An interdisciplinary approach of a local peer-to-peer energy trading model for a more sustainable power grid

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ABSTRACT

This work investigates a novel distance-based electricity tariff applicable to energy communities. Based on a mixed integer linear optimization model computational studies are conducted to investigate the effects of this tariff on a small-scale community consisting of 22 consumers and 5 prosumers. Additionally, the potential of electric storage systems supporting the use of locally produced energy is investigated. The results of the computational model prove that an energy community generates incentives photovoltaic plants and the installation of energy storage systems. Complementary to the simulations, the flexibility options are supported by a user survey focusing on technology attributes for local energy market models, proving that there is a significant awareness for the use of energy storage systems.

KEYWORDS

P2P energy trading, energy communities, electrical storage, photovoltaic, renewable energy source, sustainability

INTRODUCTION

To be able to achieve the Paris climate targets [1], the required electricity demand must be covered by renewable energy sources (RES). The increased use of RES means that electricity production is becoming more and more decentralized. This circumstance is due to the increasingly widespread use of photovoltaic (PV) systems, as they are also attractive to private individuals. Since, in general, the production of these RES does not coincide with the consumption profiles of the owners, there is always a surplus portion that is commonly sold to the grid operator. By means of an EU directive, it should now be possible to form so-called local energy communities (LECs) [2], so that it should be possible to utilize this energy locally at more favorable rates.

According to European Union (EU) [3], LECs are a special form of so-called local energy markets (LEMs). A LEM can consist of several prosumers and consumers, and energy supply companies can also participate. A LEC differs from a LEM in that the community can also own other production facilities, such as PV plants or wind turbines. Also, the settlement system for the LEC is common property.

For LECs, new marketing strategies are required to ensure that it is possible to offer locally produced energy at better conditions for the prosumer and the consumer [4]. In such a LEC, the

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feed-in tariff must be higher than the fixed feed-in tariff. At the same time, however, the consumer must pay a lower price than that offered by the energy supplier. Only under these two conditions such a business model makes sense for both consumer and prosumer. Such a model can be implemented for example by means of a peer-to-peer (P2P) [5] trading strategy. In order to implement such strategies in reality, far-reaching changes in the network infrastructure are necessary. For example, every household must be equipped with a smart meter [6].
An example of this can be found in [7], where a blockchain-based energy management system was presented. Here, the physical constraints are formulated as an optimization problem, where a bilateral trading mechanism is also built into the problem. Furthermore, the complete trading mechanism is mapped via smart contracts. This results in a reduction of the electricity import by 15% and a reduction of the peak imports by 50%.
In [8], the interaction of P2P trading with electricity storage was investigated. Based on a stochastic programming approach, the buy or sell decision is made by incorporating generation uncertainties and the spot price. It was shown that a reduction of 20-30% of the costs can be achieved by storage or P2P-trading. In combined application this leads to a reduction of 60% of the costs. In [9] a P2P trading system based on a two-tier model was published. In the upper level the aggregators work together and in the lower level the prosumers maximize their profit. Where the aggregators are higher-level instances of several prosumers combined into a cluster. In Mengelkamp et al. [10] two different models for a LEC were presented, a direct P2P trade and a closed order book market. The two trading models are then simulated with an intelligent agent and a non-intelligent agent. The simulation with the intelligent agents shows the best results for self consumption and the lowest average price of energy This paper investigates the effects of implementing a distance metric controlling the energy prices between individual participants of an energy community. Here, prices are proportional to the Euclidian distances between market participants. Another prerequisite is that the local electricity prices are within the spread of the tariff provided by the grid operator, i.e., the difference of feed-in and procurement price. This creates an incentive to participate in the energy community. However, the best business model is of no use if it is not accepted by the customers. Therefore, this study involves the customer group by means of participative research.
The remainder of this paper is structured as follows: In the Methods section, the market model part, the equations describing the MILP model are presented. The consumer participation section covers the methodology used to conduct the survey. In the Results section, the results of the simulations and the survey are evaluated and discussed. Finally, the conclusion section gives a brief summary of the main results.

METHODS

MARKET MODEL

The basis for the computational investigation of the afore mentioned LEM is a so-called Mixed Integer Linear Program (MILP). A MILP formulation of the LEM's electricity market is solved for different market configurations, e.g .: with different price tariffs or with a energy storage system (ESS) for every household. Let P be the set of households selling energy to the global grid at price p_{feed} at a certain time. Let C be the set of households buying energy from the grid at a certain time. Furthermore T is the set over all timesteps of the simulation. Hence, the price p_{ij} for locally traded energy must obey the inequation (1) so that there are no arbitrage possibilities, where $i \in C$ and $j \in P$.

$$p_{feed} \leq p_{ij} \leq p_{grid} \tag{1}$$

The local energy trading is formulated as a linear optimization problem, with the objective of minimizing the energy costs (2) for the consumers. Based on this basic assumption it is secured that the local energy is bought first and at the same time the prosumer gets a higher price for excess energy .

$$min\left(\sum_i \sum_j \sum_k p_{ij} L_{ijk} + \sum_i \sum_k p_{Grid} L_{ik}^{grid}\right) \tag{2}$$

Here p_{ij} is the energy price for the i-th consumer for energy which provided by the j-th prosumer. In (2) L_{ijk} and L_{ik}^{grid} denotes the local energy flows and the energy flows from the global grid to the customers. The constraints in this problem formulation are based on the law of energy conservation.

$$D_{ik} - SOC_{ik}^{discharge} + SOC_{ik}^{charge} = \sum_j L_{ijk} + L_{ik}^{grid} \ \forall\, i \in C \tag{3}$$

Here D_{ik} is the demand of the i-th consumer at timestep k. In equation (3) SOC_{ik}^{charge} is the power which is stored at timestep k in the ESS of customer i and $SOC_{ik}^{discharge}$ is the power which is supplied by the storage.

$$SOC_{ik-1} + T\left(SOC_{ik}^{charge} - SOC_{ik}^{discharge}\right) = SOC_{ik} \tag{4}$$

Here SOC_{ik} is the state of charge of the ESS from consumer k at timestep i and SOC_{ik-1} at the timestep before. In equation (4) T is the stepsize of the simulation. The energy storage is bounded by the three following equations.

$$SOC_{ik} \leq SOC_{max} \tag{5}$$

$$SOC_{ik}^{charge} \leq SOC_{max}^{charge} \tag{6}$$

$$SOC_{ik}^{discharge} \leq SOC_{max}^{discharge} \tag{7}$$

The maximum capacity SOC_{max} of the ESS (equation 5) is set to $13.5kWh$ and the charge and discharge power $SOC_{max}^{charge}, SOC_{max}^{discharge}$ (equation 6-7) are set to $4.6kW$ [11]. The energy storage should only be used to store energy for later consumption. Subsequently, it is necessary that the storage cannot be charged and discharged at the same timestep.

$$\sigma_{ik}^{charge} + \sigma_{ik}^{discharge} \leq 1 \quad \sigma_{ik}^{charge}, \sigma_{ik}^{discharge} \in [0,1] \tag{8}$$

Here $\sigma_{ik}^{charge}, \sigma_{ik}^{discharge}$ are the state variables for charging and discharging, respectively. The state variables are connected to the power flows through equations (9-12).

$$0 \leq -SOC_{ik}^{charge} + (SOC_{max}^{charge} + 1kW)\sigma_{ik}^{charge} \tag{9}$$

$$-SOC_{ik}^{charge} + (SOC_{max}^{charge} + 1kW) \leq SOC_{max}^{charge} \tag{10}$$

$$0 \leq -SOC_{ik}^{discharge} + (SOC_{max}^{discharge} + 1kW)\sigma_{ik}^{discharge} \tag{11}$$

$$-SOC_{ik}^{discharge} + (SOC_{max}^{charge} + 1kW)\sigma_{ik}^{discharge} \leq SOC_{max}^{discharge} \tag{12}$$

The balance for the energy production is modelled by the following equation.

$$P_{jk} = \sum_i L_{ijk} + P_{jk}^{grid} \ \forall\, j \in P \tag{13}$$

P_{jk} represents the production of the j-th prosumer at timestep k. In equation (13) P_{jk}^{grid} denotes the excess energy which is sold to the global grid. The price distribution over the distance is modelled using the sigmoid function, because of the specific "s" shape. The energy price p_{ij} from the j-th prosumer to the i-th consumer is described by the following equation (14).

$$p_{ij}(x_{ij}) = \left(p_{feed} + p_{spread}\frac{1}{1+e^{\alpha_j(x_{ij}-\overline{x}_j)}}\right)(1-\delta_{ij}) \tag{14}$$

Here x_{ij} is the distance between the i-th consumer to the j-th prosumer. In (14) δ_{ij} stands for the Kronecker delta which is in this case identical with the identity matrix. p_{spread} denotes the difference between the energy procurement and the feed in price of the energy provider.

$$p_{spread} = p_{grid} - p_{feed} \tag{15}$$

The median distance $\bar{x}_j$ is the median of the set of distances X_j for all consumers to the prosumer j.

$$\overline{x}_j = med(X_j) \tag{16}$$

The parameter α_j is used to scale the change in price over distance and is chosen such that the first quartile the price is $p_{feed} + \frac{p_{spread}}{4}$.

$$\alpha_j = \frac{-1}{(x_{j,0.25} - \overline{x}_j)ln(3)} \tag{17}$$

The MILP model was implemented with the Python based modelling framework Pyomo [12] [13]. As solver Gurobi [14], version 9.1 was used, were MIP-Gap was set to 5% , which is the gap between the lower and upper bound, and the MIP-Focus was set to 2. This means that the focus during the optimization is on proving the optimality of the solution . The demand profiles for the different households (see Appendix) were generated using the LoadProfileGenerator [15].

CONSUMER PARTICIPATION

To identify consumer groups that accept the LEM model, a k-means cluster analysis was conducted. Therefore, survey data were collected by means of an online questionnaire. The questionnaire measures the importance of different attributes on innovative technologies used in LEM models mainly by means of closed Likert type items. The items were derived from the results of two focus group discussions. One focus group was conducted with consumers, the other one with companies. Exemplary derived attributes are acquisition costs, system reliability during operation, energy efficiency and storage capacity.

Data were collected by means of a panel survey in order to obtain a representative sample for Austria. The sample consists of 450 participants between 30 and 70 years of age (M = 49.88, SD = 10.68). 48% of the respondents were female and 52% male.

In order to create a robust base for a concise cluster analysis, the dimensions of the variables were pooled into fewer scales. For this purpose, a principal component analysis was carried out and a varimax rotation with Kaiser normalization [16,17]. Items with loadings below an absolute value of 0.40 or that load on multiple components were removed. Cronbach's alpha was computed to assess the internal reliability of each scale [18]. By means of a principal component analysis, it was possible to identify five scales describing attributes of technologies in LEM models, as shown in Table 1. All scales have values above 0.60 and can be regarded as at least "questionable" [19]. Due to the explorative character of this study stage, all scales are used for further analyses. Based on these scales, a k-means cluster analysis was conducted to identify groups of respondents with distinct profiles regarding attributes on innovative technologies.

RESULTS

At first, an overview of the results obtained by the questionnaire is given. The five scales obtained by means of a principal component analysis describe the attributes "cost", "environmental friendliness", "technology awareness", "smart storability" and "appearance", as shown in Table 1.

Table 1. Constructs and sample description

Attribute	M	SD	Alpha
Cost	5.44	0.53	0.85
Environmental friendliness	5.29	0.63	0.77
Technology awareness	4.26	0.92	0.66
Smart storability	4.16	0.99	0.63
Appearance	3.80	1.21	0.63

n = 450, M = scale mean, SD = standard deviation, Alpha = Cronbach's alpha

The attribute cost is considered most important (M = 5.44, SD = 0.53), slightly more important than the environmental friendliness (M = 5.29, SD = 0.63) of innovative technologies used in energy market models. Other rather important attributes are technology awareness and popularity (M = 4.26, SD = 0.92) as well as the attribute smart storability (M = 4.16, SD = 0.99). A moderate important attribute is the appearance of the technology (M = 3.80, SD = 1.21).

Based on the five scales presented before, a cluster analysis supports a three-cluster solution. In comparing the groups and their importance associations (see Figure 1), it is apparent that the groups are rather similar with respect to the attributes cost and environmental friendliness. However, they differ greatly among the attributes technology awareness, smart storability and appearance.

The first cluster, comprising 31% of the participants, assigns the lowest importance to the attributes technology awareness (M = 3.79, SD = 0.92), smart storability (M = 3.58, SD = 1.08) and appearance (M = 2.42, SD = 0.64). The second cluster comprises 38% of the participants.

These ones assign all attributes most importance, especially smart storability (M = 4.88, SD = 0.61). The remaining cluster, again comprising 31%, gives moderate importance to the attributes technology awareness (M = 3.88, SD = 0.76), smart storability (M = 3.85, SD = 0.70) and appearance (M = 4.18, SD = 0.72).

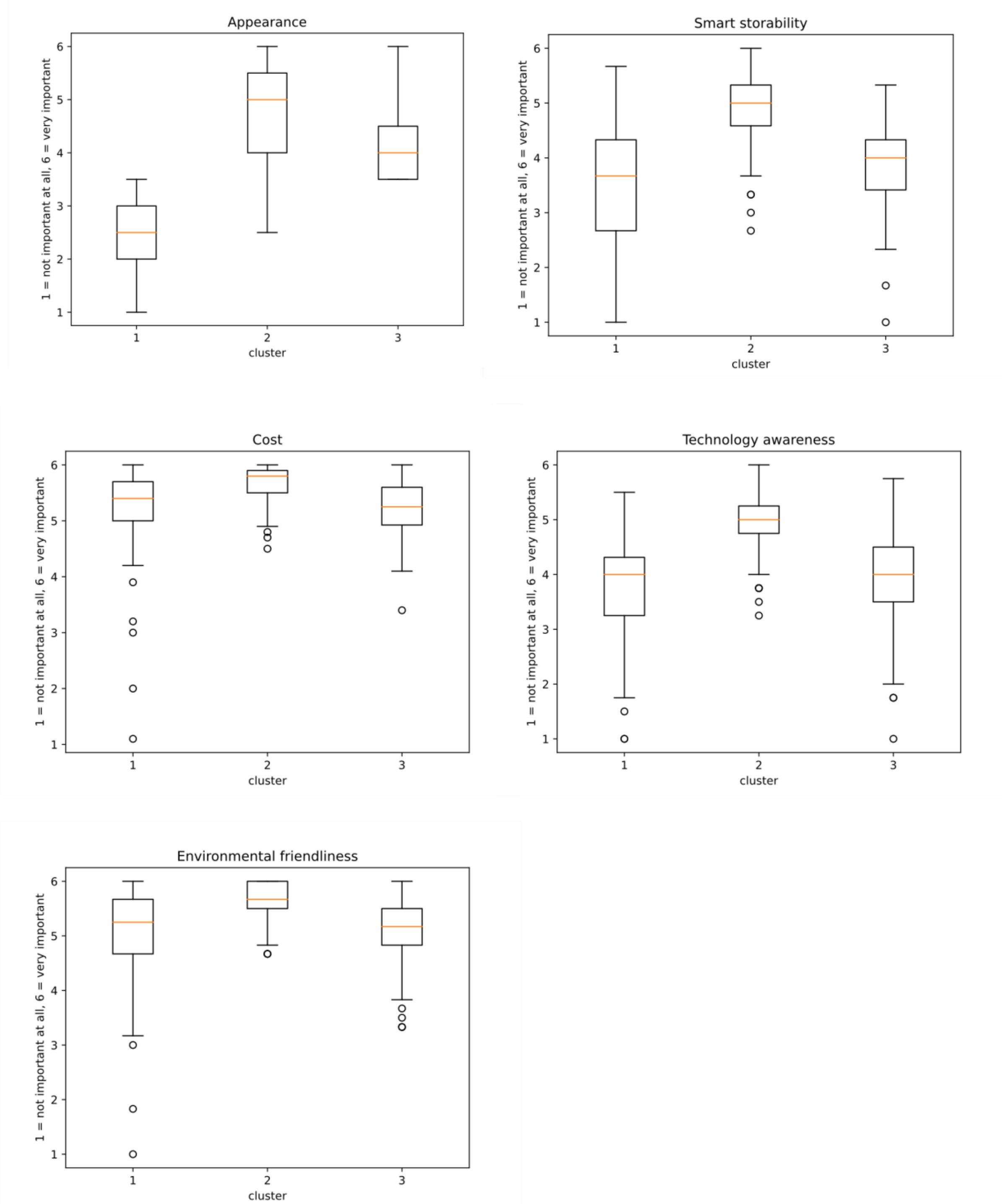

Figure 1 Cluster proportions according to the constructs of attributes on innovative technologies

Based on the data presented in this article, 38% of the population consider electricity storages important in LEM models. Thus, there is an obvious need to investigate the impact of electricity storage in the energy community. Following the survey, the simulation study was conducted using 5 prosumers and 22 consumers. In Table 2, the statistical properties of the LEM can be seen here once for the distances and secondly for the price distributions.

Table 2. Distribution of the consumers

	P1	P2	P3	P4	P5
Consumer distance M	225.5 m	206 m	168.4 m	146.1 m	179.3 m
Consumer distance SD	145.6 m	101.6 m	99 m	106.7 m	114 m
Price M	7.6 ct	7.5 ct	6.6 ct	6.9 ct	7 ct
Price SD	2.4 ct	2.2 ct	2 ct	2.3 ct	2.3 ct

The designation of consumers in this chapter continues to take place as in the "market model" section with c_i where i is defined by $i \in \{\mathbb{N} | 1 \leq i \leq 22\}$. In the following, the individual prosumers are designated using the nomenclature p_j, where j is defined as $j \in \{\mathbb{N} | 1 \leq j \leq 5\}$. The production data of the individual PV systems are simulated using the Python library PVlib[19]. First, an annual simulation of the energy community was conducted using a feed-in tariff of $p_{feed} = 4\, ct. kWh^{-1}$ [21] and an electricity purchase price of $p_{grid} = 10.3\, ct. kWh^{-1}$ [22] is assumed. Figure 2 shows that the difference between procurement price and feed-in tariff, i.e., the spread (equation 15), is an important control parameter of the energy community. The higher the spread, the higher the savings of the consumers, but at the same time the revenue of the prosumer is exactly the opposite. This can be explained by the fact that the spread is the only parameter in equation 5 that can be changed directly.

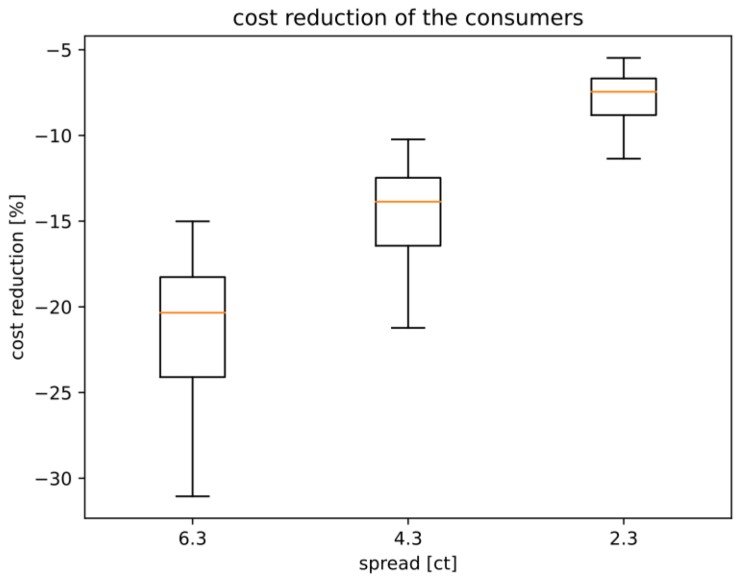

Figure 2 Consumer price reduction dependent on the spread

Figure 3 shows an exemplary power flow in 15-minute resolution for prosumer p3 over 10 hours, which is the relevant timespan for PV production. The blue dotted line represents the load profile. The green line represents the idealized PV production. Furthermore, you can see the energy which is drawn from the grid and the self-consumption of the PV production. Figure 3 shows that the own energy consumption is first paid off by the PV production and only then other energy sources such as the grid or prosumers are used. This can be seen in Figure 3 in the grid consumption, which is only greater than zero if no PV production is available. Based on the data shown in Figure 3, it is shown that the energy flows calculated by the model correspond to those that would be expected. Furthermore, it is necessary that the real distances in the grid between the market participants are also of the same order as the spatial distances.

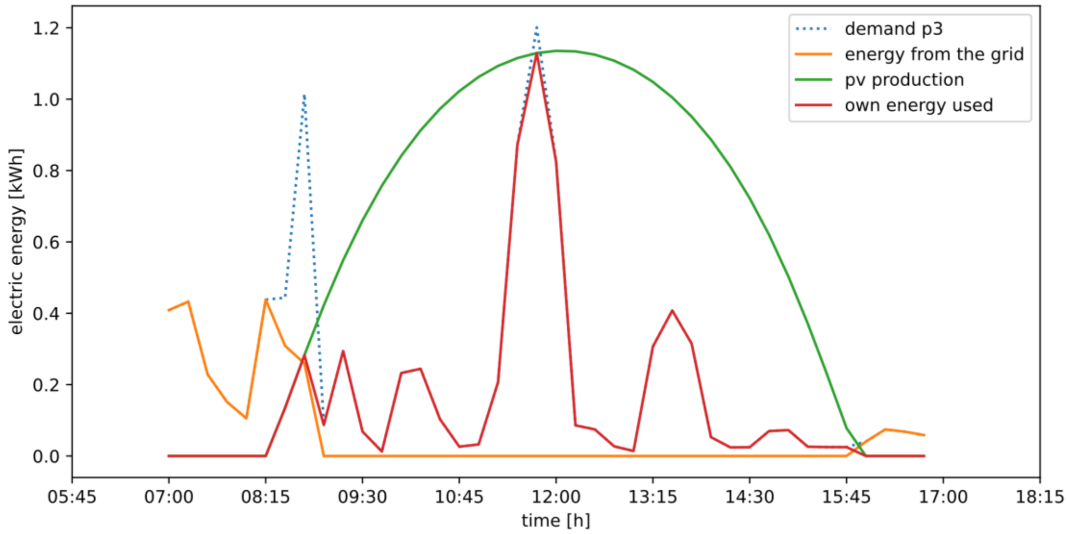

Figure 3 Energy flows for one prosumer

Table 3 summarizes the number of energy trades of each prosumer of the LEM and the traded amount in kWh per year. In total, the LEM prosumers conduct 71 trades with an average of 75.45 kWh (SD = 196.76) per year. This ensures that several households in the vicinity of the prosumers benefit from discounted energy. Furthermore, the results for a scenario where the energy tariff and the demand and production time series are the same, but each household has an additional ESS are shown in Table 3. In this scenario, only 35 energy trades are conducted. A Poisson model indicates the reduced amount of 49.29% (with a confidence interval of [10.94%, 57.10%]) significant ($p < 0.001$). However, the amount of the traded energy increases to 223.17 kWh/a on average (SD = 964.94). A Wilcoxon signed-rank test indicates this difference significant yielding in a small effect ($W = 6{,}965$, $p < 0.001$, $r = 0.24$ [0.11, 0.34]). As a result, there is a greater supply of locally produced energy.

Table 3. Local peer-to-peer energy trading scenario key figures

	Scenario without ESS			Scenario with ESS		
Prosumer	Trades	M	SD	Trades	M	SD
p1	21	122.93	322.31	9	538.70	1,846.51
p2	14	66.30	171.69	6	215.41	783.28
p3	13	75.74	190.35	6	116.26	576.29
p4	11	69.63	130.18	6	129.22	411.20
p5	12	42.67	96.97	8	116.26	371.59
Total	71	75.45	196.76	35	223.17	964.94

Trades = number of energy trades, M = mean traded kWh/a, SD = standard deviation

In Figure 4 the x- and y-axis show the prosumers and consumers of the LEM, respectively. The right plot in Figure 4 depicts the results for the scenario with ESS. In the lower part of the heatmaps where the prosumers are shown, the recognizable diagonal structure results from the self-consumption of the individual prosumers. Furthermore, it can be seen that consumer c20 can massively increase its locally purchased electricity from prosumer p1 based on the ESS, the same is true for consumer c22. A similar case can be seen for the trade between consumer c15 and prosumer p2. The increase of locally traded energy based on electricity storage can also be found in the trading relationship between prosumers p3 and p5. An interesting outcome of the computational studies is that the distribution of energy in the local electricity market is limited to fewer market participants due to the use of electricity storage. The data indicates that effect in the area of energy sold by prosumer p2 to consumers c13-c15. This is because the use of ESS increases the amount of c15 purchased and at the same time decreases the amount of c13 and c14 purchased. The advantage of consumer c15 is certainly due to the fact that it is closest to prosumer p2 ($47.9m$ in contrast to c13 with $105.6m$ and c14 with $121.3m$). In this scenario, it is now clear that the surplus energy is distributed to fewer consumers. This is mainly due to the fact that the individual consumer now also includes his ideal future electricity consumption for the whole year in the energy purchases. What is remarkable here is that through the use of storages in the entire energy community, the share of energy that prosumers sell to the grid operator is reduced to zero.

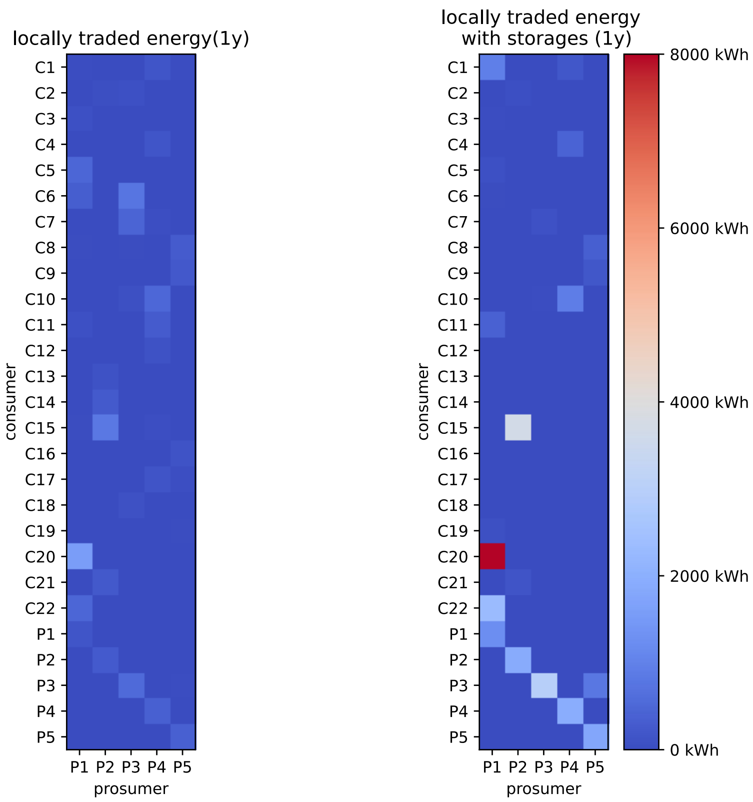

Figure 4 Heatmaps for the cumulative traded energy over one year, without ESS (left) and with ESS (right)

An exemplary SOC for an ESS is shown in Figure 5. It can be observed that the majority of the storage volume is used for stockpiling at the beginning of the year (2020-01-01 – 2020-09-01).

After that, in the period from 2020-09-01 to 2020-13-01 the stored energy is used up and subsequently followed by another charging phase. The weak point of the full year optimization is that the information about consumption and PV production is available in the model for the entire optimization period, in this case one year. This is obviously an idealization of the MILP model subsequently leading to the fact that the results in the model certainly differ from reality.

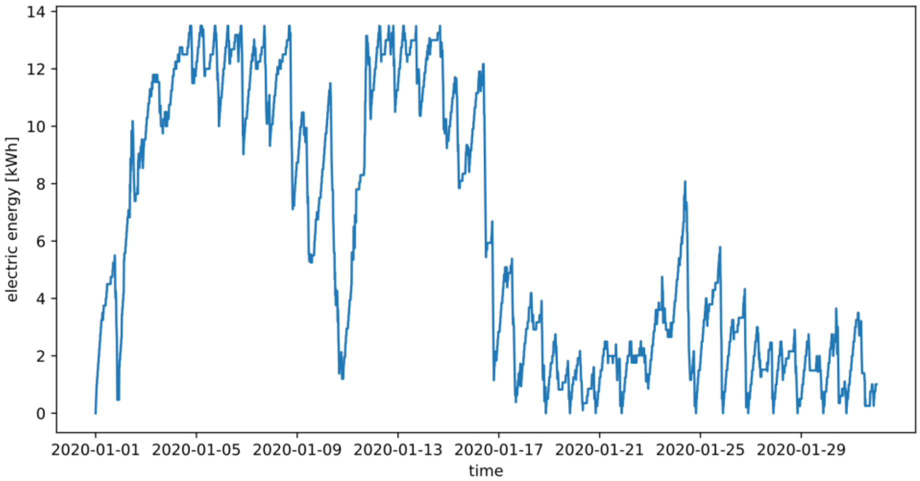

Figure 5 State of charge of the ESS of consumer c5

CONCLUSION

In this article, a marketing strategy for a local energy market is presented. The energy price is calculated on the basis of the distance between the prosumer and the consumer. Since the local energy price is better than the price set by the energy supplier, all market participants have an incentive to actively participate in this market. The calculations presented here show that this creates economic incentives for all participants. Furthermore, the better temporary energy prices, which are available when the PV production exceeds the current consumption in the grid, create the incentive to use flexibilities such as electricity storage. Especially the issue of flexibilities in LECs needs further investigation. This topic is particularly interesting because there is already flexibility potential in households that could be activated at low cost, especially heating and water heating.

However, the market model proposed here only has a very local influence on energy trading, i.e. only consumers located in the immediate vicinity of a prosumer benefit. In order to be able to integrate more users, it is also necessary to gain several prosumers distributed locally. Furthermore, it is necessary to investigate to what extent this model supports the concentration of the complete production power in one point. With increasing PV power, higher and higher prices can be achieved locally. Future efforts focus on simulating the LEC using a reduced time horizon in contrast to the presented annual simulation. Thus, a more realistic behavior of the system components can be obtained and subsequently conclusion for a real-world implementation of such a market strategy can be drawn.

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NOMENCLATURE

Symbols in the manuscript should be included in a nomenclature list grouped into symbols, subscripts/superscripts, and acronyms/abbreviations with placement before the references.

RES	Renewable Energy Sources
PV	Photovoltaic
LEC	Local energy community
LEM	Local energy market
MILP	Mixed Integer Linear Programming
ESS	Energy storage system
p_{feed}	feed in price
p_{ij}	price between the i-th consumer and the j-th prosumer
p_{grid}	procurment price
L_{ijk}	power flow from the j-th prosumer to the i-th consumer at timestep k
L_{ik}^{grid}	power flow from the grid to the i-th consumer at timestep k
D_{ik}	demand of the i-th consumer at timestep k
$SOC_{ik}^{discharge}$	discharge power of the i-th ESS at timestep k
SOC_{ik}^{charge}	charge power of the i-th ESS at timestep k
SOC_{ik}	state of charge of the i-th ESS at timestep k
T	time step of the simulation
σ_{ik}^{charge}	variable which indicates that the i-th ESS is charging at timestep k
$\sigma_{ik}^{discharge}$	variable which indicates that the i-th ESS is discharging at timestep k
P_{jk}	power production of the j-th prosumer at timestep k
P_{jk}^{grid}	power production of j-th prosumer at timestep k which is sold to the grid
x_{ij}	distance between the i-th consumer and the j-th prosumer
p_{spread}	difference between procurment price and feed in price
X_j	set of the distance between all consumer an the j-th prosumer
$\bar{x}_j$	median of the distance between all consumer an the j-th prosumer
$x_{j,0.25}$	first quantil of X_j
α_j	scale parameter of the j-th prosumer price function
M	mean
SD	standard deviation

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APPENDIX

Distances between the market participants

	P1	P2	P3	P4	P5
C1	86.7	149.8	213.8	22.0	56.7
C2	370.0	76.2	67.9	296.6	132.2
C3	107.1	174.3	342.3	111.8	140.5
C4	232.1	196.6	67.9	22.4	231.6
C5	119.5	146.9	262.2	124.1	314.9
C6	96.2	107.1	84.9	131.9	159.8
C7	357.6	242.3	55.7	100.4	265.9
C8	199.5	290.1	95.1	269.5	56.7
C9	296.6	353.7	287.3	417.9	56.7
C10	546.0	256.6	37.6	22.4	286.8
C11	92.0	230.3	209.8	62.3	119.5
C12	370.0	230.3	200.4	75.6	123.2
C13	201.1	105.6	152.3	236.3	153.3
C14	370.0	121.3	200.4	258.8	160.8
C15	269.5	47.9	199.5	67.9	274.5
C16	424.8	353.0	221.1	108.4	123.2
C17	370.0	221.7	370.0	52.8	77.5
C18	232.1	209.8	149.9	140.5	323.6
C19	26.5	353.0	278.6	250.3	47.4
C20	25.7	272.3	75.6	67.7	142.0
C21	425.4	76.2	138.7	357.6	417.9
C22	74.8	363.2	184.6	169.8	399.3
P1	0.0	262.2	123.2	119.5	290.1
P2	262.2	0.0	313.1	129.7	281.2
P3	123.2	313.1	0.0	169.6	46.5
P4	119.5	129.7	169.6	0.0	159.8
P5	290.1	281.2	46.5	159.8	0.0

All values in meter