end{aligned} \quad (42)$$

$$\begin{aligned} \min \quad & L_j^{\mathrm{P2}} \\ \text{s.t.} \quad & -C_j^{\mathrm{mg}*} + C_j^{\mathrm{P2P}} \geq -C_j^{\mathrm{mg0}*}, \\ & C_j^{\mathrm{P2P}} = \sum_{i=1,i\neq j}^{|\mathcal{M}|} \sum_{t=1}^{T} \pi_{j-i,t}^{\mathrm{P2P}} P_{j-i,t}^{\mathrm{P2P}\,*}, \end{aligned} \quad (43)$$

to obtain $\pi_{i-j,t}^{\mathrm{P2P},k+1}$ and $\pi_{j-i,t}^{\mathrm{P2P},k+1}$.

6: Update Lagrange multipliers, i.e., $\lambda_{i-j,t}^{\mathrm{P2},k+1} = \lambda_{i-j,t}^{\mathrm{P2},k} + \rho_i^{\mathrm{P2}} \left(\pi_{i-j,t}^{\mathrm{P2P},k+1} - \pi_{j-i,t}^{\mathrm{P2P},k+1}\right)$.

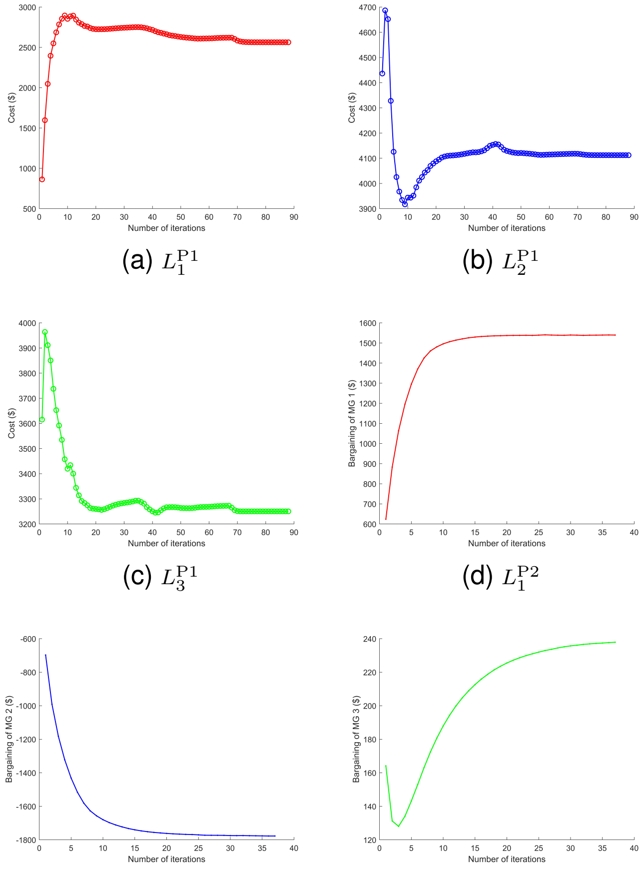
7: Update the number of iterations, i.e., $k^{\mathrm{P2}} = k^{\mathrm{P2}} + 1$.

8: **end while**

IV. Case Studies

A. Parameters and Settings

The optimal cooperative operation of the system of three multi-energy MGs, as shown in Fig. 1, is utilized to validate the effectiveness of the proposed model and solution methods. The parameters of equipment are from [12]. The forecast errors of PV, wind generation, electric, and thermal loads obey the normal distributions, all the means are 0, and the standard deviations are 8%, 10%, 2%, and 3% of the predicted values, respectively. Monte Carlo sampling is used to generate 1000 scenarios, and then k-means is used to obtain 8 typical scenarios and corresponding probabilities.



(a) L_1^{P1} (b) L_2^{P1}

(c) L_3^{P1} (d) L_1^{P2}

(e) L_2^{P2} (f) L_3^{P2}

Fig. 3. Convergences of Algorithms 1 and 2.

B. Discussions and Analyses of Case Study Results

1) Convergence Analyses of the Algorithms: In this paper, ADMM-based methods are used to solve the two subproblems mentioned above. Figs. 3a–3c shows the convergence results of L_1^{P1}, L_2^{P1}, and L_3^{P1} of the social welfare maximization subproblem. It can be seen from these figures that L_1^{P1}, L_2^{P1}, and L_3^{P1} gradually converge to the optimal value during the alternating iterative solution process, and the proposed method achieves convergence (reaching the convergence standard) after 88 iterations. Figs. 3d–3f demonstrates the convergence results of L_1^{P2}, L_2^{P2}, and L_3^{P2} of the energy trading payment bargaining subproblem. It can be seen that L_1^{P2}, L_2^{P2}, and L_3^{P2} gradually converge to the optimal value during the alternating iterative solution process, and the proposed method achieves convergence after 39 iterations. These convergence results prove that the distributed solving methods based on the ADMM have good convergence performance and can realize distributed and efficient solution to the two subproblems. At the same time, these methods can protect the private information of each agent.

2) Traded Electricity and Transaction Prices: The sum of the amount of traded electrical energy of each MG and the electricity transaction prices between MGs are shown in Figs. 4 and 5, respectively. The sum of the amount of traded electrical energy of MG 1 represents the sum of the amount of traded electrical energy between MG 1 and MG 2 and the amount of traded electrical energy between MG 1 and MG 3; other MGs follow the same pattern.

As can be seen from Fig. 4, during 00:00–8:00 and 17:00–24:00, the renewables of MG 1 are surplus, so the power is transferred to MG 2 and MG 3, which are unable to generate power at night for the renewables of MG 2 and MG 3. From 8:00–17:00, the surge of electric loads leads to the supply shortage of MG 1 itself, and the renewable generation of MG 2 and MG 3 is at its peak, so the power is transmitted to MG 1. The consumption of renewables has the highest priority. Under the premise of optimizing its own internal power scheduling, the MG participates in the overall power coordination optimization of the alliance. After participating in P2P transactions, the renewable consumption rates of the three MGs are all 100%. Therefore, P2P trading can effectively improve the consumption rate of renewables.

The P2P transaction pricing proposed in Section III-C can enable MGs to sell electricity at prices higher than the electricity buying prices by the grid and purchase renewable power at prices lower than the electricity selling prices by the grid, thus effectively improving the benefit of each MG.

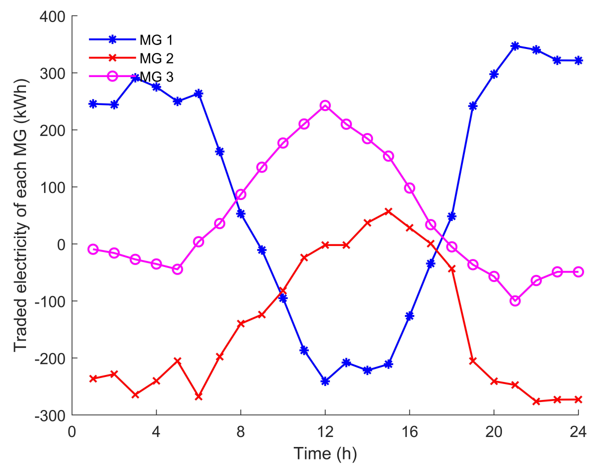


Fig. 4. Sum of the amount of traded electrical energy of each MG.

3) Benefits and Carbon Emissions of Each MG and the Entire Alliance: The costs, $C_i^{\mathrm{mg}*} (i = 1, 2, 3)$, and benefit increases of each MG and all MGs before and after participating in P2P transactions are shown in Table I. The carbon emission quantity of each MG and all MGs before and after participating in P2P, the quantity of carbon emissions reduced after participating in P2P, and the reduction rate of carbon emissions after participating in P2P are shown in Table II. It can be seen from Tables I–II that the benefits of participants have been effectively improved by P2P. Each participant can obtain a fair share of benefits according to their energy contribution. The carbon emissions and the carbon trading costs decrease after participating in P2P. Meanwhile, the integration

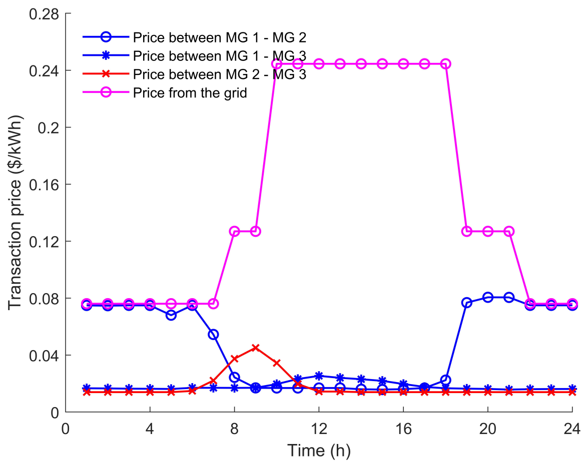


Fig. 5. Electricity transaction prices between MGs.

of CCSs and P2G can effectively reduce the carbon emissions of CHP and promote the low-carbon operation of MGs.

TABLE I
COSTS AND BENEFITS BEFORE AND AFTER P2P

	Cost before P2P ($)	$C_i^{\mathrm{mg}*}$ $i=1,2,3$	Cost after P2P ($)	Benefit increase ($)
MG 1	2162	2563	1024	1138
MG 2	6255	4112	5876	379
MG 3	3391	3250	3025	366
All MGs	11808	9925	9925	1883

TABLE II
CO_2 EMISSIONS BEFORE AND AFTER P2P

	Emissions before P2P (kg)	Emissions after P2P (kg)	Reduction (kg)	Reduction rate (%)
MG 1	25234	22981	2253	8.9
MG 2	17175	16699	476	2.8
MG 3	14900	13422	1478	9.9
All MGs	57309	53102	4207	7.3

V. CONCLUSION

In this paper, based on statistic programming and GNB, an optimal operation model of multi-energy MGs is established, and it is equivalently converted into the two subproblems that are easy to solve. Then, the ADMM-based solution methods are proposed to solve the two subproblems in turn. The rationality and validity of the proposed model and methods are verified by case studies. The main conclusions are as follows.

1) The solution methods based on the ADMM have good convergence characteristics. Compared with the centralized method, the distributed methods proposed in this paper can greatly reduce the communication transmission burden, protect the operation privacy of the MG (the interactive information between MGs is only the expected interactive power), and realize the efficient solution to the joint operation problem of the system of MGs.
2) Through cooperative operation, the operation benefit of each MG and the alliance benefit of all MGs are significantly improved compared with the situation without cooperation. At the same time, for the power grid, the cooperative operation of MGs can promote the consumption of renewables, and has a noticeable peak-shaving effect. The efficient use of renewable resources is realized.
3) The GNB-based benefit distribution method can realize the reasonable distribution of benefits, which is conducive to improving the enthusiasm of all participants and attracting more participants to join the alliance.
4) The integration of CCSs and P2G devices into traditional CHP units can reduce CO2 emissions. The joint operation of MGs can also reduce carbon emissions and contribute to environmental protection.

In this paper, the treatment of uncertainty is rough and the load types are not rich enough. In the next step, we will carry out relevant research on these problems.

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