Working paper

2023-02

Statistics and Econometrics
ISSN 2387-0303

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Abstract

The distributed integration of renewable energy sources plays a central role in the decarbonization of economies. In this regard, energy communities arise as a promising entity to coordinate groups of proactive consumers (prosumers) and incentivize the investment on clean technologies. However, the uncertain nature of renewable energy generation, residential loads, and trading tariffs pose important challenges, both at the operational and economic levels. We study how this management can be directly undertaken by an arbitrageur that, making use of an adequate price tariff system, serves as an intermediary with the central electricity market to coordinate different types of prosumers under risk aversion. In particular, we consider a sequential futures and spot market where the aggregated shortage or excess of energy within the community can be traded. We aim to study the impact of the integration of hydrogen production and storage systems, together with a parallel hydrogen market, on the community operation. These interactions are modeled as a game theoretical setting in the form of a stochastic two-stage bilevel optimization problem, which is latter reformulated without approximation as a single-level mixed-integer linear problem (MILP). An extensive set of numerical experiments based on real data is performed to study the operation of the energy community under different technical and economical conditions. Results indicate that the optimal involvement in futures and spot markets is highly conditioned by the community's risk aversion and self-sufficiency levels. Moreover, the external hydrogen market has a direct effect on the community's internal price-tariff system, and depending on the market conditions, may worsen the utility of individual prosumers.

Keywords: Energy community, Hydrogen market, Risk management, Sequential energy markets, Storage systems

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1. Introduction

1.1. Motivation and Aim

In recent decades, many countries have been exploring distributed forms of renewable energy sources (RES) such as solar, wind, hydro, biomass, geothermal, and marine to address the unprecedented environmental climate problem and alleviate the energy shortage from a potential fossil fuel crisis [1, 2]. Moreover, RES are also part of the green recovery package that can tackle other disruptions (e.g., the COVID-19 pandemic) as they are more sustainable, distributed and less dependent on human labor [3].

The end consumers are motivated to become proactive prosumers to manage their energy consumption and production by implementing residential-scale photovoltaic (PV) technologies, combined heat and power plants, storage systems or wind farms into their energy system [4]. Meanwhile, the recent integration of advanced communications, metering, control and energy management systems, in the contest of a smart grid, provide the technical support needed for the effective coordination of prosumers [5]. In particular, both distributed RES and smart grid devices give prosumers more autonomy and flexibility in their energy procurement and foster their direct participation in energy markets [6]. As a result, a new paradigm; the energy community, has been envisioned as an entity to favor this participation, by regulating and coordinating the trading of several small-scale prosumers with distributed RES. The formation of energy communities is been promoted and implemented in E.U., U.S., Australia, or New Zealand [7]. As an example, the European Commission in [8] has launched two types of community project evaluation: the Energy Communities Repository in the urban area and the Rural Energy Community Advisory Hub in the rural area. Both projects implement "citizen energy communities", which stimulate consumer participation, or "renewable energy communities", which emphasize the integration of renewable energy.

The energy community aims to manage energy resources to provide its members environmental, social, and economical benefits [9]. However, the intermittent and uncertain renewable energy generation, the hard-to-predict nature of disaggregated residential energy loads, and the volatile price of the spot market (SM) pose important challenges for their efficient operation [10]. In this regard, multiple approaches have been proposed to model and hedge against uncertainty in the technical and economical operation of energy communities and distributed RES; see, e.g.,[11, 12, 13, 14, 15, 16, 17, 18, 19].

In this contest, we seek to extend these approaches to shed light on how market design and the integration of new technologies (e.g. batteries, photovoltaics, and hydrogen production and storage) can impact and facilitate the operation and risk management of energy communities. We analyze the impact of community's risk-averse behavior when forward contracts and storage systems are available. For this purpose, we study the interaction of two types of entities within the local energy community in a two-stage setting. We consider an arbitrageur who acts as the community aggregator and serves as an intermediary between the wholesale market and a group of prosumers with distributed RES. The arbitrageur, in the first stage, decides the amount of energy that has to be purchased in the futures market (FM) through a forward contract at a fixed price. Then, in the second stage, it has to decide the amount of energy to trade (buy or sell depending on the community net balance) at an hourly SM. Finally, in the second stage, too, it has to settle an adequate price-tariff to resell all the energy purchased in both FMs and SMs to the prosumers, which are price-responsive. Following the current functioning of most electricity markets, we assume that the first-stage decision has to be taken some weeks or months in advance to the energy delivery at the second-stage, and hence the arbitrageur faces the uncertainty of RES availability, net load of the community, and SM prices. Moreover, the energy community includes several heterogeneous prosumers with small-scale renewable generation and storage systems: PVs, electrical batteries, and hydrogen. Hence, at the second-stage, each prosumer optimizes the operation of its residential system to meet its individual demand and by trading the surplus or deficit energy with the arbitrageur at the given price tariff. Indeed, we are particularly interested in the impact of hydrogen production and storage technologies in the community operation, and how prosumers may benefit from an external hydrogen market.

As energy communities are conceived as non-profit organization, we assume that possible net profits by the arbitrageour would need to be reinvest in the community, either to reduce the prosumers operating costs or to incentive future renewable investments. Therefore, we will also analyze the total overall costs of all community members as a measure of community performance.

We consider a Stackelberg game to model the interactions between the arbitrageur (Leader) and several prosumers (Followers). This hierarchical scheme is very adequate to model the timeline of the decision-making process, i.e., the arbitrageur seeks the best first-stage decision (FM) by anticipating the optimal operation (reaction) of the community in the second stage. This game is recast as a Mathematical Problem with Equilibrium Constraints (MPEC) as the prosumers are in a competitive equilibrium. In particular, we use a bilevel formulation, wherein the upper-level problem of the arbitrageur solves a two-stage problem by anticipating the reaction of the prosumers in the second stage (the lower-level problem). Furthermore, by making use of the lower-level optimality conditions and some exact linearization techniques, the bilevel problem is reformulated without approximation as a single-level mixed-integer linear problem (MILP). The uncertainty and risk is incorporated via an stochastic approach based on a discrete sample of scenarios.

1.2. Literature review

In the following, we revise the state-of-the-art on the main topics addressed in this work to better position it and to highlight its main contributions.

1.2.1. The forward contract

Most electricity markets worldwide introduce sequential trading mechanisms to help agents to hedge risk [11]. In general, the trading is firstly operated trough forward contracts, (e.g., a FM), and then in a SM, (e.g. a day-ahead or real-time market) once the uncertainty is realized.

A simple two-period model of an oligopoly is proposed by [20] to represent the sequential process of operations in FM and SM. The results show that firms can hedge their risk and improve their profit on the SM through forward contracts. The forward contract acts as a financial derivative to control the price and energy fluctuation in the SM [12]. The forward contract can also assist the energy market in social welfare and efficiency. In [13], authors found that the retailer can offer forward contracts to curb market power and maximize social welfare. [14] develops a contract portfolio optimization method to formulate an electricity retailer's objective to fulfill an uncertain demand by hedging spot price exposure with forward contracts for the later delivery of electricity. [15] extends the model in [20] to a FM for several producers with nonidentical linear cost functions, and conclude the forward trading increases market efficiency.

In addition to forward trading at the transmission level in the wholesale electricity market, forward trading at the local level has attracted great attention with the integration of smart grids that can actively manage distribution networks [21]. A novel contract-based incentive scheme is proposed in [22] to obtain the optimal contract for the short-term market with deterministic energy supply and the optimal contract for the long-term market with a significant uncertain energy supply. [23], which is motivated by markets with cyclical contractual relationships [24], proposes bilateral contract networks as a new scalable market design for peer-to-peer energy trading. Then, FM and real-time markets are introduced to incentivize coordination between the owners of large-scale and small-scale energy resources at different levels of the power system. A novel contract theoretical framework was developed in [25] to study the interactions between an aggregator and different scales of electricity suppliers in the smart grid under both base-load and peak-load scenarios.

1.2.2. Uncertainty quantification and risk-averse modeling

Uncertainty in the output power of the RES and demand loads has a great effect on the decision-making process of the energy community. Several approaches have been proposed to properly quantify these uncertainty levels. Probabilistic methodologies [26] based on standard statistical or Machine Learning techniques [27] have been used to forecast renewable energy generation and load consumption levels.

The simulation of scenarios with high or low probability of occurrence and the explicit modeling of risk aversion are considered in several energy trading applications. Based on historical data, [28] uses a seasonal autoregressive integrated moving average model to generate 500 scenarios for electricity demand, day-ahead and real-time market prices, and exported PV power. [29] conducts scenario modeling using Monte

Carlo simulations to analyze load demand, wind, and PV generation, including the risk associated with low probability scenarios with a critical effect.

Moreover, compared to the risk-neutral strategies, risk-averse decision makers adjust the probabilities of critical risk scenarios (e.g. high cost scenarios or low profit scenarios) to ensure acceptable levels of profit or costs [30]. Among the different approaches to modeling risk aversion, a coherent risk measure, the Conditional Value at Risk (CVaR), is widely used, as it can be obtained from the solution of a linear optimization problem, and can be easily incorporated into large-scale problems [31]. In [16], the strategic behavior of a distribution company in the day-ahead market is modeled using a stochastic bilevel problem with CVaR. In [29], a two-stage optimization approach with a hybrid demand response program is proposed. The economic demand response is used in the first stage, while a risk-based demand response is used to minimize the risk index determined through CVaR. CVaR has also been implemented at the local energy community level in [17], [18] and [30]. Moreover, [19] applies the CVaR to analyze the differences between risk aversion in markets with perfect and imperfect locational prices. The authors extend the electricity market in a multi-stage model, which includes transmission investment, generation investment, backup capacity, market operation, and redispatch.

1.2.3. Energy storage systems

Distributed storage systems serving as backup can not only support the balance between energy supply and demand loads, but also help end users for peak shaving, valley filling, and smoothing the price variability [32]. The energy storage systems can be classified into two categories: energy storage at the community (shared community energy storage) and household (individual batteries) levels. Research on the use of storage systems within energy communities mainly pays attention to the management of the entire community, considering both energy sharing [33, 34] and profit sharing [35, 36] in cooperative or non-cooperative game strategies. While the energy storage at the household level aims to optimize operation to be self-sufficient [37] or minimize costs [38]. Moreover, [38] considers a generalized problem for both the physical and financial storage rights, where prosumers can actively decide on the share of storage capacity to offer to other peers.

Several alternatives to store energy have been recently proposed, such as well-known battery storage, hydrogen storage, and heat or ice storage. Batteries are one of the most extended storage systems in small applications [39]. Various researchers studied the combination of PV-battery energy systems in microgrids [40] and energy communities [41]. Notably, renewable hydrogen produced from electrolysis fueled by renewable electricity acts as a prominent energy vector, especially in medium-term scenarios. [42] and [43] incorporate hydrogen storage into a solar-related energy system and use fuel cells (FCs) to convert the hydrogen into electricity. Furthermore, [44] states that renewable hydrogen is mainly used in hydrogen FC vehicles, which can serve as daily cruise and energy storage facilities to address the intermittence and instability of RES [45].

1.3. Findings and Contributions

Energy communities have been widely studied from the aspects of market framework, risk trading, and renewable generation and storage assets. The main findings of the studies mentioned above are summarized as follows.

- Most of the studies mainly focus on energy trading in wholesale markets (i.e., FMs and SMs) or local energy community markets separately. Furthermore, under a high penetration of renewable energy and uncertainty in the trading, it is vital to account for sequential trading mechanisms (FMs) to hedge stochastic short-term horizons (e.g., day-ahead) for both the wholesale and local daily markets (LDMs).
- Considering uncertainty in SMs and LDMs, risk aversion can be efficiently modeled by incorporating the CVaR in large-scale optimization problem.
- The residential storage systems, including hydrogen technologies, have attracted increasing attention but mostly focus on self-supply and load shifting strategies. However, new possibilities are opened if, as expected in the energy community paradigm, prosumers are allowed to resell their stored electricity to the grid or their hydrogen to an external potential buyer or market.

On the basis of the above analysis, we aim to investigate the energy operation and coordination under uncertainty within a local energy community considering risk aversion and different energy storage technologies, in a game-theoretical setting. Our main contributions can be recast as follows:

- Regarding the modeling of the comunity interactions, a Stackelberg game (Bilevel optimization) is adopted to model the operation of the energy community which extends standard competitive Nash-equilibrium frameworks. This is motivated by the temporal sequence of the decision making process, as the arbitrageour (leader) needs to decide beforehand the optimal forward contracting by anticipating the subsequent optimal response of prosumers (followers).
- Regarding the risk assessment, both the arbitrageur with forward contracts and prosumers with storage systems deal with uncertainty at each stage. The CVaR, is applied to estimate the optimal risk-averse strategy for the energy community, where forward contract is incorporated as a possible tool to hedge risk.
- Regarding the economical and technical analysis, we show how the arbitrageur can efficiently manage the energy community, and coordinate the prosumers, through an adequate real time price tariff system. Moreover, we focus on studying the impact of integrating hydrogen production and storage systems, together with a parallel hydrogen market. Hydrogen provides a novel alternative for prosumers to balance their decisions between hydrogen-to-electricity and hydrogen-to-sell.

The rest of the paper is organized as follows. Section 2 presents the stochastic two-stage bilevel optimization model and equivalent MILP formulas used to manage the energy community. Section 3 describes and analyzes the case study and provide insights form the numerical results. Section 4 summarizes the conclusions of this work and proposes future lines of research.

2. Model Description

We consider an energy community consisting of an arbitrageur and several prosumers $n \in N$, as depicted in Figure 1. The interactions among the community members are modeled with a two-stage stochastic decision-making process. In the first stage, also named FM, the arbitrageur signs forward contracts with the upstream grid to agree on the amount of hourly energy to be distributed within a medium-term horizon (e.g., several weeks or months in advance). Moreover, the upstream grid settles the price in the contract while the arbitrageur accepts it without bargain rights. Hence, it behaves as a price-taker in FMs.

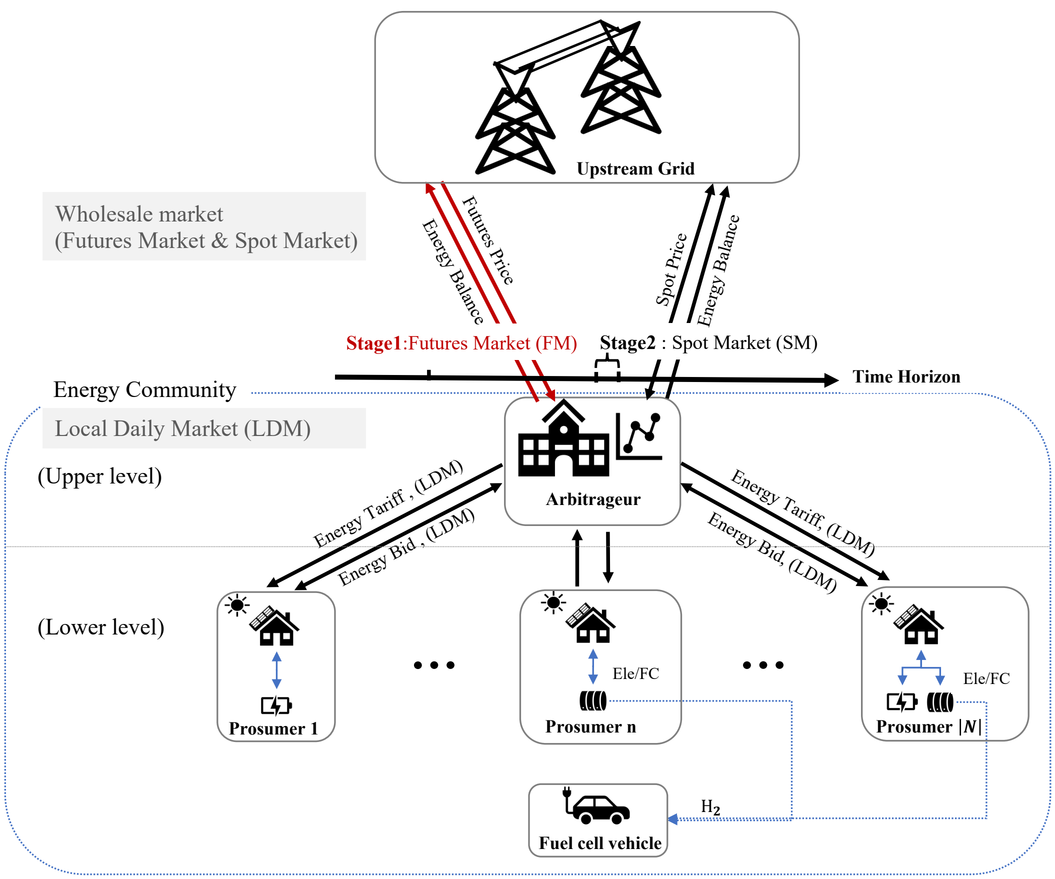


Figure 1: Structure of the energy community

In the second-stage, energy is traded with prosumers in a shorter-term horizon (e.g., One day in advance) in the LDM. In this stage, the arbitrageur anticipates possible wholesale market realizations and energy community production and load conditions. This is illustrated by generating a set of scenarios, $\omega \in \Omega$, representing the potential realizations of the SM prices, the generation of PV energy, and the net demand for each prosumer. In this LDM, also at the second-stage, the arbitrageur acts as the Leader and determines the best price tariff to interchange energy with prosumers. Prosumers play the role of Followers, which means that they design their strategies after observing the price tariff offered by the arbitrageur. Meanwhile, the arbitrageur receives the energy traded in the forward contract and buys or sells extra energy for trading with the upstream grid in the SM, at a wholesale spot price, to balance the possible net energy shortage or surplus of the community for each hour of the considered day.

Each prosumer possesses roof-top PV and energy storage systems. The energy flows within the prosumers are depicted as blue lines in Figure 1. The prosumer uses its PV system to generate energy to cover its energy demand and sell the surplus to the arbitrageur. Moreover, some of the prosumers can use the excess of electricity to charge their battery storage systems or to convert electricity to hydrogen by the electrolyzer (Ele). If the prosumer has a battery storage system, its energy can be used to cover its demand at different hour or to sell it to the arbitrageur. For instance, the prosumer can import and store electricity at low price hours and use it to cover its demand at high price hours. Moreover, if the prosumer has a hydrogen storage system, on the one hand, its hydrogen can be converted to electricity by FC for its own energy demand or to be sold to arbitrageur; on the other hand, its hydrogen can directly be sold to a potential buyer or market, or used for its own FC vehicle system, which is modeled as a potential revenue to the prosumer.

Based on the characteristics of the battery and hydrogen storage system [46], we select a daily circle (0 AM to 12 PM) as a short-term simulation. We also consider time slots $t \in T$ to optimize the whole operation of the community at the second stage of our stochastic model.

2.1. Nomenclature

The main notation used in the model formulation is introduced in the following for quick reference.

Indices:

- n Index for prosumers, where $n \in N$
- t Index for operating time units, where $t \in T$
- ω Index for possible local daily market scenarios, where $\omega \in \Omega$

Parameters:

P_t^h The price of hydrogen at time t

$D_{n\omega t}$ Energy demand load of prosumer n at time t under scenario ω

$S_{n\omega t}$ Energy generation of prosumer n at time t under scenario ω

$\overline{Q}_{nt}$ Energy trading bounds of prosumer n at time t

E_n^{BAT} The rated stationary energy storage capacity of prosumer n

E_n^{HT} The rated hydrogen tank storage capacity of prosumer n

R_n^{BAT} The rated stationary energy storage capacity for trading of prosumer n

R_n^{HT} The rated hydrogen tank storage capacity for trading of prosumer n

C^F The price of energy trading between grid and arbitrageur in futures market

$C_{\omega t}^S$ Spot market price at time t under scenario ω

$\overline{q}^F$ Bounds of energy trading between grid and arbitrageur in futures market

$\overline{q}_t^S$ Bounds of energy trading in the spot market at time t

$\overline{p}$ Bounds of the market clearing price in local daily market

η_{BAT}^- The efficiency of energy conversion from chemical energy to electrical

η_{BAT}^+ The efficiency of energy conversion from electrical to chemical energy

η_{Ele}^+ The efficiency of the electrolyzer

η_{FC}^- The efficiency of the fuel cell

M Large constant value (Big M)

Variables:

$h_{n\omega t}^{out}$ Hydrogen sold quantity of prosumer n at time t under scenario ω

$Q_{nt\omega}^S$ Energy trading quantity of prosumer n in local daily market at time t under scenario ω

$e_{n\omega t}$ Stationary battery storage quantity of prosumer n at time t under scenario ω

$e_{n\omega t}^{+/-}$ Stationary battery storage charging/discharging quantity of prosumer n at time t under scenario ω

$h_{n\omega t}$ Hydrogen storage quantity of prosumer n at time t under scenario ω

$h^{+/-}_{n\omega t}$ Hydrogen storage charging/discharging quantity of prosumer n at time t under scenario ω

q^F The quantity of energy traded between grid and arbitrageur in the futures market, which is daily delivered

$q^S_{\omega t}$ Spot market energy trading amount at time t under scenario ω

$p^S_{\omega t}$ The price of energy trading in local daily market at time t under scenario ω

2.2. Bilevel model of arbitrageur and prosumers

The strategic operation of the energy community is modeled as a bilevel model where the arbitrageur minimizes costs in the upper-level problem by anticipating the reaction of prosumers in the lower-level problem. These two inter-related problems are presented below.

2.2.1. Upper-level model: costs minimization by arbitrageur

At the upper-level, the arbitrageur minimizes the energy community total costs (negative profit) by making optimal trading decisions q^F and $q^S_{\omega t}$ in the wholesale (FM and SM) market and by setting an optimal price tariff $p^S_{\omega t}$ for the prosumers in the LDM. More specifically, at the first-stage, the arbitrageur decides the optimal involvement q^F in forward contracts (FM) at a given futures price. Then, at the second-stage, the arbitrageur decides the optimal spot trading and LDM price-tariff under each possible scenario ω (scenario dependent). These two types of decisions, despite being separately in time, belong both to the upper-level problem, as they are taken by anticipating the prosumers possible operating response, for each scenario ω, in the lower-level problem. The upper-level problem formulation is as follows:

$$\min_{q^F, q^S_{\omega t}, p^S_{\omega t}, \Xi} \quad f^A = C^F q^F + \sum_{\omega \in \Omega} \pi_\omega \left[\sum_{t \in T} \left(C^S_{\omega t} q^S_{\omega t} - p^S_{\omega t} \sum_{n \in N} Q^S_{n\omega t} \right) \right] \tag{1a}$$

s.t.

$$\sum_{n \in N} Q^S_{n\omega t} = \frac{1}{|T|} q^F + q^S_{\omega t}, \ \forall \omega, t \tag{1b}$$

$$0 \leq q^F \leq \overline{q} \tag{1c}$$

$$-\overline{q}_t \leq q^S_{\omega t} \leq \overline{q}_t, \ \forall \omega, t \tag{1d}$$

$$0 \leq p^S_{\omega t} \leq \overline{p}, \ \forall \omega, t \tag{1e}$$

$$\Xi \in \text{Lower-level model of prosumers (2)} \tag{1f}$$

Precisely, the upper-level problem (1) represents the minimization of the arbitrageur's total negative profit (cost minus revenue) in the wholesale (FMs and SMs) and LDM, subject to technical and economical constraints, and to the lower-level problem. The first term of the objective function (1a) corresponds to the cost in FM to purchase an amount of energy q^F at the fixed import price C^F. We assume that once q^F is purchased, $q^F/|T|$ is the amount of energy to be delivered during each time period of the target day in the second stage. The second term of the objective function shows the expected cost / revenue in the SM to import / export the amount of electricity $q^S_{\omega t}$ from the upstream grid at time t under scenario ω. Note that π_ω represents the probability associated with scenario ω. The third term of the objective function states the expected revenue for the arbitrageur from selling the electricity to the prosumers at the LDM price tariff $p^S_{\omega t}$. For each scenario ω at time t, the arbitrageur's energy trading balance is represented by (1b), where the total trading amount of prosumers in LDM, $\sum_{n\in N} Q^S_{n\omega t}$, equals the sum of the amount of daily distributed electricity q^F in FM and the energy exchange $q^S_{\omega t}$ in SM under scenario ω at time t.

To avoid unbounded non-realistic solutions, we fix $\overline{q}^F$ as an upper bound for q^F in the forward contract. The boundary $\overline{q}^S_t$ in the constraint (1d) is set to be coherent with boundaries of q^F and $Q^S_{n\omega t}$. Additionally, constraint (1e) sets an upper bound, $\overline{p}$, for the LDM price tariff, $p^S_{\omega t}$, decided by the arbitrageur. Finally, (1f) states that some decisions (e.g. $Q^S_{n\omega t}$) are taken within the lower-level problem, being Ξ the set containing all of them.

2.2.2. Lower-level model: cost-minimization of prosumer

At the lower-level problem, each prosumer $n \in N$ decides the optimal amount of energy to trade with the arbitrageur $Q^S_{n\omega t}$ at the price tariff $p^S_{\omega t}$, the operation of stationary battery storage, and the amount of hydrogen to produce, sell and store, for each scenario ω, to minimize their expected energy cost in the LDM. Note that prosumers can postpone their operating decisions until the uncertainty is resolved. Therefore, all the decision variables of the prosumers, recast as Ξ, are second-stage decisions and depend on scenario ω.

$$\min_{\Xi} f^p_n = \sum_{\omega\in\Omega} \pi_\omega \left[\sum_{t\in T} \left(p^S_{\omega t} Q^S_{n\omega t} - P^h_t h^{out}_{n\omega t} \right) \right] \tag{2a}$$

s.t.

$$e^+_{n\omega t} + h^+_{n\omega t} - \eta^-_{BAT} e^-_{n\omega t} - \eta^-_{FC} h^-_{n\omega t} = S_{n\omega t} + Q^S_{n\omega t} - D_{n\omega t} \qquad : \lambda_{n\omega t},\ \forall n, \omega, t \tag{2b}$$

$$e_{n\omega t} - e_{n\omega(t-1)} = \eta^+_{BAT} e^+_{n\omega t} - e^-_{n\omega t} \qquad : \mu^{BAT}_{n\omega t},\ \forall n, \omega, t \tag{2c}$$

$$h_{n\omega t} - h_{n\omega(t-1)} = \eta^+_{Ele} h^+_{n\omega t} - h^-_{n\omega t} - h^{out}_{n\omega t} \qquad : \mu^H_{n\omega t},\ \forall n, \omega, t \tag{2d}$$

$$-\overline{Q}_{nt} \le Q^S_{n\omega t} \le \overline{Q}_{nt} \qquad : \upsilon^{min}_{n\omega t}, \upsilon^{max}_{n\omega t},\ \forall n, \omega, t \tag{2e}$$

$$0 \le e_{n\omega t} \le E^{BAT}_n \qquad : \epsilon^{min}_{n\omega t}, \epsilon^{max}_{n\omega t},\ \forall n, \omega, t \tag{2f}$$

$$0 \leq e^{+}_{n\omega t}, e^{-}_{n\omega t} \leq R^{BAT}_{n} \qquad : \epsilon^{+,min}_{n\omega t}, \epsilon^{+,max}_{n\omega t}, \epsilon^{-,min}_{n\omega t}, \epsilon^{-,max}_{n\omega t}, \ \forall n, \omega, t \tag{2g}$$

$$0 \leq h_{n\omega t} \leq E^{HT}_{n} \qquad : \zeta^{min}_{n\omega t}, \zeta^{max}_{n\omega t}, \ \forall n, \omega, t \tag{2h}$$

$$0 \leq h^{+}_{n\omega t}, h^{-}_{n\omega t} \leq R^{HT}_{n} \qquad : \zeta^{+,min}_{n\omega t}, \zeta^{+,max}_{n\omega t}, \zeta^{-,min}_{n\omega t}, \zeta^{-,max}_{n\omega t}, \ \forall n, \omega, t \tag{2i}$$

$$0 \leq h^{out}_{n\omega t} \leq R^{HT}_{n} \qquad : \zeta^{out,min}_{n\omega t}, \zeta^{out,max}_{n\omega t}, \ \forall n, \omega, t \tag{2j}$$

where $\Xi = [Q^{S}_{n\omega t}, e_{n\omega t}, e^{+}_{n\omega t}, e^{-}_{n\omega t}, h_{n\omega t}, h^{+}_{n\omega t}, h^{-}_{n\omega t}, h^{out}_{n\omega t}]$. We assume that the initial state of charge (SOC) of battery $e_{n\omega(t=0)}$ and the initial SOC of hydrogen $h_{n\omega(t=0)}$ are zero. The dual variables of problem (2): $\Theta = [\lambda_{n\omega t}, \mu^{BAT}_{n\omega t}, \mu^{H}_{n\omega t}, \upsilon^{min}_{n\omega t}, \upsilon^{max}_{n\omega t}, \epsilon^{min}_{n\omega t}, \epsilon^{max}_{n\omega t}, \epsilon^{+,min}_{n\omega t}, \epsilon^{+,max}_{n\omega t}, \epsilon^{-,min}_{n\omega t}, \epsilon^{-,max}_{n\omega t}, \zeta^{min}_{n\omega t}, \zeta^{max}_{n\omega t}, \zeta^{+,min}_{n\omega t}, \zeta^{+,max}_{n\omega t}, \zeta^{-,min}_{n\omega t}, \zeta^{-,max}_{n\omega t}, \zeta^{out,min}_{n\omega t}, \zeta^{out,max}_{n\omega t}]$, are indicated after the corresponding constraints separated by a colon.

The first term in the objective function (2a) states the expected trading cost or revenue of the prosumer in the LDM. Positive values of $Q^{S}_{n\omega t}$ represent energy imports from the arbitrageur to meet an energy shortage. The negative values of $Q^{S}_{n\omega t}$ indicate the surplus energy exports sold to the arbitrageur at a price $p^{S}_{\omega t}$. The second term refers to the expected revenue from selling hydrogen to a potential buyer at a price P^{h}_{t}. Especially, the prosumer makes a trade-off to decide to export the electricity to the arbitrageur or convert it into hydrogen. Similarly, π_{ω} is the probability associated with scenario ω.

For each scenario ω and time t, the prosumer n ensures its energy balance by constraint (2b). The trading amount $Q^{S}_{n\omega t}$ is related to the PV generation $S_{n\omega t}$, the energy demand $D_{n\omega t}$, and the charging/discharging energy from the storage systems. Constraint (2c) and (2d) set the energy flow balance in the battery and hydrogen storage systems. Specifically, the energy losses during the process of charging and discharging are represented by efficiency rates, η^{+}_{BAT},η^{-}_{BAT} in the battery system, η^{+}_{Ele} for the Ele, and η^{-}_{FC} for the FC in the hydrogen storage system. (2f) and (2h) restrict the rated capacity of the storage system, while (2g), (2i) and (2j) bound the usable capacity of the storage systems. As indicated, all decision variables for prosumers are scenario dependent (second stage decision variables), and hence problem (2) can be decomposed and solved independently per scenario.

2.3. MPEC formulation of arbitrageur and prosumer

Since the price tariff for energy trading in SM ($p^{S}_{\omega t}$) is decided by the arbitrageur (upper-level), it is considered as a parameter in the prosumer lower-level problem. This makes the objective function of the prosumer and its constraints linear and thus convex. Therefore, we can calculate the Karush-Kuhn-Tucker (KKT) optimality conditions for each prosumer problem (2) as follows:

$$p^{S}_{\omega t} - \lambda_{n\omega t} - \upsilon^{min}_{n\omega t} + \upsilon^{max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3a}$$

$$\mu^{BAT}_{n\omega t} - \mu^{BAT}_{n\omega(t+1)} - \epsilon^{min}_{n\omega t} + \epsilon^{max}_{n\omega t} = 0, \quad \forall n, \omega, t < T \tag{3b}$$

$$\mu^{BAT}_{n\omega T} - \epsilon^{min}_{n\omega T} + \epsilon^{max}_{n\omega T} = 0, \quad \forall n, \omega, t = T \tag{3c}$$

$$\lambda_{n\omega t} - \mu^{BAT}_{n\omega t}\eta^{+}_{BAT} - \epsilon^{+,min}_{n\omega t} + \epsilon^{+,max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3d}$$

$$-\lambda_{n\omega t}\eta^{-}_{BAT} + \mu^{BAT}_{n\omega t} - \epsilon^{-,min}_{n\omega t} + \epsilon^{-,max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3e}$$

$$\mu^{H}_{n\omega t} - \mu^{H}_{n\omega(t+1)} - \zeta^{min}_{n\omega t} + \zeta^{max}_{n\omega t} = 0, \forall n, \omega, t < T \tag{3f}$$

$$\mu^{H}_{n\omega T} - \zeta^{min}_{n\omega T} + \zeta^{max}_{n\omega T} = 0, \quad \forall n, \omega, t = T \tag{3g}$$

$$\lambda_{n\omega t} - \mu^{H}_{n\omega t}\eta^{+}_{Ele} - \zeta^{+,min}_{n\omega t} + \zeta^{+,max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3h}$$

$$-\lambda_{n\omega t}\eta^{-}_{FC} + \mu^{H}_{n\omega t} - \zeta^{-,min}_{n\omega t} + \zeta^{-,max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3i}$$

$$-P^{h}_{t} + \mu^{H}_{n\omega t} - \zeta^{out,min}_{n\omega t} + \zeta^{out,max}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{3j}$$

$$0 \leq \overline{Q}_{nt} - Q^{S}_{n\omega t} \perp \upsilon^{max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3k}$$

$$0 \leq \overline{Q}_{nt} + Q^{S}_{n\omega t} \perp \upsilon^{min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3l}$$

$$0 \leq e_{n\omega t} \perp \epsilon^{min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3m}$$

$$0 \leq E^{BAT}_{n} - e_{n\omega t} \perp \epsilon^{max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3n}$$

$$0 \leq e^{+}_{n\omega t} \perp \epsilon^{+,min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3o}$$

$$0 \leq R^{BAT}_{n} - e^{+}_{n\omega t} \perp \epsilon^{+,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3p}$$

$$0 \leq e^{-}_{n\omega t} \perp \epsilon^{-,min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3q}$$

$$0 \leq R^{BAT}_{n} - e^{-}_{n\omega t} \perp \epsilon^{-,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3r}$$

$$0 \leq h_{n\omega t} \perp \zeta^{min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3s}$$

$$0 \leq E^{HT}_{n} - h_{n\omega t} \perp \zeta^{max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3t}$$

$$0 \leq h^{+}_{n\omega t} \perp \zeta^{+,min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3u}$$

$$0 \leq R^{HT}_{n} - h^{+}_{n\omega t} \perp \zeta^{+,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3v}$$

$$0 \leq h^{-}_{n\omega t} \perp \zeta^{-,min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3w}$$

$$0 \leq R^{HT}_{n} - h^{-}_{n\omega t} \perp \zeta^{-,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3x}$$

$$0 \leq h^{out}_{n\omega t} \perp \zeta^{out,min}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3y}$$

$$0 \leq R^{HT}_{n} - h^{out}_{n\omega t} \perp \zeta^{out,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{3z}$$

$$\lambda_{n\omega t}, \mu^{BAT}_{n\omega t}, \mu^{H}_{n\omega t} \quad \text{free}, \quad \forall n, \omega, t \tag{3aa}$$

$$\text{Contraints (2b)} - \text{(2d)} \tag{3ab}$$

Then, by replacing each lower-level problem by its optimality conditions in (1), we would obtain a single-leveled MPEC:

$$\min_{q^F, q^S_{\omega t}, p^S_{\omega t}, \Xi, \Theta} \quad f^A = C^F q^F + \sum_{\omega \in \Omega} \pi_\omega \left[\sum_{t \in T} \left(C^S_{\omega t} q^S_{\omega t} - p^S_{\omega t} \sum_{n \in N} Q^S_{n\omega t} \right) \right] \tag{4a}$$

s.t.

$$\sum_{n \in N} Q^S_{n\omega t} = \frac{1}{|T|} q^F + q^S_{\omega t}, \ \forall \omega, t \tag{4b}$$

$$0 \leq q^F \leq \overline{q} \tag{4c}$$

$$-\overline{q}_t \leq q^S_{\omega t} \leq \overline{q}_t, \ \forall \omega, t \tag{4d}$$

$$0 \leq p^S_{\omega t} \leq \overline{p}, \ \forall \omega, t \tag{4e}$$

$$\text{KKT optimality conditions (3)}, \forall n \in N \tag{4f}$$

2.4. Linearised MPEC Formulation

To simplify and speed up the solving process, exact linearization techniques are adopted to transform the nonlinear MPEC formulation into the MILP problem. For the complementarity conditions (3k)-(3z) the disjunctive mixed-integer linear formulation [47] is applied. Specifically, the complementarity conditions of the form $0 \leq \mu \perp x \geq 0$ (equivalent to $\mu \geq 0$, $x \geq 0$ and $\mu x = 0$) are replaced by $\mu \geq 0, x \geq 0, \mu \leq \alpha M, x \leq (1-\alpha) M, \alpha \in \{0, 1\}$, where α is an auxiliary binary variable and M is a large positive constant ("Big M"). The linearised complementarity conditions are formulated in the Appendix A.2.

Besides, the nonlinear term $p^S_{\omega t} \sum_{n \in N} Q^S_{n\omega t}$ from the objective function (4a), can be linearized by using the strong duality equality (9) derived in Appendix A.1.

$$\sum_{t \in T} p^S_{\omega t} Q^S_{n\omega t} = g^p_{n\omega} + \sum_{t \in T} P^h_t h^{out}_{n\omega t}. \qquad \forall n, \omega \tag{5}$$

By linearizing the complementarity conditions, as indicated above, and replacing (5) into (4a), we obtain the final MILP formulation of MPEC (4).

2.5. Risk-based linearised MPEC Formulation

To reduce the negative effect of high-cost scenarios, a coherent risk measure, CVaR [31], regarded as the mean loss or the average value at risk by calculating the expected cost among $(1-\alpha) \times 100\%$ worst scenarios, is included in the linearized single-level version of the MPEC (4). The objective function (4a) is reformulated as

$$\min_{q^F, q^S_{\omega t}, p^S_{\omega t}, \Xi, \Theta, \eta, z_\omega} \quad (1-\beta) f^A + \beta \left\{ \eta + \frac{1}{1-\alpha} \sum_{\omega \in \Omega} \pi_\omega z_\omega \right\} \tag{6}$$

and the following constraints are added to the problem: $z_\omega \geq f^A_\omega - \eta, z_\omega \geq 0, \beta \in [0, 1], \alpha \in (0, 1)$, $\forall \omega$. f^A denotes the objective function (4a) in the model (4), η stands for the value-at-risk at the optimal solution, and z_ω is an auxiliary variable. Furthermore, α is the confidence level of CVaR, and β is the trade-off parameter of the objective function (4a) and the corresponding CVaR [31].

3. Numerical Study and Discussion

The case study focuses on investigating the influence of risk aversion, the storage technologies adopted by prosumers, and the external hydrogen energy market on the operation of the energy community. In the first part of the case study, we set the price of hydrogen as a fixed value and a range of risk-aversion levels are tested to analyze the resulting market equilibrium. Then we focus on analyzing the arbitrageur's cost, its decisions, and each prosumer's operation of the PV and storage systems. In the second part, we study how prices of hydrogen may affect the energy community market outcomes. Moreover, we analyze the cost and revenue components in the objective function of each prosumer to shed light on the relationship between the storage technology and the trading behavior.

3.1. Data description

We consider a local energy community with one arbitrageur and three prosumers. Renewable energy and storage assets for each prosumer are listed in Table 1. The parameters of the battery and hydrogen storage systems are calibrated based on [37]. The rated battery unit capacity is 7 kWh, while the usable battery unit capacity is 6.6 kWh. The efficiencies of charging η^+_{BAT} and discharging η^-_{BAT} of the battery inverter are 90%. In the hydrogen storage system, the Ele's power input and the FC's electric power are 7 kWh. So we set the rated and usable capacity of the hydrogen tank to 7 kWh. The efficiency of the Ele inverter for producing hydrogen η^+_{Ele} is 75%, and the efficiency of the FC inverter for consuming hydrogen η^-_{FC} is 90%. Based on the minimum and median price of hydrogen in Europe in 2020 [48], we consider the price of hydrogen to vary within the interval [5.13, 8.4] €/kg. According to the technical setting of Ele in [37], we consider an input electricity of 7 kW and an output of 0.15 kg of hydrogen per hour. Hence, we can assume the hydrogen energy price to vary within [110, 180] €/MWh (Table 2).

Table 1: Renewable assets of prosumers

Prosumers	**PVs**	**Battery Storage**	**Hydrogen Storage**
$n = 1$	✓	✓	×
$n = 2$	✓	×	✓
$n = 3$	✓	✓	✓

Table 2: Samples of hydrogen price

p^H	**Samples**							
€/kg	5.13	5.60	6.07	6.53	7.00	7.47	7.93	8.40
€/MWh	110	120	130	140	150	160	170	180

We use hourly price and demand values in the SM of the real-world data source: the Spanish part of the Iberian market for 2020 [49]. Furthermore, we tailor each standardized one-month data to the corresponding monthly household scale according to energy production and consumption in [37]. Then, we calculate each hour's mean value and covariance value based on one-month sample data. Lastly, 300 scenarios are generated by a multivariate normal distribution to describe possible realizations of the uncertainties. To study the respective seasonal dependencies more clearly, we implement computational experiments on three representative days corresponding to the Winter, Midseason, and Summer months. Table 3 reports the energy generation (PV) and demand in these three representative days, which are sampled from the months of February, March, and August [37]. Note that the Winter day is characterized by a low level of PV generation and high demand, the Summer day with high levels of PV generation and low demand, and the Midseason day by an approximately equal levels of both.

Table 3: Energy production (PV) and consumption for each representative day

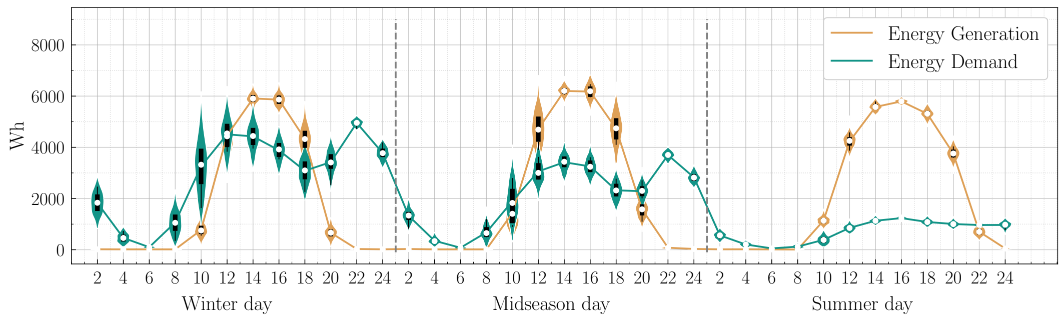
Day	**PV generation [kWh]**	**Demand [kWh]**
Winter	624.23	1017.12
Midseason	769.07	781.13
Summer	823.30	265.70

The considered SM price is equal to the Iberian market's spot price [50], and a normal distribution with the same mean value and standard deviation is used to generate the corresponding scenarios. Meanwhile, the mean value of the randomly generated SM prices is used to fix the FM price (non-arbitrage assumption). All the boundary values (e.g., the maximum storage amount, the maximum trading amount and the maximum price) are set according to the technical characteristics of the storage system or the real-world trading price. In particular, to allow for a proper comparison, all the parameter-setting is the same for all prosumers.

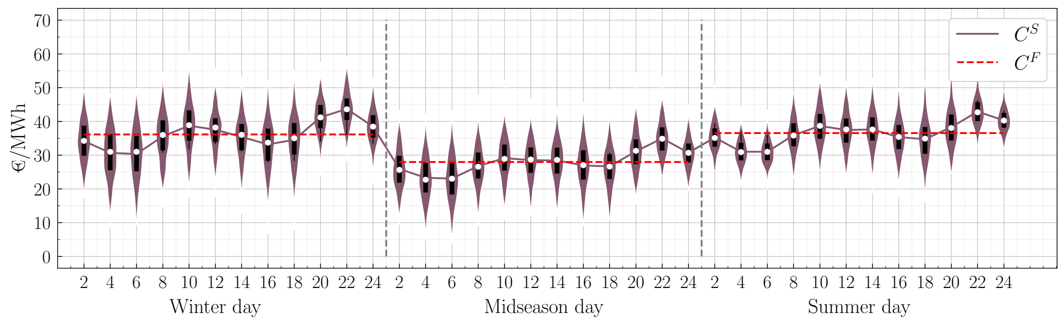
Due to the high computational burden of the resulting large-scale MILP problem, we approximate the entire daily time horizon by 12 pairwise time intervals (two hours). Fig 2 displays the final data sample. The violin plots show the scenario distribution for energy generation and demand, as well as the SM price, for each representative day. The red dashed horizontal line shows the FM price considered for each representative day.

3.2. Computational Setup

We address the solution of the MILP formulation of the MPEC problem (presented in Section 2.4) with Gurobi Optimizer version 9.5.0 under python 3.9.7 on a system with an Intel i7 processor with 64GB RAM computer clocking at 2.90 GHz. When addressing the problem for the midseason and summer days, the optimality gaps are relaxed to 1%. For the winter case, the time limit for the solver is set to 10 hours, which results in optimality gaps that do not exceed 1.7%.



(a) Two-hour interval of PV energy generation and prosumers' energy demand



(b) Two-hour interval of spot market price

Figure 2: Sample data on three representative days

3.3. Impact of risk aversion on energy community

In this section, we analyze the operation of the entire energy community from neutral, $\beta = 0$ to highly risk-averse $\beta = 0.99$, with a CVaR confidence level $\alpha = 0.9$. At the same time, we assume the price of hydrogen is fixed to the price considered in [48] of 180 €/MWh.

Figure 3 depicts the cost distribution of the arbitrageur for increasing risk-aversing degrees in the three representative days. The violin-shaped pattern covers the cost of 300 scenarios corresponding to each degree of risk aversion, β. The black box inside shows the 20th and 80th cost quantiles. The cost mean value is the white circle in the middle of the black box and is linked by the black line. The blue line shows the CVaR with the confidential level $\alpha = 0.9$. The results show that as the arbitrageur becomes more risk-averse, the cost volatility reduces as it tends to make more conservative decisions. Moreover, increasing risk aversion leads to a lower CVaR, preventing the arbitrageur from high-cost situations on all three representative days. We can observe that both the CVaRs in Winter and Midseason days decrease dramatically from risk neutral ($\beta = 0$) to slight risk averse ($\beta = 0.01$) and then remain stable. In comparison, the CVaRs in Summer days reduce slowly from risk neutral ($\beta = 0$) to a risk aversion level of $\beta = 0.5$ and then it stabilizes. This indicates that the arbitrageur risk exposure is higher on Winter and on Midseason than in the Summer days. However, it should be noted that the costs in all three representative days converge with high-risk aversion levels.

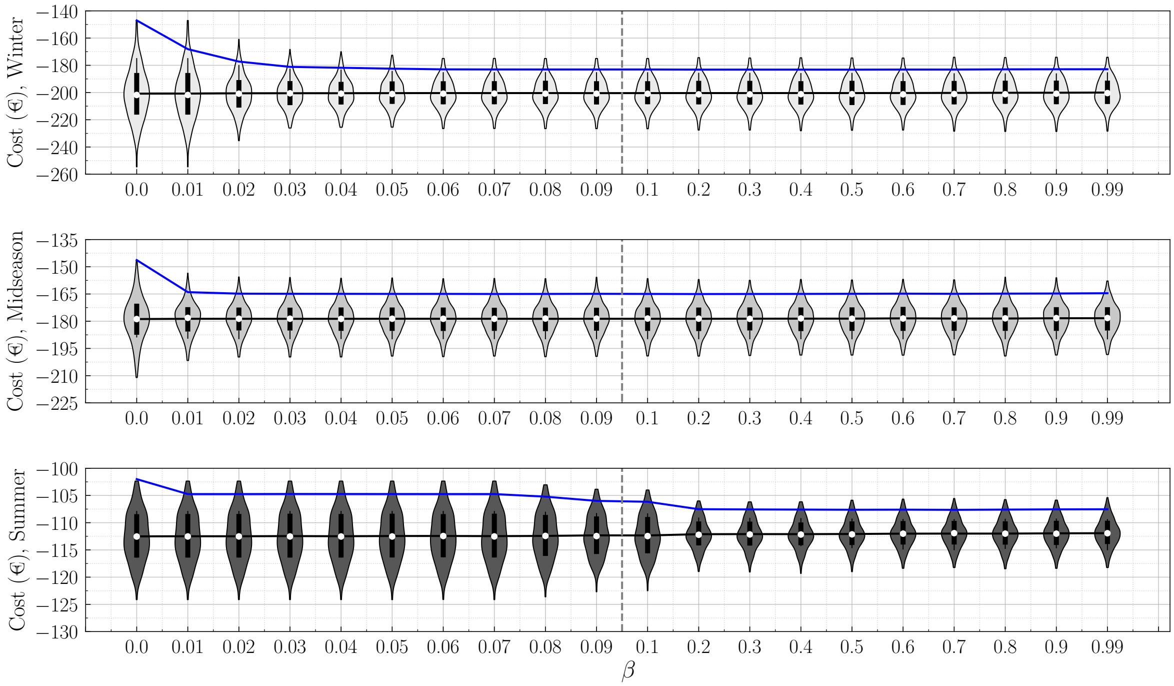


Figure 3: The cost (€) of the arbitrageur under risk aversion in three typical seasonal days.

Table 4 provides the costs for all the energy community members in more detail. As we can observe for the arbitrageur, there is not much difference in the mean values of costs for different levels of risk aversion (β) and seasons. On the other hand, the standard deviations of costs decrease significantly, which is displayed as the decreased cost dispersion for a high-risk preference in Figure 3. However, the standard deviation of the costs for the three prosumers remain quite stable with risk aversion, being comparatively much higher than the arbitrageur ones. Based on the designed market trading mechanism, the arbitrageur hedges risk in a two-stage setting (FM, SM and LDM). In contrast, prosumers only trade in the second-stage (the scenario dependent LDM) and are fully exposed to uncertainty.

By analyzing the costs between prosumers, we found that prosumer $n = 1$ with the battery storage system has a higher cost than prosumer $n = 2$ and $n = 3$, with hydrogen storage systems. In particular, the costs of prosumer $n = 2$ almost equal the costs of prosumer $n = 3$. Despite the costly conversion of energy-to-hydrogen and prices of electricity and hydrogen, prosumer $n = 2$ and $n = 3$ can reduce their costs by participating in the external hydrogen market. A similar cost evolution can be found for the Midseason and Summer days.

Table 4: The mean value and standard deviation of cost (€). f^A, $f^{n=1}$, $f^{n=2}$, $f^{n=3}$ represents the costs of arbitrageur, prosumer $n = 1$, prosumer $n = 2$, prosumer $n = 3$, respectively.

β	**Cost (€) in Winter (Energy Generation <Energy Demand)**				
	f^A	$f^{n=1}$	$f^{n=2}$	$f^{n=3}$	**Total**
0	-200.82±18.14	17.64±4.72	16.18±4.7	16.18±4.7	-150.82±17.84
0.04	-200.50±10.27	17.63±4.72	16.18±4.72	16.18±4.72	-150.51±6.62
0.08	-200.39±9.83	17.61±4.71	16.19±4.73	16.19±4.73	-150.39±4.88
0.1	-200.42±9.83	17.62±4.71	16.19±4.74	16.19±4.74	-150.40±4.88
0.4	-200.38±9.87	17.61±4.71	16.18±4.73	16.18±4.73	-150.40±4.53
0.8	-200.19±9.93	17.56±4.72	16.20±4.73	16.20±4.73	-150.23±4.48
0.99	-200.02±9.87	17.50±4.72	16.38±4.82	16.38±4.82	-149.74±4.73
β	**Cost (€) in Midseason (Energy Generation ≈ Energy Demand)**				
	f^A	$f^{n=1}$	$f^{n=2}$	$f^{n=3}$	**Total**
0	-178.81±11.65	0.92±3.21	-0.40±3.33	-0.40±3.33	-178.68±8.98
0.04	-178.67±7.91	0.8±3.23	-0.26±3.35	-0.26±3.35	-178.39±2.53
0.08	-178.68±7.85	0.8±3.18	-0.26±3.41	-0.26±3.41	-178.40±2.54
0.1	-178.64±7.83	0.77±3.18	-0.24±3.41	-0.24±3.41	-178.35±2.48
0.4	-178.58±7.82	0.73±3.17	-0.17±3.43	-0.17±3.43	-178.19±2.48
0.8	-178.51±7.86	0.70±3.21	-0.18±3.38	-0.18±3.38	-178.17±2.35
0.99	-178.34±7.88	0.57±3.21	0.03±3.42	0.03±3.42	-177.71±2.40
β	**Cost (€) in Summer (Energy Generation >Energy Demand)**				
	f^A	$f^{n=1}$	$f^{n=2}$	$f^{n=3}$	**Total**
0	-112.51±4.49	-23.46±1.05	-24.74±1.27	-24.74±1.27	-185.45±3.98
0.04	-112.49±4.48	-23.56±1.03	-24.68±1.28	-24.68±1.28	-185.42±3.97
0.08	-112.43±4.19	-23.59±1.04	-24.67±1.28	-24.67±1.28	-185.36±3.64
0.1	-112.34±3.63	-23.61±1.05	-24.65±1.27	-24.65±1.27	-185.26±2.96
0.4	-112.10±2.55	-23.58±1.02	-24.68±1.28	-24.68±1.28	-185.03±1.42
0.8	-112.00±2.51	-23.73±1.02	-24.58±1.26	-24.58±1.26	-184.89±1.35
0.99	-111.93±2.49	-23.87±1.04	-24.51±1.24	-24.51±1.24	-184.83±1.36

Interestingly, when we move from Winter to Midseason, and then to Summer, prosumers produce more energy and consume less, according to Table 3. Meanwhile, the costs of prosumers decrease from Winter to Midseason days, and they even earn significant profits (negative costs) for selling surplus energy on Summer days. Oppositely, the arbitrageur makes less profit in Summer as prosumers need to purchase less energy from the grid. The energy community (last column of Table 4) achieves a net expected profit for all days and the risk aversion levels considered, decreasing slightly with the risk aversion level, but also reducing their standard deviation. The higher total profits are obtained in the Summer days, due to high levels of PV generation.

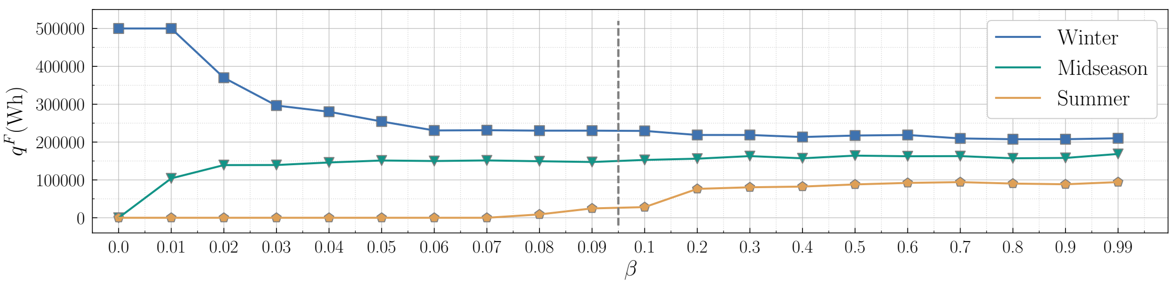
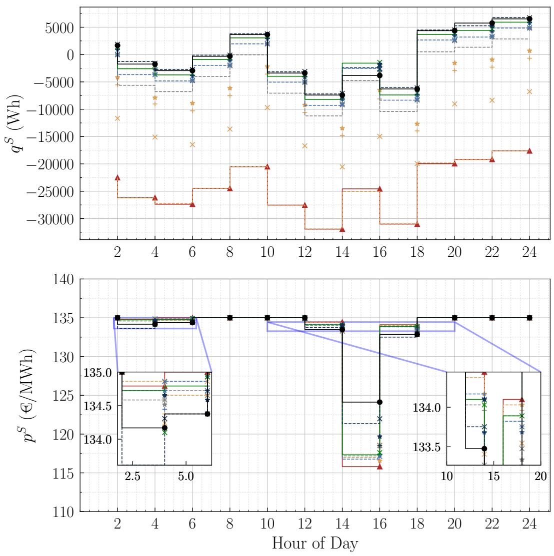


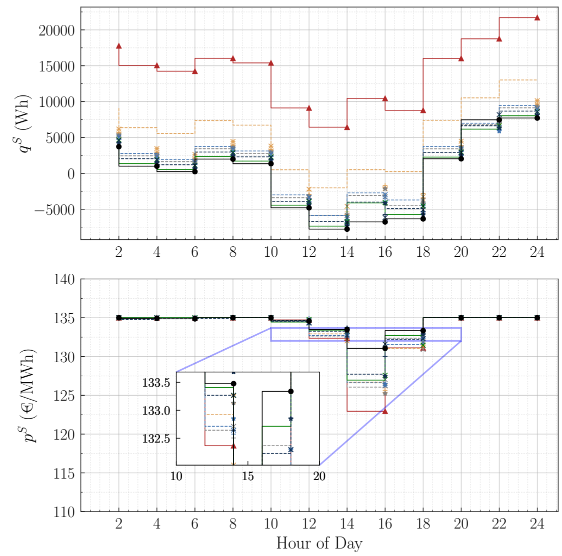
Figure 4: Arbitrageur's trading amount in forward contracts with risk aversion

Figures 4 and 5 show the arbitrageur's optimal trading levels in the forward (q^F) and SMs (q^S), as well as the price tariffs (p^S) submitted to prosumers for each time period in the LDM, for different levels of risk aversion. Notably, the trading amount in forward contracts in Figure 4 displays an opposite behavior between the Winter days and the other two seasonal days. For the Winter day, the risk-neutral ($\beta = 0$) arbitrageur trades a large amount of energy through the forward contract. This indicates that the arbitrageur would like to ensure the supply of sufficient energy to prosumers in Winter days when there is less PV generation and a high demand load. Nevertheless, the negative trading amount in Figure 5(a) shows that the risk-neutral arbitrageur returns part of the energy surplus from the forward contract to the grid in the SM. Moreover, from Figure 4 and Figure 5, we can observe that the risk-averse arbitrageur ($\beta > 0$) reduces the level of forward trading and increase the level of spot trading in Winter days, which converge with high risk-aversion levels.

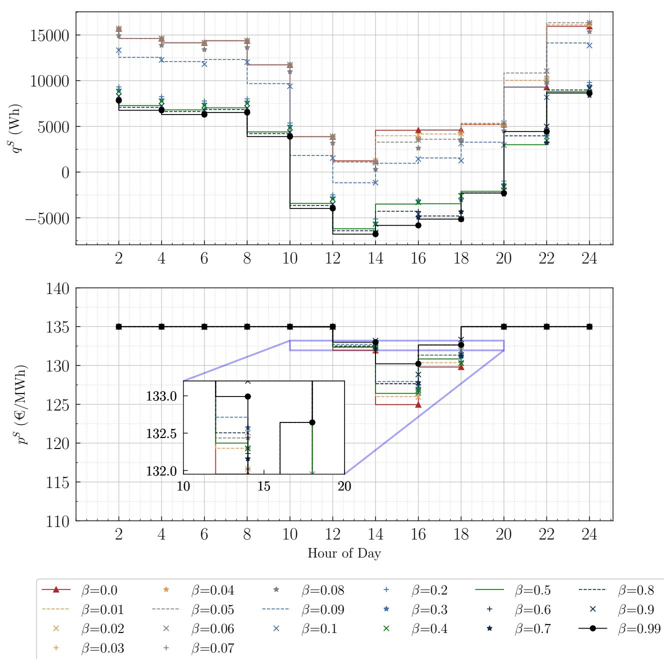
In contrast, the risk-neutral ($\beta = 0$) arbitrageur on the Midseason and Summer days does not purchase energy in the FM, $q^F = 0$ (Figure 4). This is because the risk-neutral arbitrageur is less motivated to sign forward contracts in advance when the prosumers can supply their own demand loads, on expectation. Moreover, for the Midseason day, the arbitrageur starts to trade by forward contracts once the risk level increases above $\beta = 0.01$. While for the Summer day, the arbitrageur behaves insensitive to the risk aversion level up to $\beta = 0.08$ and then increases its forward trading slowly. In other words, the higher self-sufficiency of the energy community on Summer days leads to a slight increment of forward trading with the increase of risk aversion. Besides, the risk-



(a) Winter



(b) Midseason



(c) Summer

Figure 5: Average quantities and prices in the LDM.

neutral ($\beta = 0$) arbitrageur on the Midseason and Summer days only imports energy from the grid in the SM, which is displayed as the upper red line in Figure 5(b), (c). With the increase of risk aversion, we can observe from Figure 4 and Figure 5 that the arbitrageur reallocates its trading from the SM to the FM and converges with high levels of risk aversion.

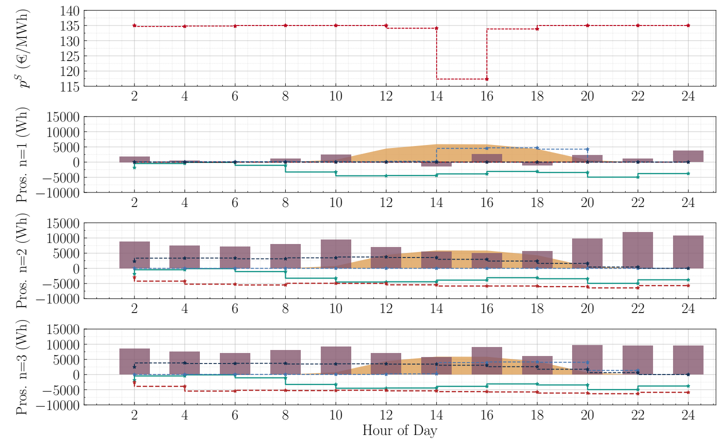
Analogously, on all three representative seasonal days, it can be seen that the LDM price tariffs are increased by the arbitrageur and become more stable through the day when risk aversion level rises. To sum up, a risk-neutral ($\beta = 0$) arbitrageur with high levels of self-sufficiency within the energy community, would prefer to trade mainly in the SM; in contrast, a risk-neutral ($\beta = 0$) arbitrageur with a self-insufficient energy community, is motivated to increase the FMs trading. Moreover, with an increase in the risk aversion level, the arbitrageur's trading amounts in the forward contracts converge to 62.5% of the total trading.

To study the respective seasonal dependencies more clearly, we present each prosumer's optimal power operation with a fixed risk level of $\beta = 0.5$ in the three representative seasonal days, as shown in Figure 6. The price tariffs in the LDM are displayed in the upper part of Figure 6(a), (b), and (c). Figure 6 also illustrates the power flow of each prosumer: The energy sources such as power bought from the arbitrageur, PV generation, and SOC for battery or hydrogen system are shown above zero. The power surpluses sold to the arbitrageur, its load demand, and hydrogen sales are plotted below zero.

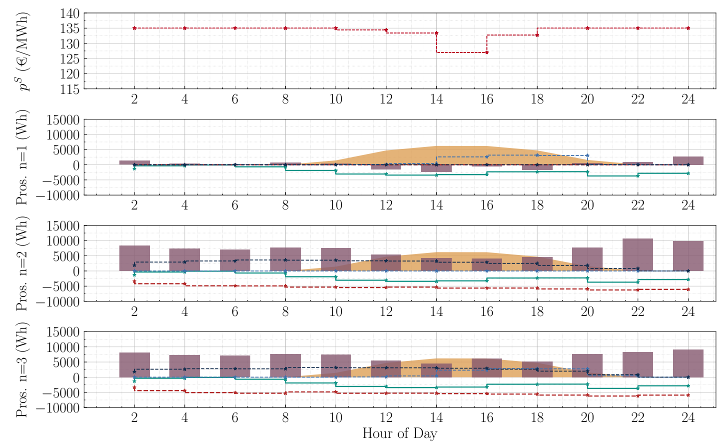
Given the PV generation and demand loads for each representative day in Table 3, and the LDM prices, each prosumer decides its trading amount with the arbitrageur, the SOC for battery and hydrogen, and the amount of generated hydrogen to be sold. Here, we found that the prosumer $n = 1$, who owns only the battery, buys energy from the arbitrageur during several specific hours (e.g., 0:00-10:00, 15:00-16:00, and 20:00-24:00) in Winter day, whereas this prosumer buys smaller amounts of energy during periods with low PV generation (e.g., 0:00-10:00, 22:00-24:00) in Midseason and Summer days. Moreover, prosumer $n = 1$ sells its energy surplus to the arbitrageur in those hours with high PV generation.

Interestingly, it can be seen that prosumer $n = 1$ starts to charge its battery by importing energy from the arbitrageur when the price tariff goes down (from hour 14:00) in Winter and by storaging its PV generation surplus from hour 12:00, for both Midseason and Summer days. Then the prosumer $n = 1$ keeps the storage at full capacity until the hour 20:00, when the price tariff rises to the maximum value. Prosumer $n = 1$ can shift its imported energy load by charging/discharging the battery system. The prosumer $n = 3$ operates in a similar charging/discharging way its battery system.

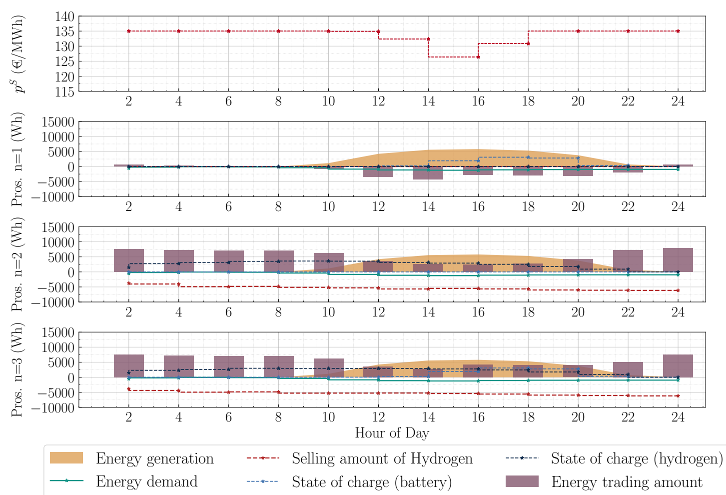
On the other hand, two parts of the hydrogen system work in parallel, the Ele converts the purchased energy into hydrogen, and the stored hydrogen in the tank is sold out. Because of favorable hydrogen prices, prosumer $n = 2$ and $n = 3$ are driven to convert electricity to hydrogen by buying a large amount of energy from the arbitrageur



(a) Winter



(b) Midseason



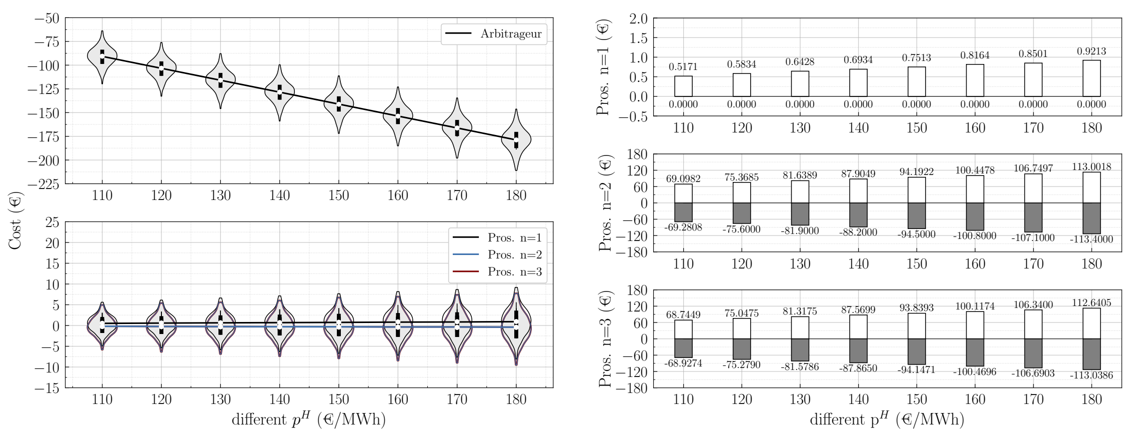
(c) Summer

Figure 6: Power operation for each prosumer in three representative days for $\beta = 0.5$.

and using its surplus PV power to produce hydrogen. The main difference between the prosumer $n = 2$ and $n = 3$ is that the prosumer $n = 3$ can use its battery system to store energy when the tariff is cheaper at 16:00 and release the energy from the battery at the time of 20:00-22:00 to reduce its cost. It is worth mentioning that prosumer $n = 1$ and $n = 3$ only charge their battery system once a day as there is only one valley in the price tariff evolution in the LDM. This leads to the similar cost observed for prosumer $n = 2$ and $n = 3$, which is shown in Table 4. In comparison, the prosumer $n = 2$ and $n = 3$ make use of their hydrogen system in each hour of the day. That's why there is significant difference in the cost of prosumer $n = 1$ and $n = 3$ in Table 4.

3.4. Impact of an external hydrogen energy market

In this section, we analyze the impact of an external hydrogen market on the performance of the entire energy community. The aim is to see how a variation of the hydrogen price (expected to decrease with technological improvements in the coming years) may affect the trading strategies and the LDM outcomes. For this study, we focus on the risk neutral case ($\beta = 0$), and on the representative Midseason day, although similar qualitative results can be obtained for the rest of the cases analyzed in the previous section. Based on the hydrogen price ranges in [48], we select eight possible values of the hydrogen price belonging to the interval [110, 180] €/MWh with an increasing step of ten €/MWh, as reported in table 2.



(a) Total Costs

(b) Cost components

Figure 7: Impact of hydrogen price P^H on (a) cost (€) distribution of the arbitrageur and prosumers, and (b) energy importing cost (white bar) and hydrogen sales (grey bar).

Figure 7 presents the cost evolution in a risk-neutral energy community considering different hydrogen prices. The upper part of the figure 7(a) shows that the cost of the arbitrageur decreases significantly when the price of hydrogen increases. From the lower part in Figure 7(a) and figure 7(b), it can be seen that the expected cost of prosumer

$n = 1$ increases slightly, while there exist few reductions in the costs of prosumers $n = 2$ and $n = 3$, which include hydrogen production and storage technologies. The figure 7(b) infers that, as the price of hydrogen increases, both the cost of energy importation and the revenue of hydrogen sales increase for prosumers $n = 2$ and $n = 3$.

Table 5: The mean value and standard deviation of cost (€). f^A, $f^{n=1}$, $f^{n=2}$, $f^{n=3}$ represents the cost of arbitrageur, prosumer $n = 1$, prosumer $n = 2$, prosumer $n = 3$.

p^H (€/MWh)	Cost (€) in Midseason (Energy Generation ≈ Energy Demand)				
	f^A	$f^{n=1}$	$f^{n=2}$	$f^{n=3}$	**Total**
110	-90.74±9.53	0.52±1.94	-0.18±2.06	-0.18±2.06	-90.59±9.02
120	-103.32±9.77	0.58±2.12	-0.23±2.25	-0.23±2.25	-103.20±9.00
130	-115.90±10.04	0.64±2.31	-0.26±2.43	-0.26±2.43	-115.78±8.99
140	-128.46±10.29	0.69±2.47	-0.30±2.60	-0.30±2.60	-128.36±8.99
150	-141.07±10.63	0.75±2.65	-0.31±2.81	0.31±2.81	-140.93±8.99
160	-153.66±10.96	0.82±2.84	-0.35±2.97	-0.35±2.97	-153.54±8.98
170	-166.20±11.29	0.85±3.02	-0.35±3.16	-0.35±3.16	-166.05±9.01
180	-178.81±11.65	0.92±3.21	-0.40±3.33	-0.40±3.33	-178.68±8.98

Table 5 details the costs for the arbitrageur, prosumers and the entire energy community. Overall, a high hydrogen price increases the profits (negative costs) of all members of the community, except the prosumer $n = 1$ with no hydrogen technology. But this also increases the cost variability. Note that the standard deviation of the arbitrageur increases from 9.53 to 11.65. Moreover, prosumers have a 33.33% increment (1.94 to 3.21 and 2.06 to 3.33) of their cost standard deviation. Especially compared to prosumer $n = 1$, prosumer $n = 2$ and $n = 3$ have larger standard deviations, as they integrate hydrogen technologies.

Figure 8 illustrates the trading amounts and price tariffs of the arbitrageur in the LDM during the representative day. Similarly to the risk-neutral behavior reported in Figure 4, for the Midseason day, the arbitrageur does not purchase energy in the FM ($q^F = 0$) despite the increasing hydrogen price. Meanwhile, the upper Figure 8 shows that the arbitrageur trades in the SM are not significantly affected by the hydrogen price. On the contrary, as can be appreciated in the lower part of Figure 8, the arbitrageur raises substantially the LDM price tariff offered to prosumers as the hydrogen price grows.

In summary, according to Figures 7, 8 and Table 5, the varying hydrogen price in the external hydrogen trading market impact the price tariff inside the energy community but has few effects on the trading amounts of the arbitrageur and prosumers. As a price-maker in the local market, the arbitrageur tends to increase the price tariff once the hydrogen price rises, which induces a higher revenue for the arbitrageur. On the other hand, as price-takers, prosumers face higher purchasing electricity costs. However, prosumer $n = 2$ and $n = 3$ can compensaty this cost increment by selling the produced hydrogen, while the prosumer $n = 1$, who does not possess the hydrogen system, is forced to purchase energy at a higher price.

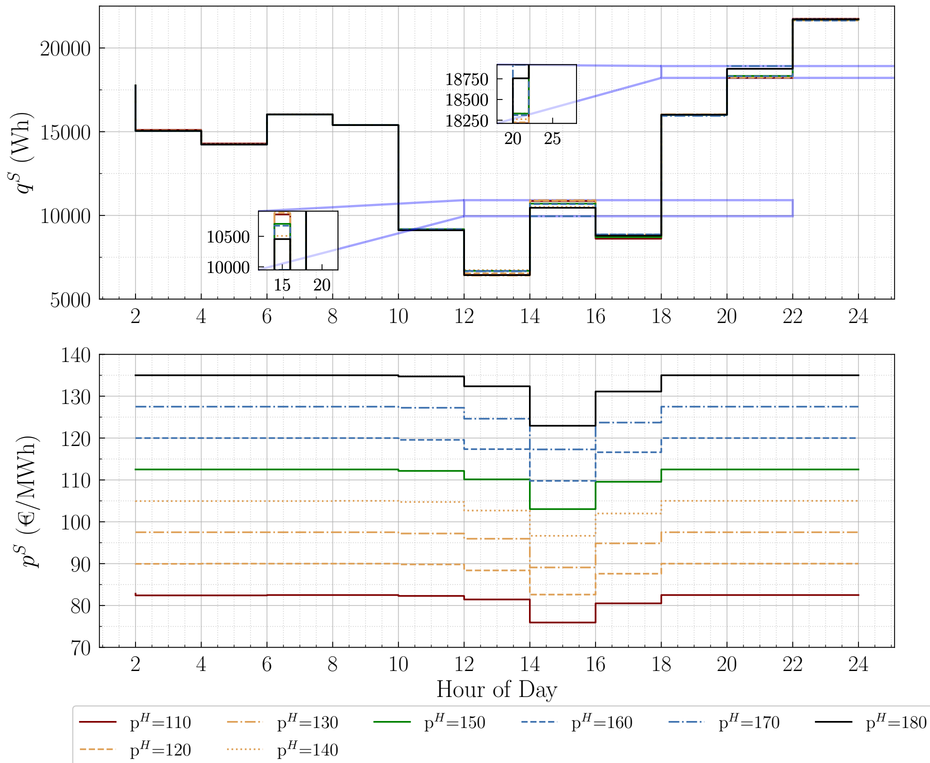


Figure 8: Average trading amounts of arbitrageur in the SM q^S and average trading price between arbitrageur and prosumers in LDM p^S as a function of the hydrogen price.

4. Conclusion and Future Work

In this paper, we analyze the operation of an energy community under uncertainty considering both medium- and short-term time horizons. We show how an arbitrageur can effectively coordinate the operation of several prosumers and manage uncertainty by participating in two-stage wholesale markets and by setting an adequate local price tariff system.

The arbitrageur hedges its risk by allocating the trading amount in forward and SMs, and prosumers incorporate storage technologies into their residential renewable energy system. Moreover, we study the influence of prosumers with hydrogen systems on the performance of the entire energy community because they can participate in an external hydrogen market. Furthermore, we consider prosumers can trade their net surpluses or shortage of energy at a LDM where the price tariff is decided by the arbitrageur.

In order to appropriately model the interaction of the arbitrageur and prosumers, we consider a Stackelberg game and apply bilevel modeling techniques. Moreover, a stochastic two-stage decision framework is used to model the arbitrageur's strategy in forward and SMs. The uncertainty in the second-stage (SM and LDM) is represented with large number of scenarios.

Numerical studies carried out give insight into the effects of risk aversion, renewable integration, storage technologies, and external hydrogen markets on the management of the energy community. Regarding the risk trading part, we can observe that the higher the self-sufficiency level of the energy community, the lower the impact of potential unfavourable scenarios. For the arbitrageur, the optimal involvement in FMs and SMs is highly conditioned by the community's risk aversion and self-sufficiency levels. For instance, we have observed how high risk aversion levels may decrease forward trading in periods with low renewable generation. Moreover, the battery storage system can effectively assists in load shifting for the prosumers, reducing their operation costs and benefiting the entire community. Meanwhile, an external hydrogen market can help prosumers to yield additional profits while managing their cost volatility.

Several studies anticipate that economies of scale and technological development will reduce the costs of hydrogen-based technologies, so that the hydrogen price is expected to decrease significantly between 2020 and 2050. Hence, we have also studied the impact of lower hydrogen prices in the community supply chain. Results suggest that the external hydrogen market has a direct effect on the community's internal price-tariff system, and depending on the market conditions and the systems installed by each prosumer, may significantly worsen their utility.

Future lines of research work may include: i) To explore alternative types of contracts between the grid and the arbitrageur. ii) To study the impact of investment costs for battery and hydrogen storage systems for each prosumer, since hydrogen assets are more costly than batteries. iii) From the computational perspective, decomposition techniques can be adopted to speed up the solution of large scale equilibrium problems, like the one introduced in this work.

Acknowledgements

The authors gratefully acknowledge the financial support from MCIN/AEI/10.13039/501100011033, project PID2020-116694GB-I00 and Wenxiu Feng also acknowledges the support from China Scholarship Council, Grant No. 202106890026.

References

[1] European commission climate strategies and targets 2050 long-term strategy, https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2050-long-term-strategy_en.

[2] B. Muruganantham, R. Gnanadass, N. P. Padhy, Challenges with renewable energy sources and storage in practical distribution systems, Renewable and Sustainable Energy Reviews 73 (2017) 125–134.

[3] Global offshore wind report 2020, https://gwec.net/global-offshore-wind-report-2020 (Jan 2021).

[4] N. Jenkins, C. Long, J. Wu, An overview of the smart grid in great britain, Engineering 1 (4) (2015) 413–421.

[5] D.-M. Han, J.-H. Lim, Smart home energy management system using ieee 802.15. 4 and zigbee, IEEE Transactions on Consumer Electronics 56 (3) (2010) 1403–1410.

[6] A. Dimeas, S. Drenkard, N. Hatziargyriou, S. Karnouskos, K. Kok, J. Ringelstein, A. Weidlich, Smart houses in the smart grid: Developing an interactive network., IEEE Electrification Magazine 2 (1) (2014) 81–93.

[7] V. Z. Gjorgievski, S. Cundeva, G. E. Georghiou, Social arrangements, technical designs and impacts of energy communities: A review, Renewable Energy 169 (2021) 1138–1156.

[8] Energy communities, https://energy.ec.europa.eu/topics/markets-and-consumers/energy-communities_en.

[9] D. Frieden, A. Tuerk, J. Roberts, S. d'Herbemont, A. Gubina, Collective self-consumption and energy communities: Overview of emerging regulatory approaches in Europe, Compile, 2019.

[10] M. Daneshvar, B. Mohammadi-Ivatloo, S. Asadi, A. Anvari-Moghaddam, M. Rasouli, M. Abapour, G. B. Gharehpetian, Chance-constrained models for transactive energy management of interconnected microgrid clusters, Journal of Cleaner Production 271 (2020) 122177.

[11] K. Ito, M. Reguant, Sequential markets, market power, and arbitrage, American Economic Review 106 (7) (2016) 1921–57.

[12] F. S. Oliveira, C. Ruiz, A. J. Conejo, Contract design and supply chain coordination in the electricity industry, European Journal of Operational Research 227 (3) (2013) 527–537.

[13] E. J. Anderson, X. Hu, Forward contracts and market power in an electricity market, International Journal of Industrial Organization 26 (3) (2008) 679–694.

[14] J. Kettunen, A. Salo, D. W. Bunn, Optimization of electricity retailer's contract portfolio subject to risk preferences, IEEE Transactions on Power Systems 25 (1) (2009) 117–128.

[15] C.-L. Su, Analysis on the forward market equilibrium model, Operations Research Letters 35 (1) (2007) 74–82.

[16] P. Sheikhahmadi, S. Bahramara, J. Moshtagh, M. Y. Damavandi, A risk-based approach for modeling the strategic behavior of a distribution company in wholesale energy market, Applied energy 214 (2018) 24–38.

[17] J. C. Do Prado, U. Chikezie, A decision model for an electricity retailer with energy storage and virtual bidding under daily and hourly cvar assessment, IEEE Access 9 (2021) 106181–106191.

[18] M. Dolanyi, K. Bruninx, J.-F. Toubeau, E. Delarue, Risk-based constraints for the optimal operation of an energy community, IEEE Transactions on Smart Grid (2022).

[19] M. Ambrosius, J. Egerer, V. Grimm, A. H. van der Weijde, Risk aversion in multilevel electricity market models with different congestion pricing regimes, Energy Economics 105 (2022) 105701.

[20] B. Allaz, Oligopoly, uncertainty and strategic forward transactions, International Journal of Industrial Organization 10 (2) (1992) 297–308.

[21] E. Cazalet, D. M. Paul, J. Price, E. Woychik, J. Caldwell, Transactive energy models, Tech. rep., MD, USA (2016).

[22] B. Zhang, C. Jiang, J.-L. Yu, Z. Han, A contract game for direct energy trading in smart grid, IEEE Transactions on Smart Grid 9 (4) (2016) 2873–2884.

[23] T. Morstyn, A. Teytelboym, M. D. McCulloch, Bilateral contract networks for peer-to-peer energy trading, IEEE Transactions on Smart Grid 10 (2) (2018) 2026–2035.

[24] T. Fleiner, Z. Jankó, A. Tamura, A. Teytelboym, Trading networks with bilateral contracts, CoRR abs/1510.01210 (2015). arXiv:1510.01210.
URL http://arxiv.org/abs/1510.01210

[25] U. Amin, M. J. Hossain, W. Tushar, K. Mahmud, Energy trading in local electricity market with renewablesa contract theoretic approach, IEEE Transactions on Industrial Informatics 17 (6) (2020) 3717–3730.

[26] M. Q. Wang, H. Gooi, Spinning reserve estimation in microgrids, IEEE Transactions on Power Systems 26 (3) (2011) 1164–1174.

[27] M. Motevasel, A. R. Seifi, Expert energy management of a micro-grid considering wind energy uncertainty, Energy Conversion and Management 83 (2014) 58–72.

[28] J. C. Do Prado, W. Qiao, A stochastic bilevel model for an electricity retailer in a liberalized distributed renewable energy market, IEEE Transactions on Sustainable Energy 11 (4) (2020) 2803–2812.

[29] H.-S. Ryu, M.-K. Kim, Two-stage optimal microgrid operation with a risk-based hybrid demand response program considering uncertainty, Energies 13 (22) (2020) 6052.

[30] N. Vespermann, T. Hamacher, J. Kazempour, Risk trading in energy communities, IEEE Transactions on Smart Grid 12 (2) (2020) 1249–1263.

[31] R. T. Rockafellar, S. Uryasev, Conditional value-at-risk for general loss distributions, Journal of banking & finance 26 (7) (2002) 1443–1471.

[32] Z. Liu, G. Fan, D. Sun, D. Wu, J. Guo, S. Zhang, X. Yang, X. Lin, L. Ai, A novel distributed energy system combining hybrid energy storage and a multi-objective optimization method for nearly zero-energy communities and buildings, Energy 239 (2022) 122577.

[33] W. Zhong, K. Xie, Y. Liu, C. Yang, S. Xie, Multi-resource allocation of shared energy storage: A distributed combinatorial auction approach, IEEE transactions on smart grid 11 (5) (2020) 4105–4115.

[34] H. Nagpal, I.-I. Avramidis, F. Capitanescu, A. G. Madureira, Local energy communities in service of sustainability and grid flexibility provision: Hierarchical management of shared energy storage, IEEE Transactions on Sustainable Energy 13 (3) (2022) 1523–1535.

[35] Z. Wu, M. Zhou, J. Wang, E. Du, N. Zhang, G. Li, Profit-sharing mechanism for aggregation of wind farms and concentrating solar power, IEEE Transactions on Sustainable Energy 11 (4) (2020) 2606–2616.

[36] C. Wu, D. Zhou, X. Lin, F. Wei, C. Chen, Y. Ma, Y. Huang, Z. Li, S. M. Dawoud, A novel energy cooperation framework for community energy storage systems and prosumers, International Journal of Electrical Power & Energy Systems 134 (2022) 107428.

[37] J. Lokar, P. Virtič, The potential for integration of hydrogen for complete energy self-sufficiency in residential buildings with photovoltaic and battery storage systems, International Journal of Hydrogen Energy 45 (60) (2020) 34566–34578.

[38] N. Vespermann, T. Hamacher, J. Kazempour, Access economy for storage in energy communities, IEEE Transactions on Power Systems 36 (3) (2020) 2234–2250.

[39] F. Vivas, A. De las Heras, F. Segura, J. Andújar, A review of energy management strategies for renewable hybrid energy systems with hydrogen backup, Renewable and Sustainable Energy Reviews 82 (2018) 126–155.

[40] J. L. Torres-Moreno, A. Gimenez-Fernandez, M. Perez-Garcia, F. Rodriguez, Energy management strategy for micro-grids with pv-battery systems and electric vehicles, Energies 11 (3) (2018) 522.

[41] E. Gul, G. Baldinelli, P. Bartocci, F. Bianchi, P. Domenghini, F. Cotana, J. Wang, A techno-economic analysis of a solar pv and dc battery storage system for a community energy sharing, Energy 244 (2022) 123191.

[42] C. Mokhtara, B. Negrou, N. Settou, A. Bouferrouk, Y. Yao, Design optimization of grid-connected pv-hydrogen for energy prosumers considering sector-coupling paradigm: Case study of a university building in algeria, International Journal of Hydrogen Energy 46 (75) (2021) 37564–37582.

[43] C. Marino, A. Nucara, M. Panzera, M. Pietrafesa, V. Varano, Energetic and economic analysis of a stand alone photovoltaic system with hydrogen storage, Renewable Energy 142 (2019) 316–329.

[44] R. Secretariat, Renewables global status report, https://www.ren21.net/reports/global-status-report/ (Sep 2022).

[45] J. Liu, Y. Zhou, H. Yang, H. Wu, Uncertainty energy planning of net-zero energy communities with peer-to-peer energy trading and green vehicle storage considering climate changes by 2050 with machine learning methods, Applied Energy 321 (2022) 119394.

[46] P. Kelm, R. Mieński, I. Wasiak, Energy management in a prosumer installation using hybrid systems combining ev and stationary storages and renewable power sources, Applied Sciences 11 (11) (2021) 5003.

[47] J. Fortuny-Amat, B. McCarl, A representation and economic interpretation of a two-level programming problem, Journal of the operational Research Society 32 (9) (1981) 783–792.

[48] A. Christensen, Assessment of hydrogen production costs from electrolysis: United states and europe, https://theicct.org/wp-content/uploads/2021/06/final_icct2020_assessment_of-_hydrogen_production_costs-v2.pdf (June 2020).

[49] ESIOS, Red Eléctrica España (2022).
URL https://www.esios.ree.es

[50] OMIE, OMIE (2022).
URL https://www.omie.es

Appendix

A.1 The Primal-Dual formulation of prosumer

The objective function of prosumer n primal problem under scenario ω can be simplified as

$$\min_{\Xi} f^p_{n\omega} = \sum_{t\in T} \left[p^S_{\omega t} Q^S_{n\omega t} - P^h_t h^{out}_{n\omega t} \right] \tag{7}$$

The dual problem of prosumer is

$$\begin{aligned} \max_{\Theta} g^p_{n\omega} = &\sum_{t\in T} \left[\left(S_{n\omega t} - D_{n\omega t}\right) \lambda_{n\omega t} - \overline{Q}_{nt} \upsilon^{max}_{n\omega t} - \overline{Q}_{nt} \upsilon^{min}_{n\omega t} - E^{BAT}_n \epsilon^{max}_{n\omega t} - R^{BAT}_n \epsilon^{+,max}_{n\omega t} \right] \\ &+ \sum_{t\in T} \left[-R^{BAT}_n \epsilon^{-,max}_{n\omega t} - E^{HT}_n \zeta^{max}_{n\omega t} - R^{HT}_n \zeta^{+,max}_{n\omega t} - R^{HT}_n \zeta^{-,max}_{n\omega t} - R^{HT}_n \zeta^{out,max}_{n\omega t} \right] \end{aligned} \tag{8a}$$

s.t.

$$- \lambda_{n\omega t} - \upsilon^{max}_{n\omega t} + \upsilon^{min}_{n\omega t} = p^S_{\omega t}, \quad \forall n, \omega, t \tag{8b}$$

$$\begin{aligned} &\mu^{BAT}_{n\omega t} - \mu^{BAT}_{n\omega(t+1)} - \epsilon^{max}_{n\omega t} + \epsilon^{min}_{n\omega t} = 0, \quad \forall n, \omega, t < T \\ &\mu^{BAT}_{n\omega T} - \epsilon^{max}_{n\omega T} + \epsilon^{min}_{n\omega T} = 0, \quad \forall n, \omega, t = T \end{aligned} \tag{8c}$$

$$\lambda_{n\omega t} - \eta^+_{BAT} \mu^{BAT}_{n\omega t} - \epsilon^{+,max}_{n\omega t} + \epsilon^{+,min}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{8d}$$

$$- \eta^-_{BAT} \lambda_{n\omega t} + \mu^{BAT}_{n\omega t} - \epsilon^{-,max}_{n\omega t} + \epsilon^{-,min}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{8e}$$

$$\begin{aligned} &\mu^H_{n\omega t} - \mu^H_{n\omega(t+1)} - \zeta^{max}_{n\omega t} + \zeta^{min}_{n\omega t} = 0, \quad \forall n, \omega, t < T \\ &\mu^H_{n\omega T} - \zeta^{max}_{n\omega T} + \zeta^{min}_{n\omega T} = 0, \quad \forall n, \omega, t = T \end{aligned} \tag{8f}$$

$$\lambda_{n\omega t} - \eta^+_{Ele} \mu^H_{n\omega t} - \zeta^{+,max}_{n\omega t} + \zeta^{+,min}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{8g}$$

$$- \eta^-_{FC} \lambda_{n\omega t} + \mu^H_{n\omega t} - \zeta^{-,max}_{n\omega t} + \zeta^{-,min}_{n\omega t} = 0, \quad \forall n, \omega, t \tag{8h}$$

$$\mu^H_{n\omega t} - \zeta^{out,max}_{n\omega t} + \zeta^{out,min}_{n\omega t} = -P^h_t, \quad \forall n, \omega, t \tag{8i}$$

$$\lambda_{n\omega t}, \mu^{BAT}_{n\omega t}, \mu^H_{n\omega t} \quad free, \quad \forall n, \omega, t \tag{8j}$$

$$\begin{aligned} &\upsilon^{min}_{n\omega t}, \upsilon^{max}_{n\omega t}, \epsilon^{min}_{n\omega t}, \epsilon^{max}_{n\omega t}, \epsilon^{+,min}_{n\omega t}, \epsilon^{+,max}_{n\omega t}, \epsilon^{-,min}_{n\omega t}, \epsilon^{-,max}_{n\omega t}, \zeta^{min}_{n\omega t}, \zeta^{max}_{n\omega t} \geq 0 \\ &\zeta^{+,min}_{n\omega t}, \zeta^{+,max}_{n\omega t}, \zeta^{-,min}_{n\omega t}, \zeta^{-,max}_{n\omega t}, \zeta^{out,min}_{n\omega t}, \zeta^{out,max}_{n\omega t} \geq 0, \quad \forall n, \omega, t \end{aligned} \tag{8k}$$

where $\Theta = [\lambda_{n\omega t}, \mu^{BAT}_{n\omega t}, \mu^H_{n\omega t}, \upsilon^{min}_{n\omega t}, \upsilon^{max}_{n\omega t}, \epsilon^{min}_{n\omega t}, \epsilon^{max}_{n\omega t}, \epsilon^{+,min}_{n\omega t}, \epsilon^{+,max}_{n\omega t}, \epsilon^{-,min}_{n\omega t}, \epsilon^{-,max}_{n\omega t}, \zeta^{min}_{n\omega t}, \zeta^{max}_{n\omega t}, \zeta^{+,min}_{n\omega t}, \zeta^{+,max}_{n\omega t}, \zeta^{-,min}_{n\omega t}, \zeta^{-,max}_{n\omega t}, \zeta^{out,min}_{n\omega t}, \zeta^{out,max}_{n\omega t}]$.

The strong duality equality imposes that, at the optimal solution

$$f^p_{n\omega} = g^p_{n\omega} \quad \forall n, \omega \tag{9}$$

A.2 Linearised MPEC Formulation

To simplify and speed up the solving process, the linearization techniques are adopted to transform the MPEC formulation into the MILP problem.

For the complementarity conditions (3k)-(3z) in MPEC Formulation (4), the disjunctive mixed-integer linear formulation can be applied to linearise these components.

Linearization of constraints (3k)-(3l):

$$\upsilon_{n\omega t}^{max} \geq 0, \quad \forall n, \omega, t \tag{10a}$$
$$\overline{Q}_{nt} - Q_{n\omega t}^{S} \geq 0, \quad \forall n, \omega, t \tag{10b}$$
$$\upsilon_{n\omega t}^{max} \leq \alpha_{n\omega t}^{(1)} M, \quad \forall n, \omega, t \tag{10c}$$
$$\overline{Q}_{nt} - Q_{n\omega t}^{S} \leq \left(1 - \alpha_{n\omega t}^{(1)}\right) M^{QB}, \quad \forall n, \omega, t \tag{10d}$$
$$\upsilon_{n\omega t}^{min} \geq 0, \quad \forall n, \omega, t \tag{10e}$$
$$\overline{Q}_{nt} + Q_{n\omega t}^{S} \geq 0, \quad \forall n, \omega, t \tag{10f}$$
$$\upsilon_{n\omega t}^{min} \leq \alpha_{n\omega t}^{(2)} M, \quad \forall n, \omega, t \tag{10g}$$
$$\overline{Q}_{nt} + Q_{n\omega t}^{S} \leq \left(1 - \alpha_{n\omega t}^{(2)}\right) M^{QB}, \quad \forall n, \omega, t \tag{10h}$$

Linearization of constraints (3m)-(3n):

$$\epsilon_{n\omega t}^{min} \geq 0, \quad \forall n, \omega, t \tag{11a}$$
$$e_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{11b}$$
$$\epsilon_{n\omega t}^{min} \leq \alpha_{n\omega t}^{(3)} M, \quad \forall n, \omega, t \tag{11c}$$
$$e_{n\omega t} \leq \left(1 - \alpha_{n\omega t}^{(3)}\right) M^{E^{BAT}}, \quad \forall n, \omega, t \tag{11d}$$
$$\epsilon_{n\omega t}^{max} \geq 0, \quad \forall n, \omega, t \tag{11e}$$
$$E_{n}^{BAT} - e_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{11f}$$
$$\epsilon_{n\omega t}^{max} \leq \alpha_{n\omega t}^{(4)} M, \quad \forall n, \omega, t \tag{11g}$$
$$E_{n}^{BAT} - e_{n\omega t} \leq \left(1 - \alpha_{n\omega t}^{(4)}\right) M^{E^{BAT}}, \quad \forall n, \omega, t \tag{11h}$$

Linearization of constraints (3o)-(3r):

$$\epsilon_{n\omega t}^{+,min} \geq 0, \quad \forall n, \omega, t \tag{12a}$$
$$e_{n\omega t}^{+} \geq 0, \quad \forall n, \omega, t \tag{12b}$$
$$\epsilon_{n\omega t}^{+,min} \leq \alpha_{n\omega t}^{(5)} M, \quad \forall n, \omega, t \tag{12c}$$
$$e_{n\omega t}^{+} \leq \left(1 - \alpha_{n\omega t}^{(5)}\right) M^{R^{BAT}}, \quad \forall n, \omega, t \tag{12d}$$
$$\epsilon_{n\omega t}^{+,max} \geq 0, \quad \forall n, \omega, t \tag{12e}$$

$$R_n^{BAT} - e_{n\omega t}^{+} \geq 0, \quad \forall n, \omega, t \tag{12f}$$

$$\epsilon_{n\omega t}^{+,max} \leq \alpha_{n\omega t}^{(6)} M, \quad \forall n, \omega, t \tag{12g}$$

$$R_n^{BAT} - e_{n\omega t}^{+} \leq \left(1 - \alpha_{n\omega t}^{(6)}\right) M^{R^{BAT}}, \quad \forall n, \omega, t \tag{12h}$$

$$\epsilon_{n\omega t}^{-,min} \geq 0, \quad \forall n, \omega, t \tag{12i}$$

$$e_{n\omega t}^{-} \geq 0, \quad \forall n, \omega, t \tag{12j}$$

$$\epsilon_{n\omega t}^{-,min} \leq \alpha_{n\omega t}^{(7)} M, \quad \forall n, \omega, t \tag{12k}$$

$$e_{n\omega t}^{-} \leq \left(1 - \alpha_{n\omega t}^{(7)}\right) M^{R^{BAT}}, \quad \forall n, \omega, t \tag{12l}$$

$$\epsilon_{n\omega t}^{-,max} \geq 0, \quad \forall n, \omega, t \tag{12m}$$

$$R_n^{BAT} - e_{n\omega t}^{-} \geq 0, \quad \forall n, \omega, t \tag{12n}$$

$$\epsilon_{n\omega t}^{-,max} \leq \alpha_{n\omega t}^{(8)} M, \quad \forall n, \omega, t \tag{12o}$$

$$R_n^{BAT} - e_{n\omega t}^{-} \leq \left(1 - \alpha_{n\omega t}^{(8)}\right) M^{R^{BAT}}, \quad \forall n, \omega, t \tag{12p}$$

Linearization of constraints (3s)-(3t):

$$\zeta_{n\omega t}^{min} \geq 0, \quad \forall n, \omega, t \tag{13a}$$

$$h_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{13b}$$

$$\zeta_{n\omega t}^{min} \leq \alpha_{n\omega t}^{(9)} M, \quad \forall n, \omega, t \tag{13c}$$

$$h_{n\omega t} \leq \left(1 - \alpha_{n\omega t}^{(9)}\right) M^{E^{HT}}, \quad \forall n, \omega, t \tag{13d}$$

$$\zeta_{n\omega t}^{max} \geq 0, \quad \forall n, \omega, t \tag{13e}$$

$$E_n^{HT} - h_{n\omega t} \geq 0, \quad \forall n, \omega, t \tag{13f}$$

$$\zeta_{n\omega t}^{max} \leq \alpha_{n\omega t}^{(10)} M, \quad \forall n, \omega, t \tag{13g}$$

$$E_n^{HT} - h_{n\omega t} \leq \left(1 - \alpha_{n\omega t}^{(10)}\right) M^{E^{HT}}, \quad \forall n, \omega, t \tag{13h}$$

Linearization of constraints (3u)-(3z):

$$\zeta_{n\omega t}^{+,min} \geq 0, \quad \forall n, \omega, t \tag{14a}$$

$$h_{n\omega t}^{+} \geq 0, \quad \forall n, \omega, t \tag{14b}$$

$$\zeta_{n\omega t}^{+,min} \leq \alpha_{n\omega t}^{(11)} M, \quad \forall n, \omega, t \tag{14c}$$

$$h_{n\omega t}^{+} \leq \left(1 - \alpha_{n\omega t}^{(11)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14d}$$

$$\zeta_{n\omega t}^{+,max} \geq 0, \quad \forall n, \omega, t \tag{14e}$$

$$R_n^{HT} - h_{n\omega t}^{+} \geq 0, \quad \forall n, \omega, t \tag{14f}$$

$$\zeta_{n\omega t}^{+,max} \leq \alpha_{n\omega t}^{(12)} M, \quad \forall n, \omega, t \tag{14g}$$

$$R_n^{HT} - h_{n\omega t}^{+} \leq \left(1 - \alpha_{n\omega t}^{(12)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14h}$$

$$\zeta_{n\omega t}^{-,min} \geq 0, \quad \forall n, \omega, t \tag{14i}$$

$$h_{n\omega t}^{-} \geq 0, \quad \forall n, \omega, t \tag{14j}$$

$$\zeta_{n\omega t}^{-,min} \leq \alpha_{n\omega t}^{(13)} M, \quad \forall n, \omega, t \tag{14k}$$

$$h_{n\omega t}^{-} \leq \left(1 - \alpha_{n\omega t}^{(13)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14l}$$

$$\zeta_{n\omega t}^{-,max} \geq 0, \quad \forall n, \omega, t \tag{14m}$$

$$R_n^{HT} - h_{n\omega t}^{-} \geq 0, \quad \forall n, \omega, t \tag{14n}$$

$$\zeta_{n\omega t}^{-,max} \leq \alpha_{n\omega t}^{(14)} M, \quad \forall n, \omega, t \tag{14o}$$

$$R_n^{HT} - h_{n\omega t}^{-} \leq \left(1 - \alpha_{n\omega t}^{(14)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14p}$$

$$\zeta_{n\omega t}^{out,min} \geq 0, \quad \forall n, \omega, t \tag{14q}$$

$$h_{n\omega t}^{out} \geq 0, \quad \forall n, \omega, t \tag{14r}$$

$$\zeta_{n\omega t}^{out,min} \leq \alpha_{n\omega t}^{(15)} M, \quad \forall n, \omega, t \tag{14s}$$

$$h_{n\omega t}^{out} \leq \left(1 - \alpha_{n\omega t}^{(15)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14t}$$

$$\zeta_{n\omega t}^{out,max} \geq 0, \quad \forall n, \omega, t \tag{14u}$$

$$R_n^{HT} - h_{n\omega t}^{out} \geq 0, \quad \forall n, \omega, t \tag{14v}$$

$$\zeta_{n\omega t}^{out,max} \leq \alpha_{n\omega t}^{(16)} M, \quad \forall n, \omega, t \tag{14w}$$

$$R_n^{HT} - h_{n\omega t}^{out} \leq \left(1 - \alpha_{n\omega t}^{(16)}\right) M^{R^{HT}}, \quad \forall n, \omega, t \tag{14x}$$

Where $\alpha_{n\omega t}^{(i)}, i \in \{1, 2, \cdots 16\}$ is the binary variable of prosumer n in local daily market at time t under scenario ω, and $M^{(.)}$ (big M) is the constant large enough, (.) denotes the index, eg. E^{BAT}.