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Optimizing Power Exchange Cost Considering Behavioral Intervention in Local Energy Community

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Abstract: In order to encourage energy saving and the adoption of renewable sources, this study provides a comprehensive experimental framework that integrates socioeconomic and behavioral objectives for the local energy community. The experiment aims to find out how successfully using behavioral interventions might encourage customers to save electrical energy and encourage them to adopt renewable energy, e.g., solar photovoltaic energy, in the present case. Using this method, we can calculate the causal impact of the intervention on consumer participation in the local electricity sector. The study uses consumer data on the import and export of electrical power from retailer electricity utilities at a predetermined power exchange price and a midmarket price for local energy community power transactions. The local energy community model simulates the consumption, storage, and export of 20 residential customers who, in different scenarios, are the test subjects of an empirical experiment and embrace electricity conservation and renewable energy. We address the optimization issue of calculating the power exchange cost and revenue in various scenarios and comparing them with the base case cost. The cases are built on the customers' behavioral interventions' empirical response. The findings demonstrate that the interaction of socioeconomic and behavioral objectives leads to impressive cost savings of up to 19.26% for energy utility customers. The policy implication is suggested for local energy utilities.

Keywords: behavioral economics; cost optimization; energy community; energy conservation; energy economics; energy policy; local electricity market; renewable energy; social nudge

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1. Introduction

Reducing the world's energy needs through efficient electricity consumption is now more crucial than ever. This situation calls for challenging the current efficiency policies' investment-focused concepts and the involvement of behavioral interventions [1] that encourage electricity conservation and utilize renewable energy. Our present culture requires energy conservation and appropriate energy resource management to address significant issues like global warming mitigation and heat regulation within a particular range [2]. The renewable energy revolution cannot be governed as a purely technical or commercial endeavor as it was in the past due to its extensive societal impacts [3]; it should be understood as developing a sophisticated sociotechnical system that necessitates novel types of cooperation. The ability to test innovative concepts such as energy auctions [4] and energy-saving behavior [5] should be provided in order to develop relevant contextual factors for business and technology models that aid in the achievement of the environment and energy policy priorities [6]. The research in [7] suggests three energy policies using solar PV and battery storage; the results showed that self-usage of generated power and energy strategy focused on capital expenditure or subsidies would give customers more financial benefits. The study in [8] suggests that a behavioral intervention method for energy conservation can increase the willingness of energy users to adopt and engage in lowering their energy consumption.

A case study is used in the research [9] to identify the best electrification options based on the unique characteristics and needs of an isolated energy community without electricity. Several specific system behavioral findings based on yearly, monthly, and hourly energy patterns with seasonal fluctuations were also displayed to demonstrate how well the ideal microgrid solution performs. In this energy community, it was possible to construct load consumption, power loss, voltage profile, and storage as optimization issues in order to reduce system costs. This was acheived by taking into account the technological uncertainties associated with the generation of renewable energy [10]. As solar photovoltaic power generation [11] is frequently uncertain, it may affect the planning and operational performance of the system [12], yet, research in [13] proved that by taking an optimization approach in uncertain power generation, a cost saving up to 15% could be achieved. In the proposed optimization model of our paper, any uncertainty in solar power generation would result in higher energy storage in the battery and so power export will be optimized accordingly. We introduced a power balance equation to minimize the effect of such uncertainty.

Scholars in various disciplines have begun to pay more attention to electricity conservation and have presented novel ideas, theories, and methods. However, only a few studies try to capture the various aspects of electricity conservation in a more comprehensive manner. The findings of the study [14] imply that by taking into account the role of cognitive mechanisms that underlie the implementation of electricity-saving activities, our comprehension of these behaviors may be enhanced. A field experiment [15] conducted on 237 individuals confirmed that 6% of electricity was achieved by sending behavioral interventions. The authors of [16] conducted a social comparison treatment for electricity saving on 525 households and found a 6.7% reduction in electricity use. A study on the same objective of electricity conservation in 2927 households showed electricity savings of 8.6% using the social nudge approach [17]. An energy-saving nudge approach reported a 10% reduction in electricity usage in the field experiment [18] conducted for 528 households. The possibility of reducing home energy usage with non-fiscal rewards that respond to consumer environmental values was looked at in [19]; the results showed a 5% monthly reduction in energy consumption. In research conducted on a government workplace, electricity savings of up to 14% resulted from social nudges that contained comparable energy consumption facts [20]. In the quarter year from the intervention, an 8.5% electricity saving was achieved, while social power participants sustained saving more electricity in an experiment conducted [21] in Switzerland. A meta-analysis [22] found that electricity consumption has been reduced by about 3.91% from the most recent experimental results of publications. The study suggests a few points for policy implications, e.g., the inclusion of control groups with and without incentives, collection of sociodemographic information, focus on individual incentives, and more experimental analysis. In order to help regulators, utilities, and politicians use energy efficiency as a resource, the study [23] offers insights into the economics of consumer-subsidized efficiency initiatives. Conclusive proof for energy saving was discovered by the authors, suggesting that regions with lower energy savings compared to retail sales can expand the scope of their energy efficiency plans without significantly increasing the electricity costs saved. The authors describe cases of energy efficiency predictions and prospective modeling and pinpoint technical advancements essential to utilities and energy providers.

Interventions in behavior that rely on social pressure might be potential tools for changing people's preferences to opt for renewables. In contrast to other actions, it is important to be more circumspect before implementing a norm-based intervention since different people may interpret the same information differently. Consequently, it is essential to identify the type of behavior that has to be altered. It is challenging to draw in customers when they have little knowledge or engagement. [24]. It is possible that people will not pick renewable energy since they are worried about the high purchase prices associated with it because it demands an initial investment. The fact that humans have a propensity to myopically overrate things that are close in time and underrate those that are far in the future is the root cause of this phenomenon [25]. Individuals may also choose not to utilize renewable energy since they overestimate the cost reductions in the future owing to a lack of knowledge needed to make optimal judgments, as is believed by rational decision-making. It may be useful to change attitudes toward renewables by letting them know that their peers have made the same decision and have already adopted solar electricity. Making the potential cost reductions from renewables more visible may prove to be a successful method for assisting the local electricity community in appreciating the benefits of renewables in the future. Additionally, heterogeneity in behavior may influence a variety of personal decisions. Considering the behaviors practiced by others in the relevant social environment is another important consideration when determining whether to embrace new technology [26]. A research study in [27] suggests that customers have the chance to choose low-emission electrical retailers inside the liberalized market, helping to reduce pollutants from power-producing facilities. The study [28] looks at how customer aspirations to adopt smart appliances are impacted by both interpersonal and technology-specific views. The results show that there are differences in the proportional weight of personal views and particular technologies across different smart energy offers.

Service quality and behavioral intention have a large and favorable impact on a person's decision to purchase smart appliances. In a laboratory experiment [29] involving 300 participants, researchers looked at how social norms and decision observability affect acceptability for renewable electricity, even at one's own financial cost. According to the findings, when requested to adhere to pro-environmental public standards, individuals contributed 35% more to a running renewable energy program compared to their control groups. This suggests that the government might enlighten people more about the renewable energy sector so they may make better purchase decisions. Information does not, however, guarantee a change in energy consumption behavior [30] or a movement in the preferences of the electricity community. Instead, when information is presented in a way that respects community members' poor information processing abilities, it may be more successful in altering behavior. The authors of the work [31] combined studies on societal support for energy policy with the idea of vocal partisanship for energy conservation. An optimization approach was proposed in [32] to model the local energy market by considering a mid-market rate tariff for prosumers. A demand response program [33] was suggested to motivate customers to participate in the energy transition.

By suggesting behavioral economics as a path from the root to determine how behavioral aspects can be used to understand energy costs and to supplement conventional interventions aimed at addressing them, this research involves an idea that emphasizes the significance of human initiative in affecting energy conservation and the adoption of renewable energy sources. The goal is to emphasize how behavioral economics might offer an enhancing competencies framework to analyze and handle the challenging problem of lowering the cost of energy rather than to give an exhaustive overview of the pertinent literature. We provide a local energy community model that illustrates and includes socioeconomic elements and investigates the effects of these factors on operational costs. Beyond its theoretical appeal, the study's justification is to investigate the notion that, in order to enhance the current policy, policymakers should take advantage of the many components and be conscious of the results of their interactions.

The structure of the paper is as follows: Section 2 describes the synergy of behavioral interventions and the energy community; Section 3 provides the details of the mathematical model, case study, and result details; We provide a general discussion and policy implication suggestions in Section 4; and the conclusion is discussed in Section 5.

2. Behavioral Intervention and Energy Community

2.1. Behavioral Economics and Intervention

Behavioral economics acknowledges the enormous effect that situation has on conduct. The specifics of the choice issue, in particular, impact the chance that decisions may display implicit dissonance. Individuals are also more likely to regard things as more important when they are closer in time or when they may provide greater benefits if delayed from now on [1]. This method focuses on the short-term costs and long-term benefits of energy measures such as energy conservation and renewable energy adoption. Behavioral intervention methods, such as energy conservation measures, may provide monetary benefits to residents in a nearby local energy region. Giving advice on the most effective approach to save energy, for example, might encourage improved energy consumption habits and, as a result, save money. To modify behavior that is recognized as a situational social practice, a more detailed investigation of behavior determinants beyond the focus on people is required. People also demonstrate persuasive departures from prudent choice suspicions in behavioral economics, in addition to demonstrating mental abnormalities. People differ not just in their preferences but also in their levels of personal responsibility and inspiration [34]. People are considered sane leaders with limited mental assets, such as bounded rational individuals, in the behavioral science perspective, and as a result, when making decisions under limited self-assuredness, they choose different methods.

The ethical consequences of legislation and technology interventions have recently received much attention throughout the world [35]. The hypothesis [36] anticipates that people's behavior is unaffected by their surroundings and results in decisions based on a scientific connection of the costs and benefits associated with alternative choices, which can be changed simply by adjusting financial motivators and providing additional data. Using commitment devices [37] is one technique for overcoming the challenge of energy-saving behavior. It is a system that pushes people to follow through on their goals by laying out negative consequences, such as financial or social repercussions, if they do not.

2.2. Energy Community

An energy community would be prepared to engage in renewable energy even in the presence of advantages or government subsidies that are greater than costs is explained by a variety of motives and levels of self-interest. In a consumer-centric energy community [38], significant advantages are provided by the electricity savings brought about by energy efficiency [39]. These include lowering regional emissions, enhancing business efficiency, lowering home energy costs, increasing productivity, enhancing resident wellbeing, and helping to lower energy scarcity. Energy conservation strategies may have various other benefits for the community in addition to lowering energy costs. Living in disadvantaged areas has a negative impact on a community's ability to build the social capital required to impose desirable behaviors via socialization.

From an economic viewpoint, the choice to invest in renewable power is generally portrayed as being driven by energy and cost reserves. This suggests that the energy community may decide to put resources into environmentally friendly energy, considering that this is monetarily ideal. Adopting renewable energy does not just increase the probability that the energy objectives are accomplished; it likewise improves individuals' self-achievement and mental self-portrait discernments by giving them the option to accomplish the presented objectives. Saving electricity or making investments in renewable energy is a choice to advance the common good and is thus a form of ethical behavior.

Given that the local energy community may make various assumptions from the sort of information presented, social interventions should be built with extra care. When people are simply informed about other people's electricity consumption habits, for instance, a boomerang effect could occur. This would have a positive impact on people who were previously using more electricity than recommended and a negative impact on people who were previously using less electricity than recommended. As a result, for behavioral interventions to be successful, it is crucial to accurately assess the behavior that needs to change. The social problem that results from encouraging electricity conservation in a community is caused by the conflict between each family's individual and communal goals, which is to consume energy as they see fit. It is important to understand the barriers to energy-efficient technology, which may lead to insight into locally based solutions for adaptability so that distributed electricity production from renewable sources may be incorporated [40]. Strategies for information dissemination account for the influence of energy community behavior. These actions significantly contribute to strengthening the energy community's knowledge of their rights and market rates and their comprehension of common electricity issues and energy conservation consciousness. By being encouraged to carry out beneficial activities, the energy community may improve their willingness to do so and, in turn, improve their level of self-efficacy, which is often lower due to the social isolation brought on by their status on the periphery.

3. Empirical Study and Analysis

3.1. Mathematical Model

The power cost minimization is considered an optimization problem and is solved by a mixed integer linear programming method. The objective of cost minimization is shown in Equation (1):

$$\text{Minimize}\left(\sum_{t=1}^{N_t}\sum_{x=1}^{N_x}\left(\mathrm{C}_{x,t}^{import} - \mathrm{R}_{x,t}^{export}\right) + \mathrm{FC}_{x,t}\right) \tag{1}$$

where $\mathrm{C}_{x,t}^{import}$ is the cost associated with the import of electrical power and $\mathrm{R}_{x,t}^{export}$ is the revenue made by customers while exporting power, and $\mathrm{FC}_{x,t}$ is the fixed charge paid by x customers for utilizing the energy community resources.

Equations (2) and (3) signify the cost and revenue for buying and selling electricity to the utility by all players in time t, subject to constraints (4)–(8):

$$\mathrm{C}_{x,t}^{import} = \left(l_{x,t}^{buy} \times \mathrm{E}_{x,t}^{buy} \times \mathrm{P}_{x,t}^{buy}\right) \times dt \quad \forall x \in \mathrm{N}_x, \ \forall t \in \mathrm{N}_t \tag{2}$$

$$\mathrm{R}_{x,t}^{export} = \left(l_{x,t}^{sell} \times \mathrm{E}_{x,t}^{sell} \times \mathrm{P}_{x,t}^{sell}\right) \times dt \quad \forall x \in \mathrm{N}_x, \ \forall t \in \mathrm{N}_t \tag{3}$$

where $\mathrm{E}_{x,t}^{buy}$ and $\mathrm{E}_{x,t}^{sell}$ denote the electric power purchase and sell to the community, respectively. $\mathrm{P}_{x,t}^{buy}$ and $\mathrm{P}_{x,t}^{sell}$ are the buy and sell price of electric power, and dt is the time period adjustment factor. The power loss multipliers for power purchase and sell are $l_{x,t}^{buy}$ and $l_{x,t}^{sell}$, correspondingly. The sum of the power loss multipliers is taken as 5% [41].

In this local energy community model, the customers are limited to buy or sell electric power within their upper limits of power import and export, as per Equations (4) and (5). They are also limited to buy or sell the power in the community at the same time, as per constraints Equations (6)–(8):

$$0 \leq \mathrm{E}_{x,t}^{buy} \leq \mathrm{E}_{x,t}^{buy\ max} \times \mathrm{X}_{x,t}^{\mathrm{EB}} \quad \forall x \in \mathrm{N}_x, \ \forall t \in \mathrm{N}_t \tag{4}$$

$$0 \leq \mathrm{E}_{x,t}^{sell} \leq \mathrm{E}_{x,t}^{sell\ max} \times \mathrm{X}_{x,t}^{\mathrm{ES}} \quad \forall x \in \mathrm{N}_x, \ \forall t \in \mathrm{N}_t \tag{5}$$

where the upper limits for power purchase and sell are designated as $\mathrm{E}_{x,t}^{buy\ max}$ and $\mathrm{E}_{x,t}^{sell\ max}$, respectively. The binary variables for power purchase are $\mathrm{X}_{x,t}^{\mathrm{EB}}$ and for power sale is $\mathrm{X}_{x,t}^{\mathrm{ES}}$. They are introduced to limit the power trading simultaneously:

$$0 \leq \mathrm{X}_{x,t}^{\mathrm{EB}} \leq 1 \quad \forall x \in \mathrm{N}_x, \ \forall t \in \mathrm{N}_t \tag{6}$$

$$0 \leq X^{ES}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{7}$$

$$X^{EB}_{x,t} + X^{ES}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{8}$$

In some cases, the customers are permitted to exchange power at a mid-market price. A mid-market price allows customers to buy power from the local community at a lower price and sell power at a higher price compared to utility grid prices. The condition for this power transaction in the local community, as per Equation (9), is the total electric power buy and total electric power sell should be the same. The mid-market price is calculated as Equation (10) [42]:

$$\sum_{x=1}^{N_x} E^{buy\ mmp}_{x,t} = \sum_{x=1}^{N_x} E^{sell\ mmp}_{x,t} \quad \forall x \in N_x, \ \forall t \in N_t \tag{9}$$

$$P^{mmp}_{x,t} = \frac{\min(P^{buy}_{x,t}) + P^{sell}_{x,t}}{2} \quad \forall x \in N_x, \ \forall t \in N_t \tag{10}$$

where $E^{buy\ mmp}_{x,t}$ and $E^{sell\ mmp}_{x,t}$ are electric power buy and sell by the customer at a mid-market price $P^{mmp}_{x,t}$. It should be noted that power trading at mid-market price will also follow a similar power exchange constraint as per Equations (11)–(15):

$$0 \leq E^{buy\ mmp}_{x,t} \leq E^{buy\ max}_{x,t} \times X^{EB\ mpp}_{x,t} \quad \forall x \in N_x, \ \forall t \in N_t \tag{11}$$

$$0 \leq E^{sell\ mpp}_{x,t} \leq E^{sell\ max}_{x,t} \times X^{ES\ mmp}_{x,t} \quad \forall x \in N_x, \ \forall t \in N_t \tag{12}$$

The binary variables, at a mid-market price, for power purchase is $X^{EB\ mmp}_{x,t}$ and the same for power sale is $X^{ES\ mmp}_{x,t}$. They are limiting factor power exchange simultaneously as mid-market price:

$$0 \leq X^{EB\ mmp}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{13}$$

$$0 \leq X^{ES\ mmp}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{14}$$

$$X^{EB\ mmp}_{x,t} + X^{ES\ mmp}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{15}$$

Further, power purchase from the utility grid and from the local energy community is limited as per Equation (16), and the same goes for power sell, as per Equation (17):

$$X^{EB}_{x,t} + X^{EB\ mmp}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{16}$$

$$X^{ES}_{x,t} + X^{ES\ mmp}_{x,t} \leq 1 \quad \forall x \in N_x, \ \forall t \in N_t \tag{17}$$

The customers can store the electrical power generated by their solar PV in a battery; the battery power is estimated by Equation (18):

$$E^{bat}_{x,t} = E^{bat}_{x,ini} + E^{bat\ ch}_{x,1} \times \eta_{x,ch} - \frac{E^{bat\ dch}_{x,1}}{\eta_{x,dch}} \quad \forall x \in N_x \tag{18}$$

where $E^{bat}_{x,t}$ is the electric energy content of the battery, $E^{bat}_{x,ini}$ is the initial electric energy of the battery, $\eta_{x,ch}$ and $\eta_{x,dch}$ are the charging and discharging efficiencies of the battery, respectively. The battery charging power $E^{bat\ ch}_{x,1}$ and discharging power $E^{bat\ dch}_{x,1}$ are limited to staying within the maximum limit of the battery, and customers can either charge or discharge the battery at the same time. Equation (19) represents power balance:

$$E_{x,t}^{buy} + E_{x,t}^{bat\ dch} + E_{x,t}^{gen} = E_{x,t}^{load} + E_{x,t}^{sell} + E_{x,t}^{bat\ ch} \quad \forall x \in N_x, \ \forall t \in N_t \tag{19}$$

where $E_{h,t}^{gen}$ is power generated by the customers and $E_{h,t}^{load}$ is the electric load.

3.2. Case Study and Result Analysis

The study is carried out for a total of five cases to determine the operating cost of a small local energy community consisting of 20 household customers. All these customers are assumed to be prosumers, i.e., they own the solar PV power generation and the battery storage according to their contracted power limits with the power grid. The first case is a base case where the customers buy and sell electric power without energy conservation and without adopting higher PV installation. In case 01, it is assumed that half of the customers respond positively to the energy conservation interventions and reduce their electric power consumption by 3–5%. However, this case does not include behavioral interventions for adopting a higher PV installation. Case 02, on the other hand, considers a 3–5% higher PV installation by half of the total customers collectively, resulting from responding positively to behavioral interventions. Case 03 is formulated as all customers being nudged by energy conservation and higher PV installation requests. In this case, it is assumed that half of the customers reduce their power consumption by 3–5% and the other half increase their PV installation capacity by 3–5% collectively. Case 04 is similar to case 03, but in this case, the customers are allowed to exchange their power at the mid-market price in their local community. All these assumptions are based on the studies and proof provided in the literature [14–20]. As this is an empirical study, the authors have also taken liberty with assumptions, yet at a level acceptable based on the literature. The various cases are depicted in Table 1.

Table 1. Cases under study.

Case	Energy Conservation	Higher PV Installation	Mid-Market Price
Base case	No	No	No
Case 01	Yes	No	No
Case 02	No	Yes	No
Case 03	Yes	Yes	No
Case 04	Yes	Yes	Yes

The system under study consists of a total of 20 customers, which is a part of the system used in research [42,43] and is available publicly to download and use [44]. All the community participants have a contract with a retailer about the power buy/sell limits, power exchange rate, fixed cost to use resources, and storage of power. The power consumption, generation, and storage are recorded by a smart meter, and aggregators or system operators may use it to forecast future values. In the proposed energy community model, forecasted data can also be used to estimate the system cost and revenue. The local energy community system specifications are listed in Table 2. The power capacity of the battery and solar PV installation for each customer is shown in Figure 1. The power trade prices are shown in Figure 2.

The simulation platform is MATLAB, and a mixed integer linear programming optimization problem is solved by using the TOMLAB toolbox. The results of system cost $C_{x,t}^{import}$ and customer revenue $R_{x,t}^{export}$ were obtained for five cases, as stated in Table 3.

Table 2. System specification.

Parameter	Symbol	Value		Unit
		Min	Max	
Number of customers	N_x	20		-
Customers' buy limit	-	4.6	10.35	kW
Customers' sell limit	-	2.3	5.175	kW
Fixed cost	$FC_{x,t}$	0.32	0.62	EUR/day
Power buy price	$P_{x,t}^{buy}$	0.0922	0.1836	EUR/kWh
Power sell price	$P_{x,t}^{sell}$	0.045		EUR/kWh
Mid-market price	$P_{x,t}^{mmp}$	0.0686	0.0937	EUR/kWh
Electric load of customer	$E_{x,t}^{load}$	0	7.07	kW
Generation of customer	$E_{x,t}^{gen}$	0	7.75	kW
Initial battery power	$E_{x,ini}^{bat}$	0		kW
Battery capacity of customers	$E_{x,t}^{bat}$	13.5	15	kWh
Charging efficiency of battery	$\eta_{x,ch}$	90%		-
Discharging efficiency of battery	$\eta_{x,dch}$	90%		-

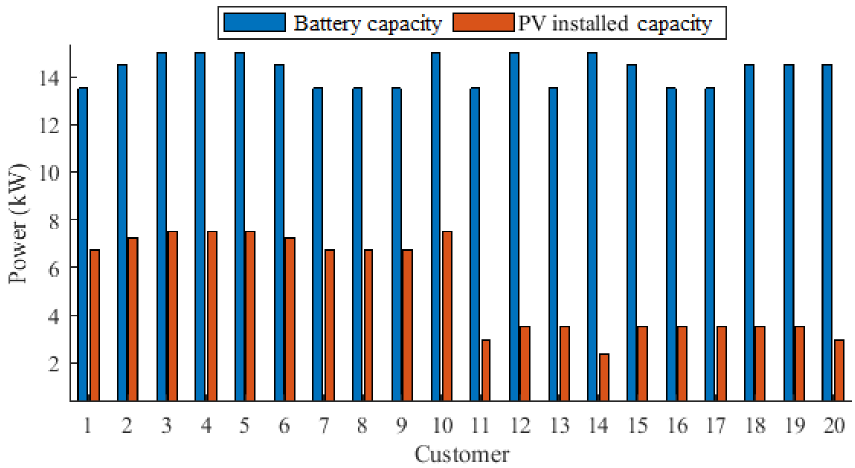

Figure 1. Battery capacity and PV installed capacity.

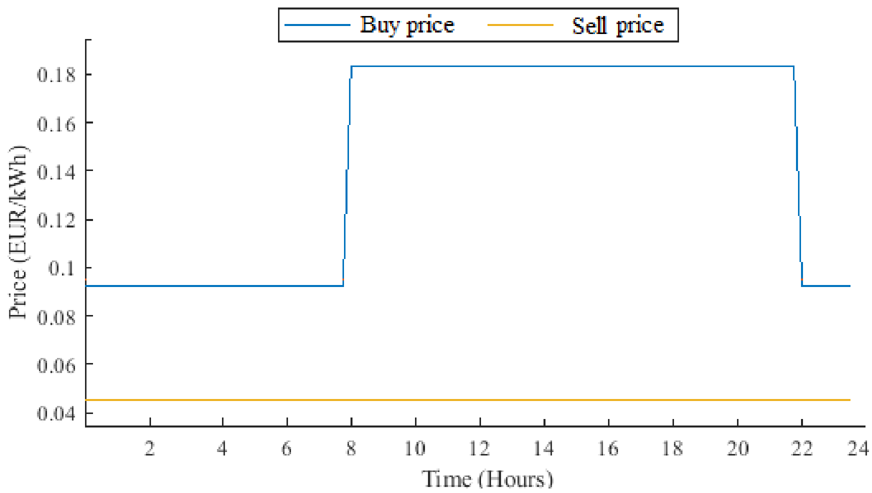

Figure 2. Buy and sell energy prices.

Table 3. System cost results, cost saving, and revenue.

Case	System Cost (EUR)	% Cost Saving	Revenue (EUR)
Base case	42.25	-	2.09
Case 01	39.88	5.60%	2.13
Case 02	41.04	2.86%	2.42
Case 03	38.70	8.40%	2.46
Case 04	34.11	19.26%	5.48

The system cost was highest in the base case and lowest in case 4. The cost reduction was achieved in each case with respect to the base case. The economic savings were in the range of 2.86–19.26%. This result indicates that when the behavioral interventions work positively for energy conservation and increase solar power adoption in the mid-market price scenario, the local energy community achieved an economic benefit of 19.26%. While considering the revenue of customers for selling the power, the lowest revenue was observed in the base case. If the customers responded positively to interventions and changed their behavior for energy conservation and adoption of solar power at the same time, i.e., comparing the base case with case 03, an economic benefit of 17.7% was obtained by the local energy community. The same behavior with the mid-market price increased the revenue from EUR 2.09 to EUR 5.48. In overall comparison, case 04 was the most economical way of operating the system, as it corresponded to the lowest system cost and the highest revenue.

Figure 3 depicts the peak power export of all twenty customers. As the optimization model for reducing the economic cost of the community ran, it was discovered that only a few customers exported a negligible quantity of energy to the community. Therefore, the most cost-effective option for these consumers was to generate their own electricity. On the other hand, exporting excess electricity to a utility or community was the best method to reduce system costs, so few customers had a substantial quantity of excess electricity. Comparing the average power exported in all five cases, the base case exported the least power, while case 04 exported the most.

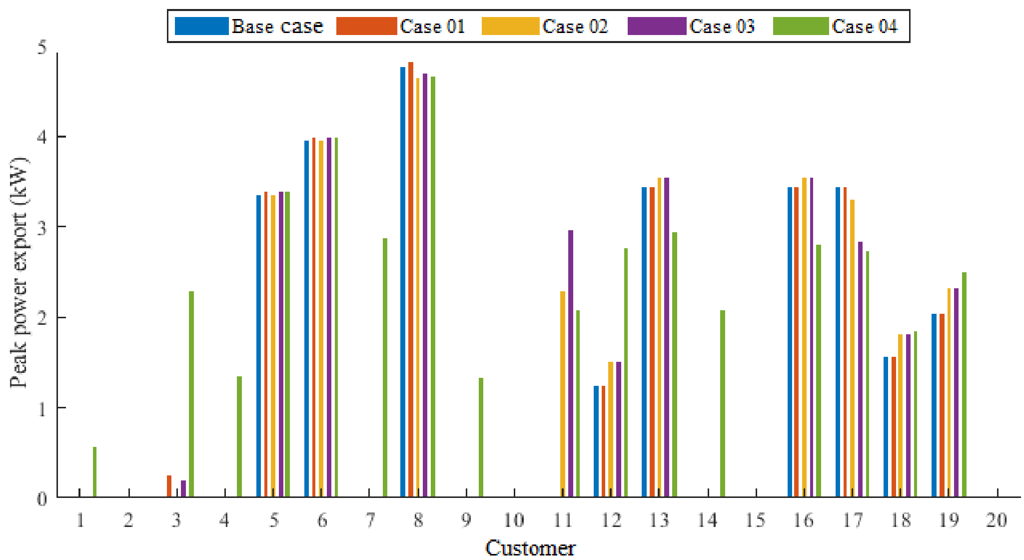

Figure 3. Peak power export by customers.

Table 4 and Figure 4 present the statistics for the local cost of purchasing electricity for five cases. The case-by-case results presented in Table 4 depict the minimum and maximum power purchase costs incurred by customers, the average power purchase cost, and the reduction in power purchase costs compared to the base case. In this context, average power buy cost refers to the ratio of the sum of power buy costs for all customers in a specific case to the total number of customers. Figure 4 depicts the comprehensive results of the power purchase cost for all consumers in all circumstances.

Table 4. Power buy cost values.

Case	Cost Range (Min–Max) (EUR)	Average Cost (EUR)	% Reduction in avg. Power Buy Cost
Base case	0.46–3.13	1.788	-
Case 01	0.40–3.13	1.671	6.53%
Case 02	0.46–2.99	1.745	2.40%
Case 03	0.40–2.93	1.628	8.95%
Case 04	0.66–2.49	1.262	29.41%

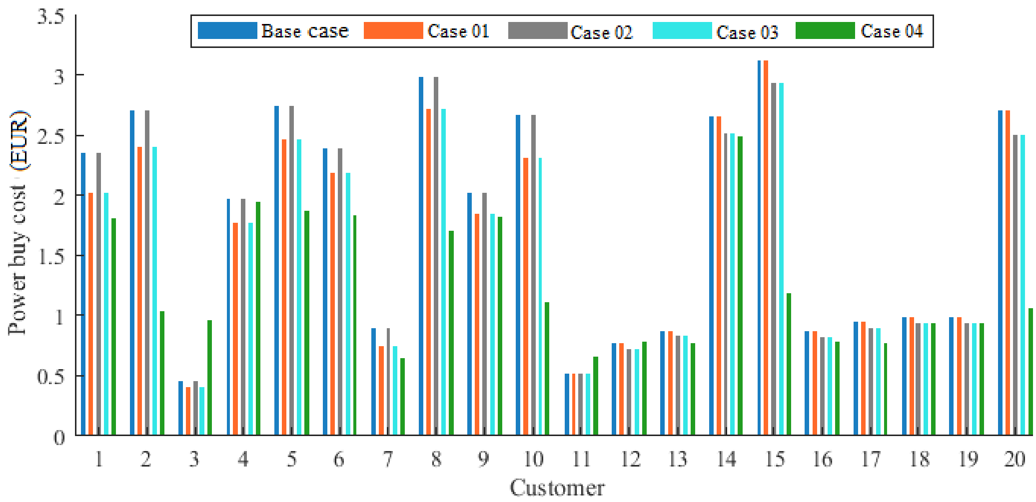

Figure 4. Cost of power bought in community.

Case 04 was the exception; in all other instances, consumers purchased power from the utility power grid at a price indicated in Figure 2's price chart. In case 04, consumers were permitted to purchase electricity at the calculated mid-market price (5). Considering battery energy storage, case 04 gave optimum results compared to the other cases. Battery power trading was the most economical, as the lowest system cost and highest revenue were reported. According to the results, it is evident that the base case had the maximum power purchase cost, and case 04 had the lowest.

Table 5 and Figure 5 detail the revenue derived from the sale of energy to the community. Comparing all cases, it is evident that the base case had the lowest economic benefit for customers, while case 04 had the highest. Case 04 has an average revenue of 0.274 EUR, which was 163.46% higher than the base case. Customers were permitted to sell power in their local community at a mid-market price that was less than the utility grid export price, and they were also permitted to purchase power at a mid-market price that was less than the utility grid import price.

Table 5. Power sold revenue values.

Case	Revenue Range (Min–Max) (EUR)	Average Revenue (EUR)	% Increase in Avg. Power Sell Revenue
Base case	0–0.398	0.104	-
Case 01	0–0.559	0.106	1.92%
Case 02	0–0.553	0.121	16.34%
Case 03	0–0.561	0.123	18.26%
Case 04	0–0.874	0.274	163.46%

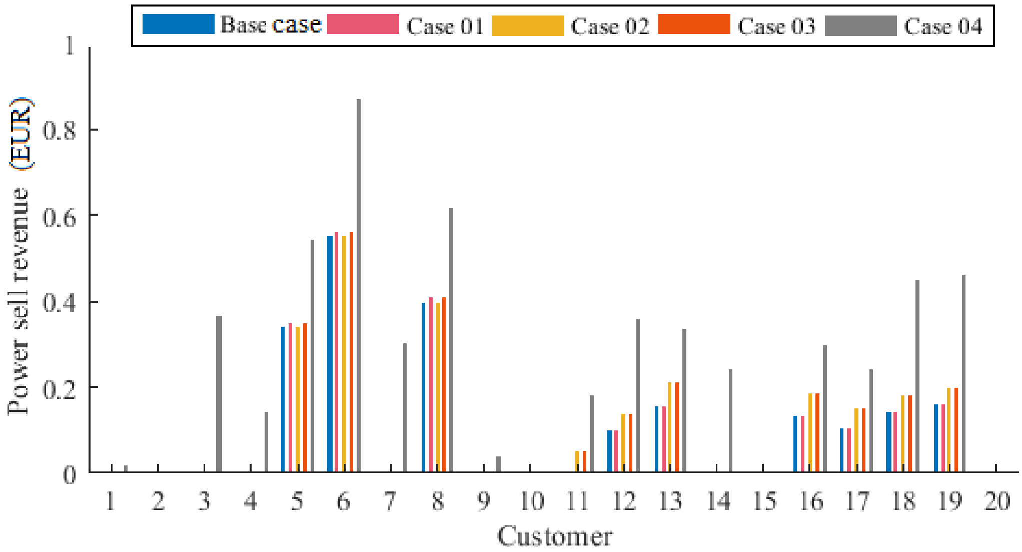

Figure 5. Revenue of power sold in the community.

4. Discussion and Policy Implication

We will now go through how the experiment's findings could be relevant to policy-makers who are debating whether to execute a behavioral intervention or a cost-based intervention aimed at encouraging consumers to use less energy and switch to renewable sources. When people are unable to charge higher premiums, social intervention may be a particularly attractive policy instrument to urge them to conserve electricity. We contend that motivating factors and social position, in addition to economic reasons, also play a role in making judgment calls and that policymakers may take advantage of these elements to boost policy effectiveness. We conducted an experiment based on the local energy community members' heterogeneity, a characteristic common to social computational science, to examine how a policy will progress after the socioeconomic drivers of electricity savings and renewable energy adoption are taken into consideration. The research we used to develop an effective approach to electricity community simulation is a good illustration of how behavioral elements, including ecological issues, are becoming more and more important to policymakers. Additionally, our findings imply that a further step is required: details on objectives should be collected in a way that enables communicating their relative importance within the energy community member's decision-making strategy in order to obtain a complete picture of the policy receivers.

Overall, by experimentally examining the effect of local energy communities on costs, our results add to studies on energy conservation and the uptake of renewable energy sources. Despite this, there are certain limitations to our study. First, this study evaluated a hypothetical decision between adopting renewable energy sources and energy conservation. Even so, we think that this analysis offers policymakers an important empirical understanding of how to deploy interventions for local power cost reduction, despite some evidence to the contrary. Secondly, we assume the infrastructure required for communication is in a ready condition in the local electric community. For instance, it gave decision-makers new instruments for influencing social behavior as well as new perspectives for more precisely forecasting the effects of current policies. Social interventions are commands to do or not do something that are supported by the acceptance or rejection of others. Social influencing frequently promotes collaboration and has a significant impact on behavior in the local community. They may be successful, for instance, in lowering energy use. Because of this, social interventions may be used to address significant social problems. This is particularly vital for the energy local area because, by saving more energy costs, they will have more monetary assets accessible for other important merchandise that they generally can not manage.

While we have reproduced intervention-based cases independently, further examination ought to explore the possibility in future that behaviorally informed interventions could be utilized mixed with conventional ones, for example, how and what mixtures of traditional, behavioral, and socially informed instruments are powerful at advancing energy viability choices. One method for evaluating its viability would be by investigating the instruments on which such combinations work. An incentive-based policy proposal might be interesting research work in the future.

Due to its explicit behavior expectations and good mathematical representation, the projected model can be used as a reference for policymaking. Policymakers can address the social drivers of energy saving and embracing renewables by planning interventions that recognize that people are not generally judicious leaders, particularly when the unfortunate circumstances where they live drain the mental assets important for reasonable direction. Only behavioral interventions that are fair to the target population, that are designed to meet people's demands and aspirations, and that stop the private sector from creating deceptive interventions should be supported by policymakers. Nevertheless, relying solely on behavioral economic perspectives is insufficient for policymakers to determine if the behavioral intervention has been successful in encouraging better choices and results at a wider level, if it should be improved, whether it can be scaled up, or if it is reproduced in other locations. They must make use of the insights from impact evaluations in order to rely on the strongest evidence. According to this branch of study, interventions can produce the best evidence because they make it possible to establish the ideal circumstances to take into account when developing an intervention's effects.

The proposed model would also work in the urban population. However, if the local community is larger, i.e., customers exchanging the power are located at a far distance, the internal power losses would significantly affect the system cost. In such cases, a sophisticated optimization model with customer groups in large quantities would be an option to get the optimum system cost.

5. Conclusions

Behavioral economics emphasizes economic incentives and offers a wider view of the problem that considers the diversity of people. We also offer an additional explanation that involves the social framework in which contact takes place via behavioral intervention. Most people agree that social involvement encourages technology adoption through emulation. To encourage more consumers to modify their energy behavior and foster bottom-up initiatives, an energy policy that provides more opportunities for investment in renewable power and behavioral interventions for energy conservation is required.

To the best of our knowledge, this is the first empirical study experiment that uses behavioral intervention results to calculate the system cost of a local energy community. In this study, we looked at how much behavioral changes like electricity conservation and renewable energy adoption may lower the cost of the local electrical grid. Based on the efficacy of interventions for a locally controlled power system, we examined a variety of instances. While adopting energy conservation only and while adopting higher PV generation individually, the system cost was reduced by 5.60% and 2.86%, respectively. The lowest system cost of EUR 34.11 for case 04 and the highest revenue of EUR 5.48 in the same case were achieved. The average cost reduction of up to 29.41% was achieved in case 04 compared to the base case, and also the average power sell revenue increased by up to 163.46% when energy conservation and higher renewable power generation were considered. The results point to favorable effects and give policymakers proof to use when adopting behavioral intervention strategies for energy conservation and preference for renewable energy sources. Outcomes of an empirical study show that when socioeconomic and behavioral objectives are taken into consideration, policy interventions may result in paradoxical results, notwithstanding a few constraints. The findings also imply that the path followed is worthwhile continuing as long as this kind of modeling is improved, and perhaps as quantitative social science develops by gathering additional qualitative data on the judgment process of the energy community.

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Nomenclature

Indices

x	customers
t	periods
Parameters	
N_x	number of customers
N_t	number of periods
$E_{x,t}^{buy\ max}$	power purchase upper limit
$E_{x,t}^{sell\ max}$	power sell upper limit
$E_{x,ini}^{bat}$	initial battery energy
dt	time period adjustment factor
$FC_{x,t}$	fixed cost
$E_{h,t}^{load}$	electric load of customer
$E_{h,t}^{gen}$	power generation of customer
$\eta_{x,ch}$	charging efficiency of battery
$\eta_{x,dch}$	discharging efficiency of battery
$P_{x,t}^{mmp}$	mid-market price
$P_{x,t}^{sell}$	power sell price
$P_{x,t}^{buy}$	power buy price
$l_{x,t}^{sell}$	power loss multiplier for power sell
$l_{x,t}^{buy}$	power loss multiplier for power buy
Variables	
$E_{x,t}^{buy}$	power purchased by community members
$X_{x,t}^{EB}$	binary variable for power purchase
$E_{x,t}^{buy\ mmp}$	power buy at mid-market price
$X_{x,t}^{EB\ mpp}$	binary variable for power buy at mid-market price
$E_{x,t}^{sell}$	power sell by community member
$X_{x,t}^{ES}$	binary variable for power sell
$E_{x,t}^{sell\ mmp}$	power sell at mid-market price
$X_{x,t}^{ES\ mmp}$	binary variable for power sell at mid-market price
$E_{x,t}^{bat}$	electric energy content of the battery
$E_{x,t}^{bat\ ch}$	battery charging power
$E_{x,t}^{bat\ dch}$	battery dis-charging power
$C_{x,t}^{import}$	cost of power import from grid
$C_{h,t}^{lem}$	cost of power buy in LEM
$R_{x,t}^{export}$	revenue from power export to grid
$R_{h,t}^{lem}$	revenue from power sell in LEM

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