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A two-layer nested game for an active energy community including shared energy storage and multiple prosumers under renewable portfolio standards

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ABSTRACT

The renewable portfolio standards (RPS) offers a promising solution to the challenge of high-level penetration of renewable energy into the next-generation power grid. The shared energy storage (SES) has emerged as a crucial innovation that significantly aids prosumers in fulfilling RPS requirements. This paper proposes a two-layer nested game model to capture the interactions between SES and prosumers in an active energy community, and with the external main grid, hydropower station, and wind farm. In the upper layer, a Stackelberg game model is established, in which SES acts as the leader maximizing profit by offering electricity prices, while the alliance of prosumers is the follower responding to the prices through demand response and peer-to-peer (P2P) energy exchange. In the lower layer, a cooperative game is constructed for the prosumer alliance, the contributions of individual prosumers are scored and the asymmetric Nash bargaining is utilized to fairly allocate the total expense within the prosumer alliance. The alternating direction method of multipliers (ADMM) is adopted for privacy protection. A case study of a real active energy community in Southwest China demonstrates effectiveness and robustness of the proposed model under diverse conditions. The computational results also confirm the model achieves greater stability, reduces prosumers' expenses, and mitigates the dependence on SES.

1. Introduction

To address the global energy crisis and greenhouse gas emissions, China has introduced the ambitious "dual carbon" target aimed at achieving carbon peaking and carbon neutrality [1]. Within the framework of smart grids, the large-scale integration of distributed renewable energy on demand side transforms traditional consumers into new prosumers characterized by low predictability and controllability. In the energy domain, prosumers act as dual-role end-users of the power grid, capable of both producing and consuming electricity. Meanwhile, in the information domain, prosumers function as autonomous intelligent agents that can actively collect data, analyze system states, and optimize production or consumption behaviors to maximize individual profit. Collectively, numerous prosumers form the active energy community in the smart grid and engage in peer-to-peer (P2P) energy transaction. Despite the benefits of low pollution and high efficiency, the decentralized and unpredictable nature of renewable energies present significant challenges to the stability and safety of power system [2,3].

Nomenclature

Abbreviations	
RPS	Renewable portfolio standards
SES	Shared energy storage
ADMM	Alternating direction method of multipliers
P2P	Peer-to-peer
PV	Photovoltaic
Parameters	
$\mathbb{T}$, t	Set of time slots and index of a time slot
Δt	Duration of each time slot (Unit: h)
$\mathbb{I}$, i	Set of prosumers and index of a prosumer
θ	RPS quota of a prosumer
φ	Contribution score of a prosumer in the alliance
η_{S+} ,η_{S-}	Efficiencies of SES charging and discharging
Decision variables	
r,$\boldsymbol{r}$	Electricity price (Unit: CNY/kWh) and the relevant vector
P,$\boldsymbol{P}$	Electric power (Unit: kW) and the relevant vector
Q	Electric energy stored in SES (Unit: kWh)

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(*continued*)

Nomenclature	
U_{S+} ,U_{S-}	Boolean variable indicating charge/discharge state of SES
U_{S2C},U_{C2S}	Boolean variable indicating transaction state between SES and prosumers
Naming conventions	
The subscripts "S", "C", "H", "W", "G" denote SES, prosumers, hydropower station, wind farm, and external main grid, respectively.	
The subscript "i" refers to a specific prosumer i.	
The superscript "t" indicates the association with a specific time slot t.	
The bars over and below variables denote the upper and lower limits, respectively.	
The superscript "[k]" indicates the k-th iterative update.	

Renewable Portfolio Standards (RPS) is currently the dominant policy for promoting renewable energy integration. RPS mandatorily stipulates a specific quota of renewable energy consumption for each entity, which can be achieved either through direct renewable energy consumption or through the purchase of green certificates [4]. Extensive studies have explored RPS in terms of definition, development, operating principles, design frameworks, and case studies [5,6]. These investigations have demonstrated the effectiveness of RPS in optimizing power supply structures [7], increasing renewable energy capacity [8], reducing social costs [9], attracting investment in renewable energy development [10,11], and lowering the wholesale electricity prices [12]. RPS has been successfully implemented in Australia [13], the United States [14], Western Europe [15], and Japan [16].

However, the rapid growth of prosumers leads to both excesses and shortages in renewable energy supply. To maintain system stability, photovoltaic (PV) and wind power production are often curtailed, resulting in substantial renewable energy wastage [2]. Additionally, mismatches between renewable energy supply and the load demand complicate prosumers' efforts to fulfill RPS quotas. Energy storage systems are essential resources that can buffer intermittent renewable energy generation and enhance the flexibility and resilience of power systems [17,18]. However, it is not economically viable for numerous small-capacity prosumers to independently own and operate private energy storage systems due to the high cost of investment and maintenance, although prices are decreasing [19].

The emerging concept of shared energy storage (SES) offers a viable solution for enhancing the utilization of energy storage systems within the active energy community. SES provides economic benefits by improving renewable energy accommodation and increasing revenue from energy transaction [20,21]. The SES in community achieves higher utilization of demand [22], reduces operation cost, achieves peak-shaving on load profiles [23]. Moreover, in industrial parks, SES promotes the consumption of excess renewable energy, such as wind and solar power [24]. Studies have shown that integrating SES on the supply side can reduce dependency on renewable power plants, while enhancing social welfare [25]. Furthermore, a cost-benefit optimization model for SES proposed in [26], demonstrates its potential to effectively reduce the costs of energy retailers. From the perspective of community energy efficiency, a game-theory-based P2P energy sharing management model proposed in [27] offers a new approach to managing energy-efficient building communities. Despite the theoretical and practical advantages of SES [28], few studies have explored the SES coordination with the existing emission regulation policies, such as RPS. In the context of electricity marketization, economic measures such as pricing are essential for collaborative scheduling among prosumers. Therefore, it is crucial to introduce SES to address renewable energy consumption challenges faced by prosumers under RPS in local.

The electricity marketization has intensified the coupling between energy sources and loads, transforming the traditional vertically regulated structure into active community involving multiple autonomous market participants [29]. Consequently, the conventional centralized approaches are inadequate for describing the P2P interaction [30] or solving complex problems [31], especially in dynamic environment with diverse tasks [32]. As independent stakeholders, SES and prosumers each pursue their own interests and strive to maximize individual benefits. However, uncoordinated competition often arises from information asymmetry, severely diminishing market efficiency [33]. Game theory and multi-agent system are both recognized as effective methodologies to address these challenges [34]. Despite of the high parallelism, multi-agent system is resource-intensive and time-consuming, which may lead to operational conflicts [35]. In contrast, game theory is more streamlined, with stronger interpretability, simpler models, and reduced computational resource requirements [36]. Considering the problem scale of the studied real-world case studied in this paper, we adopt game theory as the primary methodology.

Game theory encompasses various models to describe strategic interactions among participants. For instance, non-cooperative games focus on individual rationality and decision-making process, aimed at maximizing self-interest, while cooperative games consider collective interests to achieve optimal overall benefits [37]. Numerous studies have proposed game theoretic approaches for addressing energy trading problems. In [38], a Stackelberg game model is established for electricity transactions between participants with conflicting interests, in which the multi-microgrid system acts as the leader and the load aggregator serves as the follower. To enhance economic efficiency, a cooperative game model is built to reduce the operational costs of integrated energy service providers [39]. A market-based operation mechanism for demand response resources is developed by using game theory to analyze strategic interactions between power companies and consumers capable of demand response [40]. A cooperative game model for P2P energy among interconnected microgrids is introduced, addressing electricity, heat, and gas transactions with the goal of achieving fair profit allocation and optimal system efficiency [41]. These studies illustrate that game theory provides a robust framework for systematically analyzing strategic behaviors, optimizing resource allocation, and ensuring a fair and efficient market mechanism.

The alternating direction method of multipliers (ADMM) is an optimization technique that decomposes a large global problem into multiple smaller, independent subproblems by introducing auxiliary and Lagrange multipliers. These subproblems are solved locally and iteratively, with only limited data exchange during each computation step, thereby enhancing of privacy protection [42,43]. ADMM is particularly suitable for distributed optimization scenarios where data privacy is a concern.

In response to the challenges of renewable energy integration under RPS, this paper proposes a two-layer nested game model that simultaneously addresses the competitive and cooperative interactions among market participants. The contributions of our work can be summarized as follows:

(1) Framework of two-layer nested game:

A two-layer nested game framework is proposed to facilitate electricity transactions and enhance renewable energy accommodation amongst various prosumers under RPS requirements.

(2) Upper-layer Stackelberg game:

The upper-layer model employs a Stackelberg game to address the competitive interaction between SES (leader) and the prosumer alliance (follower) through offering and responding to the price under RPS. The obtained equilibrium benefits both parties.

(3) Lower-layer cooperative game:

The lower-layer model adopts a cooperative game, the contribution of each individual prosumer is evaluated. The asymmetric Nash bargaining and ADMM algorithm are applied to ensure fair allocation and privacy protection.

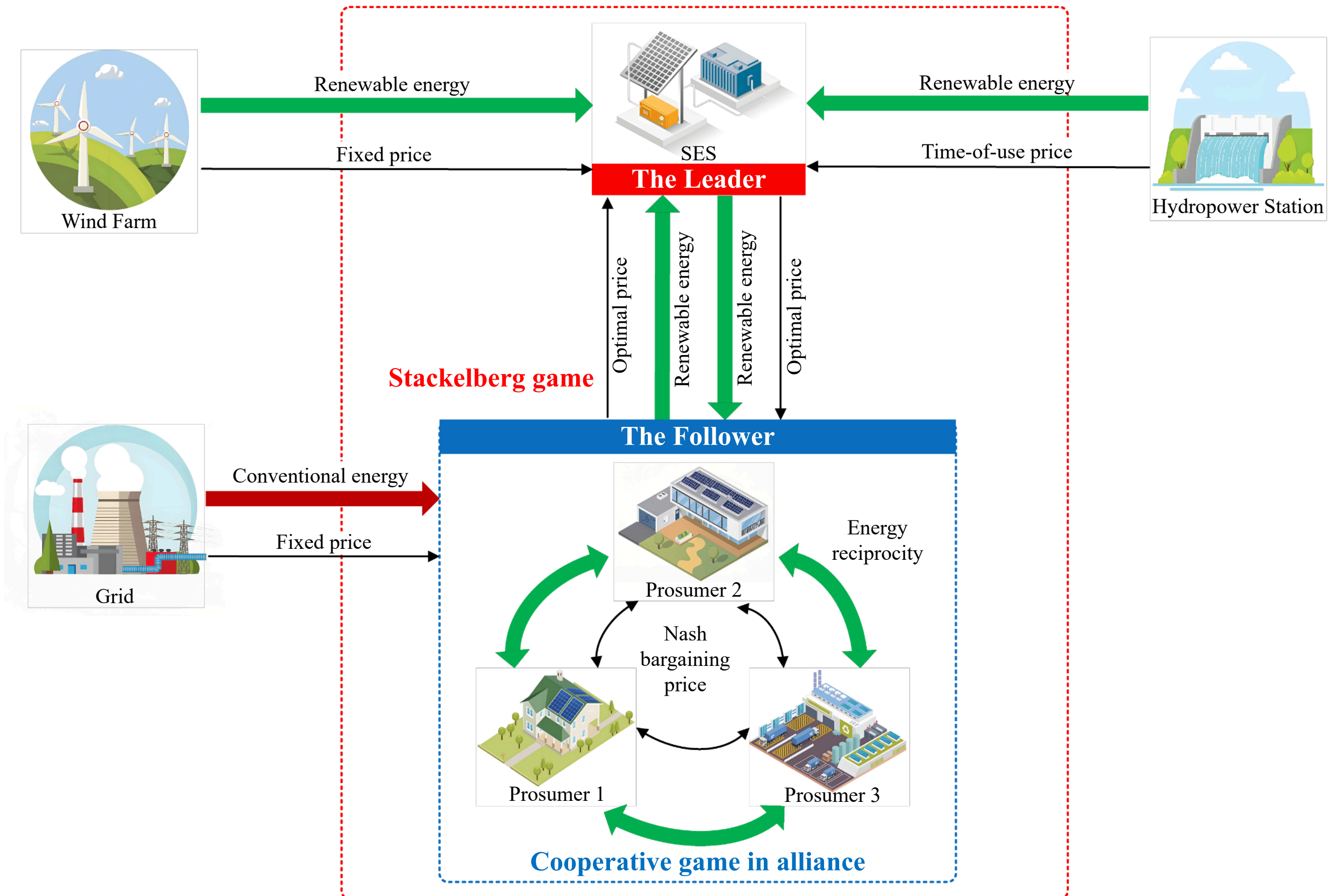


Fig. 1. The schematic diagram of two-layer nested game in active energy community.

(4) Case study and validation:

A realistic case in Southwest China is studied to evaluate the effectiveness, robustness, and practical advantages of the proposed model. The results provide valuable insights and references for improving local transaction and accommodation of renewable energy under RPS.

The remainder of this paper is organized as follows. Sections 2 describes the problem and formulates the two-layer nested game model. Section 3 illustrates the solution process. A realistic case study is performed in Section 4 for quantitative analysis and discussion. Finally, we draw the concluding remarks in Section 5.

2. Problem formulation

2.1. Game and players

Consider an active energy community as shown in Fig. 1. This community comprises an SES and multiple prosumers, while external entities include the main grid, a hydropower station, and a wind farm. All entities are independent, which are invested and operated by different parties.

Main grid supplies conventional energy (primarily thermal power) to prosumers at a fixed price. The energy from the main grid can only be consumed to satisfy prosumers' load demand, but cannot be applied toward fulfilling the RPS quota.

Hydropower station supplies renewable energy (hydropower) to SES at a time-of-use price. The energy from hydropower station can be consumed to meet both load demand and the RPS quota.

Wind farm supplies renewable energy (wind power) to SES at a fixed price. The energy from wind farm is eligible for both satisfying load demand and fulfilling the RPS quota.

SES is the large buffer for renewable energy, which charges when surplus energy (from prosumers, hydropower station, and wind farm) is available at low prices, and discharges when prosumers face unsatisfied demand. SES aims to maximize profit by capitalizing on price differences between charging and discharging. Since only renewable (hydraulic/wind/solar) energy can be charged in or discharged from SES, it is helpful for prosumers to trade with SES for both satisfying the load demand and completing the RPS quota.

Prosumers are dual-role entities which are capable of both consuming and producing electricity. The set of prosumers is denoted by $\mathbb{I} = \{i\}_{i=1}^{I}$. Notice that the prosumer only produces renewable energy with its own PVs. Each prosumer is assigned a specific RPS quota, which determines the minimum ratio of consumed renewable energy to total consumption. Each prosumer minimizes the electricity expense subject to the RPS constraint.

A prosumer can satisfy its energy demand in four ways:

1. consuming its own renewable energy (PV) production,
2. buying renewable energy (PV) from other prosumers,
3. buying renewable energy (hydraulic and wind) from SES,
4. buying conventional energy from main grid.

Notice that only the first three ways contribute to fulfilling the RPS quota. Conventional energy purchased from the main grid is not eligible for RPS quota completion.

A prosumer can also sell excess renewable energy production to other prosumers or to SES, thereby generating additional revenue.

As a result, a prosumer can minimize the electricity expense by cooperating with other prosumers and modifying the demand in response to the varying prices offered by SES. And the benefits of cooperation can be allocated to each prosumer according to its contribution on the cooperative alliance.

The interaction in an active energy community can be described by a hierarchical nested game. In the upper-layer Stackelberg game, SES and prosumer alliance are the leader offering price and the follower responding to the price, respectively. In the lower-layer cooperative game, the peer-to-peer (P2P) alliance is formed, the individual contribution of each prosumer on the alliance is evaluated, and the benefits of cooperation is allocated among prosumers.

It is assumed that the nested game is performed on a series of discrete time slots denoted by $\mathbb{T} = \{t\}_{t=1}^{T}$, each of duration Δt.

2.2. Stackelberg game in upper-layer

2.2.1. Objective function of SES

As the leader of Stackelberg game, SES aims to maximize the profit F_S by optimizing its pricing strategy.

$$\max F_S = \max(F_{S2C} - F_{C2S} - F_{H2S} - F_{W2S}) \tag{1}$$

where F_{S2C} denotes the revenue of SES for selling electricity to the prosumer alliance, F_{C2S}, F_{H2S}, and F_{W2S} denote the expense of SES for purchasing electricity from the prosumer alliance, the hydropower station, and the wind farm, respectively.

$$F_{\alpha 2\beta} = \sum_{t\in\mathbb{T}} r^t_{\alpha 2\beta} P^t_{\alpha 2\beta} \Delta t,\ \alpha 2\beta \in \{\text{'S2C'}, \text{'C2S'}, \text{'H2S'}, \text{'W2S'}\} \tag{2}$$

where r and P are the transaction price and power, respectively. t (as the superscript) and i (as the subscript) are the indexes of time slots and prosumers, respectively. 'α2β' denotes that the energy transaction is from α to β.

2.2.2. Constraints of SES

(1) Power constraints

$$0 \leqslant P^t_{S+} \leqslant U^t_{S+} \overline{P}_S \tag{3}$$

$$0 \leqslant P^t_{S-} \leqslant U^t_{S-} \overline{P}_S \tag{4}$$

$$U^t_{S+} + U^t_{S-} \leqslant 1 \quad U^t_{S+}, U^t_{S-} \in \{0,1\} \tag{5}$$

$$0 \leqslant P^t_{S2C} \leqslant U^t_{S2C} \overline{P}_X \tag{6}$$

$$0 \leqslant P^t_{C2S} \leqslant U^t_{C2S} \overline{P}_X \tag{7}$$

$$U^t_{S2C} + U^t_{C2S} \leqslant 1 \quad U^t_{S2C}, U^t_{C2S} \in \{0,1\} \tag{8}$$

$$P^t_{S+} - P^t_{S-} = P^t_{C2S} + P^t_{H2S} + P^t_{W2S} - P^t_{S2C} \tag{9}$$

Eq(3)-(4) and Eq(6)-(7) indicate the charging/discharging power of SES and the transaction power between SES and prosumers are all bounded. Eq(5) and Eq(8) indicate the incompatibility of charging and discharging, and of buying and selling with SES during the same time slot. Eq(9) presents the power balance of SES.

(2) Energy storage constraints

$$Q^t_S = Q^{t-1}_S + \eta_{S+} P^t_{S+} \Delta t - \frac{P^t_{S-}\Delta t}{\eta_{S-}} \tag{10}$$

$$0 \leqslant Q^t_S \leqslant \overline{Q}_S \tag{11}$$

$$\left| \frac{Q^T_S}{Q^1_S} - 1 \right| \leqslant \delta \tag{12}$$

Eq(10) presents the update of stored energy in SES, where η_{S+} and η_{S-} are the efficiencies of charging and discharging, respectively. Eq(11) indicates the stored energy in SES cannot exceed the capacity. Eq(12) presents the energy storage "reset" in the beginning and in the end of every cycle. Notice that a small deviation is acceptable considering practical reasons.

(3) Price constraints

$$0 < \underline{r}^t_{S2C} \leqslant r^t_{S2C} \leqslant \overline{r}^t_{S2C} \tag{13}$$

$$0 < \underline{r}^t_{C2S} \leqslant r^t_{C2S} \leqslant \overline{r}^t_{C2S} \tag{14}$$

The transaction prices between prosumers and SES are bounded within the corresponding lower and upper limits.

2.2.3. Objective function of prosumers

As the follower in Stackelberg game, the prosumer alliance performs demand response to the SES-offered price, and aims to minimize the electricity expense.

$$\min F_C = \min(F_{S2C} + F_{G2C} - F_{C2S}) \tag{15}$$

where F_{G2C} denotes the expense of prosumer alliance for purchasing conventional energy from the external main grid.

$$F_{G2C} = \sum_{t\in\mathbb{T}} r^t_{G2C} P^t_{G2C} \Delta t \tag{16}$$

2.2.4. Constraints of prosumers

(1) Demand response constraints

$$P^t_{i,L} = P^t_{i,L0} + \overline{P}^t_{i,L-} - P^t_{i,L-} + P^t_{i,L+} \tag{17}$$

$$\sum_{t\in\mathbb{T}} P^t_{i,L-} = \sum_{t\in\mathbb{T}} P^t_{i,L+} \tag{18}$$

$$0 \leqslant P^t_{i,L-} \leqslant \overline{P}^t_{i,L-} \tag{19}$$

$$0 \leqslant P^t_{i,L+} \leqslant \overline{P}^t_{i,L+} \tag{20}$$

$$P^t_{i,L0} \leqslant P^t_{i,L} \leqslant \overline{P}^t_{i,L} \tag{21}$$

Eq(17) presents the update of load after demand response. Eq(18) assumes that the load of prosumer can only be shifted but cannot be removed. Eq(19)-(21) indicate the bound limits of the decreased, increased, and final values of load, respectively.

(2) Power balance constraints

$$\left| P^t_{i,L} - P^t_{i,PV} \right| = \begin{cases} P^t_{S2i} + P^t_{G2i} + \sum_{j\in\mathbb{I}, j\neq i} P^t_{j2i} & P^t_{i,L} > P^t_{i,PV} \\ 0 & P^t_{i,L} = P^t_{i,PV} \\ P^t_{i2S} + \sum_{j\in\mathbb{I}, j\neq i} P^t_{i2j} & P^t_{i,L} < P^t_{i,PV} \end{cases} \tag{22}$$

Eq(22) indicates that prosumer i can buy electricity from other prosumers, SES, and the external main grid if the load demand cannot be satisfied by its own PV generation, and can sell electricity to other prosumers and SES if there is excess PV generation.

$$\sum_{i\in\mathbb{I}} (P^t_{i,L} + P^t_{i2S}) = \sum_{i\in\mathbb{I}} (P^t_{i,PV} + P^t_{G2i} + P^t_{S2i}) \tag{23}$$

Eq(23) indicates the power balance within the whole prosumer alliance.

(3) RPS quota constraints

$$\frac{\sum_{t\in\mathbb{T}} (P^t_{i,L} - P^t_{G2C})\Delta t}{\sum_{t\in\mathbb{T}} P^t_{i,L}\Delta t} \geqslant \theta_i \quad \forall i \in \mathbb{I} \tag{24}$$

Eq(24) indicates that each prosumer is required to fulfill the RPS quota, which determines the minimum ratio of consumed renewable energy to the total energy consumption.

2.3. Cooperative game in lower-layer

2.3.1. Contribution score

As the follower in Stackelberg game, multiple prosumers form a cooperative alliance to jointly respond to the price offered by SES and to minimize the total expense. The electricity is also exchanged in peer-to-peer (P2P) manner among prosumers within the alliance. Nash bargaining theory [44] can well balance the interests of multiple player in a cooperative game, and the Nash equilibrium can realize the individual rationality and Pareto optimality. However, general Nash bargaining ignores the individual difference of contribution and can only obtain equal distribution results [45,46,47]. On the contrary, asymmetric Nash bargaining considers different bargaining ability of players in negotiation according to asymmetry of information or status [48,49,50]. An exponential function-based mapping approach is used to evaluate the contribution score of each prosumer on the alliance during P2P energy reciprocity, and the asymmetric Nash bargaining model is built for the lower-layer cooperative game.

The total supply and demand by prosumer i during the P2P energy reciprocity in a cycle are as follows:

$$q_i^+ = \sum\nolimits_{t\in\mathbb{T}}\left(\sum\nolimits_{j\in\mathbb{I},j\neq i}P_{i2j}^t\Delta t\right) \quad \forall i\in\mathbb{I} \tag{25}$$

$$q_i^- = \sum\nolimits_{t\in\mathbb{T}}\left(\sum\nolimits_{j\in\mathbb{I},j\neq i}P_{j2i}^t\Delta t\right) \quad \forall i\in\mathbb{I} \tag{26}$$

Let $Q^+ = \max_{i\in\mathbb{I}}\{q_i^+\}$, and $Q^- = \max_{i\in\mathbb{I}}\{q_i^-\}$, the contribution of prosumer i on the alliance can be scored according to its performance in the P2P energy reciprocity.

$$\varphi_i = \exp\left(\frac{q_i^+}{Q^+}\right) - \exp\left(\frac{q_i^-}{Q^-}\right) \quad \forall i\in\mathbb{I} \tag{27}$$

2.3.2. Asymmetric Nash bargaining model

The contribution score is adopted in the asymmetric Nash bargaining optimization model of multi-prosumers participating in P2P transactions. The objective is to reduce the expenses of all prosumers.

$$\begin{cases} \max\prod\limits_{i\in\mathbb{I}}\left[F_i^0 - F_{i,\mathrm{Co}} - F_{i,\mathrm{P2P}}\right]^{\varphi_i} \\ \text{s.t.} \quad F_{i,\mathrm{P2P}} = \sum\nolimits_{j\in\mathbb{I},j\neq i}\left(\sum\nolimits_{t\in\mathbb{T}}r_{i2j}^t P_{i2j}^t\Delta t\right) \\ \sum\nolimits_{i\in\mathbb{I}}\left(\sum\nolimits_{j\in\mathbb{I},j\neq i}P_{i2j}^t\right) = \sum\nolimits_{j\in\mathbb{I}}\left(\sum\nolimits_{i\in\mathbb{I},i\neq j}P_{i2j}^t\right) \\ F_i^0 - F_{i,\mathrm{Co}} - F_{i,\mathrm{P2P}} \geqslant 0 \end{cases} \tag{28}$$

$$\begin{cases} \min\left\{-\sum\nolimits_{i\in\mathbb{I}}\varphi_i\ln\left[F_i^0 - F_{i,\mathrm{Co}} - F_{i,\mathrm{P2P}}\right]\right\} + \sum\nolimits_{j\in\mathbb{I},j\neq i}\sum\nolimits_{t\in\mathbb{T}}\lambda_{i,j}^t\left(r_{i2j}^t - r_{j2i}^t\right) + \sum\nolimits_{j\in\mathbb{I},j\neq i}\frac{\rho_i}{2}\sum\nolimits_{t\in\mathbb{T}}\left(r_{i2j}^t - r_{j2i}^t\right)^2 \\ \text{s.t.} \quad F_i^0 - F_{i,\mathrm{Co}} - F_{i,\mathrm{P2P}} \geqslant 0 \\ \underline{r}^t \leqslant r_{i2j}^t \leqslant \overline{r}^t \\ F_{i,\mathrm{P2P}} = \sum\nolimits_{j\in\mathbb{I},j\neq i}\sum\nolimits_{t\in\mathbb{T}}r_{i2j}^t P_{i2j}^t \end{cases} \tag{32}$$

where F_i^0 denotes the independent operation expense of prosumer i, i.e. the cooperation rupture point. $F_{i,\mathrm{Co}}$ is the expense of prosumer i after cooperation. $F_{i,\mathrm{P2P}}$ represents the expense of prosumer i in energy reciprocity. r_{i2j}^t represents the price that prosumer i needs to pay for energy reciprocity P_{i2j}^t in time slot t. Eq(28) aims to maximize the expense reduction of the prosumer alliance as compared to the non-cooperation. Due to the monotonically increasing convex feature of logarithmic function, Eq (29) is equivalent to the minimization problem below.

$$\min -\sum_{i\in\mathbb{I}}\varphi_i\ln\left[F_i^0 - F_{i,\mathrm{Co}} - F_{i,\mathrm{P2P}}\right] \tag{29}$$

3. Solution methodology

3.1. Solution of upper-layer problem

First, the SES (leader) initializes the price sequence $\{\boldsymbol{r}_{\mathrm{S2C}}^{[0]}, \boldsymbol{r}_{\mathrm{C2S}}^{[0]}\}$, where $\boldsymbol{r}$ is a vector of T dimension, $\boldsymbol{r} = [r^1, \cdots, r^T]$; the prosumer alliance (follower) responds to the price by minimizing the constrained objective function (*Eqs*.17–24) and derives the optimal transaction quantity $\{\boldsymbol{P}_{\mathrm{S2C}}^{[0]}, \boldsymbol{P}_{\mathrm{C2S}}^{[0]}\}$; the SES receives the transaction quantity, re-optimizes price by maximizing the constrained objective function (*Eqs*.3–14), and updates the price $\{\boldsymbol{r}_{\mathrm{S2C}}^{[1]}, \boldsymbol{r}_{\mathrm{C2S}}^{[1]}\}$; the prosumer alliance sequentially updates the optimal transaction quantity $\{\boldsymbol{P}_{\mathrm{S2C}}^{[1]}, \boldsymbol{P}_{\mathrm{C2S}}^{[1]}\}$. The strategies of leader and follower are iteratively updated until the Nash equilibrium is achieved, if neither player in the game can improve its payoff by modifying strategy.

$$\begin{cases} \gamma_1^* = \{\boldsymbol{r}_{\mathrm{S2C}}^*, \boldsymbol{r}_{\mathrm{C2S}}^*\} = \operatorname*{argmax}_{\boldsymbol{r}} F_{\mathrm{S}}(\boldsymbol{r}_{\mathrm{S2C}}, \boldsymbol{r}_{\mathrm{C2S}}, \boldsymbol{P}_{\mathrm{S2C}}^*, \boldsymbol{P}_{\mathrm{C2S}}^*) \\ \gamma_2^* = \{\boldsymbol{P}_{\mathrm{S2C}}^*, \boldsymbol{P}_{\mathrm{C2S}}^*\} = \operatorname*{argmin}_{\boldsymbol{P}} F_{\mathrm{C}}(\boldsymbol{r}_{\mathrm{S2C}}^*, \boldsymbol{r}_{\mathrm{C2S}}^*, \boldsymbol{P}_{\mathrm{S2C}}, \boldsymbol{P}_{\mathrm{C2S}}) \end{cases} \tag{30}$$

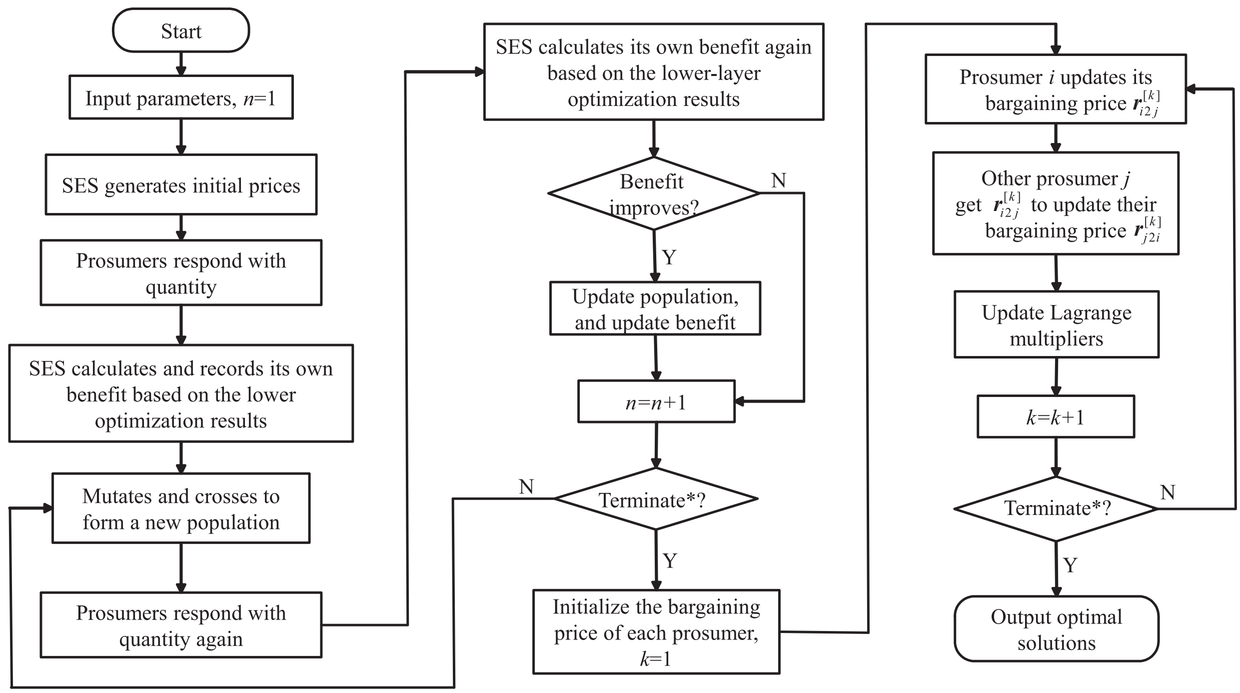
Since the proposed Stackelberg game model belongs to the bi-level optimization problem, the above hierarchical framework can be transformed into a single-level optimization process, in which genetic algorithm is used to deal with the optimization of the leader within the follower stage adopting YALMIP/ CPLEX toolbox. The optimal solutions are continuously updated until the Nash equilibrium is obtained.

3.2. Solution of lower-layer problem

Based on the optimal solution of upper Stackelberg game, the asymmetric Nash bargaining model is established in the lower layer to allocate the cooperative benefit of prosumers, which is solved by ADMM for privacy protection. The bargaining price can be decoupled by price consensus between prosumer i and j:

$$\left|r_{i2j}^t - r_{j2i}^t\right| < \varepsilon \tag{31}$$

where r_{i2j}^t and r_{j2i}^t represents the bidding price of prosumer i and j for $P_{i,j}^t$, respectively. And the augmented Lagrangian function of prosumer i is expressed as:



*Terminate: Satisfy convergence condition or reach the maximum number of iterations.

Fig. 2. The flowchart of the two-layer nested game model.

where $\lambda_{i,j}^t$ and ρ_i are Lagrange multiplier and penalty factor, respectively.

The solution of lower layer model is shown as below.

Inputs: The solutions of upper layer problem.
Initialization.
for $k = 1$ to K **do**.
(1) Distributed calculation.
Each prosumer i updates its strategy $\boldsymbol{r}_{i2j}^{[k+1]}$ by:
$\boldsymbol{r}_{i2j}^{[k+1]} = \mathrm{argmin}_{\boldsymbol{r}} L_i\left(\boldsymbol{\lambda}_{i,j}^{[k]}, \boldsymbol{r}_{i2j}^{[k]}, \boldsymbol{r}_{j2i}^{[k]}\right)$
Other prosumers j get $\boldsymbol{r}_{i2j}^{[k+1]}$ to update their strategy $\boldsymbol{r}_{j2i}^{[k+1]}$ by:
$\boldsymbol{r}_{j2i}^{[k+1]} = \mathrm{argmin}_{\boldsymbol{r}} L_i\left(\boldsymbol{\lambda}_{i,j}^{[k]}, \boldsymbol{r}_{i2j}^{[k+1]}, \boldsymbol{r}_{j2i}^{[k]}\right)$
(2) Update Lagrange multipliers by:
$\lambda_{i,j}^{[k+1]} = \lambda_{i,j}^{[k]} + \rho_i\left(\boldsymbol{r}_{i2j}^{[k+1]} - \boldsymbol{r}_{j2i}^{[k+1]}\right)$
(3) $k \leftarrow k + 1$, and return to (1).
end for.

The flowchart of the proposed nested game model is shown in Fig. 2.

4. Numeric studies

4.1. Basic data

This research investigates a renewable energy active distribution network demonstration project near Hongfeng Lake, as shown in Fig. 3, approximately 27 km from Guiyang in Southwest China. This studied case includes an SES and three prosumers forming an active energy community. External entities include the main grid, a hydropower station, and a wind farm. In reality, the three prosumers are apartment buildings, canteens and restaurants, and factories for experimental education, respectively. Each prosumer is equipped with a central energy management system, smart meters, bi-directional communication infrastructure, traditional electrical appliances, smart electrical appliances, electric vehicle charging stations, and PV generation facilities.

The external main grid and hydropower station are assumed infinite power sources. The 24-h prediction of power profiles of three prosumers and the wind farm are depicted in Fig. 4. Relevant parameters of prosumers and SES are shown in Table 1. The simulation environment is, Intel (R) Core (TM) i7-7700 @ 3.6 GHz, 8 GB DDR3 RAM, MATLAB-2018a, Cplex12.8, Mosek10.0. Notice that some data are modified to protect commercial confidentiality and maintain scientific rigor.

4.2. Results analysis

4.2.1. Economic advantages of nested game model

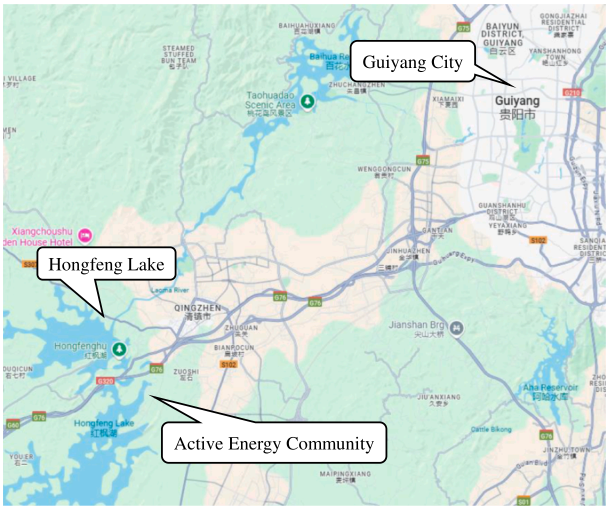
Aiming to verify the effectiveness and advantages of the proposed model, this subsection investigates four different trading modes as follows:

- *Mode* 1: There is neither a Stackelberg game nor a cooperative game, i.e., there does not exist an SES in this community; prosumers directly purchase renewable energy from hydropower station and wind farm, and there is no energy reciprocity among prosumers.
- *Mode* 2: There is only the cooperative game, i.e., there does not exist an SES in this community; prosumers form a cooperative alliance, purchase renewable energy from the hydropower station and the wind farm, and exchange energy within the alliance.
- *Mode* 3: There is only the Stackelberg game, i.e., there exists an SES in this community; each prosumer independently trades renewable energy with the SES, and there is no energy reciprocity among prosumers.
- *Mode* 4: There are both the Stackelberg game and the cooperative game, i.e., there exists an SES and the prosumer alliance in this community; and the interaction can be described by the two-layer nested game model proposed in this paper.

Table 2 lists the expenses of prosumers and the revenue of the SES under the four trading modes. It is assumed that the total expense of the prosumer alliance is distributed by using the general Nash bargaining model.

1) The significance of prosumers’ cooperation

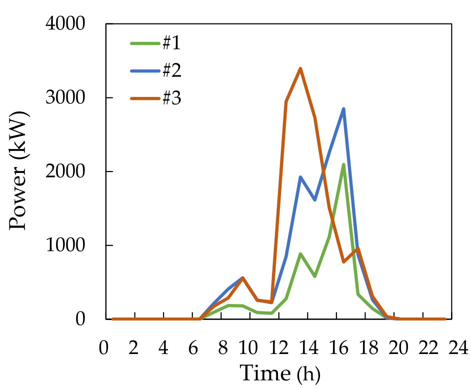
We compare the prosumer expenses under Mode 2 with those under Mode 1 to demonstrate the significance of prosumer cooperation. As



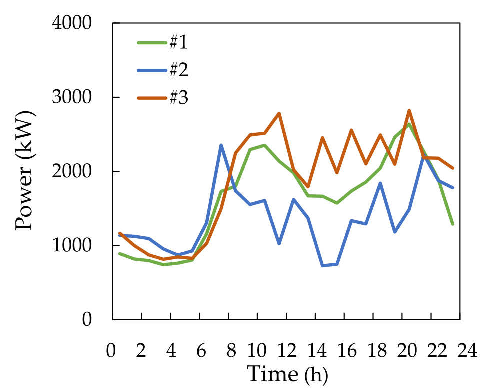
(a) Geographical location.

(b) Satellite image.

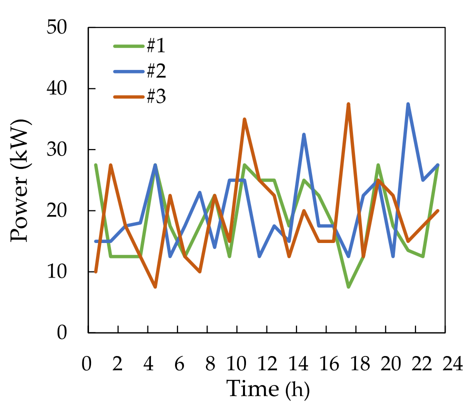
Fig. 3. The studied case of active energy community on Google Maps.



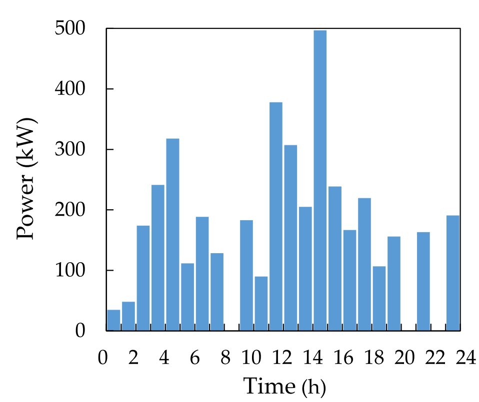
(a) PV generation of prosumers.



(b) Load demand of prosumers.



(c) Reducible load demand of prosumers.



(d) Output of wind farm.

Fig. 4. The predicted power profiles of prosumers and wind farm.

shown in Table 3, the individual expense of each prosumer and the total expense of prosumers are reduced by 7.08 %, 9.94 %, 7.33 %, and 7.93 %, respectively. The reason is that the internal energy reciprocity among prosumers significantly increases the flexibility of renewable energy consumption due to the potential complementarity and reduces the dependency on external power sources, such as main grid, hydropower station, and wind farm.

Table 1
Simulation parameters.

Parameters	Value	Parameters	Value
θ_1	0.78	r_W(CNY/kWh)	0.699
θ_2	0.82	r_H^t(CNY/kWh)	0.772(Peak), 0.542(Flat), 0.226 (Valley)*
θ_3	0.80	r_G(CNY/kWh)	0.08
Q^1(kWh)	3250	$\overline{r}_{S2C}^t$(CNY/kWh)	r_H^t
$\overline{Q}$(kWh)	12,000	$\underline{r}_{S2C}^t$(CNY/kWh)	$0.75 \cdot r_H^t$
$\overline{P}_S$(kW)	8000	$\overline{r}_{C2S}^t$(CNY/kWh)	0.072
$\overline{P}_{H2S}$(kW)	10,000	$\underline{r}_{C2S}^t$(CNY/kWh)	0.016
$\overline{P}_{W2S}$(kW)	10,000	η_{S+} ,η_{S-}	0.98
$\overline{P}_X$(kW)	15,000	δ	0.1

*. Valley periods: 0:00 ~ 3:00; 14:00 ~ 16:00; 21:00 ~ 24:00; Flat periods: 3:00 ~ 14:00; 16:00 ~ 18:00;
Peak periods: 18:00 ~ 21:00.

Table 2
Comparisons under different trading modes.

Mode	Expense of prosumer 1 (CNY)	Expense of prosumer 2 (CNY)	Expense of prosumer 3 (CNY)	Total expense of prosumers (CNY)	Revenue of SES (CNY)
1	11,140	7930.2	10,756	29826.2	N/A
2	10351.4	7141.8	9967.6	27460.8	N/A
3	10514.9	7823.1	10240.2	28578.2	7551.4
4	9994.5	6799.6	9628.6	26422.7	6676.1

2) The significance of SES' participation

We compare the prosumer expenses under Mode 3 with those under Mode 1 to demonstrate the significance of SES' participation. As shown in Table 3, the individual expense of each prosumer and the total expense of prosumers are reduced by 5.61 %, 1.36 %, 4.81 %, and 4.19 %, respectively. Moreover, the SES can obtain the revenue of 7551.4 CNY by playing the role of energy broker. As a result, it is beneficial for both two parties to participate in the Stackelberg game, where the SES and prosumers are leader and follower, respectively.

3) The advantages of two-layer nested game.

We compare the prosumers' expenses under Mode 4 with those under Mode 2 to demonstrate the improvement due to the upper-layer interaction in addition to prosumers cooperation. As compared to Mode 2, Mode 4 reduces the individual expense of each prosumer and the total expense of prosumers by 3.45 %, 4.79 %, 3.41 %, and 3.78 %, respectively. Mode 4 also can bring in the revenue of 6676.1 CNY to the SES.

We compare the prosumers' expenses and the SES' revenue under Mode 4 with those under Mode 3 to demonstrate the improvement due to the lower-layer cooperative game in addition to the transaction between the SES and prosumer alliance. As compared to Mode 3, Mode 4 reduces the individual expense of each prosumer and the total expense of prosumers by 4.95 %, 13.09 % and 5.97 %, and 7.54 %, respectively. Mode 4 also reduces the revenue of the SES by 11.59 %. Since it can better balance the interests of market players and promote the participation of prosumers in cooperation, the proposed two-layer nested game model is favorable for the economic and low-carbon operation of the active energy community under RPS.

4.2.2. Impact of forecast variations

Assuming that the maximum variation is ± 5 %, we investigate three

Table 3
Impact of same-direction variation of forecast source and load.

Mode	Expense of prosumer 1 (CNY)	Expense of prosumer 2 (CNY)	Expense of prosumer 3 (CNY)	Total expense of prosumers (CNY)	Revenue of SES (CNY)
1	11,862	7825	11541.1	31228.1	N/A
2	11041.7	6999.6	10722.5	28763.8	N/A
3	11,226	7767	11,016	30,009	7929.7
4	10671.2	6648	10,385	27704.2	7002

Table 4
Impact of opposite-direction variation of forecast source and load.

Mode	Expense of prosumer 1 (CNY)	Expense of prosumer 2 (CNY)	Expense of prosumer 3 (CNY)	Total expense of prosumers (CNY)	Revenue of SES (CNY)
1	11779.7004	7793	11506.2	31078.9004	N/A
2	10989.5026	6969.9	10682.1974	28641.6	N/A
3	11,147	7718.7	10941.3	29,807	7946.8
4	10615.3979	6612.8	10330.6021	27558.8	7023.2

Table 5
Impact of random variation of forecast source and load.

Mode	Expense of prosumer 1 (CNY)	Expense of prosumer 2 (CNY)	Expense of prosumer 3 (CNY)	Total expense of prosumers (CNY)	Revenue of SES (CNY)
1	11625.2	7669.9	11328.9	30,624	N/A
2	10852.4	6883.7	10548.79591	28284.89591	N/A
3	10981.1	7597.4	10,774	29352.5	7756.2
4	10,346	6512	10,173	27,031	6857

scenarios of forecast profiles variation in source and load as follows:

1. Same-direction variation: the source and load profiles both increase 5 % during each time slot;
2. Opposite-direction variation: the source and load profiles increase 5 % and decrease 5 % during each time slot, respectively;
3. Random variation: the source and load profiles both randomly vary within ± 5 % during each time slot.

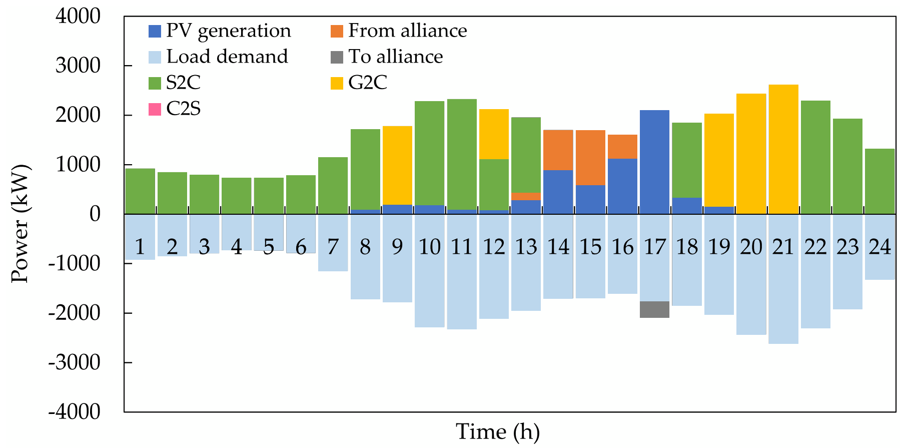
Numeric experiments are conducted under the four trading modes aforementioned in section 4.2.1, the results of three scenarios of forecast profile variation are shown in Table 3, Table 4 and Table 5.

In all of the three scenarios of forecast variation, the proposed model outperforms the other three trading modes. The robustness and advantages of the proposed model in various scenarios are demonstrated.

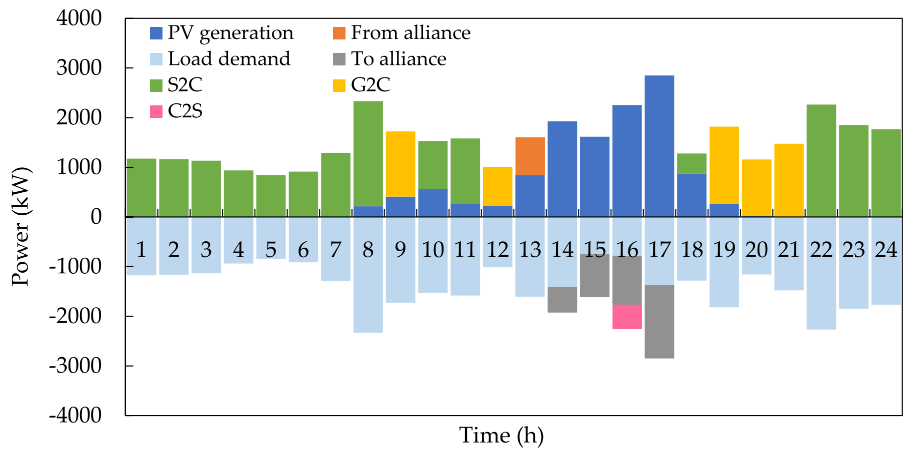
4.2.3. Power balance of individual prosumers

Fig. 5 depicts the optimized power balance of each prosumer. As for a prosumer, the positive bars illustrate the PV generation of its own and the received energy from SES, other prosumers, and external main grid; and the negative bars illustrate the load demand of its own and the offered energy to SES and other prosumers. Fig. 5 demonstrates the energy reciprocity among prosumers in details.

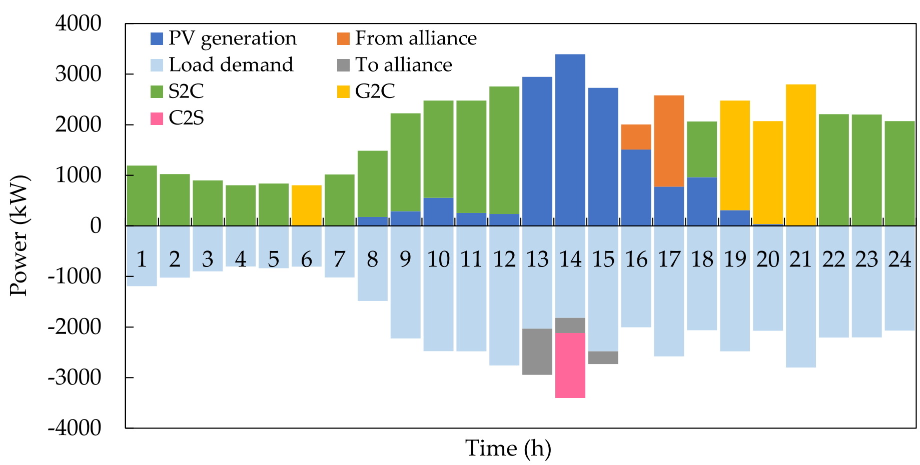
From Fig. 5(a)-(c), we can draw three general behaviors of prosumers. Firstly, it is observed that there is no energy reciprocity among prosumers during most time slots. Since the PV generation can hardly satisfy the demand, Prosumers have to purchase energy from SES or external main grid, rather than exchanging within the alliance. Secondly, the consumption of conventional energy mainly happens in the evening, i.e. mostly in 18:00–21:00, due to the shortage supply and the peak price of renewable energy. As rational market players, prosumers prefer to consuming renewable energy at lower prices to reduce the



(a) Prosumer 1.



(b) Prosumer 2.



(c) Prosumer 3.

Fig. 5. Optimization results of prosumers.

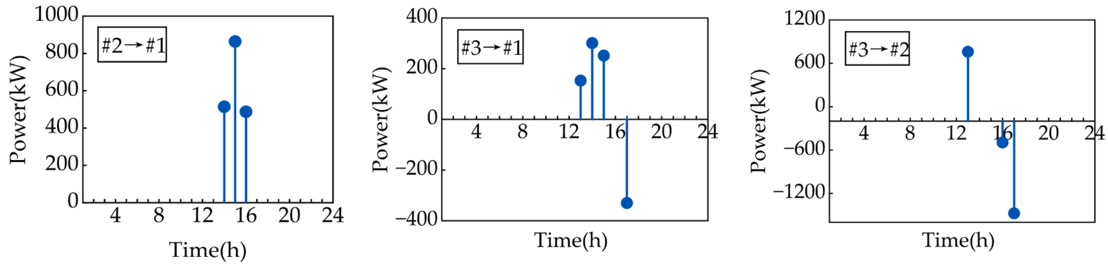


Fig. 6. Energy reciprocity among prosumers.

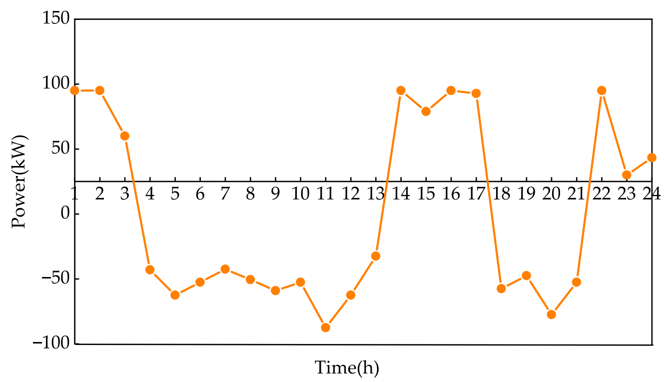


Fig. 7. Changes between optimal and original load of the alliance.

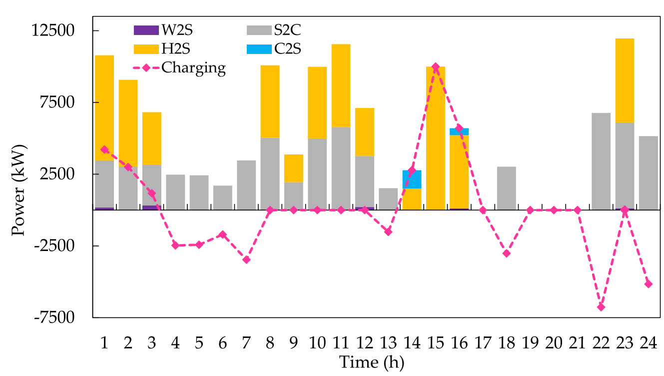


Fig. 8. Energy dispatch of SES.

expense and complete RPS quota. Thirdly, it is demonstrated that the energy reciprocity within alliance mainly takes place in 12:00–17:00. The oversupplied and undersupplied prosumers cooperate via energy reciprocity. Furthermore, the surplus energy in alliance can be sold to the SES for more profit. This complementarity validates the necessity and significance of forming the cooperative alliance.

In addition, from Fig. 6 we can see that each prosumer gives and receives different amounts of renewable energy. We will further consider this contribution difference in the subsequent section of allocation. Changes of the optimized load with respect to the original one are shown in Fig. 7. We can observe the increment during the daytime, the decrement during peak price periods at night, and the slight fluctuation in the flat price periods. It is shown that the prosumer alliance compromises the RPS task and electricity expense by the demand response to the price offered by SES.

4.2.4. Charge and discharge of SES

As shown in Fig. 8, there exist frequent electrical interaction between SES and the prosumer alliance during the whole day, i.e. 0:00–16:00, 17:00–18:00, and 21:00–24:00. It is observed that the SES charges during 0:00–3:00 and 13:00–16:00, by making use of hydropower at valley price and of the surplus PV generation of prosumers, respectively. It is also observed that the SES discharges during 3:00–7:00, 12:00–13:00, 17:00–18:00, 20:00–21:00 and 23:00–24:00, when it offers relatively low prices, since prosumers tend to buy cheap renewable energy from the SES to simultaneously satisfy the load demand and complete the RPS quota.

Fig. 9 shows the transaction price between the SES and the prosumer alliance. The SES offers favorable prices to prosumers in cases of both selling and buying, and the optimized price in the Stackelberg game is bounded by the upper and lower limits of the benchmark price, which aligns with the interests of SES. If the bargaining space is large, the SES can offer lower prices to incentivize the prosumer alliance to increase the purchasing quantity to improve the total revenue. It is beneficial for both prosumers and SES to participate in this transaction, where the optimal price of SES mainly meets the demand of prosumer alliance. In turn, the SES can also profit from the price difference.

4.2.5. Expense allocation within alliance

In the cooperative game, it is significant to allocate the total expense of the whole alliance to multiple prosumers. The general Nash bargaining is adopted for implementing this purpose. However, this subsection takes the contribution scores of prosumers into account, and applies the asymmetric Nash bargaining to implement a more sensible expense allocation.

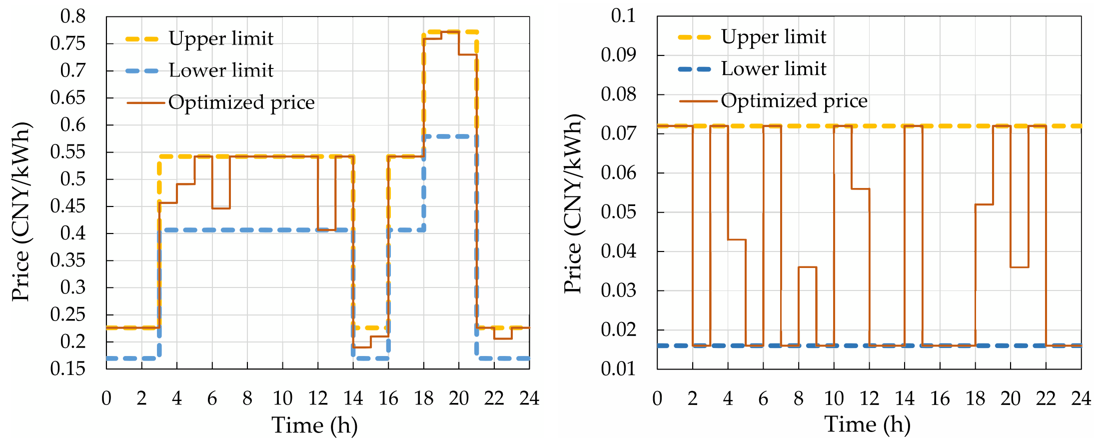
For the sake of privacy protection, ADMM is adopted as the solving algorithm due to the inherent distributed characteristics and the high computational efficiency [51]. Thus, it is not required for prosumers to announce the equipment parameters and decision constraints.

As shown in Fig. 10, the general and Asymmetric Nash bargaining models converge in 81 and 45 iterations, respectively. Besides, the computing time is 65 and 43 s, respectively.

As shown in Fig. 11, the bargaining generally takes place during the hours when prosumers have complementary energy, i.e.11:00–17:00. Notice that the bargaining price is always bounded by the purchase and sale price offered by the SES. Based on the cooperative transaction mode in lower layer, each prosumer can independently bid without unconditionally sacrificing individual interests for overall alliance, the individual interest of each prosumer can be guaranteed. It also reduces their dependency on the SES and increase bargaining priority, which is entirely consistent with the primary purpose of encouraging renewable energy development with energy exchanging.

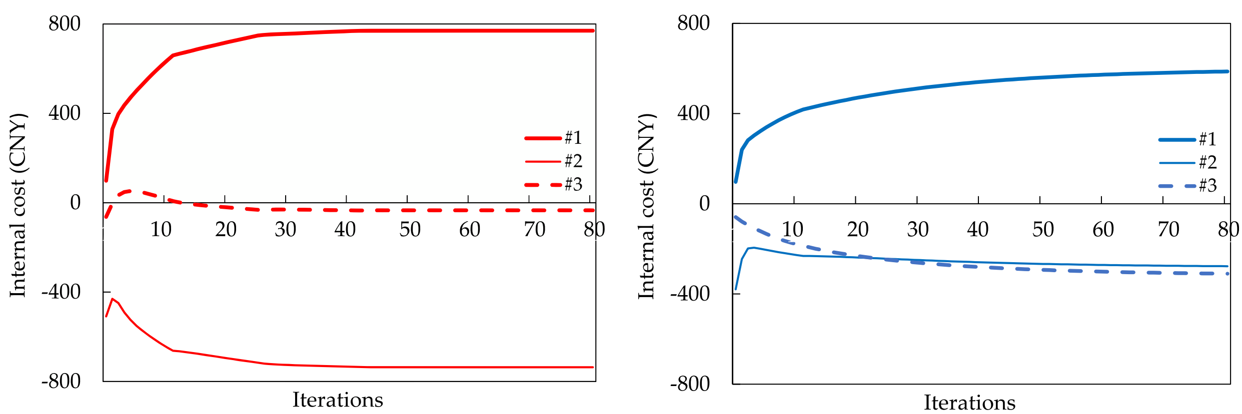
As listed in Table 6, the general Nash bargaining allocates the total expense to three prosumers as 9994.5 CNY, 6799.6 CNY, and 9628.6 CNY, respectively. And the expense saving amounts of prosumers are almost the same, since the general Nash bargaining does not take into account the contribution scores of prosumers on the expense saving during the energy reciprocity in alliance.

On the contrary, the asymmetric Nash bargaining considers the contribution score of each prosumer. As listed in Table 7, three prosumers have quite different contribution factors. Prosumer 2 and Prosumer 1 have the highest and lowest contribution scores in energy reciprocity of cooperation game, respectively. And the expense saving



(a) S2C price. (b) C2S price.

Fig. 9. Transaction price between SES and prosumer alliance.



(a) Asymmetric Nash bargaining. (b) General Nash bargaining.

Fig. 10. Algorithm convergence of bargaining.

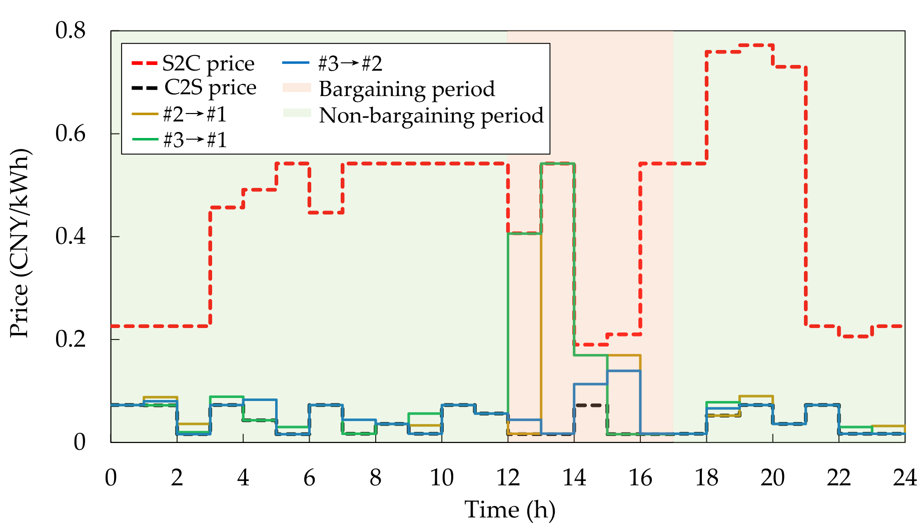


Fig. 11. Asymmetric Nash bargaining price among prosumers.

Table 6
The expense allocation scheme based on general Nash bargaining.

Prosumer	Renewable energy from alliance (kWh)	Contribution score	Bargaining expense (CNY)	Total expense (CNY)	Expense saving amount (CNY)
#1	2239.6	N/A	586.8	9994.5	1145.5
#2	−3077.1	N/A	−276.8	6799.6	1130.6
#3	837.4	N/A	−309.9	9628.6	1127.4

Table 7
The expense allocation scheme based on asymmetric Nash bargaining.

Prosumer	Renewable energy from alliance (kWh)	Contribution score	Bargaining expense (CNY)	Total expense (CNY)	Expense saving amount (CNY)
#1	2239.6	0.7221	770.1	10177.7	962.3
#2	−3077.1	1.9741	−736.2	6340.2	1590.1
#3	837.4	1.0564	−33.9	9904.7	851.3

amount of each prosumer is 962.3 CNY, 1590.1 CNY, and 851.3 CNY, respectively. It is verified that the more contribution of cooperation, the less bills should be paid in reallocation, i.e. prosumer 2, indicating asymmetric Nash bargaining can get more rational distribution results based on cooperative contribution by considering the interests of individuals, which encourages “more pains, more gains” to motivate participants make contributions to improve welfare. Furthermore, compared with mode 1, mode 2 and mode 3 mentioned in section 4.2.2, it can be seen that expense results based on asymmetric Nash bargaining distribution is acceptable to all participants, with the lowest electricity expense of prosumers under RPS and favorable revenue of SES. It verified the effectiveness of the proposed two-layer hybrid model.

5. Conclusion

This paper addresses the challenge of renewable energy consumption under RPS by proposing a two-layer nested game model that integrates Stackelberg game and cooperative game. The asymmetric Nash bargaining and ADMM are applied for expense allocation and privacy protection, respectively. The feasibility and effectiveness of the proposed model are validated through realistic case simulation and comparative analysis. The key conclusions can be drawn as follows:

(1) Effective cost reduction and profit enhancement. The upper-layer Stackelberg game captures the mutual influence of SES and prosumers’ decisions. By optimizing pricing strategies, the proposed model effectively reduces the electricity expenses for prosumers and enhances SES profit under RPS conditions. This approach aligns well with the interests of various market participants.
(2) Fair expense allocation. The asymmetric Nash bargaining in the lower-layer cooperative game considers the individual contribution of each participant in energy reciprocity, and allocates trading expense accordingly. This mechanism not only reduces overall electricity expense for all prosumers but also maintains the high participation enthusiasm by ensuring fair and reasonable expense allocation.
(3) Robust and applicable framework. The proposed two-layer nested game model provides a comprehensive and robust framework for modeling complex interactions among SES and multiple prosumers. Its robustness and adaptability make it a valuable reference for both scientific research and practical applications in future.

CRediT authorship contribution statement

Yaxin Tan: Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization. **Weisheng Xu:** Supervision, Funding acquisition. **Zhiyu Xu:** Project administration, Funding acquisition, Formal analysis. **Ruining Tong:** Software, Resources, Investigation. **Yuanbo Zhang:** Visualization, Software, Data curation.

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.

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Appendix A. The working principle of the ADMM algorithm

For an optimization problem:

$$\begin{cases} \quad \min_{x,z} f(\boldsymbol{x}) + g(\boldsymbol{z}) \\ \text{s.t.} \quad \boldsymbol{Ax} + \boldsymbol{Bz} = \boldsymbol{c} \end{cases} \tag{A1}$$

where $\boldsymbol{x} \in \mathbb{R}^n$ and $\boldsymbol{z} \in \mathbb{R}^m$ are vectors of decision variables; $\boldsymbol{A} \in \mathbb{R}^{p\times n}$, $\boldsymbol{B} \in \mathbb{R}^{p\times m}$, and $\boldsymbol{c} \in \mathbb{R}^p$ are coefficient matrices/vectors.
The augmented Lagrange function of the above formula can be expressed as:

$$L(\boldsymbol{x},\boldsymbol{y},z) = f(\boldsymbol{x}) + g(\boldsymbol{z}) + \boldsymbol{y}^{\mathrm{T}}(\boldsymbol{Ax} + \boldsymbol{Bz} - \boldsymbol{c}) + \frac{\rho}{2}\|\boldsymbol{Ax} + \boldsymbol{Bz} - \boldsymbol{c}\|_2^2 \tag{A2}$$

where $\boldsymbol{y} \in \mathbb{R}^p$ is the Lagrange multiplier, ρ is the penalty factor.
The iterative optimization process of ADMM is as follows:

$$\boldsymbol{x}^{[k+1]} := \operatorname*{argmin}_{\boldsymbol{x}} L(\boldsymbol{x}, \boldsymbol{z}^{[k]}, \boldsymbol{y}^{[k]}) \tag{A3}$$

$$\boldsymbol{z}^{[k+1]} := \operatorname*{argmin}_{\boldsymbol{z}} L(\boldsymbol{x}^{[k+1]}, \boldsymbol{z}, \boldsymbol{y}^{[k]}) \tag{A4}$$

$$\boldsymbol{y}^{[k+1]} := \boldsymbol{y}^{[k]} + \rho(\boldsymbol{Ax}^{[k+1]} + \boldsymbol{Bz}^{[k+1]} - \boldsymbol{c}) \tag{A5}$$

The ADMM algorithm dissolves the original problem by fixing other variables and updating only one variable each time, and carries out iterative calculation until the condition of iteration stop is met.

Data availability

Data will be made available on request.

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