IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 25 May 2023, accepted 7 June 2023, date of publication 19 June 2023, date of current version 27 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3287323

RESEARCH ARTICLE

Prosumer Segmentation Strategies for Local Electricity Market Partaking by Monetary Reward

PRATIK MOCHI[1], KARTIK S. PANDYA[2], (Senior Member, IEEE), RICARDO FAIA[3], AND JOÃO SOARES[3], (Member, IEEE)

[1]Department of Electrical Engineering, CSPIT, Charotar University of Science and Technology, CHARUSAT Campus, Changa 388421, India
[2]Anand 388001, India
[3]LASI—Intelligent Systems Associate Laboratory, GECAD—Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, School of Engineering (ISEP), Polytechnic of Porto, 4200-072 Porto, Portugal

Corresponding author: Pratik Mochi (pratikmochi.ee@charusat.ac.in)

The work is supported by FEDER Funds through COMPETE program and by National Funds through FCT (Fundação para a Ciência e a Tecnologia) where we duly acknowledge the work facilities and equipment provided by GECAD (Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development) research center (UIDB/00760/2020 and UIDP/00760/2020) to the project team. Additionally, João Soares is supported by FCT grant CEECIND/00420/2022. The authors also acknowledge the support provided by the Thematic Network 723RT0150 "Red para la integración a gran escala de energías renovables en sistemas eléctricos (RIBIERSE-CYTED)" financed by the call for Thematic Networks of the CYTED (Ibero American Program of Science and Technology for Development) for 2022.

ABSTRACT In order to pave the way for a modernized electricity grid with distributed energy sources and storage, a direct energy transaction among peers in the local electricity market (LEM) is emerging. The design of the local energy market has frequently concentrated on its structures and technological problems, but little on how to increase the willingness of customers to participate by using a customer-centric approach. In this article, we provide consumer engagement strategies in LEM with a focus on maximizing financial return while exchanging energy with peers. The empirical investigation is subjected to two stages of optimization, the first of which has a goal of minimizing system costs and the second of which has a goal of maximizing consumer rewards. We present four methods for rewarding customers financially for taking part in LEM. Segmentation of customers is proposed to achieve the profit maximization goal. The system cost is calculated for two cases and cost saving is used to distribute among the market participants. The proposed LEM model results in 12.87% cost savings which is used to incentivize the active participants of the market. Thus policy makers can be recommended to integrate such market mechanisms to ensure a flexible and efficient market mechanism.

INDEX TERMS Peer-to-peer energy trading, local energy market, energy policy, energy economics, customer engagement, optimization strategy.

NOMENCLATURE

Indices

h	Households.
t	Periods.

Parameters

N_p	Number of prosumers.
N_c	Number of consumers.
N_h	Number of households.
N_t	Number of periods.
$\mathbb{P}_{h,t}^{buy\,max}$	Power purchase limit.
$\mathbb{P}_{h,t}^{sell\,max}$	Power sell limit.
$\mathbb{PE}_{peak}^{value}$	Peak power export in value segment.
$\mathbb{PE}_{peak}^{mass}$	Peak power export in mass segment.
$\mathbb{PE}_{peak}^{premium}$	Peak power export in premium segment.
$\mathbb{PE}_{avg}^{value}$	Average power export in value segment.
$\mathbb{PE}_{avg}^{mass}$	Average power export in mass segment.
$\mathbb{PE}_{avg}^{premium}$	Average power export in premium segment.
$\mathbb{P}_{h,ini}^{bat}$	Initial battery power for prosumers.
dt	Time period adjustment factor.
$\mathrm{FC}_{h,t}$	Fixed Cost.
$\mathbb{P}_{h,t}^{load}$	Load of each households.
$\mathbb{P}_{h,t}^{gen}$	Generation of each households.

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

$\eta_{h,ch}$	Charging efficiency of battery.
$\eta_{h,dch}$	Discharging efficiency of battery.
$\mathbb{P}_{h,t}^{bat\ max}$	Maximum battery power.
$\mathbb{P}_{h,t}^{bat\ ch\ lim}$	Battery charge limit.
$\mathbb{P}_{h,t}^{bat\ dch\ lim}$	Battery discharge limit.
$\Psi_{h,t}$	Lowest buy price of households.
$\theta_{h,t}^{lem}$	LEM price.
$\theta_{h,t}^{feed\ in}$	Feed in price to grid (sell price).
$\theta_{h,t}^{buy}$	Power buy price from grid.
$\mathrm{M}^{\mathrm{min}}$	Minimum reward.
$\mathrm{M}^{\mathrm{max}}$	Maximum reward.
CS	Cost saving.
$\Phi_{h,t}^{value}$	Reward limit for value segment.
$\Phi_{h,t}^{mass}$	Reward limit for mass segment.
$\Phi_{h,t}^{premium}$	Reward limit for premium segment.
Variables	
$\mathbb{P}_{h,t}^{buy}$	Power purchased from grid.
$\lambda_{h,t}^{\mathbb{P}\mathrm{B}}$	Binary Variable for Power purchase from grid.
$\mathbb{P}_{h,t}^{buy\ lem}$	Power buy from LEM.
$\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}$	Binary Variable for Power Buy from LEM.
$\mathbb{P}_{h,t}^{import}$	Power import by households.
$\mathbb{P}_{h,t}^{export}$	Power export by households.
$\mathbb{P}_{h,t}^{sell}$	Power sell to grid.
$\lambda_{h,t}^{\mathbb{P}\mathrm{S}}$	Binary Variable for Power sell to grid.
$\mathbb{P}_{h,t}^{selllem}$	Power sell to LEM.
$\lambda_{h,t}^{\mathbb{P}\mathrm{S\ lem}}$	Binary variable for Power sell to LEM.
$\mathbb{P}_{h,t}^{sell\ no\ pay}$	Power sell to Grid without pay.
$\mathrm{M}_{h,t}^{value}$	Monetary reward for value segment.
$\lambda_{\mathrm{M}_{h,t}^{value}}$	Binary variable of value segment reward.
$\mathrm{M}_{h,t}^{mass}$	Monetary reward for mass segment.
$\lambda_{\mathrm{M}_{h,t}^{mass}}$	Binary variable of mass segment reward.
$\mathrm{M}_{h,t}^{premium}$	Monetary reward for premium segment.
$\lambda_{\mathrm{M}_{h,t}^{premium}}$	Binary variable of premium segment reward.
$\mathbb{P}_{h,t}^{bat}$	Power in the battery.
$\mathbb{P}_{h,t}^{batch}$	Battery charging power.
$\lambda_{\mathbb{P}_{h,t}}^{batch}$	Binary variable of battery charging power.
$\mathbb{P}_{h,t}^{bat\mathrm{dch}}$	Battery dis-charging power.
$\lambda_{\mathbb{P}_{h,t}}^{bat\ \mathrm{dch}}$	Binary variable of battery dis-charging power.
$\mathrm{C}_{h,t}^{grid}$	Cost of power purchase from grid.
$\mathrm{C}_{h,t}^{lem}$	Cost of power buy in LEM.
$\mathrm{R}_{h,t}^{grid}$	Revenue from power sell to grid.
$\mathrm{R}_{h,t}^{lem}$	Revenue from power sell in LEM.

I. INTRODUCTION

Globally, upgrades to the power distribution systems are being made as part of the move toward resilience systems. Moving away from a centralized, traditional energy systems and toward more accessible, sustainable, and renewable alternatives is on trend [1]. Due to volatility of household energy usage [2], it is useful to initially take into account general principles of market design coupled with the inherent value of energy market stability in order to prepare for the upcoming task of rethinking procurement frameworks for distributed energy resources (DER) and storage. The goal of procurement strategies should be the development of efficient and profitable economic delivery systems for relevant market needs [3]. Such energy transition can be facilitated by local electricity market (LEM) by enabling the exchange of energy, which will increase the acceptable integration of DER [4]. Notwithstanding the development of the smart grid and the present appearance of LEM, considerable regulatory obstacles must be solved before the adoption of such energy market becomes relatively common [5]. LEM theoretically enables prosumers to directly share their assets among peers in electricity trading. By allowing customers the freedom to select how they exchange their electricity, these marketplaces are based on a customer centric approach. Future studies should encourage methods to integrate LEM with the current wholesale marketplaces so that customers may move between them whenever it is most practical [6].

An energy sharing among peers in LEM can bring overall cost saving for the system while not affecting the grid operation prominently [7]. An LEM model was suggested in a study in [8] to analyze the impact of consumer battery storage in various scenarios. Results indicated a 31% reduction in power costs over the scenario without LEM and battery storage. An investigation with peer to peer energy transaction in LEM is presented in [9] for four scenarios considering the battery operation. The results suggest that energy saving up to 13% is achieved when prosumers are engaged in internal energy transactions, while the energy saving up to 25% is gained when battery energy storage is considered. The study [10] examines how a LEM affects peak power capacity planning since industrial users are subject to a significant peak power for grid consumption. The findings indicate that it is possible to save between 6.8% and 11.0% on power expenditures by using energy trading among peers. Peak shaving is the main driver of the net cost reductions since it lowers peak power costs by up to 25%. The authors of [11] suggest using a blockchain trading system to model the power exchanges for 11 contemporary smart homes in LEM while taking into account a variety of market pricing. The power produced locally reduces the cost of the system by 16.5% and benefits the users. The research in [12] investigated the effectiveness of various optimization algorithms and evaluated the advantages that LEM may offer to market players through several case studies that took into account end customers with varied features. Results reveal that compared to a base case without LEM, the suggested market mechanism improves market participants' overall expenses by about 30–40%. With the objective of energy cost minimization in energy trading among peers, an investigation [13] has proposed prosumer reward gain up to 22%. A twofold auction-based LEM is suggested in [14] while taking into account several Cases in order to confirm how well the platform performs in showcasing the potential of local energy usage. The findings demonstrate that local energy production and use may be balanced even at minor engagement with the utility grid. Also authors claimed to obtain tremendous cost saving up to 45%.

These investigations can be considered as an excellent research and, the efforts of authors are admirable. However, the study should not end up to cost savings only when it is about empowering small prosumers and social welfare. The optimal use of this saved cost in terms of rebate program or financial incentive would encourage customers in energy transition and participating in new market platform like LEM. Giving consumers incentives for their support of the electricity network, is a solution that is socially optimal [15] for the well-being of the entire community and, can lead to changing individual behavior [16]. A large scale field experiment [17] concludes that the customers show higher willingness to participate in innovative market framework when it is subjected to incentive based policy.

One of the few research on financial incentive strategies for lowering peak home energy use is presented in the publication [18]. In order to address the problems of loss aversion and the size of the financial gain discovered while examining the obstacles to consumer involvement with time of use tariffs, the financial incentive schemes investigated were novel, authors claimed. In order to create the best possible plan for maximizing the benefits of demand response (DR), incentive based DR [19] method is investigated the article [20] using the demand-price elasticity approach. Results indicate that the planned DR strategy results in considerable savings for customers' power bills as well as for the distributed system operator (DSO). Considering a price optimization problem, a research in [21] show that a well-constructed time varying retail tariff offers adequate incentives for setting up and running a hybrid energy system. Future study should take into account incentive schemes for self-use of energy, according to the authors. The prices that best combines market flexibility and the accompanying costs to economic efficiency is likely to be a mix of time of use and flexible price incentives [22]. The research in [23] has focused on reduction of electricity bills of customers while using the locally generated power and sharing of the revenue has been suggested. While the investigation in [24] has revealed the effectiveness of game theoretic approach in revenue distribution among the peers involved in local energy transactions. In an interesting work [25], authors have proposed two stage game theoretic strategy in an incentive based demand response program with 21% of energy cost savings.

Thus, it becomes an emerging research question that, how the electricity market operators ensure the engagement of the customers by encouraging them? The authors [26] consider this as an important research question which should be addressed urgently with concern of net zero target by 2050. When key motivators of the relevant behavior are targeted, policy to promote sustainable energy behaviors will be more successful for which, multiple strategies may be used to promote sustainable behaviors of various customer

TABLE 1. Cases under study.

Case	Scenario & Strategy		Monetary Reward	Reward function
Case 01	Without LEM	-	×	-
Case 02	With LEM	Strategy 01	✓	Equal for all
		Strategy 02	✓	30% of revenue
		Strategy 03	✓	Max power export
		Strategy 04	✓	Average power export

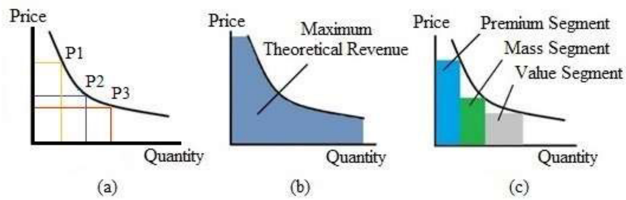

FIGURE 1. Demand curve and customer segments.

in a groups or segments [27], [28]. The methods of segmentation may be applied in a variety of ways within the operations of a power distributor for example, the creation of electricity tariffs in each group of customers, enabling savings to the individual consumer [29] and even for a cluster of microgrids [30]. A strong evidence is provided in the investigation [31] on the financial benefits to peers while sharing the energy locally in small groups. The amount of consumer engagement is not expected to significantly rise unless the flexible market operation & techniques are in line with the customer's preferences. Understanding customers' motives and values, such as self-reliance and monetary reward, would require a customer centric approach [32] in order to achieve their engagement [33]. The study in [34] proves that the fiscal incentives motivates households to invest in or upgrade to energy efficient assets. All of this raises the possibility that comprehensive strategies for customer engagement are required, such as an approach that empowers the customer and seeking more subtle and optimized solutions to make use of their resources. We declare this as our research goal statement.

In light of the foregoing, the novelty and contribution of this work are as follows:

- Two stage optimization approach is proposed in LEM for system cost minimization and monetary reward maximization for prosumers
- A novel tactic is suggested for prosumer segmentation based on optimized power export which is the result of first stage of optimization
- Four strategies are proposed for calculation of monetary reward of prosumers, of which, two strategies take account the prosumer segments for reward maximization

The structure of the paper is as follows. The section II describes proposed methodology with functional diagram of market operation, the mathematical modeling of the

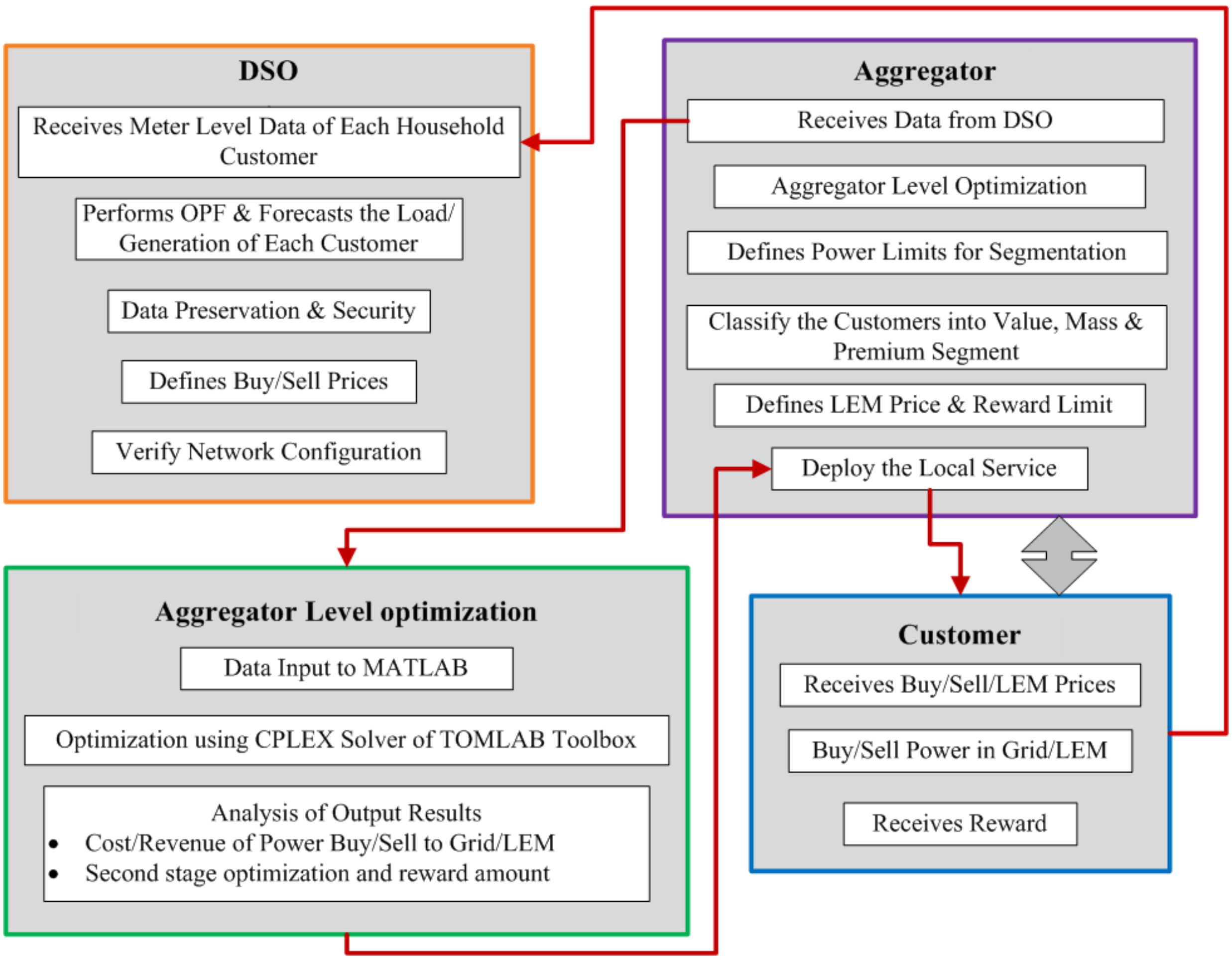

FIGURE 2. Market operation.

problem is formulated in section III, the details of empirical investigation and system specifications are described in section IV, section V is the result analysis and the conclusion are discussed in section VI.

II. PROPOSED METHODOLOGY

In this paper, we simulate an LEM network with 36 household customers in which 30 customers are prosumers i.e. having their own solar PV generation and battery energy storage and they are allowed to buy/sell electrical power, while 6 customers are normal consumers who can only import the power and cannot generate or sell the power. The power transaction cost of this network is calculated for two cases, one without LEM and other with LEM. In case 1, the power exchange is allowed with utility grid only where customer can purchase electricity at retail price and prosumers can sell power to utility grid at feed in price. In addition to utility grid power exchange as case 1, in case 2, customers are allowed to purchase power from their peers at LEM price or mid-market price, as per equation (19). Also in case 2, prosumers can sell power in grid at feed in price or they can sell power to peers at LEM price. Customers are growing more eager to have various rate alternatives available to them so they may reduce their electricity bills [35].

An LEM price being lesser than retail electricity purchase price and higher than feed in price, case 2 ensures the cost saving compared to system cost of case 1. We suggest that the cost savings can be optimally allocated among them in terms of financial compensation in order to engage and attract consumers and prosumers, without compromising the revenue stability of grid operators. The customers would be strongly encouraged to participate actively in the system by this financial incentive. As indicated in table 1, we suggest four distinct ways in our study to provide financial advantages to clients. In our study, the monetary reward is exclusively given to prosumers and not to non-prosumers. The only benefit for non-prosumers or consumers is the ability to purchase energy at LEM prices, which are lower than utility grid retail prices. On seeing the monetary benefit to prosumers, consumers would be interested in becoming prosumers and take part in LEM. Additionally, such economically advantageous energy affordability initiatives may be useful when making an investment in energy-efficient equipment [35].

For this test study, the first two strategies are applied at the end of first stage optimization to calculate the reward amount. In strategy 1, the cost saving is distributed equally among prosumers. While exporting power to grid/LEM, prosumers would generate a revenue, which is used to calculate reward in

TABLE 2. Segmentation and reward limit.

Segment	Strategy 3		Strategy 4	
	Peak power export (kW)	Reward limit (% of max reward)	Average power export (kW)	Reward limit (% of max reward)
Value	0 - 2	65%	0 – 0.2	60%
Mass	2 - 5	85%	0.2 – 0.4	80%
Premium	> 5	150%	> 0.4	125%

strategy 2. We consider a reward amount to be 30% of revenue in our study. In strategy 3 and strategy 4, we use second stage of optimization with objective of monetary reward maximization. Also we take a reference of the concept of demand curve as explained in [36]. The concept of demand curve can be seen in fig.1. below, followed by our hypothesis for strategy 3 and strategy 4.

The demand curve shows the relation between quantity of a product to be sold and the respective price. At higher price, less quantity would be sold. Similarly, at lower price, more quantity would be sold. As shown in fig.1. (a), there are three pricing points P1, P2 and P3 with their corresponding quantity to be sold in a market. Here P1 and P3 are highest and lowest prices which corresponds to lowest and highest quantity to be sold. For medium price point P2, the product sold would be medium. Thus, there could be three types of customers or there could be three ways the product could be sold. However, the revenue to seller would depend on the multiplication of price with quantity sold which is the area covered underneath the demand curve. If seller wants to make the maximum revenue, the price and quantity multiplication should cover maximum area as shown in fig.1. (b). However, this would be a maximum theoretical revenue and not a practical case. As suggested in [36], a seller has to find a way to sell a product at multiple price to multiple customers. This means that a product of different brands can have different prices and can have interest of different types of customers. There exists a customer who would buy cheaper product and seller can have highest business for the same. On contrary, there exists a customer who are willing to pay higher than an average product price but seller may have less number of such customers. Lastly, a large mass of customers is there who would buy an average brand of a product at average price. This suggest a segmentation of customers in multiple numbers to maximize the business and revenue. Utility companies must provide a variety of goods and services to clients in order to meet their wide range of tastes and take advantage of customer-side resources, even in the electricity industry [35]. Looking to this, fig.1. (c) shows three segments of customers as value segment, mass segment and premium segment, which covers all three types of customers.

Since the demand curve applies to the entire community, it is utilized to segment the customer base into three groups. In the opposite situation, where a single customer is offered an energy transaction by several aggregators, the supply curve might be helpful. In this scenario, a customer would utilize the supply curves of several aggregators and may segment aggregators for the most profitable power exchange. Another agent who may function as a liaison between clients and aggregators is invited by this activity. The supply curve-based multi aggregator LEM model may be the subject of future research. In order to maximize profits for sellers in a market. We adopted an economic interpretation of the demand curve in our work, for which the reference paper [37] was used to understand the concept.

In our strategy 3 and strategy 4, we hypothesize to segment the customers, not to sell any product, but to provide the monetary reward. The major motivation behind the suggestion of these strategies is the customer engagement in local level trading of power which can result in win-win situation for prosumers and utility company. We take the base of power exported by prosumers at the end of first stage of optimization and classify the customers into three segments. In strategy 3, the prosumers are classified into value segment, mass segment and premium segment based on peak value of power export. Similarly, for strategy 4, the prosumers are classified into value segment, mass segment and premium segment based on average value of power export. In both strategies, prosumers under value segment would get a lowest reward, mass segment prosumers would get medium reward and premium segment prosumers would get highest reward. This kind of strategy would also motivate the prosumers to upgrade themselves towards highest reward. Yet the sum of reward given to all prosumers collectively is restricted below the cost saving.

Customer segmentation boosts the efforts for customer engagement and successful local energy trading. In addition to enabling highly focused and more successful customer segmentation gives aggregators a deeper knowledge of the all consumers and their requirements. Aggregators may gain a deeper understanding of customers through segmentation. With this knowledge, they may adjust segmentation rules and reward policy for customer profit maximization. Additionally, market operators be able to design targeted advertising and marketing campaigns that appeal to and attract more consumers to become prosumers. The segmentation rule and reward limits are depicted in table 2 below.

The suggested work serves as a test case for evaluating the proposed LEM model utilizing an empirical research methodology. There is currently no established standard for segmentation-based consumer reward because no research has been done in this area at best of our knowledge. The segment rules and reward amount limits were determined empirically by the authors. The reward limits for the value segment, mass segment, and premium segment, respectively, are taken into consideration for this test research. The system cost savings and the maximum incentive are taken into account when determining these rates, such that the total reward received by all prosumers should be less than or nearly equal to the cost savings. We also agree that there might be another combination of segmentation rules and reward amount limits which may be give expected results for particular LEM network.

As seen in fig. 2, a market operation uses a step-by-step methodology. DSO, Aggregator, and participants are described along with their duties and responsibilities, as well as how they relate to one another. The optimization carried out in the current study is detailed at the aggregator level, and there is no market clearing since the aggregator controls the community and proposes the optimum transaction solution taking the objective function into account. The aggregator is the one to ensure the cost saving and based on that offer the power exchange and monetary rewards to prosumers.

III. PROBLEM FORMULATION

In the first stage of optimization, the overall system cost is calculated considering the power buy/sell in utility grid/LEM. The objective is to minimize the system cost as per equation 1.

$$\text{Minimize}\left(\sum_{t=1}^{N_t}\sum_{h=1}^{N_h}\left(\mathrm{C}_{h,t}^{grid}-\mathrm{R}_{h,t}^{grid}\right)+(\mathrm{C}_{h,t}^{lem}-\mathrm{R}_{h,t}^{lem})+\mathrm{FC}_{\mathrm{h,t}}\right) \tag{1}$$

where, the time period is t, number of household customers is h, the cost of power purchase from grid and LEM are marked as $\mathrm{C}_{h,t}^{grid}$ and $\mathrm{C}_{h,t}^{lem}$ respectively and the revenue for power sell in grid and LEM are denoted as $\mathrm{R}_{h,t}^{grid}$ and $\mathrm{R}_{h,t}^{lem}$ respectively. The fixed cost for each customer is $\mathrm{FC}_{\mathrm{h,t}}$.

While making power transaction with grid, the cost and revenue are calculated as per equation (2) and (3) respectively, followed by the constraints (4) – (8).

$$\mathrm{C}_{h,t}^{grid}=\left(\mathbb{P}_{h,t}^{buy}\times\theta_{h,t}^{buy}\right)\times dt\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{2}$$

$$\mathrm{R}_{h,t}^{grid}=(\mathbb{P}_{h,t}^{sell}\times\theta_{h,t}^{feed\ in})\times dt\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{3}$$

where, $\mathbb{P}_{h,t}^{buy}$ and $\theta_{h,t}^{buy}$ are the amount of power purchase from grid and its price respectively. $\mathbb{P}_{h,t}^{sell}$ and $\theta_{h,t}^{feed\ in}$ are the amount of power sell to grid and feed in price respectively and dt is time period adjustment factor.

$$0\le\mathbb{P}_{h,t}^{buy}\le\mathbb{P}_{h,t}^{buy\ max}\times\lambda_{h,t}^{\mathbb{P}\mathrm{B}}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{4}$$

$$0\le\mathbb{P}_{h,t}^{sell}\le\mathbb{P}_{h,t}^{sell\ max}\times\lambda_{h,t}^{\mathbb{P}\mathrm{S}}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{5}$$

where, the constraints (4)-(5) bounds the power transaction amount with the grid where the maximum limit of power buy and power sell are $\mathbb{P}_{h,t}^{buy\ max}$ and $\mathbb{P}_{h,t}^{sell\ max}$ respectively. $\lambda_{h,t}^{\mathbb{P}\mathrm{B}}$ and $\lambda_{h,t}^{\mathbb{P}\mathrm{S}}$ respectively are the binary variables associated to power buy and sell to grid.

$$0\le\lambda_{h,t}^{\mathbb{P}\mathrm{B}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{6}$$

$$0\le\lambda_{h,t}^{\mathbb{P}\mathrm{S}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{7}$$

$$\lambda_{h,t}^{\mathbb{P}\mathrm{B}}+\lambda_{h,t}^{\mathbb{P}\mathrm{S}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{8}$$

where, the upper and lower values of binary variables are stated in (6) and (7). The limitation (8) confines the simultaneous operation of prosumer for buying or selling power with grid in time period t.

While making power transaction with grid, the cost and revenue are calculated as per equation (9) and (10) respectively, followed by the constraints (11) – (15).

$$\mathrm{C}_{h,t}^{lem}=(\mathbb{P}_{h,t}^{buy\ lem}\times\theta_{h,t}^{lem})\times dt\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{9}$$

$$\mathrm{R}_{h,t}^{lem}=(\mathbb{P}_{h,t}^{sell\ lem}\times\theta_{h,t}^{lem})\times dt\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{10}$$

where, the power purchase and power sell in LEM are $\mathbb{P}_{h,t}^{buy\ lem}$ and $\mathbb{P}_{h,t}^{sell\ lem}$ respectively and $\theta_{h,t}^{lem}$ is LEM price for all prosumers.

$$0\le\mathbb{P}_{h,t}^{buy\ lem}\le\mathbb{P}_{h,t}^{buy\ max}\times\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{11}$$

$$0\le\mathbb{P}_{h,t}^{sell\ lem}\le\mathbb{P}_{h,t}^{sell\ max}\times\lambda_{h,t}^{\mathbb{P}\mathrm{Slem}}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{12}$$

where, the constraints (11) – (12) bounds the power transaction amount with LEM where the maximum limit of power buy and power sell are same as for grid power transaction. $\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}$ and $\lambda_{h,t}^{\mathbb{P}\mathrm{S\ lem}}$ respectively are the binary variables associated to power buy and sell in LEM.

$$0\le\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{13}$$

$$0\le\lambda_{h,t}^{\mathbb{P}\mathrm{S\ lem}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{14}$$

$$\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}+\lambda_{h,t}^{\mathbb{P}\mathrm{S\ lem}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{15}$$

where, the bounds of binary variables are stated in (13) and (14). The constraint (15) limits a prosumers' action in LEM, i.e., a one can either purchase or sell power in LEM in the time period t.

$$\lambda_{h,t}^{\mathbb{P}\mathrm{B}}+\lambda_{h,t}^{\mathbb{P}\mathrm{S\ lem}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{16}$$

$$\lambda_{h,t}^{\mathbb{P}\mathrm{B\ lem}}+\lambda_{h,t}^{\mathbb{P}\mathrm{S}}\le 1\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{17}$$

$$\sum_{h=1}^{N_h}\mathbb{P}_{h,t}^{buy\ lem}=\sum_{h=1}^{N_h}\mathbb{P}_{h,t}^{sell\ lem}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{18}$$

According to the constraint equation (16), a prosumer cannot buy the power from grid and sell to LEM at a same time period t. Similarly, according to constraint (17), a prosumer cannot buy power from LEM and sell it to grid at same time period t. The equation (18) represents that the total buy power and total sell power in LEM is same. Equations (19) and (20) shows the calculation of LEM price which is the mean value of minimum buy price of prosumers and feed in price [38].

$$\theta_{h,t}^{lem}=\frac{\Psi_{h,t}+\theta_{h,t}^{feed\ in}}{2}\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{19}$$

$$\Psi_{h,t}=\min(\theta_{h,t}^{buy})\ \ \forall h\in \mathrm{N}_h,\forall t\in \mathrm{N}_t \tag{20}$$

where $\Psi_{h,t}$ signifies the minimum buy price of each prosumer.

The equations (21) and (22) are the battery energy balance equation for prosumers.

$$\mathbb{P}^{bat}_{h,1} = \mathbb{P}^{bat}_{h,ini} + \mathbb{P}^{batch}_{h,1} \times \eta_{h,ch} - \frac{\mathbb{P}^{batdch}_{h,1}}{\eta_{h,dch}} \quad \forall h \in \mathrm{N}_h \tag{21}$$

$$\mathbb{P}^{bat}_{h,t} = \mathbb{P}^{bat}_{h,t-1} + \mathbb{P}^{batch}_{h,t} \times \eta_{h,ch} - \frac{\mathbb{P}^{batdch}_{h,t}}{\eta_{h,dch}} \quad \forall h \in \mathrm{N}_h, \forall t \in [2, N_t] \tag{22}$$

where $\mathbb{P}^{bat}_{h,t}$ represents the battery power status, $\mathbb{P}^{bat}_{h,ini}$ is the initial battery power, $\eta_{h,ch}$ and $\eta_{h,dch}$ represents the charging and discharging efficiencies of battery respectively. The equation (21) is related at first charging time period when t = 1 while equation (22) is applied for other charging time periods. The energy balance equations follow the constraints (23) – (25).

$$0 \leq \mathbb{P}^{bat}_{h,t} \leq \mathbb{P}^{bat\,max}_{h,t} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{23}$$

$$0 \leq \mathbb{P}^{batch}_{h,t} \leq \mathbb{P}^{batch\,lim}_{h,t} \times \lambda^{batch}_{\mathbb{P}_{h,t}} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{24}$$

$$\mathbb{P}^{batd\,ch}_{h,t} \leq \mathbb{P}^{batd\,ch\,lim}_{h,t} \times \lambda^{batd,ch}_{\mathbb{P}_{h,t}} \quad \forall h \in N_h, \forall t \in \mathrm{N}_t \tag{25}$$

where, the equations (23) relates the battery capacity $\mathbb{P}^{bat}_{h,t}$ and maximum power level in battery $\mathbb{P}^{bat\,max}_{h,t}$. The constraints (24) – (25) limits the charging and discharging of battery within bounds. Where the charging and discharging power are denoted as $\mathbb{P}^{batch}_{h,t}$ and $\mathbb{P}^{bat\,dch}_{h,t}$ respectively and, their respective binary variables are $\lambda^{batch}_{\mathbb{P}_{h,t}}$ $\lambda^{batdch}_{\mathbb{P}_{h,t}}$. The limits of charging and discharging are expressed as $\mathbb{P}^{batch\,lim}_{h,t}$ and $\mathbb{P}^{bat\,dch\,lim}_{h,t}$ respectively.

$$0 \leq \lambda^{batch}_{\mathbb{P}_{h,t}} \leq 1 \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{26}$$

$$0 \leq \lambda^{bat\,dch}_{\mathbb{P}_{h,t}} \leq 1 \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{27}$$

$$\lambda^{batch}_{\mathbb{P}_{h,t}} + \lambda^{bat\,dch}_{\mathbb{P}_{h,t}} = 1 \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{28}$$

where, the binary variables $\lambda^{batch}_{\mathbb{P}_{h,t}}$ and $\lambda^{bat\,dch}_{\mathbb{P}_{h,t}}$ are restricted by (26) and (27). The limitation (28) confines the battery operation at time t i.e. battery can be either charged or discharged at same time.

A comprehensive set of power balancing equations and limitations are given in (29) – (32) to make the problem more realistic. The power balancing equation, which is applied to each prosumer in each time period, is represented by equation (29).

$$\mathbb{P}^{import}_{h,t} + \mathbb{P}^{bat\,dch}_{h,t} + \mathbb{P}^{gen}_{h,t} = \mathbb{P}^{load}_{h,t} + \mathbb{P}^{export}_{\mathrm{h,t}} + \mathbb{P}^{batch}_{h,t} \quad \forall z \in \mathrm{N}_z, \forall t \in \mathrm{N}_t \tag{29}$$

where, the power imported by prosumers is denoted as $\mathbb{P}^{import}_{h,t}$, $\mathbb{P}^{batdch}_{h,t}$ represents the battery discharge power, $\mathbb{P}^{gen}_{h,t}$ is the power generation by prosumers, $\mathbb{P}^{load}_{h,t}$ is load power, $\mathbb{P}^{export}_{h,t}$ is the exported power, $\mathbb{P}^{batch}_{h,t}$ is the charging power of the battery. The equation (30) estimates the imported power which is summation of power buy from grid and LEM by prosumers at time t.

$$\mathbb{P}^{import}_{h,t} = \mathbb{P}^{buy}_{h,t} + \mathbb{P}^{buy\,lem}_{h,t} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{30}$$

The power export is calculated as per equation (31), where $\mathbb{P}^{sell\,no\,pay}_{h,t}$ represents the power sell without payment i.e. the excess power exported past contracted power. The bounds for power sell without pay (32) limits the power export under maximum contracted power.

$$\mathbb{P}^{export}_{h,t} = \mathbb{P}^{sell}_{h,t} + \mathbb{P}^{sell\,lem}_{h,t} + \mathbb{P}^{sell\,no\,pay}_{h,t} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{31}$$

$$0 \leq \mathbb{P}^{sell\,no\,pay}_{h,t} \leq \mathbb{P}\mathrm{S}^{max}_{h,t} \times \lambda^{\mathbb{P}\mathrm{S}}_{h,t} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{32}$$

The second stage of optimization is also formulated as mixed integer linear programming method and is clarified below.

$$\text{Maximize}\left(\sum_{t=1}^{N_t}\sum_{h=1}^{N_h}\left(\mathrm{M}^{value}_{h,t} + \mathrm{M}^{mass}_{h,t} + \mathrm{M}^{premium}_{h,t}\right)\right) \tag{33}$$

The equation (33) signifies the objective function of second stage optimization where, $\mathrm{M}^{value}_{h,t}$, $\mathrm{M}^{mass}_{h,t}$ and $\mathrm{M}^{premium}_{h,t}$ are the monetary reward for prosumers under value segment, mass segment and premium segment respectively. The objective is to maximize the monetary reward to prosumers.

$$0 \leq \mathbb{P}\mathrm{E}^{value}_{peak} < 2 \tag{34}$$

$$2 \leq \mathbb{P}\mathrm{E}^{mass}_{peak} < 5 \tag{35}$$

$$\mathbb{P}\mathrm{E}^{premium}_{peak} \geq 5 \tag{36}$$

$$0 \leq \mathbb{P}\mathrm{E}^{value}_{avg} < 0.2 \tag{37}$$

$$0.2 \leq \mathbb{P}\mathrm{E}^{mass}_{avg} < 0.4 \tag{38}$$

$$\mathbb{P}\mathrm{E}^{premium}_{avg} \geq \mathbf{0.4} \tag{39}$$

The upper and lower limit of the peak power export in three prosumers segments are stated in the equations (34), (35) and (36) for strategy 3. While, upper and lower limit of average power export for prosumer segments are stated in equations (37), (38) and (39) for strategy 4. Here the peak power export value of prosumers under value segment, mass segment and premium segment are $\mathbb{P}\mathrm{E}^{value}_{peak}$, $\mathbb{P}\mathrm{E}^{mass}_{peak}$ and $\mathbb{P}\mathrm{E}^{premium}_{peak}$ respectively. And the average power export value of prosumers under value segment, mass segment and premium segment are $\mathbb{P}\mathrm{E}^{value}_{avg}$, $\mathbb{P}\mathrm{E}^{mass}_{avg}$ and $\mathbb{P}\mathrm{E}^{premium}_{avg}$ respectively.The peak power export values and average power export values are not a variable and they are extracted from optimized power value $\mathbb{P}^{export}_{h,t}$ which was resulted from first stage of optimization, as mentioned in table 2 and equations (34 – 39).

$$\mathrm{M}^{\min} = 0 \quad \forall h \in \mathrm{N}_h, \forall \mathbf{t} \in \mathrm{N}_\mathbf{t} \tag{40}$$

$$\mathrm{M}^{\max} = \frac{CS}{\mathrm{N}_p} \quad \forall h \in \mathrm{N}_h, \forall t \in \mathrm{N}_t \tag{41}$$

The minimum reward $\mathrm{M}^{\min}$ and maximum reward $\mathrm{M}^{\max}$ are calculated by equations (40) and (41) where CS is the cost saving which difference between system cost without LEM and system cost with LEM.

$$0 < M_{h,t}^{value} \leq \Phi_{h,t}^{value} \times M^{\max} \times \lambda_{M_{h,t}^{value}} \quad \forall h \in N_h, \forall t \in N_t \tag{42}$$

$$0 < M_{h,t}^{mass} \leq \Phi_{h,t}^{mass} \times M^{max} \times \lambda_{M_{h,t}^{mass}} \quad \forall h \in N_h, \forall t \in N_t \tag{43}$$

$$0 < M_{h,t}^{premium} \leq \Phi_{h,t}^{premium} \times M^{max} \times \lambda_{M_{h,t}^{premium}} \quad \forall h \in N_h, \forall t \in N_t \tag{44}$$

The equations (42), (43) and (44) are limits of monetary reward of each segment in relation to maximum reward amount. The parameters $\Phi_{h,t}^{value}$, $\Phi_{h,t}^{mass}$ and $\Phi_{h,t}^{premium}$ represents the reward limit for respective segments. For value segment, the reward limit is up to 65% of maximum reward. For mass and premium segments, the respective reward amount is limited up to 85% and 150% of maximum reward in strategy 3. For strategy 4, the equations (42) – (44) remains the same with reward amount limited to 60%, 80% and 125% of maximum reward in value segment, mass segment and premium segment respectively. Here, $\lambda_{M_{h,t}^{value}}$, $\lambda_{M_{h,t}^{mass}}$ and $\lambda_{M_{h,t}^{premium}}$ are the binary variables for respective segmented prosumers, and their values are limited by constraints (45) – (47). The 0 value of binary variable signifies that prosumers are not under particular segment and will not get reward while, while when it is 1, the prosumer will receive reward. The binary variables are further constrained by equations (48) – (49).

$$0 \leq \lambda_{M_{h,t}^{value}} \leq 1 \quad \forall h \in N_h, \forall t \in N_t \tag{45}$$

$$0 \leq \lambda_{M_{h,t}^{mass}} \leq 1 \quad \forall h \in N_h, \forall t \in N_t \tag{46}$$

$$0 \leq \lambda_{M_{h,t}^{premium}} \leq 1 \quad \forall h \in N_h, \forall t \in N_t \tag{47}$$

$$\lambda_{M_{h,t}^{value}} + \lambda_{M_{h,t}^{mass}} + \lambda_{M_{h,t}^{premium}} = 0 \quad \forall h \in N_h, \forall t \in N_t \tag{48}$$

$$M_{h,t}^{value} < M_{h,t}^{mass} < M_{h,t}^{premium} \quad \forall h \in N_h, \forall t \in N_t \tag{49}$$

The constraints (48) signifies that the prosumer can receive reward from one segment only while constraint (49) differentiates the level of reward amount.

$$M_{h,t}^{mass} + M_{h,t}^{value} + M_{h,t}^{premium} \leq CS \quad \forall h \in N_h, \forall t \in N_t \tag{50}$$

The equation (50) restricts the total amount of reward to be equal or below than the cost saving. Just like other empirical investigations, our work is also not free from assumptions. For our proposed work, it is assumed that the infrastructure needed for information flow and power transaction is available and network constraints are within limit. Additionally, considering higher variation in battery power, load and generation, the more number of segmentation would work better in the suggested strategies. This will cover large range of power variations and still falling within a segment.

IV. CASE STUDY DETAILS

In order to support the recommended optimization model, the case study details are supplied in this section. The case study examines two scenarios, the first of which excludes LEM power transactions for the system and the second of which includes them while allowing prosumers to take part. Prosumers are not segmented in case one and are not given reward, but they are segmented in case two and are rewarded in case two, there are four strategies proposed to calculate the reward amount of each prosumer. The various cases and strategies used to evaluate the model is presented in Table 2. There are a total of 36 electrical power end users in the system under investigation, of whom 30 are prosumers and 6 are consumers. A part of the network, that is created and utilized for study, is the system data of research [39], [40], [41], [42]. The source makes the data available for public download and use [43].

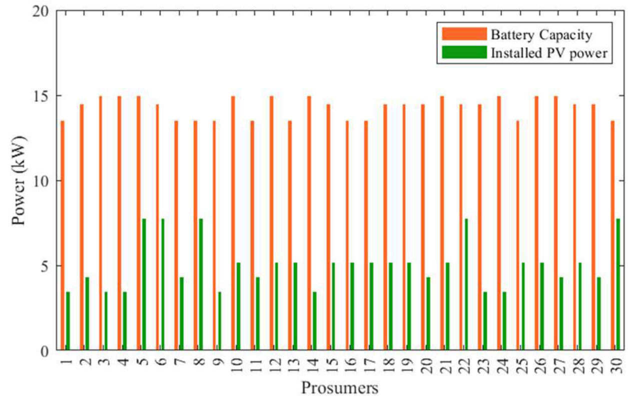

FIGURE 3. Battery capacity & installed PV power of prosumers.

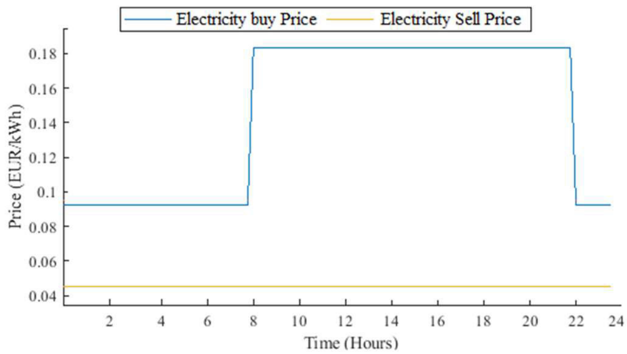

FIGURE 4. Electricity buy/sell price.

The installed PV energy source and battery storage unit's power capacity are shown in Fig. 3. Prosumers use one of three different battery storage unit types ranging from 13.5kWh to 15kWh. A total of 430 kWh can be stored by all prosumers. The prosumers' installed PV capacity ranges from 3.5 kW peak at the lowest end to 7.76 kW peak at the highest. A combined peak PV output of 150.9 kW has been installed by prosumers. Prosumers, who have decided to export electricity to the grid, pay a fixed price depending on the contractual power with the retailer. Each prosumer's fixed cost value ranges from 0.3251 EUR per day to 0.6209 EUR

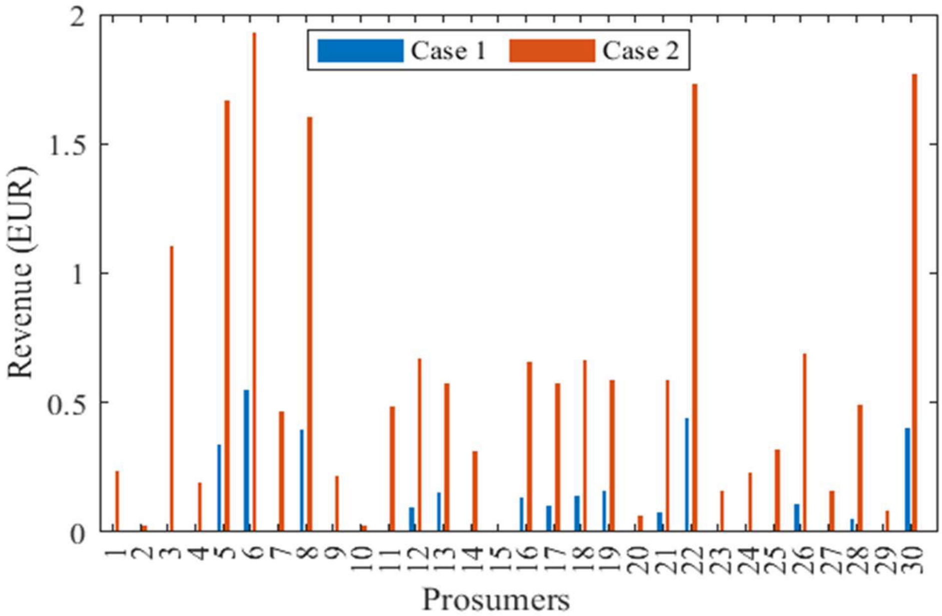

FIGURE 5. Prosumer revenue.

TABLE 3. System specifications.

Parameter	Symbol	Value Min	Value Max	Unit
Number of Consumers	N_c	6		-
Number of Prosumers	N_p	30		-
Number of households	N_h	36		-
Power buy limit of players	$\mathbb{P}_{h,t}^{buy\,max}$	4.6	10.35	kW
Power sell limit of players	$\mathbb{P}_{h,t}^{sell\,max}$	2.3	5.175	kW
Fixed Cost	$FC_{h,t}$	0.3251	0.6209	EUR/day
Minimum buy price of prosumers	$\Psi_{h,t}$	0.0922	0.0924	EUR/kWh
Power buy price from grid	$\Theta_{h,t}^{buy}$	0.0922	0.1836	EUR/kWh
Feed in price (sell price)	$\Theta_{h,t}^{feed\,in}$	0.045	0.095	EUR/kWh
LEM price	$\Theta_{h,t}^{lem}$	0.0686	0.0937	EUR/kWh
Load of each player	$\mathbb{P}_{h,t}^{load}$	0	7.07	kW
Generation of each player	$\mathbb{P}_{h,t}^{gen}$	0	7.75	kW
Initial power of battery of player h	$\mathbb{P}_{h,ini}^{bat}$	0		kW
Battery capacity of players	$\mathbb{P}_{h,t}^{bat\,max}$	13.5	15	kWh
Battery charge limit for players	$\mathbb{P}_{h,t}^{bat\,ch\,lim}$	2.867	5.0	kW
Battery discharge limit for players	$\mathbb{P}_{h,t}^{bat\,dch\,lim}$	2.867	5.0	kW
Charging efficiency of battery	$\eta_{h,ch}$	90%		-
Discharging efficiency of battery	$\eta_{h,dch}$	90%		-

per day. According to the power contract with the retailer, they are subject to buy/sell limitations. The power buy range is 4.6 – 10.35kW while power sell range is 2.3 – 5.175kW. The rest of the system specifications are listed in Table 3.

Fig.4. shows the electricity purchase price from utility grid and power sell price i.e. feed in price.

V. RESULT ANALYSIS

MATLAB 2021b was used to run the simulation. This optimization issue involving mixed integer linear programming was solved using the CPLEX solver of the TOMLAB toolbox. System cost findings are obtained for two cases with the goal of lowering system costs and a cost saving comparing both cases. Results are based on 2021 Portuguese feed-in tariffs of 0.045 EUR per kWh [40]. Case 1 forbids all players from taking part in LEM, but Case 2 allows all players to take part. In both situations, case 1 does not offer reward whereas case 2 does. Table 4 below displays the first stage's optimization outcomes.

In the case 1, the optimized system cost is 103.42 EUR which reduces to 90.10 EUR in case 2. Thus when LEM power transaction is allowed, a cost saving of 13.32 EUR i.e. 12.87% is achieved. The revenue generated by prosumers while selling the power in both cases is shown in Fig.5.

The cumulative revenue gained by prosumers, in case 1, is 3.19 EUR where lowest revenue received by prosumer is 0 and highest revenue received by prosumer is 0.55 EUR. For case 2, i.e. with LEM, the cumulative revenue generated by prosumers is 19.23 EUR where the range of revenue is 0 – 1.93 EUR. Here, there are two things worth to note. First, some of the prosumers are earning very low or almost zero revenue because, according to objective of system cost minimization, they are exporting very less power to grid/LEM or best way is to use generated power by themselves only. Secondly, the revenue generated in case 2 is much higher than that of case 1 because in case with LEM power transaction,

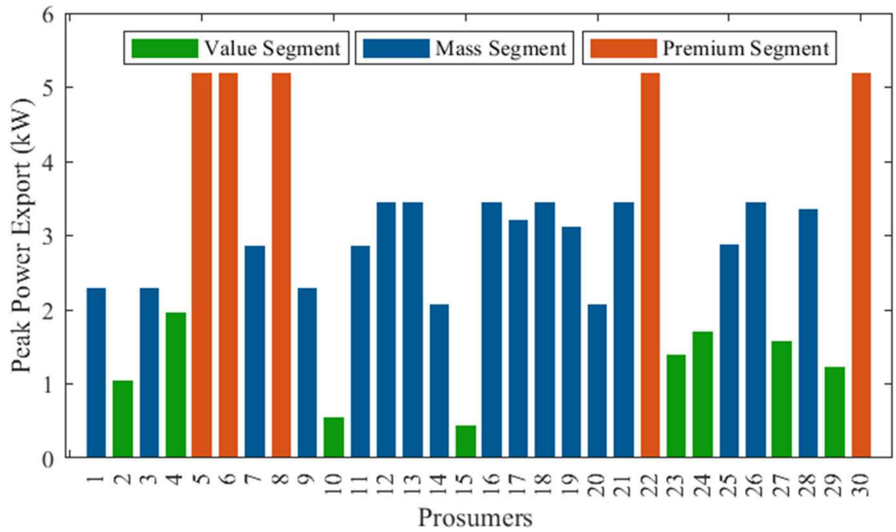

FIGURE 6. Prosumer segments by peak power export.

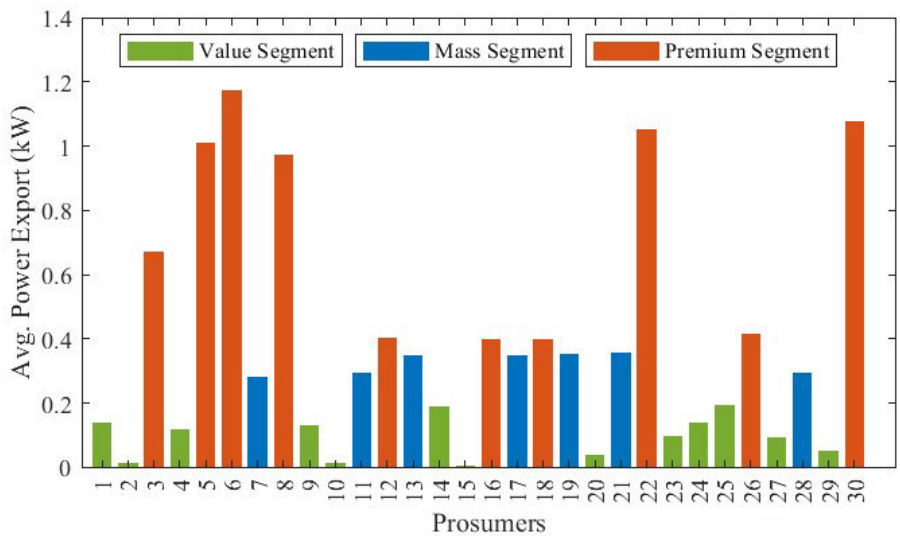

FIGURE 7. Prosumer segments by average power export.

the prosumers are allowed to sell power at LEM price which is higher than sell price to utility grid at retail feed in price and at a same time, prosumers are allowed to buy power at LEM price which is lesser than the power buy price from retailer. This is the same reason that system cost is lesser in case 2 compared to case 1.

A cost savings of 13.32 EUR is realized by comparing the system costs of cases 1 and 2. To disperse this cost savings across prosumers as monetary reward, we propose four strategies. The circular economy idea would incentivize current prosumers to invest in and expand their renewable and storage capacity, which would increase their willingness to engage in LEM. in all strategies, the common constraint is that the total amount of monetary reward is less or equal to cost saving. In strategy 1, the cost saving amount is equally distributed among all prosumers. While in strategy 2, the prosumers get 30% amount of the revenue they have generated by selling power to grid/LEM in case 2.

TABLE 4. Case study results.

Case	System Cost (EUR)
Without LEM	103.42
With LEM	90.10
Cost Saving = 13.32 EUR	

The strategy 3 and strategy 4 are based on the second stage of optimization where we make use of optimized value of power export which is the result of first stage of optimization.

The peak power export by each prosumer in time period t and average power export by each prosumer in time period t are shown in Fig.6. and Fig.7. respectively. Moreover, the

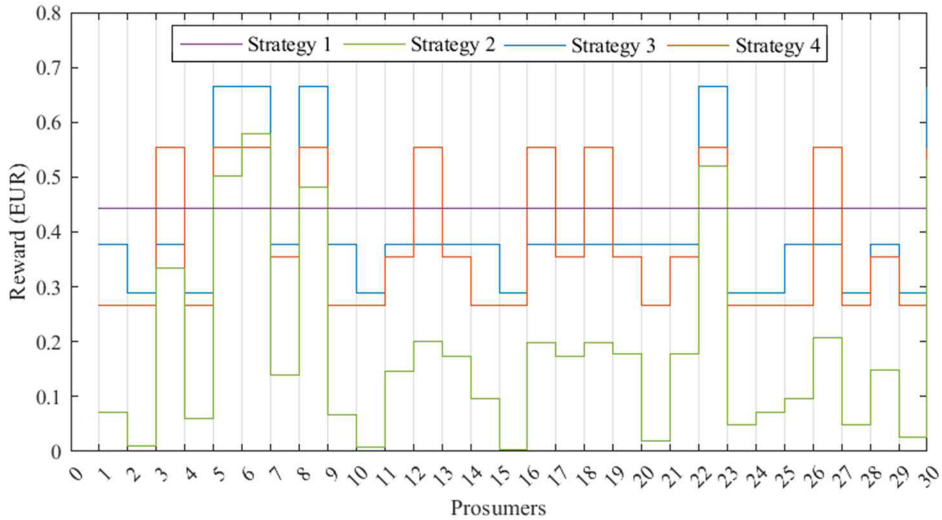

FIGURE 8. Prosumer reward.

TABLE 5. Reward statistics.

Strategy	Min Reward (EUR)	Max Reward (EUR)	Average Reward (EUR)	Total Reward (EUR)
Strategy 1	0.444	0.444	0.444	13.32
Strategy 2	0.003	0.580	0.184	5.51
Strategy 3	0.288	0.666	0.401	12.05
Strategy 4	0.266	0.555	0.383	11.49

prosumers are segmented based on their peak power export and average power export. Analyzing the Fig.6. for strategy 3, there are 8 prosumers in value segment, 17 prosumers in mass segment and 5 prosumers in premium segment. All prosumers in premium segment has reached the maximum power export limit of 5.175kW which is the contracted power limit with utility grid. Similarly, for strategy 4, the Fig.7. shows there are 13 prosumers in value segment, 7 prosumers in mass segment and 10 prosumers in premium segment. The reward amount to each prosumer in all four strategies is compared in Fig 8.

Here, it is seen that all prosumers, according to their segment, reaches to highest possible monetary reward amount. Also it seems that many prosumers receive the same reward who are in same segment, keeping the sum of reward by all prosumers below the cost saving. We have also tried to add the constraint for prosumers' reward not to be the same amount within same segment, which resulted in different reward amount in same segmented prosumers but keeping total sum of reward much lesser than cost saving. As the aim of study is to maximize the reward and to make full utilization of cost saving, the result with different reward amount were not considered as an optimum result. For suggested segmentation rules and reward limit, highest level of exploiting the cost saving is considered as final results.

In strategy 4, the prosumers, according to their segments, reaches to highest possible reward. The table 5 shows the comparison of reward amount in all four strategies.

As per the comparison of reward amount gained by all prosumers in four strategies is shown in Fig.8. here, one can compare the reward amount of each prosumer in all strategies. It is observed that each prosumer gets different amount of reward in all four strategies. Furthermore, the minimum reward, maximum reward, average reward and total reward amount are compared in table 5.

VI. CONCLUSION

Prosumer segmentation for profit maximization and providing the best reward to prosumers are the ideas underlying the suggested LEM model. In the first stage of optimization, the work's goal is to lower system costs, and in the second stage of optimization, it's to maximize financial rewards for participants. A system comprising 30 prosumers using solar PV systems with battery storage and 6 consumers was the subject of an empirical investigation. Using the CPLEX solver from the TOMLAB toolbox, the mixed integer linear programming problem is resolved in MATLAB. The findings of the first stage of optimization were utilized to determine each prosumer's optimum power export. The first strategy suggests giving all prosumers an equal financial compensation, whereas the second strategy computed rewards based on how much money prosumers made by selling power to the grid or LEM. In the third and fourth strategies, consumers are divided into value, mass, and premium segments based on peak and average power exports. Prosumers' monetary benefits are established based on their market sectors in addition to their revenue from power export to the grid or LEM. Two scenarios, one without LEM operation and the other with LEM power transactions, are used to calculate the system expenses. The LEM operation results in a 13.32 EUR cost saving. It is assumed that the necessary infrastructure for information and power transfer is in place.

The findings indicate that the total reward in all suggested techniques is either lower than or equal to the cost savings. The customer profit maximization can be accomplished by implementing the suggested strategies. The suggested approach can be used by LEM system operators to increase energy customers' desire to engage in LEM. With the help of this new paradigm, both consumers and power distributors operating in LEM may overcome significant obstacles. The dependence on grid power import could be decreased with more prosumers in LEM. Future research may examine the multiple aggregator system, novel segmentation criteria, novel incentive approach, and limits taking cost-saving measures into account.

REFERENCES

[1] V. Mehr, S. Kahrobaee, and M. Avendano, "Harnessing the full potential of clean energy: The role of southern California's utility distributed energy resource pilots," *IEEE Power Energy Mag.*, vol. 19, no. 4, pp. 28–40, Jul. 2021, doi: 10.1109/MPE.2021.3072816.

[2] M. Simonsen, C. Aall, H. Jakob Walnum, and B. K. Sovacool, "Effective policies for reducing household energy use: Insights from Norway," *Appl. Energy*, vol. 318, Jul. 2022, Art. no. 119201, doi: 10.1016/j.apenergy.2022.119201.

[3] N. Lal, T. Price, L. Kwek, C. Wilson, F. Billimoria, T. Morrow, M. Garbutt, and D. Sharafi, "Essential system services reform: Australian market design for renewable-dominated grids," *IEEE Power Energy Mag.*, vol. 19, no. 5, pp. 29–45, Sep. 2021, doi: 10.1109/MPE.2021.3088959.

[4] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path toward fully transactive energy systems," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4081–4088, Sep. 2019, doi: 10.1109/TPWRS.2018.2833959.

[5] F. Lezama, T. Pinto, Z. Vale, G. Santos, and S. Widergren, "From the smart grid to the local electricity market," in *Local Electricity Markets*. New York, NY, USA: Academic Press, 2021, ch. 4, pp. 63–76, doi: 10.1016/B978-0-12-820074-2.00023-X.

[6] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 104, pp. 367–378, Apr. 2019, doi: 10.1016/j.rser.2019.01.036.

[7] M. F. Dynge, P. Crespo del Granado, N. Hashemipour, and M. Korpås, "Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations," *Appl. Energy*, vol. 301, Nov. 2021, Art. no. 117404, doi: 10.1016/j.apenergy.2021.117404.

[8] A. Lüth, J. M. Zepter, P. Crespo del Granado, and R. Egging, "Local electricity market designs for peer-to-peer trading: The role of battery flexibility," *Appl. Energy*, vol. 229, pp. 1233–1243, Nov. 2018, doi: 10.1016/j.apenergy.2018.08.004.

[9] R. Faia, J. Soares, T. Pinto, F. Lezama, Z. Vale, and J. M. Corchado, "Optimal model for local energy community scheduling considering peer to peer electricity transactions," *IEEE Access*, vol. 9, pp. 12420–12430, 2021, doi: 10.1109/ACCESS.2021.3051004.

[10] G. Sæther, P. Crespo del Granado, and S. Zaferanlouei, "Peer-to-peer electricity trading in an industrial site: Value of buildings flexibility on peak load reduction," *Energy Buildings*, vol. 236, Apr. 2021, Art. no. 110737, doi: 10.1016/j.enbuild.2021.110737.

[11] S.-V. Oprea and A. Bâra, "Devising a trading mechanism with a joint price adjustment for local electricity markets using blockchain. Insights for policy makers," *Energy Policy*, vol. 152, May 2021, Art. no. 112237, doi: 10.1016/j.enpol.2021.112237.

[12] F. Lezama, J. Soares, R. Faia, Z. Vale, O. Kilkki, S. Repo, and J. Segerstam, "Bidding in local electricity markets with cascading wholesale market integration," *Int. J. Electr. Power Energy Syst.*, vol. 131, Oct. 2021, Art. no. 107045, doi: 10.1016/j.ijepes.2021.107045.

[13] C. Samende, J. Cao, and Z. Fan, "Multi-agent deep deterministic policy gradient algorithm for peer-to-peer energy trading considering distribution network constraints," *Appl. Energy*, vol. 317, Jul. 2022, Art. no. 119123, doi: 10.1016/j.apenergy.2022.119123.

[14] O. Jogunola, Y. Tsado, B. Adebisi, and M. Hammoudeh, "VirtElect: A peer-to-peer trading platform for local energy transactions," *IEEE Internet Things J.*, vol. 9, no. 8, pp. 6121–6133, Apr. 2022, doi: 10.1109/JIOT.2021.3109613.

[15] V. B. F. Costa, L. C. Pereira, J. V. B. Andrade, and B. D. Bonatto, "Future assessment of the impact of the COVID-19 pandemic on the electricity market based on a stochastic socioeconomic model," *Appl. Energy*, vol. 313, May 2022, Art. no. 118848, doi: 10.1016/j.apenergy.2022.118848.

[16] A. Chapman, A. Fraser, L. Jones, H. Lovell, P. Scott, S. Thiebaux, and G. Verbic, "Network congestion management: Experiences from bruny island using residential batteries," *IEEE Power Energy Mag.*, vol. 19, no. 4, pp. 41–51, Jul. 2021, doi: 10.1109/MPE.2021.3072818.

[17] Z. Wang, H. Li, N. Deng, K. Cheng, B. Lu, B. Zhang, and B. Wang, "How to effectively implement an incentive-based residential electricity demand response policy? Experience from large-scale trials and matching questionnaires," *Energy Policy*, vol. 141, Jun. 2020, Art. no. 111450, doi: 10.1016/j.enpol.2020.111450.

[18] P. Bradley, A. Coke, and M. Leach, "Financial incentive approaches for reducing peak electricity demand, experience from pilot trials with a UK energy provider," *Energy Policy*, vol. 98, pp. 108–120, Nov. 2016, doi: 10.1016/j.enpol.2016.07.022.

[19] M. A. Fotouhi Ghazvini, J. Soares, N. Horta, R. Neves, R. Castro, and Z. Vale, "A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers," *Appl. Energy*, vol. 151, pp. 102–118, Aug. 2015, doi: 10.1016/j.apenergy.2015.04.067.

[20] A. Asadinejad and K. Tomsovic, "Optimal use of incentive and price based demand response to reduce costs and price volatility," *Electric Power Syst. Res.*, vol. 144, pp. 215–223, Mar. 2017, doi: 10.1016/j.epsr.2016.12.012.

[21] S. Varghese and R. Sioshansi, "The price is right? How pricing and incentive mechanisms in California incentivize building distributed hybrid solar and energy-storage systems," *Energy Policy*, vol. 138, Mar. 2020, Art. no. 111242, doi: 10.1016/j.enpol.2020.111242.

[22] I. Bejan, C. L. Jensen, L. M. Andersen, and L. G. Hansen, "Inducing flexibility of household electricity demand: The overlooked costs of reacting to dynamic incentives," *Appl. Energy*, vol. 284, Feb. 2021, Art. no. 116283, doi: 10.1016/j.apenergy.2020.116283.

[23] M. Manuel De Villena, S. Aittahar, S. Mathieu, I. Boukas, E. Vermeulen, and D. Ernst, "Financial optimization of renewable energy communities through optimal allocation of locally generated electricity," *IEEE Access*, vol. 10, pp. 77571–77586, 2022, doi: 10.1109/ACCESS.2022.3191804.

[24] J. Li, Y. Ye, D. Papadaskalopoulos, and G. Strbac, "Computationally efficient pricing and benefit distribution mechanisms for incentivizing stable peer-to-peer energy trading," *IEEE Internet Things J.*, vol. 8, no. 2, pp. 734–749, Jan. 2021, doi: 10.1109/JIOT.2020.3007196.

[25] S. Mohseni, A. C. Brent, S. Kelly, W. N. Browne, and D. Burmester, "Strategic design optimisation of multi-energy-storage-technology micro-grids considering a two-stage game-theoretic market for demand response aggregation," *Appl. Energy*, vol. 287, Apr. 2021, Art. no. 116563, doi: 10.1016/j.apenergy.2021.116563.

[26] H. Hampton, A. Foley, D. F. Del Rio, B. Smyth, D. Laverty, and B. Caulfield, "Customer engagement strategies in retail electricity markets: A comprehensive and comparative review," *Energy Res. Social Sci.*, vol. 90, Aug. 2022, Art. no. 102611, doi: 10.1016/j.erss.2022.102611.

[27] L. Steg, R. Shwom, and T. Dietz, "What drives energy consumers?: Engaging people in a sustainable energy transition," *IEEE Power Energy Mag.*, vol. 16, no. 1, pp. 20–28, Jan. 2018, doi: 10.1109/MPE.2017.2762379.

[28] N. Wang, Z. Liu, P. Heijnen, and M. Warnier, "A peer-to-peer market mechanism incorporating multi-energy coupling and cooperative behaviors," *Appl. Energy*, vol. 311, Apr. 2022, Art. no. 118572, doi: 10.1016/j.apenergy.2022.118572.

[29] A. M. Alonso, E. Martín, A. Mateo, F. J. Nogales, C. Ruiz, and A. Veiga, "Clustering electricity consumers: Challenges and applications for operating smart grids," *IEEE Power Energy Mag.*, vol. 20, no. 3, pp. 54–63, May 2022, doi: 10.1109/MPE.2022.3150826.

[30] A. Jafari, H. Ganjeh Ganjehlou, T. Khalili, and A. Bidram, "A fair electricity market strategy for energy management and reliability enhancement of islanded multi-microgrids," *Appl. Energy*, vol. 270, Jul. 2020, Art. no. 115170, doi: 10.1016/j.apenergy.2020.115170.

[31] R. Duvignau, V. Heinisch, L. Göransson, V. Gulisano, and M. Papatriantafilou, "Benefits of small-size communities for continuous cost-optimization in peer-to-peer energy sharing," *Appl. Energy*, vol. 301, Nov. 2021, Art. no. 117402, doi: 10.1016/j.apenergy.2021.117402.

[32] H. Hampton, A. M. Foley, D. F. Del Rio, and B. Sovacool, "Developing future retail electricity markets with a customer-centric focus," *Energy Policy*, vol. 168, Sep. 2022, Art. no. 113147, doi: 10.1016/j.enpol.2022.113147.

[33] P. De Martini, L. Gallagher, E. Takayesu, R. Hanley, and P. Henneaux, "Unlocking consumer DER potential: Consumer-centric approaches for grid services," *IEEE Power Energy Mag.*, vol. 20, no. 4, pp. 76–84, Jul. 2022, doi: 10.1109/MPE.2022.3167597.

[34] M. Koengkan, J. A. Fuinhas, F. Osmani, E. Kazemzadeh, A. Auza, N. K. Alavijeh, and M. Teixeira, "Do financial and fiscal incentive policies increase the energy efficiency ratings in residential properties? A piece of empirical evidence from Portugal," *Energy*, vol. 241, Feb. 2022, Art. no. 122895, doi: 10.1016/j.energy.2021.122895.

[35] S. Sergici and L. Lam, "Retail pricing: A low-cost enabler of the clean energy transition," *IEEE Power Energy Mag.*, vol. 20, no. 4, pp. 66–75, Jul. 2022, doi: 10.1109/MPE.2022.3167590.

[36] *Coursera Course on Customer Value in Pricing Strategy*. Accessed: Nov. 26, 2022. [Online]. Available: https://www.coursera.org/learn/uva-darden-bcg-pricing-strategy-customer-value

[37] F. Zhao, T. Zheng, and E. Litvinov, "Economic interpretation of demand curves in multi-product electricity markets—Part I: Theory," *IEEE Trans. Power Syst.*, vol. 35, no. 6, pp. 4880–4887, Nov. 2020, doi: 10.1109/TPWRS.2020.3001755.

[38] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5, doi: 10.1109/PESGM.2017.8274546.

[39] R. Faia, J. Soares, M. A. F. Ghazvini, J. F. Franco, and Z. Vale, "Local electricity markets for electric vehicles: An application study using a decentralized iterative approach," *Frontiers Energy Res.*, vol. 9, Nov. 2021, Art. no. 705066, doi: 10.3389/fenrg.2021.705066.

[40] P. Mochi and K. S. Pandya, "Two stage optimization for customer fiscal incentive in local electricity market," in *Proc. IEEE Int. Power Renew. Energy Conf. (IPRECON)*, Kollam, India, Dec. 2022, pp. 1–6, doi: 10.1109/IPRECON55716.2022.10059623.

[41] P. Mochi and K. S. Pandya, "The impact of social nudge on system cost & revenue optimization in local electricity market," in *Proc. Int. Conf. Power Electron. Energy (ICPEE)*, Bhubaneswar, India, Jan. 2023, pp. 1–5, doi: 10.1109/ICPEE54198.2023.10060025.

[42] P. Mochi, K. Pandya, J. Soares, and Z. Vale, "Optimizing power exchange cost considering behavioral intervention in local energy community," *Mathematics*, vol. 11, no. 10, p. 2367, May 2023, doi: 10.3390/math11102367.

[43] R. Faia, J. Soares, M. A. F. Ghazvini, J. F. Franco, and Z. Vale. (2021). Energy Consumption and PV Generation Data of 50 Prosumers and Energy Consumption of 40 Electric Vehicles—15-Minute Resolution. Zenodo. [Online]. Available: https://doi.org/10.5281/zenodo.4737293

PRATIK MOCHI received the bachelor's degree in electrical engineering from Gujarat University (GTU), Gujarat, in 2010, and the M.E. degree in electrical engineering, with automation control and power system as a major from the L. D. College of Engineering, GTU, in 2012. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, CSPIT, CHARUSAT, India. Since July 2012, he has been an Assistant Professor with the Department of Electrical Engineering, CSPIT, CHARUSAT. His research interests include local electricity market, customer engagement strategy, engineering optimization, energy economics, and energy policy.

KARTIK S. PANDYA (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from The Maharaja Sayajirao University of Baroda, India. His research interests include power system optimization, machine learning, computational intelligence methods, restructured power systems, smart grid, and renewable integrations. He has won many IEEE and CIS sponsored Smart Grid Optimization Competitions. His team's proposed optimization methods titled Levy DEEPSO and EE-CMAES had secured third and second ranks at the IEEE PES Optimization Competitions at the IEEE PES General Meetings, USA, in 2017 and 2018, respectively. His team's proposed optimization methods titled EVDEPSO and IC-DEEPSO had secured second and fourth ranks in the IEEE PES and CIS sponsored optimization competitions on Evolutionary Computation in Uncertain Environments: A Smart Grid Application at the IEEE WCCI Conference 2018, Rio De Janeiro, Brazil. Also, his team's proposed optimization method titled HL_PS_VNSO and GM_VNPSO secured second and third ranks, respectively, at the IEEE CEC Conference, New Zealand, and the GECCO 2019, Czech Republic, in 2019.

RICARDO FAIA received the bachelor's degree in renewable energies engineering from the Institute Polytechnic of Bragança, in 2013, the M.Sc. degree in power systems from the Polytechnic Institute of Porto, in 2016, and the Ph.D. degree from the University of Salamanca, Salamanca, Spain, in 2022. Currently, he is a Researcher with the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), Polytechnic Institute of Porto. His research interests include electricity markets, local electricity markets, optimizations problem, metaheuristics, and decision support systems.

JOÃO SOARES (Member, IEEE) received the B.Sc. degree in computer science and the master's degree in electrical engineering from the Polytechnic Institute of Porto, in 2008 and 2011, respectively, and the Ph.D. degree in electrical and computer engineering from UTAD University, in 2017. He is currently a Researcher with ISEP/GECAD. His research interests include optimization in power and energy systems, including heuristic, hybrid, and classical optimization.