Evaluation of Energy Sharing on a Local Energy Market Through Comparison of Energy Management Techniques

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Abstract:

Local energy markets (LEMs) are a promising way to solve the challenges of the increasing extension of decentralized energy systems and to promote the further integration of renewable energy sources. LEMs enable costumers with distributed energy resources to trade and share their electrical energy with each other. In the existing literature, the research focus is mostly on the development and evaluation of specific elements of LEMs, such as bidding strategies or market designs. The paper contributes a comprehensive evaluation of a LEM and the quantification of its benefit regarding the market-based device operation. For the evaluation in terms of financial outcome and local energy exchange, a centralized and a decentralized operation optimization serve as upper and lower references. In centralized optimization, the system boundary comprises the entire neighbourhood. In decentralized optimization, each building is balanced separately. For the LEM, we introduce a distributed market design with the involvement of an auctioneer. We focus there on the implementation of learning bidding strategies and a double-sided auction with non-iterative market clearing rules. For all three energy management techniques, the operating schedules of the devices are determined using mixed-integer linear programming. In several case studies we investigate different neighbourhoods in order to evaluate the influence of different technologies and their penetrations as well as the impact of the building stock in terms of building type and construction year. We evaluate the market outcome with multiple key performance indicators (KPIs) such as the supply- and demand-cover-factor, the total operation costs and the peak load. The results show that total energy costs can be reduced by up to 6.4 %. For the energy exchange, it is shown that the electricity surplus is up to 72 % and the electricity demand of the QUartier decreases by up to 6.8 % compared to the decentralized optimization and increases by up to 14.3 % compared to the centralized optimization. Further, we noted up to 46.2 % higher peak loads.

Keywords:

Local Energy Market, Evaluation, Energy Trading, Optimization Approaches

1. Introduction

For a successful energy transition, the energy supply in neighborhoods has to undergo substantial developments. Two of these developments are the increasing integration of distributed energy resources (DERs) as well as the electrification of the heating and mobility sectors. The end-users are responsible for the purchase of the corresponding devices. LEMs however can promote the further integration of renewable energy sources by giving households financial incentives. Auction-based local energy markets enable the trading and the exchange of energy between producers and consumers within a local area and participating households can reduce their energy costs this way.

For LEMs various market designs have already been developed. They differ with regard to the degree of centralization and topology, which influences the market clearing as well as the decision-making processes of operating and bidding strategies [1, 2]. Market clearing rules which select the admitted participants, determine the trading volumes and prices can be different for LEM. Further, several pricing mechanisms such as uniform pricing or pay-as-bid can be used in electricity markets [3, 4]. Also markets auctions can be divided into different types. These include whether the auction is open-cry or sealed-bid and whether it is one-sided or double-sided [5]. Various bidding strategies with different computation methodologies can be applied for placing promising bids on the market [6].

However, to fully understand the potential benefits and drawbacks of market processes there is a need of finding appropriate evaluation methods. They help to identify the most relevant technical aspects of the market design that increase efficiency and profitability of the electricity trading between consumers and prosumers on LEMs.

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Within this work, we propose an evaluation methodology for LEMs in which decentralized and centralized optimization serve as worst-case and best-case references. We specify an auction-based market and a neighborhood of 20 households. The building energy systems (BES) of the households contain of heat pumps (HPs), combined heat and power plants (CHPs), thermal energy storages (TES) as well as photovoltaic (PV) and batteries (BAT). With different scenarios we analyze the influence of the different technology shares and the usage of a price signal for the LEM. We analyze the operation of a neighborhood regarding the energy exchange within and with the superordinate grid, the costs and revenues as well as the the caused emissions.

1.1. Evaluation of Local Energy Markets

The concept of LEMs has gained great traction in recent years for promoting renewable energy and energy efficiency. Evaluations of LEMs are important for understanding the market dynamics like trading volumes within a neighborhood and the resulting prices for the single households. Comprehensive and detailed evaluations are necessary to improve market outcomes in terms of trading efficiency, price fairness and thus cost savings for the households.

Zhou et al. [7] evaluated three different energy sharing mechanisms and two techniques for the convergence of market trading. The used mechanisms were supply-demand-ratio, mid-market rate and bill sharing mechanisms which mainly differ in terms of their iterative pricing. To achieve convergence in trading, change rates of prices and energy volumes were limited and a learning process is involved in the prosumers decision-making process. Three economic indexes and three technical indexes are proposed for the evaluation. The economic KPIs measure the realized overall benefits, the individual benefit compared to trading with fixed tariffs and the income equality within the households. With the technical KPIs the energy exchange with the superordinate grid, the peak power and the electricity demand that is covered by local generation are measured.

Okwuibe et al. [8] analyzed the electricity trading in hierarchical LEMs for different market structures. The market structure differs in the number of layers which result by introducing sub-LEMs that limit the number of trading end-users. Additionally, two market clearing mechanisms which are the double-sided pay-as-bid and the double-sided pay-as-clear are investigated. The different combinations of market structures and market clearing mechanisms are evaluated with KPIs like cost savings through market trading, the internal and external energy exchange, and average trade rate with varying market clearing mechanisms. Finally, the individual savings of different consumer and prosumer types are analyzed.

Sousa et al. [9] gave a comparison of different market designs with differences in the level of centralization and communication structure. A full peer-to-peer, a community-based, and a hybrid peer-to-peer market were analyzed and compared in terms of welfare, total import costs and export revenues to the superordinate grid as well as energy exchange within the market.

El-Baz et al. [10] identified the major factors influencing the market outcome and energy exchange. Several aspects of market design, microgrid configurations and user behavior were investigated for selected scenarios. For example the number of installed PV systems and their capacities are studied. Based on a double-sided auction-based LEM simulation the impact on the market dynamics and energy balance are analyzed and evaluated. For the evaluation, a reference model without a market-based operation is implemented. The four key performance indicators self-sufficiency, self-consumption, peak load and costs were calculated.

Schiera et al. [11] simulated a LEM with two trading systems that differ in terms of the pricing mechanisms. The pricing mechanisms and different member compositions were evaluated regarding the benefits of the neighborhood to identify new considerations in market design. A central mixed-integer linear programming was used as optimization model. The selected member compositions had various penetrations of PV systems and batteries. The results were evaluated with economic and technical indicators like single and total savings, the imported and exported energy as well as the self consumption ratio and the peak-to-average ratio.

Cramer et al. [12] compared an iterative auction-based LEM with a central optimization approach and a self-consumption approach. By aiming to maximize social welfare, an independence indicator is determined that relates self-consumption and traded energy to electricity demand within the neighborhood. This indicator determined for different flexibility levels.

1.2. Contributions

Most papers concentrate on analyzing different market designs to evaluate specific aspects of the design like market structure, market clearing rules or bidding strategies. However, there is a lack of publications that provide comprehensive evaluations of LEM by comparing them with other energy management techniques for neighborhoods. While there are many publications that provide detailed analysis of different market designs with a bunch of KPIs, only few publications deal with LEM using other optimization approaches and these existings ones rather offer superficial/simplified evaluations.

Furthermore, few studies still deal with the participation of flexible heat generators in LEM while most studies focus on the participation of prosumers that have PV systems and batteries.

The main contributions of this paper to research are:

- We implement two operational optimization approaches to evaluate the performance of an auction-based LEM in a comparative and comprehensive way. The decentralized optimization approach provides a lower benchmark without energy trading or coordinated energy exchange. The centralized optimization approach provides a upper benchmark with a controller having all informations.
- We implement an auction-based LEM where individual market participants perform their decision-making processes autonomously without information about other's trading behavior.
- We analyze the impact of the heat generators' shares by varying the number of the corresponding devices.
- We analyze the importance of approaches for shifting consumption and generation to the same times with the exemplary application of a price signal.
- We compare different prosumer types within the neighborhood, namely prosumer with PV systems and batteries and prosumer with CHP.

The following sections are structured as follows. In section 2., we firstly highlight the differences in modeling and balancing of the decentralized and centralized optimization approaches and introduce the evaluated LEM. Afterwards, we present the KPIs and the analyzed scenarios. We compare and evaluate the results on the scenarios in section 3.. The evaluation results finally are discussed and further research needs identified in section 4..

2. Methodology

2.1. Decentral and central optimization approaches

Decentralized optimization and centralized optimization are two different approaches to set-up optimization problems. The key difference between these optimization approaches are the degree of coordination and the decision-making authority. The difference in balance boundaries is shown in figure 1 by the red dashed lines.

Decentralized optimization refers to a scenario where the components or agents act autonomously and communicate with each other only when requested. Decentralized optimization can be more robust and efficient in situations where communication between agents is limited or when the system is large and complex. [1]

Centralized optimization refers to a scenario where a single entity, typically a central controller, collects all relevant information and decides based on that information to optimize the entire system. The central controller has complete control over every entity of the system and can optimize it as a whole. A centralized optimization model can run quickly into high complexity and scalability problems. [1]

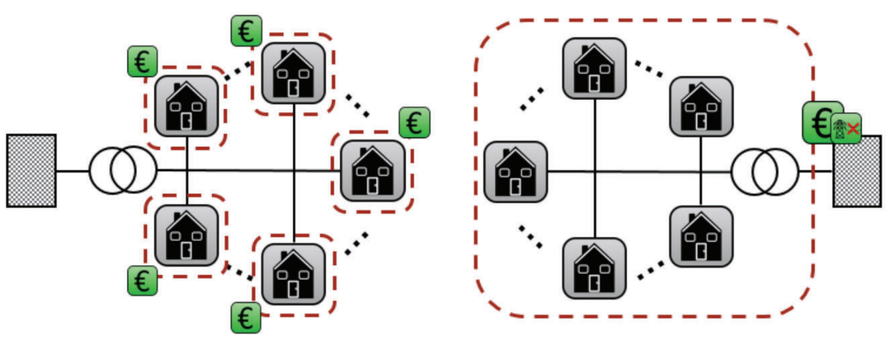

Figure 1: Balance boundaries (red dashed lines) for decentralized optimization (left) and centralized optimization (right)

For the optimal operation of the single BES and the entire neighborhood, we implement mixed-integer linear programs (MILP) of the corresponding systems. The BES model consists of constraints for the minimum and maximum power of the devices as well as for the maximum capacity of the energy storages. The state-of-charge of the storages is inserted as time-coupling constraint. The electricity balance of the BES is given by

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equation 1 in which the power of the devices is coupled for every time step t with electrity demand from and the feed-in power into the grid. Thus, we assume that each building is connected to the local distribution network.

$$P_{\text{imp,t}} + P_{\text{PV,t}} + P_{\text{CHP,t}} + P_{\text{BAT,dch,t}} = P_{\text{inj,t}} + P_{\text{HP,t}} + P_{\text{ER,t}} + P_{\text{dom,t}} + P_{\text{BAT,ch,t}} \tag{1}$$

The objective functions of the decentral optimization approach are the minimization of the operational costs incurred from the purchasing minus the revenues for feed-in (equation 2).

$$min \quad C_{\text{BES}} = \Delta t \cdot \sum_{t \in T} (p_{\text{gas}} \cdot P_{\text{gas,t}} + p_{\text{imp}} \cdot P_{\text{imp,t}} - p_{\text{inj}} \cdot P_{\text{inj,t}}) \tag{2}$$

For the modeling of the entire neighborhood, the previously mentioned equations are extended by the electricity purchase and the electricity feed-in of the neighborhood into the superordinate grid level at the grid connection point (GCP) as well as the natural gas purchase (equations 3 - 5).

$$P_{\text{gas,t}} = \sum_{n} P_{\text{n,gas,t}} \tag{3}$$

$$P_{\text{GCP,imp,t}} = \sum_{n} P_{\text{n,imp,t}} \tag{4}$$

$$P_{\text{GCP,inj,t}} = \sum_{n} P_{\text{n,inj,t}} \tag{5}$$

For the centralized optimization approach, the objective function is the minimization of the operating costs and additionally of the peak load. In this case, the operating costs are the purchasing costs minus feed-in revenues at the local network station, because the system boundary includes the entire neighborhood.The peak load is considered in the objective function through a penalty factor (equation 6).

$$min \quad C_{\text{NH}} = \Delta t \cdot \sum_{t \in T} (p_{\text{gas}} \cdot P_{\text{gas,t}} + p_{\text{imp}} \cdot P_{\text{GCP,imp,t}} - p_{\text{inj}} \cdot P_{\text{GCP,inj,t}}) + pen \cdot P_{\text{GCP,inj,t}} \tag{6}$$

2.2. Local Energy Market Model

In this work, we evaluate an auction-based LEM with a hierarchical structure. This structure consists of two levels, the market platform and the operating system, as shown in the figure 2. On the market platform, the auctioneer performs market trading according to predefined rules. On the operating level, the building energy management system of each household determines autonomously the operational schedules of the corresponding devices taking into account a price signal sent by the market platform.

In the first step of the market procedure, each BES performs its operational optimization considering the price signal in the objective function instead of the fixed tariffs. With the information of the external power demand or the energy surplus to be fed into the power grid, the market agents create then the bids. In addition to the amount of energy, these bids also consist of the bid price. The market agents determine the bid price by using a Roth-Erev learning algorithm as bidding strategy. This algorithm combines two principles, namely reinforcing propensities regarding positive outcomes and flattening the learning curve over time. By this, the market agents consider the results of the historical market rounds as well as the success of the bids, which is incorporated into the probability distribution for future bidding [13]. [14, 15] have shown that the Roth-Erev learning algorithm enables the households to achieve promising economic benefits in energy trading.

In the second step, the auctioneer collects all the submitted bids of the supply side and the demand side and sorts them in step functions according to the bid prices. The underlying auction mechanism determines the market clearing price and the clearing quantity based on the received bids. In this work, the uniform pricing mechanism and therefore the intersection of the sorted supply and demand step functions is used to determine the market clearing price and the clearing quantity. [4]

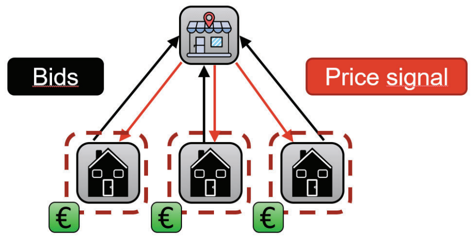

Figure 2: Structure of the local energy market and data exchange during market procedures

After the market clearing, the auctioneer sends the respective market outcome back to the market agents and the successful trades are performed. If in some market rounds there is insufficient local generation to satisfy the demand or excess generation, a superordinate grid with constant tariffs serves as a backup. Finally, a price signal is computed with the supply-demand-ratio mechanism and sent to the BES. This signal indicates, how the price trend for trading is going to develop in the next market rounds. The calculation is based on the hourly values of total supply and demand in the future time steps [7].

2.3. Key Performance Indicators

In this section, we introduce the following KPIs used to analyze the neighborhood operations of the three approaches and to and evaluate the auction-based market trading.

- Single costs and revenues: summed costs and revenues of the individual households within the neighborhood.
- Import and export energy: summed energy quantities imported from and exported to the superordinate grid.
- DCF and SCF: two energetic indicators that are calculated based on load and feed-in profiles of the BES. With them the coverage of the local electrical load by the local electrical generation and the share of self-used generation within the neighborhood are calculated. [16]
- Peak load: incurred during operation measured at the neighborhood's GCP.
- Emissions: caused by device operation in the neighborhood.

2.4. Use Case And Scenarios

To model the neighborhoods, we use our developed tool called "districtgenerator" [17]. It generates the annual profiles of the electrical load and heat demands of each building by using different tools. Using the TEASER tool, envelope areas and building physics parameters are calculated based on building type, floor area and construction year [18]. Additionally, it simulates thermal demands using a 5R1C model, while generating annual electrical load profiles and domestic hot water profiles through stochastic methods [19–21].

The building energy systems within the neighborhood contain electricity based heat generation devices for the heat provision. The single-family houses are equipped either with heat pumps or gas boilers, while the multi-family houses are heated with combined heat and power plants or gas boilers. Accordingly, electricity is also generated locally in the multi-family houses by the combined heat and power plants. Electricity generation at the single-family houses is achieved by PV systems in selected scenarios. Thermal storage and electrical battery storage systems are also taken into account. The technology penetrations vary across the studied scenarios and are presented in table 1.

In this study, we size the heat generators in accordance with german standards [22] and thermal energy storages based on [23]. The PV modules have standard size of 1.65 m^2. In the scenarios with PV systems, there are 20 modules per single-family house with a south orientation and an inclination of 35°, whereby the peak power is 6.38 kW. Furthermore, we use the specified discharge/charge power of 3.4 kW and storage capacity of 5 kWh, which data of commercial batteries.

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Scenario	Constr. year	HP	CHP	Boiler	PV	BAT
16 HP	1996	80 %	20 %	0 %	0 %	0 %
8 HP	1996	40 %	20 %	40 %	0 %	0 %
0 HP / 4 CHP	1996	0 %	20 %	80 %	0 %	0 %
8 PV	1996	40 %	0 %	20 %	40 %	0 %
8 PV + BAT	1996	40 %	0 %	20 %	40 %	40 %

Table 1: Selected scenarios with the construction year and the share of devices

For the centralized and decentralized optimization approaches, the purchase electricity price is 42.0 ct/kWh, the feed-in tariffs are 8.2 ct/kWh for PV and 19.28 ct/kWh for CHP. The cost of the gas is 13.4 ct/kWh. For energy trading on the LEM, the purchase electricity price represents the maximum bid price and the feed-in tariffs represent the minimum bid price. We perform the operational optimization approaches and the LEM for a time horizon of an entire year.

For the Roth-Erev learning algorithm, we selected an experimentation parameter of 0.99 and a recency parameter of 0.08. Each scenario was pre-simulated for one year to obtain pre-learned propensities.

3. Results

3.1. Impact of the heat generator shares and the price signal

This section analyzes the summed costs and revenues of the households and the energy exchange at the GCP for different shares of heat pumps. Figure 3 shows the corresponding results. The costs for electricity and gas (dashed bars) as well as the revenues for electricity feed-in (lightened bars) are compared for different shares of heat pumps. Additionally, the electricity supply and feed-in (lightened bars) to the superordinate power grid are considered. The number of heat pumps supplying single-family homes varies, while all four multi-family homes are supplied with CHPs.

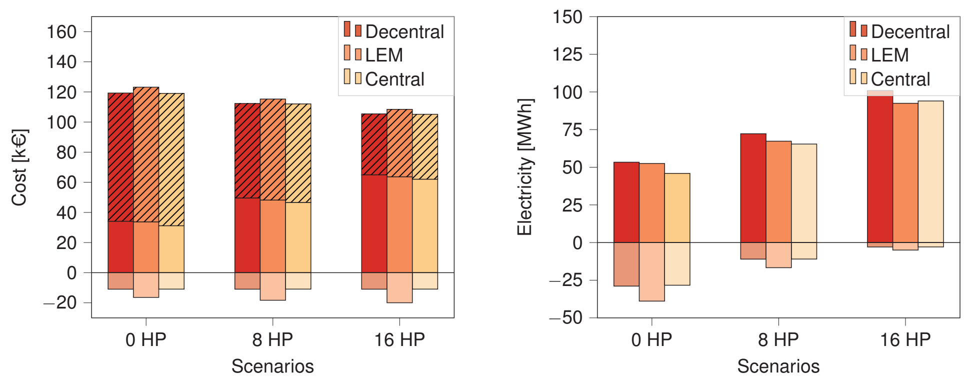

Figure 3: Summed costs and revenues of the households (left) and the energy exchange at the GCP (right) for different shares of heat pumps

In all three scenarios, the summed electricity costs of the households are highest with the decentralized optimization approach, amounting to 34.1 k€, 49.6 k€, and 65.0 k€, respectively. In contrast, the total costs for electricity consumption with the centralized optimization approach are the lowest, amounting to 31.2 k€, 46.6 k€, and 62.0 k€, respectively. Through electricity trading on the LEM, the total costs amount to 33.8 k€, 48.2 k€, and 63.7 k€. Compared to the decentralized optimization approach, the costs are thus reduced by 1.1 % to 2.7 %, while compared to the centralized optimization approach, the costs are 2.7 % to 7.6 % higher. Regarding electricity feed-in, households can achieve the highest compensation through trading on the LEM. These amount to 16.4 k€, 18.3 k€, and 20.0 k€, and are thus up to 83.0 % higher compared to both the decentralized and centralized optimization approach. Noticeable about the results is that the gas costs are highest with 44.8 k€, 67.0 k€ and 89.4 k€ for market-based operation. Thus, compared to the centralized optimization approach, 3.8 % more gas is consumed. Compared to the decentralized optimization approach, gas consumption is up to 10.7 % higher.

The price signal ensures that loads are shifted over time and that heat storages are loaded higher. This increases households' chances of benefiting from lower market prices, but also results in higher energy losses of the heat storages. To compensate these losses, the electricity demand of the heat pumps increases on the

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one hand, and on the other hand the gas consumption of the CHPs increases. Furthermore, the operation of the heat pumps is no longer exclusively optimized for favorable outside temperatures to achieve the highest COP, which further increases the electricity demand of the heat pumps.

Another noticeable aspect are the higher revenues for electricity feed-in with an increasing share of heat pumps while the number of CHPs remains constant. The reason is the resulting market clearing prices of the individual scenarios. The average market clearing price is 30.7 ct/kWh in the scenario without heat pumps, 32.8 ct/kWh in the scenario with 8 heat pumps, and 34.2 ct/kWh in the scenario with 16 heat pumps. This increase in the average market price can be explained, on the one hand, by the increased demand for electricity and, on the other hand, by the learning bid strategies. With increased demand and a constant supply on the LEM, bids with higher prices are offered by the learning bidding strategy in the long term to increase the chance of being considered in the market clearing process.

Considering the total energy costs minus the revenues, the LEM performs better up to 1.4 % in the scenario without heat pumps, up to 4.3 % in the scenario with 8 heat pumps, and up to 6.4 % in the scenario with 16 heat pumps. The best result in the last scenario is mainly due to the high revenues. The highest average market price of 34.2 ct/kWh in this scenario, explains the highest revenues, although the number of CHPs and thus the electricity generation remains approximately the same. The high market prices are further an indication that the sellers profit more from energy trading than the buyers, because the difference from the market prices is on average smaller to p_{max} than to p_{min}.

		CO_2e [t]	Peak load [kW]	SCF [%]	DCF [%]
16 HP	Decentral	148	65	95	35
	LEM	159	95	93	43
	Central	155	63	95	36
8 HP	Decentral	210	40	81	39
	LEM	222	62	77	46
	Central	216	34	81	4
0 HP	Decentral	274	31	49	34
	LEM	287	33	47	40
	Central	280	24	50	38

Table 2: Results of caused emissions, peak load, self-cover-factor and demand-cover-factor

As shown in figure 3, the amounts of electricity fed into the superordinate grid are highest in all three scenarios for the market-based operation. Compared to the centralized optimization approach, these amounts are 37.2 % to 72.0 % higher, and compared to the decentralized optimization approach they are 34.4 % to 69.4 % higher. These results can be explained by the fact that increased load shifts in market-based operation of the CHPs lead to greater heat losses and the compensation of these losses results in increased electricity generation. These results are also reflected in the results of the self-cover-factor as seen in table 2. With a high share of heat pumps, the absolute difference in electricity feed-in between market-based and optimization-based operation is significantly lower. Electricity consumption is up to 6.8 % lower than in the decentralized optimization approach in all scenarios. Compared to the centralized optimization approach, the electricity consumption of the quarter is 14.3 % and 3.0 % higher in scenarios 1 and 2, respectively, while it is 1.6 % lower in scenario 3. These results show that the used price signal improves local electricity consumption, which is also supported by the demand-cover-factors in table 2.

Figure 4 exemplarily shows the course of the residual load for a cold week of scenario 2. During this period, three peak loads can be seen for the decentralized optimization approach. These peak loads are avoided both with the centralized optimization approach and with the market-based operation under usage of the price signal. Nevertheless, the results of the peak loads for the entire seasonal period (table 2) show that the peak loads are significantly higher at individual time steps. This presumably happens when the price signal triggers opposing operational adjustments. Heat pumps collectively shift their electricity consumption to a favorable time step, while the power generation of the CHPs is shifted away from it.

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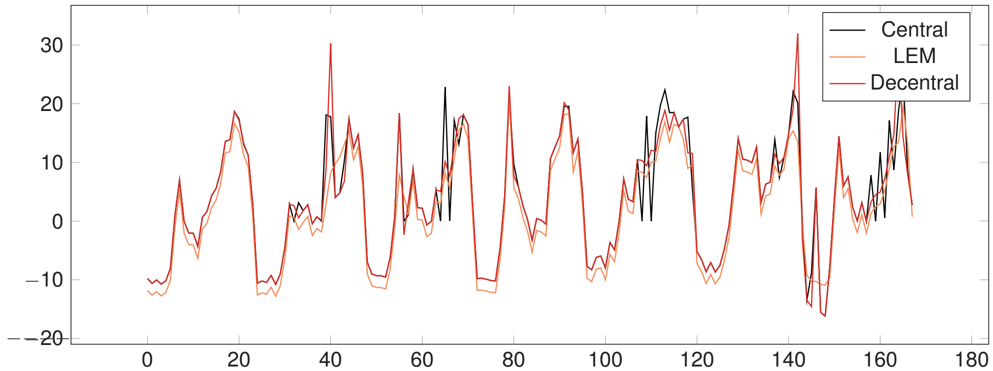

Figure 4: Residiualload of the neighborhood at the GCP

3.2. Impact of the PV systems and batteries

The following section analyzes the impact of the electricity generation systems on the market outcomes and electricity exchange of the neighborhood. Scenario 2, in which four CHPs provide electricity generation in the neighborhood, scenario 6, in which six PV systems generate electricity in the neighborhood, and scenario 7, in which BESs have battery storage in addition to PV systems, are compared. In these three scenarios, heat is provided to six single-family homes by heat pumps.

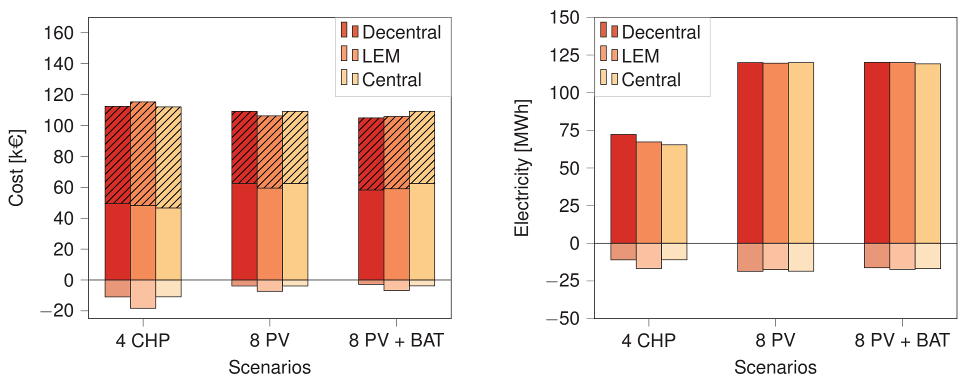

Figure 5: Summed costs and revenues of the households (left) and the energy exchange at the GCP (right)

Figure 5 shows the results of the summed costs and revenues of the households and the energy exchange at the GCP. As seen in the previous section, the revenues are again higher for the scenarios with PV systems with the market-based operation than with the optimization-based operations. While the cost of electricity and gas is slightly lower for the PV scenarios compared to the CHP scenario, the revenues are lower.

Figure 5 further shows that the market-based operation with price signal has only a slight impact on the electricity exchange at the GCP. This is due to the electricity demand of the heat pumps, which exists especially in the cold periods. At these times, however, there is less solar irradiation and thus less power feed-in from the PV systems. Consequently, the potential energy exchange and the trading volume is significantly lower.

		CO_2e [t]	Peak load [kW]	SCF [%]	DCF [%]
4 CHP	Decentral	210	40	81	39
	LEM	222	62	77	46
	Central	216	34	81	41
8 PV	Decentral	175	58	61	19
	LEM	172	57	63	20
	Central	175	47	61	19
8 PV + BAT	Decentral	174	58	53	13
	LEM	172	76	65	19
	Central	174	47	64	20

Table 3: Results of caused emissions, peak load, self-cover-factor and demand-cover-factor

Table 3 shows the remaining results. When comparing operating methods, again that the market-based operation with the usage of the price signal causes significantly increased peak loads. The comparison between generation technologies shows that PV systems causes significantly less emissions, but also results in lower local self-supply and local self-consumption compared to the scenario with CHPs.

4. Conclusions

In this study, we proposed an evaluation of a local energy market by comparing it with a decentralized and a centralized optimization approach. An auction-based LEM with uniform pricing as market clearing process was introduced and learning bidding strategies for the market agents were implemented. To obtain convergence in supply and demand on the market, a price signal was sent to the building energy systems, which served as input to the operational optimization. We examined a neighborhood with single-family and multi-family buildings and analyzed several scenarios with different shares of heat pumps, combined heat and power plants, PV systems and batteries.

We demonstrated that auction-based energy trading can reduce household electricity costs compared to operating the decentralized optimization approach. However, we must emphasize that in the decentralized and centralized optimization approaches, no deviating tariffs for electricity purchase and feed-in were possible. Therefore, it should be examined whether the costs and revenues of the two optimization-based approaches should be allocated with adjusted tariffs in the future in order to improve comparability.

For the overall cost and revenue analysis, the costs and revenues of each household were summed. In the future, a comprehensive evaluation should also examine individual costs and revenues more detailed to determine the fairness of the energy trading.

We have also shown that market-based operation leads to more energy inefficient operation of heat generators. The operation of the heat pumps is no longer geared only to outdoor temperature, and the increased use of heat storage increases heat losses in the neighborhood. Therefore, an indicator should be considered in the future that takes the energetic losses into account.

By using the price signal, we were able to show that the energy exchange and trading compared to decentralized operation can be improved. However, higher maximum peak loads indicate that at individual time steps, load shifting from the generation and demand side can result in opposite directions. Considering that we have used a price signal based only on supply and demand quantity, in the future parameters should include in the calculation of the price signal, which avoid higher peak loads. In addition, to improve energy exchange and trading for auction-based LEM, further techniques for convergence of generation and demand need to be identified and analyzed.

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