

Local Flexibility Markets for Energy Communities: flexibility modelling and pricing approaches

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Abstract—The increasing integration of renewable energy sources and decentralized generation requires demand-side flexibility to improve grid stability and balance local energy flows. Local Flexibility Markets (LFMs) provide a framework for optimizing flexibility transactions within energy communities. This paper presents a model for quantifying and pricing residential resources flexibility, enabling prosumers to submit bids in an LFM managed by the Community Manager. The methodology relies on a linear optimization problem, where a Home Energy Management System first determines optimal consumption baselines. Then an iterative sensitivity analysis estimates upward, and downward flexibility bands and sets offer prices per resource. The market operates as two asymmetric voluntary pools, clearing flexibility offers and requests. Results show that Battery Energy Storage Systems and Electric Vehicles provide the most effective flexibility, significantly reducing energy costs. Future research should improve pricing mechanisms and scalability to support LFM adoption in different residential settings.

Index Terms— Flexibility Modelling, Flexibility Pricing, Local Flexibility Market, Energy Community.

I. INTRODUCTION

According to the International Energy Agency (IEA), the residential sector represents the largest share of final energy consumption, around 32% in member countries [1]. Demand Response (DR) programs have been applied to residential consumption for several decades [2], with some implementations dating back to the 20th century in advanced market models [3]. The main objective of these programs is to manage residential consumption while preserving user comfort and certain preferences.

More recently, smart grids and the digitization of bidirectional communication between utilities and consumers have improved Demand Management [4]. In parallel, advances in communication modules for household appliances and Home Energy Management Systems (HEMS) have enabled dynamic pricing in real-time markets [5] and another strategies by allowing automated load scheduling with user participation [6]. This improves the flexibility of energy resources and household devices, leading to more efficient residential consumption and

enhancing the grid operator's ability to provide system services [7]. In this context, directives [5] and [8] set the legal framework for this new paradigm, integrating residential demand-side DERS, allowing consumers to organize into communities and trade energy more freely. These developments create a supportive environment for local system service markets, including flexibility services.

The modelling of residential consumption flexibility for trading in local markets has been widely discussed in the literature. According to [9], a local flexibility market (LFM) dependent on the local electricity market (LEM) is presented in [10], where the Distribution System Operator (DSO), Balance Responsible Party (BRP), and community members can submit bids and requests. However, this work does not detail how these bids are formulated or how residential technical flexibility is determined. In [11], a similar model is proposed, excluding the BRP and maintaining the same limitations as [10]. In [12] and [13], flexibility is explored in peer-to-peer (P2P) markets, where prosumers trade directly with each other, but without an aggregation methodology. Additionally in [14], an evolutionary computational model improves flexibility in HEMS, focusing on energy efficiency. Similarly, [15] introduces a virtual battery model to aggregate flexibility but lacks details on how household energy profiles are combined.

The main identified limitations include the lack of standardization in flexibility quantification, weak aggregation methods, and an imbalance between economic optimization and user comfort. Recent multi-objective models address these gaps [16], [17] but require high processing times, limiting real-time application, particularly in residential settings. In [18], an alternative approach based on linear optimization and sensitivity analysis defines flexibility bands, taking these limitations into account. However, it assumes a uniform price, making its pool market implementation unfeasible. Thus, a pricing mechanism is essential, but literature still lacks a direct solution to this challenge. Paper [19] focuses on distributed optimization but relies on real-time information exchange. Meanwhile, [20] proposes flexibility bands for energy communities but does not address independent price definition by the HEMS. The approach in [21] is based on dynamic

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pricing and cost-sharing, which is impractical for pre-planning without market data. Lastly, the authors of [22] integrate dynamic pricing for flexibility, but their method requires external information, preventing its autonomous application within HEMS.

This paper is organized as follows: Section II presents the proposed methodology to address the gaps identified in the literature, including the mathematical formulation and the sensitivity analysis heuristic. Section III introduces a case study of a Renewable Energy Community (REC) with residential Battery Energy Storage Systems (BESS) and Electric Vehicle (EV) chargers. Finally, Section IV summarizes the main conclusions of this work.

II. FLEXIBILITY MODELLING, PRICING AND TRADING IN ENERGY COMMUNITIES

This section presents the methodology for determining optimal consumption and flexibility bands (bids) for residential flexible resources, as well as the structure of the LFM where these offers are traded. Figure 1 illustrates the process, from individual consumption optimization to the formation of the local flexibility market.

residential energy costs while ensuring that operational constraints and user preferences are met.

Once optimal consumption is determined, the next step is to define flexibility bands (bids) for upward (UW) and downward (DW) flexibility for each FR, along with their offer prices. This is done through incremental sensitivity analysis, where the optimization problem is solved multiple times per period with varying energy buy and sell prices. This approach simulates each resource's response to price changes, determining the maximum and minimum consumption adjustments each device can provide. The flexibility offer price is then calculated based on the baseline tariff - the LEM buy and sell prices - adjusted according to the resource's sensitivity to price variations. If a FR responds to small incentives (early price increments), its offer price remains close to the baseline tariff. Conversely, if a resource responds only to higher incentives, its offer price increases, reflecting lower responsiveness.

The final step models the operation of the local LFM, where the Community Manager (CM) manages prosumers' offers, and the DSO submits flexibility requests at different price levels. Prosumers' offers are complex, as they are divided into blocks with different quantities and prices. Each block corresponds to

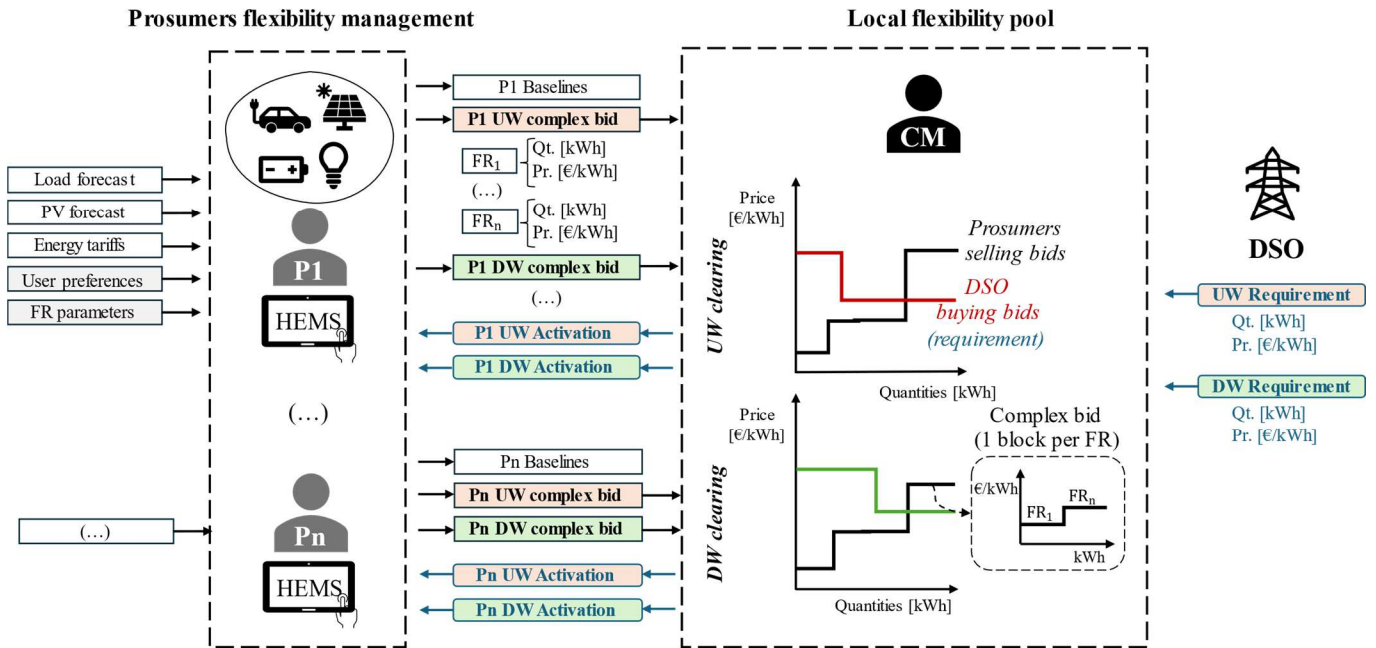


Figure 1. Overview of the proposed methodology for the local flexibility market, based on the modelling of flexibility bids quantity and pricing.

The methodology is divided into three main parts: (II.A) optimizing the scheduling of prosumers' flexible resources, (B) quantification and pricing technical flexibility bands through sensitivity analysis, and (C) defining the local flexibility market, where offers are cleared in an asymmetric, voluntary pool-based environment.

The first step optimizes the consumption of flexible resources (FR), specifically BESS and EV charging. The HEMS solves a linear optimization problem to determine baselines, which define the optimal consumption schedule for each one of them over a time horizon. This optimization considers expected LEM tariffs. The objective is to minimize

a specific FR, whose technical characteristics prevent full flexibility aggregation. The market follows an asymmetric, voluntary pool-based structure, where transactions are cleared through a market-clearing mechanism. This pool structure aligns with the LEM, allowing prosumers to participate in both local markets.

A. Optimal Scheduling of Prosumers' Resources

The linear programming (LP) problem - (1) to (7) - optimizes the scheduling of each prosumer's household resources for the next day (simulation horizon T), defining the flexible units baselines. The objective function (1) minimizes

the cost of energy purchased ($E_{H(t)}^{\text{buy}}$) and sold ($E_{H(t)}^{\text{sell}}$) in LEM, where $\pi_{H(t)}^{\text{buy}}$ and $\pi_{H(t)}^{\text{sell}}$ represent the marginal purchase and sale prices, respectively.

$$\min p^{\text{cost}} = \sum_{t \in T} \left(E_{H(t)}^{\text{buy}} \cdot \pi_{H(t)}^{\text{buy}} - E_{H(t)}^{\text{sell}} \cdot \pi_{H(t)}^{\text{sell}} \right) \quad (1)$$

Constraint (2) represents the difference between purchased energy $E_{H(t)}^{\text{buy}}$ and surplus energy sold $E_{H(t)}^{\text{sell}}$, corresponding to the energy value recorded on the prosumer's meter $E_{H(t)}^{\text{met}}$.

$$E_{H(t)}^{\text{met}} = E_{H(t)}^{\text{buy}} - E_{H(t)}^{\text{sell}}, \quad \forall t \in T \quad (2)$$

Similarly, $E_{H(t)}^{\text{met}}$ is constrained by condition (3), where $E_{H(t)}^{\text{load}}$ represents the expected consumption of non-flexible or unmodeled resources and loads, $E_{H(t)}^{\text{gen}}$ denotes the forecasted self-generation, $E_{B(t)}^{\text{ch}}$ and $E_{B(t)}^{\text{dch}}$ correspond to the energy charged and discharged by the residential BESS, respectively, and $E_{EV(t)}^{\text{ch}}$ represents the energy charged by the prosumer's electric vehicle during each period.

$$E_{H(t)}^{\text{met}} = E_{H(t)}^{\text{load}} + E_{B(t)}^{\text{ch}} + E_{EV(t)}^{\text{ch}} - E_{H(t)}^{\text{gen}} - E_{B(t)}^{\text{dch}}, \quad \forall t \in T \quad (3)$$

Constraints (4) and (5) refer to the BESS ($E_{B(t)}$) and the EV ($E_{EV(t)}$), energy content in each period, respectively. The energy stored in the previous period ($t - 1$) is added to the charged energy or subtracted from the discharged energy in this period, considering the respective charging and discharging efficiencies. Also in (4) the parameter $E_{EV(t)}^{\text{trip}}$ represents the energy required for the user's trip per period.

$$E_{B(t)} = E_{B(t-1)} + \left(E_{B(t)}^{\text{ch}} \cdot \eta_B^{\text{ch}} - \frac{E_{B(t)}^{\text{dch}}}{\eta_B^{\text{dch}}} \right), \quad \forall t \in T \quad (4)$$

$$E_{EV(t)} = E_{EV(t-1)} + \left(E_{EV(t)}^{\text{ch}} \cdot \eta_{EV}^{\text{ch}} \right) - E_{EV(t)}^{\text{trip}}, \quad \forall t \in T \quad (5)$$

Constraints (6) and (7) define the maximum charging power of the BESS (\overline{P}_B) and the EV (\overline{P}_{EV}). the parameter $\delta_{EV(t)}^{\text{connect}}$ only allows charging of the vehicle at times (t) when it is connected to the charger.

$$\frac{E_{B(t)}^{\text{ch}}}{\Delta t}, \frac{E_{B(t)}^{\text{dch}}}{\Delta t} \leq \overline{P}_B, \quad \forall t \in T \quad (6)$$

$$\frac{E_{EV(t)}^{\text{ch}}}{\Delta t}, \frac{E_{EV(t)}^{\text{dch}}}{\Delta t} \leq \overline{P}_{EV} \cdot \delta_{EV(t)}^{\text{connect}}, \quad \forall t \in T \quad (7)$$

Additional constraints also ensure that the state of charge of both the BESS and the EV stays within the manufacturer-specified maximum and minimum limits.

B. Modelling and Pricing of Flexibility Bands per FR

This methodology iteratively solves optimization problem A with varying energy purchase and sale prices, allowing the assessment of each resource's response, the construction of flexibility bands, and the determination of their prices. The process begins by determining the optimal consumption of each

resource without external incentives, establishing baseline values for each flexible resource $f \in \text{FR}$, denoted as $E_{(f,t)}^{\text{base}}$. Next, for each period t , prices are adjusted to encourage consumption changes. To determine downward flexibility ($F_{\text{DW}(f,t)}^{\text{bid}}$), the selling price $\pi_{H(t,i)}^{\text{sell}}$ is increased, and the buying price $\pi_{H(t,i)}^{\text{buy}}$ is decreased, promoting lower consumption and/or increased surplus energy sales to the distribution grid. On the other hand, for upward flexibility ($F_{\text{UW}(f,t)}^{\text{bid}}$), $\pi_{H(t,i)}^{\text{sell}}$ is decreased, and $\pi_{H(t,i)}^{\text{buy}}$ is increased, incentivizing higher consumption. In each iteration i , the optimization problem is solved again, and the new consumption $E_{(f,t,i)}^{\text{new}}$ is compared to the baseline (8).

$$E_{(f,t,i)}^{\text{new}} = p \left(E_{(f,t)}^{\text{base}}, \pi_{H(t,i)}^{\text{buy}}, \pi_{H(t,i)}^{\text{sell}} \right), \quad \forall t \in T, f \in \text{FR} \quad (8)$$

If a change occurs, the variation and the number of iterations needed to trigger it (it) are recorded. The process repeats until consumption stabilizes (stopping criterion), defining the flexibility band limits according to (9) and (10). The values $E_{(f,t)}^{\text{new}}$ and $\overline{E}_{(f,t)}^{\text{new}}$ represent the minimum and maximum consumption limits reached by the resource during the iterations, respectively.

$$F_{\text{DW}(f,t)}^{\text{bid}} = E_{(f,t)}^{\text{base}} - \underline{E}_{(f,t)}^{\text{new}}, \quad \forall t \in T, f \in \text{FR} \quad (9)$$

$$F_{\text{UW}(f,t)}^{\text{bid}} = E_{(f,t)}^{\text{base}} - \overline{E}_{(f,t)}^{\text{new}}, \quad \forall t \in T, f \in \text{FR} \quad (10)$$

Once the flexibility bands are determined, the offer price for each resource is set based on the number of increments required to trigger a response. For downward flexibility ($F_{\text{DW}(f,t)}^{\text{bid}}$), the offer price is given by (11), where $\pi_{H(t)}^{\text{sell}}$ represents the baseline energy selling tariff, and $it_{(f,t)}^{\text{DW}}$ is the number of iterations needed to reduce consumption. The parameter α adjusts the impact of the resource's price sensitivity. For upward flexibility ($F_{\text{UW}(f,t)}^{\text{bid}}$), the method follows the same structure but considers the buying price (12).

$$\pi_{\text{DW}(f,t)}^{\text{sell}} = \pi_{H(t)}^{\text{sell}} + \alpha \cdot it_{(f,t)}^{\text{DW}}, \quad \forall t \in T, f \in \text{FR} \quad (11)$$

$$\pi_{\text{UW}(f,t)}^{\text{sell}} = \pi_{H(t)}^{\text{buy}} + \beta \cdot it_{(f,t)}^{\text{UW}}, \quad \forall t \in T, f \in \text{FR} \quad (12)$$

The entire process is repeated for all periods within the horizon T . In the end, each resource obtains a discrete flexibility profile, represented by a set of value pairs submitted to the LFM, as defined in (13).

$$O_f = \left\{ \left(F_{\text{DW}(f,t)}^{\text{bid}}, \pi_{\text{DW}(f,t)}^{\text{sell}} \right), \left(F_{\text{UW}(f,t)}^{\text{bid}}, \pi_{\text{UW}(f,t)}^{\text{sell}} \right) \right\} \quad (13)$$

Thus, in each period, the CM receives the available flexibility quantities and their corresponding prices, adjusted based on each resource's sensitivity to tariff variations.

C. Local Flexibility Pool Market

The LFM operates as a symmetric voluntary pool and is represented by the LP problem (14) to (17). The proposed formulation applies to both the UW and DW flexibility pool markets. The objective function m^{profit} represents the Social Welfare Function, which is maximized by (14), where $F_{M(t)}^{\text{buy}}$

and $F_{M(f,p,t)}^{sell}$ are decision variables representing the flexibility acquired by the DSO in the local market and allocated to each prosumer FR, respectively. Note that the set R represents the requirement blocks submitted by the DSO, which can vary in quantity and price based on this priority, according to the merit order. Similarly, the activated flexibility is determined per resource (FR set) to match the structure of the complex offer blocks submitted by prosumers ($p \in P$).

$$\begin{aligned} \max m^{profit} = & \sum_{t \in T} \left(\sum_{r \in R} \pi_{M(r,t)}^{buy} \cdot F_{M(r,t)}^{buy} \right. \\ & - \sum_{p \in P} \sum_{f \in FR} \pi_{M(f,p,t)}^{sell} \\ & \left. \cdot F_{M(f,p,t)}^{sell} \sum_{p \in P} \pi_{M(f,p,t)}^{sell} \cdot F_{M(f,p,t)}^{sell} \right) \end{aligned} \quad (14)$$

The constraints ensure that the flexibility acquired by the DSO does not exceed the defined requirements (15) and that the flexibility offered by prosumers remains within the technical limits per FR determined in II.B (16). Additionally, constraint (17) maintains market balance by ensuring equilibrium between flexibility supply and demand.

$$0 \leq F_{M(r,t)}^{buy} \leq F_{M(r,t)}^{req}, \quad \forall t \in T, r \in R \quad (15)$$

$$0 \leq F_{M(f,p,t)}^{sell} \leq F_{M(f,p,t)}^{bid}, \quad \forall t \in T, p \in P \quad (16)$$

$$\sum_{r \in R} F_{M(r,t)}^{buy} = \sum_{p \in P} F_{M(f,p,t)}^{sell}, \quad \forall t \in T \quad (17)$$

Both pool markets operate under a uniform pricing mechanism to encourage community participation in the local framework.

III. CASE STUDY

A. Case definition

The mathematical models developed in II were implemented in Python and tested using the CPLEX solver for a typical summer day (August 2023). The study considered an energy community with 16 prosumers, divided into four groups based on their total and flexible resources, as shown in Table I. For prosumers in the [5–8] range, flexibility was assumed to come from lighting and cold appliances. As this flexibility is not modeled in the mathematical framework, a fixed $\pm 10\%$ band of both of these resources forecasted consumption was assumed, with the LFM offer price based on the energy tariff.

Each range includes four prosumers, representing different household types with varying numbers of occupants, consumption patterns, solar PV systems, and flexible resources technical parameters. Table II presents the daily consumption and installed PV capacities. Consumption data were sourced from the Household Electricity Study dataset by Cambridge Architectural Research [23], which provides detailed load breakdowns, including heating, lighting, appliances, and audiovisual devices. Solar generation forecasts were obtained using synthetic data from the *PV_lib* library, considering the

coordinates of Porto, Portugal. Table III outlines the technical parameters of BESS and EVs for each household type. A state-of-charge constraint was applied, limiting all batteries to 20–80% of their maximum capacity, with a global efficiency of 90%. EV parameters were based on the BMW i3 and Tesla Model S, while charging preferences were assigned by household type: Type I and II consumers primarily charge in the early morning, Type III consumers prefer nighttime charging, and Type IV consumers charge mainly at lunchtime.

TABLE I. CLASSIFICATION OF PROSUMERS BY AVAILABLE RESIDENTIAL RESOURCES AND FLEXIBLE SOURCES.

Prosumers range	Available Resources	Flexible Resources
[1 - 4]	PV, BESS, other loads	BESS
[5 - 8]	PV, other loads	Lighting, cold appliances
[9 - 12]	BESS, EV, other loads	BESS, EV
[13 - 16]	PV, BESS, EV	BESS, EV

TABLE II. ENERGY CONSUMPTION AND SOLAR PV GENERATION PARAMETERS BY PROSUMER TYPE.

Type	Household occupants	Consumption [kWh]	Generation	
			Capacity [kW]	Energy peak [kWh]
I	1	[0.30 – 2.76]	5.0	4.5
II	2	[0.32 – 3.72]	8.0	7.2
III	3	[0.28 – 4.02]	10.0	9.0
IV	4	[1.00 – 6.00]	15.0	13.5

TABLE III. TECHNICAL PARAMETERS OF BESS AND EV CONSIDERED BY PROSUMER TYPE.

Type	BESS		EV	
	Capacity [kWh]	Power [kW]	Capacity [kWh]	Power [kW]
I	5.0	3.5	42.2	10.0
II	10.0	4.6		
III	15.0	5.8	95.0	22.0
IV	25.0	6.9		

Additionally, it was assumed that prosumers purchase energy based on MIBEL's day-ahead market prices for the day under analysis, ranging from 9 to 14 cents per kWh. Selling prices were set according to Portugal's average feed-in tariff from 2015, varying between 4 and 6.5 cents per kWh under a four-period time-of-use schedule. In the local flexibility market, the full upward ($F_{UW(f,t)}^{bid}$) and downward ($F_{DW(f,t)}^{bid}$) flexibility bands calculated for each resource were offered at the determined price. Synthetic DSO requirements were defined based on the aggregated generation and load profiles of the community prosumers. These requirements aim to represent typical network conditions, such as peak demand periods or local generation surpluses, and are derived from simplified assumptions regarding the magnitude and timing of the required flexibility.

B. Main Results

The results validated the methodology and demonstrated the positive impact of LFM participation for community prosumers. In all cases, the optimization successfully converged to optimal solutions

Table IV presents the average residential costs for different prosumer groups under two scenarios: (i) considering only the optimal scheduling of resources (Baseline Cost) and (ii) after participating in the LFM. In addition, Flexibility Activation Costs column represents the cost of adjusting consumption from the optimal schedule to meet flexibility market requests. However, the revenue from LFM participation (LFM Profit) offsets this cost, reducing overall energy expenses. The [13–16] group achieved the highest savings with a 19.81% cost reduction, followed by the [1–4] group at 15.80%. The [9–12] group had smaller reductions, averaging 5.12%, while the [5–8] group saw no cost reduction. These results show that market viability largely depends on the availability and capacity of FR. Households with BESS and EVs gained the most economic benefits, confirming their role as key flexibility providers. The [13–16] group, which has both BESS and EVs, achieved the highest savings due to PV generation, which also enhances the flexibility of their resources. In contrast, the group relying only on lighting and refrigeration appliances did not benefit financially from market participation. These findings indicate that smaller flexible loads have minimal impact on the LFM, making their inclusion negligible and justifying the decision not to model them mathematically. The average savings across all prosumers was 10.18%, though in some cases, the reduction was significantly higher, such as for prosumer 15, who achieved a 24.6% cost reduction.

IV. CONCLUSIONS

LFMs have emerged as structured platforms that facilitate the trading of demand-side flexibility within energy communities, enabling prosumers to actively participate in grid-balancing services.

This study presents a model to quantify and price residential flexibility, allowing prosumers to submit bids in an LFM managed by the community manager. The methodology is based on a linear optimization problem, where a HEMS defines residential consumption baselines, considering flexible resources such as BESS and EVs. Then, an incremental sensitivity analysis estimates upward, and downward flexibility bands and sets offer prices for each resource. The market operation is modelled as two asymmetric voluntary pools, for both flexibility types, where prosumers submit flexibility offers, and the DSO defines requirements.

The results showed that LFM participation reduced costs for all prosumers, with savings depending on available resources. Prosumers with BESS, EVs, and PV achieved the highest cost reductions, while those with only smaller flexible loads, such as lighting and cold appliances, had minimal or no financial impact. Energy tariffs directly influenced flexibility offers, with higher prices discouraging upward flexibility and increasing downward flexibility. Households with higher consumption saw smaller percentage savings, as flexibility made up a smaller share of their total demand. EV flexibility was constrained by connection time and stricter technical limitations, reducing its availability and market participation. In contrast, BESS offered higher technical flexibility and played a more significant role in the local market.

TABLE IV. AVERAGE COSTS PER PROSUMER RANGE BEFORE AND AFTER LFM PARTICIPATION AND COST REDUCTION.

Prosumers range	Flexible Resources	PV?	INITIAL (i) Baseline Cost [€]	LFM profit [€]	Flexibility activation cost [€]	FINAL (ii) Cost after LFM [€]	Cost reduction [%]
[1 - 4]	BESS	Yes	-7.42	2.40	1.02	-8.8	15.80
[5 - 8]	Lighting, cold appliances	Yes	-3.55	0.01	0.00	-3.56	0.00
[9 - 12]	BESS, EV	No	26.56	1.65	0.29	25.20	5.12
[13 - 16]	BESS, EV	Yes	3.08	1.51	0.90	2.47	19.81

Households with more occupants showed a lower relative cost reduction, averaging below 4%, while smaller households achieved around 9%. This is because the share of flexible resources in total consumption decreases as overall demand increases. Consequently, the economic impact is less significant for larger consumers.

Finally, BESS demonstrated exceptional performance, accounting for approximately 71% of the flexibility traded in LFM pools due to their more competitive offer prices. This is due to their fewer technical constraints compared to EV charging. These results emphasize the need for further analysis of BESS as key flexibility assets and their role in enhancing the market's economic viability.

For future work, it is recommended to compare this model with existing approaches, explore new pricing strategies, and assess the scalability of the LFM in communities of different sizes and topologies. These developments could improve local market efficiency and encourage demand-side flexibility to offset the loss of supply-side flexibility resulting from the decarbonization process.

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