IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 10 January 2024, accepted 22 February 2024, date of publication 26 February 2024, date of current version 5 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3370040

RESEARCH ARTICLE

Design of a Prosumer-Centric Local Energy Market: An Approach Based on Prospect Theory

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This work was supported in part by the Flexible Energy Production, Demand and Storage-based Virtual Power Plants for Electricity Markets and Resilient DSO Operation (FEVER) Project (Horizon 2020 EU Research and Innovation Program under Grant 864537; in part by the TwinERGY project (Horizon 2020 EU Research and Innovation Program under Grant 957736; and in part by the ENERgy-Efficient Manufacturing System MANagement (ENERMAN) Project (Horizon 2020 EU Research and Innovation Program under Grant 958478.

ABSTRACT The energy sector is undergoing a transformative shift, driven by advancements in Distributed Energy Resources (DERs), the digitization of the energy supply chain and decarbonization policy objectives across the world. This paradigm shift has led to the emergence of Local Energy Markets (LEMs), which enable small-scale prosumers to actively participate in the energy market, trade power, and leverage their flexible resources. To ensure the success and acceptance of LEMs, this paper proposes a cooperative game-theoretic approach that fosters prosumer engagement and fair profit allocation. We utilize prospect theory from behavioural economics to examine the decision-making process of prosumers and incorporate their preferences for changes in wealth status. By adopting a cooperative game structure, prosumers can pool their resources, reduce transaction costs, and enhance data utilization. The paper introduces a novel pricing algorithm inspired by prospect theory that incentivizes prosumer participation and accounts for the uncertainty involved in LEM operations. Additionally, a computationally efficient method for profit allocation based on the variation of the Shapley value is proposed to ensure scheme stability. A use case evaluation is conducted on a real-world low-voltage network, demonstrating the effectiveness of the proposed approach in terms of economic efficiency and market characteristics. The results highlight the benefits of the consumer-centric LEM, including improved local trading dynamics, fair profit distribution, and enhanced grid stability. Overall, this research contributes to the design and development of LEMs that prioritize prosumer engagement, community cooperation, financial inclusion and democratization of the energy market.

INDEX TERMS Behavioral economics, cooperative game theory, distributed energy resources, energy market democratization, fair profit allocation, local energy market, prospect theory, prosumer engagement.

NOMECLATURE

$\pi^*(s)$:	Market-clearing premium for demand state s.
π:	Price premium above the marginal cost.
D_s:	Energy demand function for state s.
c_0:	Marginal cost for each unit of energy.
Q_k:	Capacity of large-scale energy suppliers.
Q_c:	Prosumers' generated capacity.
$G(\pi)$:	Function representing additional costs for a prosumer from the normal distribution.
P_{nc}:	Energy consumed by a prosumer from its solar asset.
P_{nd}:	Energy demand of each prosumer.
P_{npv}:	Photovoltaic production of each prosumer.
P_{nsur}:	Energy surplus offered to the market by a prosumer (seller).
P_{ndef}:	Energy need of a prosumer (buyer).

The associate editor coordinating the review of this manuscript and approving it for publication was Dinesh Kumar.

C_n:	Cost to each prosumer in the buyers' group.
U_n:	Revenue to each prosumer in the sellers' group.
p_{int}:	Internal price within the LEM.
N_s:	Group of prosumers acting as sellers.
N_b:	Group of prosumers acting as buyers.
$P_{m,def}$:	Energy need of each buyer.
L:	Cooperative game model.
N:	Set of participants in the LEM.
g:	Value function denoting the coalition's monetary value.
p_i:	Final clearing price in the LEM.
p_{int}:	Internal price determined by the LEM pricing algorithm.
Dual values:	Sensitivity to changes in uncertain constraints.
Voltage deviation:	Penalties based on deviation from operational limits set by the DSO.
ϕ_i:	Shapley value for participant i in the coalition.
HHI:	Hirschman-Herfindahl Index, a measure of market concentration.
s_i:	Market share of the i^{th} LEM participant.
RSI:	Residual Supply Index, measuring the market's ability to meet demand without its largest supplier.
Total Supply:	Total amount of energy supply available in the market.
Largest Seller's Supply:	Supply contribution from the largest energy seller in the LEM.
Total Demand:	Total energy demand within the LEM.

I. INTRODUCTION

A. BACKGROUND AND CURRENT TRENDS IN THE ELECTRICITY SECTOR

The electricity sector is on the verge of a major paradigm shift, with innovation occurring in two key areas: the massive penetration of Distributed Energy Resources (DERs) into the grid and the digitization of the energy domain. Advances in Information Communications Technologies (ICT) are taking place in tandem with the progress in DERs, indicating a more digital and decentralized energy future. As new technologies and business models arise, the relationship between small-scale energy consumers and utility providers is shifting from a one-way provision of power to a bi-directional interaction, leading to the emergence of a new energy entity known as prosumers. This entity can produce and consume electricity or trade their flexible demand through Demand Response (DR) schemes [1]. Consumers can track their electricity use through smart appliances and meters, paving the way for digital platforms that facilitate the decentralization of the electricity markets.

B. EMERGENCE AND SIGNIFICANCE OF LOCAL ENERGY MARKETS (LEMS)

The concept of LEMs is central to the energy transformation; it is a platform that empowers small-scale prosumers to actively participate in energy markets, trade power, and leverage their flexible resources, thus forming a Transactive Energy System (TES). LEMs, inspired by the sharing economy, prioritize consumer preferences, enable trading among participants, and establish local prices as signals for stimulating flexibility provision. This leads to a structural shift from the conventional utility-based model towards a more collaborative and decentralized paradigm. By engaging in a LEM, prosumers can trade power among themselves in a coordinated manner, leading to a fundamentally different structure than the present utility-based paradigm as illustrated in Fig. 1. Fig. 1 demonstrates the diverse range of participants in a LEM. This includes households without Distributed Energy Resources (DERs), contributing through Demand Response (DR) activities, homes equipped with DERs like rooftop solar panels or Electric Vehicles (EVs), and independent small-scale producers, typically owning photovoltaic (PV) installations. As such, the nature of LEM stakeholders is multifaceted, encompassing various forms of energy production and management.

C. CHALLENGES AND OBJECTIVES OF LEMS

Despite their potential, LEMs face challenges inherent to decentralized markets, such as matching heterogeneous buyers and sellers and devising a market pricing model that supports efficient scheduling and dispatch. Addressing these challenges requires efficient aggregation of dispersed data streams and minimizing transaction costs. This paper proposes a cooperative game-theoretic approach, utilizing insights from behavioral economics, specifically prospect theory, to foster prosumer engagement and ensure fair profit allocation in LEMs.

LEM's growth is based on four pillars: Decentralization, Digitization, Democratization, and Diversity (4D-LEM). Decentralization is driven by technological advancements that have reduced upfront costs for investing in DERs. The penetration of digital technologies in the energy sector creates a massive volume of energy-related data for diagnostic analytics and other applications (digital energy). LEM democratization refers to the unfettered participation of all interested parties in the energy market (user-centric energy markets) including even those without energy assets. Lastly, LEM diversity refers to the diversification of generation

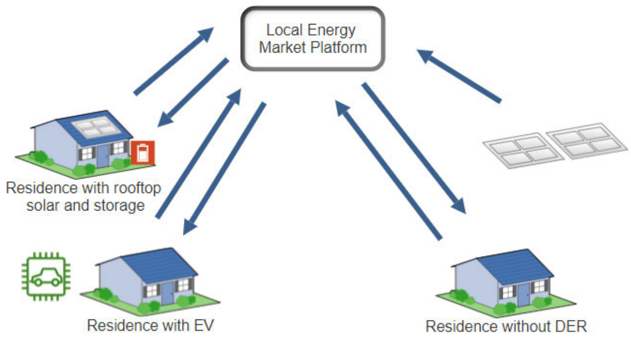

FIGURE 1. LEM architecture.

assets that comprise a LEM. These assets include PVs, EVs, batteries, small-scale wind turbines, DR, etc., creating a robust LEM and enhancing the security of supply.

D. CONTRIBUTIONS AND STRUCTURE OF THE PAPER

In this paper, we propose a LEM cooperative game structure to enhance the potential of social cooperation among prosumers aiming to develop a consumer-centric LEM. By pooling their resources, prosumers can reduce transaction costs while utilizing data more efficiently. This approach not only helps to overcome the challenges of decentralized markets but also fosters a sense of community and social responsibility among LEM participants. To increase customer engagement and LEM liquidity in this work we apply results from the field of behavioural economics, specifically prospect theory. The objective is to analyze prosumers' decisions for participation in a LEM platform [2].

Prospect theory acknowledges that individuals may consider sources of utility beyond consumption when making choices. This paper investigates how proper pricing can incentivize prosumers to participate in a LEM platform. In addition to prospect theory, the paper deploys cooperative game theory to model the LEM architecture and prove that interested parties will always benefit from market participation and are not better off if they leave the coalition. It also introduces a novel pricing algorithm, inspired by prospect theory, that considers the uncertainty involved in LEM operations and their impact on the grid. Finally, a computationally efficient method for profit allocation that ensures the LEM's architecture stability is applied.

The paper's contributions are summarized as follows:

1) Provision of a solid mathematical formulation of a LEM design architecture based on game theory, specifically cooperative game theory, that proves interested parties will always benefit from participating in LEM.
2) Development of a novel pricing algorithm that aims to motivate prosumer engagement inspired by prospect theory.
3) Proposal of a pricing method that incorporates the uncertainty of different operational LEM parameters while accounting for their impact on the physical grid.
4) Establishment of a fair profits allocation mechanism by introducing a variation of the Shapley value that improves LEM's scalability by significantly reducing the computational time of market clearing.
5) Introduction of an evaluation process of the proposed LEM regarding economic efficiency by employing three widely used Key Performance Indicators (KPIs) in the electricity market sector.

The remainder of the paper is organized as follows: Section II provides a literature review related to LEMs, cooperative game theory, and prospect theory. Section III presents a detailed presentation of the LEM framework, including the game theoretical model, while in IV the pricing algorithm and the profit allocation algorithm are analysed. Sections V and VI present the use case and simulation results respectively, while Section VII summarizes the findings.

II. RELATED WORK

LEMs are characterized by a decentralized structure where participants utilize their resources to produce, purchase, trade, or distribute goods and services. This market evolution is aided by the massive penetration of IoT appliances, smart appliances, and meters which allow consumers to have greater control over their energy consumption [3]. The main objective of LEM is to solve grid problems at a local level by empowering prosumers via the provision of local flexibility and increased deployment of DERs [4], [5]. LEM encourages trading by offering energy services to consumers under better terms than the existing remuneration mechanisms and monetary rewards without intermediaries.

At the same time prosumers can have unfettered access to hierarchical multi-tier electricity markets, creating new value streams, while supporting various functions like congestion management, balancing, and ancillary services [6]. LEM's pricing strategy is an integral part of its structure; various algorithms have been proposed for the clearing of economic transactions. In [7] authors propose two computationally efficient mechanisms to form a stable coalition of prosumers in a Peer to Peer (P2P) energy trading scheme, based on cooperative game theoretical principles. The authors in [8] introduce a platform via which the aggregator and participants communicate directly to determine energy costs, facilitating efficient flexibility procurement. In [9], a comprehensive framework for energy sharing in smart buildings is proposed, while authors in [10] employ a data-driven distributionally robust optimization technique for P2P energy trading, resulting in better performance compared to other stochastic optimization methods. In [5] authors introduce a regulated peer-to-peer market structure for residential prosumers, where energy demand and supply curves are bid into a market that can be directly used by the utility to dispatch demand flexibility. The paper emphasizes the mitigation of negative impacts arising from unregulated price-reactive agents, proposing a utility-regulated structure to maintain balance and efficiency in the energy market. The methodology involves a decentralized approach, ensuring computational efficiency, privacy, and reliability. The system architecture includes various modules addressing building modelling, energy consumption, and thermodynamics. The proposed framework is tested in a simulation environment, with results showing that the proposed solution can reduce peak load and ramp rates by nearly 50% while promoting the consumption of locally generated electricity. In [11] authors introduce a novel day-ahead electricity trading model, utilizing a Multi-Agent System (MAS) with a hierarchical bottom-up architecture. This three-layer architecture facilitates electricity trading across different scales of end-users, including residential consumers, renewable energy sources, and EVs. The framework employs Mixed Integer Linear Programming for load and generation optimization, ensuring privacy and decentralization. Authors, also propose a parallel peer-to-peer market with algorithmic matching, enhancing autonomy. The effectiveness of the proposed solution is demonstrated through a case study on Crete's electrical power system, highlighting its potential for integrating diverse energy resources and consumers. Similarly, in [12] a novel pricing mechanism is introduced to address the uncertainty in local markets, including Preference Marginal Price (PMP), Uncertainty Marginal Price (UMP), and Local Marginal Price (LMP). The authors in [13] present a hybrid market-clearing method consisting of deep reinforcement learning and optimization algorithms. The method employs a generalized Bass model to depict the P2P energy market diffusion process in the relevant ecosystem, while the dynamic network usage costs are included in the system operator's model. In [14] a two-stage social welfare maximization approach is developed, which incorporates network voltage constraints. The validity of the model has been tested on the IEEE-14 bus network and has been compared to two other models in three different scenarios, showing better results in terms of social welfare. Authors in [15] demonstrate a P2P trading scheme through validation in software-in-loop and hardware-in-loop setups. The results show that the proposed model guarantees stable and fair outcomes for all participants while satisfying network constraints.The challenge of reducing carbon emissions from electricity generation power plants, is addressed by the authors in [16] which apply a game theory approach to Generation Expansion Planning (GEP), incorporating government regulations such as carbon tax and subsidies. The study, focusing on Iran as a case study, explores four strategic approaches to achieve carbon reduction goals and provides a comprehensive sensitivity analysis based on variations in carbon tax and government subsidies.

Evolutionary game-based management schemes are proposed in [17], [18] and in [19], while authors in [20] apply the Stackelberg game for P2P energy trading. Cooperative game-based P2P energy management schemes in smart grids are proposed in [21] and in [22]. In [23], the problem of providing high-quality energy service is addressed by a cloud-based pricing scheme called SmartPrice, designed to ensure high-quality service from microgrids is proposed as a solution to this problem. To support consumers' decision on whether or not to be involved in LEMs, researchers employ prospect theory, which describes the way in which decision-makers evaluate and decide upon their actions under risky or uncertain conditions by considering their psychological perceptions and risk preferences [2]. In [24], authors developed a bidding model for a power market based on prospect theory while fully accounting for irrational consumer behaviour and personal preferences. In [25], authors refine consumer behaviour models with sigmoidal functions to obtain maximum utility, and in [26] authors analyze how behavioural economics impact the demand response model, showing that preferences can have a profound effect on demand response and it makes sense to appeal to them when procuring demand response.

The vast body of literature dedicated to LEMs, while comprehensive, has significant gaps regarding the methodologies employed. In Table 1, we present a taxonomy of the papers in the literature, highlighting their methodology and key characteristics. This comprehensive analysis allows us to draw intriguing conclusions and identify specific gaps in the existing research, which our work aims to address and fill. At first, a large subset of LEM designs focus on either static or relatively simplistic pricing mechanisms. Such approaches often fall short in capturing the dynamic interplay of energy demand and supply, more so with renewables entering the energy mix. In response to this evident gap, we present a pricing algorithm inspired by prospect theory, which is adeptly designed to reflect the fluctuations inherent in real-world energy markets. Moreover, many LEM designs have overlooked the profound influence of prosumer behaviour. Our work combines game theory with the principles of behavioural economics, particularly prospect theory. This integration guarantees that our model merges technical expertise with the particularities of behavioral dynamics. Another important aspect of LEM adoption is their scalability. As LEMs expand, the computational challenge of incorporating a growing number of participants emerges. Our proposed two-stage Locational Shapley value methodology is an innovative countermeasure, promising efficiency even as the LEM scales. While many LEMs excel on the technical front, they occasionally neglect pivotal aspects like fairness and trust. Drawing from the cooperative game-theory field, complemented by a Shapley value-driven benefit allocation, our design envisions a LEM ecosystem perceived as equitable by all stakeholders, ensuring its sustained appeal. Finally, our study extends beyond traditional designs, introducing robust KPIs which guard against manipulation attempts, fostering a more transparent and trustworthy market environment. In identifying and addressing these gaps, we seek to go beyond just making incremental progress. Our proposed methodology, grounded in a cooperative game-based LEM architecture and enhanced by an innovative pricing algorithm, aims to lead transformative developments in LEM designs.

TABLE 1. Comparison between this work and the relative literature.

Paper	Focus Area	Approach-Methodology	Key Characteristics	Research Gap Addressed
[3]	IoT and smart appliances in energy consumption	Technology-driven	Enhances consumer control over energy usage through advanced technology.	Advanced integration and utilization of IoT technology beyond basic control and monitoring in LEMs.
[4], [5]	Prosumer empowerment & DER deployment	Local flexibility and DERs	Offers better terms for energy services, promoting local trading and monetary rewards without intermediaries.	Novel strategies or models for local flexibility or DERs deployment.
[6]	Access to multi-tier electricity markets by prosumers	Market support functions	Supports functions like congestion management, balancing, and ancillary services.	Unique solutions for market access challenges or new value streams not explored in this reference.
[7]	Stable coalition in P2P energy trading	Cooperative game theory	Proposes efficient mechanisms based on cooperative game theoretical principles.	Game theory-based LEM design, proving benefit for all LEM participants.
[8]	Direct communication in energy trading	Communication platform	Facilitates efficient flexibility procurement by determining energy costs.	Novel pricing algorithm inspired by prospect theory for prosumer engagement.
[9]	Energy sharing in smart buildings	Comprehensive framework	Offers a comprehensive approach for energy sharing in smart buildings.	Incorporating operational uncertainty in pricing method for LEMs.
[10]	Optimization in P2P energy trading	Robust optimization technique	Uses a robust optimization technique, showing better performance compared to other methods.	Fair profit allocation in LEMs using a variation of the Shapley value.
[11], [12]	Regulated P2P market for prosumers	Market structure	Reduces peak load and ramp rates, promoting local electricity consumption.	Evaluation of LEM efficiency using KPIs in the electricity market sector.
[13], [14], [15]	Various aspects of market-clearing and pricing	Hybrid methods and simulations	Includes a variety of techniques for market-clearing and pricing in LEMs.	Innovative solutions and methodologies for enhancing LEMs operations and efficiency.

This approach seeks to establish models that are in tune with the complex and continually changing dynamics of our energy landscape.

III. LOCAL ENERGY MARKET DESCRIPTION

LEMs are becoming increasingly popular as they enable energy trading among prosumers, remove market entry barriers and create new value streams and benefits for small-scale DER owners who otherwise would not be able to participate in the energy markets. This market evolution leads to significant structural market changes, the introduction of new products and services and efficient market outcomes. To maintain a high level of trust, LEMs need to establish prices consistent across the entire energy value chain that constantly balance supply and demand while simultaneously protecting against fraud and market manipulation. Achieving these goals requires a compromise between two objectives: designing market mechanisms that integrate distributed information and minimizing user involvement.

This work focuses on a cooperative-based LEM structure and examines how the proposed pricing strategy can attract more participants while mitigating the uncertainty regarding the local generation as well as the potential grid losses associated with LEM transactions. Additionally, we address the computational complexity of the optimal allocation of rewards through the use of a modified Shapley value, which requires fewer computational resources to calculate.

A. TRADITIONAL MARKETS AND P2P SCHEMES

Let us consider a large-scale energy producer having a cost $k(q)$, to generate q units of energy with a marginal cost c_0 for each unit and a prosumer with no upfront but only a marginal cost $c_0 + c$, where the cost c derives from the normal distribution G. Both, offer their capacity to consumers with variable demand $D_s(p)$, where s is the demand derived from the normal distribution H, and p is the market price ($D_s(p)$ is increasing in s and decreasing in p). The amount of generated capacity by large-scale energy suppliers is denoted as Q_k, while Q_c is the prosumers' one. In the demand state s the prosumers get their marginal costs and the market clears at a price p. Since all producers have a marginal cost of at least c_0, the market price is $p = c_0 + \pi$, where $\pi > 0$ is the price premium. The price premium that clears the market when $D_s(c_0) > Q_k$ is given by:

$$\pi^*(s) = \pi | D_s(c_0 + \pi) = Q_k + G(\pi)Q_c \tag{1}$$

where $D_s(c_0 + \pi)$ denotes the energy demand and $Q_k + G(\pi)Q_c$ the supply. This equation calculates the market-clearing premium, given the demand state $D_s(p)$ and the energy supply in the market. Eq. 1 determines the extra cost above the marginal production cost at which the market clears, considering both traditional energy suppliers and prosumers.

The market-clearing premium $\pi^*(s)$ can be calculated by:

$$\pi(s) = \begin{cases} \pi = 0, & \text{if } D_s(c_0) < Q_k \\ \pi^*(s), & \text{if } D_s(c_0) \geq Q_k \end{cases} \tag{2}$$

Eq. 2, defines the condition for setting the price premium, based on whether the demand can be met by the existing supply. It helps in understanding how the market price premium is adjusted based on the relationship between demand and supply, emphasizing the role of prosumers in market stability.

Fig. 2 shows the market clearing price with and without prosumers' participation. In the case of low demand where $\pi = 0$, traditional large-scale energy suppliers are rewarded with their marginal cost. As demand increases, there is a higher price premium. Without any prosumers, the energy supply is fixed at Q_k, leading to potential high price variability [27]. On the other hand, prosumers' participation implies that short-run supply will be more elastic, and therefore demand variability will be partially accommodated by a supply increase, resulting in more stable prices [28].

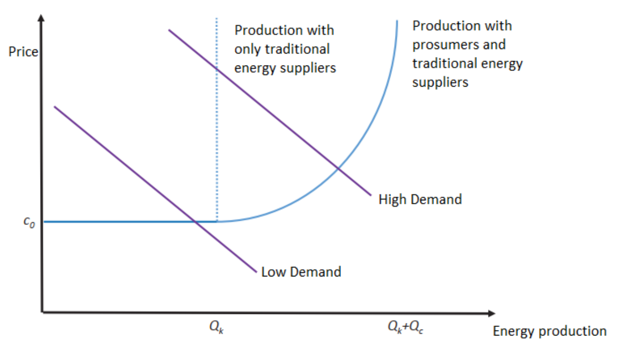

FIGURE 2. Price differentiation with and without prosumers.

LEM protects small-scale producers against price fluctuations, making them more resilient. It is noteworthy that an extra unit of energy from a large energy supplier can have a more significant impact on prices than an equivalent extra unit from a prosumer, due to the lower marginal costs of the latter. In addition, large-scale energy producers are more vulnerable to price fluctuations since they aim to sell in every demand state, which could lead to a sharp decline in their profits. The higher the demand variability the higher the potential engagement of prosumers. In a LEM environment, where the demand is highly variable, it is essential to have energy capacity that is procured in specific time windows or extreme cases. This requirement implies that large-scale energy suppliers have to incur higher upfront costs compared to prosumers who can provide a more elastic short-run energy supply. As such prosumers are in a better position than traditional energy suppliers with variable demand since they can avoid incurring their marginal costs in the event of high demand. In contrast, a dedicated seller must incur an upfront cost in all demand states.

B. COOPPERATIVE GAME THEORY APPROACH

When designing a LEM, it is crucial to ensure that the market design architecture provides incentives to resource owners to participate to increase efficient pricing and liquidity.

The engagement of prosumers in the LEM is efficient under two critical conditions. Firstly, if the production costs for prosumers are low, their participation is based on their true underlying subjective value cost. This can help reduce market power and ensure fair competition. Additionally, low entrance and exit costs are crucial since they make it less likely for any single participant to have enough power to manipulate the market leading to an inefficient LEM. With our approach, we deploy a coalition game in which participants offer their production based on their actual value cost, while the entrance and exit costs are kept to a minimum. This approach can create a trustworthy, transparent market without any manipulation strategies among the participants. By encouraging resource owners to bid or offer their true subjective value cost, this approach can help to ensure fair competition and improve the overall efficiency of the market. In this Section, we present the Game Theory mathematical formulation and the consumer-centric LEM architecture.

1) GAME THEORY MATHEMATICAL BACKGROUND

The choice of game model in any context is shaped by the nature of interactions and desired outcomes. In the context of LEMs, the cooperative game approach was selected due to its inherent ability to reflect collective utility maximization and mutual benefit realization, which aligns with the objectives of local energy markets. However, we recognize the potential for non-cooperative games in certain scenarios. The selection of cooperative over non-cooperative game has been driven by the intrinsic goals of local energy communities. The essence of LEMs is mutual benefit, collective action, and resource optimization - values that cooperative games inherently uphold. In such a context, cooperative game models naturally offer mechanisms that emphasize collective welfare over individualistic gains. By collaborating, prosumers can achieve efficient energy exchanges, maximizing the utility derived from available resources. Cooperative games inherently emphasize transparent and equitable distribution of benefits. In the context of LEMs, this translates to fair pricing, equitable energy distribution, and just profit allocation. Such fairness fosters trust among community members, ensuring that participants remain engaged and committed to the LEM, thereby enhancing its longevity. LEMs often struggle with high volatility in energy demand and supply, primarily due to their reliance on renewable sources. Cooperative games, due to their collective outlook, offer mechanisms that absorb such shocks more effectively. The collaborative pooling of resources ensures that even during periods of low energy generation or heightened demand, the community can navigate challenges more seamlessly than individualistic, non-cooperative entities. In terms of socio-environmental aspects, LEMs are deeply intertwined with broader socio-environmental objectives, such as promoting renewable energy, ensuring sustainability, and reducing carbon footprints. Cooperative games, by emphasizing collective welfare, naturally align with these objectives, ensuring that LEMs not only optimize energy transactions but also contribute positively to broader societal goals. While the above points elucidate our rationale for choosing cooperative games, we acknowledge the potential advantages of non-cooperative models. They can indeed capture competitive dynamics, offering mechanisms to ensure individualistic optimization. However, within the broader context of LEMs, the cooperative game paradigm offers a more strategic and holistic approach. In conclusion, while both cooperative and non-cooperative games have their merits, the unique challenges and objectives of LEMs make cooperative games a more fitting choice. Their alignment with the foundational principles of local energy communities ensures that our LEM design remains robust, equitable, and future-ready.

Cooperative game theory is a well-established approach used extensively in energy markets. This approach, which focuses on how players in a game can benefit by working together, is not a new concept in the realm of energy markets. Our work goes beyond the conventional use of cooperative game theory, marrying it with a pricing model that is deeply influenced by prospect theory. Our core argument is not just about the utilization of cooperative game theory. Instead, our emphasis lies in the innovative way we have paired this game theory with our designed pricing model. With this integrated approach, we do not just aim for optimal energy trade outcomes but also strive to ensure that the system remains resilient, even when faced with unpredictable shifts in energy demand and supply. Furthermore, this combination led to the creation of a pricing algorithm that closely mirrors the real-world behaviour and preferences of prosumers. This is not just a mere application; it is a significant enhancement of the game theory, rendering it highly suitable for real-world LEM applications. Moreover, a standout feature of our research is the introduction of a refined two-stage Locational Shapley value methodology that meticulously optimizes profit distribution and emphasizes fairness and equity among all involved parties. This attention to equitable distribution is vital as it plays a pivotal role in ensuring the overall system's stability, trustworthiness and strengthening the bond between prosumers in LEMs. Besides, we took on the challenge of scalability and computational efficiency, often associated with large-scale applications of cooperative game theory. Our approach, which involves calculating the Shapley value at specific nodes, drastically improves computational speed and broadens scalability.

We consider a LEM with N participants. Each prosumer $n \in N$ is a small-scale energy customer, while a subset of them are owners of rooftop solar. Moreover, every participant is also equipped with a smart meter. We denote the energy demand and PV production of each prosumer as $P_{n,d}$, and $P_{n,pv}$ respectively. The amount of energy consumed by each prosumer from its own solar asset can be expressed as:

$$P_{n,c} = min(P_{n,d}, P_{n,pv}) \tag{3}$$

This equation is fundamental in the LEM framework for understanding the interaction between prosumer demand, solar production, and consumption.

Depending on the demand and production values, a participant is considered either as a producer offering his energy surplus ($P_{n,sur}$) to the market, or as a buyer with energy need ($P_{n,def}$) thus creating two separate groups of participants, namely producers N_s and buyers N_b within the LEM. The values of $P_{n,sur}$ and $P_{n,def}$ are calculated as follows:

$$P_{n,sur} = P_{n,pv} - P_{n,c} \tag{4}$$
$$P_{n,def} = P_{n,d} - P_{n,c} \tag{5}$$

Eq. 4 and Eq. 5 segment the prosumers into two groups: those who can offer surplus energy and those who need to buy energy; this is crucial for understanding the dynamics of energy trade within the LEM.

The cost C_n and the revenue U_n to each prosumer n from participating in a LEM is:

$$C_n = p_{int} * P_{n,def}, \quad \forall n \in N_b \tag{6}$$
$$U_n = p_{int} * P_{n,sur}, \quad \forall n \in N_s \tag{7}$$

where p_{int} denotes the LEM price.

Through Eq. 6 and Eq. 7, we calculate the economic impact of each prosumer's participation in the LEM regardless if he buys or sells energy.

Outside an operating LEM, a consumer would meet its demand by buying energy from the external grid at a price f_{out}, while a prosumer would sell its products at a price f_{in} as determined by the electricity market. However, this pricing scheme creates a lack of motive for the prosumers to trade with the external grid, since $f_{in} \ll f_{out}$ thus profits are marginal. On the contrary, LEM with its competitive pricing provides an alternative option for prosumers and consumers to trade energy with each other. The total amount of energy available for trading within the LEM platform is:

$$\sum_{n \in \mathcal{N}_s} P_{n,\text{sur}} = \sum_{n}^{N_s} P_{n,\text{pv}} - \sum_{n}^{N_s} P_{n,c}, \tag{8}$$

where $\sum_{n}^{N_s} P_{n,c} = min(\sum_{n}^{N_s} P_{n,\text{pv}}, \sum_{n}^{N_b} P_{n,d})$. The total energy need for LEM buyers is:

$$\sum_{n \in \mathcal{N}_b} P_{n,\text{def}} = \sum_{n}^{N_b} P_{n,d} - \sum_{n}^{N_b} P_{n,c}. \tag{9}$$

Equations 8 and 9 aggregate the total surplus and need across all prosumers, providing a comprehensive view of the LEM's energy balance.

A cooperative game is characterized by a set of players, in our case sellers and buyers respectively, that form a coalition, and a value function g that denotes the coalition's monetary value. The proposed game can be mathematically described as:

$$L = \{\mathcal{N}, g\} \tag{10}$$

Eq. 10 sets the foundation for the cooperative game-theoretical approach, highlighting the collective action and optimization in the LEM. Here, g refers to the benefit that the participating prosumers attain by trading within the LEM platform, the proposed L is a cooperative game with transferrable utility and its value function g is derived from:

$$\begin{aligned} g(\mathcal{N}_s \cup \mathcal{N}_b) = f_{in} \max\left(0, \left(\sum_{n \in \mathcal{N}_s} P_{n,\text{sur}} - \sum_{m \in \mathcal{N}_b} P_{m,\text{def}}\right)\right) \\ - f_{out} \max\left(0, \left(\sum_{m \in \mathcal{N}_b} P_{m,\text{def}} - \sum_{n \in \mathcal{N}_s} P_{n,\text{sur}}\right)\right) \end{aligned} \tag{11}$$

Eq. 11 quantifies the economic benefits of forming a coalition in the LEM, ensuring that the cooperative game model accurately reflects the market dynamics and financial incentives.

During the hours when the LEM has an energy surplus, the energy is sold to the external grid. The first objective of the proposed coalition-based LEM is to meet the local energy needs internally, and then, if necessary, participate in the wholesale market to buy the rest of the demand or sell its requirements to be successful and sustainable [29].

1) Benefit of cooperation: In a cooperative-based LEM no sub-group can benefit by leaving the grand coalition and by acting non-cooperatively. This is associated with the property of superadditivity of the value function of the game.
2) Stability of coalition: The revenue needs to be distributed in such a way that no individual or subgroup of prosumers has any incentive to withdraw from the LEM. Our proposed pricing method meets both of these requirements as it is proven in the Appendix.

2) CONSUMER-CENTRISM LEM ARCHITECTURE

A critical factor for LEM's success is to have a consumer-centric architecture. According to the rational economic model [30] and the positive reinforcement model [31] a market operation that incorporates both model properties has a very high possibility of being accepted by the participants (consumer-centric scheme). For the proposed LEM, the cooperative game L satisfies the rational economic model. In particular:

1) The value of the coalition is defined in terms of monetary revenue thus offering a stimulus to participants.
2) It is shown that the core of the proposed L is non-empty. Therefore, none of the participants had any monetary incentive to leave LEM.
3) It is shown that the revenue that each prosumer obtains by using LEM lies within the core of the game leading to a stable coalition.

All the prosumers participating in the proposed market consistently achieve satisfactory monetary revenues. In the context of LEMs, the positive reinforcement property suggests that prosumers will be motivated to join the market if they receive positive incentives each time they engage. In this study, prosumers receive financial benefits when they participate in the LEM. Hence, the proposed LEM conforms to the positive reinforcement model, demonstrating its fulfilment of both the positive reinforcement property and the consumer-centric market structure. This further substantiates the advantages of prosumer involvement in LEMs.

IV. PRICING

Local pricing mechanisms are used to facilitate local trading by determining a set of competitive buying and selling prices for the participants. We argued that one of the main challenges LEMs face is to attract new participants and retain the existing ones for maximum liquidity. One way to address this issue is by creating a pricing mechanism that is simple and at the same time creates the necessary motives for prosumers to participate.

Two pricing mechanisms are usually deployed, the Mid-Market Rate (MMR) and the Bill Sharing (BS) pricing. MMR sets prices based on the average price of electricity in the market. The BS model calculates prices based on the proportion of electricity consumed and generated by each prosumer in the local network. Even though the MMR and BS pricing mechanisms are easy to implement, the solutions for reward distribution may not always be at the core of the prosumer coalitional game. Our proposed pricing mechanism is inspired by the prospect theory requiring minimum consumer involvement while resulting from the forecasted values of local demand and generation. The main advantages of the proposed sigmoid pricing are:

- Simplicity; Our pricing is simple to implement and without any significant computational complexity.
- Robustness; Pricing incorporates the uncertainty of LEM operation.
- Grid-awareness; The pricing integrates the penalties due to violations that may occur during energy trading.
- Prosumer-friendly; The participants are not obliged to actively participate in LEM pricing clearing via bidding or auctions. This minimum engagement to market process results in increased acceptance.
- LEM stability; The proposed pricing ensures that the core of the value function is non-empty, thus LEM is considered a stable coalition.

The two key aspects of our pricing methodology are presented next: the prospect theory and the profit distribution methodology.

A. PROSPECT THEORY

The decision to participate in a LEM can be considered as a decision making under risk. Traditionally, such decision-making has been analyzed using the expected utility theory. However, empirical studies have shown that individuals tend to deviate from rationality axioms when making decisions [2], [32]. Contrary to the premise that certainty is preferred, it has been found that certainty intensifies the aversiveness of losses and the attractiveness of gains. Therefore, it is the changes in wealth (the value function), that determine satisfaction or utility. The value function consists of two factors: the reference point and the magnitude of change from the reference point. We assume that the value function for changes in wealth is normally concave above the reference point ($v''(x) < 0$, for $x > 0$) and often convex below it ($v''(x) > 0$, for $x < 0$). As evidence from various domains has shown, sigmoidal functions offer a better view of the utility function [33], [34], [35]. We claim that the value function for decisions made under risk shares the same properties as the ones made under riskless conditions. As reluctance towards changes in welfare is larger for losses than gains, the value function for losses is steeper than that for gains. In summary, the value function is concave for gains and convex for losses. Fig. 3 represents a value function derived from prospect theory, displaying the subjective evaluation of potential outcomes. The x-axis represents the magnitude of gains and losses, while the y-axis represents the subjective value or utility associated with those gains and losses. The graph consists of two distinct regions: one for gains and the other for losses. In the gains region, the value function exhibits concavity, indicating risk aversion. As gains increase along the x-axis, the marginal utility of each additional gain diminishes. This implies that individuals experience diminishing satisfaction or utility as they accumulate more gains. Consequently, the slope of the value function gradually becomes less steep, reflecting the

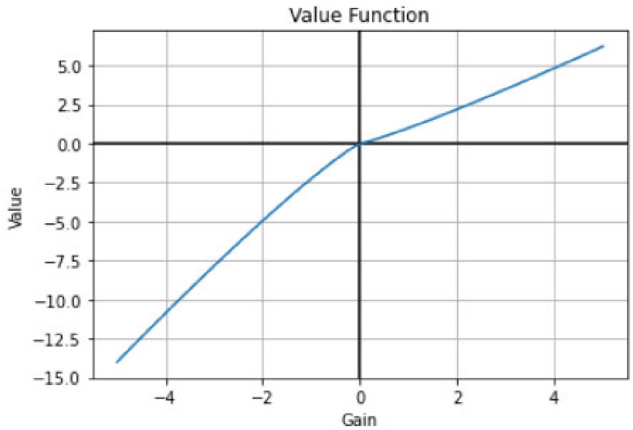

FIGURE 3. Value function for decisions under risk. The value function is steeper for losses than gains indicating that losses outweigh gains.

decreasing rate of utility increase for larger gains. In the losses region, the value function displays convexity, implying risk-seeking behaviour. As losses increase along the x-axis, the marginal utility of each additional loss magnifies. This indicates that individuals experience a heightened emotional response to larger losses. Consequently, the slope of the value function becomes steeper, reflecting the increasing rate of utility decrease for larger losses. The graph also highlights the concept of loss aversion, a key aspect of prospect theory. The value function exhibits a steeper slope in the losses region compared to the gains region. This indicates that losses elicit stronger emotional reactions than equivalent gains. Loss aversion implies that individuals are more sensitive to losses, and the negative impact of losses outweighs the positive impact of equivalent gains. This psychological bias leads to a reference point where individuals experience a stronger preference to avoid losses rather than seek gains.

Adjusting the classical value functions for our model, we consider the following sigmoidal utility function that represents the LEM pricing (Fig. 4).

The pricing algorithm is described in detail in Algorithm 1. The algorithm has a resolution of one hour, similar to the price signals of the external wholesale Day Ahead Market (DAM), but it can be adjusted to the special needs of each market while the granularity of the algorithm's solution is determined by how often the system updates its information and control signals. The main advantage of the proposed pricing approach over existing ones is that the clearing price is determined solely by the local production and consumption values, creating an automated bid-less market without active prosumers' participation. This feature makes the proposed LEM more accessible to a wider range of potential members, as it minimizes the market's entry barriers and offers a "consumer-friendly" property to LEM. In addition, the proposed LEM is resilient against market speculation or manipulation, as the market clearing results from objective parameters only, i.e., smart meter values. The proposed algorithm also ensures that the local market is cleared at a

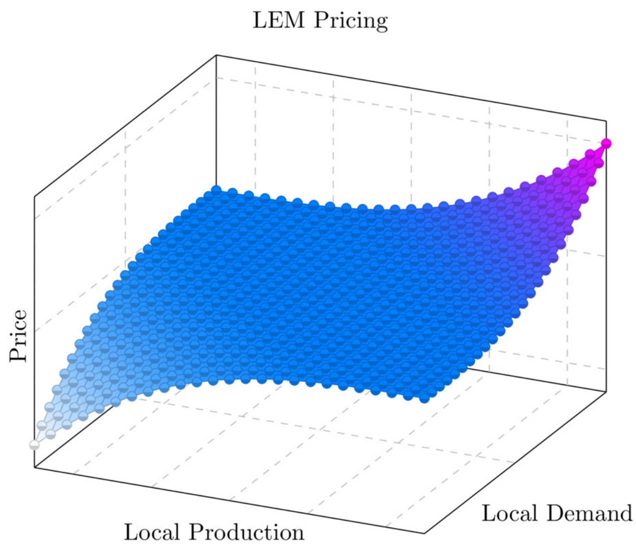

FIGURE 4. Pricing surface depending on the local values of production and demand.

price lower than the selling price of the retail external grid and higher than the buying price of the external grid, taking into account the feed-in (the price that the producers are rewarded for supplying their energy to the grid) and feed-out prices (the price that the consumers pay) as hard constraints. The proposed LEM settles internally before coordinating with the external electricity grid, allowing the maximum amount of energy to be cleared locally. Overall, the proposed pricing algorithm offers several advantages over existing approaches, including accessibility, safety against market manipulation, and simplicity. These properties make it a promising solution for the emerging LEM market, with the potential for widespread adoption.

Algorithm 1 Sigmoid Pricing algorithm

Input: feed-in tariff (π_{buy}), feed-out tariff (π_{sell}), production (p), consumption (c)
Output: internal clearing price(p_{int})

Get π_{buy}, π_{sell}
Surface representing production and consumption
Assign sigmoid values to the surface
if ($c = 0$) **then**
    $p_{int} \leftarrow \pi_{buy}$
end if
if ($p = 0$) **then**
    $p_{int} \leftarrow \pi_{sell}$
end if
if ($c = p$) **then**
    $p_{int} \leftarrow (\pi_{buy} + \pi_{sell})/2$
end if
Interpolate the diagonals with a predetermined function
Mirror the results to the remaining diagonals
Do a weighted interpolation from the closest calculated values

Following the market clearing, the final pricing is calculated. The final settlement price consists of three factors namely the pricing from the algorithm analyzed above, a part that accounts for the uncertainty of LEM operation and a factor that depicts the burden that local energy transactions pose on the distribution grid. In this work, we deploy a chance optimization to tackle the generation's stochasticity [36]. The local pricing mechanism encompasses various factors to ensure efficient operation and grid stability. One of these factors is the uncertain pricing component, which is derived from the dual variables associated with uncertain constraints (Equations 12-13 in [36]). This component represents the deviation penalty that prosumers must pay and serves as a motivation to improve forecasting techniques and adhere to the LEM schedule. Another pricing factor is the impact of LEM operations on the distribution grid. To guarantee grid stability, the Distribution System Operator (DSO) conducts a power flow analysis. In case of voltage violations, penalties are imposed on specific nodes based on their deviation from the operational limits set by the DSO. These penalties reflect the degree of voltage deviation and can be positive (in case of under-voltage) or negative (in case of over-voltage). In Fig. 5 the proposed process is illustrated. The market settlement process begins with the collection of forecasted values for essential inputs such as production, demand, and feed-in/out prices. These inputs are then utilized by the pricing algorithm to calculate the pricing surface and local clearing price for each hour. To address the stochastic nature of local production, the pricing algorithm incorporates a stochasticity component derived from the dual variables of the uncertain constraints. These dual variables quantify the sensitivity of the objective function to changes in the constraint's right-hand side and encourage improvements in the accuracy of the LEM's forecasting methods, thereby reducing balancing costs. Additionally, the voltage violation information obtained through the DSO's power flow analysis is incorporated in determining the final local price. The DSO notifies the LEM operator of the total voltage incidents in their area, and penalties are imposed on participants per node based on their contribution to the violations. These penalties

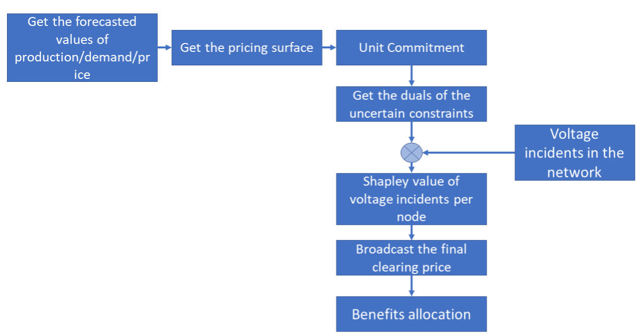

FIGURE 5. Proposed LEM process.

are proportional to the per-unit deviation from the normal operational limits.

The market settlement process incorporates the local pricing p_{int} resulting from the forecasted values of demand and generation, utilizes a pricing algorithm with a stochasticity component, and includes information regarding voltage violation to determine the final local price. In particular, the final clearing price is calculated by:

$$p_i = p_{int} + dual\ values + voltage\ deviation \tag{12}$$

where p_i denotes the final clearing price, p_{int} is the sigmoid price, the dual values result from the uncertain constraints of the optimization problem and the voltage deviation is the voltage difference from the upper/ lower voltage limits (1.05 and 0.95 pu) in %. Eq. 12 ensures that the final price reflects the actual operational and market conditions, including the impact of local energy transactions on the distribution grid and the uncertainty in generation.

B. PROFIT DISTRIBUTION

The way profits are distributed is fundamental to LEM's stability and sustainability. To achieve the twofold objective of fairly remunerating existing participants and attracting new members, we deploy the Shapley value approach. The Shapley value is grounded in three axioms: efficiency, symmetry, and balanced contribution, which ensure a fair distribution of profits among the participants [37]. Specifically, the Shapley value measures the contribution of each member to the coalition by computing the marginal contribution of each member to all possible sub-coalitions. The resulting value represents each member's fair share of the total profits earned by the coalition. By using the Shapley value approach, we can distribute the LEM's profits in a manner that aligns with the principles of fairness and transparency, while incentivizing current members to continue their participation and attracting new members to join the LEM.

Let $\phi_i(\mathcal{N}, V)$ be the Shapley value of participant i in coalition $\mathcal{N}$ with value function V. Then, based on the three axioms of the Shapley value, $\phi_i(\mathcal{N}, V)$ is:

$$\phi_i(\mathcal{N}, V) = \frac{1}{|\mathcal{N}|!} \sum_{\gamma \in \Gamma} [V(\mathcal{N}(\gamma, i) \cup \{i\}) - V(\mathcal{N}(\gamma, i))] \tag{13}$$

where Γ is the set of all $|N|!$ orderings of N and $N(\gamma, i)$ is the subset of N which includes the participants whose order precedes i in the ordering γ. This equation is used to ensure fair and equitable profit distribution among LEM participants, accounting for each member's marginal contribution.

By distributing the revenue based on each participant's Shapley value, benefits are equitably shared, with each peer receiving a share proportional to their actual contribution to the collaboration. However, the computational cost of computing the Shapley value is significant and rises rapidly as the number of participants increases. This is due to the requirement to account for all possible permutations of participants when calculating Eq. 13. To alleviate this computational complexity, we introduce a variation of the classical Shapley value, which considers the nodes of the distribution grid namely the two-stage locational Shapley value, inspired by Locational Marginal Pricing (LMP) [38]. The allocation of profits is accomplished in two stages. First, we calculate the Shapley value for each node, and profits are distributed among them. Then, the nodal profits are further allocated among the participants under each node. This approach makes profit distribution scalable and more efficient, as we will demonstrate in the following section.

V. USE CASE

To evaluate the effectiveness of our proposed method, we conduct experiments on the CIGRE low voltage network [39]. The original network consists of 15 loads, 37 lines, 44 buses, and 3 MV/LV transformers, all of which are connected to the external grid. To enhance the realism of our use case, we augment the network with an additional 40 residential loads, 15 PV assets, and 15 storage units. The relevant data are obtained from a pilot site run by a DSO in central Germany, where all the energy assets and loads are equipped with smart meters. We focus on the day-ahead LEM clearing process and adopt a time resolution of one hour, consistent with the wholesale paradigm. This setup enables us to demonstrate the efficacy of our approach in a practical, real-world context.

The LEM results in universal pricing across the three nodes of the network. To verify the efficiency of the proposed algorithm, we compare it against the fairness pricing method [36] and the outcomes of two state-of-the-art algorithms namely the MMR and BS. After the market clearing the two-stage Locational Shapley value is calculated for each node of the system. The economic efficiency of the market is then evaluated by deploying three widely used KPIs in electricity markets that are for the first time utilized for a LEM case, namely Hirschman-Herfindahl Index (*HHI*), Pivotal Supplier Index (*PSI*) and Residual Supply Index (*RSI*) [40]. These KPIs provide insight into the concentration of market power, the impact of key participants on the market, and the market's ability to maintain stability under stress.

To measure the market concentration we employ *HHI* which is an index of market competitiveness. *HHI* is calculated by:

$$HHI = s_1^2 + s_2^2 + \cdots + s_n^2 \tag{14}$$

where s denotes the market share of each LEM participant. *HHI* assesses the level of competition within the LEM and ensures the diversity and competitiveness of the particular energy market.

To examine whether the LEM can be manipulated by any participant, we deploy two widely used measures of market power: the *PSI* and the *RSI*. The *PSI* measures the degree to which a single participant is critical to meeting the total demand in the market. Specifically, it is equal to 1 when the demand cannot be met without the supply from the participant

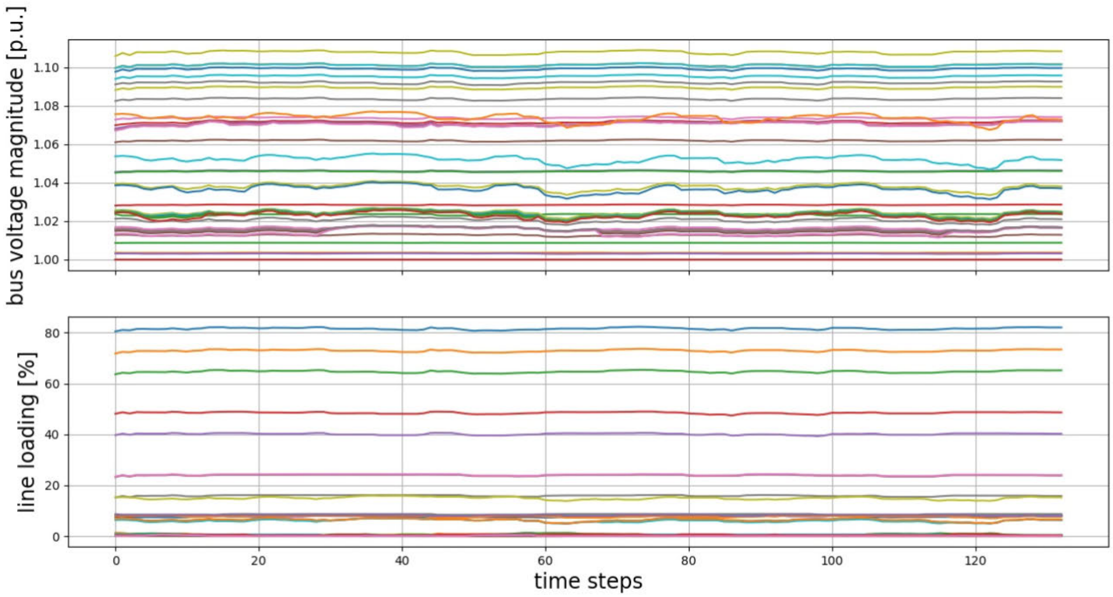

FIGURE 6. Nodal voltages and line loading for the examined use case.

being studied and is 0 when demand could be satisfied without the participant's supply. On the other hand, the *RSI* measures the percentage of load (in *MWh*) that can be met without the largest supplier. Both indices are calculated for each participant and provide valuable insights into the level of market power held by each player. This allows us to assess the overall competitiveness of the LEM and determine whether any participant can manipulate the market outcome. The *RSI* is calculated by:

$$RSI = \frac{Total\ Supply - Largest\ Seller's\ Supply}{Total\ Demand} \tag{15}$$

RSI index assesses the market power of an individual participant and consequently its influence on the overall stability of the LEM.

VI. RESULTS

In this section, we present the analysis of the experimental results from our use case. We begin by discussing the voltage analysis, followed by a comparison of pricing methods and local trading dynamics. Then, we examine the benefits and payments to participants, propose a fair and scalable benefit allocation approach, and evaluate the economic efficiency and market characteristics of the proposed LEM.

A. VOLTAGE ANALYSIS

Fig. 6 illustrates the voltages for each node in the LEM. It is evident that more than half of the nodal voltages exceed the upper limit of 1.05 pu. To address this issue, as explained in Section IV, our pricing methodology incorporates the penalties imposed by the Distribution System Operator (DSO) for overvoltage incidents. This ensures that the final local pricing reflects the impact of overvoltage events on the system.

B. PRICING COMPARISON AND LOCAL TRADING

The hourly local buy and sell prices resulting from MMR, BS, the fairness algorithm and the proposed Sigmoid algorithm are compared against the grid import and export prices in Fig. 7-Fig. 8. It is evident that all pricing methods, provide local prices within the grid import and export price limits thus prosumers are more likely to participate in a cooperative energy initiative due to the more attractive local prices. This inclination towards local trading is further bolstered by the familiarity of prosumers with each other, and their tendency to trust within their own network. Furthermore, local

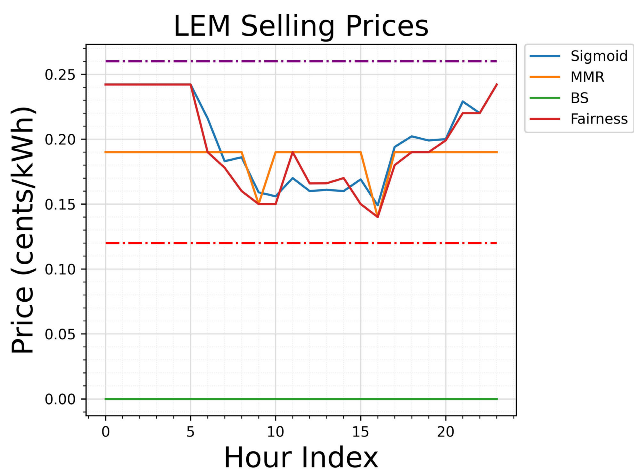

FIGURE 7. Comparison of hourly local selling prices under different pricing schemes and the grid import and export prices.

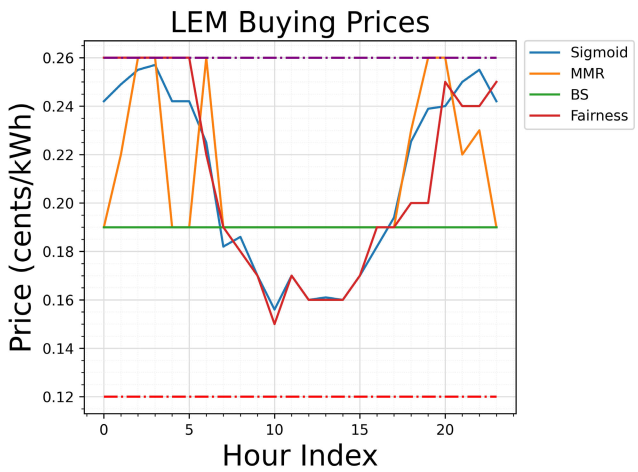

FIGURE 8. Comparison of hourly local buying prices under different pricing schemes and the grid import and export prices.

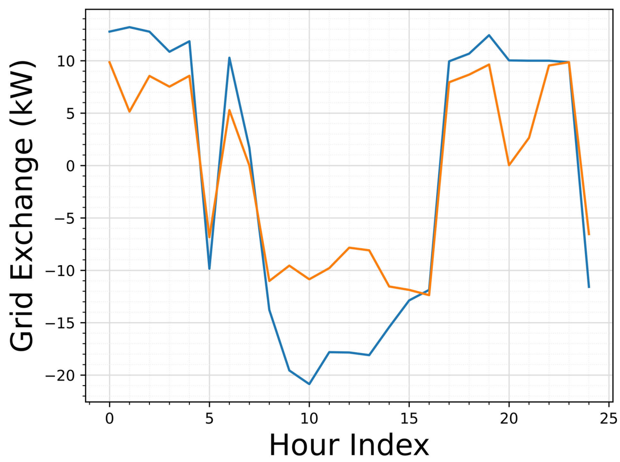

FIGURE 9. The aggregate grid exchange schedule of the LEM without (blue curve) and with the coalition (orange curve).

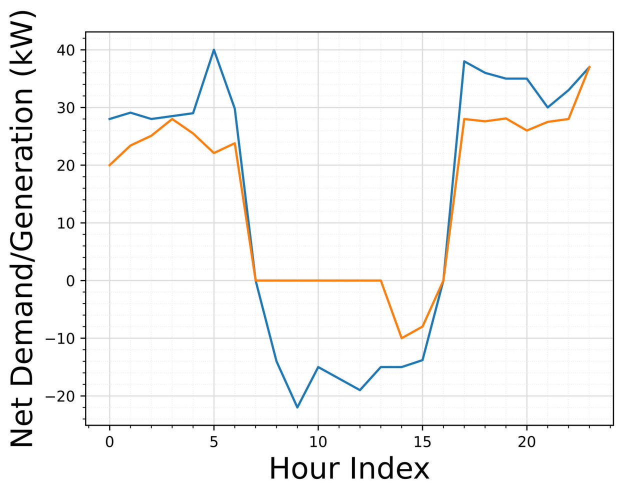

FIGURE 10. Net demand/generation of the LEM without (blue curve) and with the coalition (orange curve).

trading eliminates the potential for market manipulation, as prosumers are more likely to be transparent with each other and adhere to mutually agreed-upon terms. This makes local trading a lucrative alternative for prosumers, as it allows them to access the same level of energy transactions as with an external retailer, but at a much more enticing price. For the BS algorithm, the local selling prices are lower than the prices retailers can export them for, resulting in lower revenue for prosumers and leading to potential lower participation levels.

Focusing on the two similar approaches, the fairness algorithm and the sigmoid one, both prices are similar during periods of high solar energy generation. This is expected since the algorithms have similar characteristics at this time and the price reflects the residual load. As a result, when there is high PV production, the prosumer is not rewarded enough and LEM's power requirement is low. Conversely, during night hours (7 pm-6 am), the proposed sigmoid algorithm has lower prices. This happens because the edges of its sigmoid pricing function are sharper in order to account for risk aversion among LEM members. The effectiveness of conventional and proposed local energy trading mechanisms in terms of local balancing and RES absorption is compared. In particular, in Fig. 9 and Fig. 10 the grid exchange schedule and the net demand/generation of the coalition, are illustrated respectively for two different scenarios namely without and with LEM.

It can be observed that the adoption of LEM leads to a more self-sustained scheme, resulting in a schedule that closely follows the net demand profile. Additionally, LEM operation reduces peak demand and leads to more balanced local demand and supply compared to a no-LEM alternative. Moreover, the proposed pricing mechanisms incentivize prosumers to trade their generation surplus within the local market, resulting in successful energy sharing, as opposed to independent operation, where generation excess is injected into the grid via an aggregator under unfavourable terms.

C. BENEFITS AND PAYMENTS

Table 2 shows the comparison of consumers' payments and producers' profits using different pricing methodologies. The proposed sigmoid pricing methodology results in the lowest payments for consumers while providing higher profits for producers. This indicates that the proposed approach offers better monetary benefits, which can act as a motivation for increased participation in the LEM. Moreover, the sigmoid pricing mechanism enhances market stability and efficiency, allowing buyers and sellers to benefit from price changes, ultimately leading to better outcomes for all participants.

TABLE 2. Total payment and profit in euros.

	No LEM	Fairness Algorithm	Sigmoid	MMR	BS
Payment	48.55	37.08	35.98	38.12	39.52
Profit	36.67	51.09	51.29	49.98	39.52

D. FAIR AND SCALABLE BENEFIT ALLOCATION

As we discussed calculation of the Shapley value can be computationally burdensome, especially for large-scale systems. To overcome this challenge, we propose a novel two-stage approach that combines the advantages of the Shapley value with improved scalability. Our approach calculates the Shap- ley value at the nodal level, enabling us to allocate profits to participants within each node. This method significantly enhances computational efficiency compared to calculating the Shapley value for the entire system. Additionally, by distributing profits among nodes instead of calculating them for all participants, our approach improves the scalability of the system. This results in a more time-efficient and cost-effective benefit allocation process. Our approach ensures a fair and equitable distribution of benefits to all participants while enhancing the overall scalability of the LEM system. In our use case, applying the two-stage Locational Shapley value results in a more equitable distribution of profits, with benefits for nodes S_1, S_2, and S_3 increasing to 16.922, 18.325, and 16.047, respectively, as can be seen in Fig.11. This new benefits distribution not only improved the fairness of the structure but also strengthened the stability and trustworthiness of the LEM.

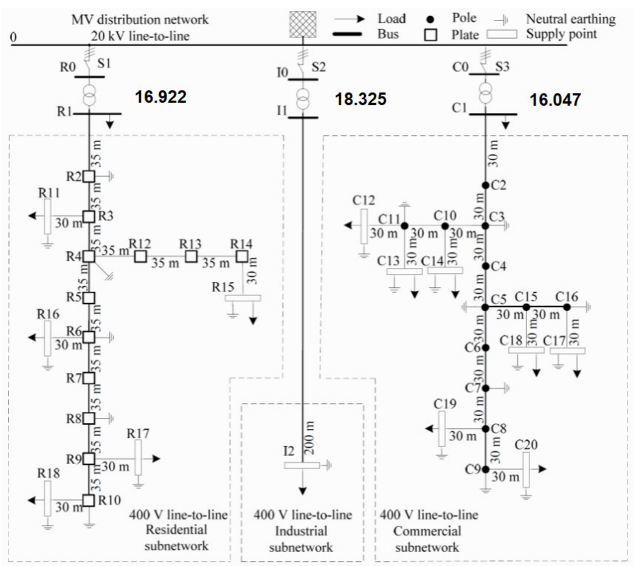

FIGURE 11. Profits with Locational Shapley value.

Similarly, in Fig. 12 the payments for each node based on the Locational Shapley value are illustrated. Under normal conditions the payments for nodes S_1, S_2 and S_3 are 9.91, 15.121 and 10.95 respectively. By applying the Locational Shapley value the payments are 9.836, 15.775 and 10.369 for the investigated nodes. For both the payments and the profits each node is rewarded or charged based on its contribution to the coalition.

Interestingly, node S_2 receives significantly more rewards and pays more compared to the other nodes. This is because

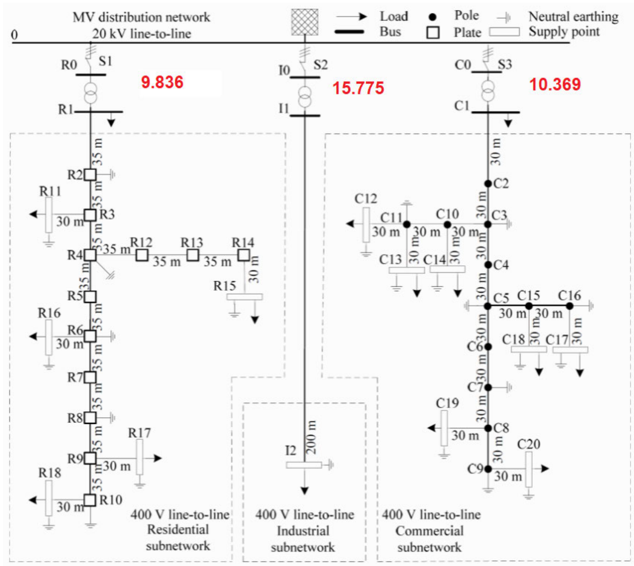

FIGURE 12. Payments with locational shapley value.

node S_2 contains an industrial load consuming considerable energy, and has more connected PV assets than the other nodes. Thus, the contribution of this node to the total energy surplus and demand is accurately reflected by its Shapley value in both cases. Next, we calculate the Shapley value for each prosumer under each node. Table 3 illustrates the benefits and payments of an average prosumer during the examined day. The application of the Shapley value results in differences between the values for the same hour. During peak hours of PV production, Shapley value leads to higher profits, reflecting the actual contribution of prosumers and rewarding it accordingly. In contrast, during peak load hours, the Shapley value results in lower payments. Although the differences are not substantial in monetary terms, the added value of our proposed method lies in the stability of the coalition, which is ensured by the application of the Shap- ley value. Our proposed approach not only improves the fairness of benefits distribution in local energy markets but

TABLE 3. Profits and payments.

Hour	Actual Profit	Shapley Value-Profit	Actual Payment	Shapley Value-Payment
8 am	0.0594	0.0553	0.483	0.471
9 am	0.4315	0.3975	1.236	1.099
10 am	0.9414	0.8679	1.64	1.66
11 am	16.318	16.258	1.95	2.026
12 am	15.33	15.448	1.634	1.642
13 am	19.81	20.308	1.623	1.629
14 am	22.56	24.245	1.483	1.422
15 pm	11.728	11.407	0.672	0.687
16 pm	14.349	14.10	0.572	0.633
17 pm	0.972	0.9342	0.2	0.2152
18 pm	0.31	0.2889	1.2	1.184
19 pm	0.032	0.0348	1.86	1.765

also considerably reduces the computational time needed for calculating the values.

As shown in Table 4, the computational time is presented for a varying number of participants, where the experiments were run on an Intel Core i7-8750H CPU at 2.20GHz using 16GB of RAM running Linux Ubuntu 22.10. The computational time was measured in seconds. The results indicate that for a small number of participants, the difference between the two approaches is not significant. However, as the number of participants increases, the computational time for the Shapley approach becomes significantly greater. In fact, for the last two cases, namely 45 and 55 participants, the Shapley approach could not reach a solution. On the other hand, by applying our alternative two-stage approach, not only can the algorithm reach a solution, but also in a fair amount of time. Therefore, our proposed approach not only improves the fairness of benefits distribution but also enhances LEM's scalability.

TABLE 4. Computational time in seconds.

Number of Participants	Shapley Value	Locational Shapley Value
15	66 sec	55 sec
25	102 sec	63 sec
35	327 sec	86 sec
45	Did not converge	132 sec
55	Did not converge	256 sec

To examine the stability of the coalition we leverage the concept of the greatest excess which represents the maximum difference between the total benefit achieved by a sub-coalition and the benefit it would receive as part of the larger coalition. In other words, it measures the extent to which prosumers in a sub-coalition can improve their individual outcomes by forming a separate group. By studying the greatest excess under different benefit distribution mechanisms, we can assess their impact on the coalition's stability. Analyzing the stability in this way allows us to understand the effectiveness of each mechanism and its ability to maintain a cohesive and stable coalition. A positive value of the greatest excess indicates that at least one sub-coalition within the larger coalition could achieve a higher benefit by breaking away. This instability encourages prosumers in that sub-coalition to form their own group. On the other hand, a non-positive value of the greatest excess suggests that all prosumers have no incentive to leave the coalition since they would not gain any additional benefit by doing so. This implies a stable benefit distribution.

Table 5 presents the results of the greatest excess analysis for the proposed sigmoid mechanism and the state-of-the-art mechanisms. The analysis is performed as the number of participants increases. The results clearly demonstrate that the sigmoid pricing, as well as the fairness mechanism, consistently achieve a non-positive greatest excess indicating that the respective benefit distribution mechanisms lead to a stable structure. Conversely, the remaining mechanisms yield mostly positive values for the greatest excess. This indicates that the benefit distributions generated by these mechanisms may not lie within the core of the prosumer coalitional game under examination. Therefore, for some prosumers, it is more advantageous to leave the grand coalition and form smaller sub-coalitions leading to instability and potential failure of the LEM structure.

TABLE 5. Greatest excess under the sigmoid pricing and state-of-the-art algorithms for different number of participants.

Number of Participants	Mechanism			
	MMR	BS	Fairness	Sigmoid
15	160.59	210.50	-10.54	-9.25
25	175.71	239.74	-17.62	-14.55
35	169.24	199.57	-22.35	-25.67
45	168.61	280.48	-15.84	-30.37
55	202.34	294.2	-32.72	-29.44

E. ECONOMIC EFFICIENCY AND MARKET CHARACTERISTICS

To examine the economic efficiency of the proposed LEM, we present the values of the KPIs introduced in Section V. The first index is the *HHI*, which measures the market concentration. By definition, if the *HHI* is lower than 1500, the examined market is not concentrated and operates competitively. In our case, the *HHI* value is 488.7, indicating that the proposed LEM is competitive and not concentrated. The second index we employ is the *PSI*, which measures the risk of market manipulation by a participant or a group of participants. In our case, the index is 0 during the whole time period, even when the number of energy suppliers is $N = 15$. This means that the risk of market manipulation in the proposed LEM is very small. Finally, we compute the *RSI* for the examined LEM, which measures the percentage of demand that can be met by local energy resources. As we observe in Fig. 13 the index is high during the day since the LEM energy assets are only PVs. Consequently, during morning hours, the self-sufficiency of the system is higher, and most importantly, the value of *RSI* indicates that a big percentage of demand can be met without the biggest

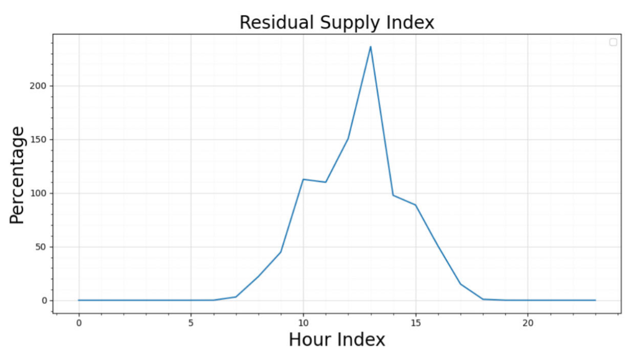

FIGURE 13. Residual supply index.

prosumer in the LEM. These results demonstrate that the proposed LEM is efficient, competitive, and resilient to market manipulation.

VII. CONCLUSION

In this paper, we proposed a cooperative game-based LEM architecture with a novel pricing algorithm inspired by prospect theory while ensuring a fair allocation of profits via a modified two-stage Locational Shapley value methodology to enhance fairness and scalability. We compared different pricing algorithms and examined the impact of the LEM on system operation and economic efficiency. Our findings indicate that the adoption of the LEM leads to a more self-sustained market evolution, with reduced peak demand and improved balancing of local demand and supply. We show that the proposed sigmoid pricing mechanism incentivizes prosumers to participate in local trading by offering attractive local prices within the grid import and export price limits. This condition coupled with the trust and familiarity among prosumers, increases the likelihood of their participation in cooperative energy initiatives. Comparing different pricing methods, we observed that the fairness algorithm and the sigmoid algorithm resulted in comparable prices during high solar energy generation periods. However, during night hours, the proposed sigmoid algorithm exhibited lower prices due to its sharper pricing function, which accounted for risk aversion among LEM members. Furthermore, our benefit allocation approach, based on the two-stage Locational Shapley value improved fairness, stability, and trustworthiness in the LEM. By calculating the Shapley value at the nodal level, we efficiently allocated profits to participants within each node, enhancing computational efficiency and scalability. The application of the two-stage Locational Shapley value resulted in a more equitable distribution of profits, with benefits increasing for specific nodes based on their contributions to the coalition. The economic efficiency of the proposed LEM was assessed using three KPIs. The *HHI* value indicated a competitive and non-concentrated market. The *PSI* remained at zero throughout the study, indicating a low risk of market manipulation. Additionally, the *RSI* showed that a significant percentage of demand could be met by local energy resources, highlighting the self-sufficiency and resilience of the LEM. In conclusion, synthesizing our findings and insights from the taxonomy table presented in Table 1, our work demonstrated the effectiveness of the proposed LEM architecture in promoting local energy sharing, balancing demand and supply, and ensuring fairness among participants. Overall, our findings support the implementation of LEMs as a viable solution for energy communities, fostering renewable energy integration, and empowering prosumers in the energy transition.

APPENDIX A
COALITION GAME THEORY

As mentioned in Section III a local market shall fulfil the following requirements to be successful and sustainable:

1) Benefit of cooperation: In a cooperative-based LEM no sub-group can benefit by leaving the grand coalition and by acting non-cooperatively. This is associated with the property of superadditivity of the value function of the game.
2) Stability of coalition: The revenue needs to be distributed in such a way that no individual or subgroup of prosumers has any incentive to withdraw from the LEM. Our proposed pricing method meets both of these requirements as it is proven in the Appendix. The set of feasible allocations of such revenues is defined as the core. Let e be the payoff vector of the revenues that each prosumer of the game L attains, and the revenue of each prosumer $n \in N$ is defined as e_n where $e_n \in e$. Then the core of the L is defined as:

$$\mathcal{C}=\left\{\mathbf{e}: \sum_{n\in\mathcal{N}} e_n = g\left(\mathcal{N}\right)\ \mathit{and}\ \sum_{n\in\mathcal{S}} e_n \geq g(\mathcal{S}), \forall\mathcal{S}\subseteq\mathcal{N}\right\} \tag{16}$$

If the core $\mathcal{C}$ of the game is non-empty, there exists a feasible allocation of revenues, in which no group has any incentive to abandon the LEM leading to a stable coalition. One way to understand whether L has a non-empty core is through using the Bondareva Shapley theorem [41]. According to the Bondareva-Shapley theorem, the core $\mathcal{C}$ of cooperative game L is non-empty, if and only if for every function $f(\mathcal{S})$, where $n \in N \sum_{\mathcal{S}\in\mathcal{P}_n} f(\mathcal{S}) = 1$, and $0 \leq f(\mathcal{S}) \leq 1$, the following inequality holds:

$$\sum_{\mathcal{S}\in\mathcal{P}\backslash\phi} f(\mathcal{S})g(\mathcal{S}) \leq g(\mathcal{N}) \tag{17}$$

where $\mathcal{P}$ is the power set of N, and $\mathcal{P}_n \subseteq \mathcal{P}$ that has n as one of the elements in all subsets.

To prove that the value function of the proposed game L is superadditive, we define:

$$\sum_{n\in\mathcal{N}_s} P_{n,\text{sur}} - \sum_{m\in\mathcal{N}_b} P_{m,\text{def}} = k \tag{18}$$

Therefore, from (11), the value function can be expressed as:

$$g = f_{in}\max(0,k) - f_{out}\max(0,-k) \tag{19}$$

We note that the value function (19) is concave. We break down the set N_b of buyers and the set N_s of sellers into subsets $N_{b,1}$ and $N_{b,2}$, and $N_{s,1}$ and $N_{s,2}$ respectively, where $N_{b,1} \cup N_{b,2} = N_b$, $N_{b,1} \cap N_{b,2} = \phi$, $N_{s,1} \cup N_{s,2} = N_s$ and

$N_{s,1} \cap N_{s,2} = \phi$. Then, due to the linearity of g:

$$\begin{aligned}\frac{1}{2}g\left[\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_b} P_{m,\mathrm{def}}\right] &= g\left[\sum_{n\in\mathcal{N}_s} \frac{P_{n,\mathrm{sur}}}{2} - \sum_{m\in\mathcal{N}_b} \frac{P_{m,\mathrm{def}}}{2}\right]\\ &= g\Bigg[\left[\sum_{n\in\mathcal{N}_{s,1}} \frac{P_{n,\mathrm{sur}}}{2} - \sum_{m\in\mathcal{N}_{b,1}} \frac{P_{m,\mathrm{def}}}{2}\right]\\ &\quad + \left[\sum_{n\in\mathcal{N}_{s,2}} \frac{P_{n,\mathrm{sur}}}{2} - \sum_{m\in\mathcal{N}_{b,2}} \frac{P_{m,\mathrm{def}}}{2}\right]\Bigg] \end{aligned} \tag{20}$$

According to [37], due to the concavity of g, (20) can be expressed based on Jensen's inequality as:

$$\begin{aligned}\frac{1}{2}g\left[\sum_{n\in\mathcal{N}_s} E_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_b} P_{m,\mathrm{def}}\right] &\geq \frac{1}{2}g\left[\sum_{n\in\mathcal{N}_{s,1}} P_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_{b,1}} P_{m,\mathrm{def}}\right]\\ &\quad + \frac{1}{2}g\left[\sum_{n\in\mathcal{N}_{s,2}} P_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_{b,2}} P_{m,\mathrm{def}}\right] \end{aligned} \tag{21}$$

From (21), the value function decreases as the number of disjoint coalitions grows, thus g is superadditive. Hence, forming a grand coalition is always beneficial for all LEM members.

The second property is stability. This property is affected by the benefits that prosumers obtain by participating in the LEM. It is critical that the local price p_{in} produces a set of revenues that makes the coalition stable. Under the current pricing scheme, where $f_{out} > f_{in}$, the proposed LEM has a nonempty core when its price p_{in} lies between $f_{in} \leq p_{in} \leq f_{out}$. To prove that the proposed pricing does not violate the stability property the resulting LEM price is examined in three different cases, namely when generation is equal to demand when generation is greater than demand and finally when generation is lower than demand.

In the first case the total surplus energy $\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}$ is cleared within the LEM and the internal price is given by:

$$p_{in} = \frac{f_{in} + f_{out}}{2} \tag{22}$$

Evidently, the p_{in} is within the range $\{f_{in}, f_{out}\}$ and thus the LEM is stable.

When generation is higher than demand, LEM, after meeting its internal energy needs, offers its excess to the grid at a price f_{in}. The LEM price is determined by the proposed pricing algorithm which is always within the range $\{f_{in}, f_{out}\}$. The selling price $p_{s,in}$ per unit of energy in this case, however, depends on the total generation $\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{pv}}$, total demand $\sum_{n\in\mathcal{N}_b} P_{n,\mathrm{d}}$, and prices p_{in} and f_{in}. In particular, $p_{s,in}$ can be expressed as:

$$p_{\mathrm{s},in} = \frac{\sum_{m\in\mathcal{N}_b} P_{m,d} \times p_{in} + \left(\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_b} P_{m,d}\right) \times f_{in}}{\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}} \tag{23}$$

In (23), the numerator refers to the total sellers' revenue. In particular, the term $\sum_{m\in\mathcal{N}_b} P_{m,d} \times p_{in}$ is the remuneration from LEM trading, and $\left(\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} - \sum_{m\in\mathcal{N}_b} P_{m,d}\right) \times f_{in}$ is the revenue gained from selling the energy surplus to the grid.

In the last case, there is a deficit in the LEM. After covering a part of its needs with local production, LEM meets its deficit from the external grid. The internal price p_{in} is determined as before by the proposed pricing algorithm. The buying price will be affected by the total surplus $\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}$, total demand $\sum_{m\in\mathcal{N}_b} P_{m,d}$ and the prices p_{in} and f_{out}. So, the buying price is as follows:

$$p_{\mathrm{b},in} = \frac{\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} \times p_{in} + \left(\sum_{m\in\mathcal{N}_b} P_{m,d} - \sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}\right) \times f_{out}}{\sum_{m\in\mathcal{N}_b} P_{m,d}} \tag{24}$$

where, $\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} \times p_{in}$ is the cost to the buyers for buying energy from LEM, and $\left(\sum_{m\in\mathcal{N}_b} P_{m,d} - \sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}\right)$ is the cost of buying energy from the grid.

To prove the stability of LEM for the latter cases, we have to show that the resulting prices $p_{s,in}$ and $p_{b,in}$ respectively, satisfy $f_{in} \leq p_{s,in} \leq f_{out}$, and $f_{in} \leq p_{b,in} \leq f_{out}$. Let us assume that:

$$\frac{\sum_{m\in\mathcal{N}_b} P_{m,d}}{\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}} = z \tag{25}$$

where $z < 1$ for the second case (since $\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}} > \sum_{m\in\mathcal{N}_b} P_{m,d}$), and based on this assumption (23) can be re-written as:

$$\begin{aligned} p_{\mathrm{s},in} &= z \times p_{in} + (1 - z) \times f_{in}\\ &= (z \times p_{in} + f_{in}) - z \times f_{in} \end{aligned} \tag{26}$$

From (22), $p_{in} > f_{in}$. Hence, from (26), we confirm that $p_{s,in} \geq f_{in}$. To show that $p_{s,in} \leq f_{out}$, first we consider that $p_{s,in} > f_{out}$, and therefore, from (26) we conclude that:

$$z \times p_{in} + f_{in} - z \times f_{in} > f_{out} \tag{27}$$

Replacing p_{in} with (22), and rearranging the terms, the previous equation can be re-written as:

$$f_{in} - \frac{z}{2}f_{in} > f_{out} - \frac{k}{2}f_{out} \tag{28}$$

which is not possible as $f_{out} > f_{in}$ and $z < 1$. Hence, $p_{s,in} \leq f_{out}$. So, $p_{s,in}$ in (21) satisfies the condition $f_{in} \leq p_{s,in} \leq f_{out}$.

Similarly, by considering:

$$\frac{\sum_{m\in\mathcal{N}_b} P_{m,d}}{\sum_{n\in\mathcal{N}_s} P_{n,\mathrm{sur}}} = z' \tag{29}$$

and following the same process as described for $p_{s,in}$, it can be proven that $p_{b,in}$ also satisfies the condition $f_{in} \leq p_{b,in} \leq f_{out}$, and thus the LEM is stable.

ACKNOWLEDGMENT

Nikos Andriopoulos would like to thank and acknowledge the valuable technical discussions he had with Prof. D. Papadaskalopoulos elaborating on various crucial points of the paper.

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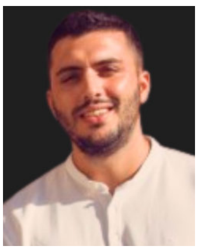

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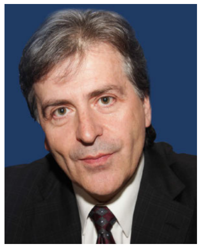

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