OPTIMIZING LOCAL ENERGY TRADING IN RESIDENTIAL NEIGHBORHOODS: A PRICE SIGNAL APPROACH IN LOCAL ENERGY MARKETS

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ABSTRACT

Energy communities can be created in neighborhoods in a geographically and structural delineated area. Local energy markets in energy communities offer a promising approach to promote local balancing of distributed power generation and consumption. These markets enable direct energy trading between prosumers and consumers, resulting in financial benefits. These benefits are dependent on local trading volumes, which can potentially be increased by shifting load profiles. Employing a price signal can enable this coordination of electricity supply and demand through the activation of operational flexibility. In this study, we develop a price signal for a local energy market utilizing price-based demand response programs. Market participants leverage the price signal for energy management to minimize their total costs. These participants can be building energy systems that feed in or purchase electricity from the grid. The price signal's determination involves a linear optimization problem that seeks to minimize the neighborhood's residual load. To estimate the potential shifts in electricity demand and supply in response to the price signal, we employ a flexibility index for the neighborhood. Given uncertainties in weather and demand forecasts, a stochastic approach is applied when optimizing the price signal. The chance constraint method is used to minimize the risk of a high residual load. We evaluate the impact of the price signal on the trading in the local energy market. Moreover, we compare the optimization-based stochastically determined price signal with a deterministically determined and a constant price signal. As a case study, we analyze a residential neighborhood in Germany with a distributed local energy market under various system technology scenarios. These scenarios result in neighborhoods with high temporal coverage or potential mismatches between generation and consumption due to generation volatility. The study analyzes firstly the influence of price signals and neighborhood characteristics on local energy market trading using selected key performance indicators. Secondly, we examine the benefits of employing a stochastically generated price signal in a system affected by uncertainties. In addition, the flexibility index and the duration of the flexibility event are further analyzed. The results indicate that implementing a price signal can lead to an increased financial benefit of up to 162 % per month for all market participants. Additionally, the supply cover factor can increase by up to 5.65 pp, allowing for the purchase of more self-generated electricity in the district. However, these effects are only achievable in districts with sufficient flexibility potential, such as extra storage, and without already existing temporal coverage of supply and demand.

1 INTRODUCTION

In 2019, the European Union (EU) adopted the Clean Energy Package as an energy policy framework to reduce greenhouse gas emissions and achieve the objectives of EU's Paris Agreement (European Union, 2019). This legislative framework encourages small market players to participate in the energy system and promotes decentralized electricity generation and consumption. Energy sharing in energy communities is promoted to overcome the challenges of changing power generation and distribution. The integration of renewable and mainly decentralized energy sources is causing higher fluctuations in

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electricity generation and grid load, which is coupled with increased electricity demand from sectors such as heating and mobility (Wagner et al., 2021). In renewable energy communities (REC) members have the right to share energy that is produced within the community (Babilon et al., 2022; Nitzsche and Huneke, 2020). As a new market structure, Local Energy Markets (LEMs) allow prosumers to bid for their own supply and demand. When embedded in RECs, LEMs enable local energy trading to directly meet local energy demand. This provides financial incentives as market participants benefit from potentially favorable prices (Javadi et al., 2022; Mengelkamp et al., 2017a). The increased number of market participants introduces complexity in terms of market operation and coordination to ensure local energy balance (Wagner et al., 2021). Demand Side Management (DSM) is a strategic approach that leverages consumer flexibility to influence the energy demand. Dynamic price signals within LEMs can promote local balancing of demand and supply by exploiting operational flexibility. DSM has been mainly considered in central energy markets. In an LEM prosumers, incentivized by these price signals, can iteratively adjust their supply and demand bids to decrease the power mismatch in the neighborhood (Albadi and El-Saadany, 2008; Cramer, 2021). The main objective of this work is to attain a high coverage of electricity demand and supply within the LEM framework, promoting a more resilient and locally balanced energy system. Therefore, we develop a dynamic price signal, that influences the supply and demand side. The price signal takes uncertainties into account.

This paper is organized as follows: Subsection 1.1 presents the fundamentals about LEMs, DSM, and discusses the current knowledge about demand response (DR) programs such as price signals. Subsection 1.2 shows the potential influence of uncertain parameters in energy models and provides an overview of the state of the art in uncertainty in energy models. Section 2 explains the methodology, starting with a description of the analyzed market model. The section examines the price signal, including deterministic and stochastic approaches, and defines use cases and key performance indicators (KPI). The results are presented and discussed in section 3. Section 4 concludes with key takeaways and provides an outlook for future research.

1.1 Demand Response in Local Energy Markets

Community-based LEMs enable the provision of flexibility by coordinating decentralized power generation, energy storage and consumption (Mengelkamp et al., 2018a). There are two directives, the Electricity Market Directive (EMD) and the Renewable Energy Directive II (RED II), that provide key guidelines for energy communities in the EU. According to RED-II and EMD, energy communities are non-commercial legal entities that are founded on the open and voluntary participation of their members. Energy communities may be formed either locally, e.g. in neighborhoods, or virtually, with a group of members pursuing a common purpose (Deutsche Energie-Agentur (Hrsg.), 2022). A neighborhood is defined as a geographically and structural delineated area containing multiple buildings that are interconnected by an energy infrastructure and are supplied by a general network. This network includes at least one energy generation facility and multiple end users (J. D. Schölzel et al., 2023).

LEMs provide a market platform for local, private actors to trade locally generated amounts of electricity of their choice (Mendes et al., 2018). Prosumers and consumers are actively integrated into the energy system and become market participants (Mengelkamp et al., 2018, 2017). Trading conditions are established between market participants (Reis et al., 2021). LEMs facilitate a local balance of energy supply and demand. By trading electricity directly, market participants can gain financial benefits and are incentivized to integrate more renewable energy sources into the LEM. However, to successfully implement LEMs, it is necessary to address challenges such as transaction costs, administrative efforts, market power problems, and strategic behavior. (Mengelkamp et al., 2017a; Wagner et al., 2021)

In LEMs, DSM is a crucial method for exploiting demand flexibility (Deutsche Energie-Agentur (Hrsg.), 2022). DSM refers to the set of activities undertaken by utility companies to control the usage of electricity by customers, with the aim of achieving desired changes in the load shape of the customers (Gellings and Parmenter, n.d.). Through DSM, consumers are encouraged to shift their demand and to best exploit the flexibility of building energy systems (BES). The flexibility of BES includes flexible generation, consumption, and storage. De Coninck and Helsen, 2016 define flexibility as the ability to

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deviate from the electrical reference load profile (De Coninck and Helsen, 2016). It addresses consumption and generation imbalances, categorized as positive and negative flexibility (Stinner et al., 2016). With positive flexibility, supply is greater than demand, so consumption should be increased, and generation reduced, vice versa with negative flexibility. De Coninck and Helsen, 2016 define a period during which flexibility can be accessed, this is called a flexibility event.

DR is one of the DSM categories, it aims to adjust electricity consumption in response to price changes or incentive payments (Shariatzadeh et al., 2015). This strategy can enhance social welfare, reduce investment in generation capacity, and improve reliability by smoothing out demand peaks (Albadi and El-Saadany, 2008). Price-based DR programs offer consumers flexibility and cost savings. However, their effectiveness can be impacted by uncertainties in electricity prices and consumer behavior (Albadi and El-Saadany, 2008; Shariatzadeh et al., 2015). DR in the form of price signals has already been used in various studies. However, this is primarily limited to the central energy market. In the following, a number of studies are presented.

The paper by de Sá Ferreira et al. (2013) proposes a quadratic programming and stochastic optimization approach for designing Time-of-Use (TOU) tariff that consider uncertainties in price elasticities of electricity demand. The approach aims to determine optimal tariff structures that maximize consumer utility and utility revenue. Challenges of designing TOU tariffs under uncertainty include setting tariffs without adjustment options and lack of data on price elasticity factors. The approach allows for flexibility in adjusting tariff structures and aims to maximize consumer benefits and utility revenues. The approach considers different consumer classes and price elasticity scenarios. It is validated by a case study that demonstrates increased total welfare and improved system load factor.

Javadi et al. (2022) use a TOU pricing mechanism in a local energy community to activate DR and induce behavioral change. They design a pool trading model to enhance community trading and reduce peak loads from the upstream grid. Using a Mixed Integer Linear Programming optimization problem to minimize the total electricity bill, building energy management system operators optimize consumption based on proposed TOU price signals. In a case study with independent and integrated scenarios, DR activation leads to cost reductions.

In Allensbach, Germany, the citizen-driven SoLAR project uses a real-time price signal in LEM to encourage self-consumption of electricity from combined heat and power (CHP) and local PV systems within a residential property. Flexible devices, acting as virtual batteries, respond autonomously to the real-time pricing (RTP) system, demonstrating efficient and effective coordination in real-time electricity markets for flexible consumers and producers. (Abschlussbericht SoLAR Phase 2, 2022)

1.2 Uncertainty in Energy Models

The consideration of uncertainties is a common challenge in modelling energy systems. Stochastic optimization is a discipline of mathematical optimization that deals with the solution of optimization problems with uncertain variables (Claus et al., 2019). One of the advantages of stochastic optimization is the direct inclusion of uncertain parameters in the decision-making process. However, it also has some disadvantages, such as the requirement of a known probability density function for the uncertain parameters and the fact that the solution is in the form of a frequency distribution, which may have limitations when dealing with a limited number of uncertain parameters (Fodstad et al., 2022; Moret, 2017; Yue et al., 2018). In stochastic programming, there is a risk of suboptimal solutions. To address this, chance constraints are utilized, ensuring satisfaction within a defined probability. Long-tailed probability distributions, though considering highly improbable scenarios, may be negligible in practical applications. Chance constrained optimization imposes constraints on the feasible region, maintaining a high probability of acceptable solutions. This balances decision-making flexibility with system operation within acceptable risk levels (Klein Haneveld et al., 2020). In the literature there are a lot of different stochastic approaches to deal with uncertain parameters.

In their work, Sharafi and ElMekkawy (2015) propose a stochastic optimization approach for hybrid renewable energy systems that accounts for uncertainties in input parameters such as solar irradiance,

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wind speed, ambient temperature, and load. Sampling average method is used to estimate the objective function for a randomly varying set of parameters within a defined probability space. The solution is approximated by calculating the mean of the objective function over multiple randomly generated scenarios.

Dvorkin et al. (2021) introduce a stochastic control framework to optimize the operation and pricing of natural gas networks. The framework considers system uncertainties and dynamics and is applied to a U.S. gas network case study. The authors demonstrate that the chance-constrained programs used in the framework result in substantial cost savings and improved performance compared to deterministic approaches, ensuring an optimized network response across the entire prediction error distribution.

1.3 Contributions

The growing presence of distributed energy resources in neighborhoods has led to the emergence of energy management techniques for local balancing of electricity generation and consumption. LEMs have been identified as a market structure that can effectively manage decentralized generation and actively involve market participants in trading activities. In addition, LEMs provide financial incentives for participants through direct trading. To promote the local balancing of supply and demand, flexibility can be leveraged on both the supply and demand side. However, DSM practices have predominantly been applied within the centralized energy market, and their potential in the context of LEMs needs further exploration. In a LEM with prosumers, DSM methods are applied not only on the demand side, but also on the supply side. One challenge associated with DR is the accounting for data uncertainty. Addressing this is crucial to ensure the effective deployment of DSM strategies in LEMs.
The contributions of this work can be summarized as follows:

- Application of a price-based DR program in distributed LEMs
- Exploration of the potential of price signals for demand and supply side
- Implementation of an LP optimization problem for the calculation of the price signal
- Consideration of uncertainties in the formulation of price signals trough chance constrained optimization
- Definition of a time-dependent flexibility index based on price elasticity
- Investigation of the influence of the price signal in neighborhoods with different characteristics

2 METHODOLOGY

2.1 Local Energy Market Model

The LEM model is based on the model presented by Schölzel et al. (2023). The market structure of the LEM is hierarchical. A coordinator oversees the trading activities within the community and facilitates coordination between the community and broader energy system. The coordinator can influence the households indirectly by sending a price signal. Market participants can decide individually on the quantity traded (Mendes et al., 2018). In this work, communities are defined as legal entities locally bound in neighborhoods.

A uniform price signal is sent to every household as a coordination signal. The price signal is constant for each time step. The energy management system of each building optimizes the operating plan, considering the price signal to minimize costs. The market agents place bids, including price and quantity, for supply and demand at the LEM. The auctioneer determines the market equilibrium. All bids within the market equilibrium are realized. The auction mechanism is two-sided and sealed bid, meaning that the bids of buyers and sellers are considered equally. In addition, market participants have no information about the bids of others. The bidding strategy is learning-intelligence based on Erev-Roth mechanism (Mengelkamp et al., 2018). The market clearing is uniform pricing. The rolling horizon method is used to predict the price signal for 36 timesteps in the future (Silvente et al., 2015).

2.2 Generation of Price Signals

We use a price-based DR program, it combines TOU and RTP. This combination enables the continuous adjustment of hourly price signals, facilitating effective transmission to the BES for energy management

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optimization. The price signal influences both the supply and demand side. We formulate a LP optimization problem to identify the optimal price signal. This price signal is described in the following as the deterministic price signal. To focus on the local balance of demand and supply, the goal is to minimize the residual load in the community. Therefore, the objective function is the minimization of the sum of the absolute residual load $L_{\mathrm{res,t}}$ over all time steps (t) in the prediction horizon (n_{PH}), see Equation (1).

$$\min \sum\nolimits_{t \in n_{\mathrm{PH}}} \left| \boldsymbol{L}_{\mathbf{res},t} \right| \tag{1}$$

s.t.

$$\boldsymbol{L}_{\mathbf{res},t} = \boldsymbol{q}_{\mathbf{d,signal},t} - \boldsymbol{q}_{\mathbf{s,signal},t} \;\; \forall t \in n_{\mathrm{PH}} \tag{2}$$

$$\boldsymbol{q}_{\mathbf{d,signal},t} = q_{\mathrm{d},t} \cdot \left(1 + \varepsilon_{\mathrm{d},t} \cdot \frac{\boldsymbol{p}_{\mathbf{signal},t} - p_{\mathrm{d,0}}}{p_{\mathrm{d,0}}}\right) \;\; \forall t \in n_{\mathrm{PH}} \tag{3}$$

$$\boldsymbol{q}_{\mathbf{s,signal},t} = q_{\mathrm{s},t} \cdot \left(1 + \varepsilon_{\mathrm{s},t} \cdot \frac{\boldsymbol{p}_{\mathbf{signal},t} - p_{\mathrm{s,0}}}{p_{\mathrm{s,0}}}\right) \;\; \forall t \in n_{\mathrm{PH}} \tag{4}$$

Equations (3) and (4) take the price signal $p_{\mathrm{signal},t}$ into account and calculate the change in demand and supply as reaction to the price signal. The residual load is the difference between demand ($q_{\mathrm{d,signal},t}$) and supply ($q_{\mathrm{d,signal},t}$), see Equation (2). The reaction to the price signal is simulated by using the price elasticity of the demand ($\varepsilon_{\mathrm{d},t}$) and supply side ($\varepsilon_{\mathrm{s},t}$). The reference point, to estimate the difference in price and demand, is the price signal of the previous time step (p_0). Additional constraints are introduced to limit the price signal and to prevent a shift in demand or supply beyond the prediction horizon. The price signal deviation between two timesteps cannot exceed 0.1 €/kWh. By avoiding large fluctuations in prices, rebound effects are to be prevented. Price elasticity is the measure of the flexibility of BES in the neighborhood and is used as flexibility index. We assume that the flexibility of the BES can only be leveraged for a limited period, the flexibility event (FE). The shifted loads have to be balanced later. The duration of the flexibility event varies significantly in the literature. While Agrela et al., 2023 and De Coninck and Helsen, 2016 define it as lasting 1-3 hours, Albadi and El-Saadany, 2008, and de Sá Ferreira et al., 2013 consider that price signals are sent over a period of 24 hours. The price elasticity is calculated continually at the beginning of a new timestep to reflect evolving market conditions. We estimate the positive and negative flexibility of all BES in the neighborhood. First, the households' bids for the prediction horizon are simulated for a reference scenario ($q(p_{\mathrm{ref}})_t$) where the price signal remains constant at the mean value between the minimum and maximum price. To estimate positive ($\Delta q_{\mathrm{pos},t}$) and negative flexibility ($\Delta q_{\mathrm{neg},t}$), we assess responses to the minimum ($q(p_{\mathrm{min}})_t$) and maximum price ($q(p_{\mathrm{max}})_t$). The difference between the reference scenario and the actual responses yields the positive and negative flexibility for both the supply and demand side:

$$\Delta q_{\mathrm{pos},t} = q(p_{\mathrm{min}})_t - q(p_{\mathrm{ref}})_t \;\; \forall t \in \text{ FE} \tag{5}$$

$$\Delta q_{\mathrm{neg},t} = q(p_{\mathrm{max}})_t - q(p_{\mathrm{ref}})_t \;\; \forall t \in \text{ FE} \tag{6}$$

The price elasticity varies during the flexibility event. For the remaining time steps the price elasticity is assumed to be 0, so no flexibility can be used, and the price signal is constant at the mean value between minimum and maximum price. To calculate the price signal, we check at each time step whether negative or positive flexibility is required to reduce the residual load. Price elasticity is calculated as the percentage change in quantity demanded or supplied divided by the percentage change in price. Equation 5 shows the calculation of the price elasticity of the demand side, if positive flexibility is available:

$$\varepsilon_{\mathrm{d},t} = \frac{\Delta q / q}{\Delta \mathrm{p} / p} = \frac{\Delta q_{\mathrm{pos},t} / q(p_{\mathrm{ref}})_t}{p_{\mathrm{min}} - p_{\mathrm{ref}} / p_{\mathrm{ref}}} \;\; \forall t \in \text{ FE} \tag{7}$$

To account for uncertain parameters, it is necessary to examine the normal distribution of the demand and supply curves. The LP for the deterministic price signal is extended by taking N samples from the probability distribution of the supply and demand curve. The determination of the probability distribution is described in 2.3. The LP for the stochastic price signal is solved for every sample. We use chance constraint stochastic programming to assess the risk of a high residual load at the neighborhood grid connection point. The conditional value at risk (CVaR) serves as the chance constraint. To simplify the equation, the sample average approximation method is used. Equation (8)

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shows the objective function for the stochastic price signal. The first summand of the objective function represents the CVaR, the second summand the expected value. ν_t is the worst value of the distribution, see Equation 11. With the CVaR the risk is limited depending on the α-level. A larger α value indicates a risk-averse attitude, where the focus is on minimizing the worst-case scenario (Rockafellar and Uryasev, 2002). We set α to 0.9, indicating a risk-affine nature of the application. The price signal acts solely as a coordination signal and is not intended for targeted risk minimization. The parameter β represents the ratio of CVaR to expected value in the objective function. We set β to 0.5, to equally take CVaR and the expected value into account. The LP for the calculation of the stochastic price signal is based on the deterministic price signal. The simplified LP is:

$$\min \sum_{t\in n_{\mathrm{PH}}} \beta \cdot \left(\boldsymbol{\nu_t} + \frac{1}{N}\sum_{i=1}^{N}\frac{1}{1-\alpha}\cdot\left(\boldsymbol{L_{\mathrm{res},t,i}} - \boldsymbol{\nu_t}\right)\right) + (1-\beta)\frac{1}{N}\sum_{i=1}^{N}\left|\boldsymbol{L_{\mathrm{res},t,i}}\right| \tag{8}$$

s.t.

$$\boldsymbol{q_{\mathrm{d,signal},t,i}} = q_{\mathrm{d},t,i}\cdot\left(1+\varepsilon_{\mathrm{d}}\cdot\frac{\boldsymbol{p_{\mathrm{signal},t}} - p_{\mathrm{d},0}}{p_{\mathrm{d},0}}\right)\ \forall t\in n_{\mathrm{PH}}, i\in I \tag{9}$$

$$\boldsymbol{q_{\mathrm{s,signal},t,i}} = q_{\mathrm{s},t,i}\cdot\left(1+\varepsilon_{\mathrm{s}}\cdot\frac{\boldsymbol{p_{\mathrm{signal},t}} - p_{\mathrm{s},0}}{p_{\mathrm{s},0}}\right)\ \forall t\in n_{\mathrm{PH}}, i\in I \tag{10}$$

$$\boldsymbol{\nu_t} \geq \boldsymbol{L_{\mathrm{res},t,i}}\ \forall t\in n_{\mathrm{PH}}, i\in I \tag{11}$$

Additionally, the constraints of the deterministic price signal apply for every sample i ∈ I in the calculation of the stochastic price signal. N is the number of samples i.

2.3 Use Case

To investigate the impact of the price signal in the LEM, we apply the described method to a neighborhood with different scenarios according to the share of devices. The neighborhood consists of 10 buildings, with eight single-family houses (SFH) and two multi-family-houses (MFH), see Table 1. The heat generators are dimensioned according to German standards (DIN EN 15450) and the thermal energy storage capacities are based on the mean heat demand of the building. The SFHs with photovoltaic (PV) are equipped with 25 modules of 1.65 m^2 each. The peak power is 6.38 kW. The batteries (BAT) have a storage capacity of 5 kWh and a charge and discharge power of 3.4 kW. The building energy management system can operate the thermal and battery storage systems.

Table 1: Number of buildings with the respective device for all district scenarios

Neighborhood	1			2			3		
Building type	SFH	SFH	MFH	SFH	SFH	MFH	SFH	SFH	MFH
Number of buildings	4	4	2	4	4	2	4	4	2
Heat Pump	x			x			x		
Combined heat and power									x
Boiler		x	x		x	x		x	
Photovoltaic		x			x			x	
Battery storage					x				

We use the district generator tool to model the neighborhood scenarios. This tool generates hourly demand and supply curves for each building in the neighborhood (RWTH-EBC / districtgenerator). To generate the heat demand, the TEASER tool is used (Remmen et al., 2018). Electrical loads are generated using random occupancy profiles based on the richardsonpy tool (Richardson et al., 2010). The main input parameters for the district generator are the weather forecast and building properties. The building properties depend on self-defined data, like construction year, gross living area, and share of devices. The occupancy profiles are subject to uncertainty. The richardsonpy tool creates deterministic occupancy profiles based on randomized assumptions. The weather forecast is based on historical weather data and is perfect foresighted. To account for the uncertainty in real data series, we generate an uncertain input data set. After creating one set of input data, another one is created to assess the uncertainty in the supply and demand curve in the neighborhood. The second dataset in generated

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by changing the air temperature, diffuse and direct solar radiation and the activity profile to random values, that represent a realistic deviation from the prediction based on previous studies. The two datasets are merged to create a limited foresight data set. At every time step n_{opt} the data for the control horizon is taken from the first data set. With the second data set, the data for the overlap horizon is given. This is repeated at the beginning of every optimization round. Consequently, the weather and user profiles deviate from the forecast. To determine the deviation of the forecast of the supply and demand curves, we compare the total demand and supply of the two input data sets. By comparing the data at every time step, the probability distribution can be obtained. For each neighborhood scenario, we determine the probability distribution for the deviation from the forecast.

The computational effort for the entire district does not allow the calculation of an entire year with the available computing capacity. Therefore, January and July are examined as examples. Those are the months with the highest electricity generation and consumption. For each neighborhood scenario, deterministic, stochastic, and no-price-signal scenarios are analyzed. Another focus of investigation is the impact of the duration of the flexibility event on trading within the LEM. Four distinct scenarios with durations of the flexibility event of 3, 6, 12 and 24 hours, respectively, are analyzed. In total, we examine 54 scenarios. p_{max} is the price, that the households would pay outside the LEM to purchase electricity, the average electricity price in Germany, 42,22 ct/kWh, in 2024 (BDEW). The minimum price, p_{min}, is the minimum of the payment for PV-generated electricity when sold to the higher grid level. This is 8,20 ct/kWh (Enercity).

2.4 Key Performance Indicators

The different scenarios of the use case described in subsection 2.3 are compared for the following KPIs:

- Supply and Demand Cover Factor (SCF, DCF): The SCF represents the percentage of locally generated energy consumed within the district. To calculate the SCF, we consider the ratio of demand bids quantity to the offered generation. The DCF represents how many demand bids can be met by offers in the LEM.
- Energy import and export: The import and export energy are calculated as the sum of the feed-in or purchase power at time step t multiplied with the duration of time step t.
- Average Market Clearing Price (AMCP): The AMCP reflects the overall price level in the market. The market clearing price (MCP) is influenced by the trading activity within the market. As more transactions take place, indicating higher trading volumes, the MCP tends to decrease.
- Gain: The accumulated gain shows the financial benefit of the market participants from selling and buying electricity on the LEM than on the higher grid level. It is calculated as the sum of the saved costs and additional profit of all participants over all timesteps.

3 RESULTS AND DISCUSSION

3.1 Impact of the price signal and the district type

This section presents the results and discusses the findings of the analysis carried out. Figure 1 shows the SCF and DCF for the studied scenarios with a flexibility event of 12 h. In January, the neighborhoods 1 and 2 exhibit greater SCF and lower DCF compared to neighborhood 3. In neighborhood 3, more electricity is generated by the CHP units in the MFHs. This increases the supply of electricity within the district and creates more surplus, which is fed-in to the higher grid level. Due to low solar radiation, the PV systems hardly generate any electricity in January. Consequently, only up to 10 % of demand can be covered in neighborhood 1 and 2. In comparison, this is up to 71 % in neighborhood 3, mainly because of the CHPs. Introducing a price signal, deterministic and stochastic, results in decreased SCF and DCF in neighborhood 3. In January in neighborhood 3, generation and consumption are largely synchronized due to the simultaneous production of electricity and heat from CHPs. The introduction of a price signal, that is based on the minimization of the residual load, can disrupt this synchronization. CHPs tend to produce more electricity when the price signal increases while households with heat pumps (HPs) consume less electricity at the same time. Conversely, neighborhoods 1 and 2 experience a slight positive impact from the stochastic price signal on the SCF and DCF. This indicates a responsiveness from HPs and BAT. In July, neighborhood 3 showed lower

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SCF and slightly higher DCF than the other neighborhoods, reflecting increased supply from additional CHP. Neighborhood 3 experiences a high impact from the price signals, with an increase of 4.58 pp in SCF and 1.96 pp in DCF for the stochastic price signal. In neighborhood 2 SCF and DCF also increase with the deterministic and stochastic price signal. The price signal ensures better use of BAT in neighborhood 2. Neighborhood 1 demonstrates minimal changes (< 0.05 pp) in SCF and DCF due to limited flexibility in households with HPs during July as the need for heat is low.

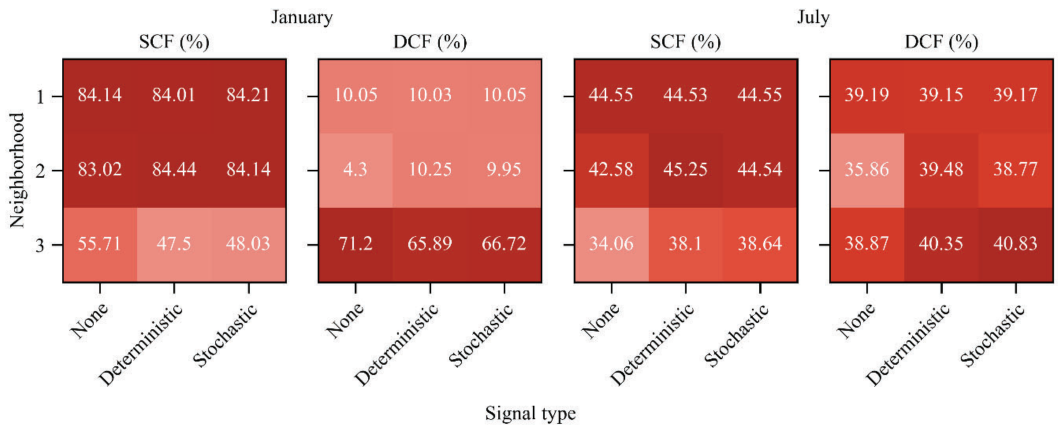

Figure 1: SCF and DCF for the studied scenarios with a flexibility event of 12 h

The analysis of Figure 2 reveals higher energy imports in January, especially in neighborhoods 1 and 2 (6481 kWh, 6500 kWh without price signal). Neighborhood 3 exhibit lower imports, 1284 kWh, and higher exports, 2523 kWh without price signal. With a price signal energy import and export increase in neighborhood 3, reflecting the contrasting effects of CHP and HP (1603 kWh, 3478 kWh with the stochastic price signal). In July, neighborhood 3 demonstrates lower imports and higher exports compared to neighborhoods 1 and 2 because of the generation of the CHPs. The price signals have nearly no influence (< 1.2 kWh) on the energy exchange with the higher grid level in neighborhood 1 due to low flexibility options. In neighborhood 2 and 3, the price signals lead to an increase in energy import and export. This is explained by the higher storage utilization in response to the price signal.

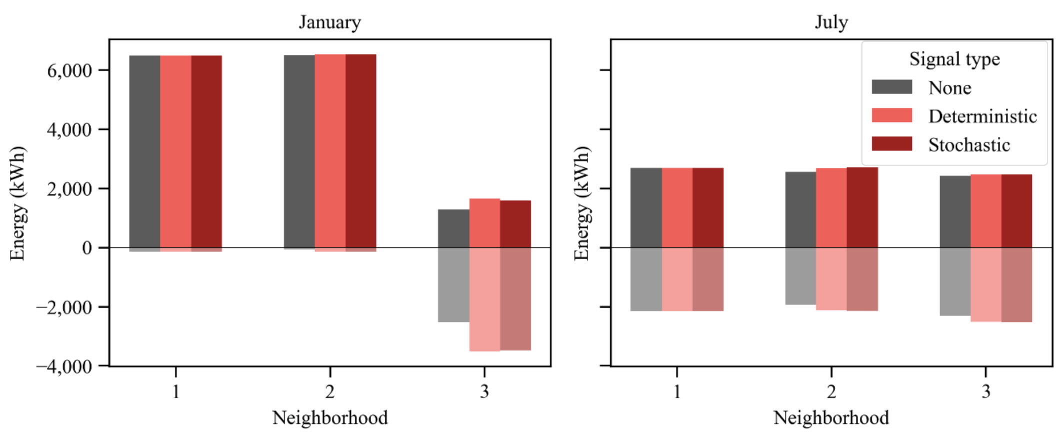

Figure 2: Energy export (lightened bars) and import for the studied scenarios with a flexibility event of 12 hours

Figure 3 displays the AMCP and accumulated gain. In January, the trading in neighborhood 3 is significantly higher due to additional CHP generation, resulting in a lower AMCP in comparison to neighborhood 1 and 2. The deterministic and stochastic price signal have only little influence in January. Neighborhoods 1 and 2 experience increased trading and lower AMCP in July, compared to January, due to higher PV generation. In July the AMCP for the scenarios with the stochastic price signal rises slightly, it increases 0.96 ct/kWh in neighborhood 2, comparing the scenario without a price signal.

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Although the SCF and DCF increase in this scenario, the AMCP increases, indicating a lower trading activity in the LEM. This can be explained by a more precise use of storage. Households with BAT can also use it to meet their own demand. In the month of January, neighborhood 3 stands out with higher gains due to increased trading volume, primarily driven by higher electricity production of the CHPs. Neighborhood 2 experiences a significant increase in gain with price signals, almost tripling the gains of the scenario without a price signal. This improvement can be attributed to the incorporation of BAT, which allows for more agile responses to market price fluctuations. In July, the dynamics shift slightly. Neighborhood 1 shows minimal changes in other KPIs, with a smaller gain observed for the stochastic scenario, suggesting that the price signal may be influencing inferior bids. Neighborhoods 2 and 3 show additional benefits from the price signals due to their higher trading volumes.

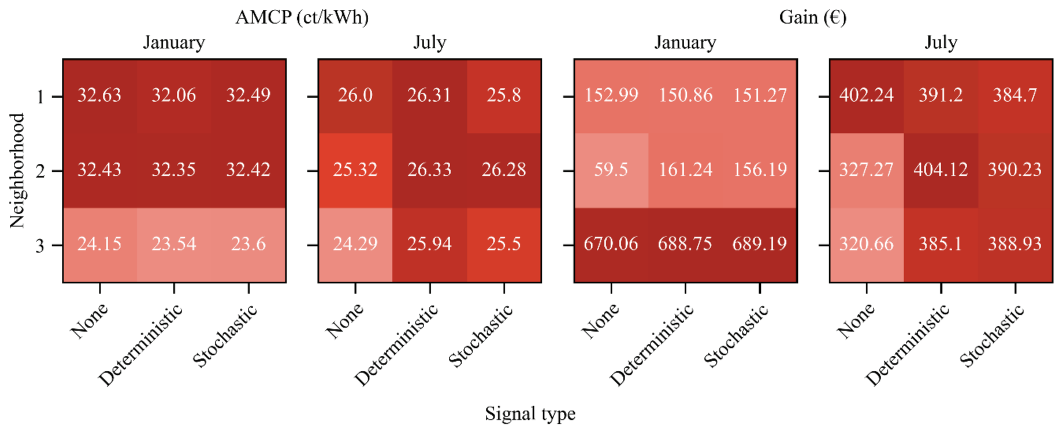

Figure 3: AMCP and total gain for the studied scenarios with a flexibility event of 12 hours

3.2 Impact of the duration of the flexibility event

The value of the flexibility index depends on the neighborhood scenario and the length of the flexibility event. The study results indicate that the price elasticity is lower for longer flexibility events, as the available flexibility is utilized over a longer period. It can also be seen that the price elasticity fluctuates depending on the available flexibility options depending on the district. In neighborhood 1, the electricity supply cannot be changed. Therefore, the price elasticity for the supply side is 0. In comparison, the price elasticity rises to an average of 0.5 in neighborhood 2 for the supply side when negative flexibility is used for a flexibility event of 3 hours in July.

Table 2: SCF and DCF in % and energy import and export in kWh for the stochastic price signal and both flexibility event scenarios

Neighbor-hood	Flexibility Event	January				July			
		SCF	DCF	Import	Export	SCF	DCF	Import	Export
1	3 h	83.99	10.02	6487	138	44.58	39.19	2690	2155
	6 h	83.36	9.94	6493	143	44.61	39.18	2693	2154
	12 h	84.21	10.05	6484	136	44.55	39.17	2691	2156
	24 h	84.23	10.05	6484	136	44.48	39.09	2693	2160
2	3 h	83.83	8.61	6563	119	44.78	36.63	2881	2053
	6 h	83.96	9.36	6582	130	46.75	39.23	2602	1913
	12 h	84.14	9.95	6527	136	44.54	38.77	2715	2141
	24 h	81.29	9.88	6587	166	44.66	38.82	2750	2162
3	3 h	38.76	52.56	2272	3977	40.37	44.89	2166	2606
	6 h	40.11	52.96	2419	4064	39.16	42.42	2367	2709
	12 h	48.02	66.72	1603	3478	38.64	40.83	2468	2704
	24 h	47.14	65.51	1663	3543	38.51	38.51	2458	2459

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Table 2 shows the SCF, DCF, energy import and export for the stochastic price signal and a flexibility event of 3, 6, 12 and 24 hours. In January, the SCF and DCF show minimal changes (less than 0.9 pp) with varying durations of the flexibility event. There is a slightly lower exchange with the higher grid level for the 12-hour event for all scenarios studied in January except the SCF for 24 h. Additionally, there is a lower energy exchange with the higher grid level for the 12-hour event, especially in neighborhood 3. As already noted, the price signals in January have little impact on trading in the LEM. Therefore, a change in the flexibility event does not lead to a change in trading either. In July, with a stochastic price signal, SCF and DCF are higher for neighborhood 1 and 2 with a flexibility event of 6 hours compared to the other scenarios. In neighborhood 3, the SCF and DCF increase with a smaller flexibility event. On the one hand, shifted loads must be compensated later, and in a 24-hour event, these compensations are delayed too long, resulting in additional demands due to storage losses. On the other hand, the length of the flexibility event must be sufficient to allow the building energy management systems to consider different system states in the future when controlling the systems.

4 CONCLUSIONS

This study presents a methodology for implementing a price signal in LEMs with the goal of increasing local trading volumes and maximizing the balance between supply and demand in the LEM. LEMs in energy communities enable prosumers and consumers to actively participate in the local market, providing financial benefits and enabling trading of locally generated power. We analyzed a residential neighborhood consisting of 10 buildings and considered three different neighborhood scenarios. To generate the price signal, we formulated a LP optimization problem. We consider price elasticity as flexibility index to predict the possible shift in demand and supply due to the price signal. We calculated the price signal with a stochastic optimization approach. To mitigate the risks associated with adverse outcomes, we employed the chance constraint method.

We found that price signals as a DSM method in the LEM have different effects depending on the characteristics of the neighborhoods. In scenarios where there is a potential mismatch between supply and demand due to generation volatility, such as in neighborhoods with PV generation and BAT, local trading increases with the use of the stochastic price signal. Therefore, research in neighborhoods that incorporate renewable energy sources, such as wind power, or use electric vehicles as additional storage capacity can provide further insights into the impact of the stochastic price signal.

This study demonstrates that in neighborhoods with high temporal coverage of electricity generation and consumption, the introduction of a price signal results in reduced trading activity in the LEM and increased energy exchange with the higher grid level. For households with HPs, the heating demand leads to an increase in electricity demand, which is met by the CHPs electricity generation. The introduction of price signals in these districts results in reduced synchronicity of generation and consumption due to opposing load shifting of HP and CHP. Therefore, it can be concluded that the use of uniform price signals is generally critical in neighborhoods characterized by a temporal coverage between production and consumption. Future research could implement different price signals for different building types to avoid conflicts between CHP and HP operations.

It was discovered that a flexibility event lasting 6 or 12 hours results in higher trading in the LEM compared to a 3- or 24-hour event. This suggests that too long flexibility events lead to delayed load compensations, while it can also be shorter than the required operating time. To determine the optimal duration of a flexibility event, additional time periods should be investigated. In addition, the potential impact of maintaining a constant price signal over multiple time steps could be further explored.

It is noteworthy that there were only minor distinctions between stochastic and deterministic price signals. This implies that the implementation of price signals has a more significant impact on market trading dynamics than the mere consideration of uncertainties. It is essential to recalibrate the uncertainties for each time step to allow for a more detailed consideration of uncertainties. In further investigations, we will examine the influence of uncertainties as a function of the system states.

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