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Transactive Energy Management for CIES Considering Tri-level Hybrid Game-Theoretic Approaches with Multiple Weight Allocation Factors

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Abstract—In city integrated energy systems, to reduce the costs of energy production and usage, it is extremely important for different entities to design proper energy management approaches since they have diverse behaviours and benefits. The hierarchy of the system is naturally divided into three layers, and hybrid game theories are employed on the basis of the vertical master–slave and horizontal equal cooperation characteristics among energy providers, aggregators, and users. First, to reflect the interactions between different levels’ entities, Stackelberg game theory is adopted vertically, and the model complexity is lessened by the KKT conditions. Then, for energy providers, the asymmetric bargaining game is improved by combining multiple weight allocation factors, which can help reduce renewable energy fluctuations and encourage the consumption of clean energy to reduce the carbon emissions of the system. Also, the results show that the proposed method can enhance the utility of renewable energy generation units by approximately 64% to 69%. Finally, the optimality and effectiveness of the proposed game theoretic approaches are verified in case studies and in strict mathematical proofs. In addition, the impact mechanisms on the demand response from the perspectives of the user load and price sensitivity are analysed. To explore pricing methods that are more suitable for user aggregators, two pricing strategies are designed for the user aggregator and compared in terms of computation time and revenue. The results show that a unified pricing strategy can increase the aggregator’s revenue by 1.24% and reduce the computation time by 24.47%.

Index Terms—City integrated energy system, Asymmetric bargaining theory, Multiple weight allocation factor, Stackelberg master–slave game theory, Demand response, Transactive energy management

I. INTRODUCTION

With the intensification of global warming, the development of renewable energy is receiving increased attention. Unlike traditional energy, which is typically centralized and can be owned and developed only by large corporations, renewable energy often has a distributed and multi-entity nature [1]. As a consequence, the integrated energy system (IES) is becoming increasingly competitive and active, which promotes the participation of more stakeholders. Nevertheless, multiple entities lack effective

coordination via traditional transactive energy management methods, leading to the ineffective consumption of renewable energy and the lowering of system efficiency [2]. In light of this, it is important to identify more economical and effective methods for IESs and to manage and optimize the generation, transformation, consumption, and trading of diverse energy sources.

Compared with building-level or park-level IESs, a city integrated energy system (CIES) consists of a number of beneficial entities, such as energy providers, aggregators, and consumers, which makes energy exchange more convenient and provides more development opportunities. Some entities encompass different distributed energy resources, such as electricity, gas, renewable energy, and heat, and includes the interconnections and interactions between them. Nevertheless, the CIES faces complex operational conditions, involving demand fluctuations, energy supply instability, transactive energy management, etc. Regulating and operating this system requires addressing these intricate operational challenges [3].

Game theory is an effective approach for solving the abovementioned challenges and has the capability to analyse and design coordination mechanisms for multiple entities, ensuring that all the relevant entities can coordinate to achieve overall system optimality. In [4], to address the issues of conflicting interests, privacy concerns, and incentive inadequacy faced by traditional centralized operational schemes, it is possible to establish an energy sharing mechanism and implement price regulation policies under Nash game theory. In [5], to ensure the operational safety of transmission lines and the allocation of line defence resources, game theory explains the interaction between defenders and attackers, addressing the shortcomings of unilateral vulnerability analysis. While these studies effectively allocate interests among various entities, they lack consideration of the impacts of interactions among the diverse behaviours of entities. More specifically, different entities exhibit independent behaviours and have varying interests, and the decision-making process involves both sequential order and mutual influence, which results in stratification. Therefore, it is necessary to classify each entity

according to its goals, and then stratify them on the basis of the influence relationships between their decisions.

Stackelberg game theory can effectively address the above situations, where there is a leader–follower relationship. Through this game model, the leader can leverage its first-mover advantage to influence the follower's decisions, ultimately achieving overall system optimization and balancing the interests of all entities. For example, the interaction between CHP units and industrial user groups in a multienergy industrial park can be simulated via a Stackelberg game. The results in [6] demonstrate that effective load peak shaving can be achieved through the game between two parties and multienergy conversion. In [7], The aggregator entity is an indispensable player in encouraging more users to participate in the electricity market. Their presence enhances the influence of consumers in the market while reducing the computational burden of market transactions.

Nevertheless, regardless of the interaction between suppliers and users, or between aggregators and users, both scenarios involve a bilevel Stackelberg game. To encourage active participation in energy trading among users and reduce the difficulty for users to engage in market transactions while also enhancing the management of users, a user aggregator (UA) becomes an indispensable player in the market. With the introduction of the UA, the bilevel Stackelberg game will no longer effectively reflect the demand–response relationship between multiple energy providers (EPs) and multiple energy users (EUs). Therefore, it is imperative to establish a tri-level Stackelberg game that includes the UA. Moreover, the tri-level Stackelberg game requires more complexity to solve than the bilevel game. Relying solely on iterative methods significantly increases the computation time, indicating the need for a redesigned solution method.

Currently, some studies have investigated the tri-level model. In [8], a tri-level optimization model was established to improve social welfare at an acceptable cost. It describes the storage location and size, storage scheduling, and market clearing, respectively, to achieve a higher level of renewable energy utilization. In [9], the authors established a tri-level model focusing on charging stations and electric vehicle users, fully considering the interaction between electric vehicle users and the UA, alleviating congestion in the transmission grid, and increasing the economic benefits of various entities. In [10], a tri-level model was established to investigate energy allocation strategies from the supply side to the demand side, providing guidance for subsequent researchers.

Nevertheless, the literature [8]–[9] focuses on electric vehicles and energy storage systems without considering other entities in the CIES, including various types of power plants and different types of users. The literature [10][11] lacks research on the cooperative and competitive relationships between the entities within each layer. More importantly, existing studies lack research, not only on the demand response mechanisms between layers but also on the

UA pricing methods. These aspects have profound implications for subsequent research on user behaviour and pricing strategies. Therefore, there is an urgent need to establish a tri-level model that considers different generating units and the game relationships among entities within each layer, while also conducting analysis and research on the demand response between different layers.

In the CIES, each entity at every level competes in pursuit of maximizing their own profits, so the allocation of interests is also a focal point of research [12]. For example, when community costs are shared with consumers, the Shapley method not only ensure fairness, but also reduces the costs for all the individual members [13]. Other researchers have reported that the distribution method based on the nucleolus approach may yield superior results compared with the Shapley approach. Although the nucleolus and Shapley approaches both effectively incentivize user participation, the computation time tends to grow exponentially with the number of users [14]. Nash bargaining (NB) solutions not only ensure the above advantages, but also guarantee individual optimality, and the computational complexity is manageable [15].

However, existing studies pay little attention to supply-side competition, and even less attention to situations where both traditional generation units and renewable energy generation units coexist, which is the real scenario that CIES faces. Traditional generation methods rely on a stable supply of fossil fuels, whereas renewable energy generation units (REGUs) depend on wind and solar power, which often have significant uncertainty. This uncertainty often results in output fluctuations for REGUs, which have not been well received by the market. Consequently, REGUs typically do not have the same bargaining power as traditional energy sources. Therefore, the Nash bargaining solution may not effectively promote the development of renewable energy.

The asymmetric bargaining (AB) solution can address this issue by introducing the concept of bargaining power information into the bargaining process. By assigning different negotiation weights to users, it is possible for different users to gain varying bargaining power in the game, thus obtaining unequal benefits. Therefore, the core of asymmetric Nash bargaining lies in how to calculate bargaining power. Scholars have determined bargaining power by analysing the transaction volumes among various entities participating in integrated energy microgrids [16]. Some scholars calculate bargaining power by assessing the contribution of energy injection from energy storage systems to microgrid nodes [17]. Some scholars have calculated bargaining power in the profit allocation between wind farms and hydrogen refuelling stations on the basis of the marginal contribution rate and energy trading contribution rate [18]. Additionally, to allocate profits between VPPs and wind farms, some scholars change their bargaining power calculations by assessing their respective marginal contributions and accuracy in following the regulation command [19].

The aforementioned study primarily allocates bargaining

power by assessing the marginal contributions to the market. However, existing studies seldom consider the influence of output prediction accuracy from renewable energy sources and carbon emissions on the market. For renewable energy sources, fluctuations in output pose a direct risk to the grid, impacting the market's reception, and accurate output forecasting can effectively help reduce output fluctuations. Conversely, for traditional gas turbines, their output is controllable and does not require prediction; thus, fluctuations are not an issue, and reducing carbon emissions becomes a critical demand for all power generation entities in the market. Therefore, there is a need for a weight allocation criterion that considers renewable energy output prediction accuracies, smooths output fluctuations, and reduces carbon emissions from traditional generator units.

Existing research on CIES lacks the consideration of different entities' characteristics from a hierarchical perspective. Most of the current literature focuses on the game between the supply side entities and aggregator, or between aggregator and users, without considering all three simultaneously. Additionally, there is competition among entities within each layer, and current research lacks attention to the competition between different power generation entities on the supply side. Furthermore, there is insufficient consideration of the characteristics of renewable energy generation, and the energy management strategies in existing research are not conducive to the development of renewable energy. Owing to page limitations, the abovementioned works have been analysed and summarized

in TABLE I.

Compared with existing works in terms of various dimensions, the main contributions, and works of this paper, consist of three parts:

(1) A tri-level Stackelberg game model for a CIES is established, accounting for different types of EPs, a UA, and EUs while considering the reducible and transferable load of users. To reduce computational complexity, the optimization of EUs is transformed into constraints that are merged into the optimization of the UA via the Karush–Kuhn–Tucker (KKT) conditions.

(2) A game-theoretical model based on the AB solution at the supply side is established; it considers the fluctuation of renewable energy output and its curtailment behaviour. Additionally, a weight allocation strategy based on the carbon emission criteria and output prediction accuracy is proposed. The proposed AB solution not only enhances the absorption of REGUs but also stabilizes the output, reducing the production of gas turbines, and thereby decreasing carbon emissions. The results are compared with those of the NB solution to verify its rationality and superiority.

(3) This paper reveals the influencing mechanism of user price sensitivity and load quantity on the demand response. Additionally, two pricing strategies for the UA towards the EU are established, namely, a unified pricing strategy and an individual pricing strategy. The appropriate strategy for the UA can be chosen by comparing the computation time and revenue.

TABLE I
COMPARISON WITH EXISTING WORKS

Cases	Stratify the entities	Tri-level model	Considering various types of power plants	Competition within each level	Different bargaining power	Beneficial for the development of REGU	Demand response mechanism
[6]	√	×	×	×	×	×	×
[7]	√	×	×	×	×	×	×
[8]	×	√	×	×	×	√	×
[9]	×	√	×	×	×	×	×
[10]	√	√	√	√	×	×	×
[11]	×	×	×	√	×	×	×
[12]	√	×	√	√	×	×	×
[13]	×	×	√	√	×	×	×
[14]	×	×	√	×	√	×	×
[15]	×	×	×	×	√	√	×
[16]	×	×	√	×	√	√	×
[17]	×	×	√	×	√	×	×
Proposed	√	√	√	√	√	√	√

The subsequent sections of this article are organized as follows. In Section II, details regarding the establishment of the CIES model are introduced. Section III presents the tri-level Stackelberg game among EPs, UAs, and EUs. Section IV introduces the energy transaction game on the basis of the AB solution among EPs. The simulation results are presented in Section V. Finally, Section VI concludes the article, and

Section VII presents the limitations and future work.

This paper introduces a tri-level CIES structure, which is delineated in Fig. 1. In this context, EPs encompass individual entities equipped with either gas turbines (GTs) or REGUs (such as wind turbines or solar PVs). The REGU and GT can conduct electricity transactions freely, which not only maximize revenue but also stabilize the REGU's output

fluctuations. Moreover, as a CHP, the GT can also trade thermal energy with other GTs to avoid overproduction and minimize production costs. The UA plays a pivotal role as an intermediary, bridging the gap between EUs and EPs. The UA formulates energy procurement strategies on the basis of the time-of-use (TOU) price furnished by EPs, subsequently issuing its TOU pricing information to EUs. At the city scale, the numerous EUs present diverse energy demands. The UA can guide users' energy usage plans through TOU pricing. Conversely, after forming their energy usage plans for each period, users will feed their energy demands back to the UA. The UA will then aggregate this information and present it to the EP, which will accordingly revise its production plans. This process establishes an information exchange flow between the supply side and the demand side. The EUs, in turn, adapt their energy consumption plan in response to these prices and provide their demand response back to the UA.

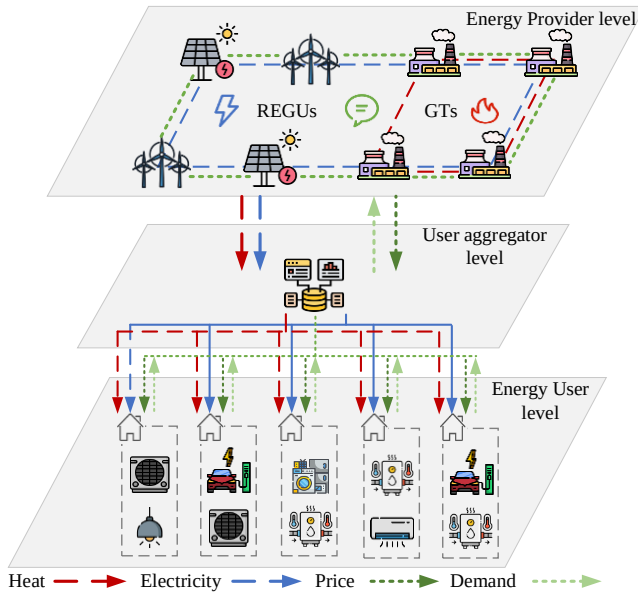


Fig. 1 Schematic diagram of the CIES

A. Mathematical models of the provider level

At the energy provider level, EPs formulate their production plans at different times according to the situation at different hours to maximize their own profit.

The EPs with GT (hereafter referred to as GT) are considered CHP units. Additionally, owing to their controllable output, they are connected to the external power grid. The output model of these EPs is expressed as:

$$P_{t,r}^{GT_produce_co} = \eta_{TR} P_{t,r}^{grid_co} + \eta_{ICE} Q_{t,r}^{gas_co} \quad (1)$$

$$H_{t,r}^{GT_produce_co} = [(1 - \eta_{ICE}) + \eta_{GB}] Q_{t,r}^{gas_co} \quad (2)$$

where $P_{t,r}^{GT_produce}$ and $H_{t,r}^{GT_produce}$ represent the electricity and heat produced by the r th ($r \in R$) GT at time t , $P_{t,r}^{grid}$ represents the electricity purchased from the external power grid, $Q_{t,r}^{gas}$ represents the gas bought from the natural fuel gas company, and η_{TR} , η_{ICE} , and η_{GB} represent the transformer efficiency parameters of the GT and heat exchanger.

The cost of the r th GT at time t is expressed as:

$$M_{t,r}^{GT_co} = (Q_{t,r}^{gas_co} C^{gas} + P_{t,r}^{grid_co} C_{t,r}^{grid}) \Delta t \quad (3)$$

where C^{gas} and $C_{t,r}^{grid}$ represent the prices of gas and electricity, respectively.

The heat and power produced by a GT can be traded to the UA or other EPs, but eventually, they will all be sold to the UA:

$$P_{t,r}^{GT_toUA_co} = P_{t,r}^{GT_produce_co} - P_{t,r}^{GT_toEP_co} \quad (4)$$

$$H_{t,r}^{GT_toUA_co} = H_{t,r}^{GT_produce_co} - H_{t,r}^{GT_toEP_co} \quad (5)$$

When the r th GT acts as a vendor to other GTs, $P_{t,r}^{GT_toEP_co}$ is positive; otherwise, it is negative, and it is the same for $H_{t,r}^{GT_toEP_co}$.

The hourly contract prices determined by EPs are established between the UA and EPs, and consist of a basic price and a growth coefficient [20]. They can be expressed as:

$$C_{t,e}^{EP_toUA_co} = C_{t,e}^{EP_base_co} + \sigma_e P_t^{UA} \quad (6)$$

$$C_{t,h}^{EP_toUA_co} = C_{t,h}^{EP_base_co} + \sigma_h H_t^{UA} \quad (7)$$

$$0 \leq C_{t,e}^{EP_base_co} \leq C_e^{EP_base_co_max} \quad (8)$$

$$0 \leq C_{t,h}^{EP_base_co} \leq C_h^{EP_base_co_max} \quad (9)$$

where $C_{t,e}^{EP_base_co}$ and $C_{t,h}^{EP_base_co}$ are the basic prices of the contract, and where σ_e and σ_h are the growth coefficients of the EPs.

The income of the r th GT consists of two parts for selling to the UA and other EPs, and is expressed as:

$$I_{t,r}^{GT_toUA_co} = (P_{t,r}^{GT_toUA_co} C_{t,e}^{EP_toUA_co} + H_{t,r}^{GT_toUA_co} C_{t,h}^{EP_toUA_co}) \Delta t \quad (10)$$

$$I_{t,r}^{GT_toEP_co} = (P_{t,r}^{GT_toEP_co} C_{t,e}^{EP_base_co} + H_{t,r}^{GT_toEP_co} C_{t,h}^{EP_base_co}) \Delta t \quad (11)$$

The utility of the r th GT is:

$$u_r^{GT_co} = \sum_t (I_{t,r}^{GT_toUA_co} + I_{t,r}^{GT_toEP_co} - M_{t,r}^{GT_co}) \quad (12)$$

For EPs with REGU (hereafter referred to as REGU), because of significant output fluctuations, they cannot directly and safely connect to the external power grid. Additionally, in contrast to GTs, REGUs are not considered CHP units. The true output of the i th REGU at time t is:

$$P_{t,i}^{RE_real} = P_{t,i}^{RE_forecast} + P_{t,i}^{RE_error} \quad (13)$$

where $P_{t,i}^{RE_forecast}$ is the day-ahead prediction output of the i th ($i \in I$) REGU, and where $P_{t,i}^{RE_error}$ is the prediction error.

Since the power supply needs to maintain stable output, REGUs must stabilize their output as much as possible to gain market acceptance. To reduce the output fluctuation, the REGU may abandon some of its output and sell the rest to the UA or other EPs.

$$P_{t,i}^{RE_real} = P_{t,i}^{RE_abandon_co} + P_{t,i}^{RE_toUA_co} + P_{t,i}^{RE_toEP_co} \quad (14)$$

$$P_{t,i}^{RE_toEP_co} \leq P_{t,i}^{RE_real} \quad (15)$$

$$0 \leq P_{t,i}^{RE_abandon_co} \leq P_{t,i}^{RE_real} \quad (16)$$

$$P_{t,i}^{RE_toUA_co} \geq 0 \quad (17)$$

where $P_{t,i}^{RE_abandon_co}$ is the abandoned output and where $P_{t,i}^{RE_toUA_co}$ and $P_{t,i}^{RE_toEP_co}$ are the electricity sold to the UA and other EPs, respectively. Again, if a REGU acts as a vendor to other EPs, $P_{t,i}^{RE_toEP_co}$ is positive; otherwise, it is negative.

Moreover, merely curtailing the output of REGUs is detrimental to the utilization of renewable energy, and results in a waste of wind and solar resources. Therefore, the cost of the REGU is the punishment of the REGU's output abandonment.

$$M_i^{RE_abandon_co} = \gamma * \sum_T P_{t,i}^{RE_abandon_co} \quad (18)$$

γ is the cost coefficient.

To alleviate output fluctuation, the average output change from all periods should be less than an upper limit.

$$M_i^{RE_fluctuation_co} = \frac{1}{T-1} \sum_{t=1}^{T-1} \left| \frac{P_{t+1,i}^{RE_toUA_co} - P_{t,i}^{RE_toUA_co}}{\Delta t} \right| \quad (19)$$

$$M_i^{RE_fluctuation_co} \leq M^{RE_fluctuation_max} \quad (20)$$

The income of the i th REGU includes two parts for selling to the UA and other EPs, and is expressed as:

$$I_{t,i}^{RE_toUA_co} = P_{t,i}^{RE_toUA_co} C_{t,e}^{EP_toUA_co} \Delta t \quad (21)$$

$$I_{t,i}^{RE_toEP_co} = P_{t,i}^{RE_toEP_co} C_{t,e}^{EP_co_base} \Delta t \quad (22)$$

The utility of the i th REGU is developed as follows:

$$u_i^{RE_co} = \sum_t (I_{t,i}^{RE_toUA_co} + I_{t,i}^{RE_toEP_co}) - M_i^{RE_abandon_co} \quad (23)$$

In the meantime, the transactions between EPs should be balanced.

$$\sum_R P_{t,r}^{GT_toEP_co} + \sum_I P_{t,i}^{RE_toEP_co} = 0 \quad (24)$$

$$\sum_R H_{t,r}^{GT_toEP_co} = 0 \quad (25)$$

B. Mathematical models of the user aggregator level

At the user aggregator level, the UA offers a chance for small-sized users to engage in market negotiations and facilitates two-way communication between energy providers and users, leading to increased demand response efficiency. As a result, the UA is assigned two primary responsibilities. First, it can create energy-purchasing plans from the EPs. Second, it can publish TOU prices for resale to EUs. The income generated at time t by selling to the k th EU can be represented as follows:

$$I_{t,k}^{UA} = (P_{t,k}^{EU} C_{t,k,e}^{UA} + H_{t,k}^{EU} C_{t,k,h}^{UA}) \Delta t \quad (26)$$

The revenue of the UA comes from selling heat and electricity. $P_{t,k}^{EU}$ and $C_{t,k,e}^{UA}$ represent the electric load and its price set by the UA for user k at time t , respectively; similarly, $H_{t,k}^{EU}$ and $C_{t,k,h}^{UA}$ represent the heat load and the price, respectively.

The cost of the UA refers to the total profit of all the EPs:

$$M_t^{UA} = (P_t^{UA} C_{t,e}^{EP_toUA_co} + H_t^{UA} C_{t,h}^{EP_toUA_co}) \Delta t \quad (27)$$

$$P_t^{UA} = \sum_R P_{t,r}^{GT_toUA_co} + \sum_I P_{t,i}^{RE_toUA_co} \quad (28)$$

$$H_t^{UA} = \sum_R H_{t,r}^{GT_toUA_co} \quad (29)$$

The goal of the UA is to maximize its revenue, so the objective function can be represented as follows:

$$\max u^{UA} = \sum_t \left(\sum_k I_{t,k}^{UA} - M_t^{UA} \right) \quad (30)$$

$$C_{k,e}^{UA,min} \leq C_{t,k,e}^{UA} \leq C_{k,e}^{UA,max} \quad (31)$$

$$C_{k,h}^{UA,min} \leq C_{t,k,h}^{UA} \leq C_{k,h}^{UA,max} \quad (32)$$

$$\sum_T C_{t,k,e}^{UA} \leq T \cdot C_e^{UA_average_max} \quad (33)$$

$$\sum_T C_{t,k,h}^{UA} \leq T \cdot C_h^{UA_average_max} \quad (34)$$

$$P_t^{UA} = \sum_K P_{t,k}^{EU} \quad (35)$$

$$H_t^{UA} = \sum_K H_{t,k}^{EU} \quad (36)$$

To ensure reasonable pricing across different periods, constraints (31)-(32) specify the range for the prices set by the UA in each period. To ensure price stability, constraints (33)-(34) regulate the upper limit of the average price over the entire period. Constraints (35)-(36) ensure that electricity and heat are balanced at all times.

To explore which pricing strategies are more suitable for the UA, a unified pricing strategy with a unified EU-wide price, and an individual pricing strategy with different prices for different EUs, are established. The above discussion applies the individual pricing strategy, whereas the unified pricing strategy applies a single price to all users, so replacing $C_{t,k,e}^{UA}$, $C_{t,k,h}^{UA}$ with $C_{t,e}^{UA}$, $C_{t,h}^{UA}$ is sufficient.

C. Mathematical models of the energy user level

At the energy user level, each EU makes its own energy consumption plan on the basis of the price set by the UA at this time to maximize its own utility.

To ensure the flexibility of EUs' energy consumption, this paper divides the EUs' electric load into fixed loads $P_{t,k}^{EU_base}$ that must be completed in each period (such as lighting and refrigeration) and transferable loads $P_{t,k}^{EU_shift}$ that can be flexibly allocated to the remaining periods on the basis of the TOU price $C_{t,k,e}^{UA}$ (such as electric vehicle charging).

$$P_{t,k}^{EU} = P_{t,k}^{EU_base} + P_{t,k}^{EU_shift} \quad (37)$$

Similarly, the user's heat load is divided into the original load $H_{t,k}^{EU_base}$, which refers to the full demand of the EU, and the reducible load $H_{t,k}^{EU_shift}$, which can be reduced on the basis of the TOU price $C_{t,k,h}^{UA}$.

$$H_{t,k}^{EU} = H_{t,k}^{EU_base} - H_{t,k}^{EU_shift} \quad (38)$$

The goal of the EU is to formulate an energy usage plan based on the TOU price to maximize their utility and reduce their energy costs. Thus, the objective function consists of both the EU's utility $f_{t,k}^{EU}$ and the cost $I_{t,k}^{UA}$.

$$\max u_k^{EU} = \sum_t (f_{t,k}^{EU} - I_{t,k}^{UA}) \Delta t \quad (39)$$

$$0 \leq P_{t,k}^{EU_shift} \leq P_k^{shift_max} \quad (40)$$

$$0 \leq H_{t,k}^{EU_shift} \leq H_k^{shift_max} \quad (41)$$

$$\sum_T P_{t,k}^{EU_shift} = W_k^{shift} \quad (42)$$

Constraints (40)-(41) ensure that transferable and reducible loads are within reasonable ranges. Constraint (42) guarantees the conservation of transferable loads throughout all periods, ensuring the completion of all tasks while maintaining the flexibility of user energy usage.

The EU's utility $f_{t,k}^{EU}$ represents the satisfaction and fulfilment of the user with their consumption strategy. Common forms of utility functions include quadratic [21]-[22] and logarithmic functions [23]. We employ a quadratic function to measure the benefits derived from electricity and heat consumption, as shown below:

$$f_{t,k}^{EU} = v_{k,e} P_{t,k}^{EU} - \frac{\alpha_{k,e}}{2} (P_{t,k}^{EU})^2 + v_{k,h} H_{t,k}^{EU} - \frac{\alpha_{k,h}}{2} (H_{t,k}^{EU})^2 \quad (43)$$

$v_{k,e}$, $\alpha_{k,e}$, $v_{k,h}$, and $\alpha_{k,h}$ are all behavioural parameters. Depending on the energy consumption behaviour of different EUs, adjusting these parameters can reflect the impact of the energy consumption strategy on the utility.

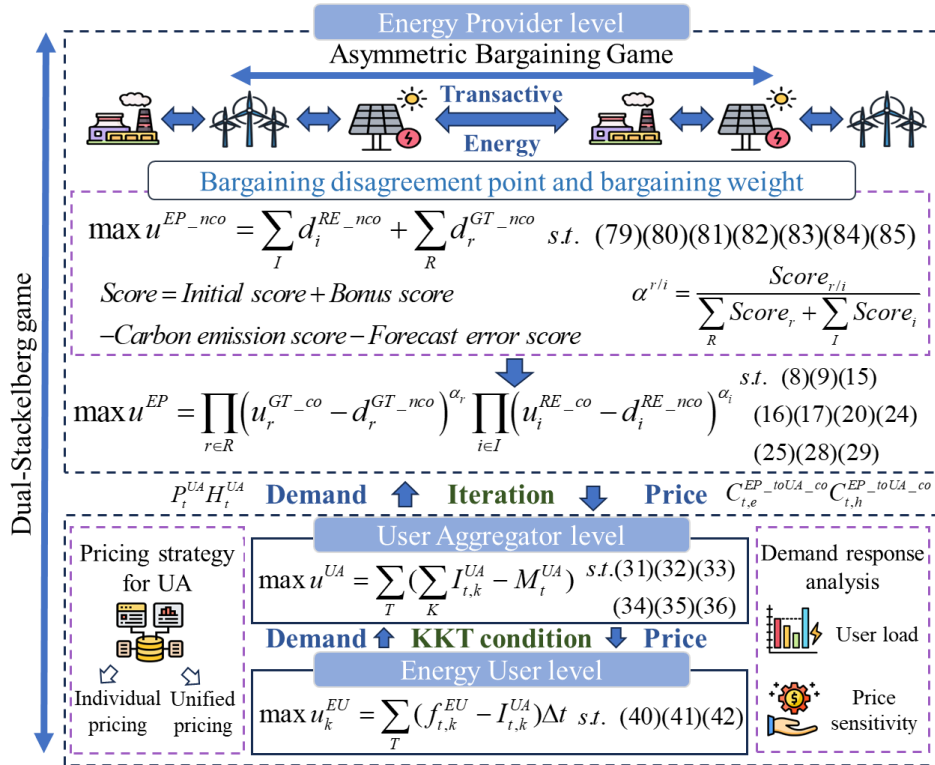


Fig. 2 Tri-level game framework

III. TRI-LEVEL GAME MODELS

In this section, on the basis of the modelling of the various layers of the CIES from the previous section, an analysis of the sequence of decision-making and the transmission of information among these layers was conducted. A hybrid game-theoretic model and methods for solving the objectives of each layer are developed on the basis of the vertical master-slave and horizontal equal cooperation characteristics.

As shown in Fig. 2, the vertical game is designed as a noncooperative tri-level Stackelberg game. Furthermore, the horizontal game among EPs is modelled by an AB-based cooperative game. In the EP layer, the process begins by calculating the revenue for EPs without energy transactions, which serves as the negotiation breakdown point. The bargaining weights under asymmetric Nash bargaining are also determined. Next, the production plans and prices set by

each EP towards the UA are computed under the scenario of mutual energy trading. Upon receiving the EPs' prices, the UA sets its prices for the EUs. The EUs then formulate their energy usage plans in response to the UA's prices. In the actual calculation, EUs are merged into the UA through KKT conditions for joint optimization. EPs influence the UA's demand through pricing, whereas the UA affects EP production by altering the demand. Horizontal asymmetric Nash bargaining promotes the sustainable development of energy industries on supply side, whereas the vertical dual-Stackelberg game ensures a balance between the supply and demand sides.

A. Dual-Stackelberg game

In the CIES, energy procurement strategies and prices interact with each other. The basic prices set by EPs influence the energy procurement of the UA. Simultaneously, the TOU prices provided by the UA change the energy

consumption strategies of the EUs. Correspondingly, the EU adjusts energy requirements on the basis of prices set by the UA. The adjusted demand subsequently influences the UA's pricing and purchasing strategies. This, in turn, further influences the basic prices determined by the EPs. Throughout this process, entities harmonize their individual interests by iteratively refining their strategies.

The energy trading process adheres to a scenario characterized by a hierarchical master-slave structure. Consequently, the energy trading in the tri-level CIES can be described via a dual-Stackelberg game.

As shown in Fig. 2, in the upper-level Stackelberg game, the EPs act as the master, whereas the UA acts as the slave. In the lower-level Stackelberg game, the UA acts as the master agent, with the EU acting as the slave.

The three elements, which are specifically player set N_s , action set δ , and utility function u of the double Stackelberg game, along with the description of the game model, are as follows:

$$G_s = \{N_s; \{\delta_{EP}, \delta_{UA}, \delta_{EU,k}\}; \{u^{EP}, u^{UA}, u_k^{EU}\}\} \quad (44)$$

Player set: The players in the game are the EP, UA, and EU. $N_s = \{EP, UA, EU\}$.

Action set: The strategy set for EP consists of the basic prices it sets. The strategy set for a UA consists of the quantity of energy it purchases and the prices it sets for the EU. The strategy set for the EU consists of energy adjustment quantities. Expressed in vectors:

$$\delta_{EP} = (C_{t,e}^{EP_base_co}, C_{t,h}^{EP_base_co}); \delta_{UA} = (P_t^{UA}, H_t^{UA}, C_{t,k,e}^{UA}, C_{t,k,h}^{UA}); \delta_{EU,k} = (P_{t,k}^{EU_shift}, H_{t,k}^{EU_shift})$$

Utility function: The utility function for EP is (91); for UA, it is (30); and for EU, it is (39).

B. Distributed implementation method

The proposed tri-level optimization involves a competitive scenario among multiple entities, thereby increasing the complexity of the problem. Currently, there is no existing method that is capable of directly solving this optimization challenge. For conventional bilevel optimization, two main strategies are commonly employed:

- (1) Transformation using KKT conditions: This method can effectively simplify complex optimization with two levels into a single optimization problem, which can then be addressed via a mixed-integer linear programming mode[24].
- (2) Designing iterative algorithms: Another approach is to design iterative algorithms for distributed systems. These algorithms can be based on analytical solutions [25] or heuristic algorithms [26].

Drawing inspiration from these strategies, this section introduces a tri-level game computing solution. The first step involves converting the individual EU optimizations into constraints within the optimization of the UA by utilizing KKT conditions. This transformation simplifies the tri-level problem into a bilevel nonlinear programming (BNLP) problem. Subsequently, by convexification, the BNLP is

transformed into a bilevel mixed-integer quadratic programming (BMIQP) problem. Finally, both the Stackelberg equilibrium between the EP and UA and the Nash equilibrium among multiple EPs can be resolved through a distributed iterative algorithm.

The optimization of EUs is converted into optimization constraints via the KKT conditions, which are formulated as follows:

$$\frac{\partial L_k^{EU}}{\partial P_{t,k}^{EU_shift}} = v_{k,e} - \alpha_{k,e} P_{t,k}^{EU} - C_{t,k,e}^{UA} + \lambda_{t,e}^{lb} - \lambda_{t,e}^{ub} + \varepsilon_k = 0 \quad (45)$$

$$\frac{\partial L_k^{EU}}{\partial H_{t,k}^{EU_shift}} = -v_{k,h} + \alpha_{k,h} H_{t,k}^{EU} + C_{t,k,h}^{UA} + \lambda_{t,h}^{lb} - \lambda_{t,h}^{ub} = 0 \quad (46)$$

$$0 \leq P_{t,k}^{EU_shift} \perp \lambda_{t,e}^{lb} \geq 0 \quad (47)$$

$$0 \leq (P_k^{shift_max} - P_{t,k}^{EU_shift}) \perp \lambda_{t,e}^{ub} \geq 0 \quad (48)$$

$$0 \leq H_{t,k}^{EU_shift} \perp \lambda_{t,h}^{lb} \geq 0 \quad (49)$$

$$0 \leq (H_k^{shift_max} - H_{t,k}^{EU_shift}) \perp \lambda_{t,h}^{ub} \geq 0 \quad (50)$$

$$\varepsilon_k \neq 0 \quad (51)$$

$$\sum_T P_{t,k}^{EU_shift} = W_k^{shift} \quad (52)$$

where L_k^{EU} represents the Lagrangian function of the k th EU. Equations (45) and (46) correspond to their partial derivatives and are set equal to zero. In this context, $\lambda_{t,e}^{lb}$, $\lambda_{t,e}^{ub}$, $\lambda_{t,h}^{lb}$, $\lambda_{t,h}^{ub}$, and ε_k denote dual variables. Equations (47)-(51) can be understood as the KKT transformations applied to inequality constraints (40)-(42). ' $\alpha \perp \beta$ ' implies that at least one of α or β is equal to zero.

C. Convexification approach

The presence of nonlinear complementarity constraints (47)-(50) alongside bilinear terms such as $P_{t,k}^{EU_shift} C_{t,k,e}^{UA}$ and $H_{t,k}^{EU_shift} C_{t,k,h}^{UA}$ in Equation (26) creates a challenge when attempting to solve the problem directly. To address this issue, the Fortuny-Amat transformation is employed. This transformation is applied specifically to constraints (47)-(50), converting them into a set of mixed-integer linear constraints. These transformed constraints are formulated as follows:

$$0 \leq P_{t,k}^{EU_shift} \leq \pi_{t,e}^{lb} M \quad (53)$$

$$0 \leq \lambda_{t,e}^{lb} \leq (1 - \pi_{t,e}^{lb}) M \quad (54)$$

$$0 \leq P_k^{shift_max} - P_{t,k}^{EU_shift} \leq \pi_{t,e}^{ub} M \quad (55)$$

$$0 \leq \lambda_{t,e}^{ub} \leq (1 - \pi_{t,e}^{ub}) M \quad (56)$$

$$0 \leq H_{t,k}^{EU_shift} \leq \pi_{t,h}^{lb} M \quad (57)$$

$$0 \leq \lambda_{t,h}^{lb} \leq (1 - \pi_{t,h}^{lb}) M \quad (58)$$

$$0 \leq H_k^{shift_max} - H_{t,k}^{EU_shift} \leq \pi_{t,h}^{ub} M \quad (59)$$

$$0 \leq \lambda_{t,h}^{ub} \leq (1 - \pi_{t,h}^{ub}) M \quad (60)$$

where $\pi_{t,e}^{lb}$, $\pi_{t,e}^{ub}$, and $\pi_{t,h}^{lb}$, $\pi_{t,h}^{ub}$ are introduced as integer variables, taking values of either 0 or 1. The parameter M represents a suitably large positive constant.

Furthermore, the terms $P_{t,k}^{EU_shift} C_{t,k,e}^{UA}$ and $H_{t,k}^{EU_shift} C_{t,k,h}^{UA}$

are converted to quadratic expressions utilizing the dual variables derived from the KKT conditions (45) and (46). These transformations are presented as follows:

$$P_{t,k}^{EU_shift} C_{t,k,e}^{UA} = P_{t,k}^{EU_shift} (\nu_{k,e} + \lambda_{t,e}^{lb} - \lambda_{t,e}^{ub} + \varepsilon_k) - \alpha_{k,e} P_{t,k}^{EU_shift} P_{t,k}^{EU} \quad (61)$$

$$-H_{t,k}^{EU_shift} C_{t,k,h}^{UA} = H_{t,k}^{EU_shift} (-\nu_{k,h} + \lambda_{t,h}^{lb} - \lambda_{t,h}^{ub}) + \alpha_{k,h} H_{t,k}^{EU_shift} H_{t,k}^{EU} \quad (62)$$

At this stage, the objective function of the UA contains only quadratic nonlinear terms. Consequently, the tri-level game framework can be successfully converted into a BMIQP problem and ultimately approached via a distributed iterative algorithm.

D. The distributed iterative algorithm

The algorithm's progression is visualized in Algorithm 1. This algorithm outlines the iterative and dynamic interplay between the EP bidding process and the energy procurement strategy of the UA.

Algorithm 1: Distributed Iterative Algorithm

Initialize the values of P_t^{UA} , H_t^{UA} and a ;

while 1

 Compute $d_i^{RE_nco}$ and $d_r^{GT_nco}$ according to (78);

 Calculate $\alpha_{r/i}$ under (90);

 Compute $C_{t,k,e}^{UA}$ and $C_{t,k,h}^{UA}$ according to (91);

 Compute u^{UA} , P_t^{UA} and H_t^{UA} according to (30),

u^{UA} save as b ;

 difference_value = $a - b$;

$a = b$;

if |difference_value| ≤ upper_limit

break

end

Show the results

First, the algorithm is initiated by randomly assigning the energy demand of the UA to the EPs, enabling the EPs to make production plans and profit distribution plans according to the demand. Then, the Stackelberg game involving the UA and EUs is resolved via the optimization tool. The adjusted UA energy procurement strategy is then communicated back to the EPs. This process is iterated until convergence until Nash equilibrium is achieved. Each EP follows this iterative process and sets its prices sequentially until the overall program execution concludes. To solve Equation (91), the objective function is first transformed into a logarithmic form and then processed via the IPOPT solver. Since equation (78) does not contain nonlinear terms, it is solved via the Gurobi solver.

IV. AB-BASED ENERGY TRANSACTION GAME

In this section, an AB solution model is developed to encourage energy transactions between EPs and to allocate revenue to all players according to their contributions to emission reduction and output stability.

In the proposed AB solution, individual participants negotiate and reach an agreement or disagreement. Suppose there are a total of k participants, where $u = (u_1, u_2, \dots, u_k)$ and $d = (d_1, d_2, \dots, d_k)$ are the costs or benefits, respectively, derived from the agreement scenario and the disagreement scenario, which indicates the negotiated goal and bargaining disagreement points [27]. The AB solution is mathematically defined as the optimal solution to the following optimization problem:

$$\max_{u_1, u_2, \dots, u_k} \prod_{i=1,2,3,\dots,k} (u_i - d_i)^{\alpha_i} \quad (63)$$

$$s.t. \quad u_i \in U, i = 1, 2, \dots, k \quad (64)$$

$$u_i \geq d_i \quad i = 1, 2, \dots, k \quad (65)$$

where U is the feasible domain of u , (63) is the Nash product, and α_i represents the bargaining power of the i th participant.

To obtain the AB solution, the first step is to solve the bargaining disagreement points. We believe that by trading heat and electricity with each other, each EP can gain more than it would otherwise. From (66)-(77), we redescribe the providers' level where there are no transactions between EPs.

$$P_{t,r}^{GT_toUA_nco} = \eta_{TR} P_{t,r}^{grid_nco} + \eta_{ICE} Q_{t,r}^{gas_nco} \quad (66)$$

$$H_{t,r}^{GT_toUA_nco} = [(1 - \eta_{ICE}) + \eta_{GB}] Q_{t,r}^{gas_nco} \quad (67)$$

$$M_{t,r}^{GT_nco} = (Q_{t,r}^{gas_nco} C_{t,r}^{gas} + P_{t,r}^{grid_nco} C_{t,r}^{grid}) \Delta t \quad (68)$$

$$C_{t,e}^{EP_toUA_nco} = C_{t,e}^{EP_base_nco} + \sigma_e P_t^{UA} \quad (69)$$

$$C_{t,h}^{EP_toUA_nco} = C_{t,h}^{EP_base_nco} + \sigma_h H_t^{UA} \quad (70)$$

$$I_{t,r}^{GT_toUA_nco} = (P_{t,r}^{GT_toUA_nco} C_{t,e}^{EP_toUA_nco} + H_{t,r}^{GT_toUA_nco} C_{t,h}^{EP_toUA_nco}) \Delta t \quad (71)$$

$$d_r^{GT_nco} = \sum_t (I_{t,r}^{GT_toUA_nco} - M_{t,r}^{GT_nco}) \quad (72)$$

$$P_{t,i}^{RE_toUA_nco} = P_{t,i}^{RE_real} - P_{t,i}^{RE_abandon_nco} \quad (73)$$

$$M_i^{RE_abandon_nco} = \gamma \sum_t P_{t,i}^{RE_abandon_nco} \quad (74)$$

$$M_i^{RE_fluctuation_nco} = \frac{\nu}{T-1} \sum_{t=1}^{T-1} \left| \frac{P_{t+1,i}^{RE_toUA_nco} - P_{t,i}^{RE_toUA_nco}}{\Delta t} \right| \quad (75)$$

$$I_{t,i}^{RE_toUA_nco} = P_{t,i}^{RE_toUA_nco} C_{t,e}^{EP_toUA_nco} \quad (76)$$

$$d_i^{RE_nco} = \sum_t (I_{t,i}^{RE_toUA_nco}) - M_i^{RE_abandon_nco} \quad (77)$$

The objective function for solving the bargaining disagreement points aims to add and maximize the benefits of all EPs, which can be expressed as:

$$\max u^{EP_nco} = \sum_i d_i^{RE_nco} + \sum_R d_r^{GT_nco} \quad (78)$$

The constraints are as follows:

$$P_t^{UA} = \sum_{r \in R} P_{t,r}^{GT_toUA_nco} + \sum_{i \in I} P_{t,i}^{RE_toUA_nco} \quad (79)$$

$$H_t^{UA} = \sum_{r \in R} H_{t,r}^{GT_toUA_nco} \quad (80)$$

$$0 \leq P_{t,i}^{RE_abandon_nco} \leq P_{t,i}^{RE_real} \quad (81)$$

$$0 \leq Q_{t,r}^{gas_nco} \leq Q_{t,r}^{gas_max} \quad (82)$$

$$0 \leq P_{t,r}^{grid_nco} \leq P^{grid_max} \quad (83)$$

$$d_r^{GT_nco} \geq 0 \quad d_i^{RE_nco} \geq 0 \quad (84)$$

$$M_i^{RE_fluctuation_nco} \leq M^{RE_fluctuation_max} \quad (85)$$

where (79) and (80) ensure that the demand for the UA is balanced with the supply of all the Eps, (81) ensures that the curtailment value of renewable energy is reasonable, and (85) requires the output fluctuation of the i th REGU to be within an acceptable range, similar to (20).

The second step calculates α_i on the basis of the credit score criteria first proposed in this paper. The advantage of the proposed criterion is that it enables quantitative determination of the weight. The credit score criteria represent each EP's contribution to carbon emissions reduction or output prediction accuracy, expressed as follows:

$$Score = Initial\ score + Bonus\ score \quad (86)$$

-Carbon emission score - Forecast error score

Each EP has the same initial credit score; if the EP is REGU, for the purpose of promoting renewable energy development, it will receive an additional bonus score to gain more bargaining power. For GTs, since their output is predictable, only the carbon emissions score must be calculated, whereas REGUs need to calculate only the output forecast error score. Finally, the scores of all EPs are added, and $\alpha^{r/i}$ is obtained on the basis of the proportion of each EP's score to the total score. The specific expressions are as follows:

$$Score_r = Initialscore_r - \varphi^{carbon} C^{GT} \quad (87)$$

$$C^{GT} = (\rho^{heat} \sum_T H_{t,r}^{GT_toUA_nco} + \rho^{ele} \sum_T P_{t,r}^{GT_toUA_nco}) \quad (88)$$

$$Score_i = Initialscore_i + Bonusscore_i - \varphi^{forecasterror} \sum_T |P_{t,i}^{RE_forecast} - P_{t,i}^{RE_real}| \quad (89)$$

$$\alpha_{r/i} = \frac{Score_{r/i}}{\sum_R Score_r + \sum_I Score_i} \quad (90)$$

where φ^{carbon} and $\varphi^{forecasterror}$ are conversion parameters, C^{GT} represents the carbon emissions of the GT, and ρ^{heat} and ρ^{ele} represent the carbon intensities [28].

The gradual depletion of traditional energy sources and global warming have led major countries worldwide to reach a consensus on the development of clean energy to replace traditional energy. According to data released by China's National Energy Administration in 2023, the share of renewable energy generation, represented by wind and solar energy, has significantly increased. However, traditional energy remains indispensable, and long-term coexistence of both types of energy is expected in the future. Unlike traditional energy, wind and solar power generation depend on natural conditions, leading to significant output fluctuations that can jeopardize grid security. According to the data from the State Grid Corporation of China, the maximum power fluctuations of wind and solar renewable energy can reach about 10% of peak load within 15 minutes and about 25% within an hour. The adjustment capabilities

of conventional power sources are insufficient to cope with the power fluctuations of renewable energy sources, which has already become the primary factor affecting the development of renewable energy [29]. Therefore, we formulate a weighting allocation strategy on the basis of the most critical issues of these two types of energy. Different entities can gain greater weight and consequently more bargaining power by reducing carbon emissions and stabilizing output.

On the basis of the obtained d and α values, the AB solution is calculated according to formula (63).

$$\max u^{EP} = \prod_{r \in R} (u_r^{GT_co} - d_r^{GT_nco})^{\alpha_r} \prod_{i \in I} (u_i^{RE_co} - d_i^{RE_nco})^{\alpha_i} \quad (91)$$

s.t. (8)(9)(15)(16)(17)(20)(24)(25)(28)(29)

V. CASE STUDY

A. Basic parameters

In this paper, the CIES consists of 5 EPs (2 GTs and 3 REGUs), 1 UA, and 5 EUs. The technical parameters for each EP can be found in TABLE II. The preference constants, denoted as $\alpha_{k,e}$ and $\alpha_{k,h}$, are randomly selected from the range (0.01, 0.05), whereas the preference constants $v_{k,e}$ and $v_{k,h}$ are chosen randomly from the interval (2, 7). Additionally, approximately 25% of the total load is assumed to correspond to translatable electric loads and cuttable heat loads [31].

TABLE II
TECHNICAL PARAMETERS

η_{TR}	0.90	η_{ICE}	0.35
η_{GB}	0.10	σ_e / σ_h	0.0005
$Initialscore$	4000	$Bonusscore$	1000
ρ^{ele}	0.785	ρ^{heat}	0.385

TABLE III
SIMULATION CASES

Cases	Transactive energy between EPs	Weight allocation
Case 1	×	×
Case 2	√	×
Case 3	√	√

Three different cases shown in TABLE III are established to demonstrate the superiority of the AB solution scheme for EPs. In Case 1, there is no transactive energy between EPs. In Case 2, there is transactive energy between EPs, but their bargaining power is the same (NB solution). In Case 3, the weight allocation strategy is introduced (AB solution). The software used for these case studies is MATLAB 2021b on a laptop powered by a 2.8 GHz Intel Core 11 i7 processor.

B. Equilibrium analysis

In the case of no transaction between EPs (NTE), the entities maintain mutual independence and seize the UA demand according to their own means of production. The profit proportions of the GTs are 24% and 23%, and those of the REGUs are 21%, 15%, and 17%. Although the overall market share of REGUs is greater than that of GTs, the share

of each REGU is low because of the penalty cost caused by the fluctuations in renewable energy output.

Under the NB solution, each EP can realize an increase in interest by trading its own energy. As shown in TABLE IV, compared with the NTE, the NB solution makes the utility growth of each EP the same. As indicated in TABLE V, GTs can increase their own income by selling electricity to REGUs, and REGUs can stabilize the output fluctuations by purchasing electricity from GTs or trading with other REGUs. However, owing to the high market share obtained by GTs without trading, if REGUs continue to purchase energy from GTs, its reducible value will not change significantly, and it will not be able to increase the consumption of renewable energy, as shown by the changes in the punishment cost in TABLE VI.

TABLE IV

INTEREST ALLOCATION RESULTS					
	GT1	GT2	REGU1	REGU2	REGU3
Utility (¥) (NTE)	3526.84	3393.02	3130.92	2328.69	2502.07
Utility (¥) (NB)	3819.03	3680.70	3429.27	2627.28	2800.75
Differential with NTE	291.34	288.11	298.36	298.61	298.63
Utility (¥) (AB)	3755.68	3631.59	3622.86	2831.49	3007.46
Weight (Bargaining power)	0.1114	0.1139	0.2570	0.2577	0.2598
Differential with NTE	228.39	238.71	491.88	502.40	505.35

TABLE V

EPS' TRANSACTION INCOME					
Transaction income (¥)	GT1	GT2	REGU1	REGU2	REGU3
NB	5.84	190.49	23.25	-164.01	-55.58
AB	-114.41	27.16	77.28	-32.67	42.64

TABLE VI

PUNISHMENT COST			
Punishment cost (¥)	REGU1	REGU2	REGU3
NTE	1801.56	2025.61	2018.93
NB	1770.51	2037.51	2002.64
AB	1659.77	1898.10	1872.09

The AB solution can effectively solve the above problems. By calculating the carbon emissions of the GTs, and the output prediction error of the REGUs, different bargaining powers are assigned to different entities. As shown in

TABLE IV, the revenue growth of each EP is proportional to its weight. Compared with the NB solution, the AB solution can effectively improve the utility of REGUs and increase their market share. In addition, as shown in TABLE V and TABLE VI, the AB solution encourages REGUs to sell electricity, thereby reducing the punishment cost and achieving the absorption of renewable energy. In TABLE VII, GTs can reduce production and thus reduce carbon emissions.

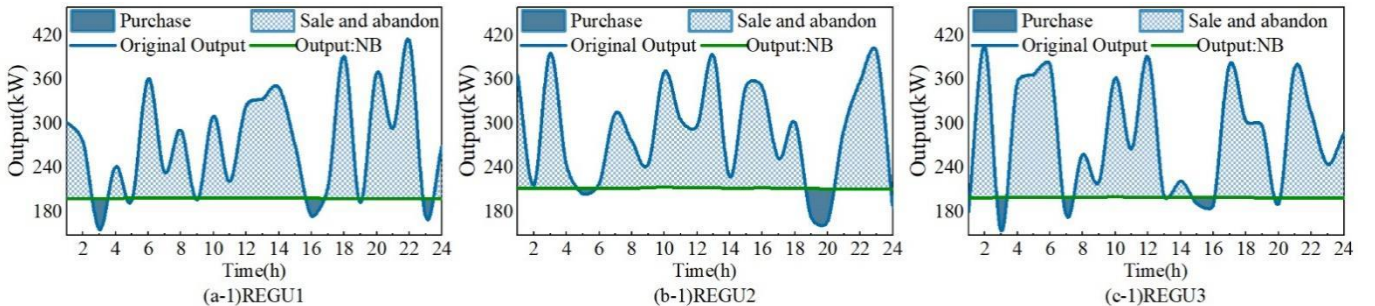
TABLE VII

GT PRODUCTION QUANTITY			
Production(kW)	NTE	NB	AB
GT1	2959.76	2893.82	2705.21
GT2	2830.35	2860.85	2668.76

Additionally, as shown in Fig. 3, the AB solution can smooth the REGU output fluctuations. REGUs are intended to stabilize output fluctuations between different periods while also minimizing the penalties incurred from discarding excess energy. Under the NTE scenario, REGUs segment their original output plans into sections with the least variance, aiming to eliminate output fluctuations within a continuous period with minimal output reduction. Hence, the final result presents a segmentation phenomenon. In the NB scenario, entities can mitigate output fluctuations through mutual trading rather than merely relying on output reduction. Under the AB scenario, more attention is given to REGU, resulting in smaller output fluctuations than those in the NB scenario. The relatively large fluctuations in the original output were set to demonstrate the effectiveness of our management strategy.

The Stackelberg game's convergence performance is illustrated in Fig. 4. The benefits of these methods stabilize after approximately the fourth iteration. As the iterations progress, the EPs' utility decreases, whereas that of the UA increases. Equilibrium is achieved when all the followers supply their optimal responses after the leader's strategy, and the leader, in turn, accepts these responses. Following this equilibrium, all players find themselves unable to unilaterally improve their benefits by altering their strategies independently. Ultimately, the UA accumulates earnings of 10200.713 yuan, whereas the benefits of GT1, GT2, REGU1, REGU2, and REGU3 converge to 3755.683¥, 3631.590¥, 3622.861¥, 2831.498¥, and 3007.461 ¥, respectively.

The equilibrium proof of the proposed game model has been proven, with the detailed content presented in APPENDIX A.



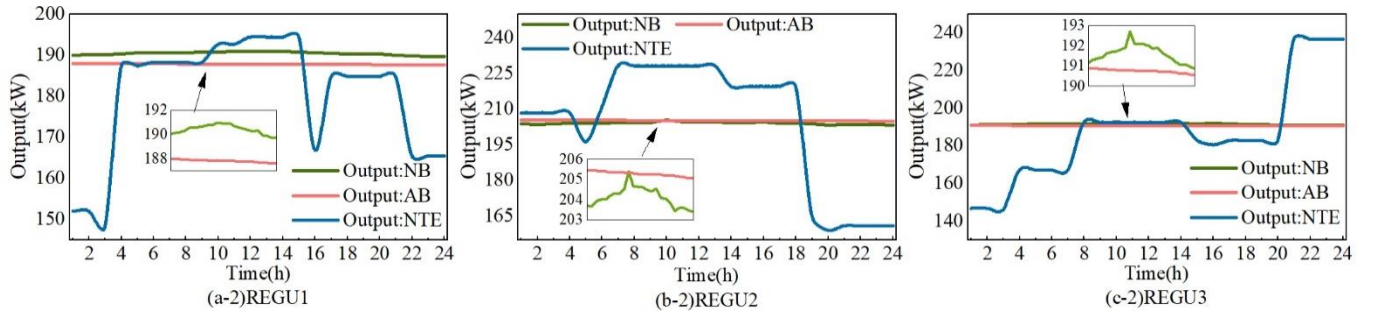


Fig. 3 REGU output (to UA)

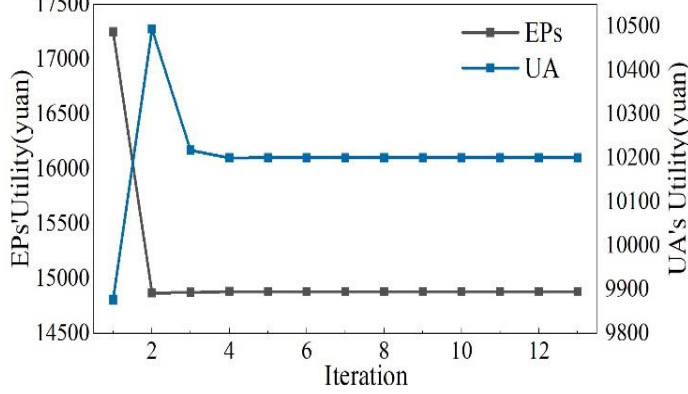


Fig. 4 Iteration results

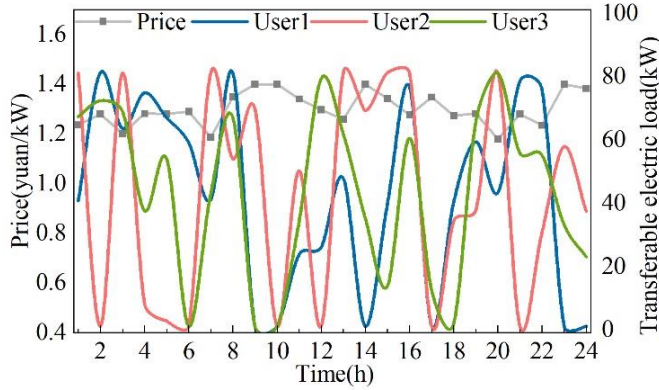


Fig. 5 Demand response between the UA and the EU

C. Interaction analysis

In the UA layer, the demand response between the UA and the EUs is analysed. Moreover, the influence of different pricing strategies on UA revenue is also considered.

Taking the example of electricity load variation, as depicted in Fig. 5 (taking any three users as an example), when electricity prices fluctuate, the transferable electric load exhibits an opposite trend, thereby altering the initial load to achieve a reduction in electricity costs, enabling demand response, and contributing to peak shaving and valley filling for the power grid. However, by comparing the transferable electric load and the reducible heat load before and after, it can be observed that the price has a relatively minor effect on the EUs' energy consumption. In some periods, the price and transferable load exhibit the same trend. This is due to the influence of users' price sensitivity and fixed load. The specific reasons for this will be explained in the next section.

TABLE VIII
COMPARISON OF PRICING STRATEGIES

	Income of UA (¥)	Solution time (s)
Individual	10200.71	7.15
Unified	10327.53	5.4

As shown in TABLE VIII, under unified pricing, all EU members follow the UA's unified price guidance. Compared with separate pricing, this leads to faster solution times and higher profits for the UA. The results show that unified pricing can increase UA revenue by 1.24% and reduce computation time by 24.47%. Although the data show that unified pricing does not lead to significant changes, please note that this result is based on only five users. For a CIES, the actual number of users will be much larger. Even when linear growth is considered, the impact will still be substantial.

D. User behaviour analysis

To analyse user behaviour in demand responses, this section separately examines the impact mechanism of user price sensitivity and fixed load quantity on demand response.

To assess the impact of prices on users, a fixed load is uniformly set for each period. The sensitivity of users to the price is altered by varying the parameter $\alpha_{k,e} \backslash \alpha_{k,h}$, which is the coefficient of the quadratic term in the user utility function. Taking the example of $\alpha_{k,e}$, first, within the control group ($\alpha_{k,e}=0.02$), the quantity of transferable load for each period is evenly distributed at approximately 41.66 kW, i.e., the total transferable load is evenly allocated among the values for 24 periods. As shown in Fig. 6, for any period (from Time Period 5 to Time Period 10, for example), to reduce user energy costs, time periods with higher prices have a smaller transferable load, whereas periods with lower prices have a larger transferable load. The reason price has a less pronounced effect on the transferable load is that for users, the effect on energy utility outweighs the effect on energy cost. By reducing $\alpha_{k,e}$ to decrease the sensitivity of user energy utility ($\alpha_{k,e}=0.0002$), the disparity in the transferable load widens compared with that of the control group, indicating that the impact of prices is amplified. Similarly, increasing $\alpha_{k,e}$ ($\alpha_{k,e}=0.2$) makes users more sensitive to energy utility than the control group, thereby diminishing the impact of prices. As a result, the transferable load, compared with that of the control group, is distributed more closely at approximately 41.66 kW.

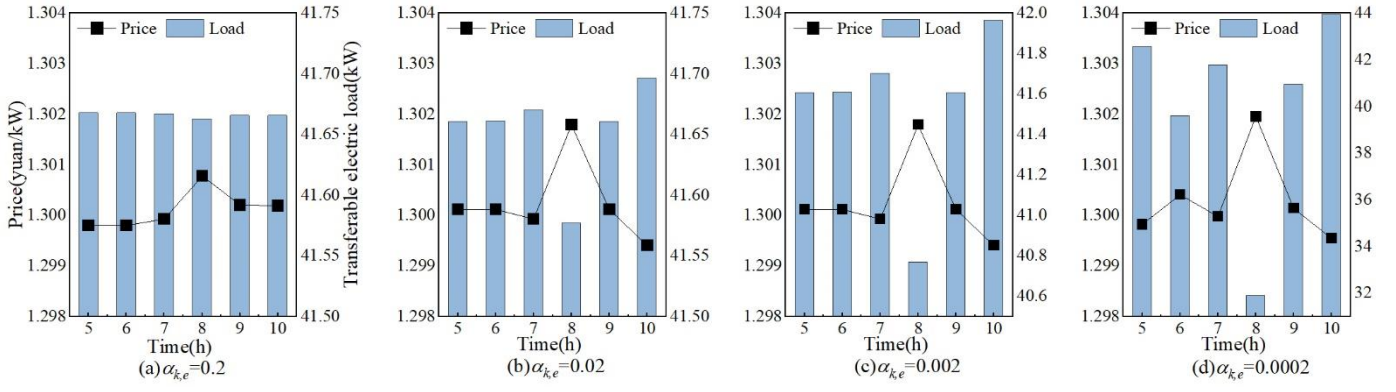


Fig. 6 Effect of price sensitivity on the demand response

With respect to the impact from the fixed load quantity, as shown in Fig. 7, when the fixed load is low (from time periods 2 to 7, for example), users' transferable load initially supplements this period. This is because during low fixed load periods, users experience a significant utility change rate with a transferable load. To maximize user utility, the transferable load supplies the load during these periods, bringing it to the same level as the load in other periods. Furthermore, the prices set by the UA will not undergo significant changes since the total load across different periods has converged through the supplementation of the transferable load. Therefore, the prices are similar, all of which are at or near the upper limit of the price mean, in compliance with constraint (33). However, when the fixed load quantity is too low (such as in periods 10, 22 and 24), even supplementing the transferable load to the upper limit as per constraint (40) cannot make the total load equal to that in the other periods, the UA will lower the price for those periods. This is because the total load in these periods is less than that in the other periods. By doing so, the UA ensures that the price mean remains below the set upper limit while creating the maximum price increase for other periods, thereby expanding the UA's revenue. Similarly, in the case where the fixed load for a particular period is greater than the rest (such as time periods 1, 8, 14, and 21), the opposite effect occurs.

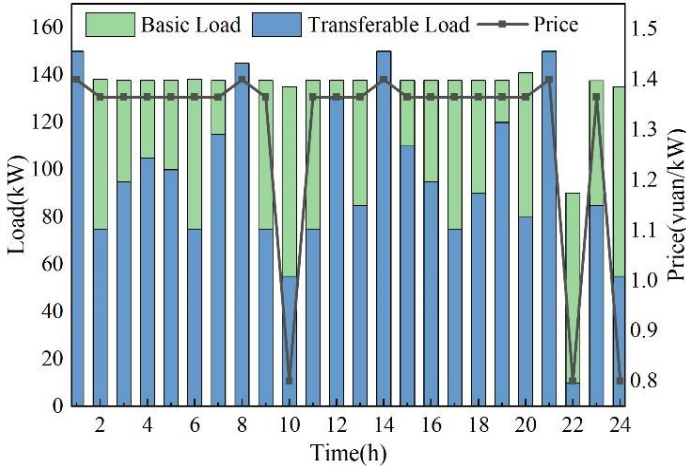


Fig. 7. Effect of the fixed load quantity on demand response

VI. CONCLUSION

This paper proposes a tri-level hybrid game model oriented towards EPs, a UA, and EUs. In the vertical dimension, the Stackelberg game reveals the demand response of the energy between the supply side and the demand side. In the horizontal dimension, the AB game facilitates energy interactions among the various EPs on the supply side, which not only enhances the benefits of each entity but also provides a better market environment for renewable energy sources.

1. The KKT conditions and the Big-M method simplify the solution difficulty of the tri-level CIES problem, achieving equilibrium after 5th iteration. The existence proof demonstrates the optimality of the result.

By utilizing the KKT conditions and the big-M method, the optimization of demand-side users is transformed into constraint aggregation, which is then handled at the aggregator level. This greatly simplifies the problem-solving process. Subsequently, price and demand information are exchanged with suppliers on the supply side, and after iteration, the optimal production and consumption plans are generated. Through the existence proof in the appendix (Part A), the established method ensures that no party can unilaterally change its decision to improve its own benefits, guaranteeing the Nash equilibrium of the results.

2. Under the proposed weight allocation scheme, REGU can obtain a bargaining weight approximately 127% higher than GT, its revenue can increase by about 64%, and its output will be more stable. The system's carbon emissions are also reduced.

When establishing asymmetric Nash bargaining among EPs on the supply side, negotiation weights are calculated by obtaining the numerical values of renewable energy output prediction accuracy and carbon emissions from traditional power generation units under the NTE condition. The established asymmetric Nash bargaining method significantly enhances the bargaining power of REGUs. Compared with ordinary Nash bargaining, the profits of REGUs are significantly increased (approximately 64% to 69%), and their market participation is greatly increased.

Additionally, the output fluctuations and the absorption of REGUs are noticeably improved. For traditional power generation units, while revenue growth is ensured, carbon emissions are significantly reduced.

3. Price sensitivity will alter users' trade-offs between energy usage utility and cost, while the fixed load amount will affect the allocation of transferable loads, thereby impacting demand response. Meanwhile, the unified pricing strategy is more suitable for UA.

According to the simulation results, when the fixed load remains constant, the higher the user's price sensitivity is, the stronger the demand response. Conversely, when the user's price sensitivity is low, users consider mainly the utility associated with energy consumption, and the demand response is not significant. For a fixed load, during periods of low fixed load, the transferable load will prioritize supplementing this period's load to make it equal to the load in other periods, thus achieving greater utility growth. If the fixed load in a certain period is too high, supplementation will be abandoned. Prices are then reduced during periods of low load to gain room for price increases during high-load periods. With respect to different pricing strategies, the simulation results show that adopting a unified pricing approach can increase the revenue of the aggregator by 1.24% and reduce the computation time by 24.47%.

VII. LIMITATIONS AND FUTURE WORK

This paper establishes a tri-level city integrated energy system and proposes hybrid game models between the layers and between the supply-side providers. However, there is a lack of research on games between EUs, and there is no energy exchange between individual EUs. In future research, we will further focus on the game between demand-side users, with a focus on how to plan their energy consumption through Nash bargaining and auctions in two stages: day-ahead and intraday. We aim to establish peer-to-peer transactions to ensure the stability of their energy supply.

APPENDIX

A. Existence proof of game equilibrium

Achieving game equilibrium means that no participant can unilaterally improve their utility by changing their own strategy [30]. In the context of this tri-level game structure, the game equilibrium is defined as $(\delta_{EP}^*, \delta_{UA}^*, \delta_{EU,k}^*)$. To establish the equilibrium in the proposed tri-level game model, it is necessary to ensure that the following conditions are met:

$$\begin{cases} u^{EP}(\delta_{EP,r}^*, \delta_{EP,-r}^*, \delta_{UA}^*, \delta_{EU,k}^*) \geq u^{EP}(\delta_{EP,r}, \delta_{EP,-r}, \delta_{UA}^*, \delta_{EU,k}^*) \\ u^{EP}(\delta_{EP,i}^*, \delta_{EP,-i}^*, \delta_{UA}^*, \delta_{EU,k}^*) \geq u^{EP}(\delta_{EP,i}, \delta_{EP,-i}, \delta_{UA}^*, \delta_{EU,k}^*) \\ u^{UA}(\delta_{EP}^*, \delta_{UA}^*, \delta_{EU,k}^*) \geq u^{UA}(\delta_{EP}^*, \delta_{UA}, \delta_{EU,k}^*) \\ u_k^{EU}(\delta_{EP}^*, \delta_{UA}^*, \delta_{EU,k}^*) \geq u_k^{EU}(\delta_{EP}^*, \delta_{UA}^*, \delta_{EU,k}) \end{cases} \quad \forall i \in I, \forall k \in K \quad (A-1)$$

where $\delta_{EP,-i}^*$ represents the set of strategies adopted by all the EPs except the i th EP. Consequently, we can represent the strategies of all the EPs as $\delta_{EP}^* = [\delta_{EP,i}^*, \delta_{EP,-i}^*]$, which is the same for $\delta_{EP,-r}^*$. Inequality (A-1) indicates that each player's optimal strategy depends on the optimal strategies of the others, and no player can gain a greater advantage by unilaterally altering their strategy.

Prior to identifying this equilibrium, it is essential to establish its existence. The equilibrium proof for the tri-level CIES is divided into three main parts:

- 1) The Stackelberg equilibrium between EPs and the UA
- 2) The Stackelberg equilibrium between the UA and EUs
- 3) The Nash equilibrium of multiple EPs

The proof conditions for the Stackelberg equilibrium are as follows [31]:

- 1) The action set of each player is nonempty, convex, and compact.
- 2) Each follower has a unique and optimal strategy once informed of the leader's strategy.
- 3) The leader admits a unique optimal strategy in light of the best-identified strategies of all the followers.

In a cooperative game, a Nash equilibrium can be found when the following conditions are met [30]:

- 1) The action set of each player is a nonempty, convex, and compact subset of a Euclidean space.
- 2) The utility functions are continuous and quasi-concave.

According to the modelling in Section II, the first condition for proving the Stackelberg game is satisfied. Then, it needs to be demonstrated that the EU has a unique optimal solution. The expression for the first-order partial derivative of the objective function (39) concerning $P_{t,k}^{EU_shift}$ and $H_{t,k}^{EU_shift}$ is as follows:

$$\frac{\partial u_k^{EU}}{\partial P_{t,k}^{EU_shift}} = v_{k,e} - \alpha_{k,e}(P_{t,k}^{EU_base} + P_{t,k}^{EU_shift}) - C_{t,k,e}^{UA} \quad (A-2)$$

$$\frac{\partial u_k^{EU}}{\partial H_{t,k}^{EU_shift}} = -v_{k,h} + \alpha_{k,h}(H_{t,k}^{EU_base} - H_{t,k}^{EU_shift}) + C_{t,k,h}^{UA} \quad (A-3)$$

The Hessian matrix for the EU is as follows:

$$Hessian_k^{EU} = \begin{bmatrix} -\alpha_{k,e} & 0 \\ 0 & -\alpha_{k,h} \end{bmatrix} < 0 \quad (A-4)$$

Owing to the constant positivity of preference parameters $\alpha_{k,e}$ and $\alpha_{k,h}$, the Hessian matrix for the EU is negative definite, indicating convexity in its objective function. Therefore, when the UA determines the selling price, the EU has a unique optimal strategy. By using the Lagrange multiplier method to satisfy the constraint (52) for a transferable electric load, the resulting optimal strategy is articulated as follows:

$$P_{t,k}^{EU_shift_op} = \frac{v_{k,e} - C_{t,k,e}^{UA}}{\alpha_{k,e}} - P_{t,k}^{EU_base} \quad (A-5)$$

$$H_{t,k}^{EU_shift_op} = \frac{C_{t,k,e}^{UA} - v_{k,h}}{\alpha_{k,h}} + H_{t,k}^{EU_base} \quad (A-6)$$

Next, we prove the existence of a unique optimal strategy for the UA side. By incorporating the optimal strategies $P_{t,k}^{EU_shift_op}$ and $H_{t,k}^{EU_shift_op}$ into the UA's objective

function, we derive its first-order partial derivative with respect to $C_{t,k,e}^{UA}$, $C_{t,k,h}^{UA}$, P_t^{UA} , and H_t^{UA} as follows:

$$\frac{\partial u^{UA}}{\partial C_{t,k,e}^{UA}} = \frac{v_{k,e} - 2C_{t,k,e}^{UA}}{\alpha_{k,e}} \quad (A-7)$$

$$\frac{\partial u^{UA}}{\partial C_{t,k,h}^{UA}} = \frac{v_{k,h} - 2C_{t,k,h}^{UA}}{\alpha_{k,h}} \quad (A-8)$$

$$\frac{\partial u^{UA}}{\partial P_t^{UA}} = -C_{t,e}^{EP_base_nco} - 2\sigma_e P_t^{UA} \quad (A-9)$$

$$\frac{\partial u^{UA}}{\partial H_t^{UA}} = -C_{t,h}^{EP_base_nco} - 2\sigma_h H_t^{UA} \quad (A-10)$$

The Hessian matrix for the UA is:

$$Hessian^{UA} = \begin{bmatrix} \frac{-2}{\alpha_{k,e}} & 0 & 0 & 0 \\ 0 & \frac{-2}{\alpha_{k,h}} & 0 & 0 \\ 0 & 0 & -2\sigma_e & 0 \\ 0 & 0 & 0 & -2\sigma_h \end{bmatrix} < 0 \quad (A-11)$$

The Hessian matrix for the UA is negative definite. Once the demand of the EU is determined, the strategy of the UA has a unique optimal solution. In brief, the Stackelberg game between the UA and EUs concludes with a distinct equilibrium.

Finally, we establish the existence of a unique optimal strategy for the EP. Accounting for constraints (28), (29), (35), and (36), the optimal strategy can be formulated as:

$$P_t^{UA_op} = \frac{-C_{t,e}^{EP_base_nco}}{2\sigma_e} \quad (A-12)$$

REFERENCES

- [1] Amar R., Satish K., Sitara K. "Accelerating renewables: Unveiling the role of green energy markets" *Appl. Energy*. vol. 366, no.15, pp. 123286, July. 2024.
- [2] Mari H., Paris L. B., Audun B., Todd L., Zhou Z., Michael B., Magnus K., and Abhishek S. "Power market models for the clean energy transition: State of the art and future research needs" *Appl. Energy*. vol. 357, no.1, pp. 122495, Mar. 2024.
- [3] Tan J., Pan W., Li Y., Hu H., Zhang C. "Energy-sharing operation strategy of multi-district integrated energy systems considering carbon and renewable energy certificate trading" *Appl. Energy*. vol. 339, no.1, pp. 120835, Jun. 2023.
- [4] Wang, Z., Dong, L., Shi, M., Qiao, J., Jia, H., Mu, Y., and Pu, T. "Market power modeling and restraint of aggregated prosumers in peer-to-peer energy trading: A game-theoretic approach". *Appl. Energy*. vol. 348, no. 15, pp. 121550, Oct. 2023.
- [5] Meng, Y., Fan, S., Shen, Y., Xiao, J., He, G., and Li, Z. "Transmission and distribution network-constrained large-scale demand response based on locational customer directrix load for accommodating renewable energy". *Appl. Energy*. vol. 350, no. 15, pp. 121681, Nov. 2023.
- [6] Hong, Q., Meng, F., Liu, J., and Bo, R. "A bi-level game-theoretic decision-making framework for strategic retailers in both local and wholesale electricity markets". *Appl. Energy*. vol. 330, no. 15, pp. 121311, Jan. 2022.
- [7] Aguiar N., Dubey A. and Gupta V., "Network-Constrained Stackelberg Game for Pricing Demand Flexibility in Power Distribution Systems," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 4049-4058, Sept. 2021.

$$H_t^{UA_op} = \frac{-C_{t,h}^{EP_base_nco}}{2\sigma_h} \quad (A-13)$$

By incorporating these variables into Equation (91), which represents the EPs' objective function, we can derive its first-order partial derivative with respect to $C_{t,e}^{EP_base_nco}$ and $C_{t,h}^{EP_base_nco}$ as follows:

$$\frac{\partial u^{EP_nco}}{\partial C_{t,e}^{EP_base_nco}} = \frac{\sum_{r \in R} P_{t,r}^{GT_toUA_nco} + \sum_{i \in I} P_{t,i}^{RE_toUA_nco}}{2} - \frac{C_{t,e}^{EP_base_nco}}{4\sigma_e} \quad (A-14)$$

$$\frac{\partial u^{EP_nco}}{\partial C_{t,h}^{EP_base_nco}} = \frac{\sum_{r \in R} H_{t,r}^{GT_toUA_nco}}{2} = \frac{-C_{t,h}^{EP_base_nco}}{4\sigma_h} \quad (A-15)$$

The Hessian matrix for the EP is negative definite. Once the UA's purchasing plan is determined, the EP's price has a unique optimal solution.

$$Hessian_{i/r}^{EP} = \begin{bmatrix} \frac{-1}{4\sigma_{e,i/r}} & 0 \\ 0 & \frac{-1}{4\sigma_{h,i/r}} \end{bmatrix} < 0 \quad (A-16)$$

The actions taken by the EPs are bound by constraints (8) and (9), both of which are evidently nonempty, convex, and compact. (A-16) implies that the EP's utility function remains continuous and quasi-concave with respect to $C_{t,e}^{EP_base_nco}$ and $C_{t,h}^{EP_base_nco}$. Consequently, the existence of a Nash equilibrium is established within the cooperative game involving multiple EPs.

- [8] Wang B., Wang X., Zhu Z., Wu X., "Siting and sizing of energy storage for renewable generation utilization with multi-stage dispatch under uncertainty: A tri-level model and decomposition approach". *Appl. Energy*. vol. 344, no. 15, pp. 121286, Jan. 2023.
- [9] Wang J., Xu J., Ke D., Liao S., Sun Y., Wang J., Yao L., Mao B., Wei C., "A tri-level framework for distribution-level market clearing considering strategic participation of electrical vehicles and interactions with wholesale market," *Appl. Energy*. vol. 329, no. 1, pp. 120230, Jan. 2023.
- [10] Wang H., Zhang C., Li K., Liu S., Li S., Yu W. "Distributed coordinative transaction of a community integrated energy system based on a tri-level game model," *Appl. Energy*, vol. 295, no. 1, pp.116972, Aug. 2021.
- [11] Du Y., Xue Y., Wu W., Shahidehpour M., Shen X., Wang B., and Sun H., "Coordinated Planning of Integrated Electric and Heating System Considering the Optimal Reconfiguration of District Heating Network", *IEEE Trans. Power Systems*, vol. 1, no.39: pp.794-808, Jan. 2024.
- [12] Wang K., Xue Y., Guo Q., Shahidehpour M., Zhou Q., Wang B., and Sun H., "A Coordinated Reconfiguration Strategy for Multi-Stage Resilience Enhancement in Integrated Power Distribution and Heating Networks", *IEEE Trans. Smart Grid*, vol. 7, no. 14, pp. 2709-2722, July 2022.
- [13] Hupez M., Toubeau J. -F., Z. Grève De and Vallée F., "A New Cooperative Framework for a Fair and Cost-Optimal Allocation of Resources Within a Low Voltage Electricity Community," *IEEE Trans. Smart Grid*, vol. 12, no. 3, pp. 2201-2211, May 2021.
- [14] Chen, Y., Park, B., Kou, X., Hu, M., Dong, J., Li, F.F., Amasyali, K., and Olama, M.M.. "A comparison study on trading behavior and profit

- distribution in local energy transaction games," *Appl. Energy*, vol. 280, no. 15, pp.115941, Dec. 2020.
- [15]Chang X, Xu Y. Sun H., "Vertex scenario-based robust peer-to-peer transactive energy trading in distribution networks," *International Journal of Electrical Power & Energy Systems*, vol. 138, pp.107903, Jun. 2022.
- [16]Wang, Z., Hou, H., Zhao, B., Zhang, L., Shi, Y., and Xie, C. "Risk-averse stochastic capacity planning and P2P trading collaborative optimization for multi-energy microgrids considering carbon emission limitations: An asymmetric Nash bargaining approach." *Appl. Energy*, vol. 357, no. 1, pp.122505, March. 2024.
- [17]Fang X., Guo H., Zhang X., Wang X., and Chen Q., "An efficient and incentive-compatible market design for energy storage participation" *Appl. Energy*, vol. 311, no. 1, pp.118731, Apr. 2022.
- [18]Mi Y., Cai P., Fu Y., Wang P. and Lin S., "Energy Cooperation for Wind Farm and Hydrogen Refueling Stations: A RO-Based and Nash-Harsanyi Bargaining Solution," *IEEE Trans. Ind. Appl.*, vol. 58, no. 5, pp. 6768-6779, Sept.-Oct. 2022.
- [19]Chen W., Qiu J., Zhao J., Chai Q. and Dong Z., "Bargaining Game-Based Profit Allocation of Virtual Power Plant in Frequency Regulation Market Considering Battery Cycle Life," *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 2913-2928, July 2021.
- [20]Wang L., Gu W., Wu Z., Qiu H., Pan G., "Non-cooperative game-based multilateral contract transactions in power-heating integrated systems," *Appl. Energy*, vol. 268, no. C, pp.114930, June 2020.
- [21]Paudel A., Chaudhari K., Long C. and Gooi H. B., "Peer-to-Peer Energy Trading in a Prosumer-Based Community Microgrid: A Game-Theoretic Model," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6087-6097, Aug. 2019.
- [22]Qin J., Wan Y., Yu X., Li F. and Li C., "Consensus-Based Distributed Coordination Between Economic Dispatch and Demand Response," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3709-3719, July 2019.
- [23]Li J., Xu D., Wang J., Zhou B., Wang M-H. and Zhu L., "P2P Multigrade Energy Trading for Heterogeneous Distributed Energy Resources and Flexible Demand," *IEEE Trans. Smart Grid*, vol. 14, no. 2, pp. 1577-1589, March 2023.
- [24]Wang J., Feng C., Xu Y., Wen F., Zhang L., Xu C., et al., "Stackelberg game-based energy management for a microgrid with commercial buildings considering correlated weather uncertainties", *IET Gener. Transmiss. Distrib.*, vol. 13, no. 11, pp. 2102-2111, Jun. 2019.
- [25]Bai J., Ding T., Jia W., Zhu S., Bai L. and Li F., "Online Rectangle Packing Algorithm for Swapped Battery Charging Dispatch Model Considering Continuous Charging Power," *IEEE Transactions on Automation Science and Engineering*, vol. 21, no. 1, pp. 320-331, Jan. 2024.
- [26]Wang Z., Yu X., Mu Y., and Jia H., "A distributed peer-to-peer energy transaction method for diversified prosumers in urban community microgrid system," *Appl. Energy*, vol. 260, Feb. 2020.
- [27]Harsanyi J. C., "Games with incomplete information played by 'Bayesian' players, III Part I. The basic model," *Manage. Sci.*, vol. 14, no. 3, pp. 159-182, Nov. 1967.
- [28]Cheng Y., Zhang N., Wang Y., Yang J., Kang C. and Xia Q., "Modeling Carbon Emission Flow in Multiple Energy Systems," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3562-3574, July 2019.
- [29]Guo J., "Challenges Facing the New Electric Power System and Mechanisms for Consideration", *China Power Enterprise Management*, no. 25, pp. 8-11, Sept. 2021.
- [30]L̃a QD, Chew YH, Soong B-H. Potential game theory. 2016.
- [31]Ali A., Liu N. and Li H., "Multi-party energy management and economics of integrated energy microgrid with PV/T and combined heat and power system", *IET Renew. Power Gener.*, vol. 13, no. 3, pp. 451-461, Feb. 2019.

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