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ABSTRACT

Peer-to-peer trading has emerged as a complement to traditional electricity supply models, with potential benefits for residential consumers and grid infrastructure. This study presents a model-based comparative analysis of three peer-to-peer market designs: auction-based pricing (ABP), supply-demand ratio pricing (SDR), and mid-market rate pricing (MMR), under both real-time pricing and fixed retail pricing. Unlike most prior work, our study incorporates long-term investment decisions and examines local grid issues. This enables a comprehensive evaluation of how different P2P pricing designs affect distributed energy resource (DER) adoption, consumer costs, system efficiency, and grid stress. We also assess whether P2P trading provides added value in settings where consumer decisions are already coordinated by dynamic prices. Our results show that peer-to-peer trading significantly reduces consumer electricity costs, but savings are less pronounced under dynamic pricing contracts. Of the mechanisms evaluated, ABP yields the lowest total consumer cost but can exacerbate local grid issues. In contrast, the MMR and SDR mechanisms alleviate congestion by spreading peak offtake and injection more evenly. Notably, we show that peer-to-peer trading could serve as a potential alternative to real-time pricing contracts, offering comparable benefits in terms of self-consumption and cost savings, while shielding consumers from price risk.

Nomenclature

Parameters

$\Delta\tau$	Time step [h].
δ	Self-discharge rate of storage [-].
$\lambda^{inj}_{d,t}$	Retail electricity injection price at hour t on day d [€/kWh].
$\lambda^{off}_{d,t}$	Retail electricity offtake price at hour t on day d [€/kWh].
$\overline{cap^{pv}}$	Maximum capacity of solar PV on one side of the rooftop [kW].
$\overline{cap^{s}}$	Maximum energy capacity of residential storage [kWh].
$\overline{w^{Inj}}$	Maximum injection power [kW].
$\overline{w^{off}}$	Maximum offtake power [kW].
Π_d	Weight of representative day d [h].
$AF^{pv1}_{d,t,i}$	Availability factor of solar PV on the first rooftop orientation of consumer i at hour t on day d [-].
$AF^{pv2}_{d,t,i}$	Availability factor of solar PV on the second rooftop orientation of consumer i at hour t on day d [-].
$B_{m,d}$	Binary parameters that indicate whether a representative day d falls within a specific month m [-].
CR	Charge/discharge rate of storage [-].
$D^{EV}_{d,t,i}$	EV demand of consumer i at hour t on day d [kW].
$D_{d,t,i}$	Non-controllable electricity demand of consumer i at hour t on day d [kW].
e^{EV}_{init}	Initial energy content in EV battery at the beginning of each day [kWh].
$Occ_{d,t,i}$	Occupancy of consumer i at hour t on day d [-].
$peak_{min}$	Monthly minimal offtake peak used to calculate capacity tariff [kW].
T_{CAP}	Capacity distribution tariff [€/kW].
η^{ch}	Charging efficiency of storage [-].
η^{dc}	Discharging efficiency of storage [-].
PIC^{s}_{i}	Perceived annualized investment cost of storage for consumer i [€/kWh/year].
PIC^{si}_{i}	Perceived annualized investment cost of storage inverter for consumer i [€/kW/year].
PIC^{pv}_{i}	Perceived annualized investment cost of solar PV panel for consumer i [€/kW/year].
PIC^{pvi}_{i}	Perceived annualized investment cost of solar PV inverter for consumer i [€/kW/year].

Variables

$\lambda^{buy}_{d,t}$	P2P market electricity buying price at hour t on day d [€/kWh].
$\lambda^{P2P}_{d,t}$	General P2P market price (for electricity traded on the P2P market) at hour t on day d [€/kWh].
$\lambda^{sell}_{d,t}$	P2P market electricity selling price at hour t on day d [€/kWh].
$\lambda_{d,t}$	Wholesale electricity price at hour t on day d [€/kWh].
cap^{pv1}_{i}	Solar PV capacity of consumer i on the first rooftop orientation [kW].
cap^{pv2}_{i}	Solar PV capacity of consumer i on the second rooftop orientation [kW].
$ch^{EV}_{d,t,i}$	EV charging of consumer i at hour t on day d [kW].
$e^{EV}_{d,t,i}$	EV energy content of consumer i at hour t on day d [kWh].
$inj_{d,t}$	Total injection of all consumers at hour t on day d [kW].
$off_{d,t}$	Total offtake of all consumers at hour t on day d [kW].
$peak_{m,i}$	Peak offtake of consumer i in month m [kW].
$w^{inj}_{d,t,i}$	Electricity injection of consumer i at hour t on day d [kW].
$w^{off}_{d,t,i}$	Electricity offtake of consumer i at hour t on day d [kW].
cap^{s}_{i}	Storage energy capacity of consumer i [kWh].
cap^{si}_{i}	Capacity of the storage inverter of consumer i [kW].

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ORCID(s):

cap_i^{pv} Total solar PV capacity of consumer i [kW].

cap_i^{pvi} Capacity of the solar PV inverter of consumer i [kW].

$ch_{d,t,i}$ Storage charging of consumer i at hour t on day d [kW].

$dc_{d,t,i}$ Storage discharging of consumer i at hour t on day d [kW].

$e_{d,t,i}$ Storage energy content of consumer i at hour t on day d [kWh].

$g_{d,t,i}^{pv}$ Solar PV generation of consumer i at hour t on day d [kW].

1. Introduction

1.1. Context

In response to the rapid growth of distributed energy resources (DERs), peer-to-peer (P2P) trading has emerged as a promising new electricity supply model. In contrast to the traditional electricity supply structure where consumers purchase and sell electricity from and to retailers, this new model allows consumers to trade electricity directly with other consumers [8]. Following its introduction in the EU Clean Energy Package [39], P2P trading has been introduced in several Member States, such as Germany and Netherlands [19].

P2P trading offers several benefits to residential consumers, including more favorable rates, stronger incentives for DER investment, and a greater self-consumption of locally produced renewable electricity [31]. It furthermore holds the potential to reduce long-distance power transmission, thereby alleviating grid congestion and reducing transmission losses [8]. P2P trading can furthermore support the local grid by lowering peak demand, potentially lowering operational and maintenance costs while improving overall system reliability [41].

In recent years, numerous studies have explored different designs of P2P markets to achieve the aforementioned benefits. These studies cover a variety of topics such as encouraging consumer participation [40], addressing challenges on privacy and cyber vulnerabilities [2, 45], accommodating diverse user preferences in electricity trading [37, 32] and integrating P2P markets into existing electricity market structures [11, 24]. The remainder of this introduction is devoted to the literature on P2P trading that is most closely connected to this paper, namely the design of P2P pricing mechanisms.

1.2. Literature on P2P market designs

Researchers have focused on different P2P pricing mechanisms and their implications. Indeed, it has been shown that the pricing mechanism can significantly affect consumer behavior, electricity bills, network congestion, as well as social welfare. Before discussing the main findings in the literature, we first need to distinguish between homogeneous and heterogeneous pricing mechanisms. Homogeneous trading implies that all participants see the same price during a particular trading period, whereas heterogeneous pricing implies that buyers and sellers can negotiate prices bilaterally and thus see different prices depending on their counterparty [21]. This paper exclusively considers homogeneous pricing mechanisms. In contrast to heterogeneous pricing, homogeneous mechanisms simplify the trading process by eliminating the need for direct negotiations. In addition, we aim to draw general conclusions, while the outcomes of heterogeneous pricing are heavily influenced by individual consumer preferences[1].

Common homogeneous pricing mechanisms are bill-sharing (BS) [49], mid-market rate pricing (MMR) [18], supply-demand ratio pricing (SDR) [25], and auction-based pricing (ABP) [47]. Each of these mechanisms has unique characteristics which will be detailed in Section 2. That said, not many studies have evaluated and compared these different mechanisms. Table 1 classifies the few studies that do, based on their modeling approaches, the market mechanisms and contract types included, and the key performance metrics.

Most studies focus on the impact of P2P trading on consumer electricity bills. In [26], the authors consider three representative market mechanisms and show that both the MMR and ABP methods can achieve greater energy cost reductions than Bill Sharing (BS). Similarly, [49] and [16] find that the SDR mechanism reduces the consumers' electricity bills even further. Note that these studies typically pair these markets with a flat retail or time-of-use (TOU) contract[2]. [20] explores a different approach by considering an auction-based P2P market integrated with a real-time pricing (RTP) tariff. Additionally, Zhang et al. explore the performance of various P2P market designs under dynamic pricing and find that the ABP mechanism favors electricity sellers while the SDR mechanism provides greater benefits to electricity buyers [47].

Some authors examine the interplay between P2P trading and the load on the distribution infrastructure. For example, [48] and [17] show that P2P trading in general can effectively better balance local generation and demand while reducing the overall peak load. These papers, however, do not compare different pricing mechanisms. To our knowledge, only Le Cadre et al. comprehensively explore the impact of different P2P trading mechanisms on the grid. They find that heterogeneous pricing tends to increase line congestion, while uniform pricing mechanisms can alleviate the burden on the grid [23]. We refer to [9] for a review of how local energy markets affect low voltage distribution systems.

A final element concerns the impact of P2P markets on consumer investment decisions. Most analyses focus only on operational aspects with exogenously determined DER technologies (see Table 1). An exception is [30], which optimizes the investment and operation of DERs in a community microgrid using a two-stage optimization model. Likewise, [7] simulate an energy-sharing neighborhood on the IEEE-33 bus test system, accounting for both DER investments and distribution network planning. Their findings highlight

[1] Hetegogeneous pricing furthermore closely resembles auction-based markets (explained later) if trades share a common valuation across participants [23].

[2] A TOU tariff is an electricity pricing structure that the cost of electricity varies based on different time periods of the day, typically divided into peak, off-peak, and sometimes mid-peak hours.

Table 1
Overview of research papers comparing different market designs and retail contracts.

Paper	Year	Model	Market mechanism	Contract	Investment	Price	Cost	Self-consumption	Grid
[49]	[2018]	Game theory	BS,MMR,SDR	Flat&TOU			×	×	*
[31]	[2017]	Simulation	ABP & BT	Flat		×	×	×	
[23]	[2020]	Optimization	ABP & BT	Flat			×		×
[26]	[2017]	Simulation	BS, ABP, MMR	Flat			×		
[30]	[2019]	Optimization	ES	TOU	×		×	×	
[20]	[2022]	Simulation	ABP	RTP			×	×	
[47]	[2019]	Simulation	ABP, MMR, SDR	Flat&RTP			×		*
[16]	[2020]	Game theory	MMR, SDR, BS, ES	Flat			×		
[7]	[2021]	Optimization	ES	Flat	×		×		×
This paper	/	Game theory	ABP, MMR, SDR	Flat & RTP	×	×	×	×	×

We classify all models that involve a (non-)cooperative game and attempt to find a Nash equilibrium as game-theoretic models.
ES: A general implementation of a collective energy-sharing community, designed without focusing on profit allocation or local market pricing. BT: Bilateral trading. Flat: Flat retail rate. TOU: Time-of-use rate. RTP: Real-time pricing contract.
*: Only assess grid impact limitedly, such as evaluating peak power levels without implementing a power flow model.

that P2P mechanisms can influence investment decisions and may significantly reduce overall planning and operating costs.

While existing studies offer valuable insights into P2P pricing mechanisms, several key limitations remain. In particular, few studies address how different pricing rules influence long-term DER investment, how P2P markets interact with dynamic retail prices, or how different designs impact the distribution grid under a unified framework. These specific gaps, which are summarized and addressed in the next section, motivate the core contributions of this paper.

1.3. Research gap & contribution

We evaluate the impact of different P2P market designs on consumer behavior, DER investments, electricity bills, and grid infrastructure. Table 1 situates our contribution. The overall goal is to provide a comparative study that evaluates different P2P electricity trading mechanisms. We aim to address three critical gaps identified in Table 1, which are discussed next.

First, most existing P2P market studies overlook the impact of P2P pricing mechanisms on long-term investment decisions. As noted in the literature, prior works typically assume exogenous DER configurations and focus only on operational outcomes. As we will demonstrate, some market designs may incentivize inefficient DER investments that offer short-term gains to participants but reduce overall social welfare. To address this limitation, we develop a modeling framework that endogenously mimics consumers' DER investment behavior, depending on the P2P design.

Second, very few studies integrate dynamic pricing contracts with P2P markets. Such contracts are increasingly being adopted in Europe, and so it is crucial to assess the added value of P2P trading in environments where hourly price signals already coordinate consumer behavior. We explicitly compare P2P outcomes under both flat-rate and real-time pricing contracts to examine whether local markets remain advantageous under both systems.

Third, the existing literature primarily focuses on consumer bills, while neglecting broader implications for the energy system, i.e. the overall system efficiency or the implications for the local grid. Our study includes a power flow model to evaluate how different market designs affect distribution-level grid performance.

Additionally, we offer a broad evaluation that incorporates multiple sensitivities to (i) ensure robustness and (ii) provide insights into which market structures are best suited to specific circumstances.

The remainder of this paper is structured as follows. Section 2 introduces the P2P market mechanisms evaluated in this paper. Section 3 describes the modeling framework and solution algorithm. Section 4 outlines the case study data and set-up, and Section 5 presents the results. Section 6 concludes.

2. Market mechanisms

This study examines three common P2P market designs: the mid-market rate (MMR), supply-demand ratio (SDR), and auction-based pricing (ABP), as well as a baseline case without P2P trading. We exclude the bill-sharing mechanism, as it provides limited incentives to engage in P2P trading and produces outcomes similar to a non-P2P trading set-up [49].

All three P2P market designs follow key principles from [25] and share some common features. First, the local P2P price remains within the bounds of retail offtake and injection prices, ensuring that consumers prefer to trade among themselves rather than with the retailer. Note that for both fixed and dynamic retail contracts, the offtake price is always higher than the injection price due to additional costs such as network fees, levies, and taxes. The gap between offtake and injection prices, however, is higher for fixed contracts because they also internalize the profile cost[3].

Second, many P2P systems can be thought of as consumers engaging in two separate types of transactions: trading what they can locally on the P2P market, and trading the

[3] An offtake profile is more expensive than an injection profile because PV typically produces when wholesale prices are low [28].

residual offtake or injection with the retailer. These transactions are priced differently. Electricity bought or sold to a retailer is respectively valued at the offtake price (λ^{off}) or the injection price (λ^{inj}), while P2P transactions are valued at a local price (λ^{P2P}) that depends on the pricing mechanism and thus lies somewhere in between these extremes. In the remainder of this paper, we take on a different perspective and define a weighted average buying or selling price. This is necessary because some pricing mechanisms do not allow for the separation of retail and local prices, making it difficult to compare the different designs. Specifically, we define a weighted average of the retail and local prices, with respect to quantities traded with the retailer and the P2P market. One can interpret this price as the average price that the consumer is exposed to. To be precise, we define the average buying and selling price as:

$$\lambda_t^{buy} = \lambda_t^{P2P} \cdot x^{off,P2P} + \lambda_t^{off} \cdot x^{off,ret} \tag{1}$$

$$\lambda_t^{sell} = \lambda_t^{P2P} \cdot x^{inj,P2P} + \lambda_t^{inj} \cdot x^{inj,ret} \tag{2}$$

With the prices defined as before, and $x^{off,P2P}$ and $x^{off,ret}$ respectively the fraction of offtake bought locally and from the retailer (likewise for injection). For example, if local production is below local demand, the participants that are offtaking need to buy the deficit from the retailer ($x^{off,ret} > 0$) and see an average buying price higher than the local P2P market price. All injection can be consumed locally ($x^{inj,ret} = 0$) such that the average injection price equals the local price.

2.1. Mid-market rate

In the MMR mechanism, the local P2P price at a given moment is computed ex-post as the simple average of the retailer's offtake and injection prices:

$$\lambda_t^{P2P} = \frac{\lambda_t^{off} + \lambda_t^{inj}}{2} \tag{3}$$

Following the conventions defined above (Eqs. 1 - 2), one can compute the consumer's average buying and selling price depending on whether the local market experiences a surplus or deficit (see Figure 1 for a visualization):

$$\lambda_t^{buy} = \begin{cases} \frac{\lambda_t^{off}+\lambda_t^{inj}}{2} & Off_t \leq Inj_t \\ \frac{Inj_t}{Off_t} \cdot \frac{\lambda_t^{off}+\lambda_t^{inj}}{2} + (1 - \frac{Inj_t}{Off_t}) \cdot \lambda_t^{off} & Off_t > Inj_t \end{cases} \tag{4}$$

$$\lambda_t^{sell} = \begin{cases} \frac{Off_t}{Inj_t} \cdot \frac{\lambda_t^{off}+\lambda_t^{inj}}{2} + (1 - \frac{Off_t}{Inj_t}) \cdot \lambda_t^{inj} & Off_t \leq Inj_t \\ \frac{\lambda_t^{off}+\lambda_t^{inj}}{2} & Off_t > Inj_t \end{cases} \tag{5}$$

2.2. Supply-demand ratio

The SDR mechanism, introduced by Liu et al. [25], is commonly implemented in P2P energy markets [49, 16]. As for the MMR approach, a market coordinator can calculate the consumer's buying and selling prices ex-post using their offtake and injection data.

This mechanism's central principle is that local market prices should reflect the local energy balance, incentivizing participants to consume when local electricity is available. To achieve this, the average buying and selling price[4] depends on the local supply to demand ratio ($SDR_t = inj_t/off_t$). We refer the reader to [25] for the exact specification and instead only illustrate the principle in Figure 1. The figure shows that when the SDR is low, i.e. when local injection is scarce, the selling price approaches the offtake price and consumers are encouraged to inject more. On the other hand, when local injection is abundant, the buying price falls to the injection price and the system hence encourages more consumption (while reducing the value of injection).

2.3. Auction-based pricing

With ABP, the P2P market functions as an auction system where participants submit bids and offers to a market coordinator. Participants must specify their trading volumes and bid prices, after which the market coordinator clears the local market and determines the market price. Since the local P2P market cannot always maintain energy balance independently, it relies on external transactions. The retailer can hence be interpreted as an auction participant who sells at retail offtake prices and buys at retail injection prices. As a result, the market-clearing price always falls between these two retail rates: the price equals the injection price when supply exceeds demand and vice versa. In a balanced market, the price can fall between these extremes and is influenced by factors like the opportunity cost of stored energy. Note that the system is much more involved than the MMR and SDR mechanisms, which can just compute buying and selling prices ex-post based on trading volumes.

3. Methods & Assumptions

We focus on a local P2P market where participants can exclusively trade within their feeder. Volumes traded with the retailer are subject to transmission and distribution network costs, as well as taxes and levies. Volumes traded locally, however, are exempt from transmission charges and taxes. P2P trading remains subject to distribution grid tariffs as it utilizes the distribution network. This setting is common in pilot P2P projects, such as the Quartierstrom project in Switzerland [1].

Figure 1 illustrates the general setup. We examine eight cases by combining three P2P market mechanisms and a conventional non-P2P trading setting, with both an RTP and a flat retail rate contract. In both contract types, the retail offtake price includes an energy cost component, network charges, and taxes. Within the P2P market, all consumers are assumed to adhere to the same contract type, with retail prices set exogenously and applied uniformly to all participants.

[4] We would like to emphasize that we are referring here to the buying and selling price, see above. This is one of the mechanisms where it is not easy to distinguish between the local price and the retail price.

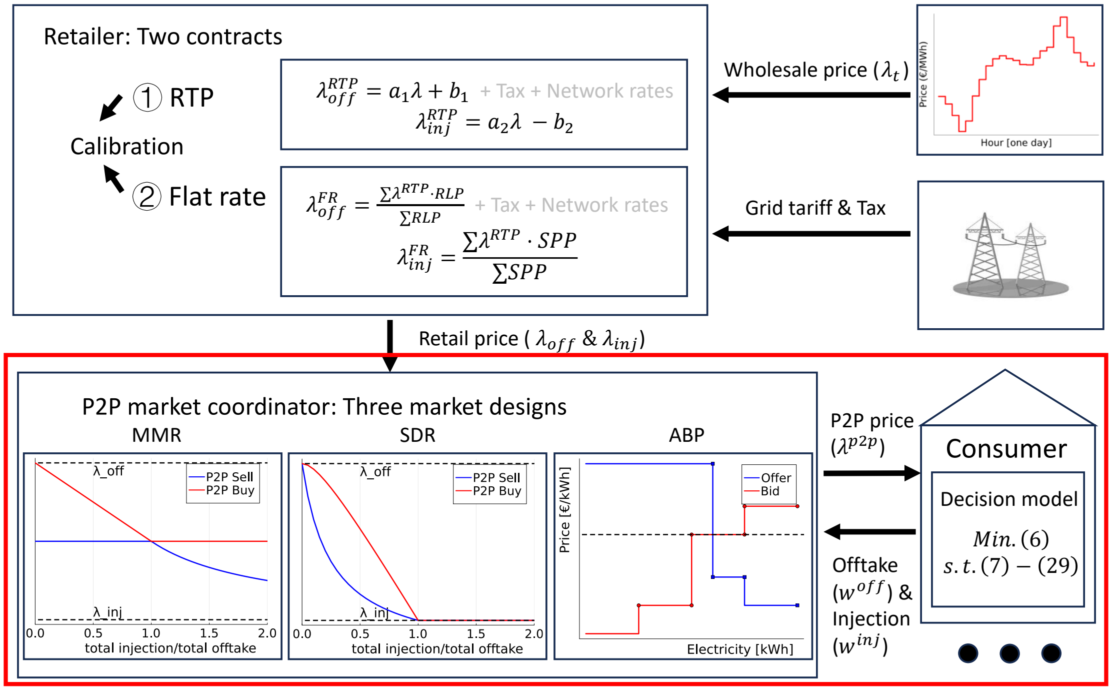

Figure 1: Overview of P2P market modeling setup. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing. RTP: real-time pricing.

The primary focus of this study is the P2P market, highlighted by the red rectangle in the figure. We model the interactions between the consumers and the local market coordinator as a non-cooperative game, for which we assume that all participants are rational price takers with perfect foresight. The goal is to establish a Nash equilibrium where no consumer can improve their outcome by changing strategies, given the decisions of others. The analysis is based on a deterministic setup in which P2P market prices and trading quantities are determined simultaneously and known with certainty. In reality, however, this is not the case. P2P prices should likely be communicated to consumers beforehand in order to incentivize a proper response. Since the pricing mechanisms discussed in Section 2 require information on offtake and injection volumes, these P2P prices are not known with certainty beforehand. A potential solution is to introduce a coordinator who announces prices ahead of time based on predicted volumes. This, however, does introduce the risk of forecast errors and potential deviations from expected behavior. Addressing these real-world uncertainties is beyond the scope of this study and is left for future research.

Each residential consumer in the P2P market is modeled as an independent decision-maker who minimizes their electricity bill by optimizing investment and operational decisions for one representative year. We represent the year at an hourly resolution with representative days to account for seasonal and daily variations. The model assumes a greenfield setup with no existing installations. Consumers can invest in solar photovoltaic (PV) systems and battery energy storage systems (BESS). Each household is also assumed to own an electric vehicle (EV) for daily commuting. While consumers' electricity demand is considered uncontrollable, their demand flexibility is approximated via EV charging and the inclusion of storage as an investment option. The market coordinator, which could function either as an algorithm-driven virtual platform or as a traditional intermediary, manages all transactions in the market and determines the P2P market price based on one of the three designs detailed in Section 2. As the local market is unlikely to be self-sufficient in all time steps, the coordinator also interacts with the retailer to trade any electricity deficit or surplus.

The remainder of this section presents the consumer's decision model (Section 3.1), the algorithmic procedure for computing the equilibrium (Section 3.2), and the power flow analysis (Section 3.3).

3.1. Decision model of consumers

The objective of each residential consumer is to minimize their annual electricity bill, as defined by Equation 6. Consumers optimize their electricity offtake ($w^{off}_{d,t,i}$) and injection ($w^{inj}_{d,t,i}$) quantities. They can invest in solar PV (cap^{pv}_i) and household batteries, and can furthermore flexibly charge their EV.

Their bill comprises energy[5], investment and distribution costs. The **energy cost** is based on the P2P buying and selling prices ($\lambda^{buy}_{d,t}$, $\lambda^{sell}_{d,t}$), as defined in Section 2. In the cases without a P2P market, these are replaced by the retail

[5]The energy cost, as previously mentioned, includes the pure energy cost combined with transmission network charges, taxes, and levies.

offtake and injection prices ($\lambda^{off}_{d,t}$, $\lambda^{inj}_{d,t}$). Investments are associated with unique perceived **investment costs** (PIC). Specifically, we assign unique discount rates to each consumer to capture consumer heterogeneity, reflecting differences in risk tolerances, market perceptions, future uncertainties, and other factors that shape the perceived costs and benefits of DER investments. Concerning the **distribution grid cost**, consumers pay a capacity tariff based on the average monthly peak offtake ($peak_{m,i}$), inspired by the tariff structure currently implemented in Flanders [44].

$$\min_{x_{i\in I}} : \sum_{d\in D,t\in T} \Pi_d \cdot (\lambda^{buy}_{d,t} \cdot w^{off}_{d,t,i} - \lambda^{sell}_{d,t} \cdot w^{inj}_{d,t,i}) + PIC^{pv}_i \cdot cap^{pv}_i$$
$$+ PIC^{pvi}_i \cdot cap^{pvi}_i + PIC^{s}_i \cdot cap^{s}_i + PIC^{si}_i \cdot cap^{si}_i$$
$$- \sum_{m\in M} peak_{m,i}/12 \cdot T_{CAP}$$
$$x_i \in \{w^{off}_{d,t,i}, w^{inj}_{d,t,i}, cap^{pv}_i, cap^{pvi}_i, cap^{s}_i, cap^{si}_i, g^{pv}_{d,t,i}, ch_{d,t,i}, dc_{d,t,i},$$
$$peak_{m,i}, e_{d,t,i}, ch^{EV}_{d,t,i}, e^{EV}_{d,t,i}\} \tag{6}$$
$$\textbf{s.t. } w^{off}_{d,t,i} - w^{inj}_{d,t,i} = D_{d,t,i} - g^{pv}_{d,t,i} + ch_{d,t,i} - dc_{d,t,i} + ch^{EV}_{d,t,i},$$
$$\forall d \in D, t \in T \tag{7}$$
$$0 \le g^{pv}_{d,t,i} \le AF^{pv1}_{d,t,i} \cdot cap^{pv1}_i + AF^{pv2}_{d,t,i} \cdot cap^{pv2}_i, \quad \forall d \in D, t \in T \tag{8}$$
$$0 \le cap^{pv1}_i \le \overline{cap^{pv}} \tag{9}$$
$$0 \le cap^{pv2}_i \le \overline{cap^{pv}} \tag{10}$$
$$cap^{pv2}_i + cap^{pv1}_i = cap^{pv}_i \tag{11}$$
$$g^{pv}_{d,t,i} \le cap^{pvi}_i, \quad \forall d \in D, t \in T \tag{12}$$
$$e_{d,t,i} = (1-\delta) \cdot e_{d,t-1,i} + ch_{d,t,i} \cdot \eta^{ch} \cdot \Delta\tau - dc_{d,t,i} \cdot \Delta\tau/\eta^{dc},$$
$$\forall d \in D, t \in T/\{1\} \tag{13}$$
$$e_{d,1,i} = (1-\delta) \cdot cap^{s}_i/2 + ch_{d,1,i} \cdot \eta^{ch} \cdot \Delta\tau - dc_{d,1,i} \cdot \Delta\tau/\eta^{dc},$$
$$\forall d \in D \tag{14}$$
$$e_{d,T,i} = cap^{s}_i/2, \quad \forall d \in D \tag{15}$$
$$0 \le e_{d,t,i} \le cap^{s}_i, \quad \forall d \in D, t \in T \tag{16}$$
$$0 \le ch_{d,t,i} \le cap^{si}_i, \quad \forall d \in D, t \in T \tag{17}$$
$$0 \le dc_{d,t,i} \le cap^{si}_i, \quad \forall d \in D, t \in T \tag{18}$$
$$0 \le ch_{d,t,i} \le CR \cdot cap^{s}_i, \quad \forall d \in D, t \in T \tag{19}$$
$$0 \le dc_{d,t,i} \le CR \cdot cap^{s}_i, \quad \forall d \in D, t \in T \tag{20}$$
$$0 \le ch^{EV}_{d,t,i} \le \overline{w^{off}} \cdot Occ_{d,t,i}, \quad \forall d \in D, t \in T \tag{21}$$
$$ch^{EV}_{d,t,i} \cdot \eta^{ch} \cdot \Delta\tau + e^{EV}_{d,t-1,i} = e^{EV}_{d,t,i}, \quad \forall d \in D, t \in T/\{1\} \tag{22}$$
$$ch^{EV}_{d,t,i} \cdot \eta^{ch} \cdot \Delta\tau + e^{EV}_{init} = e^{EV}_{d,1,i}, \quad \forall d \in D \tag{23}$$
$$D^{EV}_{d,T,i} + e^{EV}_{init} \le e^{EV}_{d,T,i}, \quad \forall d \in D \tag{24}$$
$$D^{EV}_{d,t,i} \le e^{EV}_{d,t,i}, \quad \forall d \in D, t \in T \tag{25}$$
$$0 \le w^{inj}_{d,t,i} \le \overline{w^{inj}}, \quad \forall d \in D, t \in T \tag{26}$$
$$0 \le w^{off}_{d,t,i} \le \overline{w^{off}}, \quad \forall d \in D, t \in T \tag{27}$$
$$peak_{m,i} \ge B_{m,d} \cdot w^{off}_{d,t,i}, \quad \forall m \in M, d \in D, t \in T \tag{28}$$
$$peak_{m,i} \ge peak_{min}, \quad \forall m \in M, t \in T \tag{29}$$

The behind-the-meter energy balance for each consumer is determined by Constraint 7, linking hourly net offtake with consumer's demand ($D_{d,t,i}$), electricity charged ($ch_{d,t,i}$) or discharged ($dch_{d,t,i}$) from storage, EV charging ($ch^{EV}_{d,t,i}$), and solar PV generation ($g^{PV}_{d,t,i}$). Solar PV can be installed on two sloping sides of a gabled roof. Constraint 8 limits PV generation to the capacity installed on both sides adjusted by their dedicated availability factors ($AF^{pv1}_{d,t,i}$ and $AF^{pv2}_{d,t,i}$). PV output is restricted to inverter capacity by Constraint 12, and Constraints 910 account for limited rooftop area.

Constraint 13 tracks the household battery state-of-charge, accounting for the self-discharge rate δ and efficiencies η^{ch} and η^{dc}. Cyclic boundary conditions are imposed by Constraints 14 and 15. Limitations on charging, discharging and energy capacity are imposed by Constraints 16 - 20.

EV charging is governed by Constraints 21 - 25. Constraint 21 imposes a physical limit on the EV charging power, while ensuring that charging is only possible when the vehicle is physically available, as indicated by the binary parameter $Occ_{d,t,i}$. Constraints 22 and 23 update the EV's state-of-charge. Constraint 24 ensures that the total electricity charged daily meets the EV's daily usage requirements, while Constraint 25 guarantees sufficient charge to satisfy immediate mobility needs.

Finally, Constraints 26 - 27 enforce connection capacity limits, imposing physical restrictions on injection and offtake. Constraint 28 determines consumers' monthly peak offtakes using the binary parameter $B_{m,d}$ that indicates whether a representative day d falls within a specific month m. Constraint 29 establishes a minimum monthly peak, and both constraints are used to calculate the distribution cost.

3.2. Solution algorithm

The Nash equilibrium modeled in this paper is generally solved using an iterative approach. In each iteration, every consumer optimizes their objective based on the governing prices. Given the resulting offtake and injection profiles, the coordinator (re)computes the local P2P market prices following the pricing rules described in Section 2. Consumers subsequently re-optimize their decisions based on updated prices, and so on. The process continues until the consumer's decisions and the governing P2P prices are consistent, i.e. until the Nash equilibrium is reached. We refer the reader to Appendix A for a more detailed description.

An exception to this approach is the auction-based pricing mechanism, which is solved through a single-objective optimization problem that maximizes social welfare to expedite the solution process. The overall market structure of this design is equivalent to a centralized model, as demonstrated in [23].

The models are implemented in Julia [4] using JuMP [10] and solved with Gurobi [15]. The code and data is made publicly available on a GitLab repository [27].

3.3. Power flow analysis

We conduct an ex-post power flow analysis to evaluate the impact of various P2P market mechanisms on the distribution grid infrastructure. Specifically, we leverage the Julia package *PowerModelsDistribution.jl* using the non-convex, non-linear AC power flow formulation[6] [13]. This analysis is conducted on eight independent representative feeders from

[6]The voltage bounds are set at ±10% of the nominal voltage, reflecting standard operating limits.

a real European low-voltage urban distribution network [22]. Each of the selected feeders includes both single-phase and three-phase loads which represents an unbalanced system that closely resembles real-world low-voltage distribution networks. For interested readers, we provide some summary characteristics and graphical representations of the feeders in Appendix B.

Recall that we consider P2P markets where participants can only trade within the same feeder. As explained later, we enable twenty households to engage in P2P trading. The feeders within our analysis, however, comprise more than 20 households. We randomly distribute the P2P market participants along the feeder and thus assign the offtake and injection profiles from the market model to them. The remaining households have non-controllable loads that are provided by the same dataset [22]. The distribution of P2P market participants affects grid flows, so we include several sensitivities that will be explained in Section 4.5.

4. Case study data

The case study models a P2P market with 20 residential consumers[7] across eight market cases, combining three P2P mechanisms (MMR, ABP, SDR) and a non-P2P case; with two retail contracts (dynamic and fixed). This section provides the data and explains how the sensitivities are set up.

4.1. DER parameters

All residential consumers have the option to invest in solar PV systems and BESS, with the PV investment limit set at 5 kW for a single side of the rooftop (10 kW for both sides). This limit is consistent with the maximum size of roof-mounted PV systems for single-family homes in Belgium [46]. Each household is assumed to have a dual-pitched roof with equal surface areas on each side.

Every solar PV and BESS installation requires a corresponding inverter and all techno-economic parameters for DER installations are detailed in Table 2. The investment costs for solar PV systems and their respective inverters are based on 2019 solar PV system costs reported in [29] and extrapolated to 2030 using learning rates from [12]. These costs are annualized over the technology's lifetime, incorporating each consumer's perceived discount rate. To capture consumer heterogeneity, we assign each consumer a unique discount rate randomly selected from a 46% range, reflecting differences in risk tolerances, future uncertainties, and other factors that shape the perceived costs and benefits of DER investments.

[7] The case study focuses on 20 residential customers for computational efficiency and clearer presentation of results. We additionally performed simulations with 50 consumers, which confirm that the results presented in this paper are robust and also representative for a larger number of participants.

Table 2
Techno-economic parameters for residential solar PV, BESS and EV. The data source is shown as either a reference or own model assumption (MA). Depicted investment costs are not annualized.

Parameter	Symbol	Unit	Value	Source
Solar PV				
Investment cost		€/kW	540	[29, 12]
Lifetime		years	25	[29]
PV Inverter				
Investment cost		€/kW	115	[29, 12]
Lifetime		years	15	[29]
BESS				
Investment cost		€/kWh	365	[36]
Lifetime		years	18	[36]
Charge rate	CR		1	MA
Charging efficiency	η^{ch}	%	92	[36]
Discharging efficiency	η^{dc}	%	92	[36]
Self-discharge	δ	%/hour	0.01	MA
BESS Inverter				
Investment cost		€/kW	124	[36]
Lifetime		years	20	[36]
EV				
Charging efficiency	η^{ch}	%	92	MA
Common				
Discount rate		%	4-6	MA

4.2. Time series

To capture the correlation between load patterns, solar PV generation and electricity prices, all time series data introduced in this section are sourced or simulated based on the year 2023. Hourly availability factors for residential solar PV across eight orientations are taken from *Renewables.ninja* [34]. To capture a range of rooftop orientations, we model four directional pairs: South-North, West-East, Southwest-Northeast, and Southeast-Northwest, and randomly assign these orientations to the 20 residential consumers.

Every consumer has an individual hourly electricity load ($D_{d,t,i}$) and an hourly mobility profile ($D^{EV}_{d,t,i}$), both linked via their occupancy profile $Occ_{d,t,i}$. The occupancy and load profiles are generated using the open-source tool StROBe (Stochastic Residential Occupancy Behavior) [3]. Mobility profiles are sourced from [33], which generates occupancy-based and hourly EV demand data (in kWh). We apply the same occupancy profile for both to ensure consistency.

To ensure computational tractability, we model an entire year with an hourly temporal resolution using representative days. Three days are selected per month, resulting in a total of 36 weighted representative time series, each comprising 24 hours. The representative days are selected based on the methodology of [35], using the Julia package *RepresentativePeriodsFinder.jl* [14].

4.3. EV smart charging

The EV smart charging model requires a set of assumptions. First, EV charging is allowed only when the consumer is home, implying that binary occupancy parameter $Occ_{d,t,i}$ equals one. Second, the EV battery must always be sufficiently charged to meet the demands of any upcoming trips before departure. Third, the EV battery is initialized with an energy storage level (e^{EV}_{init}) of 30 kWh at the start of the day, which is approximately half of the battery capacity of a Tesla Model 3. By the end of the day, the battery must be recharged to at least the same level.

4.4. Retail electricity contract

We consider two types of electricity contracts: a flat-rate contract, and a RTP contract. The RTP contract is based on the 2023 RTP contract from Engie, Belgium's largest electricity retailer. Hourly retail prices are calculated using the pricing formulas specified in the contract and 2023 Belgian day-ahead prices. Flat-rate retail prices are computed as a weighted average of hourly RTP retail prices in 2023, based on real load profiles (RLP) and synthetic production profiles (SPP) from the same year [42]. In practice, retailers typically charge higher fees for fixed-rate contracts to cover for their increased risk exposure [43]. However, we do not account for this effect as our analysis focuses on isolating the implications of P2P market design. Therefore, both RTP and flat-rate contracts are assumed to cost consumers the same, at least if their offtake (injection) profile aligns with the RLP (SPP).

Retail offtake prices include volumetric transmission network tariffs and excise duties on top of the energy commodity prices. The minimum monthly peak for calculating capacity tariffs is set at 2.5 kW, as stipulated by the Flemish regulation [44]. Physical limits on injection and offtake are determined according to Belgian residential connection capacity agreements [38].

4.5. Sensitivity analysis

To ensure robustness, we conduct an elaborate sensitivity analysis that comprises two stages. First, we perform 50 market simulations for each of the eight cases. Every simulation uses distinct consumer profiles randomly sampled from the time series dataset introduced in Section 4.2. The market outcomes from these simulations are then applied to five different random allocations of consumers across the eight representative feeders. In other words, we run 50 market simulations for each of the eight cases and then run 40 power flow analyses for each of those market simulations.

5. Results

This section presents an overview of the key performance metrics. Specifically, Section 5.1 discusses the consumer bills and Section 5.2 covers the P2P market prices and the DER investments. We additionally look at self-consumption and self-sufficiency indices in Section 5.3. The grid impact and the total system cost are presented in Sections 5.4 and 5.5, respectively.

5.1. Consumer bills

Figure 2 illustrates the total consumer bill under both flat-rate and RTP contracts for each P2P market mechanism, divided into three components: energy costs (including taxes and transmission fees), annualized investment costs for PV and BESS, and the capacity-based grid tariff. The bars and black dots represent average outcomes, whereas the error bars illustrate the range of outcomes across all sensitivities.

P2P trading effectively reduces consumers' electricity bills for all mechanisms. This has been shown before (e.g. [26, 16]), and is rather straightforward to explain: local P2P rates are more favorable as they fall between injection and offtake prices. We do point to two observations. First, the potential savings reach 10 % under a fixed retail contract, whereas it only reaches 5 % under dynamic pricing. As mentioned earlier, the difference between offtake and injection prices is smaller under dynamic pricing, and so is the potential gain of P2P markets to consumers. Second, P2P trading not only saves on the energy component of the bill, but also on the DER investment costs. Without P2P trading, consumers tend to invest heavily in PV installations that may not be optimally oriented. With P2P trading, those consumers can buy electricity from other participants with more favorable rooftop conditions. PV capacity therefore tends to be more concentrated on higher-yielding rooftops.

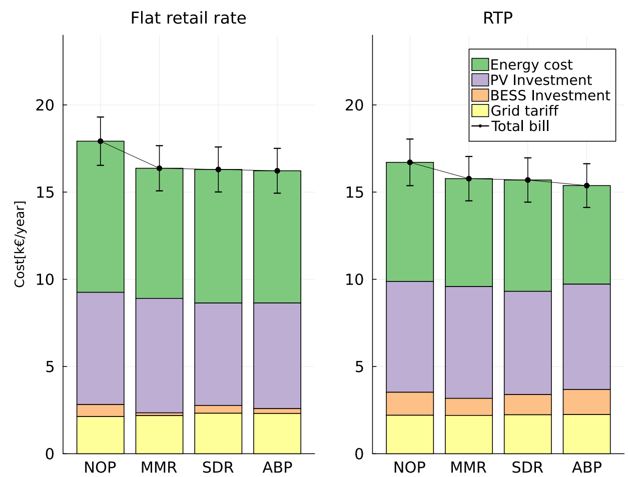

Figure 2: Total consumer bill under each P2P market mechanism combined with two different retail electricity contracts. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing. Black dots represent the average total consumer bill across all sensitivities, while error bars indicate the standard deviation of the results.

Auction-based pricing generally yields the lowest total consumer cost of all P2P market mechanisms. Then again, different mechanisms benefit different groups of consumers, which we turn to next.

5.2. Prices & Investments

Each P2P market design affects consumer behavior by shaping investment and operational decisions through distinct internal pricing mechanisms. To illustrate these effects, we start with the yearly average electricity selling and buying prices for each market design in Figure 3. The values are weighted by total offtake and injection to reflect the average prices that consumers face:

$$\overline{\lambda^{buy}} = \frac{\sum_{d\in D,t\in T} \Pi_d \cdot \lambda^{buy}_{d,t} \cdot Off_{d,t}}{\sum_{d\in D,t\in T} \Pi_d \cdot Off_{d,t}} \quad (30)$$

$$\overline{\lambda^{sell}} = \frac{\sum_{d\in D,t\in T} \Pi_d \cdot \lambda^{sell}_{d,t} \cdot Inj_{d,t}}{\sum_{d\in D,t\in T} \Pi_d \cdot Inj_{d,t}} \tag{31}$$

Without P2P trading, consumers face the lowest selling prices and the highest buying prices. P2P trading improves these rates from the consumers' perspective, but the different mechanisms do so differently. The SDR mechanism results in lower prices compared to the MMR mechanism. Frequent excess supply drives the prices toward the retail injection price under the SDR mechanism, and this effect is less pronounced under the MMR (see Figure 1). As a result, SDR is more favorable for households with little or no DER investment, while the MMR mechanism is more beneficial for solar PV investors. Auction-based pricing features the lowest buying prices and the highest selling prices because it is the only design in which injection can be sold at retail offtake prices, and offtake can be sold at retail injection prices. In addition, it is the only mechanism that balances benefits for both households with substantial DER investments and those with little or no DER investments, ensuring a relatively fair distribution of gains.

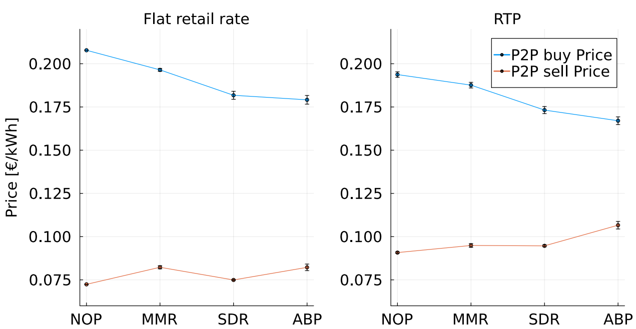

Figure 3: Average electricity prices seen by consumers in each case. In cases without P2P market, the price is set to be the average retail price. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing.

Now turning to investment decisions, PV investment is primarily driven by high P2P buying and selling prices. The former encourages PV investment to maximize self-consumption, while the latter provides an incentive for selling excess generation. As shown in Figures 2 and 3, the MMR and NOP cases lead to the highest PV investments[8] because of higher buying prices, while ABP encourages PV investment despite lower buying prices because of its higher selling prices. The difference in PV investment between flat-rate and RTP contracts is minimal, as both contracts are calibrated to align long-term price signals.

Battery investments are more complex to analyze due to their multiple uses, such as self-consumption, price arbitrage, and peak shaving. The internal pricing mechanisms in different P2P market designs influence how consumers utilize household BESS, which in turn impacts the profitability of and investment in BESS capacity. BESS charging patterns further vary among different types of consumers. For conciseness, we only provide a generalized summary.

First, batteries are used for peak shaving: shifting consumption to off-peak hours to avoid part of the capacity tariff. This can be indirectly observed from the grid tariffs paid by consumers (Figure 2). Second, in the flat-rate case without a P2P market, BESS is used exclusively for **individual self-consumption**, with all consumers following a straightforward operational strategy: they charge the battery with excess solar PV generation and discharge when needed for consumption.

With a P2P market, battery usage is optimized for **collective self-consumption**. Incentives to invest in batteries are muted in the MMR cases since excess electricity can be sold locally at relatively high P2P selling prices and thus does not need to be stored. Similarly, in SDR cases, low P2P buying prices discourage BESS investment, as buying electricity directly from the P2P market is more cost-effective.

In the ABP case with a flat retail price, consumers with low discount rates invest in batteries for (local) price arbitrage, while those with high discount rates invest less and size their batteries solely for peak shaving. With a dynamic contract, consumers are noticeably more inclined to invest in household BESS because of increased arbitrage opportunities.

5.3. Self-consumption & self-sufficiency

Figure 4 presents the collective self-consumption index (SCI) and collective self-sufficiency index (SSI) for the eight cases. The SCI quantifies the proportion of the PV production that is locally utilized over a year, and the SSI measures to what extent the local production fulfills the local demand [6]. These metrics are formally defined as:

$$SCI = \frac{\text{total production} - \text{total injection}}{\text{total production}} \tag{32}$$

$$SSI = \frac{\text{total production} - \text{total injection}}{\text{total demand}} \tag{33}$$

Two main factors affect these metrics. The first one is the inclusion of a P2P market, which facilitates local electricity sharing within the market and promotes more local consumption. Figure 4 shows that cases with P2P markets consistently exhibit higher SCI and SSI compared to cases without the P2P market under the same contract type. The second factor is DER investments. Additional PV capacity tends to increase the SSI but decrease the SCI due to higher overall production. BESS investments, in contrast, enhance both the SCI and the SSI by enabling greater self-consumption. The RTP contract consequently increases the SCI and SSI compared to the flat-rate contract because of additional BESS investments.

the ABP mechanism achieves the highest SCI and SSI on average under a dynamic contract, while the SDR mechanism performs the best under a flat retail rate contract. Both mechanisms drive the highest levels of BESS investment among all market designs within the same contract types. The SDR and ABP mechanisms under the flat retail rate

[8]PV or BESS investments can be mostly derived from the figure as they scale with investment costs. This relationship, however, does not exactly hold due to varying discount rates. The installation capacities for both PV and BESS are detailed in Appendix C.

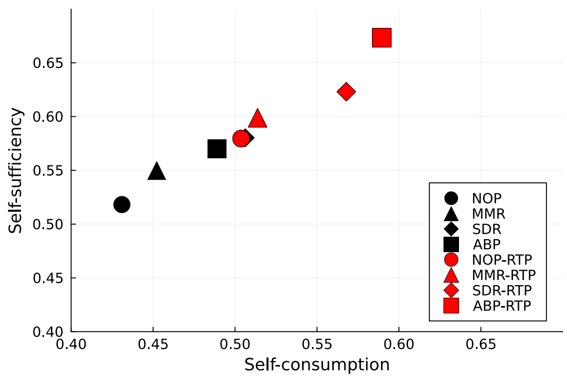

Figure 4: Average collective self-consumption and collective self-sufficiency indices in each case. Black markers represent cases with the flat-rate contract, while red markers denote cases with the RTP contract. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing, RTP: real-time pricing.

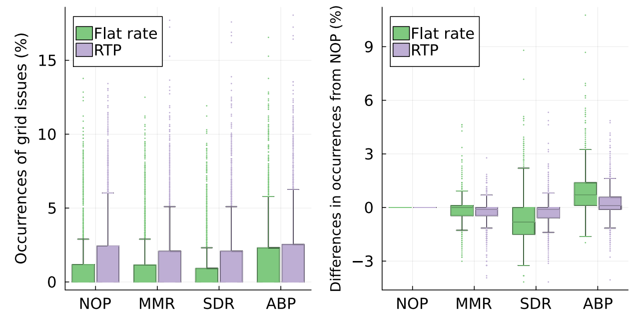

Figure 5: Left: Occurrences of grid issues in each case. Right: Relative difference in grid issue occurrences compared to the NOP case across each P2P market mechanism, combined with two retail contracts. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing. RTP: real-time pricing.

contract achieve similar SCIs and SSIs to those of the RTP contract without a P2P market. This is remarkable as they use much less BESS investment, which highlights the P2P market's effectiveness in enhancing local consumption.

5.4. Grid impact

Alleviating local congestion is one of the main potential benefits of P2P trading. Figure 5 illustrates the overall results of the power flow analyses. We consider three types of network violations: overvoltage, undervoltage and congestion. The figure includes all sensitivities and presents the number of occurrences in the left graph, and the relative difference compared to the conventional non-P2P trading cases in the right graph. Note that this section focuses on the total occurrences of network violations[9] to provide a general understanding of which mechanisms may alleviate or exacerbate grid issues. For a more detailed analysis of the severity and frequency of grid issues, including voltage and branch rating violations in different feeders, we refer the reader to Appendix D.

The RTP contract increases the frequency of network violations in nearly all market designs. In the NOP, MMR, and SDR mechanisms, the frequency of network violations under the RTP contract is almost double than that of the flat retail rate cases. This increase can be attributed to the coordinating role of wholesale price signals, which prompt consumers to react similarly by increasing their offtake during low-price periods. The difference between the two retail contracts in the ABP mechanism is relatively minor, which we return to later.

In comparison to cases without P2P trading, both the MMR and SDR mechanisms can effectively reduce the occurrences of network violations, while the ABP mechanism actually increases them (right plot in Figure 5). The MMR and SDR mechanisms both provide additional incentives for consumers to distribute offtake and injection over multiple hours, thereby alleviating congestion. The underlying mechanism is rather specific and we include a simplified example in Appendix E. Conversely, the ABP mechanism increases network violations by encouraging DER investment concentration in a few households. This concentration leads to high injections at specific nodes, thus increasing the likelihood of violations at specific nodes. Since this incentive applies to both contract types, it also explains the relatively smaller difference in occurrences of grid issues under ABP between a fixed retail price and RTP.

5.5. System cost

We compute the overall system cost to evaluate the system-wide efficiency of the P2P market. Figure 6 decomposes the system cost into energy costs (further divided into offtake and injection components) and investment costs for BESS and PV. The investment component simply equals the investment cost of PV and BESS. The energy cost represents the actual economic cost of electricity from a system-wide perspective, calculated using wholesale electricity market prices[10], as shown in Equation 34. Unlike the consumer bill metric, which captures the financial impact on individual households, the system cost reflects the broader economic implications of electricity usage within the P2P market and the overall efficiency gains it provides. Note that this metric serves as a proxy for the energy component, and that we do not value the implications for the distribution grid.

$$EC = \sum_{d \in D, t \in T} \pi_d \cdot (\lambda_{d,t} \cdot Off f_{d,t} - \lambda_{d,t} \cdot Inj_{d,t}) \tag{34}$$

RTP contracts yield approximately 10% lower system costs compared to the flat retail rate cases (Figure 6). Exposing consumers to wholesale prices encourages them to fulfill the system's needs. Although the NOP RTP case holds the most direct link to wholesale prices, the lowest system

[9]Quantified as the proportion of time steps with issues. Occurrences are calculated as: (Number of time steps with issues) / (Total number of time steps)

[10]Taxes and levies are excluded here, as they are transfers rather than actual economic costs.

cost across all cases is actually achieved under the MMR RTP case because it encourages more efficient investment patterns[11].

The inclusion of P2P markets can somewhat contribute to system efficiency, as seen in the MMR and ABP flat rate cases, as well as the MMR RTP case, but the overall effect remains limited. So P2P trading can significantly reduce consumers' bills (Section 5.1), but it has a limited impact on the overall system cost. P2P markets, in other words, introduce a distributional shift: the reduction in consumer bills is not the result of efficiency gains but instead merely a transfer at the expense of retailers.

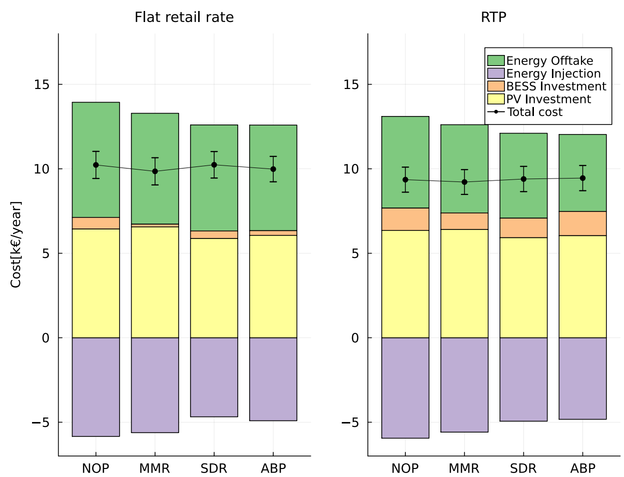

Figure 6: Total system cost in each case. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing. Black dots represent the average electricity procurement cost across all sensitivities, while error bars indicate the standard deviation of the results.

6. Conclusion

Different P2P market mechanisms produce distinct outcomes due to their unique pricing structures, influencing consumer investment and operational behavior, and impacting the overall electricity system. This study offers a quantitative comparison of three P2P market designs combined with two retail contract types: fixed and dynamic pricing. Our results show how P2P market designs affect DER investment, battery operations, consumer bills, system costs, and grid stress.

A key contribution of this work lies in incorporating long-term investment behavior into the evaluation of P2P mechanisms which is an aspect often overlooked in previous studies. Second, by analyzing P2P mechanisms under both static and dynamic pricing contracts, we assess the value that local energy trading can bring in contexts where consumers are already exposed to volatile price signals. Third, we extend beyond consumer cost impacts to evaluate overall system efficiency and the implications of different market designs for distribution grid performance.

Our results show that regardless of design, P2P markets can effectively reduce consumer cost, but the reduction is smaller under RTP contracts. P2P markets furthermore could serve as a potential alternative to RTP contracts, offering similar benefits in terms of self-consumption and consumer cost savings without exposing consumers to volatile prices , as P2P prices are typically bounded by retail offtake and injection prices. They can also contribute to system efficiency, though to a lesser extent than RTP contracts. Importantly, this contribution to efficiency is accompanied by a distributional shift, where the benefits of reduced consumer costs may come at the expense of retailers.

We also assess market mechanisms using a power flow model to capture both their economic efficiency and their direct impact on distribution grid performance. Among the evaluated designs, ABP performs well across several metrics, offering the lowest consumer cost, high collective self-consumption, and a fair distribution of gains among participants, although it may exacerbate grid issues. In contrast, MMR and SDR alleviate grid issues but offer slightly lower efficiency gains. Thus, ABP is more suitable for robust feeders, while MMR and SDR are more suited for feeders of lower resilience (e.g. those with longer branches prone to voltage violations at the end of the feeder).

This study is based on a deterministic framework with perfectly predictable demand and renewable generation. In practice, uncertainty in consumer behavior, renewable output and P2P market prices can significantly influence market dynamics. Future research could extend this analysis by incorporating stochastic modeling to assess how different P2P designs perform under uncertainty. Additionally, the passive role of electricity retailers in our analysis overlooks their potential strategic responses to P2P trading. Future studies should explore retailer adaptations to capture the dynamic interactions in the evolving electricity market.

Acknowledgments

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to enhance the quality of the text, including improving clarity and overall readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

[11]In our case study, even RTP retail prices are, in principle, distorted through additional levies.

A. Appendix: Iterative algorithm

Here is a brief introduction to the iterative algorithm used to model P2P market outcomes. An overview of the algorithm structure is presented in Algorithm 1, and the detailed implementations can be found in GitLab repository [27].

The algorithm is adapted from the Alternating Direction Method of Multipliers (ADMM), a dual decomposition method originally developed to solve convex optimization problems by dividing them into smaller subproblems [5]. However, given that we assume the electricity retailer can always balance any electricity surplus or deficit within the P2P market, the coupling constraint typically required for equilibrium is inherently satisfied.

The process begins by defining penalty rates for consumers' offtake and injection decisions (ρ_{off}, ρ_{inj}), tolerances for dual residuals (ϵ_{dual}), and a maximum iteration limit ($iter_{max}$). We then initialize the convergence status and the P2P market prices $\lambda^{P2P}_{d,t}$. These prices are iteratively updated based on the pricing mechanisms introduced in Section 2 to guide the agents towards an equilibrium. In each iteration, updated prices are announced to all consumers, who then optimize their individual objectives as detailed in Section 3.1. After all agents complete their optimization, we calculate dual residuals by comparing current and previous injection or offtake values. The algorithm repeats until convergence which represents a Nash equilibrium of the game described by Equations 6 - 29.

Algorithm 1: Iterative algorithm for computing a Nash equilibrium of the non-cooperative game

Data: All parameters belonging to all consumers' optimization problems.
Result: Nash equilibrium solution to the game.
Define ρ_{off}, ρ_{inj} , ϵ_{dual}, $iter_{max}$;
Initialize P2P market prices $\lambda^{P2P}_{d,t}$, and $conv = 0$
while $conv = False$ **and** $iter \leq iter_{max}$ **do**
    Solve 20 consumers' decision problems.
    Calculate dual residuals r_{dual}.
    Update P2P market prices.
    Update convergence: $conv = \|r_{dual}\| \leq \epsilon_{dual}$.
    $iter = iter + 1$.
end

B. Appendix: Overview of the selected feeders

In Table B1, we summarize the key characteristics of the eight feeders analyzed in this study, including the number of residential consumers, the percentage of active consumers[12], total feeder length, main path length, and average path length from the substation to all consumers on the feeder. The corresponding feeder IDs of the selected feeders are also provided. For further details, please refer to the open dataset published in [22] using the listed feeder IDs.

In Figure B1, we present the network topology using graphical representations of two feeders. The slack bus (substation) is marked as a red dot, where both the generator and high-voltage (HV) load are placed. Residential loads generally represent individual households, while multiple loads clustered around a single node indicate an apartment building.

C. Appendix: DER Investment

The total investment capacity of solar PV and BESS are shown in Figure C2 and Figure C3, respectively.

D. Appendix: Grid impact

In Section 5.4, we assess the grid impact of various P2P market mechanisms by analyzing the frequency of grid issues across different feeders. While this metric provides insights into how often grid issues occur, it does not capture their severity (e.g., magnitude of voltage violations) or scope (e.g., number of affected nodes or branches per time step). To address these limitations, we expand the analysis in this section to assess both the severity and scope of grid issues. Specifically, we examine the voltage levels of all nodes (Figure D4 and D5) and the branch use of all branches (Figure D6) per representative feeder under different market mechanisms, combined with two distinct retail contract types.

Figures D4 and D5 illustrate node voltage levels under different P2P market mechanisms with flat-rate and RTP contracts, respectively. Given the large dataset, results are derived from 25 power flow analyses (five random market outcomes with five random node allocations). In both figures, the red and blue dots represent the 99.9% quantile (red) and 0.1% quantile (blue) of node voltage levels across all power flow simulations for a given market mechanism. These values reflect the maximum and minimum voltage levels observed on the feeder. The size of the dots corresponds to the frequency of overvoltage (red) and undervoltage (blue) events, where each instance (one node at one time step) counts as one violation. Even when no violations occur, small dots mark observed voltage extremes. The position and size of these dots allow us to infer the severity and frequency of grid issues across feeders.

In Figure D4, voltage violations primarily occur on feeders D, F, and G. As noted in Section 5.4, MMR and SDR reduce both the severity (lower maximum voltage, higher minimum voltage) and frequency (smaller dot size) of these issues. In contrast, ABP exacerbates violations, leading to higher maximum voltages, lower minimum voltages, and more frequent violations (larger dots). Even feeders C and E, which experience few violations without P2P trading, show new violations or altered voltage levels under ABP. These trends hold across all feeders, despite their differences. In Figure D5, similar trends emerge under the RTP contract, especially for undervoltage issues.

[12] The percentage of active consumers is calculated as the ratio of 20 active consumers to the total number of consumers in each feeder (20/ total consumers).

Table B1
Overview of features of the selected eight feeders.

Feeder	ID	No. of consumers	Pct. of active consumers [%]	Total feeder length [km]	Main path length [km]	Average length to consumers [km]
A	65079_77940	149	13.4	1.05	0.30	0.14
B	1142831_1465663	63	31.7	1.46	0.48	0.31
C	65082_80175	56	35.7	1.32	0.37	0.24
D	1136065_1450304	44	45.4	1.17	0.35	0.24
E	65028_84569	117	17.1	2.11	0.68	0.24
F	65019_73796	30	66.7	1.13	0.65	0.44
G	1459343_1931569	32	61.5	1.55	0.63	0.33
H	65019_74478	52	38.4	0.72	0.25	0.09

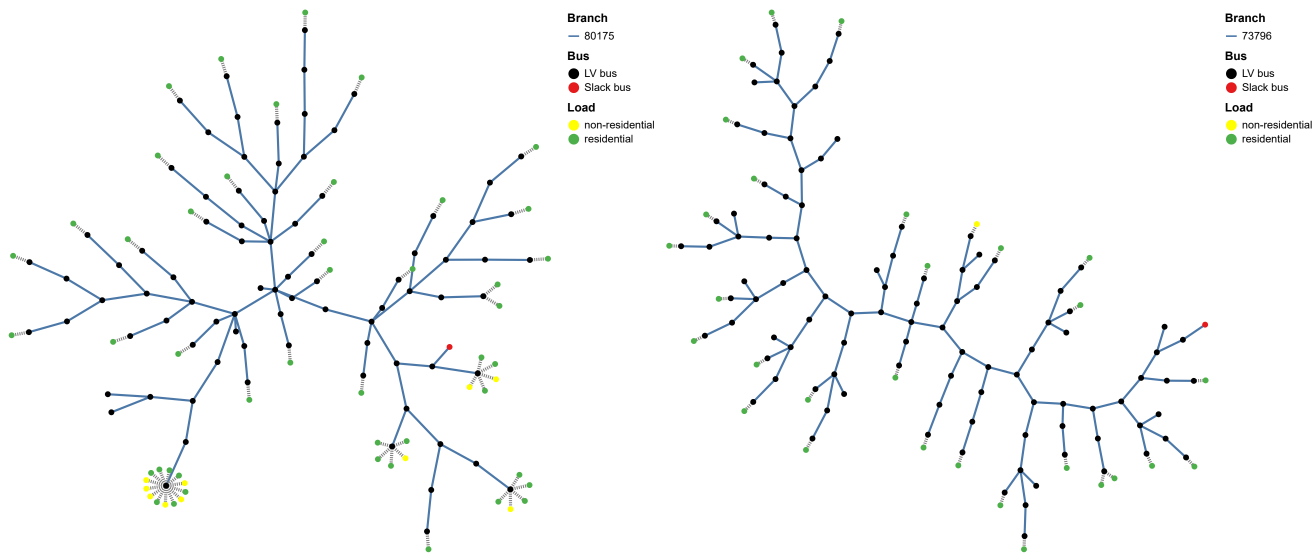

Figure B1: Graphical representations of two feeders (C, F).

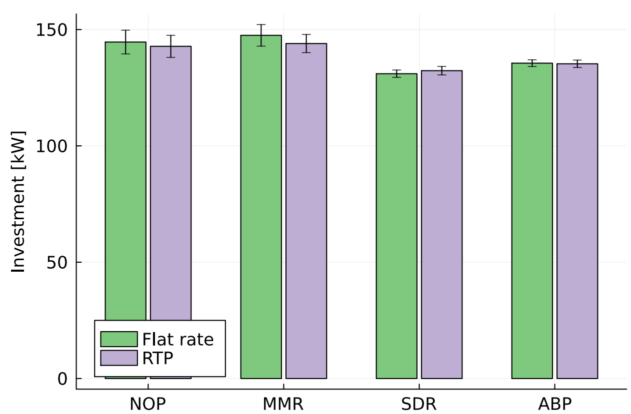

Figure C2: Capacity of solar PV investment in each case. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing, RTP: real-time pricing.

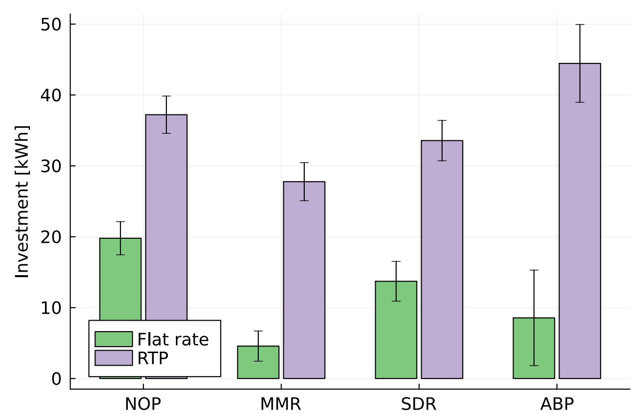

Figure C3: Capacity of BESS investment in each case. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing, RTP: real-time pricing.

Comparing Figures D4 and D5, we find that the RTP contract increases the frequency and severity of undervoltage events (lower minimum voltage and larger blue dots), but the impact on overvoltage is less significant.

In Figure D6, the maximum branch use across different cases is presented. The branch use measures how much of a branch's capacity is being used, defined as the ratio of the rated power of a branch to its actual load power. A branch use exceeding 1 indicates a theoretical overload

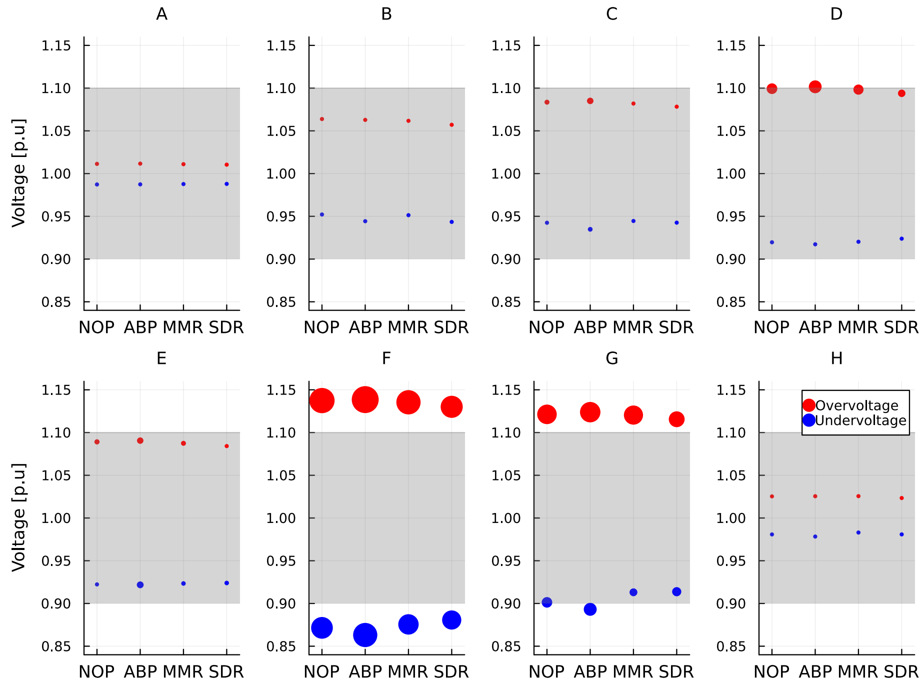

Figure D4: Frequency and severity of overvoltage and undervoltage events under different P2P market designs with flat-rate contract. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing.

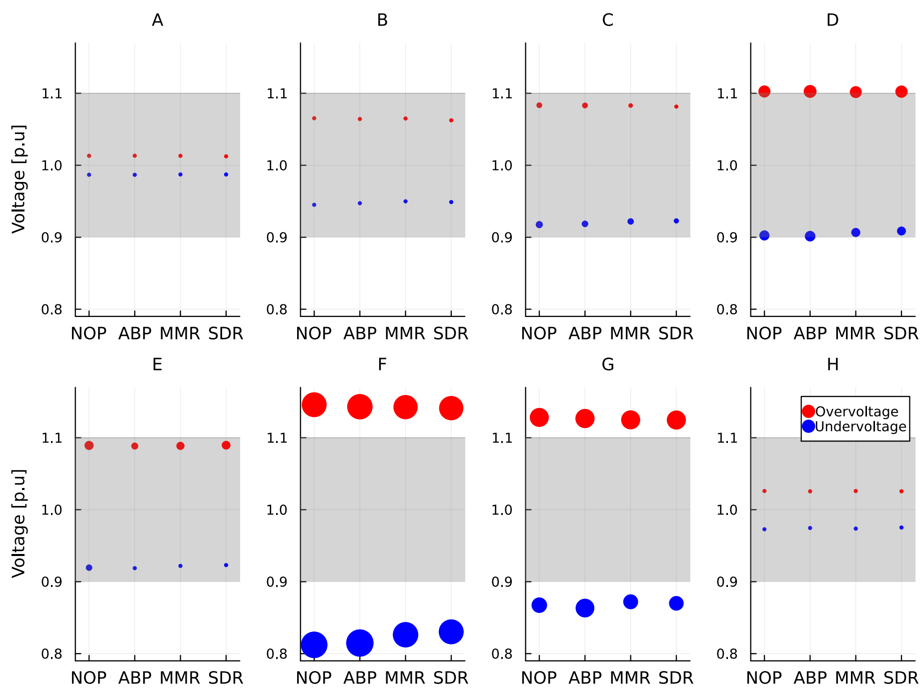

Figure D5: Frequency and severity of overvoltage and undervoltage events under different P2P market designs with RTP contract. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing.

condition. Branch rating violations are less frequent than voltage violations, occurring only on feeders C and D. However, Figure D6 confirms similar trends: MMR and SDR reduce congestion severity, while ABP increases congestion frequency and intensity.

E. Appendix: Inner pricing mechanism

This example demonstrates how the internal pricing mechanisms of the MMR and SDR models provide additional incentives for consumers to distribute their offtake

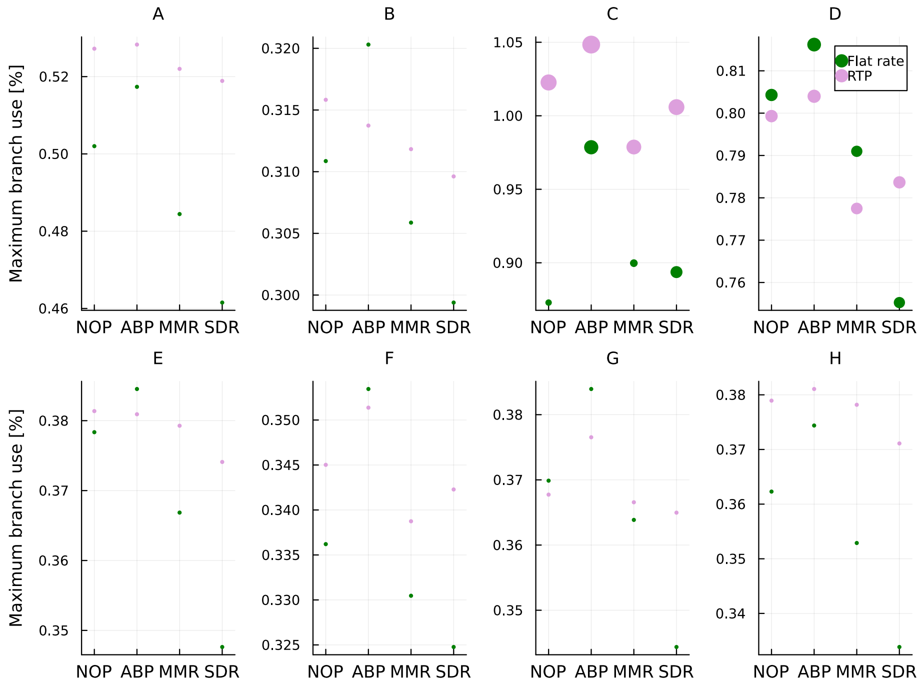

Figure D6: Maximum branch use under different P2P market designs combined with flat-rate and RTP contract. NOP: no P2P market, MMR: mid-market rate, SDR: supply-demand ratio, ABP: auction-based pricing, RTP: real-time pricing.

Table E2
Strategy in NOP case

Hour	1	2	3	4
price	0.1	0.1	0.1	0.1
offtake	50	50	50	50
Injection	60 + 10	60	60	60

and injection activities across multiple hours, rather than concentrating them in a single period.

Consider a four-hour period with an offtake retail price of 0.3 €/kWh and an injection retail price of 0.1 €/kWh. Here we only focus on the behavior of one consumer while assuming that the offtake and injection decisions of all other agents are fixed. The initial condition, detailed in Table E2, assumes a total offtake of 50 kWh and a total injection of 60 kWh by other participants each hour. Now, the consumer must decide when to inject its 10 kWh of electricity, assuming it has the flexibility to shift all electricity across any of the four hours.

Under a flat retail rate contract, this consumer would simply choose to inject all 10 kWh in Hour 1[13], given the retail injection price of 0.1 €/kWh, yielding a total income of 1 €for selling the excess electricity.

In contrast, with a P2P market using the MMR mechanism, injecting all 10 kWh in Hour 1 would result in a P2P selling price of 0.171 €/kWh, as calculated using Equation 5. This would yield a higher income of 1.7 € for the 10 kWh of electricity. However, as seen in Table E3, injecting the full

[13]Although the consumer is theoretically indifferent about which hour to inject because of identical prices, in our case study, the consumer will always choose Hour 1 due to the (dis)charging efficiency of batteries.

Table E3
Strategy 1 in MMR case

Hour	1	2	3	4
price	0.171	0.183	0.183	0.183
offtake	50	50	50	50
Injection	60 + 10	60	60	60

Table E4
Strategy 2 in MMR case

Hour	1	2	3	4
price	0.18	0.18	0.18	0.18
offtake	50	50	50	50
Injection	60 + 2.5	60 + 2.5	60 + 2.5	60 + 2.5

amount in a single hour lowers the P2P market price due to the added supply, making this strategy suboptimal.

The optimal strategy under the MMR mechanism is to spread the 10 kWh injection equally across the four hours, as shown in Table E2. This results in a P2P market price of 0.18 €/kWh in all four hours, giving the consumer a total revenue of 1.8 €, higher than if the injection had been concentrated in one hour.

This example only illustrates how the MMR mechanism encourages consumers to distribute their injections over time to maximize income. A similar principle also applies to offtake, and SDR mechanisms, though these are not elaborated here.

CRediT authorship contribution statement

Yucun Lu: Conceptualization, Methodology, Data curation, Visualization, Formal analysis, Writing - original draft, Writing - review & editing. **Jelle Meus:** Conceptualization, Methodology, Writing - review & editing. **Chiara Gorrasi:** Methodology, Writing - review & editing. **Erik Delarue:** Writing- review & editing, Supervision.

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