

Evaluating the interdependency between peer-to-peer networks and energy storages: A techno-economic proof for prosumers

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ABSTRACT

The rapid decentralization of energy generation and storage facilitates an opportunity to redesign existing energy systems. Here, peer-to-peer energy trading in local markets offers advantages for demand response and flexibility of energy delivery, yet it still faces problems of customer acceptance, namely, concerns over sharing control of batteries and the degradation impacts of increased cycles. To help overcome these hurdles, this research develops a techno-economic model that optimizes the interplay between peer-to-peer trading and energy management systems in a community. The model distinguishes between two decision making approaches in a local electricity market: decentral, where the household retains full control over its storages, and central, where the flexibilities are fully leveraged to maximize the community benefit. Both approaches demonstrate the significant monetary benefit of peer-to-peer trading, with the central approach reaching the greatest profitability potential. Negative effects on the battery lifetime only occur in the central case with bidirectional vehicles, and the degradation is comparatively slight.

1. Introduction

Power networks, and distribution networks in particular, are facing operational and planning challenges from rising levels of customer investment in distributed generation, storage and flexible loads, collectively called distributed energy resources (DER). For instance, the installed rooftop capacity of photovoltaic (PV) systems globally has grown from 8 GW in 2007 to over 400 GW in 2019 [1], and annual added battery capacity from private electric vehicle (EV) sales is projected to increase from 170 GWh in 2019 to between 1.2 and 2.6 TWh per year by 2030 [2]. Consequently, members of the community who used to be passive consumers of the electricity network are becoming prosumers – consumers who also produce electricity [3] – and are expected to play key roles in deciding how the future power systems will evolve and operate. The change in prosumers' roles within the distribution network present significant challenges to power network operators, who face daytime minimum demand challenges due to prosumers' solar export to the network [4] and the peak demand problems owing to EV ownership [5]. One potential way to address these challenges is to enable prosumers to interact among themselves and trade electricity with one another [6] – also known as peer-to-peer (P2P) trading.

P2P trading is a prosumer-centric energy sharing scheme in which prosumers in a power network can share a part of their resources, such as electricity [7], storage space [8], and negawatts [9], and information with one another to attain certain objectives. It is important to note that although existing power network regulatory regimes do not allow P2P trading to occur in the today's electricity markets, extensive pilot trials around the world [10] and government initiatives to reform the electricity sector [11] are moving towards a future where P2P trading will be integrated into the broader electricity market.

Furthermore, P2P trading has several positive characteristics, including relatively low computational and implementation overheads [12], the ability to engage extensive user participation [13], reductions in energy cost [14], and balancing local generation and demand [15] by enabling secured trading [16]. P2P trading empowers both the prosumers [17] and community managers [18] that are trading within a community, which makes it a suitable candidate to operate within future customer-focused regulatory regimes [19]. As such, research over the last five years has established P2P as an indispensable element of the future electricity market, considering its potential to benefit participating prosumers and provide useful services to other stakeholders [10]. However, to the best of our knowledge, there are still no large-scale

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Nomenclature	
CEMS	community energy management system
DER	distributed energy resource
EFC	equivalent full cycle
EMS	energy management system
EV	electric vehicle
HEMS	home energy management system
HES	home energy storage
P2P	peer-to-peer
PV	photovoltaic
<i>Parameters & variables</i>	
$C^{\text{electricity}}$	economic cost for electricity
C^{deg}	economic cost for battery degradation
C^{inv}	economic cost for battery investment
$C^{\text{tra,loc}}$	economic cost for locally traded electricity
$C^{\text{tra,ret}}$	economic cost for electricity traded with the retailer
EFC^{exp}	expected EFC until the battery's end-of-life
E^{act}	actual energy content of battery
$E^{\text{demand,local}}$	locally traded energy demand
$E^{\text{demand,retail}}$	energy demand traded with the retailer
E^{demand}	energy demand
$E^{\text{EV,act}}$	actual energy content of EV battery
$E^{\text{EV,buf}}$	buffer energy at the EV
$E^{\text{EV,CH,ext}}$	external charging energy at the EV
$E^{\text{EV,CH}}$	charging energy at the EV
$E^{\text{EV,DCH}}$	discharging energy at the EV
$E^{\text{EV,dri}}$	energy demand for driving at the EV
$E^{\text{EV,SD}}$	self-discharge energy at the EV
$E^{\text{HES,act}}$	actual energy content of HES battery
$E^{\text{HES,CH}}$	charging energy at the HES
$E^{\text{HES,DCH}}$	discharging energy at the HES
$E^{\text{HES,SD}}$	self-discharge energy at the HES
E^{Load}	energy consumption
E^{nom}	nominal energy content of battery
E^{PV}	energy provided by the PV generator
$E^{\text{supply,local}}$	locally traded energy supply
$E^{\text{supply,retail}}$	energy supply traded with the retailer
E^{supply}	energy supply
$E^{\text{trade,local}}$	locally traded electricity
$E^{\text{trade,retail}}$	electricity traded with the retailer
$E^{\text{trade,total}}$	total traded electricity
ϵ	share of locally traded electricity
$\eta^{\text{EV,CH}}$	charging efficiency of the EV
$\eta^{\text{EV,DCH}}$	discharging efficiency of the EV
$\eta^{\text{HES,CH}}$	charging efficiency of the HES
$\eta^{\text{HES,DCH}}$	discharging efficiency of the HES
N	set of households
n	household
ϕ	peer's economic incentive to trade locally
$p^{\text{EV,CH,ext}}$	external charging power at the EV
$p^{\text{EV,CH}}$	charging power at the EV
$p^{\text{EV,DCH}}$	discharging power at the EV
$p^{\text{EV,max}}$	maximum (dis)charging power of the EV
$p^{\text{HES,CH}}$	charging power at the HES
$p^{\text{HES,DCH}}$	discharging power at the HES
$p^{\text{HES,max}}$	maximum (dis)charging power of the HES
$p^{\text{purchase,retail}}$	retailer's purchase price for electricity
$p^{\text{sell,retail}}$	retailer's sell price for electricity
$\text{SOC}^{\text{EV,max}}$	maximum SOC of EV battery
$\text{SOC}^{\text{EV,min}}$	minimum SOC of EV battery
$\text{SOC}^{\text{HES,max}}$	maximum SOC of HES battery
$\text{SOC}^{\text{HES,min}}$	minimum SOC of HES battery
$\text{SOC}^{\text{preference}}$	SOC threshold for reserve energy
T	set of time steps
t	time step
x^{plugged}	binary variable, defining if vehicle is connected

development of P2P trading that is ready to be deployed in today's electricity market. The reason could be partially attributed to the fact that prosumers are more interested to use their DER such as batteries to go off-grid and become energy-neutral, rather than interacting with other stakeholders within the network, as found in [20].

A study of 268 prosumers who were asked about battery purchases reported that 70% of the survey respondents purchased their batteries to reduce personal electricity costs with intentions to less interact with other stakeholders of the network [20]. Two important factors that have motivated their decision in separating themselves from any form of interaction are (i) the fear of losing the ability to control their assets [21] and (ii) the concern about the reduction of the lifetime of their resources due to their extensive usage for the local market support [22]. These place technology developers, network operators, and policymakers in a conundrum, as the success of P2P trading and other smart energy infrastructure, relies on the proactive participation of prosumers [23], and therefore, prosumers' reluctance to share their assets can negatively impact the lived experience of P2P energy trading [22].

To this end, this paper provides empirical evidence to close two gaps in existing literature. Firstly, we incorporate the prosumer's home energy management decision-making process into the subsequent decision to trade on the local P2P market. We present an integrated P2P energy trading algorithm that empowers prosumers to use an energy management system to control their energy resources and optimally meet their home energy demand and then, whenever appropriate, share the surplus in the local P2P market. By doing so, prosumers' uncertainty of losing control of their energy assets is eliminated. Secondly, using extensive data from a Germany-based pilot trial, we demonstrate that the

extra charging and discharging cycles of prosumers' batteries due to P2P trading has minimal effect on battery lifetime.

In summary, the main contributions of the work are:

- The impacts of peer-to-peer energy trading on energy storage systems are analyzed via a novel matching mechanism for coordinating home energy management and peer-to-peer trading.
- We compare the financial performance and degradation effects of our decentralized P2P matching mechanism to a centralized approach that optimizes the overall techno-economic outcome, considering both stationary and mobile energy storages.
- The first evidence of the minimal impact on battery lifetime as well as the shared techno-economic benefits to the prosumer due to P2P trading.
- This paper examines the interaction between home energy management and P2P trading, providing a crucial technical demonstration to help overcome the techno-economic and social challenges.

The remainder of the paper is structured as follows. Section 2 introduces the methodology of analysis, P2P framework, and its mathematical formulation. The results of our analysis are presented in Section 3, discussed in Section 4, and concluded in Section 5.

2. Methods

2.1. Decentralized versus central decision making approach

We differentiate between two approaches for the energy management of households in a P2P network, as illustrated in Fig. 1. In both

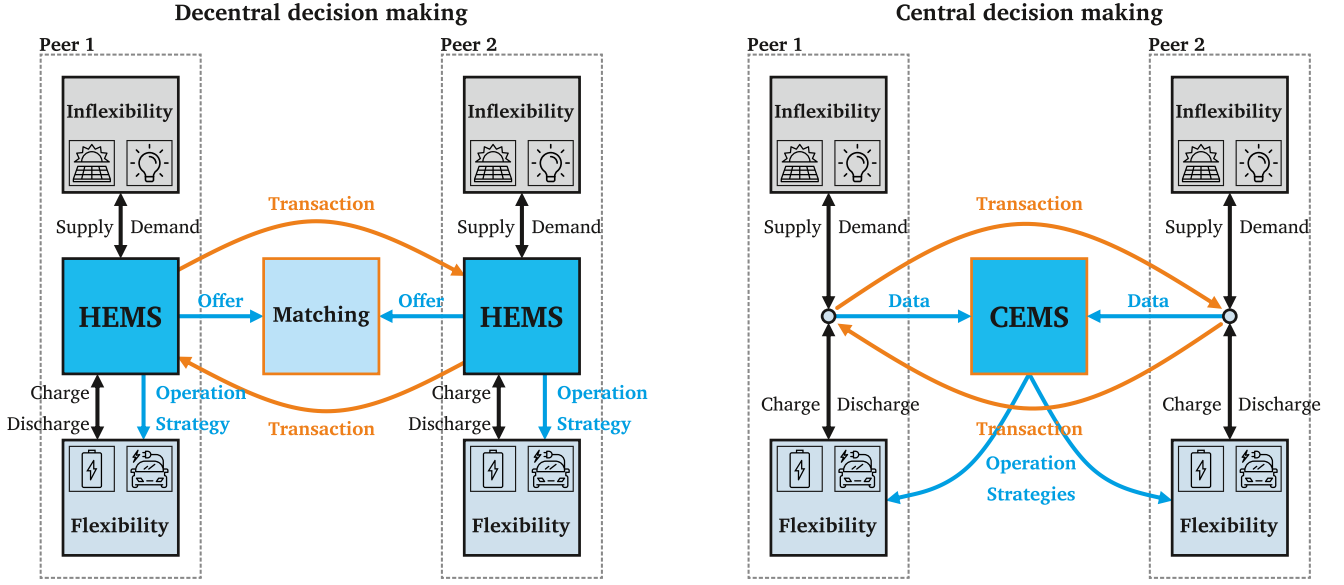


Fig. 1. Schematic illustration of decentralized and central decision making in a peer-to-peer (P2P) network. Each peer is characterized by its energy inflexibilities and flexibilities. The inflexibilities represent the supply and demand stemming from producing and consuming components. Stationary and mobile energy storages allow the flexible charging and discharging of electricity, enabling the temporal shift of supply and demand. There are two decision making approaches to calculate the offers, transactions, and operation strategies of the peers: decentralized (left) and central (right). For the decentralized approach a HEMS at each peer calculates the offers and transfers them to the matching platform of the P2P network. With the larger information base and flexibility pool, the CEMS simultaneously calculates the optimal operation strategies for all flexibilities and peers to yield the optimal techno-economic outcome.

approaches, each household contains inflexibilities, such as its electricity base demand and the supply of PV generators, as well as flexibilities, which allow for a temporal shift of supply and demand. The EMS utilizes the expected energy values from demand and supply to calculate an optimal operation strategy for the flexibilities and the techno-economic optimum for electricity demand and supply offers. Here, as shown in Eq. (1), the sum of the peers' demand and supply matched locally ($E^{\text{demand,local}}$ and $E^{\text{supply,local}}$ respectively) must be equal:

$$\sum_{n \in N} E_{n,t}^{\text{demand,local}} = \sum_{n \in N} E_{n,t}^{\text{supply,local}} \quad (1)$$

For any supply and demand unfulfilled in the local market, the electricity is cleared with the retailer.

The decentralized and central decision making approaches differ in four main ways: type of EMS, information availability, computation complexity, and market mechanism. In the decentralized approach, each peer has its own home energy management system (HEMS), whereas a central authority or community energy management system (CEMS) determines the optimal operation strategies for all households in the central approach.

To enable the central decision making, the CEMS has access to the demand and supply data, as well as system states of the flexibilities, from all peers. It also has the capability to control and operate the flexibilities in the network to maximize the P2P community's techno-economic potential. The peers have no access to data from the other households in the network. The market mechanism determines how offers are matched in the local market. Whilst offers are non-binding, once matched, these transactions between peers are binding and must be delivered.

In the decentralized approach, on the other hand, offers are determined by the HEMS and then transferred to the clearing and matching. If both demand and supply offers exist during a given trading interval, they are cleared on a community level to reach the highest share of locally traded electricity. This highest share is defined as the minimum value of the total offered demand and supply on a community level, as it is shown in Eq. (2). After the clearing, the offers are matched with respective counterparts following a 'fairness policy' (illustrated in Fig. 2). The fairness policy ensures that each received offer is considered in the matching and that the volume matched is calculated based

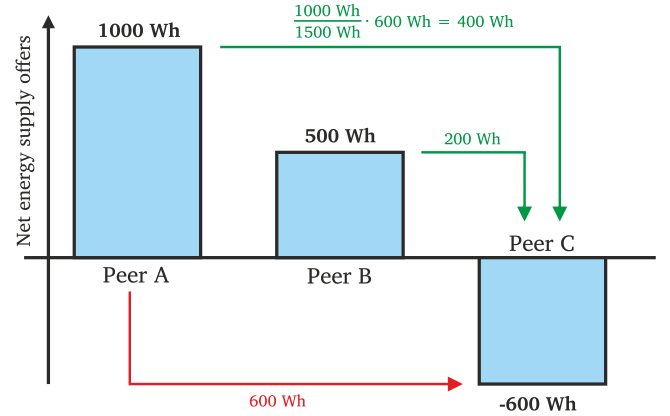


Fig. 2. Exemplary illustration of the fairness policy in a peer-to-peer (P2P) market with offers from three peers. Peers A and B have positive net energy supply offers. Although peer A could meet the full demand from peer C, this would not be fair towards peer B. With the fairness policy all offers in the P2P community are considered for the creation of binding transactions.

on the weighted offer volume (cf. Eqs. 3 and (4) for demand and supply respectively). After clearing and matching, the offers are converted into transactions and transferred to the respective peers. Every peer needs to know which offers became transactions on the P2P market, as well as the volume, timing, and counterpart of electricity transaction. In the central approach, the energy management and matching occur simultaneously. Therefore, the offers are directly converted to binding transactions and the operation strategies for all peers are calculated simultaneously.

$$\sum_{n \in N} E_{n,t}^{\text{trade,local}} = \min \left\{ \sum_{n \in N} E_{n,t}^{\text{demand}}, \sum_{n \in N} E_{n,t}^{\text{supply}} \right\} \quad (2)$$

$$E_{n,t}^{\text{demand,local}} = \frac{E_{n,t}^{\text{demand}}}{\sum_{n \in N} E_{n,t}^{\text{demand}}} \cdot \sum_{n \in N} E_{n,t}^{\text{trade,local}} \quad (3)$$

$$E_{n,t}^{\text{supply,local}} = \frac{E_{n,t}^{\text{supply}}}{\sum_{n \in N} E_{n,t}^{\text{supply}}} \cdot \sum_{n \in N} E_{n,t}^{\text{trade,local}} \quad (4)$$

2.2. Assessing the financial benefit

In our methodology, the benefit of P2P trading is characterized by ϵ , the proportion of electricity supplied or demanded in the network that is traded locally (Eq. (5)). The total traded electricity, either by household or on a community level, $E^{\text{trade,total}}$, is defined in Eq. (6) as the sum of electricity traded with other peers ($E^{\text{trade,local}}$) and with the electricity retailer ($E^{\text{trade,retail}}$).

$$\epsilon = \frac{E^{\text{trade,local}}}{E^{\text{trade,total}}} \quad (5)$$

$$E^{\text{trade,total}} = E^{\text{trade,local}} + E^{\text{trade,retail}} \quad (6)$$

In Eq. (7), ϕ represents the individual peer's incentive to trade locally in Euro. A prerequisite for the design of a local market with more favorable trading conditions than offered by the retailer is a price gap between the retail purchase and sale prices $p^{\text{purchase,retail}}$ and $p^{\text{sell,retail}}$. This price difference emerges in markets with demand-pull policies subsidizing decentralized production of electricity, where feed-in-tariffs are declining and where the retail price remains high, because risks of price fluctuations are covered by the retailer. The welfare gained due to local trading on a community level is equal to the gap between the two price signals. In our approach, this economic gain is divided equally between the peers – both the local supplier and consumer – so that the incentive to either supply or purchase local electricity is equal for both. As a result, the unit ϕ , allows us to draw general conclusions regarding the financial benefit per peer in a local market, isolating the effect of the specific underlying tariff structure, which differs with federal and state regulations.

$$\phi = \frac{p^{\text{purchase,retail}} - p^{\text{sell,retail}}}{2} \quad (7)$$

From a mathematical point-of-view, the incentive to trade electricity locally arises as soon as a price corridor exists. In our approach, the midpoint of the price corridor (average between $p^{\text{purchase,retail}}$ and $p^{\text{sell,retail}}$), is set as the static local market price. With this straightforward and simple approach, computation complexity is reduced significantly. Also, the individual incentive to trade locally, ϕ , is the same for all peers. The offers and transactions consist of electricity values and the prices for traded electricity are equal and homogeneous for all peers. This eliminates the likelihood of market manipulation and arbitrage opportunities.

$$C_{n,t}^{\text{electricity}} = E_{n,t}^{\text{demand}} \cdot p^{\text{purchase,retail}} - E_{n,t}^{\text{supply}} \cdot p^{\text{sell,retail}} - E_{n,t}^{\text{trade,local}} \cdot \phi \quad (8)$$

In the P2P network, the individual households' electricity costs, $C^{\text{electricity}}$, are given by Eq. (8), where E^{demand} , E^{supply} , and $E^{\text{trade,local}}$ denote the total electricity demanded, supplied, and traded locally by the household. The first term calculates the electricity costs, as if the full demand is covered by the retailer. If the household is a prosumer, these costs are compensated by revenues from electricity sold to the retailer (second term) and if the household participates in a local market ($E^{\text{trade,local}} > 0$), to more favorable conditions, the costs are reduced by the incentive to trade locally, ϕ .

2.3. Mathematical formulation

The developed EMS is based on a linear optimization problem that minimizes the electricity costs of the households and the P2P community. Written in the MATLAB environment, it utilizes the Gurobi solver, which offers advantages in computation performance [24].

$$\min_{z^{\text{dec}}} z^{\text{dec}} = \sum_{n \in N} \sum_{t \in T} \left(C_{n,t}^{\text{tra,ret}} + C_{n,t}^{\text{deg}} + E_{n,t}^{\text{EV,buf}} + E_{n,t}^{\text{EV,CH,ext}} \right) \quad (9)$$

$$\min_{z^{\text{cen}}} z^{\text{cen}} = \sum_{n \in N} \sum_{t \in T} \left(C_{n,t}^{\text{tra,ret}} + C_{n,t}^{\text{tra,loc}} + C_{n,t}^{\text{deg}} + E_{n,t}^{\text{EV,buf}} + E_{n,t}^{\text{EV,CH,ext}} \right)$$

(10)

Eqs. 9 and (10) show the objective functions of the decentralized and central decision making approaches respectively. Mathematically, these differ only in one respect. While the decentralized EMS minimizes the electricity costs from trading electricity with the retailer ($C^{\text{tra,ret}}$) only, the central CEMS also minimizes the electricity costs electricity shared within the local network, $C^{\text{tra,loc}}$. This additional minimization lever is attainable, because the CEMS has access to all offers placed in the market, whereas in decentralized control each EMS only knows what is occurring within one household.

Besides the maximization of the profit from sharing and trading electricity the electricity retailer and with peers in the network, Eqs. 9 and (10) also minimize the cost for cell degradation of the batteries, C^{deg} . Thus, degradation awareness is introduced to the model. Defined in Eq. (11), the cost of cell degradation is calculated using the flexibilities storage energy throughput, or equivalent full cycles (EFC) and the estimated opportunity costs per battery cycle $\frac{C^{\text{inv}}}{\text{EFC}^{\text{exp}}}$ [25]. The EFCs are derived from the change in the state of charge over time (cf. Eq. (12)). With this active degradation awareness in place, the algorithm only utilizes a battery if the financial benefit exceeds the costs of degradation.

$$C_{n,t}^{\text{deg}} = \text{EFC}_{n,t} \cdot \frac{C^{\text{inv}}}{\text{EFC}^{\text{exp}}} \quad (11)$$

$$\text{EFC}_{n,t} = \frac{|E_{n,t}^{\text{act}} - E_{n,t-1}^{\text{act}}|}{2 \cdot E^{\text{nom}}} \quad (12)$$

$E^{\text{EV,buf}}$, which is also applied in Eq. (13), incentivizes the optimization algorithm to retain a minimum state of charge (SOC) in the EV batteries reserved for driving when the vehicle is connected ($x^{\text{plugged}} = 1$). Due to the constraint formulation, the reserve SOC ($\text{SOC}^{\text{preference}}$) is not applied when the vehicle is not connected, allowing the full energy content to be used for mobility purposes. This minimum state of charge is important to the vehicle owner's peace of mind, as they might need to take a spontaneous, unplanned trip. Guaranteeing this flexibility in this model increases user acceptance [26]. $E^{\text{EV,CH,ext}}$ enables that external charging – outside of the home – is possible but discouraged by significantly less favorable conditions. Thus, the algorithm, avoids external charging when possible.

$$E^{\text{EV,nom}} \cdot \text{SOC}^{\text{preference}} \cdot x_{n,t}^{\text{plugged}} \leq E_{n,t}^{\text{EV,act}} + E_{n,t}^{\text{EV,buf}} \quad (13)$$

In addition to the objective functions, to allow real world discussions and analysis, several constraints are implemented. The most important of which are described here. Firstly, there is an energy conservation constraint for every HES and EV battery (cf. Eqs. 14 and (15) respectively). E^{act} hereby represents the actual energy content of the battery and E^{CH} as well as E^{DCH} are the corresponding energy values that are charged and discharged to and from the battery. Due to efficiency losses during charging and discharging the corresponding efficiency values η^{CH} and η^{DCH} are implemented. Ongoing energy losses due to self-discharge are represented by E^{SD} . Besides the energy conservation constraint for the HES, the EV's constraint also considers $E^{\text{EV,CH,ext}}$, which represents the energy that is charged into the EV battery externally (not at the household and not in the community). The last variable, $E^{\text{EV,dri}}$ represents the energy that is consumed during driving.

$$E_{n,t}^{\text{HES,act}} = E_{n,t-1}^{\text{HES,act}} + E_{n,t}^{\text{HES,CH}} \cdot \eta^{\text{HES,CH}} - E_{n,t}^{\text{HES,DCH}} \cdot \frac{1}{\eta^{\text{HES,DCH}}} - E_{n,t}^{\text{HES,SD}} \quad (14)$$

$$E_{n,t}^{\text{EV,act}} = E_{n,t-1}^{\text{EV,act}} + (E_{n,t}^{\text{EV,CH}} + E_{n,t}^{\text{EV,CH,ext}}) \cdot \eta^{\text{EV,CH}} - E_{n,t}^{\text{EV,DCH}} \cdot \frac{1}{\eta^{\text{EV,DCH}}} - E_{n,t}^{\text{EV,dri}} - E_{n,t}^{\text{EV,SD}} \quad (15)$$

Further constraints are included in the optimization algorithm. For instance, Eq. (16), which is the node constraint and ensures the energy conservation within each household. Therefore, all incoming energy flows must be equal to the outgoing energy flows. Other constraints

Table 1
Model parameters for the optimization algorithm, home energy storage system, electric vehicle (EV), and EV battery.

Parameter	Value	UOM	Parameter	Value	UOM
General			Electric vehicle & EV battery		
Sample time	0.25	h [33]	State of charge limitations	[5,95]	% [33]
Optimization period	24	h [25]	Battery efficiency	99	% [39]
Rolling horizon	12	h	Inverter efficiency	95	% [33,39]
Entities	1–50		Self discharge	0.6	%/month [33,39]
Annual electricity consumption	3500*	kWh [34]	Battery invest	800	EUR/kWh [27]
PV peak generation	10**	kWp	Cell temperature	25	°C [25]
Feed-in limit	70	%[35]	Electric vehicle & EV battery		
Grid charges	0.0739	EUR/kWh [36]	Cell chemistry	NMC	[40]
Distribution charges	0.0706	EUR/kWh [36]	Average consumption	189	Wh/km [40]
Electricity surcharges	0.1573	EUR/kWh [36]	Annual driving distance	13 600***	km [41]
Subsidized remuneration	0.0845	EUR/kWh [37]	Nominal energy content	65	kWh [40]
Non-subsidized remuneration	0.0280	EUR/kWh [38]	State of charge limitations	[4,96]	% [40]
Home energy storage system			Preferred minimum SOC	35	% [26]
Cell chemistry	LFP	[33]	Rated active power	11	kW [40]
Nominal energy content	7	kWh [33]	(Dis-)charging efficiency	89.4	% [42]
Rated active power	3.5	kW [33]	Self discharge	0.6	%/month [33,39]
			Battery invest	200	EUR/kWh [27]

* The values are normally distributed with a standard deviation of 500. ** The values are normally distributed with a standard deviation of 1. *** The values are normally distributed with a standard deviation of 1500.

ensure compliance with the technical limitations of the energy storages. For the HES and EV respectively, Eqs. 17 and (18) apply to the state of charge and Eqs. 19 and (20) ensure that the maximum charging and discharging power is not exceeded. For the EV, $P^{\text{EV,DCH}}$ is set to zero if the bidirectional charging is not permitted in the examined case and Eq. (20) ensures that the charging and discharging power remains zero if the vehicle is not connected ($x^{\text{plugged}} = 0$).

$$E_{n,t}^{\text{demand,local}} + E_{n,t}^{\text{demand,retail}} + E_{n,t}^{\text{PV}} + E_{n,t}^{\text{HES,DCH}} + E_{n,t}^{\text{EV,DCH}} = E_{n,t}^{\text{supply,local}} + E_{n,t}^{\text{supply,retail}} + E_{n,t}^{\text{Load}} + E_{n,t}^{\text{HES,CH}} + E_{n,t}^{\text{EV,CH}} \quad (16)$$

$$E^{\text{HES,nom}} \cdot \text{SOC}^{\text{HES,min}} \leq E_{n,t}^{\text{HES,act}} \leq E^{\text{HES,nom}} \cdot \text{SOC}^{\text{HES,max}} \quad (17)$$

$$E^{\text{EV,nom}} \cdot \text{SOC}^{\text{EV,min}} \leq E_{n,t}^{\text{EV,act}} \leq E^{\text{EV,nom}} \cdot \text{SOC}^{\text{EV,max}} \quad (18)$$

$$P_{n,t}^{\text{HES,CH}}, P_{n,t}^{\text{HES,DCH}} \leq P^{\text{HES,max}} \quad (19)$$

$$P_{n,t}^{\text{EV,CH}}, P_{n,t}^{\text{EV,CH,ext}}, P_{n,t}^{\text{EV,DCH}} \leq P^{\text{EV,max}} \cdot x_{n,t}^{\text{plugged}} \quad (20)$$

2.4. Model predictive control

At specified time intervals the optimization algorithm is executed. This model predictive control approach allows the re-evaluation of previous optimizations based on updated input data [25]. In our framework, the optimization horizon for the EMS is 24 hours to follow a full day-and-night cycle. With each new evaluation of the optimization, the algorithm is fed with updated data that lies further in the future to determine the optimal operating strategy for all flexibilities and to calculate the best offers for every household. These offers and transactions for future time steps are permitted and, once made, must be considered in future evaluations of the EMS.

In this simulation, perfect foresight information is used for electricity demand, PV generation, and EV usage patterns. However, in a real world application, these input profiles would be prediction values underlying uncertainty. To deal with the inherent uncertainty, the rolling horizon can be adjusted according to the quality of the prediction data. Thus, the strength of the model predictive control comes into play, and already optimized operation strategies are reevaluated with each update of prediction values.

2.5. Battery degradation models

We differentiate between two cell chemistries in this contribution. For the HES, a battery cell technology with a lithium-iron-phosphate (LiFePO₄) cathode is applied, which is a suitable and widely used cell chemistry for stationary storages due to its high cycle stability [27]. Due to the requirement to use battery cells with a high energy density in mobile applications [28], for the EV, established cells with lithium-nickel-cobalt-manganese-oxide (LiNiCoMnO₂) cathode material are used [29]. To consider both, calendar [30] and cycle [31] degradation processes within the two different cell technologies with graphite anodes, specific degradation models are applied. The calculation for the capacity fade in both models is examined via the battery cells' physical conditions: lifetime, temperature, voltage, and current [29]. Because of nonlinear degradation mechanisms and battery safety conditions at lower state of health levels, the end-of-life for the stationary and mobile batteries was defined as 80% [32].

2.6. Design of simulations and input data

The results of this study are based on 1903 different parameter sets (cf. Table 1). For each of the scenarios, six use cases are simulated with varying market schemes – reference (no local market), decentral, and central – and EV connection schemes – unidirectional and bidirectional. The network size ranges from one to 50 households [1:1:10,15:5:50] and the penetration rate of the technical equipment – PV generators, HES, and EV – varies from zero to one hundred percent [0%:20%:100%]. With these scenario variations, 38,892 households, 25,928 PV generators, 12,964 home energy storages, and 19,446 EVs are simulated for each case. The data and code for this study is available upon release of the paper.

For the optimization framework four profile sets are used. The energy demand of the household is derived from one-year real measurement data of German households [43]. In addition, the generation profiles from the photovoltaic (PV) generator is derived from one-year real measurement data of a PV system installed in Munich, Germany [33]. The necessary profiles for the electric vehicle (EV) are derived from the Python tool *emobpy* [44]. From *emobpy* the two profile sets for the electricity consumption during driving and the availability time series at the household were used to conduct the study. Computational time strongly varied with the complexity of the optimized case, lying between three and 20 minutes per annual optimization case (on an Intel i7-7600U processor and 16 GB RAM).

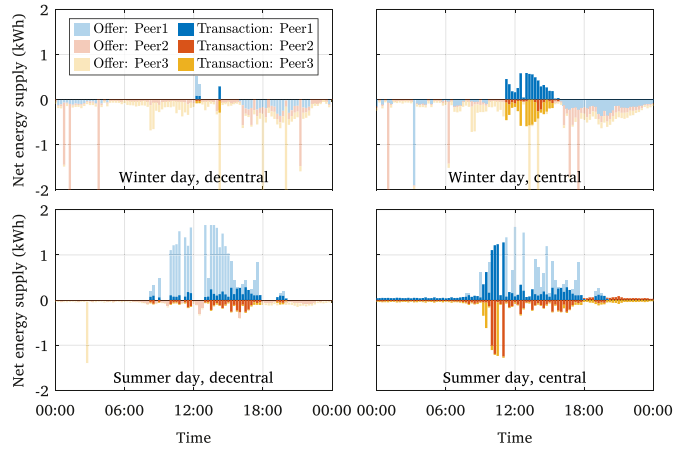


Fig. 3. Comparison of the net energy supply of a peer-to-peer network with three peers using a decentralized (left) and central (right) decision making approach. The top two figures show the results for an exemplary winter day and the bottom two figures for a typical summer day. The peers’ offers (pastel colors) for both approaches differ, as the flexibilities are utilized differently on a peer level. It can be seen that the transactions (bright colors) for three peers are more dominant in the central approach. In both approaches, peer 1 (blue) predominantly acts as an electricity supplier whereas peers 2 (red) and 3 (orange) act as net-consumers. Offers that are not matched in the local electricity market are traded with the electricity retailer. Due to the higher coexistence of supply and demand in summer, the locally traded energy is also significantly higher in this season.

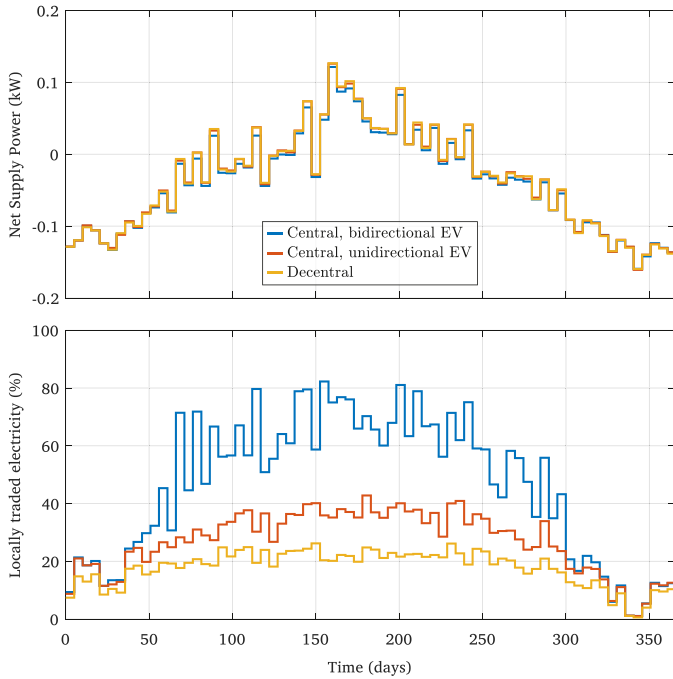


Fig. 4. The net supply power (top) of an exemplary scenario throughout a calendar year represents the net supply offers of an average peer within a local energy market. A clear increase during summer months shows the underlying effect of seasonality. The difference of the net supply power between the three cases comes from the different utilization of the flexibilities (energy storages) on a peer level. The share of locally traded electricity (bottom) distinguishes between the influence of seasonality and the effects of the network’s chosen decision making approach and electric vehicle (EV) operation scheme. Particularly during times of electricity surpluses, the central approach shows great economic advantages.

3. Results

We develop an optimization framework to evaluate the techno-economic effects on peer profitability and storage degradation within a P2P network. Our model comprises two main components: (i) the prosumer peers and their assets, and (ii) the coordination mechanism.

Prosumers have inflexible load and PV generation profiles, as well as sources of flexibility, in the form of stationary and mobile storages. Following [33] and [45], two EV connection schemes are considered: (i) unidirectional, in which the vehicle is charged only, and (ii) bidirectional, the vehicle can discharge to the building or grid (i.e. vehicle-to-X). Prosumers’ equipment penetration rates for PV, HES, and EV in the network vary across the scenarios. Although the parameters and input profiles are oriented around German households, the model can be applied to any region that has feed-in-tariffs schemes.

The technical objective of this work is to derive and validate a P2P trading platform where local electricity can be traded, so that the heterogeneity between peers increases the profitability for both the individual peer and the community as a whole, and reduces their collective reliance on energy imported from the bulk grid. The coordination mechanism we develop is a P2P training model, based on a matching procedure. Specifically, in this local energy market, all players can submit surplus energy supply or demand in the form of offers. Once cleared and matched with complementary offers, these become binding transactions. We consider two decision making approaches, decentralized and central. In the decentralized case, every household has a home energy management system (HEMS) that determines the offers made to the local energy market. In the central case, one community energy management system (CEMS) determines the offers for all households.

As a baseline, we also consider a reference case, in which a household’s power flows are optimized by the HEMS, but there is no local electricity market available for trading with peers.

3.1. Demonstration of peer-to-peer market mechanism

Our demonstration examines 1903 simulated scenarios that explore the influence of decentralized and central decision making for the energy management, at different levels of prosumer PV, HES, and EV penetration. To begin, we illustrate the rationale behind the coordination framework and the P2P mechanism, by considering results for an example network with three peers. These are given in Fig. 3, which shows the net energy supply in the form of the peers’ offers and transactions. This figure demonstrates that the offers in the decentralized and central approaches differ only slightly on the same winter or summer day, but significantly more transactions are made in the central case. This is explained by the superior information and greater optimization scope of the CEMS, which can utilize the flexibilities across prosumers to optimize the benefit for the entire community. In contrast, the HEMS’ available information and optimization scope is limited to one household and its flexibilities only. The benefit of the decentralized approach is that the participating households are not required to give the control of their flexibilities over to a central authority, nor share their supply and demand information. In addition, significantly more net supply is offered to the local market on a summer day than in the winter, due to the seasonal nature of PV generation, which results in a greater share of locally traded electricity in the summer (cf. Fig. 4 and Fig. 5).

We quantify the effects of the market mechanisms on a typical summer day in Table 2, which shows the key metrics for each peer in the reference, decentralized, and central cases. Across the three cases, the inflexible loads and PV generation are identical. The results show that the share of locally traded electricity is more than twice as high in the central case than the decentralized case, while the absolute cost reduction for both the decentralized and central cases is significant.

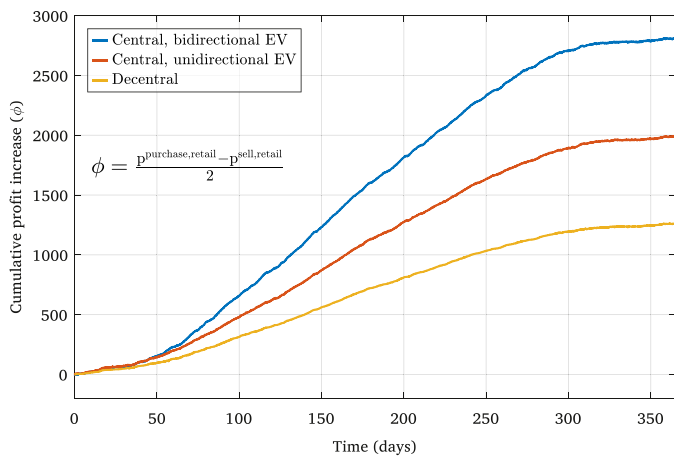


Fig. 5. Average profit increase of a peer within an exemplary scenario. The profit increase determines the economic added value compared to the same setting if no local energy market exists. Particularly during times of electricity surpluses of the peers' profit increase due to the local energy network shows high growth rates. ϕ represents the monetary incentive per peer to trade electricity locally.

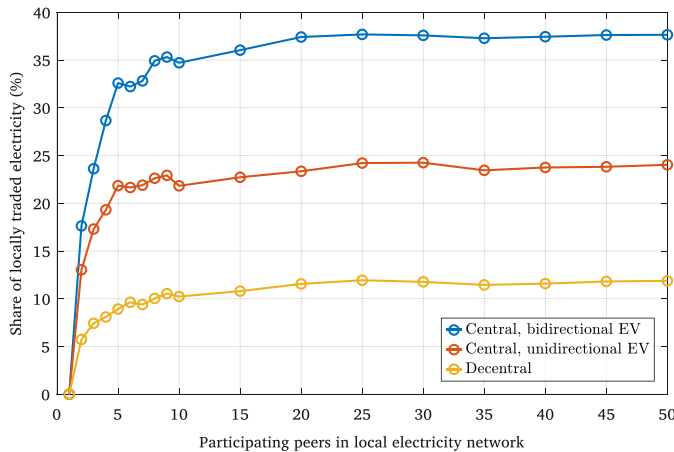


Fig. 6. The annual share of locally traded electricity in a peer-to-peer network by number of participating peers shows a saturating effect as the heterogeneity of peers declines with increasing network size. Scenarios differ in the decision making approach (central vs. decentral) and electric vehicle (EV) charging scheme (uni- vs. bidirectional).

3.2. Financial benefit of peer-to-peer trading

Building on the energy flow results, our financial results show that the benefits to individuals participating in a local P2P market are substantial, especially when decisions regarding the trading amount and trading partners are managed by a CEMS. Fig. 6 shows that the share of locally traded electricity increases strongly up to a network sizes of ten peers. There is a saturating effect up to 20 households, after which the share of locally traded electricity remains stable. This means that the marginal benefit per new peer is neither increasing nor decreasing; that is, constant returns to scale. This is a significant finding, because it shows that a community of twenty or more peers has no disadvantage in allowing additional participants to join the local energy market. Furthermore, the peers' incentive to form local markets is shown to be strong, even for small network sizes. The heterogeneity of households is the key especially in small communities, as offers are more likely to be matched when the inflexibilities of the households are dissimilar. With an increasing network size, it becomes more difficult to maintain heterogeneity, as the likelihood for similarities between the peers also rises.

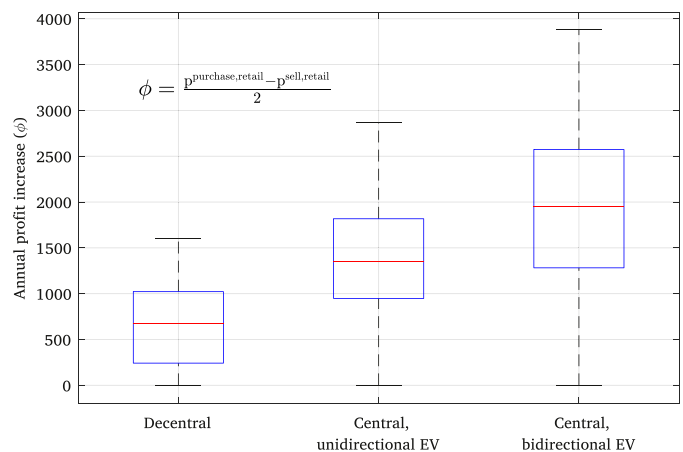


Fig. 7. Annual profit increase due to local peer-to-peer trading. The profit increase determines the economic added value compared to the reference case, where no local energy market exists. ϕ represents the monetary incentive per peer to trade electricity locally. The scenarios ($n=1,903$) were examined using different decision making approaches (central vs. decentral) and electric vehicle (EV) charging schemes (uni- vs. bidirectional).

As the share of locally traded electricity increases, the profitability on a community and peer level rises proportionally due to the preferable trading conditions on the local market. This monetary benefit per peer is measured in units of ϕ , the added value per kWh traded locally, as shown in Fig. 7. The local electricity price equals the midpoint of the gap between the electricity retailer's purchase and selling prices and forms the incentive for all peers to first trade locally. The central decision making by a CEMS yields the highest monetary benefit, because the authority to define the actions of all peers simultaneously enables the full exploitation of given heterogeneity and flexibility. Further improvements can be reached with bidirectional charging schemes for the EV, as the pool of flexibilities available to the community is expanded when the vehicles are permitted to discharge to the network. If the reference case (without P2P network) is already relatively profitable, i.e. in scenarios with high flexibility penetration, the potential for further profitability improvements through P2P trading declines.

3.3. Degradation costs of peer-to-peer trading

This article aims to provide empirical evidence on the financial and technical merits of local P2P market participation. Besides the need for a financial advantage, the concern of potential participants over reduced battery lifetimes due to P2P trading – especially where a central authority controls the peers' flexibilities – also needs to be assuaged.

Fig. 8 shows the distribution of the battery lifetimes for the EVs and HESs to compare the degradation effects of the decision making approaches. For cases with unidirectional EVs, the battery lifetime of both the stationary and mobile storages is extended in the central approach. This is highly significant, and explained by the lower average state of charge values in the central case, which positively affect the cell chemistries' calendar degradation. With bidirectional EVs, the battery lifetime of the HES is prolonged further in the central case, whereas that of the EV is reduced. Still the central bidirectional case consistently outperforms in terms of monetary benefit. The higher degradation results from the increased utilization of the EV batteries and corresponding rise in energy throughput and cycle degradation. Also, the transformation of EVs from flexible loads in the unidirectional case to bidirectional flexibilities, shifts energy throughput from the HES to the mobile storages. Significantly, due to the degradation awareness integrated in the model, the EMS considers the opportunity costs of energy throughput;

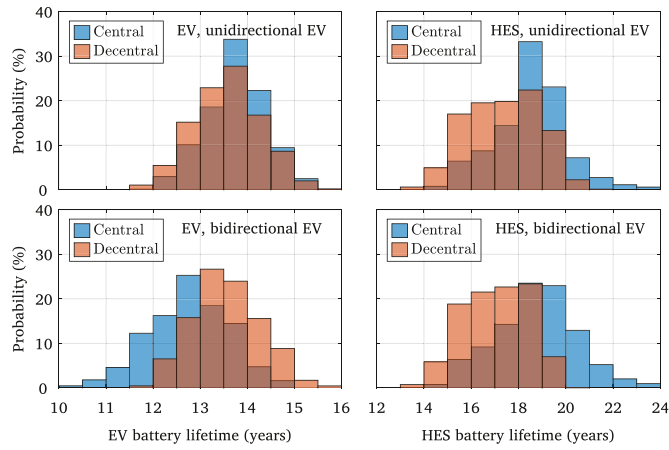


Fig. 8. Absolute change in battery lifetime of home energy storage (HES) and electric vehicle (EV) battery until reaching the end-of-life at 80% remaining capacity, compared to the reference scenario. For all scenarios, the reference case without local electricity market and the decentralized approach show very similar lifetime. In comparison to the other approaches, the central approach yields higher battery lifetimes for the HES, both in uni- and bidirectional EVs cases. The dark red areas depict the overlap of the two cases. For the EV battery lifetime the central approach shows a slight increase for unidirectional operated vehicles and a reduction in battery lifetime for the bidirectional use case. ($n_{EV}=19,446$, $n_{HES}=12,964$).

Table 2

Techno-economic results of an exemplary peer-to-peer (P2P) network with three peers and different market schemes for one summer day. The variation between the net demand of inflexibilities and offers comes from the charging and discharging of available flexibilities. Transactions represent the local offers that are matched within the community. The net electricity costs consider both the costs and revenue earned from trading electricity in the local P2P market and with the electricity retailer. The net electricity costs represent the costs minus the revenues from trading electricity. Negative values refer to the revenues that exceed the costs.

	Net supply (kWh)		Transaction	Locally traded	Net electricity costs (EUR)	Absolute cost reduction (EUR)
	Inflexibility	Offer				
P1	31.7	27.2			-0.58	
P2	-7.0	-7.0			0.53	
P3	-3.9	-4.0			0.30	
Reference	Σ 20.8	Σ 16.2			Σ 0.26	
P1	31.7	27.2	4.4	16%	-0.70	0.12
P2	-7.0	-7.0	-3.6	52%	0.43	0.10
P3	-3.9	-4.0	-0.8	20%	0.28	0.02
Decentral	Σ 20.8	Σ 16.2	Σ 0.0	Ø 29%	Σ 0.02	0.24
P1	31.7	24.6	12.8	52%	-0.85	0.28
P2	-7.0	-8.0	-8.0	100%	0.38	0.15
P3	-3.9	-4.8	-4.8	100%	0.22	0.08
Central	Σ 20.8	Σ 11.9	Σ 0.0	Ø 84%	Σ -0.25	0.51

thereby ensuring that the costs of the increased battery utilization are outweighed by its benefits.

There are no significant negative effects due to P2P trading when the decentralized approach is applied. This is explained in Fig. 9, which shows the same utilization of flexibilities in the reference and decentralized approaches. The only difference between the reference and decentralized case is that the latter trades electricity in the local P2P market before sending unmatched offers to the retailer, and the former only trades with the retailer. As a result, the stationary and mobile storages have the same degradation behavior with and without P2P trading when using a decentralized approach.

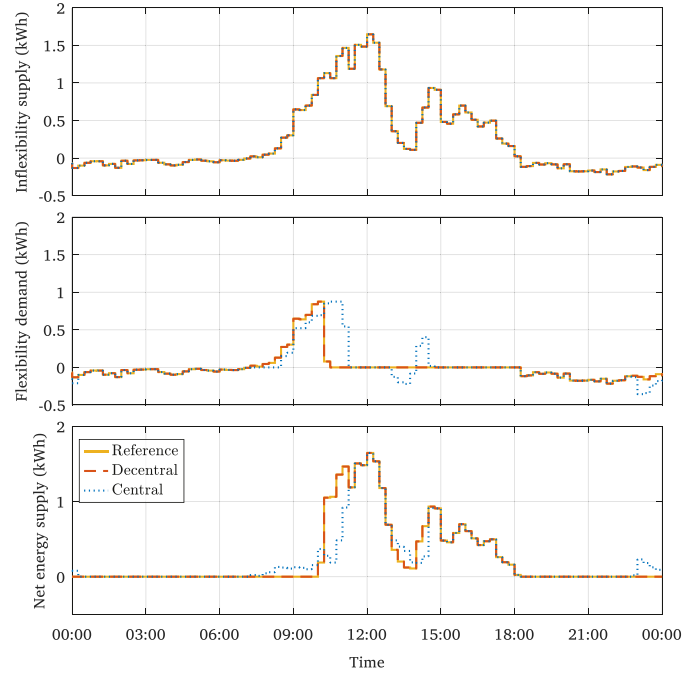


Fig. 9. Comparison of the three operation approaches – reference (no local market), decentral, and central – for the energy management system based on an exemplary day. The inflexibility energy supply (top) for all cases is the same. The flexibility demand (middle), to charge and discharge the storages, for the central approach differs from the other two approaches. Due to the equal utilization of the flexibilities, the reference and decentralized approach have the same net energy supply (bottom).

4. Discussion

Achieving the potential of this work involves addressing the social challenges of gaining user trust and acceptance [20]. Based on negative user experiences when P2P trading algorithms are opaque to users [22], we recommend that the local market designers make the mechanisms as simple, straight-forward, and transparent as possible. When market designs use dynamic price signals, arbitrage opportunities arise that are tempting to the sophisticated trader. However, to a risk averse prosumer household, the resulting complexity creates uncertainty whether they will be the winner or the loser of a trade. Our approach uses a fixed profit margin, equally distributed between trading parties. This way, it is easy for the participants to understand the benefit of trading, which will subsequently increase the likelihood of the households being convinced to participate. For policy makers who are interested in boosting the integration of renewables and the autarky of local grids, the authors recommend drafting policies that reduce or eliminate network charges and taxes on electricity traded between peers in a local market. This will further accelerate the proliferation of local P2P networks.

Despite the significant strengths, the results of this paper are limited by some assumptions. Firstly, the input profiles and parameters reflect German regulations. Secondly, network surcharges were neglected in favor of simplicity. Though these would reduce the magnitude of the trading incentive when deducted from the retail price corridor, the resulting behavior and share of locally traded electricity would not be influenced, as long as an incentive to trade locally remains. However, the published method can be applied to any region with a tariff structure and appropriately adjusted to reflect any existing surcharges. The scope of this article does not include effects on the electricity network, where storage and P2P trading [46] and network operator-coordinated battery dispatch [47] have been shown to contribute positively. Instead, we focus on P2P market approaches, with the community and its households as the primary stakeholders. Further research can build upon our

findings and explore the resulting effects on distribution grids and the distribution system operator's interests in local electricity markets.

As the central approach optimizes the benefit of the whole community, situations can arise where an individual household could be disadvantaged for the sake of the community. However, in over 99.99% of cases, this disadvantage is only momentary and outweighed by the advantages offered during a one year time period. The algorithm is not designed to prohibit that an individual can be placed at a disadvantage, as this would limit the degrees of freedom of the optimization. The threat, though negligible, of being put at a longer-term disadvantage might serve to prevent participation. Thus, it is extremely important that the business model or agreement implemented by the peers clearly defines how the generated community profit is distributed so that any provision of flexibility is remunerated appropriately. The large variety of possible business model designs and their realizations in practice present a fascinating area for further research.

5. Conclusions

Proof that the network benefits of peer-to-peer can be achieved with negligible degradation of customer assets is vital to the social acceptance that underpins such schemes. Our results provide empirical evidence for the techno-economic benefits that are possible with peer-to-peer trading when combined with home or community energy management systems. The strength of this model arises from the incorporation of 1903 scenarios, 38,892 households and consideration of specific battery cell chemistries. We show that the strongest financial potential is reached when a central authority controls the flexibilities in the network and electric vehicles are bidirectional. There are no reduced battery lifetimes in the central approach when electric vehicles are unidirectional, however, with bidirectional electric vehicles, peers need to take into account that the greater utilization of the electric vehicle battery comes at the cost of increased cycle degradation. For decentralized peer-to-peer markets, results show that local electricity trading does not affect battery lifetimes. We do not conclude which approach – central or decentral – is superior, instead evaluate their respective advantages and disadvantages. Depending on local conditions and participant preferences, market makers can apply these results and design a peer-to-peer trading market that best reflects participants' values. For instance, if independence from the electricity retailer and financial profit is prioritized in the local society, the central approach will offer a strong incentive to participate. Alternately, if participants are unwilling to share data with or cede control over their flexibilities to a central authority, the decentralized approach may foster greater acceptance and participation.

We suggest three priorities for future work necessary to realize the peer-to-peer benefits modelled by our findings: (i) This current modelling is based on the German energy market. Future work should seek to generalize the benefits of both approaches to other comparable markets, e.g. US, UK. (ii) Incentivizing customer participation is central to the success of any peer-to-peer network. Our study suggests two options suitable to cater for different user values in a specific deployment context, e.g. the desirability of a centralized approach if users value independence from electricity retailers, versus a decentralized approach which may be more favorable to a community who values control over their flexibilities. Prior to implementation, economic modelling should be complemented by social research targeting user values and local drivers of smart energy technology adoption. (iii) While beyond the scope of this present paper, further work is also vital into the effect of both approaches on grid operation and distribution systems. Bidirectional charging can be problematic for local grid management when deployed at scale and this effect should be modelled prior to implementation.

Declaration of Interests

The authors declare no competing interests.

CRedit authorship contribution statement

Stefan Englberger: Conceptualization, Validation, Writing – original draft, Methodology, Funding acquisition. **Archie C. Chapman:** Validation, Writing – original draft. **Wayes Tushar:** Writing – original draft. **Tariq Almomani:** Conceptualization, Investigation, Resources, Validation, Writing – original draft, Methodology, Resources, Formal analysis. **Stephen Snow:** Writing – original draft. **Rolf Witzmann:** Supervision, Funding acquisition. **Andreas Jossen:** Supervision, Funding acquisition. **Holger Hesse:** Conceptualization, Validation, Methodology, Resources, Formal analysis.

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