

A Two-Stage Game-Theoretic Framework for Fair Profit Allocation in Renewable Energy Communities

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Article Info	ABSTRACT
Article type: Research Article Article history: Received: ***** Received in revised form: ***** Accepted: ***** Published online: ***** Keywords: Behavioral economics, Fairness index, Local energy market, Renewable energy community, Game theory;	Renewable Energy Communities (RECs) have emerged as an effective paradigm for enabling local stakeholders to jointly manage distributed renewable generation, central energy storage, and hydrogen parking lots. While such structures can participate in local energy markets and create collective profits, fair profit allocation among heterogeneous members remains challenging. This paper proposes an integrated two-stage bi-level framework for RECs' operation and fair profit allocation in a local energy market. In the first stage, a bi-level optimization model captures the strategic interaction between the manager of REC and the Distribution System Operator (DSO), where the REC maximizes profit and the DSO minimizes operating costs. In the second stage, cooperative game-theoretic allocation mechanisms are employed to distribute the cooperative surplus among members. A utility-based fairness indicator is further introduced to assess allocation outcomes from a behavioral perspective. The proposed model is implemented in GAMS and solved using the CPLEX solver. Numerical results show that coordinated operation increases total community profit by 14.03% compared with isolated operation.

I. Introduction

1.1. Motivation

The energy landscape is undergoing a profound transformation, driven by the urgent global imperative to mitigate climate change and promote sustainable development [1]. During this transition, Renewable Energy Communities (RECs) have emerged as a promising organizational model, enabling local stakeholders to collaboratively manage and optimize renewable energy resources [2]. RECs can play an active role in the local energy market by coordinating distributed renewable generation, community energy storage, and flexibility resources to create additional economic value. The profits generated in the local energy market by such a system are allocated among the participants of the RECs. Although coordinated operation can generate additional collective value, sustained participation cannot be ensured unless the resulting benefits are distributed in a manner perceived as fair by all members. In other words, fair profit-distribution mechanisms are essential not only for ensuring financial equity, but also for safeguarding long-term participant commitment, which is crucial for the sustained stability of

the community. Allocation frameworks that accurately reflect participants' economic contributions enhance both efficiency and equity, thereby fostering reinvestment in renewable technologies and supporting sustained engagement in energy-efficiency improvements.

The commonly used proportional or consumption-based profit allocation approaches often fail to reflect the heterogeneous contributions of members. This misalignment may erode perceived fairness and reduce participants' incentives to sustain long term engagement in the community. These limitations motivate the need for contribution-aware fairness frameworks capable of objectively comparing profit allocation methods and supporting sustainable decision-making in RECs.

1.2. Literature Review

RECs constitute a fundamental transformation in the organization of power systems by promoting collective ownership and local value creation through the coordinated operation of Distributed Energy Resources (DERs). The operational success of RECs hinges on their ability to integrate a diverse portfolio of assets, creating synergies not only between generation and storage but also across different

energy vectors, including emerging solutions for mobility and sector coupling. Beyond electricity-based assets, recent research has increasingly highlighted hydrogen technologies as key enablers of sector coupling and long-term energy storage in local energy systems.

In particular, Hydrogen Vehicles (HVs) offer a zero-emission transportation solution characterized by rapid refueling and long driving ranges, thereby contributing substantially to greenhouse gas emission reduction [3]. More recently, HV parking lots and refueling infrastructures have been introduced as integral components of community-scale energy systems [4].

The long-term success of RECs critically depends on fair profit allocation mechanisms that adequately reflect heterogeneous investments and contributions, as coordinated operation alone does not guarantee sustained participation [5]. Existing studies have mainly focused on operational optimization, risk-based energy management, and local energy trading in energy communities, REC–DSO trading with flexibility constraints [6], [7]. However, although coordinated operation generally improves overall system performance, the fair allocation of the resulting profits or cost savings remains largely underexplored, particularly in RECs where heterogeneous members, including renewable generators, storage units, and electric and HVs, contribute unequally to collective value creation. Behavioral economics further emphasizes the importance of fairness in economic interactions. As demonstrated by Kahneman [8], economic agents tend to evaluate outcomes relative to reference points and regard profit distribution as fair only when it does not impose losses on other participants or violate established entitlements. Motivated by these fairness considerations, cooperative game theory has emerged as a particularly suitable framework for benefit allocation in RECs.

Driven by fairness considerations, cooperative game theory has emerged as a robust framework for benefit distribution within RECs, particularly given the social orientation of REC policies. This theoretical approach posits that the stability of a coalition is inherently contingent upon a cost or profit allocation that satisfies two fundamental criteria: rationality and efficiency. To operationalize these principles, various mathematical solution concepts have been established to derive allocation rules that are both theoretically justified and stable under cooperative interactions. Among these, classical concepts such as the Core, Shapley (SH), and Nucleolus (Nuc) are widely adopted in energy-related applications. For instance, the Core ensures rational participation by guaranteeing that no subset of players can gain more by leaving the grand coalition, while efficiency requires that the total payoff be fully distributed among participants [13]. The SH allocates payoffs based on marginal contributions and satisfies axiomatic fairness properties; however, multiple works highlight its potential

instability, as Shapley-based allocations may fall outside the core and thus fail to guarantee coalition stability [9]. The Nuc, introduced by Schmeidler, addresses this limitation by minimizing the dissatisfaction of the most disadvantaged coalitions and guarantees stability whenever the Core is non-empty. These solution concepts have been extensively applied to RECs, revealing inherent trade-offs between fairness, stability, and uniqueness of the allocation outcome [10]. Recent studies have applied cooperative allocation mechanisms to RECs. For instance, [15] investigates fair game-theoretic reward allocation in energy communities using mechanisms such as the Shapley Value, Core, and Nucleolus, while [11] shows that different allocation mechanisms—such as SH and uniform pricing—can lead to significantly different distributional outcomes despite identical total community profits, thereby affecting perceived fairness and member satisfaction; however, despite its widespread use as a benchmark contribution-based measure [12], the SH may still suffer from coalition stability limitations.

Another widely recognized cooperative allocation mechanism is the Nash Bargaining Solution (NBS), which determines the allocation outcome by maximizing the product of players' utility gains relative to a disagreement point. Unlike marginal-contribution-based rules, NBS explicitly incorporates the bargaining positions of participants and aims to achieve an outcome that simultaneously satisfies pareto efficiency, symmetry, independence of irrelevant alternatives, and scale invariance. These axiomatic properties make NBS particularly suitable for decentralized environments where participants negotiate the distribution of jointly generated benefits [13]. For instance, [14] proposed a cooperative peer-to-peer energy trading framework based on an NBS formulated as an Mixed-Integer Linear Programming (MILP), demonstrating improved social welfare and participant incentives under network constraints. However, the proposed fairness notion remains limited to utility-based proportionality and does not explicitly capture heterogeneity in marginal contributions, risk preferences, or behavioral fairness considerations. In addition to cooperative game-theoretic approaches, variance-based allocation methods have been proposed as a computationally efficient alternative that interprets fairness as outcome equality. In this regard, fairness has emerged as a key design principle for RECs, as it directly influences member satisfaction, trust, and the long-term stability of cooperative participation [16]. Because REC participants differ in their investments, flexibility resources, and risk preferences, fair profit allocation should reflect members' marginal contributions rather than rely solely on equalizing outcomes.

Studies indicate that neglecting contribution-based fairness can reduce perceived equity and weaken coalition

stability. For example, [5] shows that procedural and distributional justice significantly affect the social acceptance and sustained engagement of community energy participants. Based on this review, the main research gaps are identified as follows:

- Research Gap #1: Although numerous studies optimize the operation of RECs to minimize operational costs or maximize social welfare, the translation of these aggregate system benefits into stable, incentive-compatible, and behaviorally acceptable profit distributions remains insufficiently addressed. This disconnect between system-level optimality and member-level satisfaction constitutes a critical barrier to sustained participation and long-term coalition stability in RECs.
- Research Gap #2: While the manager of RECs has received substantial research attention, the design of fair, stable, and contribution-reflective profit-sharing mechanisms remains relatively underdeveloped. The long-term viability of RECs critically depends on allocation schemes that preserve participation incentives across heterogeneous asset types, including (photovoltaic (PV) systems, wind turbine (WT), Central Energy Storage (CES), and emerging hydrogen infrastructures.
- Research Gap #3: Although various centralized and decentralized allocation approaches have been investigated, most REC profit allocation models assume fully rational agents and therefore overlook risk preferences, and utilities, which may significantly influence members' acceptance of allocation outcomes.

1.3. Contributions

This paper addresses the problem of fair profit allocation in RECs from a fairness-oriented perspective, while proposing a comprehensive two-stage framework for emerging energy systems. In the first stage, a bi-level Stackelberg game-based optimization model is developed to characterize the strategic interaction between the manager of REC' operator and the Distribution System Operator (DSO), while explicitly capturing the coordinated operation of heterogeneous energy technologies, including PV systems, WT generation, CES, and hydrogen parking lot components. By embedding hydrogen technologies into the energy community assets, the proposed model enables a holistic approach to energy management and enhances the long-term sustainability of RECs. To account for the inherent variability of renewable generation, uncertainty is explicitly modeled using a scenario-based framework. In the second stage, the cooperative surplus generated by coordinated operation is allocated among community members through several profit allocation mechanisms including the SH, Nuc, variance-based schemes, Shapley–Nucleolus (SHNuc) hybrids, NBS, Shapley-Weighted Nash Bargaining Solution (SW-NBS) and Proportional Energy-based Allocation (PEA) approaches. Fairness in profit sharing is further evaluated from a behavioral perspective using a complementary utility-

based indicator, namely the utility-based deviation index. The main contributions of this paper can be summarized as follows:

- ✓ Contribution #1: A novel two-stage bi-level framework is proposed in which the REC manager coordinates internal asset operation and bidding decisions, while the resulting cooperative profit is allocated among members through fair and behaviorally acceptable mechanisms.
- ✓ Contribution #2: Development of several novel profit allocation mechanisms for RECs, including the SW-NBS and the SHNuc, along with a comprehensive comparison against existing methods such as PEA, SH, Nuc, Min-Variance/Core (VarC), and Nash Bargaining Solution (NBS).
- ✓ Contribution #3: A behavioral fairness evaluation approach is introduced, employing a novel utility-based indicator—the utility-based deviation index—to effectively capture members' diverse utility perceptions and preferences in assessing allocation outcomes.

2. The Proposed Framework

The proposed framework establishes an integrated modeling and evaluation architecture for fair profit allocation in RECs. As illustrated in Fig. 1, the proposed model is organized as a two stage bi-level structure that provides a comprehensive architecture seamlessly connecting physical community operation with economic profit sharing mechanisms.

In the first stage, a bi-level operational model is employed to determine the optimal participation strategy of the REC in local energy market. At the upper level, the REC manager acts as the leader and makes strategic decisions to maximize the community's total profit through the coordinated scheduling of heterogeneous assets, including PV systems, WT, CES, and hydrogen parking lot facilities. At the lower level, the DSO, as the follower, responds to the REC's decisions under network and market conditions. This leader–follower interaction is formulated through a Stackelberg game, which enables the model to capture the hierarchical and strategic nature of decision-making between the manager of REC and the system operator. To ensure robust analysis, the model captures renewable generation uncertainty through a scenario-based approach while satisfying limits on power exchange, storage, and vehicle charging demand. The number of HVs in the parking lot is modeled by a probability distribution function to reflect uncertain arrivals and departures. A normal distribution is used to represent vehicle availability over time, and Monte Carlo simulation generates a large set of scenarios. These are then reduced using K-means clustering to maintain computational tractability.

In the second stage, the cooperative profit obtained from the first stage is transferred to a fair profit allocation layer, where the total surplus created through coalition formation is distributed among REC members. This stage reflects the

fact that, although joint operation improves the collective economic outcome, the sustainability of the coalition ultimately depends on how fairly these gains are shared among participants with heterogeneous resources and contributions. Accordingly, several profit allocation methods are applied to distribute the surplus among the members of the REC. As further shown in Fig. 1, a dedicated fairness evaluation module is used to compare the outcomes of different allocation mechanisms. After applying each allocation rule, the resulting shares are assessed using the proposed utility-based deviation index so that the consistency and acceptability of each method can be systematically examined.

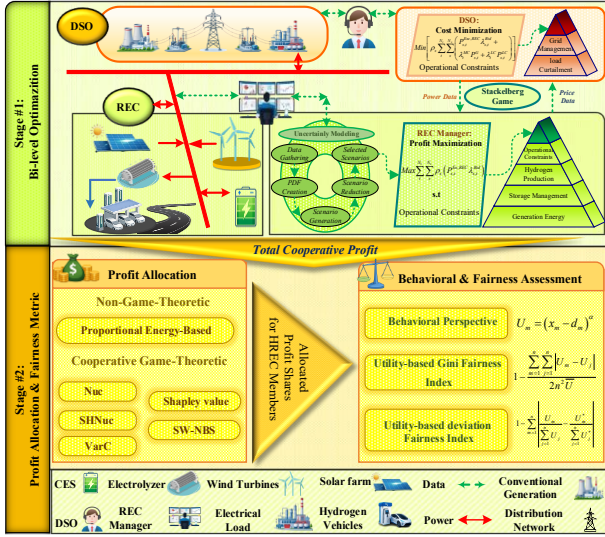


Fig. 1. Proposed model for REC.

3. First Stage: Bilevel Optimization Model

In the proposed local energy market structure, the interaction between the REC manager and the DSO is inherently sequential. The REC manager first determines its bidding strategy with the objective of maximizing the community profit. After observing this bidding decision, the DSO responds by minimizing its operating cost through optimal power procurement from the REC and the upstream grid, as well as load curtailment decisions. This leader-follower structure justifies the use of a Stackelberg game framework, as it explicitly captures the strategic dependency between the REC manager's upper-level decision and the DSO's lower-level response.

3.1. Upper-Level Problem

The objective function of the REC is shown in (1).

$$f_1: \text{Max} \sum_{t=1}^{N_t} \sum_{s=1}^{N_s} p_s (P_{s,t}^{Ex,REC} \lambda_{s,t}^{Bid}) \quad (1)$$

Eq. (1) defines the REC manager as the leader in the Stackelberg game framework, with the objective of maximizing total profit from energy exchange with the DSO in the local energy market. The upper-level decision variable directly appearing in this objective function is the REC

bidding price ($\lambda_{s,t}^{Bid}$), whereas the power exchanged between the REC and the DSO ($P_{s,t}^{Ex,REC}$) is determined within the Stackelberg-based optimization framework as a result of the DSO's lower-level response to the REC's bidding strategy. The parameter, (p_s) denotes the probability of scenario, representing the likelihood of a possible realization of renewable generation and hydrogen vehicle availability, and is used as a weighting coefficient in the expected REC profit calculation.

It should be noted that all definitions of the sets, parameters, and variables used in this study are provided in a separate supplementary file. The power balance and acceptable bidding prices are addressed in Eqs. (2) and (3).

$$P_{s,t}^{wind} + P_{s,t}^{pv} + P_{s,t}^{dch} - P_{s,t}^{ch} - P_{s,t}^{Elyz} = P_{s,t}^{Ex,REC} \quad (2)$$

$$\lambda_{s,t}^{min} \leq \lambda_{s,t}^{Bid} \leq \lambda_{s,t}^{max} \quad (3)$$

The operational constraints of the CES system are formulated in Eqs. (4)–(8).

$$SoC_{s,t}^{CES} = SoC_{s,t-1}^{CES} + (P_{s,t}^{ch} \eta^{ES}) - (P_{s,t}^{dch} / \eta^{ES}) \quad (4)$$

$$0 \leq SoC_{s,t}^{CES} \leq SoC_{max}^{CES} \quad (5)$$

$$0 \leq P_{s,t}^{dch} \leq I_{s,t}^{dch} P_{max}^{dch} \quad (6)$$

$$0 \leq P_{s,t}^{ch} \leq I_{s,t}^{ch} P_{max}^{ch} \quad (7)$$

$$I_{s,t}^{ch} + I_{s,t}^{dch} \leq 1 \quad (8)$$

(4) presents the dynamic model of the energy storage system's state of charge, which evolves over time according to the prior state of charge (SoC) level, charging and discharging activities, and the storage efficiency factor. (5) enforces operational SoC limits so that the storage level always remains within its rated capacity. Moreover, (6) and (7) define upper bounds on charging and discharging rates through binary decision variables to guarantee operational exclusivity at each time interval. Eq. (8) further strengthens this condition by explicitly prohibiting simultaneous charging and discharging of the storage unit.

Eqs. (9)–(12) model the electrolyzer hydrogen production, including the power-to-hydrogen conversion and limits on input power and hydrogen output.

$$H_{s,t}^{Elyz} = \frac{\eta^{Elyz} (P_{s,t}^{Elyz})}{\sigma^{Elyz}} \quad (9)$$

$$H_{s,t}^{Elyz} = C_{s,t}^{HV} H_{s,t}^{tank} \quad (10)$$

$$P_{min}^{Elyz} \leq P_{s,t}^{Elyz} \leq P_{max}^{Elyz} \quad (11)$$

$$0 \leq H_{s,t}^{Elyz} \leq H_{max}^{Elyz} \quad (12)$$

To accurately represent hydrogen demand within the parking facility, the number of HVs () is modeled through a probabilistic framework based on historical arrival-departure data.

3.2. Lower-Level Problem

The payment optimization model of the DSO can be formulated as follows.

$$f_2 : \text{Min} \left[\rho_s \sum_t \sum_s \left(P_{s,t}^{\text{Exc}, \text{REC}} \lambda_{s,t}^{\text{Bid}} + \lambda_t^{\text{MC}} P_{s,t}^G + \lambda_t^{\text{LC}} P_{s,t}^{\text{LC}} \right) \right] \quad (13)$$

subject to:

$$P_{s,t}^G + P_{s,t}^{\text{Exc}, \text{REC}} = \sum_d P_{d,t}^D - P_{s,t}^{\text{LC}} \quad (14)$$

$$0 \leq P_{s,t}^G \leq P_{\max}^G \quad (15)$$

$$-P_{\max}^{\text{Exc}, \text{REC}} \leq P_{s,t}^{\text{Exc}, \text{REC}} \leq P_{\max}^{\text{Exc}, \text{REC}} \quad (16)$$

$$0 \leq P_{s,t}^{\text{LC}} \leq P^{\text{LC}, \max} \quad (17)$$

In Eq. (13), the DSO minimizes expected operating cost, including REC energy payments, upstream grid purchases, and load curtailment penalties. The main decision variables associated with this lower-level problem are the power purchased by the DSO from the REC ($P_{s,t}^{\text{Exc}, \text{REC}}$), the power purchased from the upstream grid ($P_{s,t}^G$), and the curtailed load at each time period and scenario ($P_{s,t}^{\text{LC}}$). The REC bidding price is determined at the upper level and enters the lower-level problem as a strategic input.

Eq. (14) ensures power balance; Eqs. (15) and (16) limit exchanges with the upstream grid and REC, respectively. Moreover, Eq. (17) bounds load curtailment. Since the lower-level problem is linear and convex, it can be exactly replaced by its KKT conditions in the single-level reformulation.

3.3. Solution Approach to the Proposed Stackelberg Game Model

The proposed framework is a bi-level optimization problem that can be solved by standard methods [6]. Here, the lower-level problem is replaced by its KKT conditions, which are exact for linear, continuous, and convex follower problems. This converts the model into a single-level nonlinear program. The detailed derivation is provided in Appendix A of the Supplementary Material submitted together with this manuscript. Then, the nonlinear term in Eq.(1) is linearized using strong duality theory. Consequently, the proposed nonlinear bi-level optimization problem is ultimately converted into a single-level MILP model, expressed as follows:

$$\sum_t \sum_s P_{s,t}^{\text{Exc}, \text{REC}} \lambda_{s,t}^{\text{Bid}} = \frac{1}{\rho_s} \left(\sum_d \left(P_{d,t}^D \mu_{s,t}^1 - P_{\max}^G \mu_{s,t}^3 \right) - P_{\max}^{\text{Exc}, \text{REC}} \mu_{s,t}^4 - P_{\max}^{\text{Exc}, \text{REC}} \mu_{s,t}^5 - P_t^{\text{LC}, \max} \mu_{s,t}^7 \right) - \sum_t \sum_s \left(\lambda_t^{\text{MC}} P_{s,t}^G + \lambda_t^{\text{LC}} P_{s,t}^{\text{LC}} \right) \quad (18)$$

subject to:

$$\text{Equations (2) to (12)} \quad (19)$$

$$P_{s,t}^G + P_{s,t}^{\text{Exc}, \text{REC}} + P_{s,t}^{\text{LC}} - \sum_d P_{d,t}^D = 0 \quad \forall s, t \quad (20)$$

$$\lambda_t^{\text{MC}} - \mu_{s,t}^1 - \mu_{s,t}^2 + \mu_{s,t}^3 = 0 \quad \forall s, t \quad (21)$$

$$\lambda_{s,t}^{\text{Bid}} - \mu_{s,t}^1 - \mu_{s,t}^4 + \mu_{s,t}^5 = 0 \quad \forall s, t \quad (22)$$

$$\lambda_t^{\text{LC}} - \mu_{s,t}^1 - \mu_{s,t}^6 + \mu_{s,t}^7 = 0 \quad \forall s, t \quad (23)$$

$$0 \leq P_{s,t}^G \leq P_{\max}^G \quad \forall s, t \quad (24)$$

$$0 \leq (P_{\max}^G - P_{s,t}^G) \perp \mu_{s,t}^3 \geq 0 \quad \forall s, t \quad (25)$$

$$0 \leq (P_{s,t}^{\text{Exc}, \text{REC}} + P_{\max}^{\text{Exc}, \text{REC}}) \perp \mu_{s,t}^4 \geq 0 \quad \forall s, t \quad (26)$$

$$0 \leq (P_{\max}^{\text{Exc}, \text{REC}} - P_{s,t}^{\text{Exc}, \text{REC}}) \perp \mu_{s,t}^5 \geq 0 \quad \forall s, t \quad (27)$$

$$0 \leq P_{s,t}^{\text{LC}} \perp \mu_{s,t}^6 \geq 0 \quad \forall s, t \quad (28)$$

$$0 \leq (P_t^{\text{LC}, \max} - P_{s,t}^{\text{LC}}) \perp \mu_{s,t}^7 \geq 0 \quad \forall s, t \quad (29)$$

4. Second Stage: Profit Allocation Mechanisms

This section presents the profit allocation methods used to distribute the total REC revenue among participants. Both non-cooperative and cooperative game-based approaches are considered to examine different perspectives on profit sharing.

4.1. Proportional Energy-Based Allocation (Non-Game-Theoretic Framework)

The PEA approach allocates the total cooperative profit solely according to each participant's relative contribution to energy production, without incorporating coalition values or strategic interactions and coalition stability considerations. Let N denote the set of REC members, ρ_s probability of scenarios, let $E_{m,s}$ represent the energy contribution of participant $m \in N$ under scenario s . The expected energy contribution of member m over the planning horizon is defined as:

$$\bar{E}_m = \sum_s \rho_s E_{m,s} \quad (30)$$

The total expected community production is therefore:

$$\bar{E}^{\text{tot}} = \sum_m \bar{E}_m \quad (31)$$

The proportional energy share of participant m is given by:

$$\gamma_m = \frac{\bar{E}_m}{\bar{E}^{\text{tot}}} \quad (32)$$

Accordingly, the allocated profit under the PEA is determined as:

$$x_m = \gamma_m V(N) = \frac{\bar{E}_m}{\sum_{j \in N} \bar{E}_j} V(N) \quad (33)$$

Subject to:

$$\sum_{m \in N} x_m = V(N) \quad (34)$$

Here, x_m denotes the profit allocated to participant m , $v(N)$ represents the total cooperative profit (i.e., the value of the grand coalition), and $\bar{E}_m$ is the effective energy contribution of participant m to the community. Eq. (33) defines to the total energy produced by all members, while γ_m captures the relative energy share of participant m in the community. Thus, PEA allocates profits strictly proportional to each member's contribution to total energy production. The efficiency constraint (34) ensures that the entire cooperative profit is fully distributed among the participants

without surplus or deficit, guaranteeing that the allocation is collectively efficient.

4.2. Cooperative Game-Theoretic Framework for Profit Allocation

PEA is simple and transparent, but it considers only energy contribution and ignores marginal effects and coalition stability. As a result, some sub-coalitions may earn less than operating alone, which can weaken cooperation. To overcome this, a cooperative game-theoretic framework is used to model coalition values and design allocations that better reflect fairness and stability.

4.2.1. The Core

The Core is a central concept in cooperative game theory that establishes the theoretical basis for assessing the stability of allocating jointly generated and divisible benefits among the members of a coalition [13]. For the grand coalition, which includes all players, to remain stable, the payoff allocation must be structured so that no subgroup of participants has an incentive to withdraw. Formally, for a cooperative game (N, v) , a payoff vector x belongs to the Core if it satisfies [13]:

$$\sum_{m \in N} x_m = V(N) \quad (35)$$

$$\sum_{m \in C} x_m \geq V(C), \quad \forall C \subseteq N \quad (36)$$

The first condition, (35) ensures efficiency, meaning that the total profit of the grand coalition is fully distributed. The second condition, (36) guarantees coalitional rationality, ensuring that no subgroup of players has an incentive to deviate from the grand coalition.

4.2.2. Shapley Value

The SH is a widely used solution concept in cooperative game theory that allocates the total profit of a coalition based on the marginal contribution of each player [13]. It provides a unique payoff distribution that satisfies fairness axioms such as efficiency, symmetry, dummy player, and additivity. For a cooperative game (N, v) , the SH assigned to player m is defined as:

$$\phi_m(N, v) = \sum_{C \subseteq N \setminus \{m\}} \frac{|C|!(|N|-|C|-1)!}{N!} (v(C \cup \{m\}) - v(C)) \quad (37)$$

where $v(C)$ denotes the value of coalition C , and $v(C \cup \{m\}) - v(C)$ represents the marginal contribution of player m to coalition C . In the context of the REC, the SH distributes the total cooperative surplus among participating components (e.g., PV, WT, CES) proportionally to their average marginal contributions across all possible coalition formations. Although the SH ensures efficiency and fairness in terms of contribution, it does not necessarily guarantee stability, as the resulting allocation may not always belong to the Core.

4.2.3. The Nucleolus (Nuc)

To ensure the long-term sustainability of the REC, the Nuc method is adopted. The Nuc is a cooperative game-theoretic

solution concept that determines a unique and stability-oriented profit allocation by minimizing coalition dissatisfaction. Rooted in lexicographical min-max optimization, it prioritizes coalition stability by reducing the largest dissatisfaction among all possible sub-coalitions $C \subseteq N$, thereby limiting incentives for deviation and strengthening the persistence of the grand coalition [10]. Let the surplus of coalition $C \subseteq N$ under allocation x be defined as [13]:

$$\theta(C) = \sum_{m \in C} x_m - V(C) \quad (38)$$

The Nuc is obtained by maximizing the minimum surplus across all coalitions. The first-stage optimization problem is formulated as Eqs. (39)-(41):

$$\begin{aligned} \max \quad & \theta \\ \text{subject to:} \end{aligned} \quad (39)$$

$$\sum_{m \in C} x_m - V(C) \geq \theta, \quad \forall C \subset N \quad (40)$$

$$\sum_{m \in N} x_m = V(N) \quad (41)$$

where θ represents the minimum surplus among all coalitions. Maximizing θ ensures that the least-advantaged coalition is improved to the greatest possible extent. If multiple allocations yield the same optimal value θ^* , the coalitions with binding constraints are fixed and the procedure is repeated lexicographically until a unique allocation is determined. When the Core is non-empty, the Nuc belongs to the Core, thereby guaranteeing coalition stability.

4.2.4. The Min-Variance/Core (VarC)

To simultaneously promote allocation equity and coalition stability, a hybrid mechanism denoted as VarC is introduced [15]. This approach seeks a profit allocation that minimizes dispersion among community members while satisfying Core constraints to ensure coalition sustainability [17].

Let N denote the set of REC participants and x_m the profit allocated to participant $m \in N$. The total cooperative profit is given by $v(N)$. The VarC allocation problem is formulated as Eqs. (42)-(43):

$$\min \left\{ \frac{1}{|N|} \sum_{m \in N} (x_m - \bar{x})^2 \right\} \quad (42)$$

subject to:

Equations (35) to (36)

The model minimizes dispersion for equality, while Core and individual rationality ensure stability and standalone benefit.

4.2.5. Shapley-Nucleolus (SHNuc)

The Shapley-Core approach keeps profit allocation within the stability region, but it does not ensure a strictly positive surplus for every sub-coalition in the REC. As a result, it offers only weak support for long-term cooperation, especially in RECs with high-capital assets such as hydrogen electrolyzers and CES systems. To strengthen coalition

cohesion, a modified SHNuc distribution is proposed. In the first stage, it maximizes the utility of the coalition with the smallest surplus, thereby securing a strictly positive stability margin. In the second stage, the remaining profits are allocated as close as possible to the SH, preserving contribution-based fairness and improving the most disadvantaged coalition as much as possible. The resulting optimization problem is formulated as:

$$\min \left\{ \sum_{m \in N} (x_m - \phi_m)^2 \right\} \quad (44)$$

subject to

$$\sum_{m \in C} x_m - V(C) \geq \theta^*, \quad \forall C \subset N \quad (45)$$

$$\sum_{m \in N} x_m = V(N) \quad (46)$$

4.2.6. Nash Bargaining Solution (NBS)

In many REC profit allocation problems, cooperation can be viewed as a bargaining process in which members negotiate how to divide the surplus from joint operation. The NBS is a classical solution in cooperative game theory that determines the allocation by maximizing the product of players' gains over a disagreement point. In RECs, however, members have different roles and unequal contributions to value creation. Therefore, the assumption of equal bargaining power is not realistic. To capture this heterogeneity, a generalized Nash bargaining formulation with asymmetric bargaining weights β_m is adopted.

To bridge the gap between marginal contribution and strategic negotiation, this study proposes a refined asymmetric NBS. In this framework, the technical contribution of each REC member is first quantified through the SH ϕ_m , which provides an objective measure of the asset's marginal impact on the total cooperative profit. These Shapley-based contribution indices are then used to define the bargaining weights in a SW-NBS formulation, such that the bargaining power of each participant is proportional to its Sh. In this way, the final allocation simultaneously incorporates cooperative contribution fairness and negotiation-based equity, while explicitly reflecting the relative technical importance of the heterogeneous REC components. Let N denote the set of REC members and $v(N)$ the total cooperative profit of the grand coalition. Let d_m be the disagreement payoff of member $m \in N$, typically taken as its standalone profit, i.e., $d_m = v(\{m\})$. The profit allocation vector x is then determined through the following SW-NBS problem:

$$X^{SW-NBS} = \arg \max_x \prod_{m \in N} (x_m - d_m)^{\beta_m} \quad (47)$$

subject to:

$$\sum_{m \in N} x_m = V(N), \quad x_m \geq d_m, \quad \forall m \in N \quad (48)$$

$$\sum_{m \in C} x_m \geq V(C) \quad (49)$$

$$\sum_{m \in N} \beta_m = 1, \quad \beta_m \geq 0 \quad (50)$$

In this study, the bargaining weights are normalized SH, defined as:

$$\beta_m = \frac{\phi_m}{\sum_{j \in N} \phi_j} \quad (51)$$

Accordingly, the cooperative surplus $V(N) - \sum_{m \in N} d_m$ is allocated through a weighted bargaining mechanism in which each member's bargaining power is directly derived from its marginal contribution to coalition value. This formulation provides a consistent integration of contribution-based fairness (Shapley) and negotiation-based equity (Nash bargaining) within heterogeneous RECs.

5. Fairness Evaluation Metric

This paper develops a behavioral fairness evaluation framework tailored to RECs in order to rigorously compare the profit allocation methods, where participants collaborate to maximize the total coalition surplus. In this context, establishing a fair profit allocation mechanism is essential for preserving the coalition's long-term stability, as its sustainability depends heavily on the fairness perceived by the members in the resulting profit distribution. From this behavioral perspective, a utility function is introduced to assess and compare the outcomes of different profit allocation methods for REC members. Participants naturally anchor their expectations to a mental reference point, defined here as their standalone profit (i.e., the profit they would have generated operating independently outside the REC). The utility of member m is defined as:

$$U_m = (x_m - d_m)^\alpha, \quad x_m \geq d_m \quad (52)$$

where x_m denotes the cooperative profit allocated to member m , and d_m represents the standalone reference profit. The constraint $x_m \geq d_m$ inherently guarantees the individual rationality of the allocation scheme. The parameter α represents the members' risk attitude. When $\alpha = 1$, the utility reduces to the linear case, corresponding to risk-neutral behavior. For $0 < \alpha < 1$, members are risk-averse, and smaller values of α indicate stronger risk-attitude parameter, implying a higher psychological premium for safely exceeding the standalone baseline. In contrast, $\alpha > 1$ reflects risk-seeking behavior, where members place relatively greater value on larger gains and are more willing to accept uncertainty. Based on this utility framework, the fairness of each allocation mechanism is evaluated by measuring its deviation from the Shapley benchmark in the utility space.

A value approaching indicates a highly equitable profit distribution from the perspective of members' behavioral utility, effectively accounting for both capacity heterogeneity and risk-averse perceptions. In cooperative game theory, the SH is widely recognized as a gold standard for fair distribution based on marginal contributions. To

quantify the deviation from this theoretical ideal in the utility space, let x_m^* denote the ideal profit allocated to member i under the SH, yielding a reference utility of $U_m^* = (x_m^* - d_m)^\alpha$. The utility-based deviation index (Δ_U) is formulated as:

$$\Delta_U = 1 - \sum_{m \in N} \left| \frac{U_m}{\sum_{j \in N} U_j} - \frac{U_m^*}{\sum_{j \in N} U_j^*} \right| \quad (53)$$

This index quantifies the distributional proximity to the Shapley benchmark. The first term represents the normalized utility share of member i under the proposed allocation, which is compared against their expected utility share under the Shapley benchmark. A Δ_U value approaching 1 implies that the proposed allocation mechanism perfectly mimics the fair utility distribution of the SH. Together, the Δ_U provides a comprehensive and behaviorally consistent framework for evaluating both the internal equity and theoretical validity of profit allocation strategies in modern RECs.

6. Case Study

The proposed two-stage bi-level framework is validated through a numerical case study on a REC. The MILP problem is solved using the CPLEX solver within the GAMS environment. Simulations are performed on a computer equipped with an Intel Core i7-10750H processor and 16 GB of RAM. The total computational time is 4 s.

6.1. Input data

The proposed REC comprises four main components: a PV system, a WT, a CES, and a HV parking lot is equipped with an electrolyzer and HVs. The scheduling time horizon is set to 24 hours with hourly resolution. The input dataset for the PV and WT systems, as illustrated in Fig. 2, representing six generation scenarios to capture renewable production uncertainty over the scheduling horizon. Fig. 3 represents the aggregated hourly demand of the distribution network [6]. Additionally, Table 1 outlines the critical input parameters for optimizing operations. A maximum load curtailment allowance of 10% per time step is considered, with a curtailment cost set at 1.5 times the energy price purchased from the upstream grid. The technical and operational data related to the hydrogen vehicle parking facility are adopted from [4].

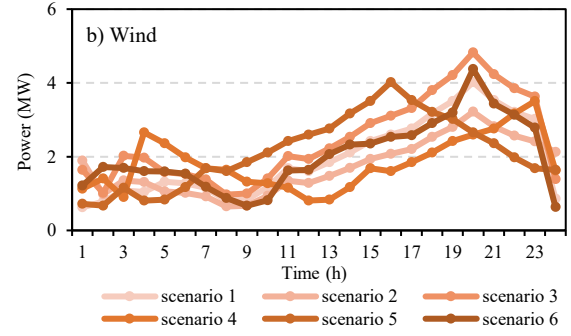
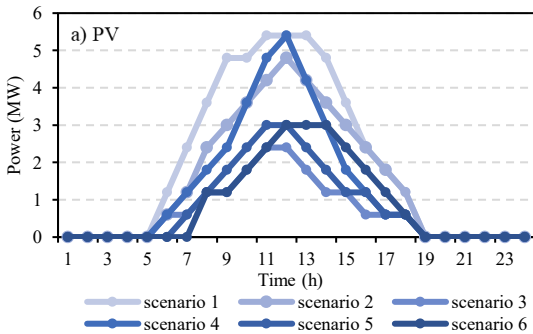


Fig. 2. The output power of a) PV b) WT system.

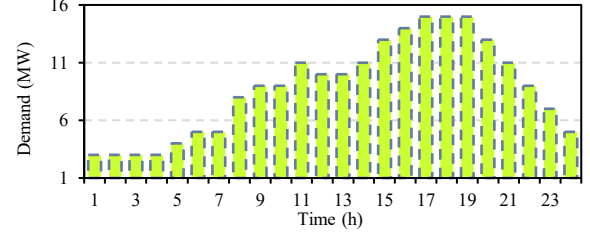


Fig. 3. Hourly grid electrical demand profile.

Table 1. The input parameters of the model.

Parameter	Value	Parameter	Value
$P_{max}^{ch/dch}$	4 (MW)	$P_{max}^{Ex.REC}$	7 (MW)
P_{max}^G	20 (MW)	η_{ES}	0.9

6.2. Results of the REC's Participation in the Local Energy Market

The Stackelberg framework enables the REC to optimize import and export decisions by considering both market price changes and asset flexibility. As shown in Figs. 4 and 5, during low-demand hours ($t = 1-4$), electricity prices are low (22–26 \$/MWh), so the REC imports about 3 MW to charge the CES and run the electrolyzer. As prices rise around midday ($t = 7-13$), the REC shifts to exporting 2–5.5 MW. When prices sharply increase from $t = 14$ and peak at 104–106 \$/MWh at $t = 18$, the REC maximizes export to nearly 7 MW. This reflects rational energy arbitrage under the Stackelberg structure: the REC maximizes its own profit, while the DSO reduces dependence on the upstream grid by buying more local power. In late evening hours ($t = 21-24$), falling prices and lower generation reduce REC exports.

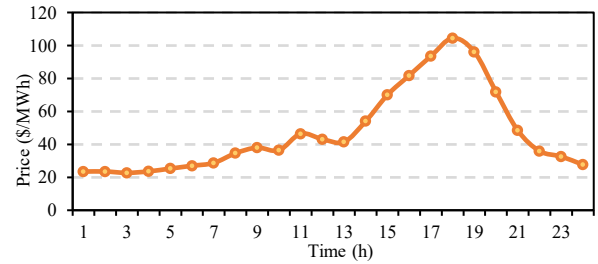


Fig. 4. The bidding price profile of the REC.

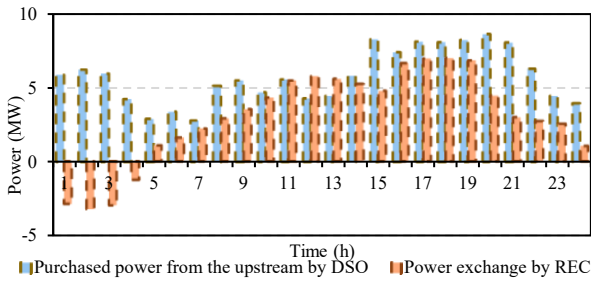


Fig. 5. Optimal power purchase from the upstream grid and REC-DN power exchange

The operational behavior of the CES system clearly reflects a price driven energy arbitrage strategy within the 24 hour scheduling horizon, as illustrated in Fig. 6. The CES is charged during low price hours ($t = 1-4$), increasing its SoC from 1.5 MWh to nearly full capacity (≈ 15 MWh). The stored energy is preserved until peak price periods, after which the CES discharges strategically during $t = 15-19$ with power levels up to 3.8 MW.

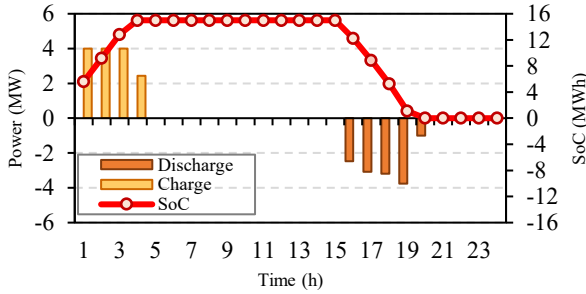


Fig. 6. The performance of the CES

Fig. 7 compares the total economic profit obtained under two operational scenarios including coordinated operation within the REC and isolated operation, where each member independently exchanges energy with the DSO. As shown, the aggregate profit under isolated operation is \$4269.2, whereas cooperative operation increases the total profit to \$4868.32.

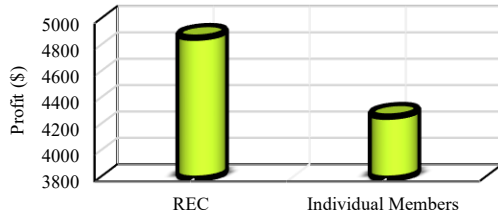


Fig. 7. Total profit.

6.3. Results of Profit Allocation Analysis and Fairness Assessment

Although generating a cooperative economic surplus is essential for the success of an REC, its long-term stability depends on a fair and rational allocation mechanism. Table 2 shows that cooperation increases total profit by combining the strengths of PV, WT, and CES. PV and WT generate energy, while CES adds value by storing surplus power and supplying it during peak or high-price periods. Although

CES has low standalone profit, its marginal contribution is high. The hydrogen vehicle parking lot is excluded from profit allocation because it is only a demand-side unit. The PEA method mainly favors PV and WT and undervalues CES. VarC performs worst case. SW-NBS uses Shapley based weights to represent bargaining power. By contrast, SH, Nuc, and SHNuc all give stable Core allocations. SH reflects average marginal contribution, Nuc emphasizes coalition stability, and SHNuc combines both by choosing the most SH-like allocation among the maximally stable Nuc solutions.

Fig. 8 demonstrates how the choice of profit-allocation mechanism can significantly alter the distribution of profits among the members of a REC. The values presented in Table 2 represent the total profit allocated to each participant under each profit allocation mechanism, whereas Fig. 8 illustrates the percentage increase in profit relative to the non-cooperative (standalone) case. In the PEA method, profits are allocated solely by energy output, increasing PV and WT shares by 25.73% and 8.15%, while giving CES only \$48.83. By ignoring CES's role in flexibility, peak support, and cost reduction, this method is unfair and destabilizing. The VarC method exhibits the most uneven distribution, allocating the highest benefit to CES and a negligible gain to WT, which points to a highly asymmetric outcome. SW-NBS uses contribution-based weights, giving CES the highest gain (16.87%), followed by PV (14.67%) and WT (12.77%), while maintaining coalition stability. This outcome stems from two structural properties of the model. First, Nash bargaining allocates the cooperative surplus, not total profit, so players with lower disagreement payoffs—like CES—see larger relative gains from similar absolute allocations. Second, Core constraints ensure coalition stability and prevent sub-coalitions, especially PV-CES, from deviating, which protects CES's minimum surplus share. Overall, SW-NBS balances contribution-based bargaining power and coalition stability, giving smaller players stronger relative incentives without weakening larger contributors' economic position. In contrast, the SH allocates payoffs according to each player's marginal contribution across all coalition formations, not just its role in the grand coalition. While PV and WT remain the main producers and capture higher absolute profits, CES has a stronger marginal impact by improving system coordination and increasing total surplus. Therefore, CES achieves the largest relative profit gain (30.98%) compared with operating alone. Overall, SH provides a fairness-oriented allocation by accounting for each member's synergistic contribution within the REC. Nuc ensures stability by minimizing the largest coalition dissatisfaction, so no member, including CES, wants to leave. SHNuc combines Shapley fairness with Nuc stability, giving the most balanced result.

Table 2. Comparison of Profit Allocation Methods for REC Members.

Methods Members	Non-cooperative	Cooperative					
	Isolated	Non-Game-Theoretic	Cooperative Game-Theoretic				
		PEA	SH	Nuc	SHNuc	VarC	SW-NBS
PV	1448.6	1821.27	1650.17	1652.02	1651.1	1732.48	1661.15
WT	2178.9	2356.52	2377.67	2376.74	2377.21	2215.82	2457.2
CES	641.7	690.53	840.48	839.55	840.02	920.01	749.95

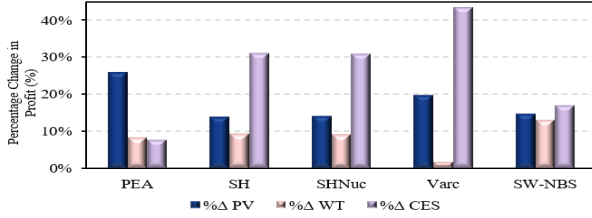


Fig. 8. Relative profit gains of REC members.

Fig. 9 illustrates the sensitivity of the deviation index with respect to the risk-attitude parameter (α). It shows how different allocation mechanisms perform under varying behavioral preferences, thereby demonstrating their robustness in terms of risk-sensitive fairness evaluation, and compares allocation methods against SH as the fairness benchmark. The deviation index Δ_U shows how closely each method matches SH, where 1 means perfect agreement. SHNuc performs best, staying very close to 1 across all risk regimes, which shows strong consistency with contribution-based fairness. SW-NBS declines moderately, while PEA drops sharply as α increases. VarC exhibits a monotonic decline in (Δ_U) from 0.913 to 0.36 as (α) increases, indicating that its variance-based allocation rule gradually loses conformity with the benchmark fairness structure under stronger behavioral sensitivity.

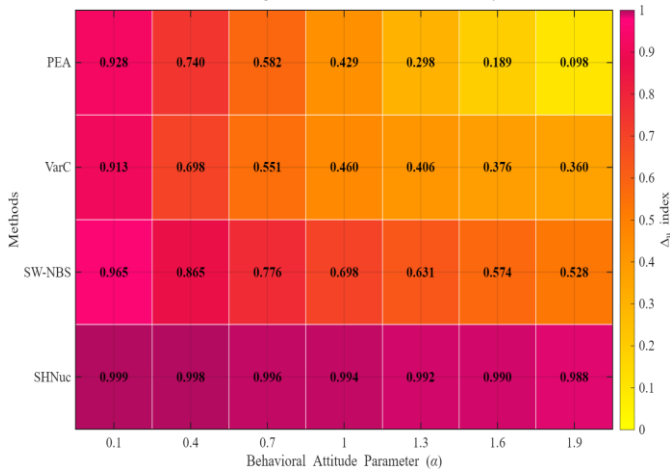


Fig. 9. Sensitivity of the deviation index with respect to α

7. Conclusions

This paper proposed a two-stage bilevel framework for the coordinated operation and fair profit allocation of RECs in a local energy market. The numerical results indicate that the cooperative participation of the REC in the local energy market significantly outperforms isolated operational strategies. The performance of various allocation mechanisms was rigorously evaluated using the proposed

utility-based deviation index under varying risk profiles. The results demonstrate that cooperative game-theoretic allocation mechanisms (SH, Nuc, SHNuc) offer superior distributive equity. These methods maintain high fairness scores (>0.99) across all risk levels, confirming their robustness against behavioral shifts. In contrast, heuristic methods like PEA proved unstable and inequitable; their equity score collapsed from a seemingly fair 0.928 to 0.098, revealing a structural inability to reward the strategic value of enabling assets like energy storage. This study concludes that for the long-term viability of RECs, allocation mechanisms must prioritize contribution equity over simple outcome equality. The proposed framework and the validated superiority of Core-based solutions offer a practical roadmap for designing economically resilient and genuinely fair decentralized energy systems. Future research could extend the proposed framework to larger-scale RECs with different asset compositions and varying market conditions, while also incorporating broader uncertainty sources and network-constrained market participation.

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systems.

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