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Distributed cooperation optimization of multi-microgrids under grid tariff uncertainty: A nash bargaining game approach with cheating behaviors

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ABSTRACT

Multi-microgrid system (MMGs) has drawn extensive attention recently because of its high energy efficiency. However, MMGs' operational efficiency can be affected by market price fluctuations and intermittent renewable energy. This paper proposes an energy-sharing model based on the Nash bargaining game between multi-microgrids. The proposed model provides a robust energy trading schedule to deal with uncertainties brought by grid tariffs and renewable energy. To ensure the model is tractable, the original game problem is equivalently converted into a system benefit maximization subproblem and an additional profit distribution subproblem to get optimal energy sharing power and prices. In addition, microgrid has the motivation to cheat for maximizing its benefits which may lead to the breakdown of cooperation. Furthermore, cheating behaviors in energy transaction are analyzed; the energy sharing scheme based on cheating equilibrium is derived by proposing an intermediary transaction mode. Finally, the alternating direction method of multipliers (ADMM) is used to protect the players' privacies in a distributed way. Simulation results show that the proposed model can realize stable cooperation, effectively reduce operating costs and immunize against multiple uncertainties and cheating behaviors.

1. Introduction

With the gradual depletion of traditional fossil energy, renewable energy development and efficient energy utilization have drawn wide attention [1,2]. Integrated energy microgrids (MG) can improve energy utilization [3], increase power generation autonomy [4], support diverse distributed energy sources and loads [5]. Nevertheless, individual microgrid has limited equipment capacity [6], and its operational efficiency is vulnerable to environmental changes. With the increasing deployment of MG, multi-microgrids system (MMGs), consisting of adjacent microgrids, allow individual microgrids to interact with each other in terms of energy and communication [7]. MMGs can achieve the complementarity of multiple energy [8] and reduce the social cost [9]. However, the heterogeneity of MG, involving composition structure, capital flow, level of supply and demand, and ownership [10], challenges the coordination and control of MMGs. Therefore, it is essential to establish the benefit distribution mechanism of MMGs to achieve stable cooperation.

Game theory is widely applied in the problem of benefit distribution [11], where the problem is commonly formulated as two types: noncooperative games [12–17] and cooperative games [18–27]. A model of P2P energy sharing for community producers based on noncooperative game models is proposed in [12]. Ref. [13] proposed an energy sharing model of producers based on generalized demand bidding and proved the existence of Nash equilibrium solution. A tri-level intelligent community framework based on Stackelberg game considering the uncertainty of renewable energy was established in [14]. Ref. [15] presented peer-to-peer energy sharing model among MGs based on noncooperative bidding. Ref. [16] adopted a multi-leader and multi-follower Stackelberg game approach to study MGs'energy trading. Ref. [17] divided MGs into buyers and sellers to maximize the social welfare. However, noncooperative games focus on individual interests while ignoring overall interests. Further, there is no guaranteed Nash equilibrium solution in noncooperative games [18].

To address the above issue, cooperative games is applied to reach a stable Nash equilibrium solution. Cooperative games achieve Pareto optimum value by paying attention to the overall interests. Cooperative games are usually modeled as coalitional games [19]-[21] or Nash bargaining models [22–28]. Ref. [19] proposed an energy sharing approach based on coalitional game for smart building. A microgrid alliance was established in [20], and the alliance profits was distributed by the Shapley value method. Ref. [21] used coalitional game approach to establish the model of sharing storage to minimize the cost of

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Nomenclature

Sets and Abbreviations

N	Number of microgrids
I,J	Index of microgrids
T	Number of time slots
t	Index of time slot
m	Index of renewable energy
ADMM	Alternating direction method of multipliers
CES	Cloud energy storage
MMGs	Multi-microgrid system
ITM	Intermediary transaction mode
GT/GB/HP	Gas turbine/ Gas boiler/ Heat pump

Parameters

η_{GT}	Generation efficiency of GT
H_{LHV}	Low calorific value of natural gas
a, b	Proportional coefficient of flexible load
e, f	Capacity coefficient of CES
E_i^{max}	Maximum capacity of CES
$P_{i,ch}^{max}, P_{i,dis}^{max}$	Maximum charging/discharging power
δ	Leakage coefficient of CES
$\eta_{GT,h}, \eta_{GB}, \eta_{HP}$	Heat power generation efficiency of GT/GB/HP
η_c / η_d	Charging/Discharging efficiency
$E_{i,0}$	Initial capacity of CES
$P_{i,t}^{buy,max}, P_{i,t}^{sell,max}$	Limitation of purchasing/selling power from/to the main grid
c_{gas}	Gas prices in the external market
$\lambda_{tran,e}, \lambda_{tran,h}$	Cost coefficients of shiftable electric/thermal load
$\lambda_{cut,e}, \lambda_{cut,h}$	Cost coefficients of interruptible load
λ_{cur}	Penalty coefficients of renewable energy
λ_{om}	Operation cost coefficients of CES
λ_E	Unit capacity lease cost of CES
λ_P	Unit power lease cost of CES
$\lambda_{b,t}^{max}, \lambda_{s,t}^{max}$	Maximum buying/selling tariffs
$\lambda_{b,t}^{min}, \lambda_{s,t}^{min}$	Minimum buying/selling tariffs

Variables

$P_{i,t}^{GT}, P_{i,t}^{HP}$	Power generation of GT/HP
$F_{i,t}^{GT}, F_{i,t}^{GB}$	Gas consumption of GT/GB
$H_{i,t}^{GT}, H_{i,t}^{GB}$	Heat power generation of GT/GB
$H_{i,t}^{HP}$	Heat power generation of HP
$L_{i,t}^{e}, l_{i,t}^{e}$	Flexible/ Basic load of microgrids
$P_{i,t}^{cut}, P_{i,t}^{tran}$	Interruptible/Shiftable power of microgrids
$E_{i,t}, E_i$	Real /Lease capacity level of CES
$P_{i,t}^{ch}, P_{i,t}^{dis}$	Charging/Discharging power of CES
P_i^{ch}, P_i^{dis}	Lease charging/discharging power of CES
$u_{i,t}^{ch}, u_{i,t}^{dis}$	State indices of charging/discharging power
$P_{i,t}^{buy}, P_{i,t}^{sell}$	Purchasing/Selling power from/to the grid
$u_{i,t}^{buy}, u_{i,t}^{sell}$	State indices of purchasing/selling power from/to the main grid
$U_{i,m}$	The uncertainty sets of renewable energy
$P_{i,t,m}$	Power generation of renewable energy
$\xi_{i,t,m}$	Predicted power of renewable energy
$\partial_{i,t,m}$	Maximum power generation deviation for renewable energy
$\lambda_{b,t}, \lambda_{s,t}$	Buying/Selling tariffs in the external market
$P_{eij,t}$	Sharing power for MMGs
τ_i	Microgrid's payment to other microgrids
ρ_{ij}	Sharing prices for MMGs
γ_i	Cheating indices of MMGs
γ_i^{limit}	Upper limits for cheating indices

electricity. However, Shapley value method is not applicable for large-scale system, because of the explosion of dimensions. Further, it brough up the issue of privacy that the centralized config.

uration and considerable information exchange of coalitional game models. Therefore, Nash bargaining (NB) models is applied to address the issue of "combinatorial explosion" and privacy protection through the alternating direction method of multipliers (ADMM) [22]. Besides, the NB models have low computational complexity because they avoid calculating the "core" and "nucleolus" [23]. Ref. [22–28] all realize energy sharing and benefit distribution of different stockholders based on Nash bargaining theory. Ref. [24] established NB model for microgrid power management problem to find the Pareto optimum solution. Ref. [25] proposed a coordinated operation method of multiple energy hubs which can greatly improve overall benefits. Ref. [26] realized the interests distribution of different stockholders in distributed energy transactions. Ref. [28] adopted Nash-Harsanyi bargaining model to allocate profits according to players' contribution. All the above studies show the feasibility of using NB model to study the cooperative operation of MMGs.

Owing to the intermittence of renewable energy [29,30] and the fluctuation of market prices [31], as well as the stockholders' motivation to cheat in order to maximize their own benefits, MMGs will face two challenging issues: the uncertainties issue of renewable energy and grid tariffs as well as the cheating issue in energy sharing. To the authors best knowledge, these have not been investigated in exiting literature. For first issue: the uncertainty of grid tariff, most of the existing literatures generate tariff uncertainty scenarios based on estimated probability density function. However, owing to the complexity of the markets, it is difficult to obtain the accurate distribution of tariffs. Consequently, it is necessary to deeply study the uncertainty of grid tariff in MMGs. For second issue: the cheating issue in energy sharing, MG deliberately provide false information for their own interests, but this may lead to the cooperation failure and affect the overall benefits. Therefore, it is important to establish a cheating equilibrium mechanism in MMGs.

Based on the above discussion, we hope to make essential improvements, such as establishing an energy sharing model of multi-microgrids system based on NB theory considering the uncertainties of renewable energy and grid tariff to solve first issue, and innovatively propose a cheating equilibrium mechanism based on intermediary transaction mode (ITM) to solve second issue. Firstly, the cooperation model of MMGs including demand response (DR) and cloud energy storage system (CES) based on NB theory is established. Secondly, to ensure the model is tractable, the original game problem is equivalently converted into a system benefit maximization subproblem and an additional profit distribution subproblem. The first subproblem adopts robust optimization (RO) methods to mitigate the adverse impact of multiple uncertainties on MMGs. The second subproblem innovatively propose a cheating equilibrium mechanism based on ITM to effectively avoid the failure of cooperation and realize optimum profits of MMGs. Thirdly, ADMM is used to protect the privacy of MMGs in a distributed way. Lastly, the efficiency of proposed model is proved for solving two challenging issues through simulation cases. The main contributions of this paper are summarized as follows:

1) A novel energy sharing model of MMGs based on RO and NB theories is proposed to maximize the MGs' profit and fully consider the multiple uncertainties as well as the cheating behaviors in bidirectional

energy transaction.

2) For the uncertainties of renewable energy and grid tariff, the proposed model uses RO to relieve the adverse impact of multiple uncertainties on MMGs which mitigates the operational risk of MMGs.

3) For the cheating behaviors in energy sharing, a novel cheating equilibrium mechanism based on ITM is presented to effectively avoid the breakdown of cooperation.

The rest of this paper is organized as follows. Section 2 introduces the whole MMGs' framework. Section 3 models the detailed individual operation of MG. Section 4 formulates the energy sharing scheme for MMGs and presents the solution methods. Section 5 analyses the simulation results. Section 6 concludes this paper.

2. System framework

The MMGs' framework including DR and CES is shown in Fig. 1. The MMGs' power flow path is shown in Fig. 2. In this framework, there are N MGs and N energy management systems (EMS) as well as a CES in a scheduling horizon T consisting of t time slots. Each time slot has a time duration Δt, e.g., one hour. Besides, each MG is composed of renewable energy generation system (such as wind turbine (WT), photovoltaic power (PV)), gas turbines (GT), gas boilers (GB), heat pumps (HP), and flexible load. MGs are connected to the market, and can purchase multiple energy from market. MGs can shary energy through distribution network. CES provides capacity and power leasing services to reduce energy storage investment costs and smooth the power fluctuation for MGs. Energy management systems (EMS) are equipped with the MGs making intelligent control and scheduling decision and realizing the interaction of energy and communication.

In this MMGs' framework, we assume that MGs are willing to form a stable cooperative coalition to increase their profits through energy sharing. In periods with low renewable energy outputs, MG can absorb energy from other MGs and share surplus energy in periods with high energy outputs. In this paper, we assume that the three microgrids are not far apart in position, and the distribution network provides auxiliary services such as the overall power flow balance of the system. Therefore, we ignore the network constraints and the similar setting can be found in [32]. However, MGs belong to different stockholders, we use NB to realize fair profits distribution. Moreover, we discuss the impact of multiple uncertainties and cheating behaviors on MMGs and propose a cheating equilibrium mechanism based on ITM to realize stable energy cooperation.

3. Individual operation models

In this section, we introduce the day-ahead individual operation model of MG. Besides, the uncertainties of renewable energy and grid tariff are analyzed. MG decides equipment scheduling plan, the purchasing/selling power from/to grid and the leasing power from CES to

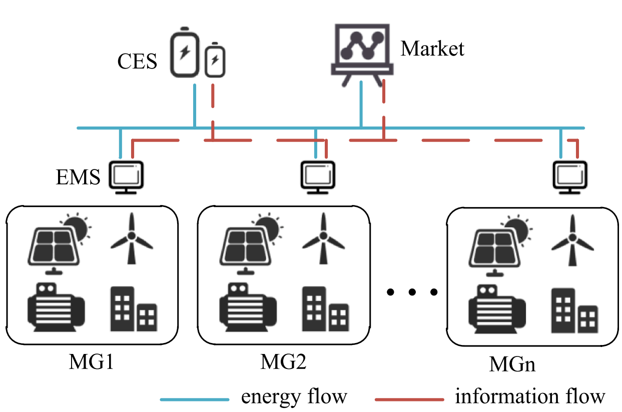


Fig. 1. MMGs'system framework.

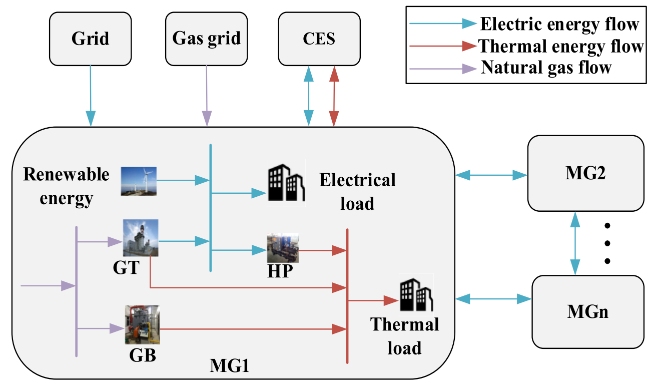


Fig. 2. MMGs'power flow path.

meet the demand. The GT generates electricity and heat energy by burning natural gas and satisfies the following constraints:

$$P_{i,t}^{\mathrm{GT}} = \eta_{\mathrm{GT}} H_{\mathrm{LHV}} F_{i,t}^{\mathrm{GT}}$$

$$H_{i,t}^{\mathrm{GT}} = \eta_{\mathrm{GT,h}} (1 - \eta_{\mathrm{GT}}) H_{\mathrm{LHV}} F_{i,t}^{\mathrm{GT}}$$

where (1), (2) denotes the relationship between $P_{i,t}^{\mathrm{GT}}$,$H_{i,t}^{\mathrm{GT}}$ and $F_{i,t}^{\mathrm{GT}}$. The GB burns natural gas and the HP consume electricity respectively for heating. Their constraint conditions are as follows:

$$H_{i,t}^{\mathrm{GB}} = \eta_{\mathrm{GB}} H_{\mathrm{LHV}} F_{i,t}^{\mathrm{GB}}$$

$$H_{i,t}^{\mathrm{HP}} = \eta_{\mathrm{HP}} P_{i,t}^{\mathrm{HP}}$$

where (3), (4) denotes the relationship between $H_{i,t}^{\mathrm{GB}}$, $H_{i,t}^{\mathrm{HP}}$ and $F_{i,t}^{\mathrm{GB}}$, $P_{i,t}^{\mathrm{HP}}$. The flexible load includes interruptible load and shiftable load which participates in demand response adjusting demand. The interruptible load cuts part of load during peak periods. The shiftable load shifts load from peak times to off-peak times. The specific constraints are as follows:

$$L_{i,t}^{\mathrm{e}} = l_{i,t}^{\mathrm{e}} + P_{i,t}^{\mathrm{cut}} + P_{i,t}^{\mathrm{tran}}$$

$$-al_{i,t}^{\mathrm{e}} \leqslant P_{i,t}^{\mathrm{cut}} \leqslant 0$$

$$-bl_{i,t}^{\mathrm{e}} \leqslant P_{i,t}^{\mathrm{tran}} \leqslant bl_{i,t}^{\mathrm{e}}$$

$$\sum_{t=1}^{T} P_{i,t}^{\mathrm{tran}} = 0$$

where (5) indicates the composition of load. Formula (6)-(8) are the constraints of flexible load limits. During the cooperation of MMGs, the "shared energy storage" mode of CES can avoid the disorder of distributed energy storage and realize the efficient utilization of energy [33,34]. The constraints of cloud electric energy storage system (CEES) are as follows:

$$eE_i \leqslant E_{i,t} \leqslant fE_i$$

$$0 \leqslant E_i \leqslant E_i^{\max}$$

$$0 \leqslant P_{i,t}^{\mathrm{ch}} \leqslant P_i^{\mathrm{ch}} u_{i,t}^{\mathrm{ch}}$$

$$0 \leqslant P_i^{\mathrm{ch}} \leqslant P_{i,\mathrm{ch}}^{\max}$$

$$0 \leqslant P_{i,t}^{\mathrm{dis}} \leqslant P_i^{\mathrm{dis}} u_{i,t}^{\mathrm{dis}}$$

$$0 \leqslant P_i^{\mathrm{dis}} \leqslant P_{i,\mathrm{dis}}^{\max}$$

$$u_{i,t}^{\text{ch}}+u_{i,t}^{\text{dis}}\leqslant 1$$

$$E_{i,t}=E_{i,t-1}(1-\delta)+\eta_{\text{c}}P_{i,t}^{\text{ch}}-\frac{P_{i,t}^{\text{dis}}}{\eta_{\text{d}}}$$

$$E_{i,24}=E_{i,0}$$

where formula (9), (11), (13) are the limit constraints of $E_{i,t}$,$P_{i,t}^{\text{ch}}$,$P_{i,t}^{\text{dis}}$. Formula (10), (12), (14) are the limit constraints of leasing capacity, charging power and discharging power, respectively. (15) indicates that simultaneous charging and discharging power are not allowed. Equation (16) denotes the relationship of real leasing capacity of CEES in adjacent moments. (17) guarantee CEES's sustainable operation. The constraints of cloud thermal energy storage system (CTES) are the same as CEES. Here, the constraints of CTES are not detailed describe.

Each MG can purchase/selling electricity from/to the distribution network and should satisfy the following constraints:

$$0\leqslant P_{i,t}^{\text{buy}}\leqslant P_{i,t}^{\text{buy,max}}u_{i,t}^{\text{buy}}$$

$$0\leqslant P_{i,t}^{\text{sell}}\leqslant P_{i,t}^{\text{sell,max}}u_{i,t}^{\text{sell}}$$

$$u_{i,t}^{\text{buy}}+u_{i,t}^{\text{sell}}\leqslant 1$$

where (18), (19) are the limit constraints of $P_{i,t}^{\text{buy}}$, $P_{i,t}^{\text{sell}}$. Formula (20) indicates that simultaneous purchasing and selling power are not allowed.

The influence of uncertainty brought by renewable energy on the cooperation of MMGs can not be ignored. We assume that the set $U_{i,m}$ to be the uncertain set of the renewable energy power generation $P_{i,t,m}$ including WT and PV power generation.

$$U_{i,m}=\{P_{i,t,m}|\forall t$$

$$P_{i,t,m}\leqslant\xi_{i,t,m}+\partial_{i,t,m}:\alpha_{i,t,m}$$

$$P_{i,t,m}\geqslant\xi_{i,t,m}-\partial_{i,t,m}:\beta_{i,t,m}\}$$

where (21), (22) are the limit constraints of $P_{i,t,m}$. Each MG can utilize $\partial_{i,t,m}$ which denotes power generation deviation to control the robustness of $U_{i,m}$. $\alpha_{i,t,m}$, $\beta_{i,t,m}$ are dual variables of (21), (22) respectively. Each MG should satisfy the demand of load. The power balance constraint is as follows:

$$P_{i,t}^{\text{buy}}+P_{i,t}^{\text{GT}}+P_{i,t}^{\text{dis}}-P_{i,t}^{\text{sell}}-P_{i,t}^{\text{HP}}$$
$$-L_{i,t}^{\text{e}}-P_{i,t}^{\text{ch}}-\sum_{j=1,j\neq i}^{N}P_{eij,t}\geqslant -P_{i,t,m}$$

Considering that the renewable energy outputs are uncertain and cannot be accurately predicted, formula (24) is used to replace the constraint described in formula (23).

$$P_{i,t}^{\text{buy}}+P_{i,t}^{\text{GT}}+P_{i,t}^{\text{dis}}-P_{i,t}^{\text{sell}}-P_{i,t}^{\text{HP}}$$
$$-L_{i,t}^{\text{e}}-P_{i,t}^{\text{ch}}-\sum_{j=1,j\neq i}^{N}P_{eij,t}\geqslant\max(-P_{i,t,m})$$

$$P_{i,t}^{\text{buy}}+P_{i,t}^{\text{GT}}+P_{i,t}^{\text{dis}}-P_{i,t}^{\text{sell}}-P_{i,t}^{\text{HP}}-L_{i,t}^{\text{e}}-P_{i,t}^{\text{ch}}$$
$$-\sum_{j=1,j\neq i}^{N}P_{eij,t}\geqslant\alpha(\xi_{i,t,m}+\partial_{i,t,m})+\beta(-\xi_{i,t,m}+\partial_{i,t,m})$$
$$\text{s.t.}\alpha-\beta\geqslant -1,\alpha\geqslant 0,\beta\geqslant 0$$

According to the strong duality theory, the objective function value of the dual problem is the same as the original problem at the optimal solution. To solve the uncertainty of renewable energy, formula (24) can be further converted into the following constraints:

In addition, each MG should satisfy the heat power balance constraint (26).

$$H_{i,t}^{\text{GT}}+H_{i,t}^{\text{GB}}+H_{i,t}^{\text{HP}}=H_{i,t}^{\text{ch}}-H_{i,t}^{\text{dis}}+L_{i,t}^{\text{h}}$$

The market has an important impact on the decision-making of the MMGs. However, due to the complexity of the market, it is difficult to obtain the accurate distribution of grid tariff [35,36]. The robust optimization only needs to know the confidence interval of the uncertain variables and not need the probability distribution function. so the uncertainty of the grid tariff can be described by RO. We assume that the set V to be the uncertain set of the grid tariff.

$$\min C_{i,0}=\begin{pmatrix}C_{i,\text{GT}}+C_{i,\text{GB}}+C_{i,\text{tran}}+C_{i,\text{cut}}\\+C_{i,\text{cur}}+C_{i,\text{CEES,om}}+C_{i,\text{CTES,om}}\\+C_{i,\text{CEES}}+C_{i,\text{CTES}}+\max C_{i,\text{grid}}\end{pmatrix}$$

where formula (27) denotes the range of price, and the dual variables.

The individual operation model of MG considering the uncertainty of grid tariff is as follows:

$$C_{i,\text{GT}}=\sum_{t=1}^{T}c_{\text{gas}}F_{i,t}^{\text{GT}}$$

$$C_{i,\text{GB}}=\sum_{t=1}^{T}c_{\text{gas}}F_{i,t}^{\text{GB}}$$

$$C_{i,\text{ grid}}=\sum_{t=1}^{T}\left(\lambda_{b,t}P_{i,t}^{\text{buy}}-\lambda_{s,t}P_{i,t}^{\text{sell}}\right)$$

$$C_{i,\text{ tran}}=\sum_{t=1}^{T}\left(\lambda_{\text{tran,e}}\left|P_{i,t}^{\text{tran}}\right|+\lambda_{\text{tran,h}}\left|H_{i,t}^{\text{tran}}\right|\right)$$

$$C_{i,\text{cut}}=\sum_{t=1}^{T}\left(\lambda_{\text{cut,e}}\left|P_{i,t}^{\text{cut}}\right|+\lambda_{\text{cut,h}}\left|H_{i,t}^{\text{cut}}\right|\right)$$

$$C_{i,\text{cur}}=\sum_{t=1}^{T}\lambda_{\text{cur}}P_{i,t}^{\text{cur}}$$

$$C_{i,\text{CEES,om}}=\sum_{t=1}^{T}\lambda_{\text{om}}\left(P_{i,t}^{\text{ch}}+P_{i,t}^{\text{dis}}\right)$$

$$C_{i,\text{CEES}}=\left(\lambda_{\text{E}}E_{i}+\lambda_{\text{P}}P_{i}^{\text{ch}}+\lambda_{\text{P}}P_{i}^{\text{dis}}\right)/365$$

$$C_{i,\text{net}}=\sum_{t=1}^{T}\lambda_{\text{net}}\lambda_{\text{loss}}P_{eij,t}$$

where (28) is the objective function of individual operation model for MG. (29), (30) are the fuel costs of GT, GB respectively. (31) is purchase cost from grid. (32), (33) are the demand response costs of flexible loads. (34) is renewable energy loss cost. (35), (36) are costs of operation and leasing services respectively. $C_{i,\text{CTES,om}}$, $C_{i,\text{CTES}}$ are the same as CEES. The transactions between microgrids are accomplished through the distribution network. There, we consider the line losses, transmission costs and service fees in (37). Where, λ_{loss} are the ratio coefficients of power losses.λ_{net} are the cost coefficients of transmission and service fees. Equation (37) should be taken into account when microgrids are operating cooperatively.

According to the duality theory, the uncertainty robust model (28)-(36) can be transformed into the following model:

$$\min C_{i,0} = \begin{pmatrix} C_{i,\mathrm{GT}} + C_{i,\mathrm{GB}} + C_{i,\mathrm{tran}} + C_{i,\mathrm{cut}} \\ +C_{i,\mathrm{cur}} + C_{i,\mathrm{CEES,om}} + C_{i,\mathrm{CTES,om}} \\ +C_{i,\mathrm{CEES}} + C_{i,\mathrm{CTES}} + \varphi \end{pmatrix}$$

$$\varphi = \sum_t \left(\lambda_{1ub,t}\lambda_{b,t}^{\max} - \lambda_{1lb,t}\lambda_{b,t}^{\min} + \lambda_{2ub,t}\lambda_{s,t}^{\max} - \lambda_{2lb,t}\lambda_{s,t}^{\min}\right)$$

$$\text{s.t.}\lambda_{1ub,t} - \lambda_{1lb,t} \geqslant P_{i,t}^{\mathrm{buy}}$$

$$\lambda_{2ub,t} - \lambda_{2lb,t} \geqslant -P_{i,t}^{\mathrm{sell}}$$

$$\lambda_{1ub,t}, \lambda_{1lb,t}, \lambda_{2ub,t}, \lambda_{2lb,t} \geqslant 0$$

$$(29) - (36)$$

4. NB-based energy sharing model

In this section, a NB-based energy sharing model for MMGs is proposed to reduce all players'costs. To ensure stable cooperation, this section presents a novely cheating equilibrium mechanism based on ITM considering the case where MG provide dishonest information in benefits distribution attempting to gain more benefits.

4.1. NB-based cooperation model considering cheating behaviors

This paper assumes that each MG belongs to different stakeholders and enjoys the power of energy trading and pricing with other MGs. As independent and rational entities, all MGs hope to maximize their benefits through cooperation. The NB-based cooperation model for MMGs is proposed to make each MG participating in energy sharing obtain Pareto optimal profits [37,38].

$$\max \prod_{i=1}^{N} \left(C_i^{\mathrm{dif}} + \tau_i\right)$$

$$\text{s.t.} C_i^{\mathrm{dif}} + \tau_i \geqslant 0$$

$$C_i^{\mathrm{dif}} = C_i^0 - C_i^1$$

$$\rho_{ij} = \rho_{ji}$$

$$P_{eij} = -P_{eji}$$

$$\tau_i = \sum_{j=1, j\neq i}^{N} \rho_{ij} P_{eij}$$

$$\sum_{i=1}^{N} \tau_i = 0$$

$$\begin{cases} |P_{eij}| \leqslant P_{eij,\max} \\ \rho_{ij,\min} \leqslant \rho_{ij} \leqslant \rho_{ij,\max} \end{cases}$$

where C_i^{dif} are defined as the cost differences before and after cooperation for MGs. ρ_{ij}, P_{eij} is energy sharing price and power between MGi and MGj respectively. MGi sells surplus energy to MGj when $P_{eij} > 0$. τ_i is bargainning payment of MGi. MGi obtain bargainning payment from other MGs when $\tau_i > 0$. Formula (42), (43), (45) are jointly-constraints of MMGs. Formula (46) is energy sharing constraint.

Nash bargainning game model (39) is essentially a non convex nonlinear optimization problem, which is difficult to solve directly. Therefore, it is converted into the following two sub problems that are easy to solve: system benefit maximization subproblem (**SP1**) and an additional profit distribution subproblem (**SP2**). The specific derivation process is shown as Appendix A.

SP1: System benefit maximization subproblem

$$\min \sum_{i=1}^{N} C_i^1$$

$$\text{s.t. } (1) - (27), (37) - (38)$$

SP2: An additional profit distribution subproblem

$$\begin{cases} \min -\sum_{i=1}^{N} \ln\left[\left(C_i^{\mathrm{dif}}\right)^* + \tau_i\right] \\ \quad \text{s.t. } (40) - (46) \end{cases}$$

In **SP1**, we utilize ADMM to realize distributed solution and consider the uncertainty of renewable energy and grid tariff. Detailed solution process is introduced in section B.

In **SP2**, we consider the cheating behavior of dishonest MG in energy sharing. By solving the cooperation model (39), we obtain the optimal solution of τ_i^*. Detailed solution process is introduced in Appendix A.

$$\tau_i^* = \left[\sum_{j\in N\backslash\{i\}} C_j^{\mathrm{dif}} - (N-1)C_i^{\mathrm{dif}}\right] \Big/ N$$

It can be seen from formula (49) that if MG provides lower cost information C_i^{dif} in benefits distribution, it can obtain more benefits. In addition, due to the need to protect privacies of each entity, MG cannot know the real information of other MGs, and this dishonest cost will not affect the electric power balance. Therefore, each MG has the motivation of cost cheating and this cheating behavior cannot be detected by system. We define dishonest cost as $C_{i,\mathrm{R}}^{\mathrm{dif}}$ which is as follows:

$$C_{i,\mathrm{R}}^{\mathrm{dif}} = C_i^{\mathrm{dif}} - \gamma_i \left|C_i^{\mathrm{dif}}\right|$$

where γ_i defined as cheating factors. Honest MG undoubtedly set the cheating factor to 0. It is noted that each MG participating in energy sharing enable achieve Pareto optimal benefits, thus all MGs will avoid cooperation failure. Therefore, after considering cheating behaviors, the following inequality constraints should be satisfied:

$$\sum_{i=1}^{N} C_{i,\mathrm{R}}^{\mathrm{dif}} > 0$$

In order to satisfy inequality (51), the cheating factor γ_i has an upper bound $\gamma_i^{\mathrm{limit}}$:

$$\gamma_i^{\mathrm{limit}} = \left(C_i^{\mathrm{dif}} + \sum_{j\in N\backslash\{i\}} C_{j,\mathrm{R}}^{\mathrm{dif}}\right) \Big/ \left|C_i^{\mathrm{dif}}\right| = \left(C_i^{\mathrm{dif}} + C_{\mathrm{R}}^{\mathrm{dif,sum}} - C_{i,\mathrm{R}}^{\mathrm{dif}}\right) / \left|C_i^{\mathrm{dif}}\right|$$

where $C_{\mathrm{R}}^{\mathrm{dif,sum}} = \sum_{j\in N} C_{j,\mathrm{R}}^{\mathrm{dif}}$. Dishonest MGs hope that their cheating factors reach to $\gamma_i^{\mathrm{limit}}$ to obtain the optimal benefits τ_i^*. However, the upper bound and optimal benefits will change dynamically under the influence of other MG' cheating behaviors. Therefore, MMGs should strive to achieve cheating equilibrium. In this case, all MGs unable increase γ_i to obtain higher income without affecting the interests of other MGs and think that their cheating behaviors can maximize their own benefits [39].

In order to ensure stable cooperation, this paper proposes a novely cheating equilibrium mechanism based on ITM which can realize the cheating equilibrium and effectively avoid the privacy leakage of entities. The ITM requires a third-party intermediary trusted by all MGs to collect cheating cost informations and feed back the results to MMGs. The solution process of cheating equilibrium mechanism based on ITM introduced above in Algorithm 1.

Algorithm 1 Based-ITM Algorithm for Cheating Equilibrium

1:Initialize iteration index $k = 1$,cheating factor $\gamma_{i,1} = 0.001$ convergence accuracy $\zeta = 0.0001$;
2:**while 1 do**

(*continued on next page*)

(*continued*)

Algorithm 1 Based-ITM Algorithm for Cheating Equilibrium

3: All MGs send cheating costs $C^{\text{dif}}_{i,\text{R},k} = C^{\text{dif}}_i - \gamma_{i,k}\left|C^{\text{dif}}_i\right|$ to intermediary transaction;
4: Intermediary transaction calculates $C^{\text{dif,sum}}_{\text{R},k} = \sum_{i=1}^{N} C^{\text{dif}}_{i,\text{R},k}$ and feed back $C^{\text{dif,sum}}_{\text{R},k}$ to each MG;
5: All MGs update cheating factors $\gamma_{i,k+1} = (1-\omega)\gamma_{i,k} + \omega\gamma^{\text{limit}}_{i,k}$,where $\gamma^{\text{limit}}_{i,k} = \left(C^{\text{dif}}_i + C^{\text{dif,sum}}_{\text{R},k} - C^{\text{dif}}_{i,\text{R},k}\right)\Big/\left|C^{\text{dif}}_i\right|$,
ω is the relaxation coefficient, $\omega = \dfrac{1}{\sqrt{k}+N}$;
6: if $\sum_{i=1}^{N}(\gamma_{i,k+1} - \gamma_{i,k}) < \zeta$ then output $C^{\text{dif}}_{i,\text{R},k}$;
7: Cheating equilibrium achieved,and break;
8: end if
9: $k = k+1$,go to step 3;
10:**end while**

4.2. Model solving

Considering that **SP1** and **SP2** have separable convex functions and constraints, ADMM can be used for distributed solution.

SP1 Solving:Introducing Lagrange multiplier λ_{ij} and penalty factor ρ to construct augmented Lagrange function (53).

$$\text{L} = \sum_{i=1}^{N}\left[\begin{array}{l} C^{1}_{i} + \sum\limits_{j\in N\backslash\{i\}}\sum\limits_{t=1}^{T}\lambda_{ij}\left(P_{eij,t} + P_{eji,t}\right) \\ + \sum\limits_{j\in N\backslash\{i\}}\sum\limits_{t=1}^{T}\dfrac{\rho}{2}\left\|P_{eij,t} + P_{eji,t}\right\|_2^2 \end{array}\right]$$

Then, the formula (53) is decomposed to obtain the distributed optimization operation model of each MG, and MG1 is taken as an example to explain:

$$\min\left[\begin{array}{l} C^{1}_{1} + \sum\limits_{j\in N\backslash\{1\}}\sum\limits_{t=1}^{T}\lambda_{1j}\left(P_{e1j,t} + P_{ej1,t}\right) \\ + \sum\limits_{j\in N\backslash\{1\}}\sum\limits_{t=1}^{T}\dfrac{\rho}{2}\left\|P_{e1j,t} + P_{ej1,t}\right\|_2^2 \end{array}\right]$$

The distributed solution algorithm of **SP1** introduced above in Algorithm 2. By solving **SP1** and realizing cheating equilibrium, the energy sharing P_{eij} and cheating costs $C^{\text{dif}^*}_{i,\text{R}}$ are obtained, and the formula (48) can be replaced by the following formula.

$$\begin{cases} \min -\sum_{i=1}^{N}\ln\left(C^{\text{dif}^*}_{i,\text{R}} + \tau_i\right) \\ \quad \text{s.t. } \rho_{ij} > \lambda_s \\ \quad C^{\text{dif}^*}_{i,\text{R}} + \tau_i > 0 \\ \tau_i = \sum_{j\in N\backslash\{i\}}\sum_{t=1}^{T}\rho_{ij,t}P^{*}_{eij,t} \end{cases}$$

SP2 Solving:Introducing Lagrange multiplier σ_{ij} and penalty factor γ to construct augmented Lagrange function (56):

$$\text{L} = -\sum_{i=1}^{N}\ln\left(C^{\text{dif}^*}_{i,\text{R}} + \tau_i\right)$$
$$+\sum_{i=1}^{N}\sum_{j\in N\backslash\{i\}}\sum_{t=1}^{T}\sigma_{ij}\left(\rho_{ij,t} - \rho_{ji,t}\right)$$
$$+\sum_{i=1}^{N}\sum_{j\in N\backslash\{i\}}\sum_{t=1}^{T}\frac{\gamma}{2}\left\|\rho_{ij,t} - \rho_{ji,t}\right\|_2^2$$

Then, the formula (56) is decomposed to obtain the distributed optimization operation model of each MG. The distributed solution algorithm of **SP2** is the same as **SP1**. Detailed solution process is introduced in Appendix C.

$$\min\left[\begin{array}{l} -\ln\left(C^{\text{dif}^*}_{1,R} + \tau_1\right) + \sum\limits_{j\in N\backslash\{i\}}\sum\limits_{t=1}^{T}\sigma_{1j}\left(\rho_{1j,t} - \rho_{j1,t}\right) \\ + \sum\limits_{j\in N\backslash\{i\}}\sum\limits_{t=1}^{T}\dfrac{\gamma}{2}\left\|\rho_{1j,t} - \rho_{j1,t}\right\|_2^2 \end{array}\right]$$

Algorithm 2 Algorithm for **SP1**

1:Initialize iteration index $k = 1$,sharing energy $P_{eij} = 0$, penalty factor $\rho = 0.01$, convergence accuracy $\zeta = 0.1$;
2:**while 1 do**
3: Receive $P^{k}_{eji,t}, \forall j,t,j \neq i$ from other MGs.Then,solve the distributed optimization operation model of MGi and output $P^{k+1}_{eij,t}, \forall j,t,j\neq i$ to other MGs;
4: All MGs update Lagrange multiplier $\lambda^{k+1}_{ij}, \forall i,j$;
$\lambda^{k+1}_{ij} = \lambda^{k}_{ij} + \rho\left(P^{k+1}_{eij,t} + P^{k+1}_{eji,t}\right)$.
5: if $\sum_{i=1}^{N}\sum_{j\in N\backslash\{i\}}\sum_{t=1}^{T}\left\|P^{k+1}_{eij,t} + P^{k+1}_{eji,t}\right\| < \zeta$
6: **SP1** achieved,and break;
7: end if
8: $k = k+1$,go to step 3;
10:**end while**

The flow chart of algorithm is shown in Fig. 3.

5. Simulation analysis

In this section, a MMGs composed of 3 MGs is studied to very the effectiveness of model.

5.1. Basic data

MG1/MG2/MG3 are equipped with WT/WT/PV power generation, respectively. Maximum power generation deviation for renewable energy $\partial_{i,t,m} = 0.05\xi_{i,t,m}, \lambda^{\max}_{b,t} = 1.1\lambda_{b,t}$. λ_{net} and λ_{loss} are 0.1 and 0.01, respectively. In **SP2**, penalty factor $\gamma = 10$, convergence accuracy $\zeta = 0.1$.The basic load profiles of MGs without demand response are shown in Fig. 4, Fig. 5. The benchmark price profiles are shown in Fig. 13. The predicted power profiles of renewable energy are shown in Fig. 14. The parameters of MMGs are also shown in Table 1. The numerical simulations are carried out in the MATLAB 2021a environment. **SP1** and **SP2** are solved through Cplex and Mosek solver.

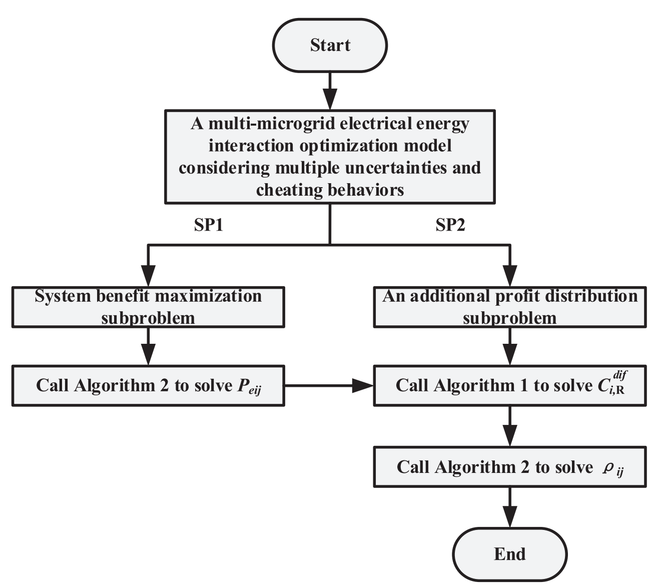


Fig. 3. The flow chart of algorithm.

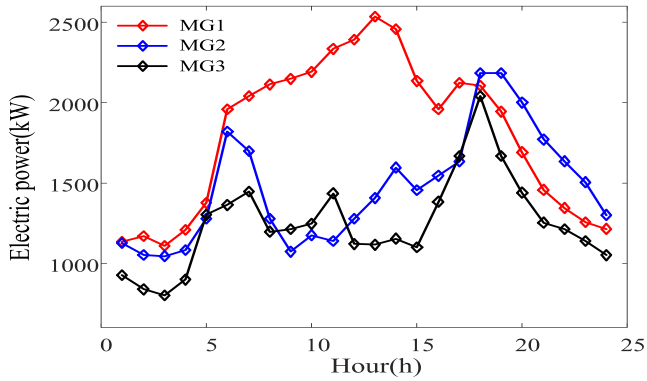


Fig. 4. Electricity load profiles.

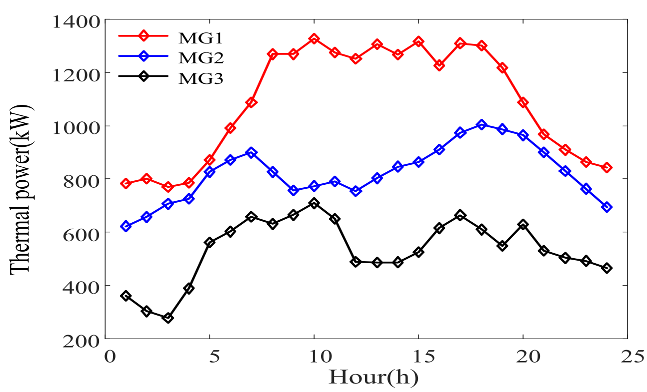


Fig. 5. Heat load profiles.

Table 1
System parameters.

Parameters	Values	Parameters	Values
$\eta_{GT}/\eta_{GT,h}$	0.3/0.8	δ	0.05
η_{GB}/η_{HP}	0.93/4.5	$E_{i,0}$(kWh)	250
a/b	0.1/0.15	λ_E(¥/kWh)	110/30
E_i^{max}(kWh)	500	λ_P(¥/kW)	37/10
$P_{i,ch}^{max}/P_{i,dis}^{max}$(kW)	250	η_c/η_d	0.98
$P_{i,t}^{buy,max}/P_{i,t}^{sell,max}$(kW)	2000	λ_{om}(¥/kW)	0.01
$\lambda_{tran,e}$ /$\lambda_{tran,h}$ (¥/kW)	0.1/0.1	e/f	0.1/0.9
$\lambda_{cut,e}/\lambda_{cut,h}$ (¥/kW)	0.3/0.3	H_{LHV}	9.7
λ_{cur}(¥/kW)	0.5	c_{gas}	2.7

5.2. Algorithms performance

The convergence curves of algorithm for **SP1** and **SP2** are as shown in Fig. 6 and Fig. 7, respectively. Fig. 6 shows the cost results of MGs for **SP1** after cooperation. The proposed algorithm converges after 22 iterations, and the calculation time is 105 s. Fig. 7 shows the convergence results of sharing prices for **SP2**. The proposed algorithm for **SP2** converges after 44 iterations, and the calculation time is 167 s.

Convergence results shows that the algorithms for **SP1** and **SP2** proposed in this paper based on ADMM have excellent convergence performance while protecting the privacy of each MG.

5.3. Energy sharing and bargainning

The results of energy sharing are shown in Fig. 8. MG1 shares surplus energy to other MGs with high wind power outputs during 18:00–23:00. In periods with low wind power outputs, MG1 absorb energy form other MGs during 07:00–15:00. During 01:00–04:00, 07:00–09:00 and 18:00–23:00, MG2 is regarded as energy shortage microgrid which the photovoltaic power generation is insufficient. At 11:00, MG3 absorb energy from other MGs, and at the rest of the time, MG3 share surplus energy to other MGs.

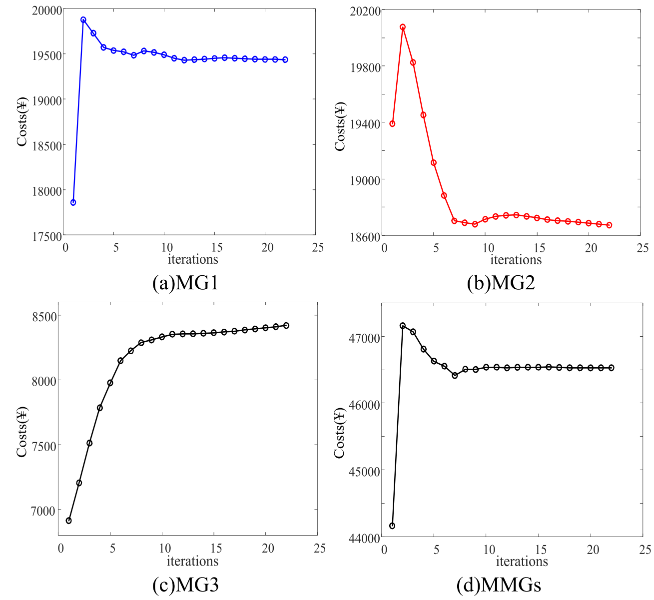


Fig. 6. Cost convergence results of SP1.

All MGs decide optimal scheduling plan after participating in energy sharing through EMS. Take MG1 as an example to illustrate scheduling results. Fig. 9 depicts the power balance results of MG1. It should be pointed out that the positive values correspond to absorbed energy from other MGs for sharing energy.

MG1 reduces the power purchased from grid and increases the power generation of GT during the period of high electricity price. The sharing power with other MGs is consistent with Fig. 8. MG1'heat power is mainly supplied by GT and HP. The CEES is mainly charged during the period of low electricity price, discharged during the period of high electricity price, and release heat power during the period of 15:00–16:00 to reduce the operation cost. Residual MGs'power balance profiles are shown as in Fig. 10.

The results of sharing prices are shown in Fig. 11. As can be seen from the Fig. 11, the sharing prices in each period are within the feed-in tariff (FiT) and time-of-use (TOU) tariff. So each MG can purchase electric power at a lower price than TOU and sell electric power at a higher price than FiT to effectively improve the benefits.

5.4. Costs analysis

This paper sets 4 cases to analysis the impact of uncertainties and cheating behaviors on cooperation of MMGs. Case1 is the proposed model in this paper; Case2 takes no account of uncertainties on the basis of Case1; Case3 takes no account of cheating behaviors on the basis of Case1; Case4 takes no account of uncertainties and cheating behaviors on the basis of Case1; The cost results of four cases are also shown in Table 2, where $C_i^r = C_i^1 - \tau_i$ is cost of each MG after energy sharing.

It can be seen from Table 2 that the cheating costs $C_{i,R}^{dif}$ in case2 are lower than case4. This is because case2 takes into account the cheating behavior in energy sharing. Each MG reduces the cost C_i^r in case2 compared with case4 by submitting smaller cheating costs to transaction intermediary. It indicates that cheating behaviors in energy sharing can improve economy. The cost C_i^0 and C_i^r of each MG in case3 are higher than case4 because case3 considers the worst situations of renewable energy outputs and grid tariff. The MMGs considering multiple uncertainties can improve the ability coping with uncertain risks. It can be

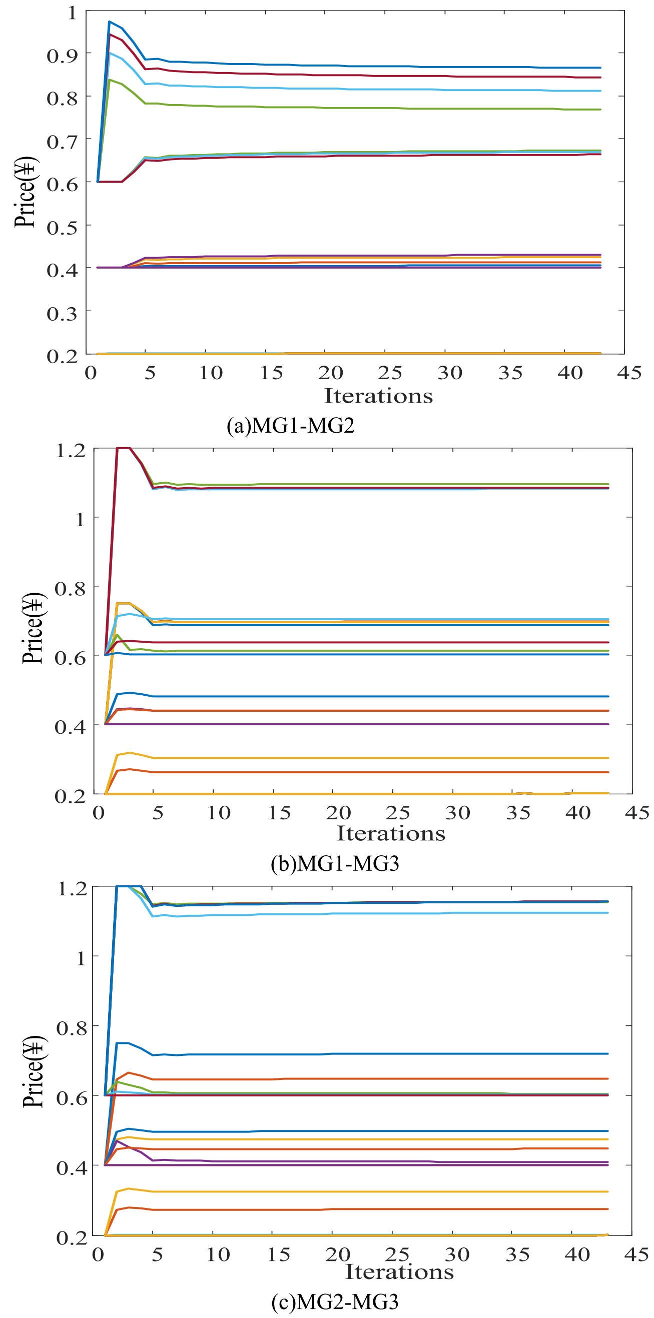


Fig. 7. Convergence results of sharing prices for SP2.

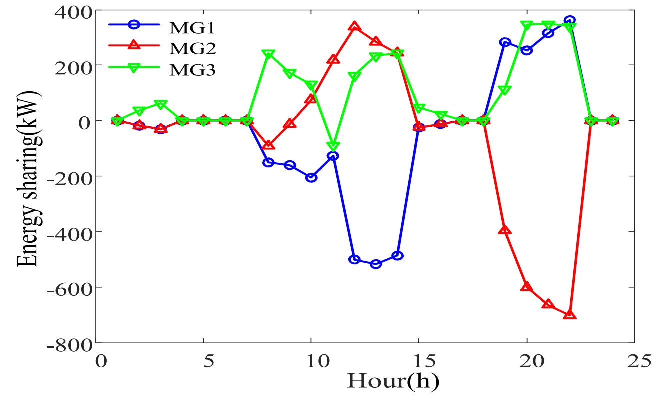


Fig. 8. Results of energy sharing.

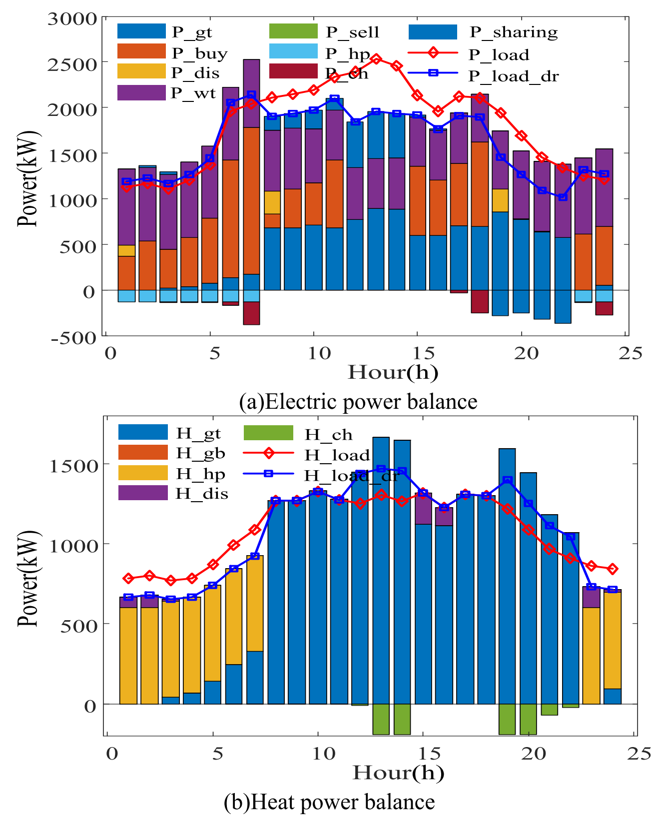


Fig. 9. Optimization results of MG1.

seen from Table 2 that the proposed model in this paper can further reduce operation costs while effectively resist uncertain risks.

5.5. Cheating equilibrium analysis

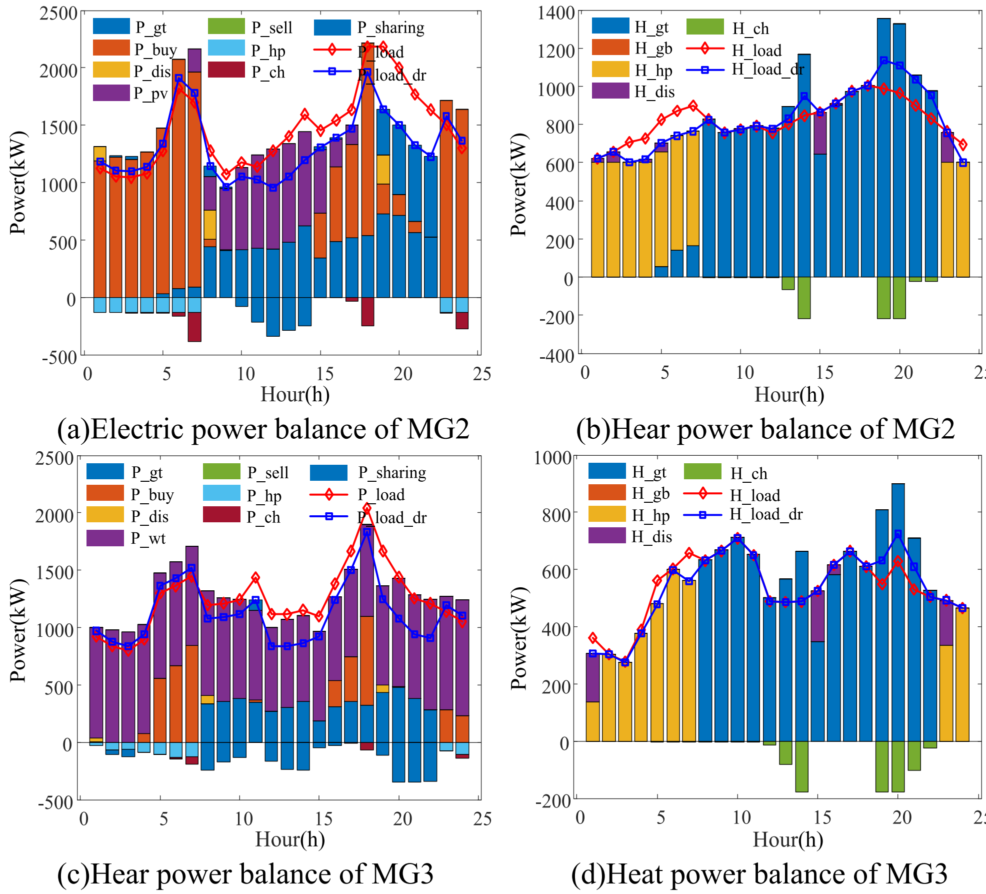
A novely cheating equilibrium mechanism based on ITM is presented to effectively avoid the break of energy sharing. Fig. 12 shows the results of cheating costs and cheating factors. It can be seen from the figure that the cheating costs of each MG gradually decrease and the cheating factors gradually increase until reach the upper bound. At this time, MMGs realize cheating equilibrium to ensure stable cooperation and MG can obtain more benefits through cheating behaviors than the honest players.

In Based-ITM Algorithm for Cheating Equilibrium, we design a adaptive relaxation parameter $\omega = \frac{1}{\sqrt{k+N}}$, which ensure faster convergence in the early stage and avoid crossing the convergence boundary in the later stage. The influence of different relaxation parameter is shown as Table 3.

It can be seen from Table 3 that cheating costs and iteration times of each MG gradually decrease when relaxation paremeters increase. Although MGs have lower cheating costs and iteration times when $\omega = 0.25$ and $\omega = 0.3$, convergence have crossed boundary. $\omega = 0.2$ has the best performance among fixed relaxation parameters. However, it requires simulation tests to obtain best value. The adaptive relaxation parameter designed is effective to find suitable value. In addition, the range of ω is $\omega = \frac{1}{\sqrt{k+N}}$ and is proved in Appendix A.

5.6. Uncertainties analysis

We propose an energy sharing model of MMGs based on NB theories and use RO to consider the adverse impact of multiple uncertainties on



(a)Electric power balance of MG2 (b)Hear power balance of MG2

(c)Hear power balance of MG3 (d)Heat power balance of MG3

Fig. 10. Optimization results of MG2, MG3.

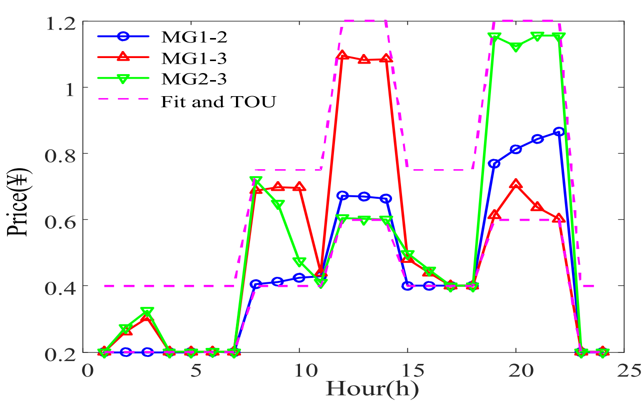


Fig. 11. Results of sharing prices.

Table 2
Cost information of four cases.

	Unities	Case1	Case2	Case3	Case4
C_i^{dif}(¥)	MG1	1317.72	1415.3	1317.72	1415.3
	MG2	2333.83	2166.01	2333.83	2166.01
	MG3	−1892.69	−1943.79	−1892.69	−1943.79
C_i^{0}(¥)	MG1	20766.95	19451.57	20766.95	19451.57
	MG2	21027.36	19699.16	21027.36	19699.16
	MG3	6541.07	5773.72	6541.07	5773.72
	MMG	48335.38	44924.45	48335.38	44924.45
$C_{i,\mathrm{R}}^{\mathrm{dif}}$(¥)	MG1	728.03	866.21	1317.72	1415.3
	MG2	1751.83	1624.48	2333.83	2166.01
	MG3	−2479.63	−2490.48	−1892.69	−1943.79
C_i^{r}(¥)	MG1	20156.08	18790.27	20233.27	18879.95
	MG2	20423.79	19045.42	20502.00	19148.68
	MG3	5932.55	5114.82	6010.29	5383.06
	MMG	46512.42	42950.51	46751.56	43311.69

MMGs. The results of grid tariff and renewable energy uncertainties are shown as in Fig. 13 and Fig. 14, respectively.

It can be seen from the Fig. 13 that the upper bound of the grid tariff is taken when the MG purchases power from grid. At this time, MMGs consider the worst case which the purchase cost from grid and the cost of MMGs are the largest. Besides, the grid tariff is regarded as 0 when MG does not purchase power from grid and sell power to grid. The case of Fig. 13 is consistent with the operation results of Fig. 9 and Fig. 10.

It can be seen from the Fig. 14 that the lower bound of the renewable energy outputs is taken when MMGs consider the worst case through RO. In this time, the cost of MMGs are the largest. The renewable energy outputs of Fig. 14 are consistent with the operation results of Fig. 9 and Fig. 10.

Through the above analysis, it is conducive to make decision for MMGs in the environment of uncertainties.

6. Conclusion

In this paper, taking into account the uncertainties of renewable energy and grid tariffs, an energy sharing model based on NB between multi-microgrids is proposed. The proposed model provides a robust energy trading schedule to relieve the operation risk of each MG when multiple uncertainties have happened. In addition, cheating behaviors in energy sharing are analyzed; the solution based on cheating equilibrium is derived by proposing an intermediary transaction mode to ensure stable cooperaiton. To ensure the model is tractable, the original game problem is equivalently converted into a system benefit

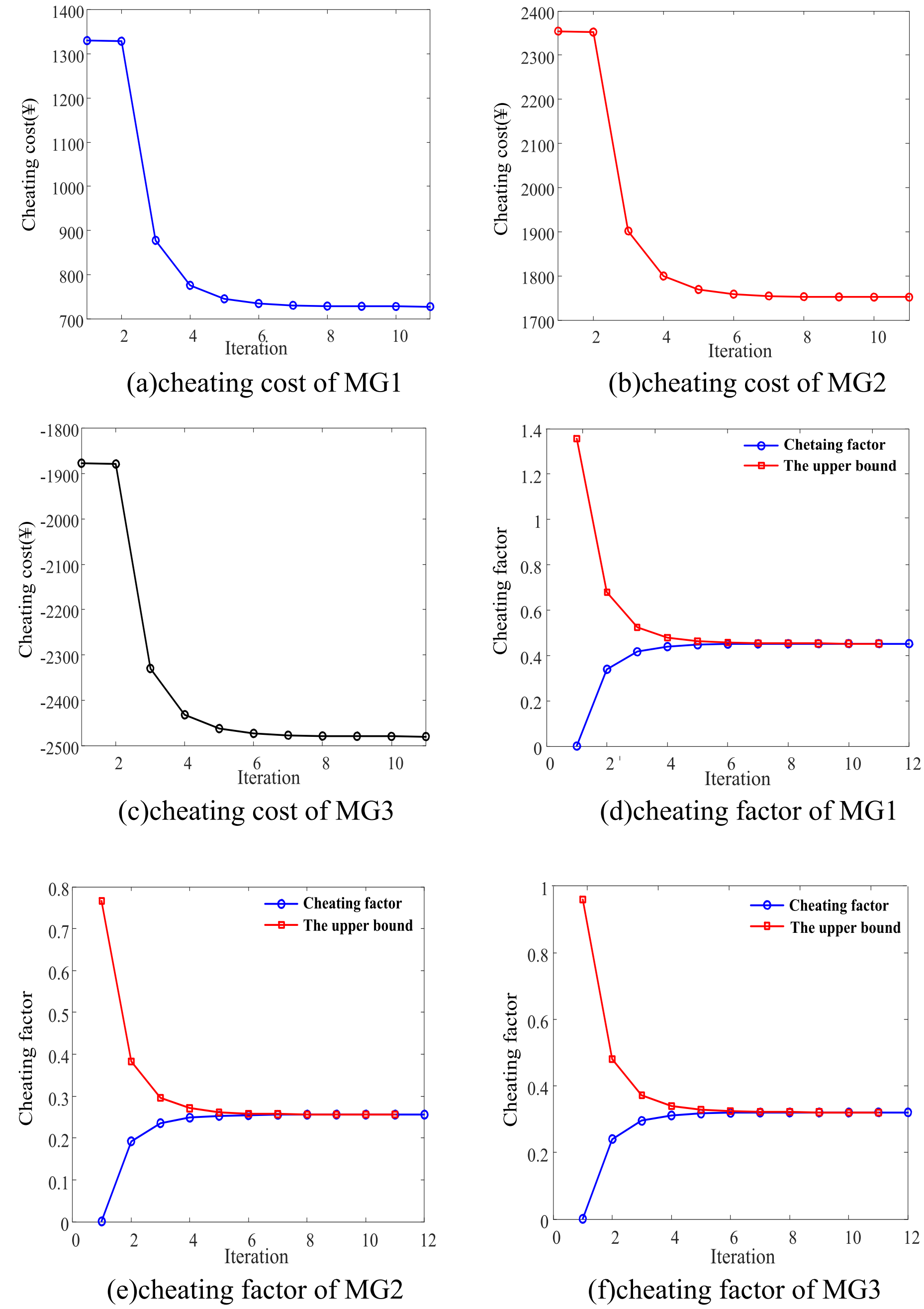


Fig.12. Results of cheating costs and factors.

maximization subproblem and an additional profit distribution subproblem. Furthermore, the alternating direction method of multipliers is used to protect the players'privacies in a distributed way. Simulation results further verify that the proposed model can effectively reduce costs and alleviate the operation risk in a stable ways of cooperation. Our future work includes integrating more functions such as the control of voltage and frequency for MMGs to apply to the practical engineering.

CRediT authorship contribution statement

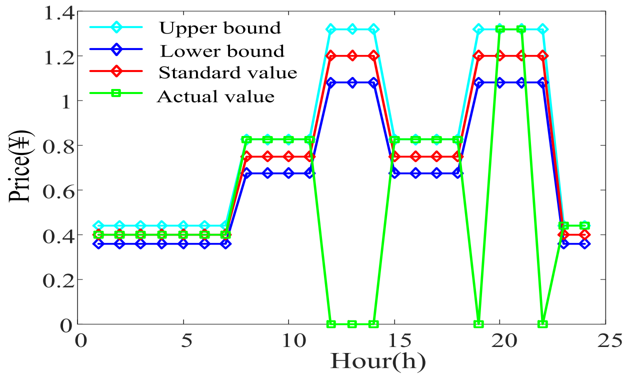
Jianan Du: Conceptualization, Investigation, Methodology, Software, Writing – original draft. **Xiaoqing Han:** Supervision, Writing – review & editing. **Jinning Wang:** Writing – original draft.

Declaration of Competing Interest

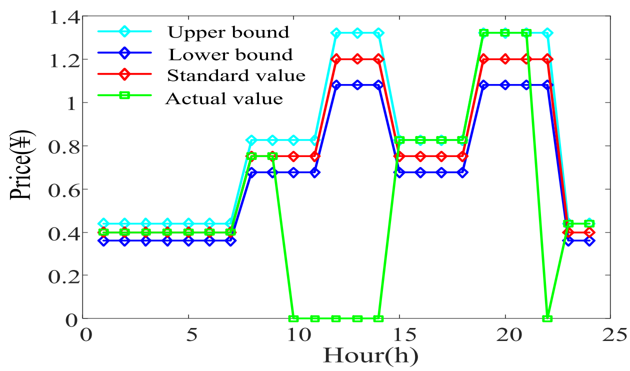
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

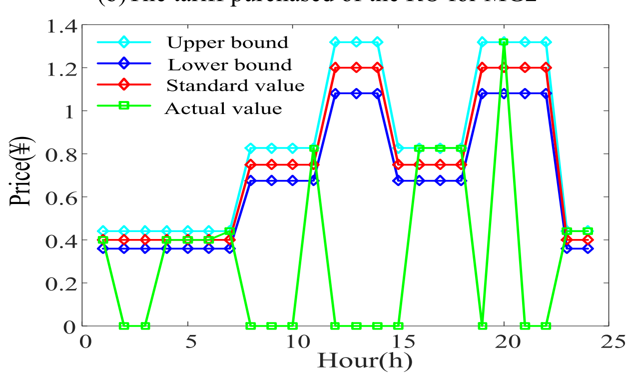
The authors are unable or have chosen not to specify which data has been used.



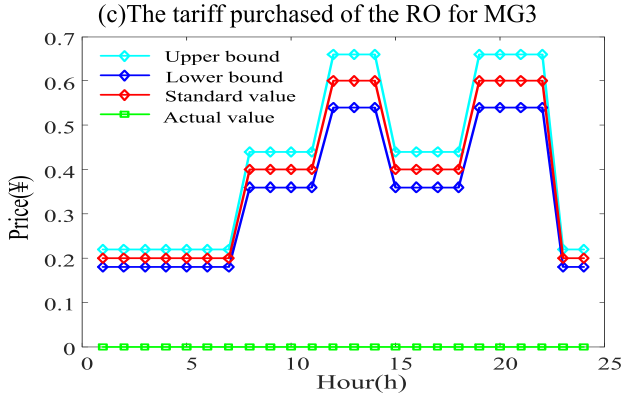
(a)The tariff purchased of the RO for MG1



(b)The tariff purchased of the RO for MG2

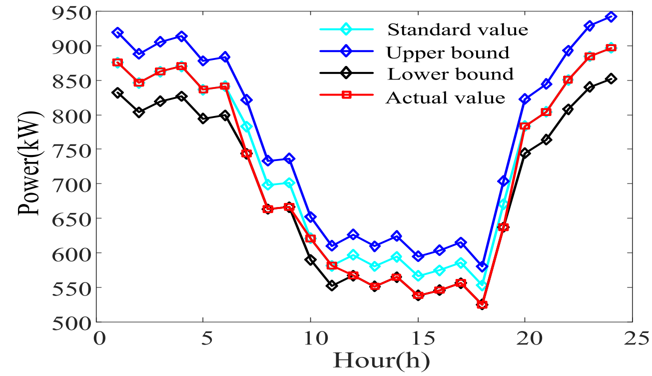


(c)The tariff purchased of the RO for MG3

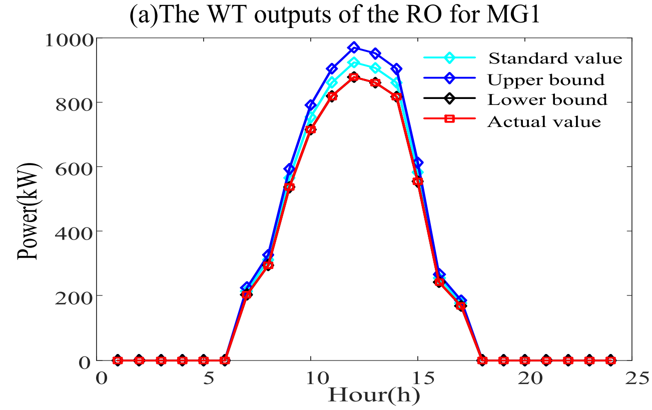


(d)The tariff selled of the RO for MGs.

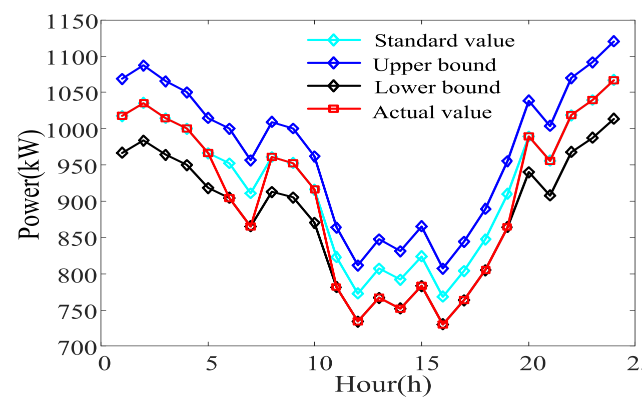
Fig. 13. Results of tariffs of the RO for each MG.



(a)The WT outputs of the RO for MG1



(b)The PV outputs of the RO for MG2



(c)The WT outputs of the RO for MG3

Fig. 14. Renewable energy outputs of the RO for each MG.

Table 3
Result of relaxation parameter.

ω	$C_{i,R}^{\mathrm{dif}}$(¥)			Iterations
	MG1	MG2	MG3	
0.05	728.29	1752.10	−2479.37	47
0.1	728.11	1751.92	−2479.55	24
0.15	728.03	1751.83	−2479.64	16
0.2	728.01	1751.82	−2479.65	11
0.25	727.99	1751.79	−2479.67	8
0.3	727.98	1751.78	−2479.68	5
$\frac{1}{\sqrt{k}+N}$	728.03	1751.83	−2479.63	11

Appendix A

The proof of algorithm for SP1 and SP2

According to the theory of mean inequality,the objective function of the model (39) is maximized when $\sum_{i=1}^{N}\left(C_i^{\text{dif}}+\tau_i\right)$ is fixed. Due to $\sum_{i=1}^{N}\tau_i=0$, we have the following equation:

$$\sum_{i=1}^{N}\left(C_i^{\text{dif}}+\tau_i\right)=\sum_{i=1}^{N}C_i^{\text{dif}}=\sum_{i=1}^{N}\left(C_i^0-C_i^1\right)$$

Because the game's disagreement point C_i^0 is fixed, model (39) is maximized when $\sum_{i=1}^{N}C_i^1$ takes the minimum value. Then, SP1 is proofed:

$$\max\prod_{i=1}^{N}\left(C_i^{\text{dif}}+\tau_i\right)\leftrightarrow\min\sum_{i=1}^{N}C_i^1$$

By solving SP1, we have $\left(C_i^1\right)^*$ and substitute it into model (39). Since the natural logarithm is a strictly monotonically increasing convex function, the original problem can be converted to the following problem:

$$\max\prod_{i=1}^{N}\left[\left(C_i^{\text{dif}}\right)^*+\tau_i\right]\leftrightarrow\min-\sum_{i=1}^{N}\ln\left[\left(C_i^{\text{dif}}\right)^*+\tau_i\right]$$

Then, SP2 is proofed.

The proof of algorithm for cheating equilibrium

By solving the model (39),we have the following equation:

$$\tau_i^*=m-C_i^{\text{dif}}=\frac{\sum_{j\in N\backslash\{i\}}C_j^{\text{dif}}-(N-1)C_i^{\text{dif}}}{N}$$

$$m=\frac{\sum_{i=1}^{N}\left(C_i^{\text{dif}}+\tau_i\right)}{N}=\frac{\sum_{i=1}^{N}C_i^{\text{dif}}}{N}$$

Each MG updates its cheating factors in parallel based ITM.

$$\begin{aligned}
&\gamma_{i,k+1}=(1-\omega)\gamma_{i,k}+\omega\gamma_{i,k}^{\text{limit}}\\
&=(1-\omega)\gamma_{i,k}+\omega\frac{\left(C_i^{\text{dif}}+\sum_{j\in N\backslash\{i\}}C_{j,\text{R},k}^{\text{dif}}\right)}{\left|C_i^{\text{dif}}\right|}\\
&=(1-\omega)\gamma_{i,k}+\omega\frac{\left(C_i^{\text{dif}}+C_{\text{R},k}^{\text{dif,sum}}-C_{i,\text{R},k}^{\text{dif}}\right)}{\left|C_i^{\text{dif}}\right|}
\end{aligned}$$

Then, each MG updates its cheating costs through the following equation:

$$\begin{aligned}
&C_{i,\text{R},k+1}^{\text{dif}}\\
&=C_i^{\text{dif}}-\gamma_{i,k+1}\left|C_i^{\text{dif}}\right|\\
&=C_i^{\text{dif}}-\left[(1-\omega)\gamma_{i,k}+\omega\frac{\left(C_i^{\text{dif}}+C_{\text{R},k}^{\text{dif,sum}}-C_{i,\text{R},k}^{\text{dif}}\right)}{\left|C_i^{\text{dif}}\right|}\right]\left|C_i^{\text{dif}}\right|\\
&=C_i^{\text{dif}}-(1-\omega)\gamma_{i,k}\left|C_i^{\text{dif}}\right|-\omega\left(C_i^{\text{dif}}+C_{\text{R},k}^{\text{dif,sum}}-C_{i,\text{R},k}^{\text{dif}}\right)\\
&=C_i^{\text{dif}}-(1-\omega)\left(C_i^{\text{dif}}-C_{i,\text{R},k}^{\text{dif}}\right)-\omega\left(C_i^{\text{dif}}+C_{\text{R},k}^{\text{dif,sum}}-C_{i,\text{R},k}^{\text{dif}}\right)\\
&=C_{i,\text{R},k}^{\text{dif}}-\omega C_{\text{R},k}^{\text{dif,sum}}
\end{aligned}$$

Then, we have the following equation:

$$\begin{aligned}
&C_{\text{R},k+1}^{\text{dif,sum}}=\sum_{i=1}^{N}C_{i,\text{R},k+1}^{\text{dif}}\\
&=\sum_{i=1}^{N}\left(C_{i,\text{R},k}^{\text{dif}}-\omega C_{\text{R},k}^{\text{dif,sum}}\right)\\
&=(1-N\omega)C_{\text{R},k}^{\text{dif,sum}}\\
&=(1-N\omega)^kC_{\text{R},1}^{\text{dif,sum}}
\end{aligned}$$

Since $C_{\text{R},k}^{\text{dif,sum}}$ converges to 0, we have $0<(1-N\omega)<1$. So the range of relaxation coefficient is $0<\omega<\frac{1}{N}$.

The solving process of SP2

Step1:Set the maximum number of iterations $k_{\max} = 100$, convergence accuracy $\zeta = 0.1$, penalty factor $\gamma = 10$, initial number of iterations $k = 1$, initial inter-microgrid interaction tariff $\rho_{ij,t} = 0$;

Step2: Solving the distributed optimal operation model for each microgrid, as shown in Eq. (56);

Step3: Update $\sigma_{ij,t}^{k+1}$:$\sigma_{ij,t}^{k+1} = \sigma_{ij,t}^{k} + \gamma\left(\rho_{ij,t}^{k+1} - \rho_{ji,t}^{k+1}\right)$;

Step4: Determine the convergence of the algorithm:$\sum_{i=1}^{N}\sum_{j\in N\setminus\{i\}}\sum_{t=1}^{T}\left\|\rho_{ij,t}^{k+1} - \rho_{ji,t}^{k+1}\right\| < \zeta$ or $k > k_{\max}$;

Step5: Otherwise $k = k + 1$ and repeat Step2 to Step4.

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