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Assessing the impact of energy communities on retailers' balancing positions in the power market

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ABSTRACT

As regulatory constraints limit energy communities' (ECs) participation in wholesale markets, these might rely on retailers' supply when local generation falls short. As balancing responsible parties, retailers are financially responsible for matching the volumes traded in the market with customers' actual needs. However, inadequate information about ECs' operations may complicate this task. This paper explores the interactions and financial implications for retailers under contractual agreements with ECs. We design a novel modelling framework, consisting of: (1) a stochastic model of a strategic retailer participating in the day ahead market considering imbalance costs, (2) a community model optimising its operations based on the agreed tariff subscription with the retailer, and (3) a simulation of the imbalance settlement process. The frameworks' applicability is demonstrated via a case study in London (UK). Results indicate that retailers' primary source of profit loss arises from the increased self-sufficiency of customers belonging to EC. On the other hand, deviations from the market commitments exerts limited effects on retailers financial outcomes. This is explained by the earnings obtained by providing passive balancing services to system operators. Also, the paper underscores retailers' need to reassess their business models, looking beyond merely establishing operational data exchange with ECs.

1. Introduction

The simultaneous adoption of distributed energy resources (DERs) and advancements in information technologies have triggered increased interest to promote more active participation of consumers in the power sector. This shift towards a consumer-centric power system has stimulated the emergence of energy communities (ECs). The European Union has provided legislative frameworks for these citizen-led initiatives in two directives: Renewable Energy Directive (2018/2001/EU) [1] and Internal Electricity Market Directive (2019/944/EU) [2]. Both documents agree on defining energy communities as non-commercial groups of end users (i.e., households, public authorities, and small and medium-sized enterprises) who come together to achieve environmental, economic and social benefits.

While the definitions presented in the regulation establish an overall idea of ECs, these provide room for interpretation of how ECs might perform and interact in specific contexts. This has fostered diverse business model ideas, exploring how ECs create value and interact with other agents of the energy system [3]. Nevertheless, current regulations place some limitations on the activities ECs can undertake. For example, they are not allowed to participate directly in wholesale markets [4,5]. Therefore, within the scope of this work, energy communities are defined as organised groups of consumers who utilise their assets to enhance their self-sufficiency, but maintain contractual agreements with power retailers to receive electricity supply from upstream generation when local production is insufficient.

Energy retailers are the intermediaries between the electricity markets and consumers. They purchase power from the wholesale market or through bilateral contracts and resell it to their customers at a subscription rate. Retailers, whether they act as balancing responsible parties (BRPs) or are part of one, are liable to face penalties if their customers' actual demand deviates from the power purchased from the market. The difference between the power purchases and the actual demand is known as *deviation*. Through penalisation, system operators incentivise retailers to make accurate forecasts of their customers' expected demand to procure adequate power volumes from the market.

Given that ECs rely on power retailers to meet their net loads, the suppliers participate in the power market to cover the predicted load of ECs as accurately as possible, thereby minimising potential penalties. However, this task might become complex if the retailer is not informed of real-time changes in the operations of ECs. The discrepancy between the actual needs of the ECs and the market position of retailers could induce balancing penalties and increase financial uncertainty on retailers.

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Therefore, this paper aims to shed light on the potential financial consequences that power retailers may encounter due to the operations of ECs, particularly when there is a lack of coordination or data exchange between them. To delve into this subject, we propose the following research questions:

- What are the financial repercussions on retailers resulting from the formation of ECs by their customers?
- How does the net load of ECs impact the balancing outcomes for retailers with and without operational data exchange?
- Can the design of ECs (e.g., technologies and tariffs) influence the financial outcome experienced by retailers, and if so, to what extent?

Exploring these questions is an important factor for the forthcoming evolution of the power system, and the consumer-centric policies directed by the EU. Understanding the interactions between ECs with other system actors is crucial for their successful integration and for anticipating potential side-effects arising from their implementation. For example, if non-flexible customers might be subjected to increased tariff as retailers attempt to mitigate additional market risks from balancing penalties.

The following section provides a background summary of the balancing system and retailers' roles and responsibilities as BRPs. Particular attention is paid to the adoption of the *single price mechanism* which is the new protocol pricing the deviations charged to BRPs in Europe. Then, Section 2 provides a literature review to identify the research gaps and contributions of the paper. Sections 4 and 5 describe the methodology and the case study. The results for both the retailer and the community are discussed in Section 6. Lastly, Section 7 presents final remarks and conclusion.

2. Background: The balancing system

The European balancing system in Europe, managed by transmission system operators (TSOs), is structured to ensure a constant equilibrium between production and consumption, which is crucial for the stable operation of the power grid. Three chronological stages in the electricity balancing process can be identified [6]: balancing planning (pre-delivery), balancing service provision (during delivery), and balancing settlement (post-delivery).

During the balancing planning phase, BRPs participate in the day-ahead market, buying/selling power according to their forecasted load/production for the following day. The volume of electricity traded in the market by a BRP is known as the contracted position and indicates the amount of power they have committed to consume/produce. Throughout the day of delivery, BRPs' forecasts may deviate from the contracted volumes agreed upon the day before. The difference between the contracted position and the actual withdrawal from the grid results in imbalances, which are often penalised. BRPs can trade volumes in the intraday market or active their internal balancing assets to manage these deviations. The final contracted positions are communicated to the TSO before the gate closure time, typically minutes before the actual physical delivery begins.

Despite the mechanisms in place during the planning phase, BRPs may fail to align their contracted position with their actual power needs/deliveries. If this occurs, the BRP could have surplus volumes if their contracted position exceeds their real electricity need, or deficit volumes if it falls short. The sum of the imbalance volumes of all BRPs within a region constitutes what is known as the system imbalance. During the balancing service provision stage, it is the TSO's responsibility to restore system balance, achieved through the activation of balancing reserves (e.g. fast-start power plants, demand response programmes). TSOs incur costs operating and managing these reserves, which are recovered by imposing charges on BRPs. These charges are proportionate to the imbalance price and the deviation volumes caused by each BRP.

Table 1
BRP economic outcome relative to its position and the position of the system.

BRP imbalance volumes	System position	BRP outcome
Surplus	Surplus	Net profit: loss
	Deficit	Net profit: gain
Deficit	Surplus	Net profit: gain
	Deficit	Net profit: loss

During the balancing settlement stage post-delivery, BRPs are charged an imbalance price whose value is a function of the system imbalance. Set by system operators, this price encourages BRPs to align their contractual positions with their actual power needs/delivery. Depending on the imbalance direction, a BRP might be charged either the long or short imbalance prices. Long imbalance prices apply to BRPs with surplus volumes in their imbalance position, while short imbalance prices are levied on those with power deficits. If the two prices have different values, the system applies the dual pricing mechanism. Conversely, if they are equal, it denotes a single pricing mechanism.

Since July 2020, the European Union's Agency for the Cooperation of Energy Regulators (ACER) established the harmonisation of the imbalance settlement protocols and selected the single pricing mechanism as the default mechanism across Europe [7]. This system is highly regarded for its efficiency in balancing costs recovery, as it is cost-neutral for TSOs and rewards the passive balancing service, contrary to double pricing schemes [8].

Passive balancing services are provided by a BRP when it indirectly assists the TSO in reducing system imbalances. This service occurs when a BRP's deviations counteract the system imbalance. In such scenarios, the BRP is compensated because its actions are interpreted as providing service to the TSO. Conversely, if the system and a BRP have matching positions – such as both being in surplus or deficit – the BRP is penalised.

Specifically, in instances when a BRP has surplus deviations, the system compensates for these volumes at the single imbalance price, henceforth referred to simply as the imbalance price. If the imbalance price surpasses the day-ahead price, the BRP profits from larger earnings than expenses. However, if the imbalance price is lower and despite receiving revenues from the balancing system, the BRP losses the difference. For BRPs in deficits, deviation volumes are purchased at the imbalance price. If these deviations are valued lower than in the day-ahead market, the BRP benefits from reduced costs, while if they are priced higher, the BRP incurs higher costs. As a result, the single pricing mechanism incentivises arbitrage by rewarding over/undercontracting in wholesale markets to diverge from the system imbalance position. Table 1 provides the economic outcome of BRPs relative to its imbalance and the system imbalance positions when the single price mechanism is applied.

3. Literature review

In recent years, ECs have received academic and political attention, given the multiple advantages for consumers such as reducing operational costs, increasing self-sufficiency, increasing democracy and consumer empowerment, among others [9]. The broad scope of the concept has led to the proposition of multiple governance structures within the literature. These structures outline the interactions among the community members, as well as their potential engagements with other agents from the power system [3,10,11]. Regarding the internal operations of ECs, scholars generally agree on dividing ECs into two main categories: centralised and decentralised communities. Centralised communities are governed by a central manager who is responsible for optimising the utilisation of the resources [12], while decentralised communities allow users to act as strategic agents, interacting with each other on trading platforms [13].

Furthermore, adopting DERs within ECs might bring technical challenges that may compromise the security and quality of the energy supply [14]. To alleviate grid-related issues, end-user flexibility can support the operations of distribution system operators (DSOs) by providing services like voltage control and congestion management [15–17].

Despite the extensive research focusing on ECs and their consequences in the network, limited attention has been given to their potential consequences on electricity retailers and BRPs, along with the potential interactions between them [18].

One area of research aims to mitigate the financial stress experienced by retailers due to price fluctuations in wholesale markets by examining the potential of prosumers delivering demand response services [19,20]. As an example, [21] present a dynamic programming model to optimise the scheduling of demand response events from retailers' customers. Building upon this work, Chanpiwat et al. [22] propose a clustering algorithm that selects and categorises customers based on the assumption that households with peak loads during high-price timesteps are likely to generate more profits. An alternative approach is presented in [23], where a bi-level optimisation technique decides the dynamic price tariff that incentivises consumers to shift their load to better align with wind and PV output. All in all, adopting demand response programmes at the prosumer level, potentially extendable to ECs, has demonstrated value creation for end-users and retailers. However, these studies primarily focus on the risks associated with price dynamics in wholesale markets, frequently overlooking the balancing responsibilities of retailers.

Alternatively, other studies have proposed adopting aggregator-based business models within ECs. These models involve individual consumers engaging in contractual agreements with a central entity (e.g., a retailer) to pool their flexibility in the market, particularly in the balancing market [24,25]. For instance, [26] propose a stochastic optimisation model for an aggregator to find the best bidding strategy for the day-ahead market by aggregating DER flexibility. Nevertheless, a significant driver behind the success of ECs among citizens is the possibility of minimising the involvement of third parties in internal decisions [27]. Accordingly, although these aggregator-based business models are viable in practical settings, some customers might still prefer to avoid participating in aggregators. In such cases, ECs typically assume that they are subscribed to retailers who ensure electricity supply during periods of low local production [12]. These business proposals may appeal customers preferring to avoid the involvement of external actors, but they often neglect the implications for retailers who continue to supply ECs.

To our knowledge, no study has provided a comprehensive analysis of the effect of ECs on retailers considering the whole market value chain from the day-ahead market to the imbalance settlement process. In their study, [28] examines possible cooperation between a prosumer and a retailer susceptible to penalties for deviations using cooperative game theory approaches. Although [28] set the foundational idea and extend the knowledge in this area, the authors simplify the imbalance settlement process using a double-pricing mechanism and not considering the passive balancing effect of the single-pricing mechanism.

This paper contributes to the literature by providing a new reasoning and developing a novel modelling approach for the interactions between retailers and energy communities, considering the possible effect of passive balancing. The sequential framework developed in this study quantifies and contributes analysing the financial outcomes of retailers and EC interacting with each other. Firstly, we develop a new stochastic optimisation model for a strategic retailer participating in the day-ahead market. The decision variable in this model is the volume of power to purchase in the day-ahead market, considering the uncertainty of potential penalties (i.e., imbalance price) for incurring in deviations. Secondly, the operations of a EC subscribed to the retailer are modelled using a deterministic optimisation model that decides the operations of storage technologies to minimise operational costs. The financial outcomes from the imbalance settlement process are computed. Four case studies are presented, each based on the type of tariff subscription and the storage technologies available in the community, to explore the effect of EC design. The method is applied to a case study in London (UK) using real-life data from different sources.

Additionally, the paper adds to the state of the art by presenting a comparative case wherein retailers have complete information on the EC's operations when participating in the wholesale market. This case provides valuable insights into the degree to which collaboration between these two entities might alleviate deviations and possible penalties for retailers. By exploring these interactions, we are contributing to exploring the effect of ECs in retailers considering the entire value chain of the power market, from the day-ahead market to the imbalance settlement process.

4. Methodology

The impact of an energy community on its retailer's balancing position in the market is analysed using a three-step framework. This approach, illustrated in Fig. 1, comprises a retailer model, a community model and an ex-post analysis of the retailer's financial outcome.

1. **Retailer Commitment Model**: The day before delivery, the retailer strategically participates in the day-ahead market to purchase electricity to meet its customers' demand, which in this context are the community members. The retailer aims to maximise profit through passive balancing provision. The stochastic model considers the uncertainties associated to the customers' net load due to uncertain local electricity production and the imbalance prices. The stochastic loads considered vary based on the information available from the community.
2. **Energy Community Model**: On the day of delivery, the community collaboratively operates the batteries and determines the peer-to-peer transactions to reduce the joint electricity bill, subsequently reducing payments to the retailer. As a deterministic model, the community decides its operations with complete information about renewable generation, load profiles, and tariff subscription. The realised renewable generation is considered to be within the retailer's set of scenarios.
3. **Ex post analysis**: The final step involves calculating the retailer's financial outcome after its commitments in the day-ahead deviate from the actual needs of the community.

In designing this framework and determining the interactions between agents and models, we took into account several key assumptions.

- The retailer is a price-taker from the day-ahead market and the balancing market.
- The retailer's final commitment communicated to the TSO equals its commitment in the day-ahead market. In other words, the retailer does not activate any balancing mechanisms on the day of delivery.
- Any penalties for frequent deviations from market commitments are considered.
- All community members are customers of the same retailer and subscribe to the same tariff scheme.
- The community does not operate to provide services (e.g., congestion management) to external stakeholders.

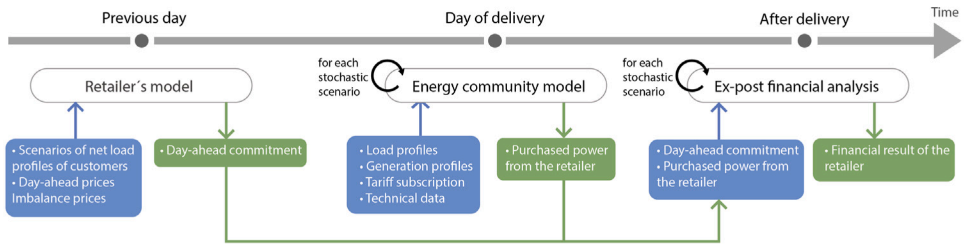

Fig. 1. Modelling framework of the three-sequential steps and the input (in blue) and output data (in green) of each model.

4.1. Retailer commitment model

The retailer's optimisation problem involves purchasing electricity volumes, x_t^*, at each time interval, $t \in T$, in the day-ahead market on the day preceding delivery. Expected surplus, $x_{t,\omega}^+$, and deficit, $x_{t,\omega}^-$, deviations are valued according to the imbalance price spread, λ_{zt}. This price is computed as the difference between the imbalance and day-ahead prices. If this price is positive, the TSO rewards surplus deviations; if negative, it rewards deficits.[1] Under this penalty/reward system, the objective function (Eq. (1)), with $\Gamma = \{x_t, x_{t\omega}^+, x_{t\omega}^-\}$, seeks to maximise the expected profit derived from providing passive balancing services.

$$\max_{\Gamma} \mathbb{E}\left[\lambda_{zt} \cdot \left(x_{t\omega}^+ - x_{t\omega}^-\right)\right], \forall t \in T \tag{1}$$

$$\min\left\{\sum_{h\in H} L_{th\omega}\right\} \leq x_t \leq \max\left\{\sum_{h\in H} L_{th\omega}\right\}, \qquad \forall \omega \in \Omega \tag{2}$$

$$x_t - \sum_{h\in H} L_{th\omega} = x_{t\omega}^+ - x_{t\omega}^-, \qquad \forall \omega \in \Omega \tag{3}$$

$$x_{t\omega}^+,\ x_{t\omega}^-,\ x_t \geq 0, \qquad \forall \omega \in \Omega \tag{4}$$

The retailer's goal is subject to constraints to meet the net load of each customer, $h \in H$. However, since the realised net load is unknown at this stage, potential net loads, $L_{th\omega}$, are captured in each scenario, $\omega \in \Omega$. Furthermore, the uncertainty associated with future imbalance prices is represented by the scenarios $z \in Z$. In Eq. (2), the day-ahead commitment is constrained between scenarios with the largest and lower sum of net loads, limiting the retailer's speculative behaviour in line with market regulations.

Finally, the deviations for each scenario ω are obtained by subtracting the net load in the same scenario from the day-ahead commitment, as indicated in Eq. (3). Note that the day-ahead commitment, as a first-stage decision variable, maintains a consistent value across all the scenarios.

4.2. Energy community model

On the day of delivery, the EC operates with complete information about loads, renewable generation and the state of charge of the batteries. The realised output of renewable energy is represented by scenario $\hat{\omega}$, which is unknown in the methodology. However, if we presume $\hat{\omega}$ belongs to the set Ω, we can estimate a range of potential outcomes by initiating a run-through of all possible scenarios.

$$\min_{\Theta} \sum_{t\in T}\sum_{h\in H} \mu_t \cdot g_{th}(\omega), \qquad \forall \omega \in \Omega \tag{5}$$

$$g_{th}(\omega) + R_{th}(\omega) + d_{th}(\omega) + i_{th}(\omega) \geq L_{th}(\omega) + c_{th}(\omega) + e_{th}(\omega), \qquad \forall t \in T, \forall h \in H \tag{6}$$

The total operational cost of the community for a given day is formed by the volumes purchased to the retailer in each household and timestep, denoted by g_{th}, priced at the subscribed retail tariff μ_t. This goal is captured in Eq. (5), where $\Theta = \{g_{th}, d_{th}, d_{th}^{EV} c_{th}, c_{th}^{EV}, i_{th}, e_{th}\}$. A balance of power demand and supply is essential for each member, as expressed in Eq. (6). The supply at each household stems from self-consuming their renewable production, R_{th}, discharging power from their storage technologies d_{th}, importing from other members i_{th} or purchasing from the retailer g_{th}. Conversely, each household's power demand comprises the load L_{th}, the charging of the storage technology c_h, and power exports to neighbours e_{th}.

As outlined earlier, the EC has the option to decide on peer-to-peer exchanges of power. Each member is allowed to supply, e_{thp}^{peer}, and receive, i_{thp}^{peer} power from a peer house $p \in H \setminus \{h\}$. Eqs. (7) through (10) ensure the total electricity traded remains within the community and the losses, ψ, are accounted for.

$$e_{th}(\omega) = \sum_{p\in H\setminus\{h\}} e_{thp}^{peer}(\omega), \qquad \forall t \in T, \forall h \in H \tag{7}$$

$$i_{th}(\omega) = \sum_{p\in H\setminus\{h\}} i_{thp}^{peer}(\omega), \qquad \forall t \in T, \forall h \in H \tag{8}$$

$$\sum_h i_{th} = \psi \sum_h e_{th}(\omega), \qquad \forall t \in T \tag{9}$$

$$\sum_h i_{thp}^{peer}(\omega) = \psi \sum_h e_{tph}^{peer}(\omega), \qquad \forall t \in T, \forall p \in H \setminus \{h\} \tag{10}$$

The storage technologies of the houses, $h \in H_{bat}$ are operated following Eqs. (11) to (15). The state of charge s_{th} in the last period is constrained by a minimum state given as the percentage of the maximum capacity, $\overline{S}$, (Eq. (14)). This lower bound is adopted to ensure the availability of electricity for the next day. In addition, to help extend the longevity of the batteries, an additional lower limit is incorporated for the remaining periods (Eq. (15)). Moreover, the battery model determines the maximum discharge, $\overline{D}$, and charge, $\overline{C}$.

$$s_{th}(\omega) \leq \overline{S}, \qquad \forall t \in T, \forall h \in H_{bat} \tag{11}$$

$$s_{th}(\omega) = s_{(t-1)h}(\omega) + \varepsilon^c c_{th}(\omega) - \frac{1}{\varepsilon^d} d_{th}(\omega), \qquad \forall t \in T \setminus \{1\}, \forall h \in C^{bat} \tag{12}$$

$$s_{th}(\omega) = I + \varepsilon^c c_{th}(\omega) - \frac{1}{\varepsilon^d} d_{th}(\omega), \qquad t = 1, \forall h \in C^{bat} \tag{13}$$

$$s_{th}(\omega) \geq \delta \overline{S}, \qquad t = |T|, \forall h \in H^{bat} \tag{14}$$

$$s_{th}(\omega) \geq \gamma \overline{S}, \qquad \forall t \in T \setminus \{|T|\}, \forall h \in H^{bat} \tag{15}$$

$$c_{th}(\omega) \leq \overline{C}, \qquad \forall t \in T, \forall h \in H_{bat} \tag{16}$$

$$d_{th}(\omega) \leq \overline{D}, \qquad \forall t \in T, \forall h \in H_{bat} \tag{17}$$

Additional constraints become pertinent when the storage technologies are EVs. Specifically, the usage patterns of EV owners determine when these vehicles are connected to the community's grid. At the time of departure $t \in T_h^{departure}$, the EVs belonging to households $h \in H_{EV}$ need to be fully charged, as in Eq. (18). Meanwhile, the state of charge at the time of arrival $t \in T_h^{arrival}$ is defined by the parameter $S_{th}^{arrival}$, as outlined in Eq. (19). The value of this parameter depends on factors

[1] Note that if $\lambda \geq 0$ the imbalance price is higher than the day-ahead price. The surplus volumes are then rewarded by valuing them at a higher price than during the day-ahead market. On the contrary, BRPs in deficits need to pay a higher price to cover the demand than tje price they would have paid if purchasing in the day-ahead market. The opposite logic applies when $\lambda \leq 0$.

such as the distance travelled and charging carried out outside the community.

$$s^{EV}_{th}(\omega) = \overline{S}, \quad \forall t \in T^{departure}_{h}, \forall h \in H^{EV} \tag{18}$$

$$s^{EV}_{th}(\omega) = S^{arrival}_{th}, \quad \forall t \in T^{arrival}_{h}, \forall h \in H^{EV} \tag{19}$$

4.3. Ex-post financial analysis

Post-delivery, a mismatch between the power sold to the community and the retailer's day-ahead commitment might result in an imbalance. This situation is represented in Eq. (20), where $dev_t(\omega)$ represents the deviation from the day-ahead commitment. The retailer's profit for each potentially realised scenario ω is denoted by $P(\omega)$, as shown in Eq. (21). The profit is computed as the difference between the cost from the day-ahead market – where its price is represented by ξ_t – and the sum of two components. The first component is the revenue obtained from selling power to the community. The second represents the repercussions – either revenues or penalty – resulting from the deviation from the day-ahead commitment valued at the imbalance price ζ_t. This part of the equation ensures that passive balancing services are rewarded, while deviations exacerbating system imbalances are penalised.

$$dev_t(\omega) = x_t - \sum_h \sum_t \mu_t \; g_{ht}(\omega) \tag{20}$$

$$P(\omega) = \sum_h \sum_t \mu_t \; g_{ht}(\omega) - \sum_t \xi_t x_t + \sum_t \zeta_t \; dev_t(\omega), \quad \forall \omega \in \Omega \tag{21}$$

5. Case study and data collection

The modelling framework outlined in the previous section is applied to an EC composed of 50 neighbouring households located in London (UK). Using the Energy Community model, the central manager of the community optimises the operations of the storage technologies (i.e., electric vehicles (EVs) and stationary batteries) as well as the peer-to-peer power transactions (with 7.6% grid losses [29]) among community members. The main goal is to minimise the total community costs of purchasing power from the retailer at a subscription rate (i.e., fixed tariff or real-time tariff).

On the other side of the arrangement, the retailer has a contractual obligation to supply power to consumers to cover their net loads. The retailer assess the load information for all households and predict possible scenarios for the renewable production of PV panels and wind turbines. However, the retailer does not have information about the peer-to-peer and battery operations; thus, the retailer only considers the net load from members who can self-consumption their own generation. Following the Retailer Commitment model (Section 4.1), the retailer purchases electricity in the day-ahead market using the predicted net load and considering the possibility of providing passive balancing services to the TSO. To mitigate the effect of price forecasting errors on the retailer's financial outcome, the retailer is assumed to have full knowledge of imbalance prices. This approach facilitates identifying and understanding the impact solely attributed to community operations.

The framework was applied for a time horizon of one year and was implemented in Python 3.8. The optimisation problems were solved using Pyomo [30,31] and the Gurobi Solver v9.5.2 [32] on a computer with CPU 1.10 GHz Intel Core i7 and 32 Gb RAM. The data and models are publicly available in GitHub.[2]

Six cases are defined to assess the financial results for a retailer under different community configurations. Each case is based on the potential storage technology integrated, and the tariff agreement with the retailer. The storage technology options considered are stationary batteries and EVs. The subscription rates are either flat-rate or real-time tariffs. The baseline cases assume that there are no peer-to-peer transactions and no storage technologies. Table 2 provides an overview of all the cases with their technical and price signal considerations.

Table 2
Cases definition based on the community storage assets and the subscribed tariff.

Cases	Storage technology	P2P	Tariff subscription
Baseline - FT	–	–	Flat-rate tariff
Baseline - RT	–	–	Real-time tariff
HomeBat - FT	Stationary batteries	Yes	Flat-rate tariff
HomeBat - RT	Stationary batteries	Yes	Real-time tariff
EVs - FT	EVs	Yes	Flat-rate tariff
EVs - RT	EVs	Yes	Real-time tariff

The retail tariffs are based on the costs of electricity consumption in England. According to the UK statistics for 2019 [33], the mean yearly bill for residential users consuming 3 600 kWh was £637. Subtracting the standing charge costs of 0.2 pence/day and the VAT of 5%, the unit rate cost for a standard consumer in 2019 was 15 pence/kWh. This value is set as the flat-rate tariff. Given that the energy component of real-time tariffs follows the seasonal and hourly fluctuations of the day-ahead price, we set the real-time tariff such that its yearly average price per kWh equals the flat-rate tariff. The day-ahead and imbalance prices for London in 2019 were retrieved from the ENTSOE-Transparency platform[3] and the Elexon platform,[4] respectively.

The half-hourly load profiles for the households were obtained from the Low Carbon London project.[5] The 50 load profiles were selected based on a pool of high-income end users as they are more likely to own DERs and exhibit a higher electricity demand [34]. As such, the average annual consumption of the chosen households is 6270 kWh. To ensure data integrity, only load profiles that had complete data entries without any missing information or outliers were included.

The EC has two sources of distributed generation: solar power and wind power.

Solar Power: The PV panels have a peak power of 4 kW and an efficiency of 2.4%. The panels are installed with a tilt angle of 35% to optimise solar exposure. To obtain a half-hourly generation profile, we utilised the technical specifications of the PV panels,[6] in combination with Global Horizontal Irradiation (GHI) and meteorological data specific to London in 2019 from the Open Power System Data (OPSD) portal.[7]

Wind power: The power supply of the small wind turbines, each with a nominal capacity of 2.4 kW, was generated using the wind speed time series from Renewables.ninja[8] along with the polynomial power curve of the turbine model defined and used by [12,35].

To represent the uncertainty of the generation assets, ten solar and wind output scenarios were generated for each technology using the autoregressive moving average (ARMA) approach [36]. The scenarios were randomly allocated to the 17 PV panels and 10 small wind turbines installed in the community. The local generation of the assets without considering grid losses covers between 39%–40% of the total load of the community in all the scenarios.

2 https://github.com/raquelal/retailer-community.

3 Day ahead prices, see: https://transparency.entsoe.eu/.

4 Imbalance prices, see: https://www.elexonportal.co.uk/.

5 https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households.

6 PV technical data is based on the commercially available panel LG Solar LG370Q1C-A5 NeON R (see e.g. https://www.photovoltaik4all.de/lg-solar-lg370q1c-a5-neon-r).

7 OPSD is a free and open data platform for power system modelling and is maintained jointly by Neon Neue Energie Okonomik, Technical University of Berlin, ETH Zurich and DIW Berlin. For further information, see https://open-power-system-data.org.

8 https://www.renewables.ninja/.

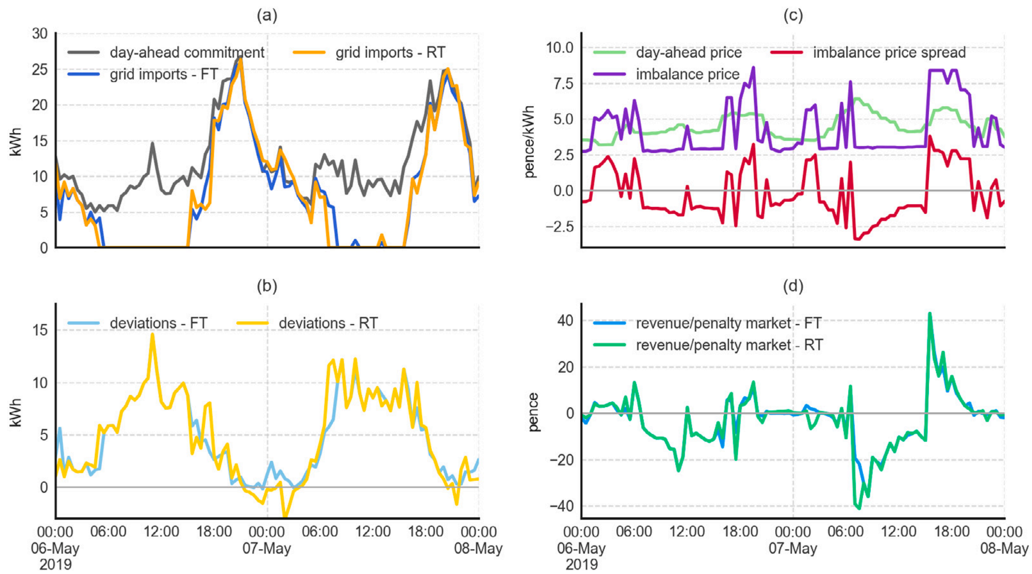

Fig. 2. Day ahead commitments, grid imports, deviations and financial outcome from the ex-post imbalance analysis for two representative days for the HomeBat-FT and HomeBat-RT cases.

Moreover, the community enhances its flexibility by installing storage technologies. In the HomeBat cases, the selected stationary batteries are small-scale lithium models from sonnenBaterie.[9] These batteries have a capacity of 4 kWh, one-way efficiency of 96%, and 2.5 kW of nominal power, complemented by a maximum inverter efficiency of 96%. To ensure optimal performance and longevity, the batteries are operated to maintain at least 20% of their capacity at all times.

For the cases with EVs, the nominal storage capacity is set to 50 kWh on all vehicles, which corresponds to the average size of the models Nissan Leaf, Volkswagen e-Golf and Tesla S [37]. The integration of EVs in the community is assumed to be 28% of EVs, resulting in 14 vehicles. This assumption is optimistic considering that the actual market share of EVs is just 4.1% [38]. Contrarily to stationary batteries, the EVs are connected to the community grid based on the behaviour of the owner. The behaviours of each EV were modelled using the scripts developed by [39], which assume that each EV disconnects and connects to the grid once per day.

6. Results and discussion

In this section, the results of the case studies are presented and discussed. First, we set the underlying dynamics between the retailer and EC interaction by showing and discussing the results on two representative days. Then, we present the yearly results for the community to later discuss and understand the financial outcomes of the retailer. An additional case is included where the retailer has access to full information about the operations of the community, which will represent the upper threshold of the benefits for the retailer to collaborate with the community.

The EC and financial results are presented for one single scenario ω, which is assumed to be the realised generation output, as they were found to not differ substantially from the results in other scenarios.

6.1. Underlying interactions

Fig. 2a illustrates the day-ahead commitment and the electricity imported by the EC over two consecutive days in May. This is demonstrated across the HomeBat-FT and HomeBat-RT cases.

At a specific time point – say 12:30 on the first day – the retailer's commitment (7.54 kWh) exceeds the actual electricity demand of the EC, which is zero. This discrepancy arises due to the substantial local electricity generation and trade among community members, which the retailer did not foresee when participating in the day-ahead market. The resulting deviations are equivalent to the entire retailer's commitment of 7.54 kWh, as depicted in Fig. 2b.

At this hour, the imbalance price (2.9 pence/kWh) is lower than the day-ahead price (4.6 pence/kWh) (see Fig. 2c). The deviation volumes are valued at a lower rate than the price at which the retailer purchased them in the day-ahead market. Subsequently, as shown in Fig. 2d, the retailer incurs a loss of 18 pence at this hour. The dynamics of the profit loss and gain vary from hour to hour, given the different types of deviations and their synergy with the imbalance price spread.

Furthermore, the deviation patterns in the HomeBat-RT and Homebat-FT cases exhibit different characteristics. In the HomeBat-Rt case, the storage technologies strategically leverage the price variations between different hours. During time intervals with low prices, the batteries get charged to discharge later during hours when the electricity prices are higher. This charging of the batteries increases the total load of the community, which, at certain hours, results in deficit deviations for the retailer. This is depicted at midnight hours in Fig. 2b. Contrarily, the absence of arbitrage opportunities inherent in flat-rate tariffs does not promote this kind of strategic behaviour.

6.2. Results for the energy community

In the Baseline case, which represents the expectation of the retailer, the community's costs under the real-time tariff are about 2% higher than those under the flat-rate scheme. This remains true despite the volume of electricity imported being the same in both cases, as illustrated in Fig. 3.

The higher costs encountered by the community under the real-time tariff are directly tied to the temporal relation between the net load and the day-ahead price fluctuations. In months with limited local electricity generation, when the overall net load is higher, the prices under the real-time tariff tend to exceed the flat-rate of the fixed scheme, as shown in Fig. 4. Consequently, when the EC relies on imports from the retailer during months with high day-ahead prices, the flat-rate tariff offers a financial hedge against them, making it a more cost-effective choice for the community. In other seasons of the year, when the flat-rate tariff exceeds the real-time tariff, the EC's high

[9] https://saegroup.com.au/wp-content/uploads/2019/09/sonnenbatterie_eco_8.0.pdf.

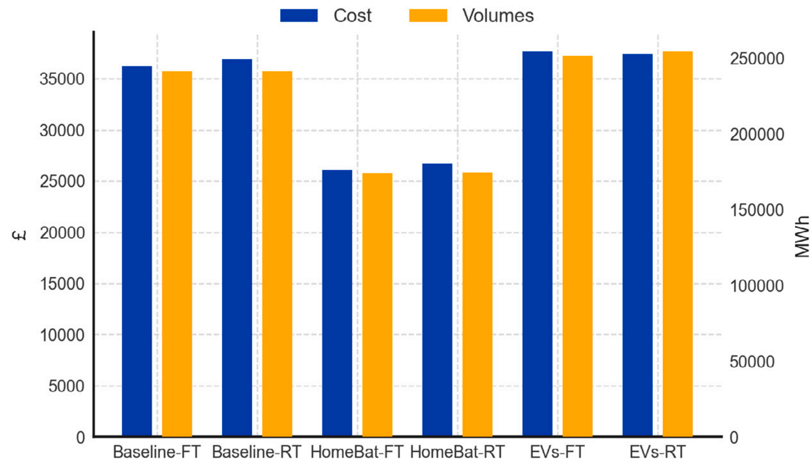

Fig. 3. Total costs (£) and volumes of grid imports (kWh) for the EC in the different cases.

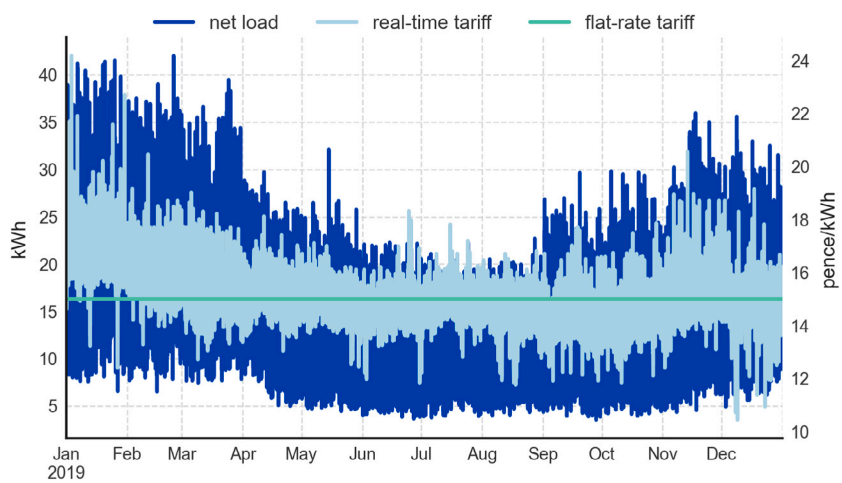

Fig. 4. Net load after self-consumption in the Baseline case compared to the retail electricity tariffs. Half-hourly resolution.

levels of self-sufficiency make the flat-rate tariff the most economical alternative.

In the HomeBat case, the flexibility provided by the stationary batteries, coupled with the trading among members, decreases the community imports from the retailer by approximately 28%, relative to the Baseline case. This is consistent for both real-time and flat-rate tariff subscriptions and leads to the same percentage of cost savings for the community.

Under the real-time tariff, the batteries' flexibility allows for exploitation of daily price variations and the storage of surplus local generation. In contrast, the absence of arbitrage opportunities under the flat-rate tariff leads to the batteries being charged solely when there is excess power. This is due to the inherent energy losses associated with charging and discharging cycles, which make it unprofitable under a flat-rate tariff. Despite real-time tariffs provide additional arbitrage opportunities, the cost of the community remains more than 2% higher than that under the flat-rate tariff, as seen in the Baseline case (Fig. 3). This suggests that the price-responsive flexibility from the batteries did not result in sufficient savings to offset the costs stemming from the dependency on the retailer's supply during seasons of high day-ahead prices.

In regard to the cases with EVs, the electricity purchased to the retailer increased by 4 and 5% under the flat-rate and real-time tariff subscriptions, respectively, compared to the Baseline case. Despite the potential of EV batteries to provide flexibility to the community as stationary batteries, there is a mismatch between RES production and the timing of the vehicles' connection to the community. In the case study, the EVs are typically disconnected during midday when solar generation is at its peak. Consequently, only 14% of the charging time coincided with available surplus electricity. This resulted in increased electricity curtailment and dependency on the retailer's supply to ensure the EVs are fully charged before delivery time.

Despite the EVs' inability to fully utilise local generation, they can, under real-time tariffs, take advantage of price fluctuations. Unlike stationary batteries, the arbitrage behaviour in EVs effectively lowered the electricity bill for the community, despite the overall increase in imported power compared to the flat-rate tariff case.

6.3. Results for the retailer

An analysis of the annual surplus and the deficit deviations across all cases yields to the following insights:

- Peer-to-peer transactions lead to surplus positions for the retailer as the EC manages to reduce its dependency on external supply.
- In the case with stationary batteries under a flat-rate tariff, only surplus deviations are observed for the retailer. This is because the batteries charge solely with excess local electricity and discharge to minimise electricity imports.
- When the community, equipped with either stationary batteries or EVs, subscribes to real-time tariffs, the volume of retailer's deviations – both surplus and deficit – increases. Under this tariff, the storage technologies get charged not only with surplus

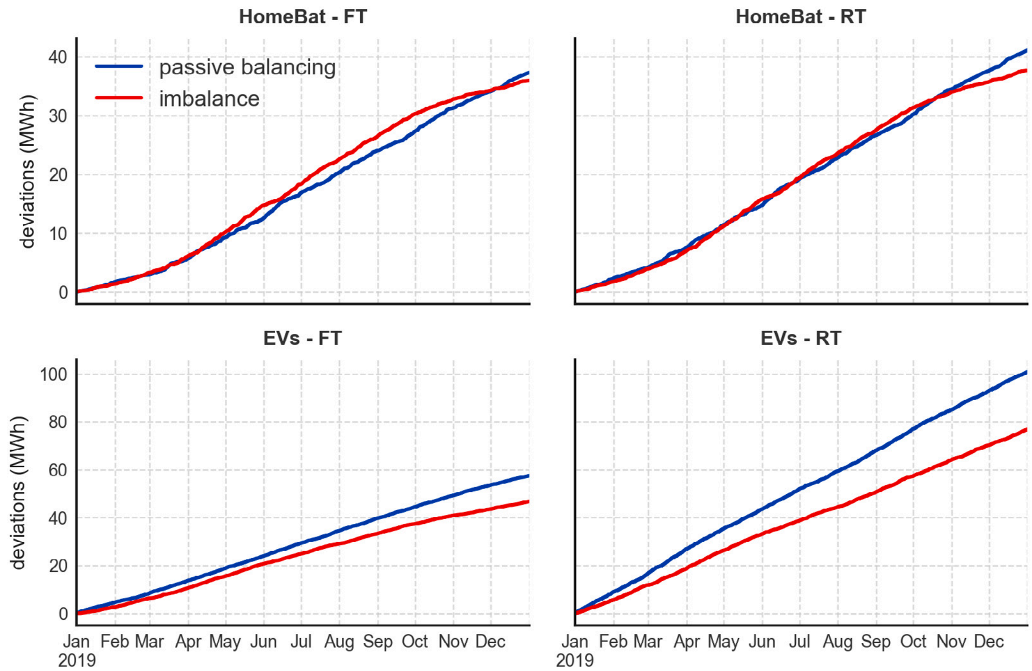

Fig. 5. Cumulative passive balancing and imbalance deviations of the retailer for the HomeBat and the EVs cases.

Table 3
Retailer's financial outcomes across all cases, measured in pounds (£). "Balancing revenues" refers to the earnings derived from selling surplus volumes at the imbalance price, while "balancing costs" represent the expenses incurred when deficit volumes are purchased at the imbalance price.

	Baseline		HomeBat		EVs	
	FT	RT	FT	RT	FT	RT
Day-ahead costs	−11 242	−11 242	−11 242	−11 242	−11 242	−11 242
Balancing revenues	277	277	3150	3401	2204	4126
Balancing costs	−148	−148	−34	−135	−2029	−3219
EC revenues	36 207	36 880	26 091	26 854	37 677	37 456
Total	25 127	25 800	17 965	18 115	26 610	27 121
Difference (rel. to Baseline) [%]			−28.5	−29.8	+5.9	+5.12

local electricity but also from imported power during periods of low pricing. This arbitrage behaviour increases the community's load, resulting in deficit volumes for the retailer. Additionally, it encourages higher surplus volumes compared to those under flat tariffs, as batteries have more electricity stored to discharge to reduce importing during periods of higher prices.

- With EV, the retailer more frequently encounters deficit volumes than surplus volumes. This outcome arises due to three factors: an overall increase in electricity demand due to EV usage, a common mismatch between times when EVs are plugged-in to the community grid and the production of local electricity; and, in case of adopting real-time tariffs, the occurrence of high peak imports in periods with low electricity prices. Moreover, under flat-rate tariffs, EVs exhibit minimal discharge activity due to the limited charging from excess local power. Consequently, EVs often act more as consumption assets than as flexibility assets with fixed electricity prices.

These factors stress the impact of the design of the EC on retailers' final position in the market. Nonetheless, whether the deviations are economically beneficial or detrimental for the retailer depends on their interrelation with the overall system's imbalance.

The cumulative deviation volumes across all cases are illustrated in Fig. 5. Here, we refer to imbalance volume to retailers' deviation that exacerbates system's imbalances, and to passive balancing volumes to those helping the TSO to restore the system's balance.

For the cases with stationary batteries, the retailer's deviations tend to equally provide passive balancing services and imbalances to the system. However, from June to October, the retailer incurs more often in imbalance volumes, particularly with the EC under the flat-rate tariff. These are months that result in high surplus positions due to the increased self-sufficiency of the EC, while the overall system is also falling in surplus. This match between the system and the retailer balance position lead to the increase in the imbalance volumes.

Differently, the EVs charging and discharging patterns contribute the retailer to end up with substantially higher passive balancing volumes than imbalance volumes. This trend is constant throughout the whole year.

Under the Baseline case, where the retailer has accurate predictions of loads and complete information about prices, it only provides passive balancing services (9.6 MWh) to maximise its profits.

Furthermore, Table 3 provides a detailed break down of the retailer's annual financial outcomes. These include day-ahead costs, balancing system revenues and costs, and earnings from supplying the EC. It is important to highlight that the revenues generated from the balancing system are not necessarily beneficial for retailers. In cases where a retailer pays a higher price in the day-ahead market than the one received in the imbalance price, losses occur. Conversely, balancing costs can result in economic benefits if the price paid in the imbalance settlement process is lower than the price required to be paid during the day-ahead market. In this table, the Baseline case depicts the best financial outcome expected by the retailer, as the passive balancing services are guaranteed at all times by assuming perfect information of real imbalance prices in the retailer's commitment model.

Table 4
Cost and revenue comparison between the full information case and the previous cases.

	HomeBat		EVs	
	FT	RT	FT	RT
Day-ahead costs [%]	−26.9	−28.5	−0.6	−9.3
Balancing revenues [%]	−100	−100	−100	−100
Balancing costs [%]	−100	−100	−100	−100
EC revenues [%]	0	0	0	0
Total [%]	−0.5	+3.9	−0.4	+0.5

The retailer's annual profit is reduced by almost 30% when the EC adopts stationary batteries. In these cases, we observe a significant increase in balancing revenues due to the high volumes of surplus induced by the community's self-sufficiency. Of these revenues, 30% were caused by imbalance volumes, meaning that the retailer's payments in the day-ahead were higher than the earnings from the imbalance market. Therefore, the retailer could reduce costs by not purchasing those volumes in the day-ahead market. The balancing costs in the HomeBat cases are significantly low, given that the stationary batteries lead to insignificant deficit volumes in the retailer. As expected, the revenues from the EC's payments are reduced compared to the Baseline case.

On the other hand, EVs limited synergy with local generation induces significant balancing costs. About 68 and 67% of the deficits for the EV-FT and EV-RT cases, respectively, were incurred while the system penalised this type of deviation. Therefore, the total cost for the retailer could have been reduced if these deficit volumes were purchased in the day-ahead market instead. Nevertheless, still the total profits of the retailer increased between 5 and 6% given the positive results from the balancing stage and the community payments.

In general, we observe that while the revenues and costs from the balancing stage can increase or reduce profits, the largest influence on retailers' financial outcomes comes from customers' payments. In the case of ECs with stationary batteries, the profits are substantially lower than expected as ECs reduce their dependency on retailers' supply. On the contrary, the increase of net load in communities from EV charging leads to higher profits.

6.4. Additional case: full information of net loads

The retailer has the potential to improve the total profits if it gets to know the net load of the community members. Under this scenario, the retailer could bid in the day-ahead market the actual needs of the customers and avoid potential penalisation from the balancing system.

Table 4 shows the difference in percentage of the different revenues and cost elements of the retailer between the full information case and the previous cases. Despite the retailer improving its participation in the day-ahead market and not inducing imbalances or passive balancing services, it does not obtain substantial changes in the total profits compared to previous cases. This underscores that acquiring full information from ECs to increase the precision of the volumes purchased may not be sufficient economically attractive for retailers. This holds when considering that transaction and digital costs are incurred to settle the information exchange.

7. Conclusions

Studying the impact of ECs on other stakeholders is essential to ensure their adoption aligns with the operational requirements of the power system. The paper explores the interplay between electricity retailers and ECs, considering the sequence of wholesale markets and the imbalance settlement process. We propose a novel modelling framework that captures the operational decisions of a strategic retailer and an energy community, and the subsequent financial outcome. Through this framework, our study sheds light on retailers' financial results caused by ECs, and vice versa.

The findings reveal that technologies or practices leveraging local generation induce significant surplus deviations for retailers as they enhance the self-sufficiency of communities. This trend is particularly noticeable in scenarios with stationary batteries and peer-to-peer trading. In contrast, EVs show a different pattern as they are often not plugged-in when there is local generation. This lack of synergy with renewable sources increases the net load covered by retailers' supply and, thereby increasing the risk of the retailer falling into deficits. Alternative EV usage patterns matching local generation could reduce deficits and increase surplus deviations on retailers.

Interestingly, cost stemming from these imbalance deviations (volumes that aggravate the system's imbalance) are relatively not significant and can be offset by the revenue from passive balancing services. The study estimates the largest retailer's profit reduction, approximately 30%, occurs when the EC integrates stationary batteries. This value, however, can fluctuate based on the storage capabilities and installed renewable sources. Consequently, the majority of the retailers' profit reduction results from enhanced EC self-sufficiency, facilitated by flexibility mechanisms like stationary batteries and peer-to-peer trading, while the balancing system plays a minor role in this reduction.

Using the proposed method, we can explore the financial outcomes for ECs under various designs and tariffs. The findings underscore the importance of tariff selection in accordance with community design. Counterintuitively, real-time tariffs are not always the most cost-effective option for all ECs types. In instances of low local generation, real-time tariff rates may exceed those offered by fixed tariffs, while the opposite occurs with high local generation. Consequently, ECs with considerable self-sufficiency could potentially benefit from flat-rate tariffs, as these often offer lower rates during periods of greater reliance on external power supply. Conversely, flexible ECs with low self-sufficiency can leverage price differences throughout the year when adopting real-time tariffs. Nevertheless, these outcomes are contingent on the design of real-time tariffs, which may differ from the one employed in this study. Nonetheless, these insights emphasise the significance of aligning the temporal synergies of tariffs with the specific design of ECs.

Given the negligible impact of deviations on profits, our research suggests there is a limited potential for business models seeking to capitalise on operational data exchange to improve retailer bidding in systems with a single imbalance pricing. This is demonstrated by the upper threshold of limiting retailer's profit loss by about 4%, without accounting for the cost associated with the business model's adoption. These findings hint at a lack of incentives for retailers to pursue simple data exchange collaboration with EVs, signalling a need for retailers to rethink their business strategies to overcome the profit loss.

However, note that this study assumes that a retailer predicts load profiles and imbalance prices. In realistic scenarios with less accurate forecasting, deviations may be larger and could have a more substantial financial impact on retailers. Future research analysing financial outcomes under varying forecast accuracy levels could yield more significant insights concerning the feasibility of the data exchange business models. Additionally, penalties for recurrent deviations, not considered in our study, may also negatively affect retailers' financial outcomes. Additional research could also investigate retailers' risk aversion towards incurring imbalance costs due to uncertainty system imbalance positions.

CRediT authorship contribution statement

Raquel Alonso Pedrero: Conceptualization, Methodology, Software, Writing – original draft, Visualization, Data curation. **Pedro Crespo del Granado:** Conceptualization, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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